Variability in Recreational Runners – A Stride Time Analysis Perspective

Michelle Norris B.Sc.

A thesis submitted to the University of Limerick in fulfilment of the requirements of the degree of Doctor of Philosophy

Supervisors: Dr. Ross Anderson and Dr. Ian C. Kenny

Submitted to the University of Limerick June 2017
Abstract

Title: Variability in recreational runners – A stride time analysis perspective.

Author: Michelle Norris

Accelerometers provide a method of collecting longitudinal running stride time (ST) and stride rate (SR) data; however, research is required to develop methods and analysis techniques which ensure the collection of valid data, interpreted correctly. The purpose of this thesis was to investigate and develop methods of collecting temporal gait data using accelerometry, in recreational distance runners. Furthermore, we wished to apply these methods to investigate SR, as a coaching orientated parameter, and ST variability, as a research orientated parameter.

Methods development was undertaken in which accelerometry self-attachment protocols and technical and processing issues which may affect ST calculation in accelerometry data were investigated. A novel method of ST calculation, utilising 2 Hz filtering, was developed which indicated good comparability to previous methods (ICCs > 0.95 and CV values < 1.5%). Following this, the methods developed were utilised to investigate SR in recreational runners during training runs, and both half and full marathon distances. Results indicated that performing with a comparable or decreased SR (compared to a similar training run) within a competitive distance running event may result in an optimal running style in relation to overall run outcome. The remaining sections of the thesis focused on ST as a research orientated parameter.

Long range correlations within running ST series have previously been linked with both injury and performance level, utilising the non-linear method Detrended Fluctuation Analysis (DFA). However, prior to implementing DFA on outdoor running time series, an investigation into how robust DFA is to outliers, which may occur due to perturbations or changes in terrain, was performed. Hereafter, DFA was applied to recreational runner's half and full marathon ST series. No significant differences ($p > 0.05$), and small (ES = 0.35) and medium (ES = 0.46) effect sizes, were identified between recreational runner's half marathon and full marathon DFA $\alpha$ values and SR, indicating that recreational runners adopt similar stride parameters when undertaking half and full marathon events, despite extended training periods. This information enhanced our knowledge of DFA during distance running, however due to extended processing times more efficient methods of utilising DFA were required. Therefore, a running analysis system was developed resulting in the output of reoccurring, real-time DFA $\alpha$ values during prolonged running. Preliminary investigation indicated output of DFA $\alpha$ values within 10 s of predetermined running time periods, enabling researchers to give real-time DFA feedback, during a prolonged run.

Overall this thesis represents a body of work encapsulating methods development, investigation into both coaching and research parameters of temporal gait and the development of a running gait analysis system. The research outlined has both sporting and clinical practical implications as the running gait methods developed can be utilised by future researchers and clinicians.
Authors Declaration

I hereby declare that the work contained in this thesis is my own, and was completed under the supervision of Dr. Ross Anderson and Dr. Ian Kenny of the Department of Physical Education and Sport Sciences, University of Limerick. This work has not been submitted to any other university or higher education institution, or for any other academic award within this University.

Furthermore within this thesis there are three published articles:


----------------------------------
Michelle Norris

----------------------------------
Dr. Ross Anderson

----------------------------------
Dr. Ian Kenny
Acknowledgements

I would like to thank all those who supported me throughout the completion of my doctoral studies. Your support has been unwavering, and has not gone unnoticed or unappreciated.
# Table of Contents

Abstract ................................................................................................................................................ i
Authors Declaration ...................................................................................................................... ii
Acknowledgements ...................................................................................................................... iii
List of Tables ..................................................................................................................................... x
List of Figures ................................................................................................................................  xii
List of Appendices ........................................................................................................................ xv
List of Abbreviations ................................................................................................................... xv
Submissions and publications arising from and related to the thesis ................... xvii
Awards ......................................................................................................................................... xviii

Chapter 1. Thesis Introduction ..................................................................................................1
  1.1 Rationale ............................................................................................................................ 2
  1.2 Thesis aims ........................................................................................................................ 5
  1.3 Thesis overview .............................................................................................................. 5

Chapter 2. Literature Review .....................................................................................................9
  2.1 Literature review sectioning ............................................................................................ 10
  2.2 Literature review part A – Inertial sensor utilisation in running ...................... 10
    2.2.2 Abstract ...................................................................................................................... 10
    2.2.3 Introduction .............................................................................................................. 11
    2.2.4 Research methods .................................................................................................... 13
    2.2.5 Results ...................................................................................................................... 14
      2.2.5.1 Research orientated kinematic output parameters ......................... 15
      2.2.5.2 Tibial/shank acceleration ................................................................. 17
      2.2.5.3 Head acceleration ..................................................................................... 18
      2.2.5.4 Shock attenuation .................................................................................... 19
      2.2.5.5 Vertical parameters ............................................................................... 20
      2.2.5.6 Angular velocity ....................................................................................... 21
      2.2.5.7 Remaining parameters .......................................................................... 23
      2.2.5.8 Coach orientated kinematic output parameters ......................... 24
      2.2.5.9 Step/stride frequency/rate ............................................................... 26
      2.2.5.10 Temporal parameters ................................................................. 28
      2.2.5.11 Gait patterns ....................................................................................... 29
      2.2.5.12 Step/stride length ............................................................................... 31
      2.2.5.13 Remaining parameters .................................................................. 31
4.3.3 Training programmes .................................................................  73
4.3.4 Training log and discomfort questionnaire .................................  74
4.4 Results .........................................................................................  75
  4.4.1 Half marathon training programme adherence .......................  75
  4.4.2 Full marathon training programme adherence .......................  76
  4.4.3 Half marathon training and race ache, pain and discomfort profile .. 77
  4.4.4 Full marathon training and race ache, pain and discomfort profile... 78
  4.4.5 General health ........................................................................  79
4.5 Discussion ....................................................................................  79
  4.5.1 Adherence to training programmes .........................................  79
  4.5.2 Injury occurrence .................................................................  80
  4.5.3 Limitations ............................................................................  81
4.6 Conclusion ....................................................................................  81
4.7 Thesis context ..............................................................................  82

Chapter 5. Processing and technical issues with stride time calculation ...... 83
  5.1 Abstract ......................................................................................  84
  5.2 Introduction ..............................................................................  85
  5.3 Methods ...................................................................................  89
    5.3.1 Data selection .................................................................  89
    5.3.2 Data alteration ...............................................................  90
    5.3.3 Data analysis .................................................................  91
  5.4 Results ....................................................................................  92
  5.5 Discussion ..............................................................................  93
    5.5.1 Sinewave data ...............................................................  93
    5.5.2 Tibial accelerometry data ..............................................  94
  5.6 Conclusion ..............................................................................  95
  5.7 Thesis context ...........................................................................  95

Chapter 6. Stride time calculation methods ...................................... 97
  6.1 Abstract ...................................................................................  98
  6.2 Introduction ..............................................................................  98
  6.3 Methods .................................................................................. 100
    6.3.1 Participants ................................................................. 100
    6.3.2 Instrumentation ............................................................ 101
    6.3.3 Data processing ........................................................... 101
    6.3.4 Data analysis ............................................................... 104
Chapter 9. Recreational runners’ stride time and stride rate variability: a half and full marathon comparison .......................................................... 155
  9.1 Abstract ................................................................................................. 156
  9.2 Introduction ............................................................................................ 156
  9.3 Methods .................................................................................................. 160
    9.3.1 Participants ....................................................................................... 160
    9.3.2 Instrumentation .................................................................................. 160
    9.3.3 Data analysis ..................................................................................... 161
    9.3.4 Statistical analysis .......................................................................... 161
  9.4 Results ..................................................................................................... 161
  9.5 Discussion ............................................................................................... 165
    9.5.1 Distributional measures .................................................................. 166
    9.5.2 Stride-to-stride variability ................................................................. 167
    9.5.3 Stride rate ......................................................................................... 168
    9.5.4 Limitations ...................................................................................... 169
  9.6 Conclusion ............................................................................................... 169
  9.7 Thesis context .......................................................................................... 170

Chapter 10. Design, verification and validation of an advanced running analysis system .................................................................................. 171
  10.1 Abstract ................................................................................................. 172
  10.2 Introduction ............................................................................................ 173
  10.3 System description .................................................................................. 174
    10.3.1 Pre-data collection process ............................................................... 175
    10.3.2 Data collection initiation ................................................................ 177
    10.3.3 Accelerometry text file generation .................................................. 178
    10.3.4 Data processing and DFA calculation ......................................... 179
  10.4 System verification experimental protocol .............................................. 180
  10.5 Results .................................................................................................... 182
  10.6 Discussion ............................................................................................... 184
  10.7 Conclusion ............................................................................................... 185
  10.8 Thesis context .......................................................................................... 186

Chapter 11. Thesis conclusions and implications ............................................ 187
  11.1 General discussion ................................................................................ 188
  11.2 Delimitations and limitations .................................................................. 189
    11.2.1 Focus on temporal gait parameters .............................................. 189
List of Tables

Table 2.1 Research orientated kinematic output article details.................................16
Table 2.2 Coach orientated kinematic output parameters ........................................25
Table 2.3 Stride variability measures identified..........................................................41
Table 3.1 Absolute difference in right and left leg pitch, roll and yaw angles between tester (v1) and participant (r1) attachment. ...................................56
Table 3.2 Bland – Altman results for right and left leg pitch, roll and yaw angles between tester (v1) and participant (r1) attachment. .....................60
Table 3.3 Intra-tester (v1) attachment reliability and intra-participant (r1) attachment reliability. ..........................................................................................61
Table 3.4 Mean tilt angle, absolute differences and range for participant reliability tilt angle measures across r1, r2 and r3. ......................................62
Table 4.1 Suggested running ability for undertaking the Hal Higdon Novice 2 Half Marathon Training Programme and the Hal Higdon Novice 2 Full Marathon Training Programme...............................................................73
Table 4.2 Example of week 1 to week 3 of the Hal Higdon Marathon Novice 2 Training Programme. “Cross” refers to cross-training...............................74
Table 4.3 Total number of times aches, pains or injuries which were reported in specific locations during the half marathon training programme and competitive event..................................................................................................................77
Table 4.4 Total number of times aches, pains or injuries which were reported in specific locations during the full marathon training programme and competitive event..................................................................................................................78
Table 5.1 Average stride time (s) calculated for raw sinewave data, sinewave data 2 Hz filtered, and sinewave data clipped and 2 Hz filtered.................92
Table 5.2 Average stride time (s) for raw tibial accelerometry data, 2 Hz filtered tibial accelerometry data, and clipped and 2 Hz filtered tibial accelerometry data. Reliability analysis results including standard error, coefficient of variance and intra-class correlation coefficient for comparison of the three variations of the tibial accelerometry dataset.93
Table 6.1 Stride time (s) calculations for all participants. a indicates the greatest difference in stride time, whilst b indicates no difference in
stride time, compared to proposed M1. The greatest and least SD values are also denoted in bold. .................................................................104

Table 6.2 Reliability statistics (standard error, coefficient of variance (%) and intra-class correlation coefficients) calculated using the proposed method (M1) against the remaining three methods (M2, M3 and M4). 106

Table 7.1 Comparative training and competitive run information for group analysis. .........................................................................................................................114

Table 7.2 Training and competitive speed, stride rate and temporal results...119

Table 7.3 Half marathon, full marathon and the 1st half of full marathon temporal, stride rate and RPE result.................................................................125

Table 7.4 Full marathon (FM) stride rate results for each run section identified via race chip timing information.................................................................127

Table 9.1 Group stride interval and stride rate characteristics for half marathon and full marathon splits. Mean values presented with range in parentheses.................................................................164

Table 10.1 Pre-data collection user input parameters. ..............................................176

Table 10.2 Number of strides (n), difference in elapsed time ∆t (s) and α value output time, and DFA α values over three running conditions at 80 % PRS, PRS and 120 % PRS.................................................................183
List of Figures

Figure 1.1 Thesis flowchart ........................................................................................................ 8

Figure 2.1 Flow chart describing the selection and exclusion of articles for inertial sensor utilisation in running .................................................................................................14

Figure 2.2 Flow chart describing the selection and exclusion of articles for stride time variability calculation measures ................................ ................................... 39

Figure 2.3 Jordan et al. (2006) representative running trial displaying the slope of the line (α) relating the log of the average window size (n) to the log of the average fluctuation size (F(n)). ................................................... 43

Figure 3.1 Shimmer 2r™ accelerometer (Abbate et al. 2014) ........................................52

Figure 3.2 Bi-lateral accelerometer attachment to the anteromedial distal tibia. On a concentrated section of the right tibia, positive axial directions of the accelerometer local coordinate system when attached are superimposed in bold arrows, with vertical and lateral directions of the lower limb global coordinate system superimposed in dashed arrows...........................................................................................................................................53

Figure 3.3 Timeline outlining intervals between data collection sessions .......... 54

Figure 3.4 Bland-Altman plots for tester-participant reliability in (a) RightPitch, (b) RightRoll, (c) RightYaw, (d) LeftPitch, (e) LeftRoll and (f) LeftYaw angles ....................................................................................................................................................59

Figure 4.1 Timeline outlining data collection periods for both half marathon and full marathon training programmes and races ................................................................. 71

Figure 4.2 Comparison of scheduled programme runs, completed runs and runs recorded for the half marathon training programme ..................................75

Figure 4.3 Comparison of scheduled programme runs, completed runs and runs recorded for the full marathon training programme ..................................76

Figure 5.1 Sample mediolateral accelerometry data during running in raw format and filtered with a 18 Hz filter cut off, a 9 Hz filter cut off and a 2 Hz filter cut off ....................................................................................................................................................88

Figure 5.2 Data alteration process for sinewave data identifying comparison datasets 1, 2 and 3 ....................................................................................................................................................90

Figure 5.3 Data alteration process for tibial acceleration data ........................................91
Figure 6.1 Acceleration patterns (m·s$^{-2}$) for a representative two second running trial utilising Method 1 (M1) for stride time calculation. Identification of beginning/end of stride times as identified by the circle.

Figure 6.2 Acceleration patterns (m·s$^{-2}$) for a representative two second running trial utilising Method 2 (M2) for stride time calculation. Identification of beginning/end of stride times as identified by the circle.

Figure 6.3 Acceleration patterns (m·s$^{-2}$) for a representative two second running trial utilising Method 3 (M3) for stride time calculation. Identification of beginning/end of stride times as identified by the circle.

Figure 6.4 Acceleration patterns (m·s$^{-2}$) for a representative two second running trial utilising Method 4 (M4) for stride time calculation. Identification of beginning/end of stride times as identified by the circle.

Figure 7.1 Single participant timeline for training programmes (TP) and run occurrence.

Figure 7.2. Raw tri-axial acceleration pattern during a 5 second period for the same subject during (a) half marathon (HM), (b) full marathon (1st half) (FM1) and (c) full marathon (2nd half) (FM2).

Figure 7.3 Comparison of 1% epoch stride rates for competitive and training runs. The unbroken diagonal line inserted representing no change in stride rate between competitive and training runs at that percentage epoch.

Figure 7.4 Comparison of 1% epoch stride rates for half marathon (FM) and the 1st half of the full marathon (FM1). Diagonal line inserted representing no change in stride rate between R1 and R2$^{\text{half}}$ at that percentage epoch. $\text{R1} =$ first third of run, $\text{R2} =$ second third of run, $\text{R3} =$ last third of run.

Figure 7.5 Stride rate values at 1% time epochs for the full marathon (FM). $+$ = Start to 21.1 km, $0 =$ 21.1 km to 30 km, $-$ = 30 km to End.

Figure 8.1 (a) Heart beat interval data from Peng et al. (1994). (b) During DFA $\alpha$ calculation the heart beat interval data are split into non-
overlapping boxes of 100 heart beat intervals and detrended using a
least fit squares................................................................. 137

Figure 8.2 DFA α values for unaltered stride time series with (a) 600, (b) 3,000
and (c) 10,000 stride values......................................................... 142

Figure 8.3 DFA α values produced when stride time series, of length 600 stride
and 1/f patterning, is altered by adding various magnitudes of
variance to various amounts of strides........................................ 144

Figure 8.4 Enlarged section of DFA α values for stride series length of 600
strides......................................................................................................... 145

Figure 8.5 DFA α values produced when stride time series, of length 3,000
strides and 1/f patterning, is altered by adding various magnitudes of
variance to various amounts of strides........................................ 147

Figure 8.6 Enlarged section of DFA α values for stride series length of 3,000
strides......................................................................................................... 148

Figure 8.7 DFA α values produced when stride time series, of length 10,000
strides and 1/f patterning, is altered by adding various magnitudes of
variance to various amounts of strides........................................ 150

Figure 8.8 Enlarged section of DFA α values for stride series length of 10,000
strides......................................................................................................... 151

Figure 8.9 (a) Original stride series length of 600 with1/f patterning (α = 1.02).
(b) Stride series length of 600 strides with 10% of strides
altered with a magnitude of ≤30% (α = 0.98)........................................ 153

Figure 9.1 Number of stride times analysed for half marathon (HM) and full
marathon (FM1 and FM2) groupings.................................................. 162

Figure 9.2 Stride time long range correlation α and stride rate values (strides
min⁻¹) for all participants for 21.1 km distance, as covered in the
competitive Half Marathon and Full Marathon groupings. * indicates
the participant which ran in both the half marathon and full marathon.165

Figure 10.1 System image.......................................................................................... 177

Figure 10.2 Process of data merging and cutting.................................................. 179

Figure 10.3 Data collection, analysis and output timeline of the running
analysis system. Visuals A1 – A12 indicate automatic data analysis
initiation........................................................................................................ 181
List of Appendices

Appendix A: Ethical Approval
Appendix B: Subject Manual Sample
Appendix C: Participant Recruitment Email
Appendix D: Hal Higdon Half Marathon Novice 2 Training Programme
Appendix E: Hal Higdon Full Marathon Novice 2 Training Programme
Appendix F: LabVIEW™ Screenshot
Appendix G: Running analysis system – MATLAB™ script (sample)
Appendix H: Published Articles

List of Abbreviations

2D Two dimensional
3D Three dimensional
9DOF Nine degrees of freedom
AMU Acceleration measurement unit
ANOVA Analysis of variance
CMC Coefficient of multiple correlation
CV Coefficient of variation
COM Centre of mass
DFA Detrended fluctuation analysis
FM Full marathon
FM1 Full marathon (1\textsuperscript{st} half)
FM2 Full marathon (2\textsuperscript{nd} half)
GPS Global positioning system
HM Half marathon
HZ Hertz
ICC Intra-class correlation
IMU Inertial measurement unit
IT Illiotibial
M1 Method 1
M2 Method 2
M3 Method 3
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>M4</td>
<td>Method 4</td>
</tr>
<tr>
<td>MEMS</td>
<td>Microelectromechanical systems</td>
</tr>
<tr>
<td>MSE</td>
<td>Multiscale entropy</td>
</tr>
<tr>
<td>PCA</td>
<td>Principal component analysis</td>
</tr>
<tr>
<td>PCT</td>
<td>Predicted completion time</td>
</tr>
<tr>
<td>PRS</td>
<td>Preferred running speed</td>
</tr>
<tr>
<td>PSD&lt;sub&gt;head&lt;/sub&gt;</td>
<td>Power spectral density of the head</td>
</tr>
<tr>
<td>PSD&lt;sub&gt;leg&lt;/sub&gt;</td>
<td>Power spectral density of the leg</td>
</tr>
<tr>
<td>R1</td>
<td>Reliability session 1</td>
</tr>
<tr>
<td>R2</td>
<td>Reliability session 2</td>
</tr>
<tr>
<td>R3</td>
<td>Reliability session 3</td>
</tr>
<tr>
<td>RES</td>
<td>Euclidean resultant</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
</tr>
<tr>
<td>RPE</td>
<td>Rate of perceived exertion</td>
</tr>
<tr>
<td>RRI</td>
<td>Running related injury</td>
</tr>
<tr>
<td>SEM</td>
<td>Standard error</td>
</tr>
<tr>
<td>SD</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>ST</td>
<td>Stride time</td>
</tr>
<tr>
<td>SR</td>
<td>Stride rate</td>
</tr>
<tr>
<td>TC</td>
<td>Time to completion</td>
</tr>
<tr>
<td>V1</td>
<td>Validity session 1</td>
</tr>
<tr>
<td>V̇o2</td>
<td>Maximal oxygen consumption</td>
</tr>
</tbody>
</table>
Submissions and publications arising from and related to the thesis

Peer-reviewed journal articles


Book chapters

Peer-reviewed conference publications


**Awards**

2016 ------ Finalist for the national Higher Education Authorities “Making an Impact” research competition – Abstract entitled “The weekend warrior”.

2015 $500 Force and Motion Travel Poster Award October 2015 – Awarded for ‘Comparison of accelerometry stride time calculation methods’.

2015 $500 Force and Motion Travel Poster Award July 2015 – Awarded for ‘Marathon stride rate dynamics: a case study’.
Chapter 1. Thesis Introduction
1.1 Rationale

In the U.S alone, in 2015, there were 1,001 marathon events (Running USA 2015), with running now one of the most popular challenges worldwide. The median finishing time for U.S marathons has increased by over 42 minutes for female runners (4:03 hrs to 4:46 hrs) and over 47 minutes for male runners (3:32 to 4:20) from 1980 to 2015, indicating an increase in recreational runner participation (Running USA 2015). Additionally, recreational runners as a cohort vary considerably with recreational marathon runners running significantly more mileage per week (44.7 km compared to 33.7 km, \( p<0.001 \)), running for significantly more time per week (4.8 hours compared to 3.9 hours, \( p<0.01 \)) and having significantly more experience (\( p<0.05 \)) than their recreational half marathon runner counterparts (Zillman et al. 2013). This has led to an increased need for research investigating the recreational running population, to gain a better understanding of the biomechanical techniques and alterations which occur when training for distance running events.

To undertake such research, it is beneficial that data collection is performed in an ecologically valid environment, to ensure results can be appropriately interpreted and are representative of the running patterns which recreational runners produce normally. Whilst laboratory settings provide a controlled environment in which conditions such as temperature (Adams et al. 1975), running terrain (Warren et al. 1986) and running speed (Mercer et al. 2002) can be controlled, altered and easily monitored, often these conditions can also be representative of ideal conditions, dependent on the variable being examined. Also, laboratory testing and equipment is a new experience for many participants (Kerr et al. 2006), and has previously been identified as threatening, increasing arousal and anxiety (Gale and Baker 1981). For recreational runners, an ecological environment in which they are familiar and comfortable is mainly represented by outdoor, overground running; a common training method employed when training for distance running events (Mooses et al. 2015, Wang 2015). Collecting biomechanical data within this environment poses increased difficulties than within a laboratory, due to the presence of unknowns and uncontrollable variables such as weather changes and altering terrain. However, the rich, ecologically valid
data that can be collected provides researchers with a true reflection of runners’ habits and running style.

Whilst footswitches have previously been utilised to derive temporal running parameters (Alvim et al. 2015), this is primarily during acute running sessions as they have been identified to not be mechanically robust over longitudinal periods and may cause discomfort to participants (Willemsen et al. 1990). Recently, inertial sensors such as accelerometers and gyroscopes have provided a popular method for collecting longitudinal running gait (Giandolini et al. 2016; Reenalda et al. 2016; Norris et al. 2014) as they are inexpensive, lightweight and can be used with relative ease outdoors. The data collected by inertial sensors, particularly accelerometers, can be utilised to derive a multitude of running parameters, useful to both coaches and researchers alike such as stride time, tibial acceleration, vertical displacement and shock attenuation (Norris et al. 2014). Of these, the temporal gait parameters of stride time (ST) and stride rate (SR) are of particular interest, primarily due to their influence on overall run outcome, and also as ST is becoming increasingly popular within investigations into the intrinsic dynamics of running (Jordan et al. 2006; Meadon et al. 2010; Fuller et al. 2016a). Intrinsic dynamics are defined as “the qualitative organisation of the state space that the system returns to following a perturbation from internal or external demands” (Vaillaincourt and Newell 2002, pg. 7), and within running, investigating intrinsic dynamics divulges information regarding runners’ stride time variability (Meardon et al. 2011) and complexity (Costa et al. 2003) amongst some parameters.

When utilising accelerometers to collect ST and/or SR data it is vital the correct hardware and software protocols are utilised to ensure valid, reliable data (Chen and Bassett 2005). Factors such as accelerometer placement location (Norris et al. 2014), accelerometer alignment with the limb of interest (Gietzelt et al. 2011), and processing techniques such as filtering (Maiwald et al. 2015) can all impact calculation of temporal gait parameters. Importantly however, research on the extent of this impact is currently limited. Along with this, accelerometer data requires extensive processing to derive discrete parameters, particularly with increased sampling rates and longitudinal data collection sessions. Efforts have been made to develop methods which increase accelerometry processing efficiency in relation to temporal gait parameters (Maiwald et al. 2015 & Capela et al. 2015),
however outdoor running can pose additional complications due to repetitive high impacts altered by factors such as changes in terrain and running speed (Giandolini et al. 2015). Therefore, further research should be performed to advance temporal gait parameter calculations in running accelerometry data.

Moving forward, when valid ST and SR values can be calculated from accelerometry data both parameters may provide important information regarding the ability and coordination of recreational runners when training for and undertaking distance running events. Recently, Lieberman et al. (2015) queried the previously suggested metabolically "optimal" SR of 90 strides min\(^{-1}\) in experienced endurance runners, suggesting a SR of 85 strides min\(^{-1}\) should in fact be used. Lieberman et al. (2015) identified 85 strides min\(^{-1}\) as the intersection between the cost of breaking forces and hip flexor moments during swing, subsequently suggesting this as the metabolically optimal SR. However, this research was completed during 5-minute running periods, which are not reflective of the running habits of recreational runners. Furthermore, ST has been identified to reveal information regarding the intrinsic running dynamics of runners, using Detrended Fluctuation Analysis (DFA) to measures variability within running stride time series. However, DFA has only been used in a limited number of running studies (Fuller et al. 2016a; Fuller et al. 2016b; Meardon et al. 2011; Nakayama et al. 2010; Jordan et al. 2006) perhaps due to the extensive number of stride times required (>500) and its complex nature, both in terms of analysis and interpretation. Whilst preliminary research indicates DFA can distinguish between trained runners and non-runners and identify runners who have been previously injured from their previously uninjured counterparts (Meardon et al. 2011), increasing the application of DFA by future researchers will allow for further development of our understanding of how this method can be used and applied in coaching, research and clinical settings.

Overall, advancing methods in accelerometry processing techniques in distance running will allow future researchers to efficiently calculate advanced, non-linear gait information and key indicators of performance and injury. Additionally, much research investigating recreational runners focuses on prospective and retrospective questionnaire based investigations into training habits and injury
onset (Junior et al. 2013 & Videbaek et al. 2015). Recreational runners can therefore be overlooked in distance running research investigating temporal kinematics; however this information may impact our knowledge of how they train and how they perform in competition.

1.2 Thesis aims

The aims of this thesis were:

1) To develop efficient and accurate methods of acquiring large accelerometry files during running, whilst investigating methods to calculate stride time from these files, and the factors which may affect this.

2) To apply these methods, and knowledge gained through a review of the literature, to a population of recreational runners training for and competing in distance running events, investigating coaching (SR) and research (ST variability) orientated parameters.

3) Develop a real-time advanced running analysis system focusing on stride time variability.

1.3 Thesis overview

The thesis is primarily divided into five sections (Figure 1.1):

- Section 1: Literature review

  Section one provides an overall review of previous literature outlining what is known surrounding the topics covered within this thesis and identifying any gaps in the knowledge. Within this review topics covered include the use of inertial sensors in running analysis and the parameters which inertial sensors can identify. Additionally, as this thesis will concentrate further on stride time, there is then a focus on stride time variability measures currently utilised within the literature. This section provides the basis for outlining the methodology utilised to collect longitudinal temporal gait measures in recreational runners, and also the application of suitable variability measures.
• **Section 2: Methods development and data collection**
Section two incorporates Chapter 3, Chapter 4, Chapter 5 and Chapter 6 and investigates methodological protocol development, longitudinal data collections and an investigation into subsequent data analysis issues. This section firstly identifies the effect that self-attachment protocols may have on tibial accelerometry data. After this two longitudinal data collection periods are undertaken and an investigation into how processing issues such as data saturation and filtering effect accelerometry data is undertaken. Based off these issues a novel method of stride time calculation was then developed and validated. This section provides support for our methods used, protocols implemented and data analysis methods utilised in further chapters.

• **Section 3: Stride rate analysis**
Having identified methods to collect accurate running accelerometry data and create stride time series, Section three (Chapter 7) provides an investigation into the coaching orientated parameter, stride rate. Section three identifies SR alterations which occur when recreational runners train for and compete in distance running events. This section answers the question “Do recreational runners’ stride rate patterns alter with the influence of competition as compared to a training environment?”.

• **Section 4: Stride time variability analysis**
The remaining chapters of the thesis focused purely on stride time variability, as there was little current research available surrounding this topic, and yet it had previously been linked with both performance (Nakayama *et al.* 2010) and injury (Meardon *et al.* 2010) in running. Therefore, Section four (Chapter 8 and Chapter 9) answers two primary questions, namely, (1): Is DFA a robust method of calculating stride time variability in longitudinal data, and (2): Do recreational runners’ stride time variability alter whether competing in half or full marathon distances.
• **Section 5: Real - time running analysis system development**
  Section Five (Chapter 10) investigates a proof of concept based on the development of a real-time feedback system, incorporating DFA. This system incorporates the methods derived from Section two, and is guided by the results of Section four. Whilst this section includes the development of the system, it also outlines the implementation of the system for bespoke single participant analysis when running at a preferred running speed (PRS), and speeds above and below this PRS.

• **Conclusion and future work**
  Lastly Chapter 11 provides a general discussion, conclusion and future work related to the findings within this thesis. This section details the application of the developed methods for athletes, coaches and practitioners.
SECTION ONE:
Chapter 2: Literature review

SECTION TWO:
Methods development and data collection
Chapter 3: Sensor self-attachment: A valid and reliable option?
Chapter 4: Longitudinal data collection and associated methodological issues
Chapter 5: Processing and technical issues with stride time calculation
Chapter 6: Stride time calculation methods

SECTION THREE:
Stride rate analysis
Chapter 7: Stride rate dynamics in distance running: Training and competition

SECTION FOUR:
Stride time variability analysis
Chapter 8: The effect of additional variance on Detrended Fluctuation Analysis (DFA)
Chapter 9: Recreational runners stride interval and stride rate variability: A full and half marathon comparison

SECTION FIVE:
Real-time running analysis system development
Chapter 10: Design, verification and validation of an advanced running analysis system
Chapter 11: Thesis conclusions and implications

Figure 1.1 Thesis flowchart.
Chapter 2. Literature Review
2.1 Literature review sectioning

This thesis aims to answer questions related to the methodology employed when collecting longitudinal running data, the analysis applied to this data post data collection and the subsequent interpretation of this analysis. Therefore, a comprehensive literature review is required to provide the background information in which this research can be grounded. Chapter 2 is therefore split into two sections, Literature review part A – Inertial sensor utilisation in running, and Literature review part B – Stride time variability. Both sections provide a comprehensive systematic review of the previous research within the appropriate field.

2.2 Literature review part A – Inertial sensor utilisation in running


2.2.2 Abstract

Inertial sensors are becoming increasingly popular within running gait analysis, and can provide a multitude of parameters to researchers and coaches alike. However, a clear understanding of the application of these sensors, along with the parameters which these sensors can provide, is required prior to their utilisation. Therefore, the purpose of this literature review was to review articles utilising accelerometers and gyroscopes to measure running gait and assess various methodologies utilised when doing so. Additionally, we aimed to identify research and coaching orientated parameters which have been previously investigated and offer evidence based recommendations as to future methodology employed when investigating these parameters. Electronic databases were searched using key related terminology such as accelerometer(s) and gyroscope(s) and/or running gait. Articles returned were then visually inspected and subjected to an inclusion and exclusion criteria after which citations were inspected for further relevance. Thirty-eight articles were then included in the review. Accelerometers, gyroscopes plus combined units have been successfully utilised in the generation of research orientated parameters such as head/tibial acceleration, vertical parameters and angular velocity and also coach orientated parameters such as stride parameters
and gait pattern. Placement of sensors closest to the area of interest along with the use of bi/tri-axial accelerometers appear to provide the most accurate results. Accelerometers and gyroscopes have proven to provide accurate and reliable results in running gait measurement. The temporal and spatial running parameters require sensor placement close to the area of interest and the use of bi/triaxial sensors. Post data analysis is critical for generating valid results.

2.2.3 Introduction
While running continues to increase in popularity so too does the number of people suffering from Running Related Injuries (RRI) (Abt et al. 2011). Injury incidence levels amongst runners have reached as high as 85% as reported in recent research (Nielsen et al. 2012). In an effort to combat RRI levels there has been increasing demand for running gait research. While previous methods of analysis have generally required well equipped research labs, recently there has been a move to produce low cost, portable equipment. This allows researchers to remove participants from an artificial laboratory environment, to measure participants in a more natural environment and uncover longitudinal information perhaps more applicable to real life practice (Higginson 2009). With this the use of accelerometers and gyroscopes has increased. These devices ‘exploit the property of inertia, i.e. resistance to a change in motion, to sense angular motion in the case of the gyroscope, and changes in linear motion in the case of the accelerometer’ (Lobo and Dias 2007). Scientists have also discovered their potential in assessing gait analysis without the restrictions of laboratory technology (Lee et al. 2010b). In addition, research has shown that typical observational kinematic measurement systems, such as video analysis techniques often employed by coaches are wholly subjective and based on the knowledge of the coach (Hood et al. 2012) and that coaches accuracy at scoring the same movement recorded using video analysis changes over time (O’ Halloran 2005). Therefore, accelerometers and gyroscopes are also bridging a gap between coaching and science performance measures providing research orientated parameters (acceleration, velocity) and coach orientated parameters (stride length, stride frequency). These parameters, both alone and combined, have in the past been linked to RRI (Hreljac 2004). The evolution of these sensors for biomechanical analysis has gathered pace as they provide direct contact with the subject in question, whilst also becoming smaller in
size and more wearable, allowing for use during more dynamic movement (Chen et al. 2011). MEMS (microelectromechanical systems) accelerometers have led the way in technology for direct measurement of acceleration. While previous optical measurement systems allow for acceleration calculation error, during the differentiation of displacement and velocity measurements (such as 2D image analysis), accelerometers avoid this while also having the benefit of utilising one or multiple axes (Higginson 2009). This has led to accelerometers being successfully validated for identifying a number of parameters when measuring running gait including centre of mass (COM) vertical displacement (Gullstrand et al. 2009), stride parameters and running speed (Hausswirth et al. 2009), and angular velocity (Channells et al. 2005). Similar to accelerometers, gyroscopes are portable, lightweight and provide direct measurement, in this case, of angular velocity. Gyroscopes when combined with accelerometers form a very useful, compact measurement system, an inertial measurement unit (IMU), which have also been successfully validated in identifying parameters when measuring running gait including stride times (McGrath et al. 2012), vertical displacement (Tan et al. 2008) and speed (Yang et al. 2011). While there has been much evidence to support the validity of accelerometers and gyroscopes in measuring running gait there is still debate regarding the techniques used while utilising these systems. A previous systematic review (Fong and Chan 2010) focused on the implementation and data processing of the sensors (i.e. study design, fixation) however that review focused only on lower limb kinematics and also included a range of activities including walking, sitting and tennis serving. While that review may aid researchers in considering implementing this analysis method across a range of activities it does not divulge critical information as to the direct methodology when performing movement at high velocity, as done in running. It is also necessary that this information is made accessible both to the science community and to running coaches, so it can be accessed by the running population. Therefore, a systematic review is necessary so that a summary of information will be collated from which biomechanists and coaches alike will be able to make educated decisions about the appropriate methods of the application of accelerometers and/or gyroscopes to assess running gait. While in this review accelerometers, gyroscopes or combined units (IMU) will be included accelerometers will feature more heavily due to their greater popularity in running
gait analysis. Regardless, from the information gathered here it is hoped in the future that scientists and coaches alike will be able to successfully identify kinematic parameters from sensor data, which may be linked with RRI.

2.2.4 Research methods

PubMed, ScienceDirect, Web of Knowledge and Google Scholar were searched to identify studies which utilised accelerometers and/or gyroscopes for running gait kinematic analysis. Searches consisted of a combination of the following keywords (1) inertial sensors or accelerometer/s or acceleration or gyroscopes or wearable sensors or sensing technology or inertial measurement unit and (2) gait or locomotion or running or running gait. Due to recent technology advances articles within the last decade were preferentially considered.

The inclusion criteria for study selection were (1) the literature was written in English (2) participants were human (3) due to recent technology advances articles within the last decade were preferentially considered (4) sensors consisted of accelerometers or gyroscopes individually or when combined within one unit (IMU) (5) participants performed running gait whilst wearing the sensors and (6) clearly defined outcome measures were kinematic parameters. Articles which did not meet the inclusion criteria after inspection of the title and abstract were omitted. Reference lists of articles which met the inclusion criteria were then physically searched to identify any potentially relevant articles which may not have been identified in the previous search. A total of 38 articles were identified (Figure 2.1).
In the 38 articles 385 participants (166 distance runners, 12 sprinters, 144 recreational runners and 63 mixed sport or unknown) were tested with a mean of 10.1 ± 7.8 participants per study. These participants performed on average 3.8 ± 3.9 trials from which accelerometer and/or gyroscope data were used, with a total of 1,488 trials completed. Of the 38 articles, only 10 articles (Bergamini et al. 2012; Bichler 2012; Cooper et al. 2009; McGrath 2012; O’Donovan et al. 2009; Stohrmann et al. 2011b; Stohrmann et al. 2012; Tan et al. 2008; Yang et al. 2011) utilised IMU’s, with combined accelerometer and gyroscope capabilities, while the remaining 28 utilised either accelerometers or gyroscopes individually.

2.2.5 Results

In the 38 articles 385 participants (166 distance runners, 12 sprinters, 144 recreational runners and 63 mixed sport or unknown) were tested with a mean of 10.1 ± 7.8 participants per study. These participants performed on average 3.8 ± 3.9 trials from which accelerometer and/or gyroscope data were used, with a total of 1,488 trials completed. Of the 38 articles, only 10 articles (Bergamini et al. 2012; Bichler 2012; Cooper et al. 2009; McGrath 2012; O’Donovan et al. 2009; Stohrmann et al. 2011b; Stohrmann et al. 2012; Tan et al. 2008; Yang et al. 2011) utilised IMU’s, with combined accelerometer and gyroscope capabilities, while the remaining 28 utilised either accelerometers or gyroscopes individually.
2.2.5.1 *Research orientated kinematic output parameters*

Of the 38 articles included in the review 23 utilised accelerometers and/or gyroscopes during running gait to derive research orientated kinematic parameters (Table 2.1).
Table 2.1 Research orientated kinematic output article details.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Tibial/shank acceleration</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Head acceleration</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Shock attenuation</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Vertical parameters</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Angular velocity</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Stride regularity /symmetry</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Accelerometry relative to $\dot{V}O_2$ and speed</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Total acceleration and kinematic patterns</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
</tbody>
</table>
2.2.5.2 Tibial/shank acceleration.

Firstly shank/tibial acceleration was identified in 12 of the 23 articles (Table 2.1). Peak tibial acceleration after impact was identified in all 12 studies which may be due to its links with overuse injury such as tibial stress fractures (Clansey et al. 2012; Crowell et al. 2010). All but 1 of the 12 studies generated peak tibial acceleration data by attaching the accelerometer to the distal anteromedial portion of the tibia. Clark et al. (2010) placed their accelerometer on the proximal tibial tuberosity. Although research has indicated that the distal anteromedial portion of the tibia is chosen as a placement site to reduce the effect of angular acceleration and rotational movement (Laughton et al. 2003), Clark et al. (2010) were not incorrect in their placement. Clark et al. (2010) were interested in tibial acceleration at the knee, of most importance in the mediolateral plane, as they investigated varus/valgus knee motion during running. By placing the accelerometer at the proximal end of the tibia Clark et al. (2010) were following protocol in line with Mathie et al. (2004) which states that accelerometer placement is key to providing accurate output and should be placed on the area of interest. Clark et al. (2010) study also led them to being the only study of the twelve which identified tibial acceleration in all three planes, vertical, mediolateral and anteroposterior, which has been previously identified as an area to be investigated due to high acceleration rates within these planes (Lafortune 1991). While their study may provide important information on knee movement one flaw can be identified, which is the size of the accelerometer used. When comparing bone and skin mounted accelerometers, while bone was found to be more accurate skin mounted were found to be acceptable as long as the mass of the accelerometer was kept minimal, <3 g suggested (Forner-Cordero et al. 2008). The accelerometer used by Clark et al. (2010) weighed 25 g, over eight times the suggested mass, which may have led to spurious data, in all planes. For the remaining articles six utilised accelerometers weighing more than 3 g (Mercer et al. 2003b; Mercer et al. 2003a; Laughton et al. 2003; Abt et al. 2011; Clansey and Hanlon 2011; Mathie et al. 2004) which question the validity of their results. Three studies utilised accelerometers weighing less than 3 g (Derrick et al. 2002; Mercer et al. 2002; Butler et al. 2007) and two (Crowell et al. 2010) did not outline the mass of the accelerometer used. It is also important to note that the majority of the 12 studies
identified peak tibial acceleration utilising uniaxial accelerometers (n=8) which, despite producing sufficient peak tibial acceleration data, has limitations.

Mercer et al. (2003b) reported that when the subject was standing the axis of the accelerometer was aligned with the longitudinal axis of the tibia however with any manipulation of stride length, as can happen in fatiguing long distance running, the axis alignment became distorted. Although previous research has stated that this misalignment leads to minimal differences in acceleration values (1-2 % impact peak magnitude) (Derrick et al. 1998) the risk of this affecting data could be minimised with the use of bi-axial and triaxial accelerometers. Four studies (Derrick et al. 2002; Mercer et al. 2003b; Mercer et al. 2002; Mercer et al. 2003a) also analysed tibial acceleration across the stance phase using the Fast Fourier transformation function to calculate power spectral density (PSD) using a previously published method (Shorten and Winslow 1992). Using the aforementioned methods tibial acceleration has been successfully identified to be reduced in high arched runners when running in cushion trainers shoes compared to motion control shoes (Butler et al. 2007) and also decrease when provided as visual feedback to those running on treadmills (Crowell et al. 2010). Tibial acceleration was also found to be increased in fore-foot strikers opposed to rear foot strikers (Laughton et al. 2003) and identified to increase mediolaterally in women during menstruation compared to ovulation (Clark et al. 2010). Lastly it has been found to increase with increases in preferred stride length (Mercer et al. 2003b) and showed mixed increases when investigated in relation to fatiguing runs (dependent on run length and training status of runner) (Derrick et al. 2002; Mercer et al. 2002; Mercer et al. 2003a; Abt et al. 2011; Clansey et al. 2012; Mathie et al. 2004).

2.2.5.3 Head acceleration.
A second variable of interest was head acceleration which was successfully identified in 7 (Derrick et al. 2002; Mercer et al. 2003b; Mercer et al. 2002; Mercer et al. 2003a; Abt et al. 2011; Clansey et al. 2012; Mathie et al. 2004) of the 23 articles which examined research orientated kinematic parameters. Head acceleration has been identified due to its role in understanding shock absorption as the body attempts to combat the repetitive forces being applied to it during
running (Clansey and Hanlon 2011). All seven studies outline that to acquire head acceleration data the accelerometer was placed on the anterior aspect of the forehead (Mercer et al. 2003b) or the frontal bone of the skull (Derrick et al. 2002) whilst all seven also provided extra strapping or adhesive to ensure attachment. Head peak impact acceleration was the key parameter investigated in all 7 studies with 4 of the studies (Derrick et al. 2002; Mercer et al. 2003a; Mercer et al. 2003b; Mercer et al. 2002) also generating the PSD value for head acceleration.

2.2.5.4 Shock attenuation.

Shock attenuation is the process of decreasing the magnitude of impact force between the leg and head and is derived from the accelerations of these segments. It was another variable commonly looked at within the 23 articles containing research orientated kinematic parameters. It was identified in 6 of the 23 articles and is important considering the repetitive nature of running thus any alteration of the body's ability to absorb shock could lead to additional stresses being placed on joints and the onset of overuse injury (Abt et al. 2011). Four of the six articles (Derrick et al. 2002; Mercer et al. 2003a; Mercer et al. 2003b; Abt et al. 2011) calculated shock attenuation using the same transfer function utilising frequency domain analysis. All of these articles identified shock attenuation as the average transfer function across similar impact frequencies ranges (10-20 Hz for Abt et al. (2011); Derrick et al. (2002) and Mercer et al. (2003b) ; 11-18 Hz for Mercer et al. (2003a). This method resulted in a shock attenuation value in decibels, with positive values indicating a gain in the acceleration signal from leg to head and negative values indicating attenuation of the signal. Of the two remaining articles, however, while one study utilised a simplified frequency domain analysis of ratio of PSD_{head} to PSD_{leg} (with a low ratio indicative of greater attenuation) (Mercer et al. 2002) the other utilised time domain analysis using averaged peak head and tibial accelerations (Clansey and Hanlon 2011, shown in Equation 1).

\[
\text{Shock attenuation} = \left(1 - \frac{\text{peak head acceleration}}{\text{peak tibial acceleration}}\right) \times 100
\] (1)

Although these methods generate a numeric value representative of shock attenuation it is thought the preferred method is using the PSD and Four Fourier
technique followed by the average transfer function. This analysis of the frequency domain allows us to attain greater understanding of the distribution of the energy in the signal, in this case acceleration, and also can let us see how quickly shock attenuation can occur. Within the 6 articles, 3 articles (Derrick et al. 2002; Mercer et al. 2003b; Mercer et al. 2002) identified shock attenuation increases, all utilising the average transfer function value at similar running impact frequencies. Whilst Derrick et al. (2002) study was based on an exhaustive run Mercer et al. (2003b) and Mercer et al. (2002) altered running conditions (stride length and frequency and speed), but commonly all three articles found an increase in stride length as well as shock attenuation. This link between shock attenuation and stride length is supported by Mercer et al. (2003a) who found decreases in shock attenuation post fatigue, but also consistent stride length pre and post. Similarly, Abt et al. (2011) and Clansey and Hanlon (2011) also found decreases in shock attenuation following fatiguing runs and indicate this is due to a highly trained population, who perhaps do not adapt stride length when facing fatigue due to enhanced coping strategies.

2.2.5.5 Vertical parameters.

Vertical acceleration, displacement or vertical oscillation was also identified in 6 of the 23 articles (Tan et al. 2008; Gullstrand et al. 2009; Lee et al. 2010b; Stohrmann et al. 2011b; Stohrmann et al. 2012; Lee et al. 2012). When measuring vertical oscillation 5 of the 6 articles located the accelerometer (Gullstrand et al. 2009; Lee et al. 2010b; Lee et al. 2012) or IMU (Stohrmann et al. 2011b & Stohrmann et al. 2012) in proximity to the centre of mass, placing it either on/near the sacrum (Gullstrand et al. 2009; Lee et al. 2010b; Lee et al. 2012) or located on the hip (Stohrmann et al. 2011b & Stohrmann et al. 2012) in order to give a true reflection of vertical displacement. On the other hand Tan et al. (2008) attached their GPS/IMU system to the top of a cyclist’s helmet which was worn by the runner. This GPS/IMU unit combined GPS (global positioning systems) capabilities of determining speed over ground and an IMU (inertial measurement unit) comprised of an accelerometer, gyroscope, 3D magnetometer and temperature sensor (Tan et al. 2008). Placement on top of the helmet was for convenience as the system was bulky and required the mounting of an antenna, as did the GPS system it was being compared to (OEM4, Novatel, Canada). Also in Tan et al.
(2008) study when compared to the GPS system (OEM4) the combined GPS/IMU system achieved a reliability of 0.02 m in vertical displacement. Given this relatively large systematic error and the author's statement that the error was as a result of both measurements containing error neither of these two systems would be recommended for future measurement of vertical displacement. Of the remaining articles Lee et al. 2012 found accelerometry acceptable in generating vertical acceleration in a transtibial amputee sprinter and Lee et al. (2010b) also found near perfect correlations and very small error between COM vertical acceleration when derived from an accelerometer and compared to 3D motion capture. This would indicate accelerometry as a highly valid method of deriving vertical COM parameters. However, while this level of validity is supported by Gullstrand et al. (2009), when compared to three-dimensional infra-red motion capture and position transducers the reliability of the accelerometer is seen to be very poor as it produces a large amount of random error (5, 7 and 11 mm). Gullstrand et al. (2009) however put this error down to changes in the orientation of the uniaxial accelerometers used. Although this was assumed to be constant the orientation was most likely altered at each step. Their suggestion for more complex sensors to be used to avoid this is supported by Lee et al. (2010b) as they used a triaxial accelerometer and their data did not suffer from this orientation alteration and therefore had small typical error (1.84 m·s\(^2\)). Of the studies which chose to analyse vertical displacement as opposed to acceleration (Gullstrand et al. 2009; Stohrmann et al. 2011b, Stohrmann et al. 2012) all studies double integrated the vertical acceleration component derived at the hip/sacrum. By using the above methods previous research has identified symmetry in running gait (Lee et al. 2010b), examined the validity of accelerometers in assessing vertical parameters (Tan et al. 2008; Gullstrand et al. 2009; Lee et al. 2010b) and shown that there is little difference between vertical acceleration in anatomical and prosthetic strides (Lee et al. 2012). Previous studies have also found conflicting results as to levels of vertical oscillation, dependent on running ability (Stohrmann et al. 2011b & Stohrmann et al. 2012).

2.2.5.6 Angular velocity.

While most of the variables identified within this review so far have been linked to acceleration patterns 2 of the 23 articles identified also looked at angular velocity
whilst running. Bergamini et al. (2012) utilised an IMU consisting of a triaxial accelerometer and a triaxial gyroscope placed on the lower back (L1) to provide analysis of amateur and elite sprinters. They found that acceleration and angular velocity profiles provided no consistent features which could be linked to foot strike and toe off, which is in contrast to previous research using lumbar based sensors (Auvinet et al. 2002a & Lee et al. 2010a). It is thought Bergamini et al. (2012) results may be due to utilising sprint trials in their study, which due to forefoot striking causes increased dampening of impact forces, making identifiable markers harder to distinguish. This raises the question whether lower back attached sensors are suitable for measuring sprint parameters. In contrast to this however Bergamini et al. (2012) was able to identify consistent events on the second derivative of angular velocity wavelet, which verified that not only is trunk rotation present in sprinting, as had been previously found in walking and long distance running, but also that this feature could be found across different levels of athletes (amateur and elite) and could be utilised to identify stride duration. Negative and positive peaks related to time of heel strike and toe-off were also found on this wavelet. While Bergamini et al. (2012) utilised gyroscopes within an IMU to identify angular velocity patterns, Channells et al. (2005) utilised accelerometry data which were then integrated. They placed an acceleration measurement unit (AMU) consisting of 2 bi-axial accelerometers (one measuring mediolateral and anteroposterior accelerations – x and y axis, the second measuring vertical accelerations - z axis) on the athlete’s shin with which they then performed a series of walking, jogging and running trials. Angular velocity data were then generated through integration which were compared to angular velocity derived through the same calculation using motion capture. They found that the AMU resulted in comparable angular velocity patterns when compared to the motion capture and this was not affected by running technique. It was, however, affected by running speed; results indicating that as speed increased so did error (percentage error ranges from 2.31 % in walking to 9.76 % at higher speeds). This increase in error could be due to increasing noise induced integration error due to poor attachment at increased speeds. Both papers found increased problems when looking at angular velocity during sprinting and so may raise the question as to techniques used by both studies. Perhaps combining the equipment used by Bergamini et al. (2012) based on its high validity and gyroscope utilisation, and the
tibial attachment site (used by Channells et al. (2005)) should be further investigated when analysing angular velocity in sprinting.

2.2.5.7 Remaining parameters.

Having identified the common themes within the 23 articles investigating research orientated kinematic parameters there were 3 papers which identified unique variables (Le Bris et al. 2006; McGregor et al. 2009; Patterson et al. 2011) utilising accelerometers. Le Bris et al. (2006) investigated the effect of fatigue on middle distance runner's stride patterns using the Locometrix system (Locometrix™, Centaure Metrix, France) located on the lower back. While they looked at stride regularity (similarity of cranial-caudal acceleration over successive strides) and stride symmetry (similarity of cranial-caudal acceleration over left and right strides) through autocorrelation, these variables are similar to those found by papers looking at vertical acceleration (Tan et al. 2008; Gullstrand et al. 2009; Lee et al. 2010b; Stohrmann et al. 2011b; Stohrmann et al. 2012; Lee et al. 2012). Of greater interest however was their use of accelerometry in the investigation into mediolateral axis acceleration patterns. While this is similar to that done by Clark et al. (2010) in their investigation of knee varus/valgus movement, Le Bris et al. (2006) located their accelerometer on the centre of the lower back, close to the COM, which gives a better indicator of whole body movement as affected by fatigue. From this they found that fatigue increased the mediolateral impulse significantly in sub-elite middle distance runners, perhaps indicating they cannot combat fatigue as effectively as elite, leading to increasing energy expenditure in an axis (mediolateral) not conducive to propulsion. McGregor et al. (2009) also investigated kinematic accelerometry patterns by locating an accelerometer on the lower back of their participants; however they wished to investigate the validity of using the accelerometer relative to \( \dot{V}o_2 \) and speed by comparing the root mean square of the three axes and the Euclidean resultant (RES) to \( \dot{V}o_2 \). They not only found that the accelerometer was highly valid and reliable in predicting \( \dot{V}o_2 \) but also looked to investigate the differences between trained and untrained runners in regards to acceleration at certain speeds, economy of acceleration relative to speed and ratio of accelerations relative to RES in all axes. By using the acceleration data derived from their trials in this manner McGregor et al. (2009) were able to divulge a wealth of information regarding acceleration pattern
differences between trained and untrained runners performing to fatigue. They found that nearly all acceleration parameters were lower in trained than untrained runners perhaps indicating enhanced running economy when reaching fatigue (through positive adaptions), which is supported through much of the research (Abt et al. 2011 & Clansey and Hanlon 2011), supporting the validity of their study. Lastly Patterson et al. (2011) looked at acceleration of the lower limb by placing a triaxial accelerometer on the shoe laces of their subject. From this they wished to investigate the relationship between the total acceleration, x and y axis accelerations and kinematic gait movements such as knee and ankle angle at various parts of the gait cycle (initial swing, mid-swing) during fatiguing runs. They were able to identify certain relationships existed, such as accelerometer variables during mid-swing being predictive of dorsi-flexor fatigue. However, their study was only performed on one subject and so these results are not necessarily generalizable to a larger population, given that gait has such individual characteristics.

2.2.5.8 Coach orientated kinematic output parameters
Having investigated research orientated kinematic parameters identified using accelerometers and/or gyroscopes it was also important to investigate coach orientated parameters. This is to ensure that these sensors were able to generate information accessible to audiences of different scientific knowledge backgrounds. Of the 38 articles included in this review 23 articles utilised accelerometers and/or gyroscopes during running gait to identify coach orientated kinematic parameters (Table 2.2).
<table>
<thead>
<tr>
<th>Step/stride frequency</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
<th>•</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temporal parameters</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Gait pattern</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Step/stride length</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Foot strike type</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Heel lift</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Speed</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Knee angle</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Sprint time</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
<tr>
<td>Upper body parameters</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
</tr>
</tbody>
</table>
2.2.5.9 Step/stride frequency/rate

Firstly, frequency or rate of step and stride, was commonly identified in 10 of the 38 articles (Mercer et al. 2002; Mercer et al. 2003a; Le Bris et al. 2006; Tan et al. 2008; Hausswirth et al. 2009; McCurdy et al. 2010; Neville et al. 2010; Neville et al. 2011; Bichler et al. 2012; Stohrmann et al. 2012). Stride frequency is important as increased stride frequency means increased repetitive impacts on the body which can lead to a higher risk of injury and degenerative disease due to increased stress on the structure of the body (Hamill et al. 1995). Of the 10 articles, 4 articles did not define how they identified step/stride frequency (Le Bris et al. 2006; Tan et al. 2008; Hausswirth et al. 2009; McCurdy et al. 2010) with some only identifying that it was analysed using the Fast Fourier Transform via MATLAB™ (Le Bris et al. 2006). Of the remaining 6 articles however 5 identified stride frequency using similar methods. Mercer et al. (2002) and Mercer et al. (2003a) identified the peak in vertical acceleration associated with foot impact and calculated stride frequency as a result of the time, while Stohrmann et al. 2012 identified peak impact by not only looking at the anteroposterior acceleration curve but combining the three planes of acceleration to calculate the magnitude. All three studies chose lower limb sensor attachment and whilst Stohrmann et al. (2012) utilised an IMU, all three papers identified results through accelerometer generated data. Neville et al. (2010) and Neville et al. (2011) again utilised accelerometer sensors combined with a zero-crossing method in MATLAB™ (not dissimilar to the previously mentioned method). Here every zero crossing in the anteroposterior plane was identified as a foot impact, which was then divided by the time between first and last impact to derive stride frequency. As there would be minimal time difference in the time of zero-crossing and impact peak and both methods successfully derived stride frequency both methods could be used. However, the zero crossing method was successfully compared to speed as measured using a stopwatch (stride frequency showing a linear trend as speed increase, r²=0.896) and GPS (r²=0.901) (Neville et al. 2011) and against various speeds as measured by GPS (walking – r²=0.820, running r²=0.838 (Neville et al. 2010). This supports its position as the method with proven validity. It is important to note, however, the use of a stopwatch as a comparison speed measurement device. This method is highly subjective and has been found to be a valid method in assessing speed only when used by a trained tester (Vicente-Rodriguez et al. 2011). It is not stated in
Neville et al. (2011) whether the tester is trained or not, which may question the derived speed accuracy. While it could be argued that Neville et al. (2010) and Neville et al. (2011) placed their accelerometers on the lower back, against that recommended by Mathie et al. (2004), foot strike here created easily identifiable markers in large peak acceleration changes and so was identifiable regardless of position. This is in contrast to that found by Bergamini et al. (2012) who utilising an IMU were unable to identify a regular pattern on the acceleration curve using the same sensor placement. However, in Bergamini et al. (2012) the subjects sprinted, which is thought to have hindered pattern identification. Lastly, in terms of identifying stride frequency, Bichler (2012) utilised an IMU, however unlike Bergamini et al. (2012) and Stohrmann et al. (2012) they utilised the gyroscope data available to identify stride frequency. They expanded the “pedestrian dead reckoning” method (a method used to give position and orientation of a subject using integration of acceleration and angular velocity, Torres-Solis and Chau 2010) to provide greater accuracy during running. This method identified the rotation of the foot prior to, during and after stance in order to derive stride parameters such as stride frequency. From this stance could be identified due to rotation below a certain threshold (<1 rad·s⁻¹) and also with combined accelerometer key markers (peak at impact) (Bichler 2012). When this method was compared to video analysis it was found to show a more regular pattern in terms of stride frequency but also that increases in speed increased parameter failure rate. However, these differences between measurement systems (IMU/GPS and video) overall were minimal and most lay within 95 % limits of agreement. Any differences could also be due to the weak comparison method of 2D analysis and stance would have been identified here as ground contact time, as opposed to with the sensor data where it was identified by level of rotational movement. By using the above methods, the use of accelerometers and/or gyroscopes to derive stride frequency has been validated (Tan et al. 2008; Hausswirth et al. 2009; Neville et al. 2010; Neville et al. 2011) and also been successfully used to derive stride frequency changes with speed (Mercer et al. 2002), fatigue (Le Bris et al. 2006 & Stohrmann et al. 2012) and its relationship to jump performance (McCurdy et al. 2010).
2.2.5.10 Temporal parameters

Secondary coach orientated kinematic parameters which were identified were temporal and covered a multitude of smaller parameters. Parameters which included foot/ground interface (foot contact time, step, stance and stride duration) and also airborne parameters such as swing time were identified through use of accelerometers and/or gyroscopes in 10 of the 24 articles (Purcell et al. 2006; O’Donovan et al. 2009; Lee et al. 2010a; Stohrmann et al. 2011a; Stohrmann et al. 2011b; Stohrmann et al. 2012; Bichler et al. 2012; Bergamini et al. 2012; Lee et al. 2012; McGrath et al. 2012). In order to identify these parameters all the studies required identification of when the foot was in contact with the ground through knowledge of when foot strike occurred and toe-off occurred. Utilising an IMU Stohrmann et al. (2011b) and Stohrmann et al. (2011a) identified foot/ground contact through an acceleration threshold, where below 2g (g=gravity) represented stance time with values increasing above this representing swing time. This use of a threshold is commonly seen in comparison analysis when using force plates (Purcell et al. 2006 & Bergamini et al. 2012) but Stohrmann et al. (2011b) and Stohrmann et al. (2011a) are the only identified studies to utilise it with accelerometry data. A more commonly identified method to generate foot contact times was by analysis of the anteroposterior accelerometry data with positive peaks identifying foot strike and smaller peaks identifying toe-off (Purcell et al. 2006; Lee et al. 2010a; Bergamini et al. 2012; Lee et al. 2012). This method can provide information easily as it can be generated through visual observation of acceleration patterns, as done in Lee et al. (2012). The validity of this method has also been tested over differing conditions including a Paralympic sprinter using a prosthetic limb, and at varying running speeds with similar results (Lee et al. 2010a & Purcell et al. 2006). Lee et al. (2010a) found that an accelerometer based sensor placed on the lower back had strong agreement and near perfect correlations (r=0.90+) to 3D motion capture, for most parameters (step, stride and stance times) at varying running speeds (low, medium and high). This was similar to Purcell et al. (2006) findings when comparing tibial accelerometry contact time measures to force plate data (r=0.89+). Gyroscope data derived from IMU units were also utilised to measure temporal parameters with O’Donovan et al. (2009), Bichler et al. (2012) and McGrath et al. (2012) all identifying foot/ground interface using angular velocity. All three studies identified different methods to analyse
angular velocity for ground contact. O’Donovan et al. (2009) used a method by Aminian et al. (2002) which utilised mediolateral angular velocity. Bichler (2012) stated that foot contact occurred between the first and last samples of angular velocity below 1 rad\(^{-1}\) in the respective foot and McGrath (2012) utilised an algorithm which calculated thresholds based on angular velocity about the y-axis (mediolateral) and also incorporated an artefact rejection routine. Two of the 3 studies validated their methods in comparison to 3D motion capture with Bichler (2012) identifying their 2D camera analysis as a limitation to their study, perhaps being too weak for a comparison method and leading to poorer results with Intra-class coefficient (ICC) results here (averaged 0.4) being lower than both O’Donovan et al. (2009) (0.86) and McGrath (2012) (0.53 +) findings. When looking at the individual parameter findings McGrath (2012) showed poor to moderate ICC (0.24 -0.66) for stance and swing times across all speeds when comparing gyroscope data to motion capture. This is in contrast to O’Donovan et al. (2009) who found high ICC values (0.85 and 0.99) for these parameters, although a major difference here is that O’Donovan et al. (2009) utilised both walking and jogging and did not differentiate the results of both or state the speeds utilised. Therefore the higher values represented by O’Donovan et al. (2009) could be due to slower speeds, which is supported by the fact that ICC values at the top of McGrath (2012) range for swing and stance time utilising gyroscopes were closer to O’Donovan et al. (2009) values (0.66 compared to 0.99 for stance time). Overall, studies which utilised gyroscopes all demonstrated limitations or require further study in the validation of this method so accelerometer data may be a more valid method of analysis in temporal parameters. In general studies which have utilised the above methods have investigated changing temporal parameters regarding fatigue (Stohrmann et al. 2012), in sprinting kinematics with the use of a prosthetics limb (Lee et al. 2012) and in the validity of accelerometers and/or gyroscopes as a measurement technique (Bergamini et al. 2012; Bichler et al. 2012; Purcell et al. 2006).

2.2.5.11 Gait patterns

Gait pattern was also identified in 3 of the 23 articles which examined coach orientated parameters (Auvinet et al. 2002b; Heiden and Burnett 2004; Wixted et al. 2010). All three studies utilised accelerometers and wished to identify key
markers of gait pattern such as the acceleration peaks at foot strike and toe off to confirm that accelerometry was feasible for gait pattern analysis. Two of the studies compared accelerometric measures to force measures, with Heiden and Burnett (2004) using force plate data as a comparison and Wixted et al. (2010) using insole shoe sensors. While Heiden and Burnett (2004) did not discuss comparison results, Wixted et al. (2010) found by visual observation that accelerometer data showed a significant negative peak in the anteroposterior plane which occurred at the approximate same time as heel strike, as shown by the insole shoe sensors. The end of foot contact, the period directly after toe off, was then characterised by vertical acceleration crossing zero positively, as foot contact and sensor pressure data ceased. Unfortunately no analysis was done on the timing of these events relative to one another and so it is not possible to compare these data to previous validation studies. Auvinet et al. (2002b) also employed visual comparison of gait pattern derived from accelerometer data (peaks in anteroposterior and vertical planes) and, in this case, 2D motion capture data and once more found a deceleration trough in the anteroposterior plane at foot strike with loading (zero crossing) at toe-off, same as Wixted et al. (2010) found. Of most interest in these three articles was Heiden and Burnett (2004) investigation as to whether the hip sensor or ankle sensor presented the most accurate data for gait pattern markers (heel strike and toe off). They reported that the hip sensor resulted in gait pattern data that could not lead to accurate and easily identifiable gait markers whereas the ankle sensor generated replicable and identifiable data. This supports Mathie et al. (2004) thoughts on sensor location but contrasts with findings by Lee et al. (2010a) and Bergamini et al. (2012). Both Lee et al. (2010a) and Bergamini et al. (2012) utilised lower back placement and successfully identified gait pattern. Although Bergamini et al. (2012) did so using the second derivative of angular velocity and it is possible Lee et al. (2010a) did so at increased velocities compared to Heiden and Burnett (2004), which they identified led to increased accelerometer peaks and easier identification. When using a lumbar sensor to derive gait pattern perhaps Lee et al. (2010a) utilised the best running speed (range 2.8-5.3 m·s⁻¹) as they successfully validated this method in comparison to Heiden and Burnett (2004) (unknown speed) and Bergamini et al. (2012) (range 5.7-10.8 m·s⁻¹) who at increased speeds found signal was dampened and markers on the accelerometer curve were unidentifiable. Easily recognised
identification of gait pattern, as seen in these three studies, provides information on basic running pattern important to coaches.

2.2.5.12 Step/stride length

Another parameter identified via accelerometers and/or gyroscopes was stride/step length, identified in 4 of the 23 articles (Mercer et al. 2002; Mercer et al. 2003a; McCurdy et al. 2010; Bichler 2012). Stride length is a key parameter for coaches as it provides information on fatigue and also has been linked with RRI in relation to lower limb stiffness (Butler et al. 2003). While McCurdy et al. (2010) did not discuss how stride length values were obtained, only that it was done so using an accelerometer attached to a waist belt, both Mercer et al. (2002) and Mercer et al. (2003a) utilised the same method, dividing treadmill speed by already attained stride frequency (as previously discussed). All 3 (Mercer et al. 2003a; Mercer et al. 2002; McCurdy et al. 2010) of these articles utilised accelerometers in attaining stride/step length whilst Bichler et al. (2012) utilised IMU derived gyroscope data also. Whilst outlining the advanced pedestrian dead reckoning method which Bichler et al. (2012) used to derive kinematic parameters, does not specifically outline the method for calculating stride length, although results show that when compared to 2D camera analysis the mean stride length calculated by the IMU differed by only 0.01 m. This parameter was most sensitive to difference at higher speeds. Within these studies accelerometers and/or gyroscopes have uncovered stride length increases with increased velocity (Mercer et al. 2002), unchanged stride length values after a graded exercise test (Mercer et al. 2003a), the relationship between stride length and jump performance in soccer players (McCurdy et al. 2010) and has also been validated to derive stride length at lower speeds (Bichler et al. 2012). However, as Bichler et al. (2012) was the only author to test the validity of stride length results generated, and this was from gyroscope data, this is an area requiring further study.

2.2.5.13 Remaining parameters.

Other parameters identified are foot strike type (Stohrmann et al. 2011a & Stohrmann et al. 2012), heel lift (Stohrmann et al. 2011b & Stohrmann et al. 2012), running speed (Hausswirth et al. 2009 & Yang et al. 2011), knee angle (Cooper et al. 2009), sprint time (Neville et al. 2010) and arm movement, trunk forward lean
and shoulder rotation (Stohrmann et al. 2012). Although measurements such as angle derivation and speed may not be commonly identified using accelerometers and/or gyroscopes this information does provide insight into advancing capabilities of these low cost transducers whilst also providing support for their validity within this research.

2.2.6 Summary

For researchers who intend to utilise accelerometers and/or gyroscopes for research and coach orientated kinematic parameters for running gait there are several recommendations. Firstly, regarding research orientated kinematics there are recommendations when investigating tibial acceleration, head acceleration, shock attenuation, vertical parameters and angular velocity among some parameters. In terms of tibial acceleration it is recommended to follow guidelines as suggested by Mathie et al. (2004) (placement closest to the area of interest), with accelerometer placement at the anterior/distal aspect of the tibia if tibia acceleration or running patterns derived from acceleration curves are of interest. It is also recommended that a biaxial or triaxial accelerometer is used as axial alignment has been found to become distorted during testing (Mercer et al. 2003b) and by having multiple axes to analyse this may have less of a negative effect on data collection. Sensor/device weight also plays an important role and it is recommended for accurate data collection to keep weight to <3 g. This may be of vital importance especially in collecting tibial acceleration data as the sensor will be placed in a body segment of small surface area (distal tibia compared to lower back placement) and by keeping sensor weight low this will maximise the unobtrusive method of data collection. Secondly, in terms of head acceleration, recommendations on placement follow those of Mathie et al. (2004) and so anterior aspect of the forehead is suggested and has been proven to be successful. This placement however can be the most obtrusive as the attachment of a foreign object onto the centre of a subject’s forehead may be uncomfortable and unwanted during running. It is therefore suggested that this placement may be of the least value, as it obtains information only on shock attenuation and head acceleration and also may have the greatest effect on running efficiency and economy depending on the subject.
Recommendations in terms of collecting vertical parameter data using accelerometers and/or gyroscopes were also generated and again sensor location was recommended closest to the area of interest, the subject’s centre of mass (lower back) for valid results. Also, biaxial or triaxial accelerometers were recommended as altered orientation had again been observed and stated as a limitation using uniaxial accelerometers (Gullstrand et al. 2009). For angular velocity both accelerometers and gyroscopes have been utilised successfully however placement has proven to be vital as lumbar placed sensors were found to produce inconsistent patterns in relation to acceleration and angular velocity peaks and dips associated with gait, making it difficult to identify parameters in subjects performing a sprint. In contrast when accelerometers on their own were utilised, while attached to the distal tibia, consistent patterns were found, although error within these patterns increased with speed. It is therefore recommended that a combination of methods is utilised in the future to generate angular velocity data, especially for sprinting analysis. The utilisation of gyroscopes, as used by Bergamini et al. (2012), to provide reliable data, followed with placement used by Channells et al. 2006) is therefore recommended for future study. While these are the main research orientated kinematic parameters, accelerometers have also been proven to generate reliable data in the mediolateral planes when located at various attachment points. When attached to the proximal tibia, accelerometers have been found to generate knee valgus/varus data (Clark et al. 2010) and when attached to the lower back have generated running efficiency data (Le Bris et al. 2006). This provides support for future studies not only investigating cranial-caudal and anteroposterior planes but also mediolateral to divulge important information.

In terms of generating coach orientated kinematic parameters through accelerometer and/or gyroscope utilisation there are also a number of recommendations. With stride frequency, identification has been successful using both the zero-crossing method and identifying the peak in the anteroposterior acceleration curves. Also, whilst stride frequency has been successfully generated on accelerometers and/or gyroscopes attached to both lumbar and lower limb attachment points (Neville et al. 2010) research has shown that sprinting analysis can lead to diminished acceleration patterns with lumbar attachment (Bergamini
et al. 2012) and so lower limb and tibia attachment are recommended. Whilst gyroscopes alone were also utilised to derive stride frequency, they were validated against a subjective comparison method (2D video analysis) and have been found to provide greater complications than accelerometers (drift etc.) and so accelerometers are recommended in terms of the sensor utilised. For temporal parameters, a common technique utilised which has also been validated at different speeds and with various subjects (i.e. Paralympian) is identifying foot contact through examination of the acceleration curves. Again, this would be recommended with tibial or lower limb attachment for distinct patterns and also to minimise time lag between accelerometer data and actual foot contact. While gyroscopes have also previously been utilised it was found that those that validated against 3D motion capture generated less accurate parameter output as speed increased. This would again lead to the recommendation of accelerometer utilisation for temporal parameter collection. For gait pattern research visual inspection of the acceleration curve (and the key gait markers associated with it) generated via accelerometers has been validated against both in-shoe sensors and 2D motion capture. Research here has also shown that lower limb (ankle) attachment has provided greater accuracy in providing gait pattern analysis than hip placement (Heiden and Burnett 2004) which is consistent in previous research. However, it is suggested that if lower limb attachment is not possible, perhaps due to limitation of sensor quantity availability, but gait information is still desired that running speed be maintained between 2.8-5.3 m·s\(^{-1}\). This speed, along with lumbar sensor attachment, has been previously validated in gait pattern analysis (Lee et al. 2010a) whilst higher speeds (5.7-10.8 m·s\(^{-1}\)) have been found to dampen gait pattern acceleration curves (Bergamini et al. 2012). For stride length limited information in the derivation of results has been outlined with only the advanced pedestrian dead reckoning method utilised by Bichler et al. (2012) and dividing treadmill speed by stride frequency (Mercer et al. 2003a & Mercer et al. 2002) being stated in the literature. Of these methods Bichler et al. (2012) is the only author to have provided validation and so this method may be the preferred. Again, though this parameter, stride length, was most sensitive to error at higher speeds and so perhaps following similar guidelines and speeds suggested for the derivation of gait pattern (previously mentioned) should be followed to control this risk of error. Accelerometers and/or gyroscopes have also been utilised in
deriving other lower body parameters such as foot strike type and heel lift and upper body parameters (arm movement, trunk forward lean etc.) however due to limited research on these parameters it is difficult to make future guidelines as to the most accurate methodology to be employed when these are of interest. However by utilising general guidelines as to the placement (Mathie et al. 2004) and weight (Forner-Cordero et al. 2008) of these sensors and by following recommendations on the derivation of similar parameters this may lead to greater accuracy in data collection. Overall, research utilising gyroscopes (individually) in the analysis of running gait has proven to be limited. Whilst ten of the articles within this review utilised IMU's some did not utilise the gyroscope capabilities of these units and most focused on the acceleration data generated. There therefore remains a question whether future research should focus on the use of gyroscopes. From the information collected within this systematic review gyroscopes have demonstrated greater limitations (i.e. drift) than accelerometers, while accelerometers have been successfully utilised to ascertain valid data gyroscopes are primarily utilised for angular velocity (Channells et al. 2006), whilst also being easier to work with. Finally, to our knowledge, while previous studies have regularly investigated short distance running trials and sprints, no authors have addressed longitudinal running gait analysis, in terms of over an extended period of time and over longer distances, using accelerometers/and or gyroscopes. This is an important area which should be addressed as information gathered over an extended period could divulge important data related to overuse injury.

Based on the evidence provided we are able to support the use of accelerometer and/or gyroscopes in the analysis of running gait, as it is clear they have been utilised, and validated, in the use of deriving research and coach orientated kinematic parameters. Within this however it is important to point out that many different methodologies have been utilised by previous researchers in areas such as attachment site, type of sensor and different calculation methods to generate kinematic data. As to which methodology is correct it is important for future scientists and coaches to clearly identify what parameters they wish to investigate and to then let this lead the methodology. The importance of accelerometers and/or gyroscopes in combating increasing levels of RRI is valid as by accurate
generation of kinematic data they may provide a wealth of information on ever-changing running patterns in an unobtrusive and natural environment.

2.3 Literature review part B - Stride time variability

2.3.2 Abstract
Stride time during running provides information regarding runners’ responses to fatigue, injury onset, and alterations in performance. However, our interpretation of stride time alterations or variability may be dependent on the methods of analysis which we use to investigate this parameter. Linear analysis methods allow us to interpret stride time variability in regards to centrality and magnitude changes whilst non-linear analysis methods may provide information on the temporal organisation of stride time series. Therefore, the purpose of this literature review was to review methods of stride time variability analysis commonly utilised. Electronic databases were searched using key related terminology such as stride time, variability and running. Articles returned were then visually inspected and subjected to an inclusion and exclusion criteria after which citations were inspected for further relevance. Eighteen articles were then included in the review. Distributional measurements of stride time variability (mean, standard deviation and coefficient of variation) are commonly used within the literature; however there is an increase in researchers using non-linear analysis methods (Detrended Fluctuation Analysis (DFA), Multi Scale Entropy (MSE)). The use of non-linear stride variability analysis methods is highly dependent on the question asked within the research. Furthermore, non-linear analysis methods require increased stride time series length during data collection, extensive processing and an in depth understanding of what these methods reveal.

2.3.3 Introduction
In 2.2.5.9 and 2.2.5.10 it was outlined how accelerometers can be utilised to derive temporal gait parameters such as stride time. Stride time is of particular interest to researchers within running gait as it is linked with overall run outcome (due to its link with stride frequency, Hunter and Smith 2007), and running technique (as both stride time and stride length are influence by support and balance time (Tartaruga et al. 2012). However, there is limited research available outlining alterations in stride time in recreational runners during distance running and
therefore this thesis proposes to address that gap of knowledge within the following chapters. To appropriately address this area, correct analysis and interpretation must be applied. In regards to gait kinematics variability of movement parameters such as stride time and stride rate has regularly been assessed, with traditional interpretation aligning variability with noise or random processes within a system (Buzzi et al. 2003). However, more recently researchers have identified the importance of variability in relation to skill learning and development, adaption to environmental surroundings and distribution of tissue stresses (Meardon et al. 2011). When assessing variability traditional distributional measures such as mean, standard deviation and coefficient of variation have been commonly utilised within the literature. Whilst these measures identify the spread of the data and provide information regarding alterations in magnitudes, they do not inform us about any patterning which may occur within a time series (Meardon et al. 2011). Within the last 15 years’ researchers (Hausdorff et al. 1995) have begun to identify fractal dynamics within gait; however this is primarily within walking. Fractal dynamics outline that a stride time at any time point is dependent on a stride time at any other time point and this dependence decays in a power law fashion, regardless of scale (Hausdorff et al. 2001). More recently researchers have begun to apply non-linear analysis methods to uncovering these fractal processes within running gait (Meardon et al. 2011; Nakayama et al. 2010; Lindsay et al. 2014), however this research is still limited. It is therefore necessary to identify which methods of stride time variability analysis have been utilised within the literature, to ensure the appropriate analysis method is applied to the stride time data collected within this thesis. Therefore, within this review an analysis of the current stride time variability measures utilised within the literature is required. It is hoped the results of this section will inform the remainder of this thesis in terms of utilising appropriate methods of stride time variability analysis.

2.3.4 Research methods

Similar methods to that utilised within Section 2.2.4 were utilised. Searches consisted of a combination of the following keywords (1) stride time or stride interval (2) variability or variance and (3) running or locomotion.
The inclusion criteria for study selection were (1) the literature was written in English (2) participants were human (3) in keeping with section 2.2.4 articles published from 2002 were preferred (4) participants performed running gait, (5) stride time was a primary kinematic parameter of interest i.e. was not only a measure used to calculate another parameter such as stride rate (6) a measure of variability was utilised for analysis. Additionally, any article which was focused on developing methods to calculate stride time was not included. Articles which did not meet the inclusion criteria after inspection of the title and abstract were omitted. Reference lists of articles which met the inclusion criteria were then physically searched to identify any potentially relevant articles which may not have been identified in the previous search. A total of 18 articles were identified (Figure 2.2).
2.3.5 Results

In the 18 articles 309 participants (70 well trained or elite runners, 196 recreational runners and 34 triathletes) were tested with a mean of $317.0 \pm 280.9$ stride times analysed per study, or $112.0 \pm 111.2$ seconds of data from which stride time was calculated. Interestingly of the 18 articles only 2 articles (Lindsay et al. 2014 & Meardon et al. 2011) utilised accelerometers or gyroscopes or combined accelerometer and gyroscope sensing units to calculate stride time. Popular methods more readily used were 3D motion analysis (4 studies, Connick and Li 2015; Chapman et al. 2008; Jordan et al. 2006; Heiderscheit et al. 2002), force plate analysis (5 studies, Riley et al. 2007; Avogadro et al. 2004; Jordan et al. 2007; Jordan et al. 2008; Divert et al. 2005), in sole sensors (4 studies, Fuller et al. 2016;
Fuller et al. 2016; Nakayama et al. 2010; Mann et al. 2015) 2D motion capture (2 studies, Castro et al. 2013; Tartaruga et al. 2009), and an electromagnetic sensing system (1 study, Barrett et al. 2008).

2.3.5.1 How is stride time variability measured?

The focus of this section of the literature review was on methods utilised within the literature to assess stride time variability. Of the 18 articles identified 8 articles utilised only distributional measures to assess stride time (Connick and Li 2015; Heiderscheit et al. 2002; Riley et al. 2007; Avogadro et al. 2004; Divert et al. 2005; Castro et al. 2013; Tartaruga et al. 2009; Barrett et al. 2008) whilst 10 articles used both distributional measures and non-linear techniques to assess stride time variability (Chapman et al. 2008; Lindsay et al. 201; Meardon et al. 2011; Jordan et al. 2008; Jordan et al. 2006; Jordan et al. 2007, Fuller et al. 2016a; Fuller et al. 2016b; Nakayama et al. 2010; Mann et al. 2015) (Table 2.3).
### Table 2.3 Stride variability measures identified.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
</tr>
<tr>
<td>Standard Deviation (SD)</td>
<td>•</td>
<td></td>
<td></td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
<td></td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
</tr>
<tr>
<td>Coefficient of variation (CV)</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td></td>
<td></td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
</tr>
<tr>
<td>Non – Linear Analysis Measures</td>
<td>Root Mean Square Error (RMSE)</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coefficient of Multiple Correlation (CMC)</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Detrended Fluctuation Analysis (DFA)</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Power spectral density (PSD)</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Multiscale Entropy (MSE)</td>
<td>•</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td>•</td>
<td>•</td>
<td>•</td>
<td></td>
<td>•</td>
<td></td>
</tr>
</tbody>
</table>
Of the 18 articles identified only 2 did not report the mean and standard deviation of stride time (Chapman et al. 2008 & Fuller et al. 2016a). However, both Chapman et al. (2008) and Fuller et al. (2016a) used alternative non-linear analysis methods (Root Mean Square Error (RMSE), Coefficient of Multiple Correlation (CMC) and Detrended Fluctuation Analysis) and therefore their questions may have been better addressed utilising non-linear methods. For example Chapman et al. (2008) investigated the reproducibility of stride time during running, in triathlete’s post cycling. CMC depicts the similarity of waveforms and is more commonly used identifying consistencies within gait cycles (Kadaba et al. 1989 & McGinley et al. 2009); however RMSE quantifies the difference or error of a measure (Willmott et al. 1985). It therefore appears Chapman et al. (2008) was not interested in the patterning of stride time variability over a stride time series, but was investigating a comparison of separate stride time series. Alternatively, Fuller et al. (2016a) investigation focused purely on the patterning of stride variability over a stride time series, as they wished to see if over training or over reaching impacted stride time variability.

Additionally, only 4 of the 18 articles (Avogadro et al. 2004; Divert et al. 2005; Riley et al. 2007; Tartarunga et al. 2009) did not utilise CV to analyse stride time, its popularity primarily due to the ease of calculation and interpretation of CV by researchers. Only one of the 18 articles did not report any distributional measure of stride time (Chapman et al. 2008), however as previously outlined Chapman et al. (2008) utilised both RMSE and CMC.

Interestingly, there is also an increase in research utilising non-linear techniques for the analysis of stride time variability with 10 of the 18 articles identified using both distributional and non-linear analysis methods (Chapman et al. 2008; Lindsay et al. 2014; Meardon et al. 2011; Jordan et al. 2008; Jordan et al. 2006; Jordan et al. 2007; Fuller et al. 2016a; Fuller et al. 2016b; Nakayama et al. 2010; Mann et al. 2015). Nine of these articles utilised Detrended Fluctuation Analysis (DFA) to calculate stride time long range correlations during running, although the number of strides from which DFA α values was calculated varied from 161 strides (Mann et al. 2015) to 661 (Meardon et al. 2011). DFA provides an investigation into the fractal processes of stride time during running and walking, and identifies that
whilst distributional measures may indicate stable stride time patterning, DFA in fact outlines that a running stride time is dependent on a previous stride time, and decays in a power-like fractal process (Jordan et al. 2006 & Meardon et al. 2011). Compared to distributional measures of variability which are relatively easy to derive and/or calculate DFA is far more complex and this may contribute to 50% of articles identified, not utilising DFA. DFA, as outlined by Peng et al. (1995), requires multiple steps in which a stride time series (length = N) is divided into non-overlapping boxes of equal length (n), a least squares fit line is applied to the data within that box and subsequently the local trend is removed. After this the root mean square of each box (F(n)) is calculated. This is repeated for all box sizes from n = 4 to N/4. Typically, F(n) will increase with box size n, and this is then plotted on a double log graph where a linear relationship is identified. The slope of the line relating F(N) to n then represents the scaling exponent α, with which DFA is identified (Figure 2.3).

Figure 2.3 Jordan et al. (2006) representative running trial displaying the slope of the line (α) relating the log of the average window size (n) to the log of the average fluctuation size (F(n)).

An α value of 0.50 indicates the presence of a random walk, where one point in time is uncorrelated to previous points in time. An α value of between 0.50 and 1.00 indicates the presence of persistent long range correlations (a long stride time will be followed by a long stride time). An α value of less than 0.50 indicates the presence of persistent long range anti-correlations (a short stride time will be followed by a long stride time and vice versa). Values greater than 1.0 indicate the
presence of long range correlations which no longer decay with increasing time lag, according to the power law (Goldberger et al. 2000 & Meardon et al. 2011). DFA has identified that running possesses long range correlations similar to that of walking, identifying that these correlations are robust to both speed and type of locomotion (Jordan et al. 2006). To date DFA has also identified that trained runners display less persistent stride patterning than their non-trained counterparts ($\alpha$ values closer to 0.5) (Nakayama et al. 2011), and that previously injured runners also display less persistent stride patterning than their non-injured counterparts ($\alpha$ values closer to 0.5) (Meardon et al. 2010). Therefore, DFA may reveal information about stride patterning which can aid our interpretation of runners mechanics.

Whilst there are programmes available which can assist with the calculation of DFA (PhysioNet Toolkit), distributional measures may still provide a more appealing, and easier to implement, method of stride time variability analysis. Furthermore, within the remaining articles which utilised non-linear analysis methods Lindsay et al. (2014) provided the most comprehensive analysis as they included all distributional measures outlined and also Detrended Fluctuation Analysis (DFA), Power Spectral Density (PSD) and Multiscale Entropy (MSE). Interestingly, whilst DFA identifies the persistence of stride time series (how one stride is dependent on another) MSE addresses a different measure of variability, complexity. Costa et al. (2003) outlines that complexity is undefined within dynamics of the human body, but is “related to our understanding, i.e. to our ability to provide a short description of a phenomenon” (Costa et al. 2003, pg. 54), however when applied to gait dynamics MSE is typically used to quantify the regularity or order of a time series (Costa et al. 2003). A higher degree of entropy is associated with increased disorder within a time series and interestingly has not been found to be associated to DFA. Therefore, Lindsay provides information both on the persistence of stride time, and also the regularity of stride time. However, in relation to PSD analysis Heneghan and McDarby (2000) outlined that DFA and spectral analysis provide comparable results for non-stationary, stochastic signals, such as that represented by running stride time series. Therefore Lindsay et al. (2014) additional use of PSD may have been unwarranted within this research.
2.3.6 Summary
Overall it is clear distributional measures of stride time variability play an important role in the analysis and interpretation of running stride time. Information regarding the magnitude and spread of stride time data informs researchers about the singular nature of stride time events. However, given the nature of running, in which a runner is continually perceiving information regarding their environment and making adaptations in response, non-linear analysis provides a more comprehensive analysis of how running stride times relate to one another (Terrier and Deriaz 2011). Whilst DFA has been identified as a reoccurring method of non-linear analysis in stride time during running, selecting a method of analysis should primarily be based on the aspect of variability which researchers are interested in.

2.4 Thesis Context
Chapter 2 provides a comprehensive review of the literature related to the use of accelerometers and gyroscope within running gait and stride time variability measures. Chapter 2 is key within the thesis as it provides the basis to the protocol employed for data collection within Chapter 4 and also an introduction to the primary analysis method utilised within the thesis, DFA.
Chapter 3. Sensor self-attachment. A valid and reliable option?
3.1 Abstract
Inertial sensors allow for longitudinal gait assessment with minimal impact upon subjects’ lives. However, issues, such as sensor misalignment, can arise as to validity of results when unsupervised sensor attachment protocols are utilised. Therefore, the purpose of this experiment was (a) to investigate the validity of accelerometer self-attachment and (b) to investigate the reliability of accelerometer self-attachment. To investigate reliability one male participant performed 3 data collection sessions (r1, r2 and r3). For r1 the participant performed a bilateral tibial accelerometer attachment protocol every ten minutes within a one hour period (r1, n=6). A single bilateral attachment was then repeated 24 hours later (r2), and again 48 hours’ post r2 (r3). For each trial a fifteen second static standing position was adopted, triaxial linear accelerations were recorded and tilt angles derived. To investigate participant -tester consistency a tester then repeated the r1 protocol (n=6), however here the tester attached the accelerometers to the participant (v1). Bland-Altman analysis and absolute differences were calculated. Reliability of within-tester and within-participant were examined using ICC’s. Paired r1 and v1 trials identified differences of up to 14º, between tester and participant attachment tilt angles. Concerning reliability, the unsupervised protocol resulted in tilt angles with a range from 1.3º for LeftRoll to 8.9º for RightYaw, across the three reliability sessions. Care should be taken when implementing unsupervised sensor attachment protocols during repeated measures data collection for gait. If this protocol is utilised it is necessary to determine accelerometer offset from attached static calibration for each individual trial so that accurate linear acceleration patterns can be derived during gait.

3.2 Introduction
Inertial sensors have become increasingly popular, primarily as they are highly transportable, have multiple attachment sites and methods of attachments, and can be used to collect data during both low and high intensity activities (Fong and Chan 2010). In general accelerometers, and inertial sensors alike, are designed to minimise the effect which factors such as temperature, mechanical wear and calibration (or time since previous calibration) may have on accelerometer data output (Kavanagh and Menz 2008). However, accelerometry data output error may still occur and nowadays researchers are equipped with post processing software
and custom developed algorithms to correct for any possible drift or offset within data (Favre et al. 2009). This has provided researchers with further assurance as to the accuracy of sensor data output, when using sensors away from a laboratory setting (Fong and Chan 2010).

The ability to move protocols from a constrained lab environment to a more ecological setting, has allowed researchers to perform accelerometry data collection in sporting venues for collection of kinematic data for elite athletes (Wixted et al. 2010), and in participants’ homes for monitoring habitual physical activity behaviour (Westerterp 2009). However, data collection protocols performed externally from a laboratory setting, especially those performed over long time periods, may increase the need for unsupervised participant sensor attachment (Khan et al. 2010). With this, further issues may arise surrounding the validity of results in regards to the sensor positioning and attachment performed by the participant (Khan et al. 2010 & Gietzelt et al. 2012). Gemperle et al. (1998) devised a "wearability guide" for body worn units, such as inertial sensors, which pinpoints locations on the body for unobtrusive sensor attachment, assisting researchers with the sensor attachment protocol. Furthermore, Kavanagh et al. (2006) investigated the effect of single and dual researcher accelerometer attachment on the reliability of segmental accelerations during gait. Kavanagh et al. (2006) found that both intra- and inter-researcher attachment resulted in minor differences in segmental accelerations, which were negligible in relation to normal motor system variability. Additionally, with protocols such as this, a researcher will have performed the attachment numerous times and is knowledgeable in the importance of sensor placement. However, with self-attachment protocols many participants may have only been provided with a familiarisation session and a manual/guide (Kringen et al. 2016 & Norris et al. 2016), and are then required to replicate valid sensor attachment protocols, unsupervised across numerous occasions. It is therefore vital that researchers have an in depth understanding of the effect that sensor self-attachment may have on data collection.

Researchers have investigated sensor displacement, with Banos et al. (2014) examining the effect of sensor displacement on activity pattern recognition. Banos et al. (2014) pg. 9998 defined sensor displacement as "a change in sensor position
with respect to the initial or intended position during use", and investigated unintentional sensor displacement compared to ideal sensor placement, as placed and attached by the researcher. Unintentional sensor displacement was mimicked via participant self-placement as the researchers deemed this would lead to slight variations to the ideal placement. This protocol would also replicate scenarios in which participants would need to self-attach sensors in their own environment (Banos et al. 2014). It was identified that sensor self-placement and attachment resulted in a loss of sensor performance, in which the sensor was unable to identify, or incorrectly identified, activity patterns, due to differences in translation and rotation induced via sensor displacement (Banos et al. 2014). This is similar to findings by Kavanagh and Menz (2008) who also identified that depending on the accuracy of sensor placement during self-attachment (in terms of distance from the joint of interest and segment alignment), accelerometers will undergo varying degrees of rotational and translational accelerations. Whilst Banos et al. (2014) undertook comprehensive research, utilising eight sensor attachment sites (including lower and upper legs, and lower and upper arms) and 33 exercises (including walking, rowing and twisting) the research did not investigate raw accelerometry data or sensor tilt angle, focusing on activity pattern recognition.

Researchers have also investigated sensor misalignment, where the local axes of the accelerometer are not correctly aligned with the Cartesian axes of the body, in relation to sensor attachment (Gietzelt et al. 2012). Gietzelt et al. (2012) identified that within supervised settings, during sensor attachment, the coordinate system of an accelerometer is manually aligned with the chosen body segment’s local coordinate system, however this is not guaranteed in an unsupervised sensor self-attachment protocol.

Whilst Gietzelt et al. (2012) further validated an algorithm to align skewed accelerometer placement to the axes of the body, their research was performed on the lower trunk. Within the current study, the attachment protocol focused on accelerometer attachment to the lower limb, the anteromedial tibia specifically. This sensor placement location has previously been identified as the optimal placement for inertial sensors collecting lower limb temporal gait parameters, such as stride and step time (Mathie et al. 2004). Furthermore, research has also
shown that when investigating gait accelerometry, accelerometer signals are increasingly attenuated as sensor location is positioned proximal of the lower limb (Norris et al. 2014). Therefore, it is more appropriate to investigate sensor attachment protocols for gait in a location positioned on the lower limb.

Lastly, whilst researchers have investigated the effect of sensor placement and attachment on sensor displacement and sensor misalignment (Kavanagh and Menz 2008 & Banos et al. 2014), there is, to the author’s current knowledge, no research investigating the effect of sensor attachment on sensor tilt angle. Within accelerometry, reproducible accelerometer orientation, represented as a tilt angle with respect to gravity, has been identified as a necessary construct over repeated trials, to aid minimisation of alignment error (Luinge and Veltink 2005). Therefore, accelerometer tilt angle is a key parameter of interest when investigating sensor attachment protocols. Also, tilt angle provides an easily calculated and understandable measure which researchers can utilise to monitor sensor self-attachment protocols. Therefore, the aims of the current experiment are (a) to investigate the validity of accelerometer self-attachment and (b) to investigate the reliability of accelerometer self-attachment over time. It is believed information from this study will influence the development of future sensor attachment protocols.

### 3.3 Methods

#### 3.3.1 Instrumentation

After Institutional approval (Appendix A), one healthy male volunteer (age: 24.4 years, stature: 1.86 m, mass: 75.5 kg) was recruited from the student population of the University of Limerick. Accelerometry data were collected using two SHIMMER triaxial accelerometers (±6 g, sensitivity= 200 mV/g, resolution = 32 bits, dimension = height 1.7 cm, width 3.5 cm, length 5.4 cm) (SHIMMER Ltd, Dublin, Ireland), attached to the participant via a purpose built elastic strap (accelerometer mass: 28 g, combined accelerometer and strap mass: 48 g, Figure 3.1). Shimmer 2r™ accelerometers were selected as they provide a compact inertial sensing unit, with sampling rates of up to 1024 Hz, and additional inertial sensing properties which could be added, such as gyroscope, GPS and magnetometer properties, if necessary. Additionally, the Shimmer 2r™ purpose built elastic straps
were adjustable to the selected attachment locations and therefore it was assumed this would increase participant sensor attachment comfort.

Figure 3.1 Shimmer 2r™ accelerometer (Abbate et al. 2014).

The sensor was placed inward, toward the tibia, to limit sensor movement. The accelerometers sampled at 204.8 Hz. Whilst accelerometers typically sampling rates are in integer format Shimmer 2r™ accelerometers require the sampling period to be an integer multiple of 1/1024 s. Prior to a familiarisation session the accelerometers underwent static calibration following manufacturer 9DOF application methods. This calibration resulted in a coordinate system which allowed for collection of mediolateral acceleration in the x axis, vertical acceleration in the y axis and anteroposterior acceleration in the z axis.

3.3.2 Attachment protocol
The attachment protocol itself outlined that the accelerometer was fastened to the distal anteromedial tibia, such that the y axis was aligned with the tibial longitudinal axis. To appropriately attach the sensor was placed on the flat surface of the tibia, which results in a local sensor coordinate system not directly aligned with the global coordinate system of the lower limb (Figure 3.2). Therefore, when attached the sensor allowed for the collection of an approximate estimate of tibial mediolateral acceleration in the x axis, tibial vertical acceleration in the y axis and tibial anteroposterior acceleration in the z axis. When attached to the tibia a positive vertical acceleration was directed proximally, positive mediolateral acceleration was directed laterally and positive anteroposterior acceleration directed posteriorly. The accelerometer was located 0.10 m superior of the centre
of the medial malleolus, and this attachment was performed bilaterally (Figure 3.2).

![Bi-lateral accelerometer attachment to the anteromedial distal tibia. On a concentrated section of the right tibia, positive axial directions of the accelerometer local coordinate system when attached are superimposed in bold arrows, with vertical and lateral directions of the lower limb global coordinate system superimposed in dashed arrows.](image)

3.3.3 **Familiarisation**

For the familiarisation session, the participant was provided with a demonstration of the attachment protocol by the principal investigator. The participant then performed multiple unrecorded attachment trials, during which feedback was provided, by the investigator, as to their accuracy of accelerometer attachment. The participant was then provided with an instruction manual (Appendix B) which outlined in text and graphically the accelerometer attachment protocol. Furthermore, the participant was also provided with a tailored calibrated card template (length =0.10 m), which could be utilised to locate the desired accelerometer attachment point, proximal of the malleoli.

3.3.4 **Data collection protocol**

To investigate participant self-attachment, reliability 3 separate data collection sessions were conducted, $r_1$, $r_2$ and $r_3$ (Figure 3.3). During all reliability sessions, the participant was required to replicate the accelerometer attachment procedure, for a specified number of times. After secure attachment, the participant was required to statically stand with their feet shoulder width apart for 15 seconds,
and then remove the sensors. A static position was selected as this investigation was focusing on the effect of self-attachment on accelerometry output, however a dynamic action could also impose additional sensor movement unrelated to original sensor placement (Bonas et al. 2014). While the tester was present throughout all data collections sessions no feedback or instructions were provided (mimicking an unsupervised environment). However, participants were permitted to utilise the materials provided during familiarisation (the instruction manual and calibrated card), as this corresponded with data collection methods to be utilised in a future study (Chapter 4). Tester presence ensured that participants performed a replicated stance position for each trial, ensuring participant positioning would not cause erroneous error.

For r1, the participant was required to attach and remove the accelerometers every ten minutes within a one hour period (n=6). For r2 (24 hours post r1), and r3 (48 hours post r2) the participant was required to replicate the attachment protocol once. This resulted in a total of 8 trials collected. The time intervals between reliability sessions were chosen as again they corresponded with data collection methods to be utilised in a future study (Chapter 4). To investigate accelerometer self-attachment validity, the tester then repeated the data collection protocol employed in r1, however here the tester attached the accelerometers to the participant (v1). V1 was performed 7 days’ post r1 (Figure 3.3).

![Timeline](image)

**Figure 3.3 Timeline outlining intervals between data collection sessions.**

### 3.3.5 Data processing

Accelerometer data were extracted and converted to m·s⁻² via manufacturer guidelines using MATLAB™ (r2009b) (MathWorks, Cambridge, UK). Raw data files were exported to MS Excel (2007) and one second periods within the static standing trials were visually identified from each trial collected. For each one
second period mean values of acceleration were calculated for each axis and therefore representative accelerations for x, y and z directions were generated. Tilt angles for x, y and z (pitch, roll and yaw) were then calculated utilising triaxial tilt measurement methods by Tuck (2007).

3.3.6 Data analysis

To investigate validity between tester and participant attachment methods, tilt angles collected during r1 and v1 were compared. R1 and v1 trials were paired (i.e. r1 trial one compared to v1 trial one) and the absolute value of the differences between trials were calculated. Also, as recommended by Bland and Altman (1986) a comparison of methods was assessed by calculating the paired difference between the attachments (r1 and v1) and the mean of the two attachments (r1 and v1). This was performed for each axis, bilaterally. The strength, direction and significance of the relationship between tester and participant attachments was assessed using linear trend lines applied to the Bland and Altman scatterplots, from which correlation coefficients (r) and slope were calculated. For intra-participant repeatability participant r1 tilt angles (n=6) were averaged to calculate a representative tilt angle. The absolute differences between the r1 representative tilt angle, r2 and r3 tilt angles were then calculated.

3.4 Results

Absolute differences between tester and participant attachment tilts angles ranged between 0.5º and 14º (Table 3.1). The greatest difference between tester and participant in right leg paired data was Trial 3 yaw angle (14º). The greatest difference between tester and participant in left leg paired data was Trial 1 yaw angle (10.8º).
Table 3.1 Absolute difference in right and left leg pitch, roll and yaw angles between tester (v1) and participant (r1) attachment.

<table>
<thead>
<tr>
<th>Trial</th>
<th>Right Leg Pitch °</th>
<th>Right Leg Roll °</th>
<th>Right Leg Yaw °</th>
<th>Left Leg Pitch °</th>
<th>Left Leg Roll °</th>
<th>Left Leg Yaw °</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.9</td>
<td>0.6</td>
<td>6.7</td>
<td>7.6</td>
<td>6.5</td>
<td>10.8</td>
</tr>
<tr>
<td>2</td>
<td>10.0</td>
<td>2.2</td>
<td>6.8</td>
<td>6.4</td>
<td>5.3</td>
<td>6.7</td>
</tr>
<tr>
<td>3</td>
<td>0.5</td>
<td>4.1</td>
<td>14.0</td>
<td>6.1</td>
<td>5.6</td>
<td>8.2</td>
</tr>
<tr>
<td>4</td>
<td>10.4</td>
<td>1.7</td>
<td>9.7</td>
<td>7.0</td>
<td>4.1</td>
<td>5.0</td>
</tr>
<tr>
<td>5</td>
<td>1.5</td>
<td>6.7</td>
<td>11.8</td>
<td>6.7</td>
<td>0.8</td>
<td>7.3</td>
</tr>
<tr>
<td>6</td>
<td>5.8</td>
<td>0.8</td>
<td>2.3</td>
<td>4.2</td>
<td>3.0</td>
<td>5.6</td>
</tr>
</tbody>
</table>

Bland-Altman results indicate the greatest agreement between participant and tester attachment occurred at Right Roll, with mean bias range of -2.7 to 2.3°, and limits of agreement of -7.4 to 2.0° (Figure 3.4). Correlation coefficient r values ranged between 0.00 and 0.88, when comparing participant and tester tilt angles for r1 and v1 (Table 3.2).
Difference between tester and participant in RightPitch°

(a)

Difference between tester and participant RightRoll°

(b)
Difference between tester and participant

**RightTheta°**

- Mean of tester and participant RightTheta°
- Mean - 2 SD
- Mean + 2 SD

**LeftPitch°**

- Mean of tester and participant LeftPitch°
- Mean - 2 SD
- Mean + 2 SD
Figure 3.4 Bland-Altman plots for tester-participant reliability in (a) RightPitch, (b) RightRoll, (c) RightYaw, (d) LeftPitch, (e) LeftRoll and (f) LeftYaw angles.
Table 3.2 Bland–Altman results for right and left leg pitch, roll and yaw angles between tester (v1) and participant (r1) attachment.

<table>
<thead>
<tr>
<th></th>
<th>Difference Mean ± SD</th>
<th>r</th>
<th>p</th>
<th>Slope</th>
<th>Limits of Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RightPitch (°)</strong></td>
<td>3.9 ± 6.3</td>
<td>0.88</td>
<td>0.02</td>
<td>-3.26</td>
<td>-8.8 to 16.6</td>
</tr>
<tr>
<td><strong>RightRoll (°)</strong></td>
<td>-2.7 ± 2.3</td>
<td>0.30</td>
<td>0.57</td>
<td>-0.50</td>
<td>-7.4 to 2.0</td>
</tr>
<tr>
<td><strong>RightYaw (°)</strong></td>
<td>8.5 ± 4.2</td>
<td>0.80</td>
<td>0.05</td>
<td>-1.39</td>
<td>0.2 to 16.9</td>
</tr>
<tr>
<td><strong>LeftPitch (°)</strong></td>
<td>-4.1 ± 5.4</td>
<td>0.44</td>
<td>0.38</td>
<td>-1.18</td>
<td>-14.9 to 6.7</td>
</tr>
<tr>
<td><strong>LeftRoll (°)</strong></td>
<td>-2.4 ± 4.3</td>
<td>0.00</td>
<td>0.99</td>
<td>-0.04</td>
<td>-11.0 to 6.1</td>
</tr>
<tr>
<td><strong>LeftYaw (°)</strong></td>
<td>2.6 ± 7.7</td>
<td>0.27</td>
<td>0.61</td>
<td>0.65</td>
<td>-12.8 to 18.0</td>
</tr>
</tbody>
</table>

Reliability was assessed firstly for intra-tester and intra-participant reliability. Intra-tester reliability indicated average alignment errors of 0.9 %, compared to an average alignment error of 1.3% for intra-participant attachment (Table 3.3.). Additionally reliability was assessed as the difference in tilt angle for each given axis, bilaterally, across r1, r2 and r3. The greatest difference in tilt angle occurred at yaw angle of the right leg, between r3 and r2 (8.9°). The smallest difference in tilt angle occurred at roll angle of the left leg, between r1 and r3 (-0.3°). Overall, the largest range of tilt angle was observed for yaw, bilaterally (8.9° for right and 4.9° for left).
Table 3.3 Intra-tester (v1) attachment reliability and intra-participant (r1) attachment reliability.

<table>
<thead>
<tr>
<th>Angle</th>
<th>v1 Mean (SD)</th>
<th>v1 Range</th>
<th>v1 max - min alignment error (%)</th>
<th>r1 Mean (SD)</th>
<th>r1 Range</th>
<th>r1 max - min alignment error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RightPitch (º)</strong></td>
<td>0.8 (1.9)</td>
<td>-1.4 to 2.6</td>
<td>0.2</td>
<td>-3.1 (4.7)</td>
<td>-8.2 to 4.5</td>
<td>2.4</td>
</tr>
<tr>
<td><strong>RightRoll (º)</strong></td>
<td>4.8 (1.5)</td>
<td>2.6 to 6.8</td>
<td>0.3</td>
<td>4.8 (1.5)</td>
<td>2.6 to 6.8</td>
<td>0.3</td>
</tr>
<tr>
<td><strong>RightYaw (º)</strong></td>
<td>4.5 (1.4)</td>
<td>2.6 to 6.3</td>
<td>0.2</td>
<td>4.5 (1.4)</td>
<td>2.6 to 6.3</td>
<td>0.2</td>
</tr>
<tr>
<td><strong>LeftPitch (º)</strong></td>
<td>-4.9 (2.6)</td>
<td>-7.9 to -1.3</td>
<td>0.7</td>
<td>-0.8 (4.0)</td>
<td>-7.9 to 3.4</td>
<td>2.0</td>
</tr>
<tr>
<td><strong>LeftRoll (º)</strong></td>
<td>4.9 (2.6)</td>
<td>2.5 to 8.4</td>
<td>0.5</td>
<td>7.3 (2.7)</td>
<td>3.2 to 10.5</td>
<td>0.8</td>
</tr>
<tr>
<td><strong>LeftYaw (º)</strong></td>
<td>2.0 (5.6)</td>
<td>-8.8 to 6.8</td>
<td>3.7</td>
<td>-0.6 (4.3)</td>
<td>-4.0 to 7.7</td>
<td>2.1</td>
</tr>
<tr>
<td><strong>Average (SD)</strong></td>
<td>0.9 (1.4)</td>
<td></td>
<td></td>
<td>1.3 (1.0)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.4 Mean tilt angle, absolute differences and range for participant reliability tilt angle measures across r1, r2 and r3.

<table>
<thead>
<tr>
<th></th>
<th>r1</th>
<th>r2</th>
<th>r3</th>
<th>Absolute difference (r1 and r2)</th>
<th>Absolute difference (r1 and r3)</th>
<th>Absolute difference (r2 and r3)</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>RightPitch (°)</td>
<td>-3.1</td>
<td>-5.0</td>
<td>-2.7</td>
<td>1.9</td>
<td>0.4</td>
<td>2.3</td>
<td>2.3</td>
</tr>
<tr>
<td>RightRoll (°)</td>
<td>7.5</td>
<td>6.9</td>
<td>3.1</td>
<td>0.6</td>
<td>4.4</td>
<td>3.8</td>
<td>4.4</td>
</tr>
<tr>
<td>RightYaw (°)</td>
<td>-4.1</td>
<td>4.8</td>
<td>-1.4</td>
<td>8.9</td>
<td>2.7</td>
<td>6.2</td>
<td>8.9</td>
</tr>
<tr>
<td>LeftPitch (°)</td>
<td>-0.8</td>
<td>-4.1</td>
<td>-3.0</td>
<td>3.3</td>
<td>2.2</td>
<td>1.1</td>
<td>3.3</td>
</tr>
<tr>
<td>LeftRoll (°)</td>
<td>4.9</td>
<td>5.9</td>
<td>4.6</td>
<td>1.0</td>
<td>0.3</td>
<td>1.3</td>
<td>1.3</td>
</tr>
<tr>
<td>LeftYaw (°)</td>
<td>-0.6</td>
<td>4.3</td>
<td>3.5</td>
<td>4.9</td>
<td>4.1</td>
<td>4.1</td>
<td>4.9</td>
</tr>
</tbody>
</table>
3.5 Discussion

Valid and reliable accelerometer attachment is vital when investigating lower limb gait temporal parameters such as stride and step time. Tilt angle represents an easily calculated and understandable parameter, derived from accelerometry data, which can reveal information about accurate sensor self-attachment protocols.

3.5.1 Validity

For validity, when comparing paired trials participant unsupervised attachment method resulted in accelerometer tilt angles up to 14º different from tester accelerometer tilt results. Previously, Kavanagh and Menz (2008) identified that changes in axes alignment are proportional to the cosine of the tilt of the angle, with respect to the global vertical or horizontal. Kavanagh and Menz (2008) therefore outlined that a change in accelerometer orientation of 5º, results in alignment error of approximately 0.4%, and therefore the maximum alignment error introduced here between participant and tester (14º) is minimal (3.0%). The results of the current study are also in line with previous research, acknowledging there will always be minor differences between researcher "ideal" sensor attachment and participant sensor self-attachment (Banos et al. 2014). Whilst Banos et al. (2014) reported that sensor self-attachment resulted in a major decline of activity pattern recognition (20 - 25% accuracy), compared to researcher sensor attachment (80 - 90% accuracy), Banos et al. (2014) participants were provided with no manual/guide to assistance them with placement and attachment. Providing a manual/guide may aid participants to increase sensor attachment validity.

3.5.2 Reliability

Participant reliability scores displayed a decreased range of tilt angles than previously discussed validity scores, with a range of 1.3º - 8.9º over the three testing session’s r1, r2 and r3. This is line with research by Kavanagh et al. (2006) investigating intra- and inter-researcher reliability, and indicates that it is in fact not prior scientific knowledge of sensor locations which is required for reliable sensor self-attachment, but familiarisation to the attachment protocol. This is supported by Stenlund et al. (2014) who stated that during sensor attachment as the number of error variance components (such as body landmark locating and
attaching the sensor) increases, reliability decreases. With intra-participant reliability, as was investigated here, there is a decrease in prominence of error variance components, as the participants repeat attachment protocols. Factors such as locating the medial malleoli and positioning the accelerometer correctly on the shank, become more familiar to participants, increasing sensor self-attachment reliability.

3.5.3 Limitations
Whilst this study contributes to understanding the validity of self-attachment protocols there are some limitations. Firstly, this was a single participant study, whilst previous similar research has recruited a greater number of participants (Banos et al. 2014). Also, only one sensor attachment site, the anteromedial distal tibia, was chosen for the current investigation. As previously stated, the chosen sensor attachment location was selected based on previous literature investigating inertial sensor use in gait research (Mathie et al. 2004).

Overall, results of the current study indicate that accelerometer alignment errors do occur when implementing an unsupervised participant self-attachment protocol over time. However, these errors are negligible and therefore should not deter researchers from using self-attachment protocols in future research. Should researchers choose to do so, steps can be undertaken to correct for any alterations which may occur in static sensor orientation. Utilising tilt correction methods by Kavanagh et al. (2004) for every trial researchers can correct for deviations from global coordination planes. Alternatively, adopting a static position for a standardised period prior to dynamic movement in gait will allow for the calculation of any static axes orientation offset (Gietzelt et al. 2012 & Tadano et al. 2013), allowing for valid acceleration pattern derivation during post processing.

3.6 Conclusion
Participant sensor self-attachment is becoming a more commonly utilised protocol within biomechanics research (Gietzelt et al. 2012) and a lower limb self-attachment protocol can result in sufficient validity and reliability in accelerometer tilt angles. Whilst participant sensor self-attachment may differ by up to $14^\circ$ from that of researcher sensor attachment, participants demonstrate reliable sensor
self-attachment over long time periods. Even though current study has provided vital information on sensor self-attachment methods, future research should focus on further technical and processing issues which are associated with accelerometry use, such as accelerometer range and post processing filtering methods.

3.7 Thesis context
Participant self-attachment validity may be enhanced by the provision of an attachment guide, as results within the current study appear to be less effected by participant self-attachment methods than results displayed by Banos et al. (2014). Additionally, participant reliability may be increased across longitudinal periods, due to familiarity with the attachment protocol. Chapter 3 therefore provides support in utilising participant sensor self-attachment within future (Chapter 4) data collection protocols.
Chapter 4. Longitudinal data collection and associated methodological issues.
4.1 Abstract

Longitudinal data collections provide additional complications for researchers, as equipment and measurement reliability can be questioned between sessions and participant adherence can be problematic (Ford et al. 2007). Nonetheless, longitudinal data collections provide invaluable information about how biomechanical parameters change over time. Within running recreational runners completing half and full marathon distances provide an intriguing group of participants, however there is little known about how they perform throughout training programmes and continuously throughout the competitive running event. Therefore, the aim of this chapter was to outline the methods utilised when performing a longitudinal accelerometry data collection in participants training for and competing in distance running events. Six recreational runners interested in completing their first half marathon and six recreational runners interested in completing their first full marathon were recruited. Participants were provided with two Shimmer 2r™ accelerometers, following a familiarisation session, and required to wear the accelerometers on their distal anteromedial tibia, bi-laterally, during training for and completion of a distance running event. Participants were supplied with a Hal Higdon half marathon (12 week) or full marathon (18 week) training programme, aligned with their previous running experience. Furthermore, participants were required to complete a weekly training log and discomfort questionnaire incorporating RPE scales, and questions regarding injury, mood, and stress. Post data collection results indicated that the 6 participants completing the half marathon training programme and competitive race completed 71.8 ± 21.0 % of the runs scheduled within the programme supplied (32.5 runs, range = 14 to 43 runs, out of 48 runs). Out of the runs completed, participants successfully captured tibial accelerometry data for 78.2 ± 23.3 % (27.1 runs, range = 6 to 40 runs). In comparison, 4 of the 6 participants recruited for the full marathon training programme completed the competitive full marathon event, as 2 participants dropped out due to injury. Of the 4 participants who completed the full marathon training programme and competitive event on average participants completed 72.2 ± 8.9 % of the runs scheduled within the programme supplied (52.0 runs, range = 43 to 58 runs, out of 72 runs). Out of the runs completed, participants successfully captured tibial accelerometry data for 49.3 ± 23.1 % (35.5 runs, range = 16 to 53 runs). Participants who completed the half marathon training
programme and competitive run reported reduced occurrences of aches, pains or injury (5.2 ± 2.2 occurrences) compared to those completing the full marathon training programme and competitive run (11.0 ± 6.2 occurrences). For the half marathon training group aches, pains or injuries were most commonly reported (in total) in the left lower leg (n = 11), followed by the right lower leg (n = 8) and the right knee (n = 7), whilst in the full marathon group aches, pains or injuries were most commonly reported (in total) in the right thigh (n = 27), followed by the left knee (n = 18) and the hips/buttocks (n = 17). Overall this chapter represents two significantly large accelerometry data collection periods. Whilst issues such as participant drop-out, sensor technical failure and ache, pain and injury occurrence affected the number of runs which accelerometry data was collected for, the data collected represents ecological, longitudinal running accelerometry data which will be utilised within the current thesis, to develop and enhance accelerometry analysis methods and to derive information regarding recreational runners running dynamics.

4.2 Introduction

Chapter 2 outlines the use of inertial sensing in distance running, identifying the multitude of parameters such as tibial accelerometry, stride rate, shock attenuation etc., which can be extracted from employing such methods. However, to date there is little research which utilises these methods, over longitudinal periods in recreational runners. Longitudinal data collections have long posed issues for researchers as there has been questions raised as to the validity and reliability of equipment, kinematic and kinetic measures (Ford et al. 2007), and with the adherence of participants. Furthermore, when specifically applied to recreational runners training for distance running events Zach et al. (2015) pg.1 outlined that “A marathon runner must adopt training habits and a lifestyle behaviour which is far beyond what is defined as recreational exercise, and beyond what is recommended for acquiring the basic health benefits of exercise. Such behaviour requires demanding psychological, physiological, and financial resources, with the high costs, and not necessarily positive” (Zach et al. 2015, pg. 1). This may suggest that those training for and completing marathons may have additional challenges they must overcome when exercising and successfully completing the marathon distance. Marathon runners, particularly recreational
runners training and completing a marathon, may therefore represent a group of participants in which adherence over a longitudinal period is never guaranteed.

Nonetheless, recreational runners completing half and full marathon distances provide an intriguing group of participants, as the number of participants within their cohort has grown significantly in the last 30 years (Buman et al. 2008), they do not necessarily have the expertise of coping strategies of trained runners (Stevinson and Biddle 1998) and the incidence of running related injuries when training for distance events varies considerably in the literature (1.4 to 94.4 %) (Kluitenberg et al. 2015). Therefore, focus should be placed on collecting biomechanical data within this group to give us a better understanding of how they train and compete in distance running events.

Chapter 4 outlines the methodology utilised to collect longitudinal accelerometry data in recreational runners training for and completing half and full marathon distances. Furthermore, it outlines the adherence levels of participants and injury occurrences which occur whilst collecting data of this nature. The data collected within this chapter will be utilised throughout the remaining chapters of the thesis to investigate temporal gait analysis methods and recreational runners running dynamics over longitudinal periods.

4.3 Methods

4.3.1 Participants

Following Institutional approval participants were recruited, for two data collection periods, via word of mouth and a recruitment email circulated within the University of Limerick (Appendix C). Due to equipment limitations (the number of Shimmer 2r™ accelerometers available), a maximum of 10 participants were required for each data collection period. To select data collection period start dates two major distance running events were selected. The first distance running event was the Great Limerick Run in which both half marathon and full marathon distances were completed sequentially on the same day, and the second distance running event was the Dublin City Marathon. The first data collection period then began 12 to 18 weeks prior to the Great Limerick Run (depending on if participants were completing the half or full marathon distance) whilst the second
data collection period began 18 weeks before the Dublin City Marathon (Figure 4.1).

![Timeline](image)

**Figure 4.1 Timeline outlining data collection periods for both half marathon and full marathon training programmes and races.**

To ensure participants were recreational runners participant eligibility included: (1) participants must have been 18 – 65 years old, (2) participants must have previously completed a competitive 10 km race, (3) participants must have been a novice half/full marathon runner (or have not completed the distance within the last three years), (4) participants must have already been interested in completing the relevant Great Limerick Run Half or Full Marathon/Dublin City Marathon, and (5) participants must have been located within the greater Limerick area. Previous 10 km road race experience was required to ensure participants had sufficient running experience, and therefore would be able to complete the provided training programme. Participants who were undertaking the full marathon distance were allowed to have previously completed a half marathon distance.

For data collection period one, 6 novice half marathon recreational runners were recruited (1 male, 5 female, age 33.5 ± 5.8 years, stature: 1.66 ± 0.08 m, mass: 71.1 ± 12.2 kg). All participants met the eligibility requirements and also had never undertaken specialised running training, ensuring they were recreational runners. Specialised running training was regarded as any training in which participants were committed solely to their specified running distance, fully committed to intense training and aiming for competitive success (Baker et al. 2005). It was then decided to cease recruitment for this data collection period, as this would allow for
spare accelerometers which could be provided to participants quickly, if accelerometer failure occurred during the training programme.

For data collection period two, 6 novice full marathon recreational runners were recruited (2 male, 4 female, age 38.0 ± 4.4 years, stature: 1.68 ± 0.12 m, mass: 67.5 ± 16.4 kg). 1 male participant within this data collection period had also completed data collection period one and the Great Limerick Run Half Marathon race. There was a 6-week period between the completion of data collection period one and data collection period two. As with data collection period one all participants met the eligibility criteria and subject recruitment was ceased when 6 participants were recruited. For both data collection periods, all participants were injury free when beginning their appropriate training programme provided.

4.3.2 Instrumentation

Due to availability, and prior validity and reliability self-attachment analysis (Chapter 3), Shimmer 2r™ accelerometers (±6 g, sensitivity= 200 mV/g) (SHIMMER Ltd, Dublin, Ireland), were utilised for data collection. Prior to undertaking their appropriate training programme participants were invited into the University of Limerick for familiarisation at attaching and utilising the accelerometers, as outlined in Section 3.3.3. As in Section 3.3.3 participants were also provided with the subject manual to assist them in self-attaching accelerometers without researcher supervision. All accelerometer parameters in terms of sampling frequency (204.8 Hz), attachment methods, accelerometer weight, alignment and calibration were as performed in Chapter 3. Briefly for the training programme (all training runs) and the competitive running event (half or full marathon), participants were required to wear a Shimmer 2r™ accelerometer, bi-laterally on their anteromedial distal tibia. During familiarisation accelerometers were provided to participants fully charged, however due to a limited number of charging docks available participants were not provided with a charging dock for the duration of the data collection periods (training programme lengths). Therefore, participants agreed to a weekly meeting with the researcher in which the accelerometers were collected, charged by the researcher, recalibrated (underwent static calibration following manufacturer 9DOF application methods) and the accelerometry data from the previous week were downloaded from the
microSD card located within the accelerometer casing. The accelerometers were then returned to the participant as soon as possible. As participants were scheduled to undertake a maximum of 4 runs per week (4.3.3) accelerometer collection occurred on the remaining days where runs were not being undertaken.

### 4.3.3 Training programmes

Following discussion with participants about past running experience, and goals for completing their chosen distance running event, participants were supplied with an appropriate running training programme. The Hal Higdon Novice 2 Half Marathon Training Programme (Appendix D) was selected for all half-marathon participants based on their previous running experience and the Hal Higdon Novice 2 Full Marathon Training Programme was selected for all full marathon participants (based on participants previous running experience) (Table 4.1).

#### Table 4.1 Suggested running ability for undertaking the Hal Higdon Novice 2 Half Marathon Training Programme and the Hal Higdon Novice 2 Full Marathon Training Programme.

<table>
<thead>
<tr>
<th>Hal Higdon Novice 2 Half Marathon Training Programme (12-week)</th>
<th>Hal Higdon Novice 2 Full Marathon Training Programme (18-week)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• People moving up from 5/10 km distance</td>
<td>• People who have been running a year, run occasional 5/10 km distance,</td>
</tr>
<tr>
<td></td>
<td>• Able to comfortably run 3-6 miles, training 3-5 days a week and covering 15-25 miles a week.</td>
</tr>
</tbody>
</table>

Hal Higdon training programmes were selected as Hal Higdon is a highly-regarded runner, having won multiple national championships in the United States of America, along with holding an American masters record for the 3,000-meter steeplechase, and also renowned within the running community for his distance running knowledge (Weismann – Yee 2009). Therefore, his training programmes are widely available and extremely popular within the running community. Additionally, the Hal Higdon website (www.halhigdon.com) provides runners with freely available additional information that participants within the current study could therefore access at their own leisure. Both Hal Higdon training programmes consisted of 4 runs a week, typically composed of two short runs, one medium run and one long run a week. Run length (km) progressed week-to-week in each
programme with a “stepback” week every third week, in which the long run was significantly reduced in distance to allow for rest and recovery (Table 4.2). Participants were free to undertake the programmes provided at their selected pace and on their chosen terrain, as many participants indicated they ran and lived in different locations and therefore would not be interested in completing the training programme in a running group environment.

Table 4.2 Example of week 1 to week 3 of the Hal Higdon Marathon Novice 2 Training Programme. “Cross” refers to cross-training.

<table>
<thead>
<tr>
<th>Week</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
<th>Sat</th>
<th>Sun</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rest</td>
<td>5km</td>
<td>8km</td>
<td>5km</td>
<td>Rest</td>
<td>13km</td>
<td>Cross</td>
</tr>
<tr>
<td>2</td>
<td>Rest</td>
<td>5km</td>
<td>8km</td>
<td>5km</td>
<td>Rest</td>
<td>14.5km</td>
<td>Cross</td>
</tr>
<tr>
<td>3</td>
<td>Rest</td>
<td>5km</td>
<td>8km</td>
<td>5km</td>
<td>Rest</td>
<td>9.5km</td>
<td>Cross</td>
</tr>
</tbody>
</table>

4.3.4 Training log and discomfort questionnaire

Additionally, participants were required to complete a weekly running and injury log (within the subject manual provided Appendix B). The training log provided further information as to the run distance and run time which the participants completed on a week-to-week basis. The discomfort questionnaire provided was included to provide further information regarding the onset of running related injury and possible drop out within the training programme. Within the discomfort questionnaire firstly participants were required to provide a RPE (rating of perceived exertion) for the long run which they completed within the week. RPE was measured utilising the Borg 15-grade RPE scale (Borg 1982), with a scale point of 6 indicating very, very light perceived exertion and 20 indicating maximum exertion. RPE was only required for the long run performed weekly as it was assumed this would be the most strenuous run which the participants would perform. Hereafter, participants answered questions within two sections, Ache, Pain or Discomfort, and General Health. The Ache, Pain or Discomfort was a subsection of the Standardised Nordic Injury Questionnaire (Kuorinka et al. 1987), and participants outlined any injuries or discomforts which occurred during the week along with the location and/or cause of the discomfort. The General Health section was comprised of questions regarding participants sleep quality and quantity, and the mood subsection of the Profile of Mood States (McNair et al. 1981) along with the stress subsection of the Depression Anxiety Stress Scale.
(Lovibond et al. 1995). These subsections were selected based on a previous study investigating the psychological, pain and injury traits of Irish dancers (Cahalan et al. 2015). Training log and discomfort questionnaires were provided in both paper and electronic format depending on participant preference. Paper training logs and discomfort questionnaires were collected by the researcher weekly, during accelerometer collection. Electronic training logs and discomfort questionnaires were supplied to participants weekly via SurveyMonkey™.

4.4 Results

4.4.1 Half marathon training programme adherence

All 6 participants completed the provided training programme and competitive half marathon. Two participants were unable to begin the training programme on week 1 and therefore began in week 2, leading them to have a reduced number of runs scheduled within their overall training programme (44 runs instead of 48) (Figure 4.2). Questionnaire results indicated that on average participants completed 71.8 ± 21.0 % of the runs scheduled within the programme supplied (32.5 runs, range = 14 to 43 runs, out of 44 to 48 runs) (Figure 4.2). Out of the runs completed, participants successfully captured tibial accelerometry data for 78.2 ± 23.3 % (27.1 runs, range = 6 to 40 runs). Total time spent running per participant, including unrecorded runs, during the 12-week training programme and competitive half marathon was 24.2 ± 6.8 hours.

![Figure 4.2](image)

**Figure 4.2** Comparison of scheduled programme runs, completed runs and runs recorded for the half marathon training programme.
Of these unrecorded runs, two participants failed to record their competitive half marathon race (participant 3 and participant 6), and therefore only 4 participants could be utilised in subsequent investigations into half marathon gait dynamics (participants 1, 2, 4 and 5). Whilst participants did not formally note why runs did not capture tibial accelerometry data most participants verbally reported it was due to either (1) forgetting the sensors or (2) sensor technical failure. In terms of mileage, on average participants ran 83.4 ± 6.9% of the mileage scheduled within the programme supplied (258.9 km, range = 96.0 to 326.0 km, out of 349.4 km).

### 4.4.2 Full marathon training programme adherence

Whilst 6 participants began the full marathon training programme 2 participants dropped out (Week 6 and Week 14) due to running related injury diagnosis (See 4.4.4). Adherence therefore was calculated relative to the four remaining participants. Questionnaire results indicated that on average participants completed 72.2 ± 8.9% of the runs scheduled within the programme supplied (52.0 runs, range = 43 to 58 runs, out of 72 runs). Out of the runs completed, participants successfully captured tibial accelerometry data for 49.3 ± 23.1% (35.5 runs, range = 16 to 53 runs) (Figure 4.3). Total time spent running per participant, including unrecorded runs, during the 18-week training programme and competitive full marathon was 59.2 ± 10.2 hours.

![Figure 4.3 Comparison of scheduled programme runs, completed runs and runs recorded for the full marathon training programme.](image-url)
Of these unrecorded runs, one participant failed to record their competitive full marathon race (participant 3), and therefore only 3 participants could be utilised in subsequent investigations into full marathon gait dynamics (participants 1, 2 and 4). In terms of mileage, on average participants ran $72.4 \pm 22.3$ % of the mileage scheduled within the programme supplied (570.4 km, range = 308.5 to 684.1 km, out of 788.3 km).

4.4.3 Half marathon training and race ache, pain and discomfort profile

During the course of the 12-week training programme and completion of the half marathon participants reported any (singular or multiple) ache, pain or injury occurring $5.2 \pm 2.2$ times. Aches, pains or injuries were most commonly reported (in total) in the left lower leg ($n = 11$), followed by the right lower leg ($n = 8$) and the right knee ($n = 7$) (Table 4.3). None of the aches, pains or injuries reported by half marathon participants were diagnosed by a healthcare professional, however they did result in $4.2 \pm 3.2$ missed runs per participant, over the course of the training programme and half-marathon.

Table 4.3 Total number of times aches, pains or injuries which were reported in specific locations during the half marathon training programme and competitive event.

<table>
<thead>
<tr>
<th>Ache, pain or injury location</th>
<th>Total number of times reported</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left lower leg</td>
<td>11</td>
</tr>
<tr>
<td>Right lower leg</td>
<td>8</td>
</tr>
<tr>
<td>Right knee</td>
<td>7</td>
</tr>
<tr>
<td>Lower back</td>
<td>6</td>
</tr>
<tr>
<td>Left knee</td>
<td>5</td>
</tr>
<tr>
<td>Right foot</td>
<td>4</td>
</tr>
<tr>
<td>Neck</td>
<td>2</td>
</tr>
<tr>
<td>Right shoulder</td>
<td>2</td>
</tr>
<tr>
<td>Hips/Buttocks</td>
<td>2</td>
</tr>
<tr>
<td>Right thigh</td>
<td>2</td>
</tr>
<tr>
<td>Left thigh</td>
<td>2</td>
</tr>
<tr>
<td>Left foot</td>
<td>1</td>
</tr>
<tr>
<td>Upper back</td>
<td>1</td>
</tr>
</tbody>
</table>
4.4.4 Full marathon training and race ache, pain and discomfort profile

During the course of the 18-week training programme and completion of the full marathon participants reported any (singular or multiple) ache, pain or injury occurring 9.0 ± 5.8 times. This included two participants which dropped out due to injury in week 6 (physician diagnosed tightness in IT band leading to inflamed tendon at knee) and week 15 (physician diagnosed seismoiditis), however when these participants were removed from the analysis the remaining full marathon participants reported an ache, pain or injury occurrence 11.0 ± 6.2 times. Aches, pains or injuries were most commonly reported in the four remaining participants (in total) in the right thigh (n = 27), followed by the left knee (n = 18) and the hips/buttocks (n = 17) (Table 4.4). Two participants who did not drop out and completed the full marathon distance were also diagnosed by a healthcare professional during the training programme as having IT band tightness and patellar tendinopathy. Overall ache, pain or discomfort resulted in 11.0 ± 6.5 missed runs per participant, over the course of the training programme and full marathon.

Table 4.4 Total number of times aches, pains or injuries which were reported in specific locations during the full marathon training programme and competitive event.

<table>
<thead>
<tr>
<th>Ache, pain or injury location</th>
<th>Total number of times reported</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right thigh</td>
<td>27</td>
</tr>
<tr>
<td>Left knee</td>
<td>18</td>
</tr>
<tr>
<td>Hips/Buttocks</td>
<td>17</td>
</tr>
<tr>
<td>Right knee</td>
<td>14</td>
</tr>
<tr>
<td>Left thigh</td>
<td>11</td>
</tr>
<tr>
<td>Lower back</td>
<td>8</td>
</tr>
<tr>
<td>Right shoulder</td>
<td>5</td>
</tr>
<tr>
<td>Left shoulder</td>
<td>5</td>
</tr>
<tr>
<td>Neck</td>
<td>4</td>
</tr>
<tr>
<td>Left lower leg</td>
<td>4</td>
</tr>
<tr>
<td>Right lower leg</td>
<td>2</td>
</tr>
<tr>
<td>Left lower leg</td>
<td>1</td>
</tr>
<tr>
<td>Left forearm</td>
<td>1</td>
</tr>
</tbody>
</table>
4.4.5 General health

Whilst the General Health section provided further information about the participant’s physiological and psychological well-being throughout the training, this area was not a primary focus of interest within the thesis. It was therefore decided that no further analysis would be completed within this section.

4.5 Discussion

Ford et al. (2007) identified that longitudinal biomechanical data can effectively be combined with epidemiological data to not only reveal injuries which may occur, but also to link movements patterns to these injuries. However, longitudinal biomechanical data can also be utilised to inform researchers about how participants perform in relation to evolving skill levels or how they adapt in relation to changing environments over time. Therefore, whilst acute data collections can provide highly controlled, environments in which parameters can be easily manipulated (running speed, gradient etc.), longitudinal data collections can provide rich, ecologically valid data, divulging evolving patterns of motion unseen over short periods of time. The current chapter outlines the methodology utilised to collect such data and the methodological issues which occur around adherence and injury occurrence, in two groups of recreational runners training for and completing long distance running events.

4.5.1 Adherence to training programmes

Within the current data collection, no participants voluntarily dropped out from the training programmes, and adherence to training runs within the programme provided was high at 71.8 % in half marathon participants and 72.2 % in full marathon participants. This was in line with previous research (Dishman and Gettman 1980) which indicates participants are far more likely to persevere with exercise programmes if they are self-motivated, as were the current participants who had indicated interest in completing a distance running event prior to recruitment. In relation to training mileage, interestingly, Yeung et al. (2001) previously identified that 55 marathon finishers in the 1998 Standard Charter New Airport Hong Kong International Marathon ran on average 51.94 km per week, compared to their non-finisher counterparts who ran on average 8.57 km per week. Within the current study full marathon participants averaged 31.69 km per week.
week (570.4 km divided across 18-weeks), resulting in successful marathon completion. Therefore, a lower weekly volume of running, compared to Yeung et al. (2001) marathon finishers, may be sufficient for marathon completion. Whilst the participants within the current study were interested in competitive run completion and not competitive run victory, Foster et al. (1977) has previously identified that training volume strongly correlates with marathon performance. Therefore, it is possible that those who completed the training programme with a higher adherence rate may have performed better in their long distance competitive run, compared to those who had a lower training programme adherence rate. Leedy (2000) identified that health and fitness concerns were the greatest motivator for runners, and therefore future studies should outline the health benefits of endurance running to participants, which may result in increased running programme adherence.

In regards to runs in which tibial accelerometry data were not collected, many participants cited this was due to forgetting the accelerometers. Due to increasing popularity in wearable technology, interest into human-device interface has grown (Dunne 2004 & Mahmood et al. 2000) with researchers identifying that as wearable technology is primarily created by those who specialise in hardware and software this can result in devices which are not functional and adaptive for the end user (Dunne 2004). Whilst the Shimmer 2r™ accelerometers, provided within the current study, were lightweight and accompanied with instructions and appropriate strapping, they were not a regularly worn device such as a fitness tracker, and their interface was complex for participants to understand initially. This was unavoidable within the current study and may have contributed to reduced adherence of wearing the accelerometers while completing training runs.

4.5.2 Injury occurrence
Overall diagnosed injury rates within the current study (4 people out of 12 people, 33 %) were in the lower end of the range previously identified for running related injuries (1.4 to 94 %, Kluitenberg et al. 2015). Within the half marathon training group occurrences of aches, pains and injuries was low (average reported occurrence of 5.2 times), resulting in average of 4.2 missed runs per participant. Previously it has been identified that running more than 64 km week increases the
risk of running related injuries for male runners (Bovens et al. 1989 & Macera et al. 1989). Whilst there was only one male runner within the half marathon group, all half marathon participants ran on average 21.56 km per week (258.9 km divided by 12 weeks), which was far less than the 64 km per week identified by Bovens et al. (1989) and Macera et al. (1989). Furthermore, more recent research (Nielsen et al. 2013) has supported claims of running volume links with running injury, and week-to-week running volume (Nielsen et al. 2014), however half marathon training programmes may not reach the volume requirements, or drastic increases in volume to induce this injury onset. Within the marathon training programme occurrences of aches, pains and injuries were higher than the half marathon programme (average reported occurrences of 11.0 times), resulting in an average of 11.0 missed runs per participant. Saragiotto et al. (2014) recently again confirmed the association of weekly running volume with running injury and therefore aligns with the fact our marathon participants reported more aches, pains or injuries than their half marathon counterparts.

4.5.3 Limitations
To the author’s knowledge, this is one of the first data collection periods to collect kinematic data across longitudinal periods in recreational runners, however there are some limitations. Due to accelerometry availability and intermittent sensor technical failure only a small sample of participants could initially be recruited. Furthermore, due to additional participant drop-out, sample size was further reduced. Also, as participants were responsible for sensor attachment prior to each run, if the participants forgot the sensors, or they were faulty, accelerometry data was not collected for that run. This resulted in large variance between participants in regards to the amount of training runs completed throughout the training programmes, and also a loss of data for some competitive runs.

4.6 Conclusion
The accelerometry data collected with this chapter provides a comprehensive collection of work which can be utilised to further our knowledge of recreational runners running patterns, and training habits. Given the nature of longitudinal data collections issues related to adherence and ache, injury or pain occurrence did occur, however these factors did not greatly affect the amount of data collected.
Future studies utilising longitudinal data collections for running data should ensure (1) participants are motivated to perform the end running distance, (2) the wearable technology utilised is user friendly, and (3) participants progress the running mileage in line with running recommendations, as these factors may increase the amount of data collected.

4.7 Thesis context
Chapter 4 provides the main data collection periods for analyses undertaken within this thesis. Much of the remaining thesis chapters utilises the tibial accelerometry data collected within Chapter 4 to develop temporal gait analysis methods and also to investigate recreational runners’ running dynamics over long periods.
Chapter 5. Processing and technical issues with stride time calculation.
5.1 Abstract

In running, tibial acceleration can vary quite considerably across runners (3 to 12 g) (Sheerin et al. 2016, Busa et al. 2016). This increases the difficulty to capture all high frequency signal components unless high range accelerometers are utilised, ultimately compromising on sensor sensitivity (Chevalier and Tuong 2013). Also, in gait accelerometry a wide range of filtering cut offs (10 - 100 Hz) have previously been utilised (Laughton et al. 2003 & Giandolini et al. 2016). Therefore, the purpose of this study was to investigate the effect of filtering and data saturation on stride time calculation, derived from accelerometry data. For this analysis two datasets were utilised. The first dataset was a surrogate sinewave dataset consisting of eleven, 60 second time series, with frequencies 0.5 - 1.5 Hz. The second dataset was 60 seconds of tibial accelerometry data, extracted from an outdoor self-paced run, performed by one male participant (data were sampled at 204.8 Hz). Both sinewave and tibial accelerometry datasets were maintained in their original raw forms, and also underwent filtering with a 2 Hz filter cut off to create a secondary comparison dataset. The “raw” datasets then also underwent data saturation, where the time series reached saturation at 80% of the maximum value within the series, and subsequent filtering with a 2 Hz filter cut off. This resulted in three comparative datasets for both sinewave and tibial accelerometry data (n = 6 datasets in total). Stride time series was calculated from all comparative datasets. A repeated measures analysis of variance (ANOVA) identified no significant difference in stride time series between raw, filtered, and clipped and filtered data, utilising both the sinewave and tibial accelerometry datasets. For the tibial accelerometry dataset coefficient of variance (1.13%) and standard error (0.008 s) values indicate good reliability between comparative datasets. Overall, a decreased accelerometry range (80% of the maximum value within the signal) has little effect on 2 Hz filtered accelerometry data, although this is dependent on sampling rate. A 2 Hz filter also provides a reliable automated method calculating stride time series. These methods should be integrated into future gait parameter calculation algorithms to allow for automated, accurate stride time series calculation.
5.2 Introduction

Accelerometers provide an unobtrusive method of recording biomechanical gait data in an ecological environment, and have become increasingly utilised in running kinematics (Norris et al. 2014). However, as previously discussed (3.2) accelerometers may incur error and whilst some of this error may occur due to sensor misalignment and misplacement during attachment, when accelerometer attachment methods are controlled for, further fluctuations may become superimposed on true accelerometry waveforms, and are known as noise. Noise is defined as ‘any unwanted portion of a waveform’ (Robertson et al. 2004, pg. 285) and may be present in the form of random (white noise), physiological noise (Brooks et al. 2013) or electrical/technical noise (Chen and Bassett 2005). In running gait, noise may be present in accelerometry data due to skin artefact, and/or sensor attachment methods during running (Shorten and Winslow 1992 & Forner-Cordero et al. 2008). This noise may affect parameter calculation and interpretation, and therefore researchers typically use filtering techniques, such as Fourier smoothing and digital filtering (Bartlett 2007). These techniques ideally result in the removal of noise components, with the preservation of the true accelerometry signal, overall improving the signal-to-noise ratio (SNR) (Wang et al. 2011). However, when applying digital filtering methods, such as the Butterworth filter, a filter cut off must be chosen by the researcher, based on known frequencies of the movement or residual analysis (Erer 2007). Within running literature, due to differing sample rates, running styles and running speeds there has been numerous filtering cut off points utilised. Giandolini et al. (2016) utilised a 10 Hz high pass filter to improve the detection of peak accelerations during trail running; Busa et al. (2016) utilised a 60 Hz low pass filter to detect peak acceleration during treadmill running, and Mercer et al. (2002) utilised a 100 Hz low pass filter to aid shock attenuation and stride length identification at increasing running speeds. Recently, Sinclair et al. (2013b) investigated the effect of varying filter cut-offs further. Sinclair et al. (2013b) examined the effect of low pass filtering a 3D marker array at 1 Hz, 3 Hz, 5 Hz, 7 Hz, 10 Hz, 15 Hz, 20 Hz and 25 Hz when calculating lower limb joint angles during running and identified significant differences in angular, angular velocity and angular acceleration parameters depending on filter cut off. Therefore, there is no specific filter cut-off preferred within running literature.
Along with this, prior to data collection, researchers must ensure they investigate the appropriate manner for collecting running kinematics using accelerometers, as factors such as weight, sensor placement, sensor sampling rate and range may affect the ability to capture accurate, valid data (Mathie et al. 2004 & Norris et al. 2014). Of the aforementioned factors, selecting an accelerometer with an appropriate range can be problematic for researchers (Morrow et al. 2014). Firstly, the majority of commercially available accelerometers (ActiPal, GENEActiv etc.), primarily used during physical activity monitoring, have a maximum accelerometer range of ± 8 g (Morrow et al. 2014). This is despite Bouten et al. (1997) recommending the use of a ± 12 g accelerometer range to ensure the collection of peak accelerations when monitoring physical activity, Furthermore, in running, peak acceleration in the longitudinal axis, measured at the distal anteromedial aspect, has previously been identified as 5 – 6 g (Creaby and Franettovich Smith 2015), and higher at 6 – 11 g (Crowell et al. 2010), and therefore can vary considerably between runners. In turn, to comprehensively capture all high frequency components of running, across runners of different abilities and running styles, researchers may have to opt for a high magnitude accelerometer range, ultimately compromising on sensor sensitivity. For example, the Shimmer 3 accelerometer, the update of the accelerometer utilised within Chapter 3 and Chapter 4 provides a range selection from 1.5 to 6 g. However, when collecting accelerometry data utilising a 1.5 g range the sensitivity is 800 mV/g, and this sensitivity is decreased to 200 mV/g when utilising the 6 g range option.

Overall, these processing and technical issues cause additional complications for researchers when employing accelerometry techniques. As such, the purpose of this study was to investigate if accelerometry processing and technical factors, including filtering at 2 Hz and saturated data, alter stride time calculation. Stride time was the chosen running gait variable as it is becoming increasingly popular within variability analysis in running (Jordan et al. 2006) and is also an vital parameter in relation to overall run outcome. The effect of filtering on stride time calculation was the main focus, as this is a commonly used practice when processing accelerometry data. Additionally, 2 Hz filter cut off was chosen as this cut off has previously been utilised to derive a sinusoidal signal of stride frequency
(Maiwald et al. 2015) and makes identification of gross running parameters relatively simple. Whilst a 2 Hz filter cut off is lower than previously utilised (10 Hz high pass filter, Giandolini et al. 60 Hz low pass filter, Busa et al. 2016) a typical stride rate for a recreational runner is between 80 and 90 stride per min\(^{-1}\) (Richardson 2013), which would represent a movement frequency of 1.6 to 1.9 Hz, below the 2 Hz filter cut off. Furthermore, a fourth order Butterworth filter with a frequency cut off of 2 Hz has also previously been utilised by Zijlstra and Hof (2003) when assessing spatio-temporal gait parameters (instant of foot contact) and therefore has warranted use within previous research. Additionally, within preliminary analysis, filter cut offs from 2 Hz to 18 Hz (increasing in 1 Hz increments) were applied to triaxial tibial accelerometry data, collected during running, to identify the effect of varying filter cut offs on running gait pattern (representative sample, Error! Reference source not found.). As outlined by Maiwald et al. (2015) it was identified that a 2 Hz resulted in a gross signal of stride frequency.

![Raw Mediolateral Accelerometry Data](image-url)
Figure 5.1 Sample mediolateral accelerometry data during running in raw format and filtered with a 18 Hz filter cut off, a 9 Hz filter cut off and a 2 Hz filter cut off.
Investigating the effect of saturated accelerometry data were also of interest to gain a better understanding of how this error in data collection may affect pattern recognition in kinematic time series data. Previously, within accelerometry data, saturation has been identified as a “problem” which may arise when attempting to classify movements such as cycling, walking and running at higher speeds (Mannini and Sabatini 2011). However, the effect of accelerometry saturation on quantitative running parameter calculation is still unknown.

5.3 Methods

5.3.1 Data selection
Two separate data sets were utilised within the current study; sinewave data and running accelerometry data. Firstly, sinewave data were generated via MATLAB™ (r2009b) (MathWorks, Cambridge, UK). Input parameters to produce multiple sinewave profiles (n=11), with fundamental frequencies of 0.5 – 1.5 Hz (in 0.1 Hz increments), were as follows: sample frequency (Hz) = 204.8, sinewave length (seconds) = 60, amplitude = 100. Secondly, the running accelerometry dataset consisted of tibial accelerometry data from 1 male recreational runner (age: 37 years, stature: 1.81 m, mass 87 kg). Informed written consent was obtained prior to data collection. As within Chapter 3 and Chapter 4 accelerometry data were recorded via a triaxial Shimmer 2™ accelerometer (SHIMMER Ltd, Dublin, Ireland), self-attached to the participant’s anteromedial distal tibia. All accelerometer parameters, including accelerometer attachment, mass, calibration and orientation were as described in Chapter 3. Additional to this, and based on the findings of Chapter 3, the participant was also asked to perform a 10 second stationary standing period pre- and post the run. Whilst this indicated run start and completion, it also allowed for the correction of static tilt, calculated during the standing period, with the x and z axis corrected to 0 m·s⁻² and the y axis corrected to +9.81 m·s⁻². Data were sampled at 204.8 Hz (± 6 g, sensitivity range = 200 mV/g). The chosen run was selected based on convenience sampling and was representative of an overground, self-paced run. For this analysis, 60 continuous seconds of the participant’s anteroposterior tibial accelerometry data were randomly extracted, from this chosen run.
5.3.2 Data alteration

The original, unprocessed sinewave and tibial acceleration datasets were regarded as raw and utilised as the comparison data set 1 (Figure 5.2 and Figure 5.3). Hereafter, to investigate the effects of technical and processing issues both data sets underwent identical data alteration. Firstly, both the sinewave (n = 11) and the tibial accelerometry data streams (n = 1) were low-pass 4th order Butterworth filtered with a filter cut off of 2 Hz, resulting in two further datasets (comparison dataset 2) representing the gross acceleration pattern (Table 5.1 and Table 5.2). Lastly the raw datasets (comparison dataset 1) were then firstly “clipped” to mimic data reaching a range threshold and being saturated. For both the sinewave and tibial accelerometry dataset a data threshold at 80% of the maximum value within the data set was chosen. The 80% data threshold was selected as it was postulated that generally researchers would ideally select an accelerometer range which covered the frequency of movement they were recording. However, perhaps due to unexpected high impact movements or changes in speed (Mannini and Sabatini 2011) this range may saturate the high magnitude components of the accelerometry signal. These datasets were then low-pass 4th order filtered with a filter cut off of 2 Hz to create comparison dataset 3 (Table 5.1 and Table 5.2).

![Figure 5.2 Data alteration process for sinewave data identifying comparison datasets 1, 2 and 3.](image-url)
1. Raw tibial accelerometry data
   *(Comparison Dataset 1)*

2. Filtered at 2 Hz tibial accelerometry data
   *(Comparison Dataset 2)*

3. Clipped and Filtered at 2 Hz tibial accelerometry data
   *(Comparison Dataset 3)*

**Figure 5.3 Data alteration process for tibial acceleration data.**

For comparison datasets 2 and 3 (2 Hz filtered, and clipped and 2 Hz filtered in both sinewave and tibial accelerometry data) a stride time series was then calculated. For sinewave data the beginning and end of stride time was identified via a positive peak and stride time calculated as the number of frames between peaks, multiplied by 1/sampling frequency. For tibial acceleration data (2 Hz filtered, and clipped and 2 Hz filtered) the novel stride time calculation method M1 outlined in Chapter 6 (6.3.3) was utilised. Briefly, an automated 2 Hz Butterworth filter was applied to mediolateral accelerometry data and the beginning and end of stride time was identified via a positive zero crossing. For the raw dataset (comparison dataset 1), as noise surrounded the maximum positive peaks, automated peak detection was not a reliable method for calculating stride time. Therefore, positive peaks were manually identified within each raw dataset and stride time calculated as before.

### 5.3.3 Data analysis

Statistical analysis, in the form of a repeated measures analysis of variance (ANOVA) and Bonferroni post hoc test, was performed across the three comparison datasets stride time series, for both the sinewave and tibial accelerometry conditions. Furthermore, to investigate reliability between stride time series calculated in the raw condition and the remaining two conditions (2 Hz
filtered and clipped and 2 Hz filtered), standard error (SEM), coefficient of variance represented as a percentage (CV %) and intra-class correlation coefficients (ICC) were calculated using methods by Hopkins (2015), previously outlined in the literature (Gindre et al. 2016).

5.4 Results
There was no significant difference between stride time series calculated using raw, 2 Hz filtered, and clipped and 2 Hz filtered sinewave data, at any given frequency (Table 5.1).

Table 5.1 Average stride time (s) calculated for raw sinewave data, sinewave data 2 Hz filtered, and sinewave data clipped and 2 Hz filtered.

<table>
<thead>
<tr>
<th>Frequency (Hz)</th>
<th>Raw (Mean ± SD)</th>
<th>2 Hz Filtered (Mean ± SD)</th>
<th>Clipped and 2 Hz Filtered (Mean ± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>2.000 ± 0.002</td>
<td>2.000 ± 0.003</td>
<td>2.000 ± 0.003</td>
</tr>
<tr>
<td>0.6</td>
<td>1.667 ± 0.002</td>
<td>1.667 ± 0.002</td>
<td>1.667 ± 0.002</td>
</tr>
<tr>
<td>0.7</td>
<td>1.429 ± 0.000</td>
<td>1.429 ± 0.002</td>
<td>1.429 ± 0.002</td>
</tr>
<tr>
<td>0.8</td>
<td>1.250 ± 0.000</td>
<td>1.250 ± 0.001</td>
<td>1.250 ± 0.001</td>
</tr>
<tr>
<td>0.9</td>
<td>1.111 ± 0.002</td>
<td>1.111 ± 0.003</td>
<td>1.111 ± 0.003</td>
</tr>
<tr>
<td>1.0</td>
<td>1.000 ± 0.002</td>
<td>1.000 ± 0.002</td>
<td>1.000 ± 0.002</td>
</tr>
<tr>
<td>1.1</td>
<td>0.909 ± 0.002</td>
<td>0.909 ± 0.002</td>
<td>0.909 ± 0.002</td>
</tr>
<tr>
<td>1.2</td>
<td>0.833 ± 0.002</td>
<td>0.833 ± 0.003</td>
<td>0.833 ± 0.003</td>
</tr>
<tr>
<td>1.3</td>
<td>0.769 ± 0.002</td>
<td>0.769 ± 0.003</td>
<td>0.769 ± 0.003</td>
</tr>
<tr>
<td>1.4</td>
<td>0.714 ± 0.002</td>
<td>0.714 ± 0.002</td>
<td>0.714 ± 0.002</td>
</tr>
<tr>
<td>1.5</td>
<td>0.667 ± 0.002</td>
<td>0.667 ± 0.002</td>
<td>0.667 ± 0.002</td>
</tr>
</tbody>
</table>

There was no significant difference between stride time series calculated using raw, 2 Hz filtered, and clipped and 2 Hz filtered tibial accelerometry data, $F(2,164) = 0.033, p = 0.862$ (Table 5.2). Average stride times for raw, 2 Hz filtered and clipped and 2 Hz filtered tibial accelerometry data were within 0.001 seconds of one another (0.709 – 0.710 s). The stride time series calculated using raw accelerometry data displayed over three times the variance (standard deviation of 0.022 s) of the remaining two tibial accelerometry datasets (0.006 s for both),
however all standard deviations remained < 0.025 s. All ICC values were >0.70, whilst all CV values were < 1.2% when comparing stride time series calculated using raw tibial accelerometry data, to the two-remaining altered tibial accelerometry datasets (2 Hz filtered and clipped and 2 Hz filtered) (Table 5.2).

Table 5.2 Average stride time (s) for raw tibial accelerometry data, 2 Hz filtered tibial accelerometry data, and clipped and 2 Hz filtered tibial accelerometry data. Reliability analysis results including standard error, coefficient of variance and intra-class correlation coefficient for comparison of the three variations of the tibial accelerometry dataset.

<table>
<thead>
<tr>
<th></th>
<th>Raw</th>
<th>2 Hz Filtered</th>
<th>Clipped and 2 Hz Filtered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stride time (s)</td>
<td>0.709 ± 0.022</td>
<td>0.710 ± 0.006</td>
<td>0.710 ± 0.006</td>
</tr>
<tr>
<td>SEM</td>
<td>N/A</td>
<td>0.008</td>
<td>0.008</td>
</tr>
<tr>
<td>CV%</td>
<td>N/A</td>
<td>1.13</td>
<td>1.13</td>
</tr>
<tr>
<td>ICC</td>
<td>N/A</td>
<td>0.79</td>
<td>0.78</td>
</tr>
</tbody>
</table>

5.5 Discussion

Accelerometers require extensive processing capabilities and technical knowledge by the researchers who utilise them, particularly in relation to gait analysis (Rueterbories et al. 2010). Along with this, contrasting methods of accelerometer filtering methods and accelerometer range selection within the literature (Bouten et al. 1997; Sinclair et al. 2013b) may cause confusion. However, the results of the current study may provide guidance for researchers in relation to some of the processing and technical issues associated with accelerometers.

5.5.1 Sinewave data

Surrogate data are commonly used when investigating gait variability measures (Myers et al. 2010 & Miller et al. 2006), and the use of a sinewave allows for the investigation of effects on a purely periodic time series (Miller et al. 2006). Within these analyses, it was identified that both filtering with a 2 Hz cut off and the combined clipping of data followed by filtering with a 2 Hz filter cut off had no effect on the calculation of stride time series within a sinewave.
5.5.2 Tibial accelerometry data

Within the tibial accelerometry investigation, ICC values of 0.018 indicate no agreement between the stride time series derived from the raw tibial accelerometry data and the remaining two altered datasets. However, this may in part be due to researcher error imposed on the raw stride time series, due to manual selection of accelerometry peaks. It is identified in running gait accelerometry that raw tibial accelerometry data may contain double peaks, or two similar high magnitude values close together, due to the high magnitude impact of the motion (Sinclair et al. 2013a). Whilst researchers may choose to select the higher magnitude peak at each instance, the position of these peaks, in relation to one another, may alternate between consecutive impacts affecting stride time. Along with this, when a filter is applied to these data the time between double peaks will subsequently alter the peak created within the smooth data. However, a low pass filter has previously been utilised within gait identification techniques to cancel double peaks, allowing for single peak identification and therefore is supported within this method (Jirawimut et al. 2003). The remaining measures of reliability indicated close agreement (CV% = 1.13, SEM = 0.008 s) between the raw tibial accelerometry datasets and the altered comparative datasets. The standard error between comparative tibial datasets (0.008 s) represented 1.1 % of the average stride time calculated within the raw tibial accelerometry dataset (0.709 s), and therefore would be of little clinical (practical) significance when applied to runners performing at this frequency (change in running frequency from 1.41 Hz running with an average stride time of 0.709, to a running frequency of 1.39 Hz running with an average stride time of 0.717 (0.709 + 0.008 s), or a running frequency of 1.43 Hz with an average stride time of 0.698 s (0.709 – 0.008 s).

To the author’s knowledge this is the first study of its kind to investigate both the effect of data filtering and saturation on accelerometry data. However, there are limitations. Firstly, one filtering cut off was utilised in the current analyses. As previously stated, a filter cut off of 2 Hz was recently utilised whilst investigating stride time from a shoe mounted accelerometer (Maiwald et al. 2015). Therefore, this filter cut off was of particular interest and was the focus of this preliminary investigation. Also, one tibial accelerometry dataset was utilised within this study, however this was due to the time-consuming manner of manually identifying peak
values within the raw tibial accelerometry dataset. Future research should investigate how multiple filter cut-off effect stride time calculation, in a larger number of participants.

5.6 Conclusion
Filtering with a 2 Hz cut off and data saturation due to limited accelerometer range has no effect on stride time series created within a purely periodic time series, whilst data saturation has minimal effect on 2 Hz filtered tibial accelerometry stride time data. This may allow for the inclusion of accelerometry data, which researchers previously thought was corrupted due to processing and technical issues, within gait analysis studies. Also, a 2 Hz filter alone appears to allow for the reliable calculation of stride time series, and therefore should be integrated in future stride time calculation algorithms. Researchers should use the information provided to aid the development of novel methods to calculate gait parameters.

5.7 Thesis context
Longitudinal tibial accelerometry data collection methods are utilised within the current thesis (Chapter 4), with an aim to derive stride time. From Chapter 5 we can now confidently utilise a 2 Hz filter in the derivation of stride time, and are reassured that, despite possible large magnitudes in tibial acceleration, the range of the accelerometer utilised will sufficiently record tibial accelerometry during distance running.
Chapter 6. Stride time calculation methods
6.1 Abstract
Inertial sensors such as accelerometers and gyroscopes can provide a multitude of information on running gait. Running parameters such as stride time and ground contact time can all be identified within tibial accelerometry data. Within this, stride time is a popular parameter of interest, possibly due to its role in running economy. However, there are multiple methods utilised to derive stride time from tibial accelerometry data, some of which may offer complications when implemented on larger data files. Therefore, the purpose of this study was to compare previously utilised methods of stride time derivation to an original proposed method, utilising mediolateral tibial acceleration data filtered at 2 Hz, allowing for greater efficiency in stride time output. Tibial accelerometry data from six participants training for a half marathon were utilised. One right leg run was randomly selected for each participant, in which five consecutive running stride times were calculated. Four calculation methods were employed to derive stride time. A repeated measures analysis of variance (ANOVA) identified no significant difference in stride time between stride time calculation methods ($p=1.00$), whilst intra-class coefficient values (all > 0.95) and coefficient of variance values (all < 1.5%) indicate good reliability. Results indicate that the proposed method possibly offers a simplified technique for stride time output during running gait analysis. This method may be less influenced by “double peak” error and minor fluctuations within the data, allowing for accurate and efficient automated data output in both real time and post processing.

6.2 Introduction
The use of low cost portable sensors, such as accelerometers and gyroscopes, has become increasingly popular in running gait analysis over the last number of years (Higginson 2009). Their decreased size and lightweight nature allows easy, ecologically valid attachment whilst still uncovering a multitude of information in a natural environment. Within running gait analysis tibial sensor attachment has been identified as superior in identifying lower limb acceleration patterns as it is
close to the area of interest, this being the lower limb (Mathie et al. 2004). This attachment allows for identification of running gait parameters such as stride frequency (Mercer et al. 2002) and ground contact time (Purcell et al. 2006). Of these parameters, stride frequency, and therefore stride time, has been identified as a major contributing factor to running economy and overall run outcome, making it a parameter of great interest (Mercer et al. 2008).

Stride time is defined as “time elapsed between the first contacts of two consecutive foot falls of the same foot expressed in milliseconds” (Beauchet et al. 2011), and numerous methods have been previously utilised to identify initial ground contact during running within tibial accelerometer data. Mercer et al. (2003) identified the minimum value before the absolute maximum value in the longitudinal axis as the beginning of foot strike. Mizrahi et al. (2000) identified the absolute maximum value in the longitudinal axis as the point of heel strike. However, there are numerous factors which may affect the ability to accurately and efficiently identify stride time from longitudinal accelerometer data streams utilising these, and similar, methods.

Firstly, many studies which have utilised previous stride time calculation methods have done so during treadmill running protocols (Mizrahi et al. 2000 & Mercer et al. 2003b) taking out any possible effect of alternate terrains on foot strike pattern and stride time calculation. Secondly, previous research (Mizrahi et al. 2000) has used secondary manual confirmation of heel strike through visual observation of data to avoid the inclusion of any “bad” data. These “bad data” may be representative of a stumble or fall, or may be due to sensor movement causing a “double peak” at heel strike. Manual confirmation to confirm the time of heel strike would be inefficient on longitudinal data sets, and where there are “double peak” error it is not possible to correctly distinguish the impact peak from the rebound peak, even using automated processes (Panther and Bradshaw 2013). Thirdly, running patterns have been found to vary between individuals with different striking patterns, rearfoot and forefoot (Laughton et al. 2003), and may be altered by gait retraining programmes and shoe variation (Giandolini et al. 2013). This may affect the validity of using stride time calculation methods utilising heel strike (Mizrahi et al. 2000), across groups of runners. Lastly, peak tibial acceleration
during impact has been found to reach up to 147.2 m·s⁻² in running studies (Flynn et al. 2004 & Crowell et al. 2010), and this may vary during self-paced running on various terrains (Giandolini et al. 2015). This may affect stride time calculation methods using thresholds (Meardon et al. 2011) in tibial acceleration peaks.

The current study sought to investigate if stride time derived from 2 Hz filtered, mediolateral tibial accelerometry data is comparable to previous methods. It is proposed 2 Hz filtered data may produce accurate and comparable results to previous methods, whilst being more efficient due to lack of manual intervention in producing stride time series in expansive, longitudinal data sets. It is also proposed that filtering running data at 2 Hz will retain the dynamics of stride time, whilst being less influenced by “double peak” error, individual foot strike patterns or various running terrains. The proposed method is not reliant on distinct peak acceleration values or individualised acceleration value threshold selection, associated with individual running styles. Lastly, the use of the mediolateral axis to derive the beginning of ground contact has been previously validated (Purcell et al. 2006) and therefore the current authors wish to ascertain if, when filtered at 2 Hz, it provides comparable results. If valid, our novel method would provide an efficient, robust method of stride time calculation in longitudinal accelerometry data, without the need for manual intervention and/or stride time confirmation, or individualised acceleration thresholds. This would allow for efficient stride time calculation across groups of runners, providing valid results regardless of running style, terrain or pace.

6.3 Methods
6.3.1 Participants
Accelerometry data from six (one male, five female) recreational runners (age: 33.5 ± 5.8 years, stature: 1.66 ± 0.08 m, mass: 71.1 ± 12.2 kg) undertaking a half marathon training programme were utilised (Chapter 4). During this half marathon training programme participants ran at a self-paced speed, which they could alter as they wished through alterations in stride time and stride frequency. Participants also ran on freely chosen terrain. This resulted in the extracted accelerometry data representing recreational running in its most natural,
uncontrolled form, with variance between participants providing a range of tibial accelerometry data. Informed consent was collected prior to data collection.

**6.3.2 Instrumentation**

Participants were required to attach a triaxial Shimmer 2r™ sensor (SHIMMER, Dublin, Ireland) to their anteromedial distal tibia bi-laterally (as described in Chapter 3) for each training run (n= 48), and the event itself (total distance covered +340km). All accelerometer parameters, including accelerometer attachment, weight, calibration and orientation were as described in Chapter 3. Training comprised of four runs per week for twelve weeks of a popular Hal Higdon (Hal Higdon 2011a) Half Marathon Novice 2 Programme (4.3.3).

**6.3.3 Data processing**

For this analysis accelerometry data collected from the Shimmer 2r™ sensor attached to each participant’s right leg were chosen from one randomly selected run (containing up to 7 million data points). Standing periods performed by the participants pre- and post each run indicated run start and completion. Based on recommendations from Chapter 3 accelerometer run data were corrected for static tilt, calculated during the standing period, with x and z axis corrected to 0 m·s$^{-2}$ and y corrected to +9.81 m·s$^{-2}$. Preliminary data processing was performed for all files using a custom-built LabVIEW™ (National Instruments, Newbury, UK) programme. Data containing six consecutive impact peaks were chosen at random from the file, resulting in the calculation of 5 strides for each participant. The number of strides derived was chosen due to manual calculation of strides in methods 2, 3 and 4, and also as previous research (Wixted et al. 2010) has utilised similar amounts of running data in accelerometer validation studies. A total of four stride time calculation methods were compared, the proposed method (M1) and three previously utilised methods.

**Method 1 (M1):** M1 was custom designed and proposed that mediolateral accelerometer data were filtered at 2 Hz using a Butterworth low-pass 4th order reverse filter (Figure 6.1). A 2 Hz filter cut-off was chosen as this cut off will still retain the gross tibial acceleration pattern created due to swing, impact and stance phases, however will negate any minor fluctuations which may be present and could result in incorrect stride time calculation when automated. Filter order was
the same as that previously utilised to derive stride duration in accelerometry data (Mercer et al. 2002 & Meardon et al. 2011). Beginning and end of stride time was identified via a positive zero crossing via a custom-built LabVIEW™ programme.

**Figure 6.1** Acceleration patterns (m·s$^{-2}$) for a representative two second running trial utilising Method 1 (M1) for stride time calculation. Identification of beginning/end of stride times as identified by the circle.

**Method 2 (M2):** Method 2 (M2) identified heel contact as the minimum acceleration value before the absolute maximum (peak impact) in the unfiltered vertical axis of the tibia (Mercer et al. 2003) (Figure 6.2).

**Figure 6.2** Acceleration patterns (m·s$^{-2}$) for a representative two second running trial utilising Method 2 (M2) for stride time calculation. Identification of beginning/end of stride times as identified by the circle.

**Method 3 (M3):** Method 3 (M3) identified the unfiltered peak or transient in the vertical axis of the tibia as heel strike occurrence (Mizrahi et al. 2000) (Figure 6.3).
Method 4 (M4): Method 4 (M4) identified the beginning of contact time as the maximum value in the unfiltered mediolateral axis (Purcell et al. 2006) (Figure 6.4).

Of the 4 stride time calculation methods employed only M1 was automated utilising MATLAB™. The remaining methods (M2, M3 and M4) all utilised manual identification to locate the point of interest for stride time calculation (maximum acceleration value or minimum acceleration value). Accelerometer placement with previously employed methods, M2 and M4, was the same as that utilised to collect the accelerometry data in the present investigation, the anteromedial distal tibia.
However, M3 employed accelerometer placement at the tibial tuberosity. Stride
time data for M1 were calculated via LabVIEW™ whilst M2, M3 and M4 were
calculated via Excel.

6.3.4 Data analysis
Both single participant and group analyses were undertaken. For single participant
analysis, distributional variability due to method type was investigated in
individual strides, using standard deviation. For group analysis, all stride times
were grouped via method type (4 methods each containing 30 strides) and
statistical analysis, in the form of a repeated measures analysis of variance
(ANOVA), was performed across the four methods. Furthermore, to investigate
reliability between M1 and the remaining three methods (M2, M3 and M4), within
the group analysis standard error (SEM), coefficient of variance represented as a
percentage (CV %) and intra-class correlation coefficients (ICC) were calculated
using methods by Hopkins (2015), previously outlined elsewhere (Gindre et al.
2016).

6.4 Results
Results illustrated that there was no significant difference between methods to
derive stride time F(3,87) = 0.03, p = 1.00. To further uncover the practical
applicability of our method a comparison of individual stride times across methods
was also undertaken (Table 6.1). The minimum stride time across all participants
was 0.677 s, whilst the maximum stride time was 0.957 s, resulting in a stride
frequency range of 1.04 – 1.48 Hz. All methods employed compared favourably to
each other resulting in low standard deviations (0.002 – 0.017 s).

Table 6.1 Stride time (s) calculations for all participants. a indicates the
greatest difference in stride time, whilst b indicates no difference in stride
time, compared to proposed M1. The greatest and least SD values are also
denoted in bold.

<table>
<thead>
<tr>
<th>Participant 1</th>
<th>Method</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stride 1</td>
<td></td>
<td>0.728</td>
<td>0.718</td>
<td>0.708</td>
<td>0.713</td>
<td>0.717</td>
<td>0.009</td>
</tr>
<tr>
<td>Stride 2</td>
<td></td>
<td>0.718</td>
<td>0.723</td>
<td>0.728</td>
<td>0.722</td>
<td>0.723</td>
<td>0.004</td>
</tr>
<tr>
<td>Stride</td>
<td>Method</td>
<td>M1 (s)</td>
<td>M2 (s)</td>
<td>M3 (s)</td>
<td>M4 (s)</td>
<td>Average (s)</td>
<td>SD (s)</td>
</tr>
<tr>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>-------------</td>
<td>-------</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>0.722</td>
<td>0.717</td>
<td>0.717</td>
<td>0.723</td>
<td>0.720</td>
<td>0.003</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>0.703</td>
<td>0.718</td>
<td>0.713</td>
<td>0.713</td>
<td>0.712</td>
<td>0.006</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>0.723</td>
<td>0.718</td>
<td>0.728</td>
<td>0.722</td>
<td>0.723</td>
<td>0.004</td>
</tr>
</tbody>
</table>

**Participant 2**

<table>
<thead>
<tr>
<th>Participant 2</th>
<th>Method</th>
<th>Stride</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.693</td>
<td>0.684</td>
<td>0.683</td>
<td>0.689</td>
<td>0.687</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.689</td>
<td>0.688</td>
<td>0.694</td>
<td>0.688</td>
<td>0.690</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.693b</td>
<td>0.698</td>
<td>0.693b</td>
<td>0.694</td>
<td>0.694</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.689</td>
<td>0.679</td>
<td>0.683</td>
<td>0.683</td>
<td>0.684</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5</td>
<td>0.693</td>
<td>0.703</td>
<td>0.699</td>
<td>0.698</td>
<td>0.698</td>
<td>0.004</td>
</tr>
</tbody>
</table>

**Participant 3**

<table>
<thead>
<tr>
<th>Participant 3</th>
<th>Method</th>
<th>Stride</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.708b</td>
<td>0.708b</td>
<td>0.708b</td>
<td>0.703</td>
<td>0.707</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.698</td>
<td>0.684</td>
<td>0.693</td>
<td>0.688</td>
<td>0.691</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.708</td>
<td>0.718</td>
<td>0.713</td>
<td>0.713</td>
<td>0.713</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.703b</td>
<td>0.703b</td>
<td>0.698</td>
<td>0.703b</td>
<td>0.702</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5</td>
<td>0.698</td>
<td>0.698b</td>
<td>0.698b</td>
<td>0.703</td>
<td>0.699</td>
<td>0.002</td>
</tr>
</tbody>
</table>

**Participant 4**

<table>
<thead>
<tr>
<th>Participant 4</th>
<th>Method</th>
<th>Stride</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.708</td>
<td>0.703</td>
<td>0.718</td>
<td>0.737</td>
<td>0.717</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.708</td>
<td>0.718</td>
<td>0.703</td>
<td>0.679</td>
<td>0.702</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.713</td>
<td>0.688</td>
<td>0.703</td>
<td>0.703</td>
<td>0.702</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.703a</td>
<td>0.728</td>
<td>0.718</td>
<td>0.742a</td>
<td>0.723</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5</td>
<td>0.708a</td>
<td>0.693</td>
<td>0.689</td>
<td>0.669a</td>
<td>0.690</td>
<td>0.016</td>
</tr>
</tbody>
</table>

**Participant 5**

<table>
<thead>
<tr>
<th>Participant 5</th>
<th>Method</th>
<th>Stride</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.718</td>
<td>0.698</td>
<td>0.708</td>
<td>0.708</td>
<td>0.708</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.698b</td>
<td>0.708</td>
<td>0.698b</td>
<td>0.693</td>
<td>0.699</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.703b</td>
<td>0.688</td>
<td>0.703b</td>
<td>0.703b</td>
<td>0.699</td>
<td>0.007</td>
</tr>
</tbody>
</table>
### Table 6.2 Reliability statistics (standard error, coefficient of variance (%) and intra-class correlation coefficients) calculated using the proposed method (M1) against the remaining three methods (M2, M3 and M4).

<table>
<thead>
<tr>
<th>Method</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEM</td>
<td>0.008</td>
<td>0.007</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CV%</td>
<td>1.077</td>
<td>0.942</td>
<td>1.346</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICC</td>
<td>0.994</td>
<td>0.996</td>
<td>0.992</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 6.5 Discussion

Of the methods compared, M2 and M4 have been previously validated for heel strike occurrence (Lafortune 1991 & Purcell et al. 2006). Therefore, using these methods to derive stride time represents a valid, accurate and accepted depiction of stride time, as defined by Beauchet et al. (2011). When compared to these methods, the method proposed here (M1) offers an accurate technique to derive stride time during running gait analysis. ICC and CV values reported (mean ICC = 0.99, mean CV = 1.12%) all indicate close agreement between the proposed method (M1) and the remaining 3 methods of stride time calculation (M2, M3 and M4). Also, current ICC and CV values are all in agreement with those previously found when deriving step frequency using three different methods (Myotest®, Optojump Next® and high speed video cameras) (mean ICC = 0.90, mean CV = 4%).

<table>
<thead>
<tr>
<th>Participant 6</th>
<th>Method</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.923</td>
<td>0.957</td>
<td>0.938</td>
<td>0.942</td>
<td>0.940</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.942</td>
<td>0.913</td>
<td>0.913</td>
<td>0.908</td>
<td>0.919</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.938</td>
<td>0.952</td>
<td>0.952</td>
<td>0.947</td>
<td>0.947</td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.933</td>
<td>0.938</td>
<td>0.938</td>
<td>0.938</td>
<td>0.936</td>
<td><strong>0.002</strong></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.942^b</td>
<td>0.947</td>
<td>0.942^b</td>
<td>0.952</td>
<td>0.946</td>
<td>0.005</td>
<td></td>
</tr>
</tbody>
</table>

All ICC values were > 0.95, whilst all CV values were < 1.5% when comparing M1 and the remaining three methods (M2, M3, M4) (Table 6.2).
Lastly, the stride frequencies present (1.04 – 1.48 Hz) represented a wider range of running stride frequencies than those found previously whilst investigating healthy recreational runners performing self-paced running (Zdziarski et al. 2015). Previous research (Purcell et al. 2006) indicates stride frequency rates above the present range, such as maximal sprint, retain the presence of a mediolateral zero crossing and therefore indicates our novel method would also result in valid stride time calculation at higher stride frequency rates.

Overall the proposed method offers an accurate and reliable method of stride time calculation. Whilst previous stride time calculation methods can be automated via the reoccurring detection of a maxima (Mizrahi et al. 2000), minima (Mercer et al. 2003) or threshold value (Meadon et al. 2011), these detection points can be highly variable, dependent on running style and terrain. Also, fluctuations surrounding maxima, minima and threshold values, such as double peaks containing two similar high magnitude values closely placed, may lead to incorrect stride time identification during automated processing (Sinclair et al. 2013a). Therefore, using specific data point detection methods researchers may attempt to confirm detection points post data collection (Mizrahi et al. 2000). However, the current proposed method can be automated without manual intervention and utilised accurately across a variety of running styles and/or terrains, as minor fluctuations are significantly reduced and the data do not contain “double peak” error, due to the smoothing associated with 2 Hz filtering. Also, within these filtered data a mediolateral zero crossing is a consistent reoccurring feature.

### 6.6 Conclusion

The ability to output running stride parameters accurately and promptly may allow for the development of an automated feedback system based on the consistency or fluctuation of these parameters. This type of system may be useful for the recreational runner, high level athletes and researchers alike as it could output information related to both health and performance. Further research should investigate our proposed method when applied to a clinical field.
6.7 Thesis context

Factors such as changes in speeds, alterations in terrain and fatigue can all alter running acceleration profiles, particularly those of the lower limb (tibial acceleration). The extensive longitudinal tibial accelerometry data collected within Chapter 4 is susceptible to all of the above factors, given its self-paced running, outdoor nature. Identifying stride time within these data would previously have required extensive data mining and possibly visual confirmation, based on previous stride time calculation methods. However, the novel, automated method of stride time calculation developed with in Chapter 6 will allow for efficient and accurate data processing.
Chapter 7. Stride rate dynamics in distance running: Training and competition
7.1 Abstract

Stride rate (SR) has been identified as a major contributing factor to running economy and run completion time and therefore is of interest when completing competitive distance running events. Whilst recreational runners train for extensive periods in the lead up to these events, the event itself imposes additional variables upon a runner such as unknown courses and competitive stress, which may impact running style, including SR, and overall run performance. Despite this there is limited research investigating SR in recreational runners during competitive distance events. Therefore, the aim of this study was to investigate the SR dynamics of recreational runners, participating in both training and competitive events. Tibial accelerometry data, collected during overground running in 4 participants (following methods outlined in Chapter 3, Chapter 4 and Chapter 5), was utilised to calculate SR. Stride rate data for a competitive half marathon (114.3 ± 12.7 mins) and a comparable training run (106.5 ± 23.7 mins) were compared. Descriptive statistics (mean, modal and range) were utilised for comparison of runs. Additionally, one of the participants, who completed both the competitive half marathon distance and also a competitive full marathon, was analysed within a single participant analysis. For single participant analysis, SR data for two runs, a half marathon (HM) and full marathon (FM), were calculated and descriptive statistics (mean, mode and range) were utilised for comparison. Analysis included, comparison of the half marathon (HM) to the first half of the marathon (FM1) and a within marathon (FM) SR investigation. Firstly, two of the four participants (participants 2 and 4) displayed increased SR in their competitive run, compared to their training equivalent. Additionally, participants 2 and 4 completing the half marathon run slower than their predicted completion time. Single participant results indicated that the participant’s modal SR in the first third of FM1 was lower than that of HM (83 vs 85 stride min⁻¹), and also displayed a wider range. For FM2, a combined decreasing trend and wider range in SR from 30 km was observed, along with an RPE of 20. Overall results indicate that performing with an equivalent or decreased SR, compared to a similar distance training run, within a competitive distance running event may result in an optimal running style in relation to overall run outcome. Furthermore, increased fluctuations to combat a decreasing trend in SR may cause increased metabolic cost and effort, ultimately resulting in diminished run performance outcome.
7.2 Introduction

As previously outlined in Chapter 2, Chapter 3 and Chapter 4, stride time is a key parameter of interest within running biomechanics, primarily related to its contribution to running efficiency and performance (Gindre et al. 2016). In running, researchers have investigated the effect of stride time variability in elite runners (Nakayama et al. 2010), and previously non-injured/injured runners (Meardon et al. 2011). Researchers have also investigated changes in stride time in relation to static stretching (Damasceno et al. 2014), varying running shoe type (Bergstra et al. 2015) and varying foot strike patterns (Stearne et al. 2014). However, when researchers investigate stride time they do not only focus on the raw temporal variable, but also use stride time in the calculation of stride rate.

Stride rate (SR), frequency or cadence is defined as "the reciprocal of the period of heel strike of one foot to the next heel strike of the same foot" (Holt et al. 1991, pg. 492), and along with stride length, is one of the determining factors of overall run performance (Mercer et al. 2008). Recently, Lieberman et al. (2015) investigated the lower limb kinematics and ground reaction forces of experienced runners, and Lieberman et al. (2015) queried the suggested metabolically "optimal" SR of 90 strides min\(^{-1}\) in endurance runners. Lieberman et al. (2015) in fact suggested an "optimal" SR of 85 strides min\(^{-1}\) should be employed by endurance runners, as this stride rate represented the optimal trade-off between braking forces and leg swing during running. However, Lieberman et al.'s (2015) runners performed at various stride rates (75 - 95 stride per min\(^{-1}\)) for 5 min periods, and this running time period is not reflective of either sprint or distance running, when performed in training or competitive environments. In sprinting, researchers regularly investigate how changes in SR influence runners attaining their maximum running velocity, related to how success is achieved within the sport (Čoh et al. 2001). However, in distance running, researchers have a greater interest on the effect of SR on the energy cost of running, given the length of the competition and as maximum running velocity is primarily only reached in the closing stages of a competitive distance run, by elite distance runners (Cavanagh et al. 1977). As distance running is a more readily engaged-in sport (than sprinting) by the wider public, it is important to further investigate changes, if any, which may occur in SR within distance running.
Due to an increasing number of recreational participants in half marathon and marathon events (Hottenrott et al. 2016), this population is of growing interest to biomechanists (Vickers and Vertosick 2016). Recently, research on recreational runners has investigated how step rate (Chumanov et al. 2012 & Heiderscheit et al. 2011) and step width (defined as the mediolateral distance from middle of the right heel to the middle of the left heel at initial ground contact, Brindle et al. 2014) alterations modify lower limb mechanics during treadmill running. However, these protocols tend to be both laboratory based and also acute running trials (15 s Chumanov et al. 2012 & 5 mins Heiderscheit et al. 2011), although this is not reflective of recreational runners’ running habits. To the current author’s knowledge there is no research, pertaining to stride rate, over a longitudinal period in a natural environment, within recreational runners.

Additionally, it has been identified that competitive stress can affect both elite and non-elite athletes (Mellalieu et al. 2009), however this is primarily based off physiological markers (Duca et al. 2006). Duca et al. (2006) identified changes in red blood cell composition following a marathon, in 8 healthy trained runners. Lambert et al. (1998) identified that when performing in a competitive 10 km run, runners’ heart rate is increased by approximately 20 beats min⁻¹, compared to performing in a training environment at the same pace. Whilst it is identified that runners’ physiological profile is altered due to competitive stress, there is no research available comparing runner’s kinematics in a competitive and training environment. Therefore, the overall aim of this study was to investigate the stride rate dynamics of recreational runners, in both training and competitive distance running events.

7.3 Methods
7.3.1 Participants
Four participants (age 32.5 ± 6.1 years, stature: 1.68 ± 0.06 m, mass: 68.4 ± 14.0 kg,) were selected as they completed both a competitive half marathon, and a comparable training run, within the larger data collection (Chapter 4). Briefly, participants were classified as recreational runners as they had not previously received specialised running training, and were each undertaking their first half
marathon distance, or had not completed the distance within the last three years. Training programmes that participants completed in the lead up to their competitive run were based on popular Hal Higdon novice distance running programmes popular, and comprised of 4 runs (3 short, 1 long run) per week for 12 weeks (Half marathon programme, Hal Higdon 2011a) and 18 weeks (Full marathon programme, Hal Higdon 2011b) (4.3.3). As specialised running training was regarded as any training in which participants were committed solely to their specified running distance, fully committed to intense training and aiming for competitive success (Baker et al. 2005), the supplied training programmes did not change the recreational runner classification of the participants.

7.3.2 Instrumentation
All participants’ accelerometry data were extracted from that of a larger data collection monitoring the lower limb accelerometry of recreational runners, whilst training for and competing in distance running events (Chapter 4). Following guidelines outlined in Chapter 2, Chapter 3 and Chapter 4 all participants were required to attach a triaxial Shimmer 2r™ accelerometer (SHIMMER Ltd, Dublin, Ireland) to their anteromedial distal tibia bi-laterally for each training run, and the distance running events. All accelerometer parameters, including accelerometer attachment, mass, calibration and orientation were as described in Chapter 3. Furthermore, participants also completed a weekly training log and discomfort questionnaire with run information (distance, completion time) and rate of perceived exertion (RPE) for each weekly long run and competitive run (Appendix B). RPE was measured utilising the Borg 15-grade RPE scale (Borg 1982), with a scale point of 6 indicating very, very light perceived exertion and 20 indicating maximum exertion.

7.3.3 Data processing
The participants’ half-marathon race data were analysed as a competitive race (114 ± 13 mins), whilst their longest recorded training run was analysed as a non-competitive comparison (106.5 ± 23 mins) (Table 7.1).
Table 7.1 Comparative training and competitive run information for group analysis.

<table>
<thead>
<tr>
<th></th>
<th>Participant 1</th>
<th>Participant 2</th>
<th>Participant 3</th>
<th>Participant 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training distance (km)</td>
<td>19</td>
<td>20</td>
<td>16.1</td>
<td>19.5</td>
</tr>
<tr>
<td>Competitive distance (km)</td>
<td>21.1</td>
<td>21.1</td>
<td>21.1</td>
<td>21.1</td>
</tr>
<tr>
<td>Training completion time (mins)</td>
<td>107</td>
<td>135</td>
<td>77</td>
<td>107</td>
</tr>
<tr>
<td>Competitive completion time (mins)</td>
<td>115</td>
<td>130</td>
<td>99</td>
<td>113</td>
</tr>
<tr>
<td>Training average speed (m·s⁻¹)</td>
<td>2.96</td>
<td>2.47</td>
<td>3.48</td>
<td>3.04</td>
</tr>
<tr>
<td>Competitive average speed (m·s⁻¹)</td>
<td>3.06</td>
<td>2.71</td>
<td>3.55</td>
<td>3.11</td>
</tr>
</tbody>
</table>

Firstly, run time was identified as a result of a static standing period performed by the participants’ pre- and post-run. As outlined in Chapter 3, accelerometer run data were corrected for static tilt, calculated during the standing period, with x and z axis corrected to 0 m·s⁻² and y corrected to 9.81 m·s⁻². Preliminary data processing was performed, for all files, using a custom-built LabVIEW™ (National Instruments, Newbury, U.K.) programme (Appendix F for visual representation of LabVIEW™ programme). A stride time series was calculated for each run utilising methods in Chapter 6, and any stride above 1 s in duration was eliminated, as this was designated to be a walking step (Rowe et al. 2011). Training average speed and competitive average speeds were calculated via distance/time, with the distance ran outlined by participants in their training log (Appendix B) or the known distance for the competitive run, and the time spent running identified via the accelerometry data. Total run time was then broken into 1% epochs and stride rate (strides minute⁻¹) was calculated for each epoch using the average stride time for the chosen epoch. Furthermore, predicted completion times (PCT) were calculated via the McMillan Running Calculator (McMillan Running 2016). PCT was calculated using the participants’ previous best 10 km time when predicting a half-marathon time, and the participant’s previous best half marathon time when predicting a full marathon time. PCT’s are commonly used by recreational runners for both half and full marathon distances as they provide critical pacing information which can be easily understood (Vickers and Vertosick 2016). Furthermore, online PCT calculators are readily available to all recreational runners. 
runners. Therefore, it was felt PCT was a parameter of interest when analysing participant’s competitive race performance.

Additionally, a single participant analysis was also undertaken. For the single participant analysis 1 male recreational runner (age: 37 years, stature: 1.81 m, mass: 87 kg) from the primary 4 participants within this analysis was selected. This participant was selected as he was undertaking both a half marathon training programme (12 week) and competitive race, and a marathon training programme (18 week) and competitive race one after another. There was a 6-week break/rest period between the completion of the competitive half marathon and the beginning of the marathon training programme (Figure 7.1). Training structures which optimise running performance often emphasise training load and appropriate relative recovery. As the participant completed a 12-week training programme followed by a 6-week recovery, prior to undertaking their marathon training programme, this resulted in an appropriate 2:1 training load to recovery ratio (Smith 2003).

![Figure 7.1 Single participant timeline for training programmes (TP) and run occurrence.](image)

Right leg accelerometry data from the 2 competitive runs (containing up to 14 million data points each) were selected and analysed. Run 1 (HM) was a competitive half marathon and run 2 (FM) was a competitive marathon. The first half of FM (FM1 Table 7.3) was compared to HM, to compare likewise distances, both within competitive races. Examples of raw accelerometry data from within the single participant analysis are provided (Figure 7.2). Whilst a representative 5 second period of the second half of the marathon (FM2) is displayed FM2 was not included for comparison with the half marathon (HM). It was decided only to compare the first half of the marathon (FM1) to the half marathon distance, as it
was assumed the participant’s mechanical work status was comparable prior to the beginning of both runs.

Figure 7.2. Raw tri-axial acceleration pattern during a 5 second period for the same subject during (a) half marathon (HM), (b) full marathon (1st half) (FM1) and (c) full marathon (2nd half) (FM2).
Subsequently HM, FM and FM1 were then sectioned into thirds via 1 % epochs (First Third = 0 to 32 %, Second Third = 33 to 65 %, Last Third = 66 to 100 %), and SR modal values and range were calculated for each third. In further participant analysis, FM was sectioned via the timings provided by race chip timing (Start to 21.2 km, 21.2 km to 30 km, 30 km to End, and 21.2 km to End).

### 7.3.4 Data analysis

Individual participant comparison was chosen due to a reduced sample size, and as runners were performing in an environment with uncontrolled variables, such as running speed, which may naturally cause large between participant variance. Absolute SR values were compared and the difference in time between the competitive completion time and PCT were calculated as an absolute value and percentage of the PCT. Both the competitive and training runs were sectioned into thirds via 1% epochs and SR modal values and range were calculated for each third. Additionally, average speed was calculated, as it was of interest when investigating the effect of competition running speed.

For the single participant analysis, absolute SR values were compared, and the difference in time between HM and FM completion times and PCTs were calculated as absolute values and as a percentage of the PCT. Modal SR and range was identified as this presented a better representation of the participants' running style throughout each run. As before modal SR was compared for each section. Linear regression was also calculated for the three sections which comprised the marathon distance (start to 21.2 km, 21.1 km to 30 km, 30 km to end) and trend lines were examined. This provided further information about how the participants’ SR potentially altered throughout a marathon distance, and was investigated in relation to the participant’s exertion assessed through RPE (noted within the participant’s weekly diary).

### 7.4 Results

#### 7.4.1 Training versus competition results

All participants ran at a higher average speed in their competitive run compared to their training equivalent (Figure 7.4). When investigating the first third of the runs, participants 2 and 4 performed at the same SR in both competitive and training
runs. However, in the middle and last thirds, participants 2 and 4 then displayed increased SR rates in their competitive run compared to their non-competitive run. Participant 2 and 4 also completed their competitive run slower than their PCT (130 and 113 mins, compared to 125 and 107 mins). In comparison participants 1 and 3 displayed equal or decreased SR in the competitive run compared to their training (except participant 3’s first third), and completed the competitive run faster than their PCT (115 and 99 mins, compared to 125 and 102.5 mins).
Table 7.2 Training and competitive speed, stride rate and temporal results.

<table>
<thead>
<tr>
<th></th>
<th>1st Third</th>
<th>2nd Third</th>
<th>Last Third</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Training absolute modal SR (range) (strides min⁻¹)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st Third</td>
<td>83 (83 to 87)</td>
<td>86 (83 to 88)</td>
<td>87 (84 to 88)</td>
</tr>
<tr>
<td>2nd Third</td>
<td>86 (86 to 89)</td>
<td>85 (83 to 86)</td>
<td>85 (84 to 87)</td>
</tr>
<tr>
<td>Last Third</td>
<td>87 (84 to 88)</td>
<td>85 (83 to 86)</td>
<td>84 (82 to 85)</td>
</tr>
<tr>
<td><strong>Competitive absolute modal SR (range) (strides min⁻¹)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st Third</td>
<td>82 (82 to 87)</td>
<td>86 (80 to 87)</td>
<td>84 (82 to 86)</td>
</tr>
<tr>
<td>2nd Third</td>
<td>86 (86 to 89)</td>
<td>85 (84 to 87)</td>
<td>85 (84 to 86)</td>
</tr>
<tr>
<td>Last Third</td>
<td>87 (85 to 88)</td>
<td>85 (85 to 87)</td>
<td>88 (84 to 89)</td>
</tr>
<tr>
<td><strong>Half marathon completion time (mins)</strong></td>
<td>115</td>
<td>130</td>
<td>99</td>
</tr>
<tr>
<td><strong>Half marathon PCT (mins)</strong></td>
<td>125</td>
<td>125</td>
<td>102.5</td>
</tr>
<tr>
<td><strong>Difference (Completion time and PCT) mins (%)</strong></td>
<td>-10.0 (-8.0)</td>
<td>+5.0 (+4.0)</td>
<td>-3.5 (-3.4)</td>
</tr>
</tbody>
</table>
Furthermore, participant 1 ran with a decreased SR during the competitive run, in all but 6 of the 1% epochs, while participants 2 and 4 ran at an increased SR during the competitive run, with participant 4 running at an increased SR in all but 6 of the 1% epochs (Figure 7.3). Participant 3’s data illustrates variation to both a higher and lower stride rate, whilst modal SR is comparable across competitive and training thirds.
Competitive Stride Rate (strides min$^{-1}$)

Training Stride Rate (strides min$^{-1}$)
Competitive Stride Rate (strides min\(^{-1}\))

Training Stride Rate (strides min\(^{-1}\))

Participant 3
Figure 7.3 Comparison of 1% epoch stride rates for competitive and training runs. The unbroken diagonal line inserted representing no change in stride rate between competitive and training runs at that percentage epoch.
7.4.2 Single participant analysis

The participant (participant 3) ran within their half marathon distance PCT for both the HM (-3.5 mins) and FM1 (0.0 mins), however their FM1 completion time was greater than HM completion time (+3.5 mins). The participant also displayed decreased modal stride rate in the first third of FM1, when compared to the first third of HM (83 vs 85 strides min\(^{-1}\)) (Table 7.3). Both HM and FM1 displayed comparable increases in modal SR over the following two thirds of the distance. FM1 also displayed increased SR variance in the first third of the run, compared to the same period in HM, as identified via a larger vertical than horizontal SR data spread (Figure 7.4), and greater SR range (80 to 85 vs 82 to 85 strides min\(^{-1}\)) (Figure 7.4). SR range for latter two thirds of HM and FM1 were comparable. The largest SR range was 80 to 91 strides min\(^{-1}\), which occurred in the last third of FM and was much greater than the SR range during the last third of HM (85 to 88 strides min\(^{-1}\)).
Table 7.3 Half marathon, full marathon and the 1st half of full marathon temporal, stride rate and RPE result.

<table>
<thead>
<tr>
<th></th>
<th>Half Marathon (HM)</th>
<th>Full Marathon (FM)</th>
<th>1st Half Full Marathon (FM1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completion time (mins)</td>
<td>99.0</td>
<td>220.0</td>
<td>102.5</td>
</tr>
<tr>
<td>PCT (mins)</td>
<td>102.5</td>
<td>208.0</td>
<td>102.5</td>
</tr>
<tr>
<td>Difference (Completion time and PCT) mins (%)</td>
<td>-3.5 (-3.4)</td>
<td>+12 (+5.8)</td>
<td>-</td>
</tr>
<tr>
<td>1st Third</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min⁻¹)</td>
<td>85 (82 to 85)</td>
<td>85 (81 to 85)</td>
<td>83 (80 to 85)</td>
</tr>
<tr>
<td>2nd Third</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min⁻¹)</td>
<td>85 (84 to 86)</td>
<td>86 (85 to 88)</td>
<td>85 (84 to 86)</td>
</tr>
<tr>
<td>Last Third</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min⁻¹)</td>
<td>85 (85 to 88)</td>
<td>86 (80 to 91)</td>
<td>86 (85 to 88)</td>
</tr>
<tr>
<td>Overall</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RPE</td>
<td>15</td>
<td>20</td>
<td>N\A</td>
</tr>
</tbody>
</table>
Figure 7.4 Comparison of 1% epoch stride rates for half marathon (FM) and the 1st half of the full marathon (FM1). Diagonal line inserted representing no change in stride rate between R1 and R2half at that percentage epoch. ☰ = first third of run, □ = second third of run, ▲ = last third of run.

Within the participant's marathon the participant’s modal SR was similar across all sections (Table 7.4) SR range for both Start to 21.1 km (81 to 86 strides min⁻¹) and 21.1 km to 30 km (86 to 88 strides min⁻¹) were less than 30 km - End section, indicating less SR consistency for the latter part of the race. In terms of RPE, the participant reported an RPE of 15 for HM and 20 (maximum exertion) for FM (Table 7.4).
Table 7.4 Full marathon (FM) stride rate results for each run section identified via race chip timing information.

<table>
<thead>
<tr>
<th>Section</th>
<th>Absolute modal SR (range) (strides min(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Marathon (FM)</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Start - 21.1 km</strong></td>
<td>85</td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min(^{-1}))</td>
<td>(81 to 86)</td>
</tr>
<tr>
<td><strong>21.1 km - 30 km</strong></td>
<td>86</td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min(^{-1}))</td>
<td>(86 to 88)</td>
</tr>
<tr>
<td><strong>21.1 km - End</strong></td>
<td>86</td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min(^{-1}))</td>
<td>(80 to 91)</td>
</tr>
<tr>
<td><strong>30 km to End</strong></td>
<td>86</td>
</tr>
<tr>
<td>Absolute modal SR (range) (strides min(^{-1}))</td>
<td>(80 to 91)</td>
</tr>
</tbody>
</table>

Strong correlation coefficients (r = 0.81) indicated SR increased linearly with percentage time ran, for the first half of the marathon race (start to 21.1 km) (Figure 7.5). This SR was then maintained from the 21.1 km to 30 km section of the race (r = 0.55). However, for the 30 km - end section FM a weak relationship (r = 0.15) was identified for SR and percentage time, indicating increased SR variance (SR range: 80 to 91 strides min\(^{-1}\)).
SR was plotted to one decimal place for better identification of data markers.

Figure 7.5 Stride rate values at 1% time epochs for the full marathon (FM). + = Start to 21.1 km, O = 21.1 km to 30 km, ♦ = 30 km to End.

7.5 Discussion
Elite runners have the ability to maintain a coordinated running form, in an effort to perform economically during distance running events (Coyle 2007). In doing so, elite runners generally control SR for the majority of a long distance run, regardless of speed, instead primarily fluctuating stride length (Cavanagh and Kram 1989). This provides us with some insight into how runners manipulate SR and stride length to perform optimally, however much of the research to date has focused on elite runners (Brisswalter and Legros 1994 & Saunders et al. 2004). Therefore, the aim of this study was to investigate the dynamics of recreational runners when undertaking training and competitive distance running.

7.5.1 A competitive and training comparison
When investigating a comparison of competitive and training SR in distance running, all of the participants (n = 4) displayed average SR values within 5% of their training run SR values (max average difference 3 strides per min⁻¹). However,
when investigating individual SR values across the comparative runs both participants 2 and 4 had periods of running, in the competitive run, in which they were performing with a stride rate ≥5 % higher than that previously used during the same period in the training run. Interestingly participants 2 and 4 also underperformed in the competitive marathon, in comparison to their predicted performance outcome.

Previously, Crews (1992) reviewed research investigating a runner’s psychological state in relation to their running economy. Crews (1992) identified that there was no change in running economy due to varied cognitive traits (such as coping, strategy and bio-feedback), however Crews (1992) suggested this may be due to compensation in other areas of the body, which within this research could be regarded as running kinematics alterations. Additionally, when investigating participant 2 and 4’s underperformance in the competitive run (underperformance here defined as completing the competitive race in a greater amount of time than their PCT), along with their combined increase in SR, physiologically, previous research indicates this underperformance was not due to an increase in oxygen consumption. Hamill *et al.* (1995) identified that increasing SR 10% above a participants preferred SR during running does not negatively influence oxygen consumption, whilst Schubert *et al.* (2014) identified that increased SR may increase running efficiency through decreased centre of mass vertical excursion. However, Chumanov *et al.* (2012) identified increased neuromuscular activity with increased SR and suggested that whilst this may have a therapeutic effect in the short term, it is unknown what effect this increased muscle activation may have on metabolic performance. This increased neuromuscular activity may have caused participant 2 and participant 4’s muscles to fatigue quicker, perhaps leading to a competitive run underperformance. When investigating average speed while participants 3 and 4 displayed identical increases in speed (0.07 m·s$^{-1}$) from training to competitive runs, participant 3 may have adopted a more efficient SR throughout the race resulting in a preferred race outcome. Additionally, participant 3 maintained a very similar SR range in both the competitive (82 – 87 strides per min$^{-1}$) and training runs (82 – 88 strides per min$^{-1}$) and therefore was utilising a SR previously used in a comparable run, throughout the competitive run. Identifying that participants 1 and 3 completed their competitive run within their
PCT, with participant 1 finishing 10 minutes quicker than predicted, it is of interest that participant 1 performed their competitive run in a SR lower than that previously used in a training run, and this was also greater than 5% lower. However, Lieberman et al. (2015) identified that runners may benefit from a stride frequency of 85 strides per min\(^{-1}\) when running at 3.0 m·s\(^{-1}\), as this was identified as the metabolically optimal stride frequency during running. Furthermore, Folland et al. (2017) identified an average stride rate of 83.4 strides per min\(^{-1}\) in an endurance running cohort of 97 runners (both elite and recreational runners). Participant 3’s average running speed was 2.96 m·s\(^{-1}\) with a modal SR of 82, 83 and 84 strides per min\(^{-1}\) for the competitive run, indicating they may have been performing optimal and in line with that suggested by Lieberman et al. (2015).

### 7.5.2 A half and full marathon comparison

When comparing the first half of the participants marathon (FM1), to their half marathon race (HM), results indicate the participant (participant 3) was able to control their SR (indicated by a narrow range), and adopted a similar SR strategy to that previously used. Leyk et al. (2007) identified that maintenance of training is key when successfully undertaking endurance events. As the participant had completed a further 18-week training programme prior to completing their marathon, this training may have allowed them to maintain their previously utilised SR strategy for the first half of the marathon. Whilst the greatest SR variability of either HM or FM1 was identified in the first third of FM1 this variability was decreased within 7 km, and may be due to a "start-up" effect experienced by recreational runners when undertaking their first marathon. Lane et al. (2006) identified that marathon runners experience intense emotional states prior to completing a competitive marathon run. Whilst, elite runners may have the specialised knowledge to understand and control this emotional state, recreational runners may not have this ability (Jones et al. 1994), and therefore it could affect their running.

Within the marathon (FM), the participant demonstrated an increasing trend in SR in both the Start to 21.1 km and 21.1km to 30 km sections of the marathon. However, a decreasing trend in SR was then identified from 30 km to the end of the run. Whilst fatigue was not explicitly measured within the current study, the
participant recorded a maximal rating of perceived exertion (20) for the full marathon distance. Hunter and Smith (2007) identified a 1-2 % decrease in SR from the beginning to the end of a 1 hour fatiguing run in a group of experienced runners. However, within Hunter and Smith (2007) group, high levels of inter-participant SR variability were present and therefore it was unclear as to why certain alterations in SR, whether decreasing or increasing due to fatigue, occurred. Within the current study, the participant also demonstrated large fluctuations in SR (SR range of 80 to 91 strides min$^{-1}$) in the latter half, and 30 km to End section, of the marathon. Previous research has suggested that increased fluctuations in SR shifts runners away from their naturally preferred stride rate/length combination, therefore increasing metabolic cost and decreasing optimal performance (Hunter and Smith 2007). Therefore, a decreasing trend in SR, along with fluctuations by the participant to combat this decrease, may have further increased metabolic cost, decreased economy and resulted in increased exertion by the participant. Overall, SR variability increase affected both 21.1 km to End time (15 mins greater than FM1) and overall R2 completion time (12 mins greater than PCT).

7.5.3 Limitations

Whilst this research provides an insight into recreational runners SR dynamics during distance running, there are some limitations. Firstly, a small sample size was utilised within the analyses which increases the difficulty in applying our results to the larger recreational runner population. However, there is currently limited information regarding SR dynamics over longitudinal periods, such as in half and full marathons. Therefore, it is vital in preliminary research to investigate the feasibility and efficiency of undertaking such analysis in a reduced sample size prior to a larger recruitment. Secondly, previous studies have investigated SR primarily during a single controlled running speed (Hamill et al. 1995; Farley and Gonzalez 1996; Hunter and Smith 2007; Morin et al. 2007; Heiderscheit et al. 2011), or when testing multiple controlled running speeds to investigate changes in SR (Nilsson and Thorstensson 1987; Mercer et al. 2002; Barnes et al. 2014). As the current analyses were performed during self-paced outdoor running only overall run average speed was calculated. Future research in SR dynamics should utilised inertial sensors with combined accelerometry and GPS capabilities, to
gather a greater understanding of recreational runners SR dynamics in relation to running speed.

7.6 Conclusion
Increasing knowledge surrounding optimal SR strategies to decrease effort during distance running may be of use to recreational runners undertaking distance events. This may lead to greater control of their SR pattern throughout the duration of the race and optimal completion times. When compared to a training environment, in a competitive environment stress and/or cognitive processes may lead some runners to perform with an increased stride rate, which may in turn lead to underperformance. Also, recreational runners have an ability to maintain stride rate strategy, for extended periods, during the first half of a novice marathon. Future research should aim to investigate additional temporal stride parameters such as stride time, to further increase our knowledge of recreational runners running dynamics during distance running events.

7.7 Thesis context
Chapter 7 provides an in-depth analysis into the coaching parameter, stride rate. This thesis investigates temporal gait parameters in recreational runners and therefore examining stride rate provides the first step in this comprehensive analysis. Furthermore, stride rate is commonly identified as an important factor effecting overall running performance outcome, and therefore to understand how the participants within the current thesis perform in distance running events stride rate analysis is essential.
Chapter 8. The effect of additional variance on Detrended Fluctuation Analysis (DFA)
8.1 Abstract

As researchers move toward non-linear methods of running gait data analysis, it is essential to understand how robust these methods are when applied to outdoor, self-paced running gait. Detrended Fluctuation Analysis (DFA) investigates long range correlations in non-stationary time series; however, within running stride time it is unknown what effect outliers have on DFA calculation and subsequent interpretation. To investigate how robust DFA is when applied to longitudinal time series, surrogate stride time series data of varying lengths (600, 3,000 and 10,000 strides), with 1/f patterning and a DFA alpha value of 1.03 (±0.01) were created via MATLAB™. Data alteration methods were performed which imposed variance to each stride time series, with magnitudes of 0 to 100 % (in 10 % increments) of the average stride time, of the chosen series. The number of strides which were altered varied from 0 to 100 % (in 10 % increments) also dependent on stride time series length. DFA was applied to each stride time series (n = 363) and as DFA interpretation was of key interest, comparisons of DFA results due to additional variance and previous DFA results within the literature were undertaken. Results indicate magnitude alterations of ≥40 % of the mean stride within a stride time series may result in DFA values which begin to indicate alternate stride patterning, and therefore change researcher interpretation of how runners are performing. Also, as stride series length increases DFA results are more rapidly affected by the presence of outliers. The implementation of soft bounded algorithms incorporating moving thresholds may detect high magnitude outliers enhancing DFA application. This may lead to the correct interpretation of DFA results, which is essential when utilising DFA to distinguish varied running cohorts.

8.2 Introduction

As outlined in Chapter 3 and Chapter 4 there are numerous technical and processing issues which must be taken into consideration when utilising accelerometry to collect running gait data and derive temporal gait parameters. However, when these are considered and valid data are acquired, appropriate statistical analysis methods must then be applied to ensure correct interpretation of data (Ferber et al. 2016). Traditionally, researchers have utilised linear approaches to gait data analysis, such as ranges and standard deviations, which
focus around the centrality of data and identify the magnitude of variation which occurs around a common point (i.e. the average) (Stergiou and Decker 2011). However, these methods typically identify errors in gait performance and do not inform researchers about the temporal organisation or structure of variability (Stergiou and Decker 2011 & Harbourne and Stergiou 2009). This temporal organisation of variability may give insight into how the complex, dynamic systems of the body, self-organise to complete a task such as running (Hausdorff et al. 2005 & Harbourne and Stergiou 2009).

Therefore, researchers have begun to utilise feature extract and non-linear data analysis methods to investigate gait data (Preatoni et al. 2013 & Chau 2001). Feature extract methods include Principal Component Analysis (PCA) (Phinyomark et al. 2016; Trudeau et al. 2015; Foch et al. 2014) which extracts movements within running that are correlated, whilst non-linear dynamic methods include entropy (Murray et al. 2017; Lindsay et al. 2014; McGregor et al. 2011) which calculates a measure of the disorder of the system during running, and Detrended Fluctuation Analysis (DFA) (Fuller et al. 2016a; Fuller et al. 2015b; Meardon et al. 2011), which identifies whether running strides are predictable and are correlated regardless of the time point in longitudinal stride time series. Of these measures, DFA is of most interest when considering the interpretation of stride time data, as PCA methods such as entropy, or specifically sample and control entropy utilise continuous accelerometry time series (McGregor et al. 2009) whilst PCA is more commonly applied to multi-segmental coordination that identifies gait defining coordinative features, such as walk to run transitions (Lamoth et al. 2009). Furthermore, various methods of gait analysis, such as those listed previously, answer different questions in relation to gait. For example McGregor et al. (2011) identified that decreased control entropy occurred when maximal constraints were placed on inter-collegiate runners, suggesting that a maximal constraint such as exhaustive fatigue causes increased regularity or order of a system (McGregor and Bollt 2012). However, another non-linear analysis method, Lyapunov exponents, identify the stability, or how runners respond to perturbations, during gait (Mehdizadeh et al. 2014 & Brujin et al. 2010).
Within the current study, DFA was identified as the most appropriate method for stride time analysis. DFA calculates a modified root mean square analysis of a random walk that produces a self-similarity parameter, $\alpha$. An $\alpha$ value of 0.50 indicates the presence of a random walk, where one point in time is uncorrelated to previous points in time. An $\alpha$ value of between 0.50 and 1.00 indicates the presence of persistent long range correlations (a long stride time will be followed by a long stride time). An $\alpha$ value of less than 0.50 indicates the presence of persistent long range anti-correlations (a short stride time will be followed by a long stride time and vice versa). Values greater than 1.0 indicate the presence of long range correlations which no longer decay with increasing time lag, according to the power law (Goldberger et al. 2000 & Meardon et al. 2011).

In doing so, DFA investigates the presence of, or lack of, long-range correlations between strides during running and to date has been able to distinguish between trained runners and non-runners (Nakayama et al. 2010) and previously injured and previously non-injured runners (Meardon et al. 2011). Additionally, as identified in 2.3.5.1 DFA is becoming an increasingly popular method to measure stride time variability. Given the method of DFA calculation which involves subtracting the trend of non-overlapping boxes (Figure 8.1 and 2.3.5.1), it is important to understand how additional outliers which may alter DFA calculation and therefore interpretation of running dynamics.
Figure 8.1 (a) Heart beat interval data from Peng et al. (1994). (b) During DFA $\alpha$ calculation the heart beat interval data are split into non-overlapping boxes of 100 heart beat intervals and detrended using a least fit squares.

An outlier is defined as “an outlying observation, or outlier, is one that appears to deviate markedly from other members of the sample in which it occurs” (Hodge and Austin 2004, pg. 85). Within a running stride time series an outlier may occur due to a stumble or fall or the missed detection of a stride time for example. To date, when investigating how robust DFA is, Chen et al. (2002) studied the effect of lost data segments and the presence of spikes or outliers on DFA. Chen et al. (2002) firstly identified that discontinuities in signals, followed by the stitching of data, does not affect the scaling of positively correlated signals ($\alpha > 0.05$), such as a running stride time series. In relation to outliers, Chen et al. (2002) identified that the effect of outliers on DFA is related to the scaling of the time series, and also the scaling of the outliers embedded within the series i.e. whether they are uncorrelated or correlated spikes. In controlled running gait (laboratory
conditions), researchers omit outliers using a threshold criteria (for example omission of any stride time > 1.5 times the interquartile range of the time series, Fuller et al. 2016a) as the controlled constraints of the running (i.e. running speed, terrain) indicate this is an outlier due to noise or error. However, in outdoor, self-paced running, particularly distance running, there is increased difficulty for researchers to identify true outliers, due to noise or error, as there are speed fluctuations and changes in terrain and gait kinematics which alter stride time naturally (Reenalda et al. 2016). Therefore, outliers can be random or uncorrelated. Based on Chen et al. (2002) findings, uncorrelated outliers, at sufficiently large enough amplitudes, embedded within a correlated signal can alter DFA results at small scales. However, it is unknown, within running gait data what percentage of outliers alters DFA, and at what amplitude. Therefore, the purpose of this study was to identify how variability, in the form of stride alteration, affects DFA calculation and more importantly our interpretation of distance running dynamics.

8.3 Methods

8.3.1 Data selection

To investigate the effect of additional variance on a time series, a surrogate stride time series of a known $\alpha$ was required. To produce this stride time series MATLAB™ code entitled ‘spatialPattern.m’ was downloaded from the MATLAB™ File Exchange, in which code users can alter the length of the time series calculated and the spectral distribution of the time series (white noise, pink noise or Brownian noise). With the current analyses three time series lengths were created, n = 600, n = 3,000 and n = 10,000. These stride series lengths were chosen because firstly previous research investigating DFA during running has used 512 strides (Nakayama et al. 2010), 661 strides (Meadon et al. 2011) and 659 strides (Jordan et al. 2006), and therefore a stride time series length of 600 was is in line with previous research. Secondly, given representative running stride times of 0.677 s and 0.957 s (minimum and maximum stride times calculated within Chapter 4) a stride time series length of n = 3,000 is approximately equivalent to 30 – 50 minutes of running, whilst a stride time series length of 10,000 is approximately equivalent to 110 - 160 minutes of running. Running programmes designed toward half and full marathon distances typical incorporate both short and long runs
(4.3.3) and therefore these stride time series lengths reflect runs which recreational runners commonly undertake. For spectral distribution, pink noise was selected for all three stride time series, which produced purely deterministic time series with DFA $\alpha$ values approximating to 1.00. An $\alpha$ value of 0.96 has previously been identified in a group of uninjured recreational runners performing running to fatigue at their self-reported 5 km pace over ground (Meardon et al. 2011) and therefore the deterministic time series produced were deemed acceptable. Whilst ‘spatialPattern.m’ produced time series with values magnitudes of between -1 and +1, to better reflect a stride time series +1 was added to each value in the time series produced, creating time series with only positive values.

### 8.3.2 Data alteration

The current study investigated (1) the effect of different amounts of variance imposed on a time series (i.e. 60 spikes or outliers imposed on a stride series length of 600), and concurrently (2) the effect of variance with different magnitudes imposed on a time series (i.e. adding high magnitude, medium magnitude and low magnitude variance to stride series). Therefore, to derive variance of differing magnitudes, the average stride time of each series was calculated and 0 to 100 % of this average was calculated in 10 % increments, and these were used as upper boundaries for variance magnitudes. For example, in a stride time series with an average stride time of 1.00 (s) a 10 % magnitude alteration would result in the addition and/or subtraction of 0.00 to 0.10 (s) to strides within the series. Similarly, in the same stride time series if a 30 % magnitude alteration was applied, this would result in the addition and/or subtraction of 0.00 to 0.30 (s) to strides within the series. To determine the number of strides which variance would be superimposed on, a similar method to deriving variance magnitudes was used. Depending on time series length (n) the number of strides variance was randomly added to, was in 10% increments also from 0 % to 100 %, however here the 10 % increments were absolute. For example, in a stride time series length of n = 600, when variance is added to 10 % of strides this results in variance added to 60 strides. This process for calculating a range of magnitudes of variance, and applying these magnitudes of variance to differing numbers of strides within a series was applied to all stride time series.
previously calculated. This resulted in a total of 363 times series (3 times series x 11 magnitudes of variance x 11 amounts of strides altered).

**8.3.3 Data analysis**

Prior to data alteration DFA was applied to all time series using the PhysioNet Toolkit to confirm 1/f patterning with a DFA $\alpha$ of 1.00. After this all data alteration and data analysis methods were completed using MATLAB™. Once data alteration had been applied to all stride time series DFA was again applied to all stride time series ($n = 363$). Within the current analysis, it was decided that the effect which variance may have on DFA is most important when interpreted in terms of running dynamics. Therefore, to investigate the effect of additional variance on DFA interpretation statistical analysis was not utilised and previously identified $\alpha$ values identified within the literature were utilised for comparison. Two running DFA $\alpha$ values were identified within the literature and used for comparison. These were (1) $\alpha = 0.96$ identified by Meardon *et al.* (2011) within an uninjured group of recreational runners performing at their self-selected 5 km, over ground until fatigue, and (2) $\alpha = 0.79$ also identified by Meardon *et al.* (2011) within a previously injured group of recreational runners performing at their self-selected 5 km, over ground until fatigue. For this analysis, it was not the relative change in DFA that was of primary interest (i.e. a change from 1.00 to 0.80, resulting in a 0.20 DFA $\alpha$ value change), but the interpretation of the absolute DFA $\alpha$ value (i.e. a change from 1.00 to 0.80, results in interpretation of a strides time moving toward random patterning in line with that of previously injured runner). Whilst further literature has identified long range correlations using DFA in running (Fuller *et al.* 2016a; Fuller *et al.* 2016b; Nakayama *et al.* 2010; Jordan *et al.* 2006) this literature has either utilised different box sizes within DFA calculation methods within the current study (Fuller *et al.* 2016a & Fuller *et al.* 2016b), not identified the mean $\alpha$ value clearly (Nakayama *et al.* 2010) or utilised treadmill protocols (Jordan *et al.* 2006). Additionally, previously injured and previously uninjured runners are cohorts with clearly distinguishable DFA $\alpha$ values, with previously injured runners indicating decreased persistence in stride patterning ($\alpha$ value closer to 0.5), possibly due to the impairment of components such as strength or balance (Meardon *et al.* 2011). Therefore, DFA is clearly interpreted differently between previously injured and previously uninjured runners, despite $\alpha$ value differences of
similar magnitude not indicating statistically significant differences in similar studies (Nakayama et al. 2011). Whilst the current study could also have discussed the effect of variance on DFA related to running performance levels unfortunately Nakayama et al. (2010) does not clearly identify the $\alpha$ values related to their trained and untrained running groups. Therefore, number of strides altered and magnitude of alteration thresholds were discussed based on values identified by Meardon et al. (2011).

8.4 Results
The mean stride time of each series prior to data alteration was 1.00 respectively. The mean $\alpha$ each series prior to data alteration was 1.03 (±0.01) indicating deterministic stride time series (Figure 8.2).
Figure 8.2 DFA $\alpha$ values for unaltered stride time series with (a) 600, (b) 3,000 and (c) 10,000 stride values.

When altered, within all stride series lengths $\alpha$ values decreased, moving toward random or white noise distribution or patterning ($\alpha = 0.5$) due to the addition of variance randomly allocated to stride time series. In the stride series length of 600, when utilising the upper $\alpha$ value identified by Meardon et al. (2011) for uninjured runners, $\alpha$ values decreased below 0.96 when strides were altered by $\leq$10 % magnitude in 100 % of strides ($\alpha = 0.95$) (Figure 8.3 and Figure 8.4). However, when strides were altered by $\leq$30 % of magnitude in 10% of strides this remained above the 0.96 threshold ($\alpha = 0.98$). When comparing the $\alpha$ value identified by
Meardon et al. (2011) for previously injured runners (α= 0.79), when strides were altered by ≤20 % magnitude in 100% of strides and ≤80 % of magnitude in 10% of strides (both α=0.80) these are interpreted as like that of a previously injured runner (Figure 8.3 and Figure 8.4).
Figure 8.3 DFA $\alpha$ values produced when stride time series, of length 600 stride and $1/f$ patternning, is altered by adding various magnitudes of variance to various amounts of strides.

Over ground fatiguing run, previously uninjured runner (Meardon et al. 2011)

$\alpha = 0.96$

Over ground, fatiguing run, previously injured runner. (Meardon et al. 2011)

$\alpha = 0.79$
Figure 8.4 Enlarged section of DFA $\alpha$ values for stride series length of 600 strides.

Over ground fatiguing run, previously uninjured runner (Meardon et al. 2011)

$\alpha = 0.96$

Over ground, fatiguing run, previously injured runner. (Meardon et al. 2011)

$\alpha = 0.79$
In the stride series length of 3,000, α values declined more rapidly due to alteration, than the decline seen in the stride series with 600 values. When utilising the upper α value identified by Meardon et al. (2011) for uninjured runners, α values decreased below 0.96 when strides were altered by ≤10 % magnitude in 100 % of strides (α= 0.86) (Figure 8.5 and Figure 8.6). However, when strides were altered by ≤10% of magnitude in 10% of strides and ≤20 % of strides this remained above the 0.96 threshold (α= 0.99 and α= 0.97). When comparing the α value identified by Meardon et al. (2011) for previously injured runners (α= 0.79), when strides were altered by ≤20% magnitude in 100% of strides (α ≤ 0.86) and ≤40 % of magnitude in 10 % of strides (both α=0.80) these are interpreted as like that of a previously injured runner (Figure 8.5 and Figure 8.6).
Figure 8.5 DFA $\alpha$ values produced when stride time series, of length 3,000 strides and 1/f patterning, is altered by adding various magnitudes of variance to various amounts of strides.

Over ground fatiguing run, previously uninjured runner (Meardon et al. 2011)

$\alpha = 0.96$

Over ground, fatiguing run, previously injured runner. (Meardon et al. 2011)

$\alpha = 0.79$
Figure 8.6 Enlarged section of DFA $\alpha$ values for stride series length of 3,000 strides.
In the stride series length of 10,000, compared to both strides series of length 600 and strides series of length 3,000, α values declined most rapidly due to alteration (Figure 8.7 and Figure 8.8). When utilising the upper α value identified by Meardon et al. (2011) for uninjured runners, α values decreased below 0.96 when strides were altered by ≥10 % magnitude in all amounts of strides, bar 10% strides (α= 0.99). When comparing the α value identified by Meardon et al. (2011) for previously injured runners (α= 0.79), when strides were altered by ≤10 % magnitude in 100 % of strides (α= 0.81) and as with the stride series length of 3,000 when strides were altered by ≤40 % of magnitude in 10 % of strides (α=0.79) these would be interpreted as like that of a previously injured runner (Figure 8.7 and Figure 8.8).
Figure 8.7 DFA $\alpha$ values produced when stride time series, of length 10,000 strides and $1/f$ patterning, is altered by adding various magnitudes of variance to various amounts of strides.

Over ground fatiguing run, previously uninjured runner (Meardon et al. 2011)

$\alpha = 0.96$

Over ground, fatiguing run, previously injured runner. (Meardon et al. 2011)

$\alpha = 0.79$
Figure 8.8 Enlarged section of DFA $\alpha$ values for stride series length of 10,000 strides.

$\alpha = 0.96$
Over ground fatiguing run, previously uninjured runner.
(Meardon et al. 2011)

$\alpha = 0.79$
Over ground, fatiguing run, previously injured runner.
(Meardon et al. 2011)
8.5 Discussion

Utilising robust methods of data analysis are key when interpreting kinematic parameters which may be susceptible to both naturally occurring variance (found during the learning of new movements) and error in movement patterns. This study expands on previous research by Chen et al. (2002) investigating discontinuities and outliers in DFA. The current results indicate that DFA is resistant to outliers at lower magnitudes (<30 % outlier magnitudes) however as stride time series length increases with a concurrent increase in the number of outliers, researcher interpretation will be ultimately affected by variance and therefore appropriate data thresholds must be applied to stride time series.

Overall within all stride time series (lengths of 600, 3,000 and 10,000) the maximum amount of variation which could be added or subtracted to strides, with $\alpha$ values retaining the properties of that outlined by Meardon et al. (2011) in uninjured runners, was ≤30 % in 10 % of strides in a series length of 600. Within the unaltered time series utilised in the current analyses this would result in the addition and/or subtraction of 0.00 to 0.30 s to 60 strides (Figure 8.9).
However, when applied to a typical running time series, with a mean stride time of 0.743 s (mean stride time calculated using M1 in Chapter 6), this would result in the addition or subtraction of 0.223 s to 60 strides within the series. Whilst Rowe et al. (2007) has identified any walking stride as 1.00 s, if this was used as an upper threshold within a running stride time series it is possible that a running stride of 0.743 s with 30% of variance (0.223 s) added to it (0.966 s) would not identified. However, as observed in Figure 8.9, visual identification of high magnitude values is possible even within longitudinal stride series. Therefore, ensuring that higher magnitude values of stride time are due to error as opposed to an increasing trend in stride time due to alterations in running speed, should be considered. The use of a soft bounded algorithm, in which a threshold is based off the standard deviation of a moving average (Hodge and Austin 2004), would take into account any increasing trend in stride time and adjust the threshold as appropriate. This process would further enhance DFA application.

Whilst altering strides with a magnitude of ≤30% in 10% of strides, in a strides series length of 600, results in α values which reflect those of a previously uninjured runner performing over ground to fatigue, as stride series lengths increase the magnitude of alteration has a greater impact on DFA calculation and therefore α interpretation. For example, within a stride series length of 600, magnitude alterations of ≤80% in 10% of strides results in α values associated
with that of a previously injured runner. However, this occurs at a lower magnitude of alteration (≤40 %) in both stride series lengths of 3,000 and 10,000. This is in line with Chen et al.’s (2002) findings who found that the addition of high magnitude uncorrelated spikes to a correlated signal (α > 0.05) affects DFA results, however, we advance this work by applying it both to a running stride time series and identifying the overall effect on variance to data interpretation.

8.6 Conclusion
DFA provides a robust method of investigating stride time predictability within longitudinal stride time series. Whilst running data collected externally to laboratory conditions may allow for increased natural variance, it also increases the probability of outlier stride times occurring due to noise or error. The importance of recognising these outliers ensures that researchers can correctly interpret DFA. Magnitude alterations of ≥40 % of the mean stride within a stride time series may result in DFA values which begin to indicate alternate stride patterning, and therefore change researcher interpretation of how runners are performing.

8.7 Thesis context
To confidently apply DFA, to longitudinal running stride series collected within Chapter 4, an investigation into how noise and/or error, which may occur during over ground running, affects DFA calculation and interpretation was required. Artificial data created within Chapter 8 outlines that magnitude alteration of ≥40 % result in the interpretation of DFA α values moving toward stride times with increasingly random patterning, associated with previously injured runners. However, with increasing stride series length, such as the stride series length collected within the current thesis, caution should be applied and soft bounded algorithms controlling data thresholds may be required to detect high magnitude outliers, as these may alter DFA interpretation.
Chapter 9. Recreational runners’ stride time and stride rate variability: a half and full marathon comparison
9.1 Abstract
An increasing number of recreational runners are participating in distance running events; however, little is known about their stride mechanics during these events. Stride time and stride rate variability were investigated during half and full marathon road running events. Tibial accelerometry data for 7 participants completing half (n = 4) and full (n = 3) marathon races completed 12 and 18-week training programmes prior to completing their relative distance running event. Participants attached accelerometers to their anteromedial distal tibia bi-laterally for their distance running event and tibial accelerometry data were collected. Stride time series were extracted for both the half marathon (HM) and full marathon events. Full marathon data were split into 21.1 km distance segments, full marathon (1st half) (FM1) and full marathon (2nd half) (FM2), resulting in analysis of three groupings, HM, FM1 and FM2. Mean, standard deviation (SD) and coefficient of variance (CV) were calculated for both stride time and stride rate. Detrended fluctuation analysis (DFA) was utilised to quantify stride time variability. Non-parametric Mann - Whitney U and Wilcoxon Signed-Rank tests were utilised to determine any differences between groupings. No significant results (p > 0.05) were identified between groupings, for any measure. Medium and small effect sizes (ES) differences for group α values were observed between HM and FM1 (ES = 0.66), HM and FM2 (ES = 0.35) and FM1 and FM2 (ES = 0.46). Results indicated that recreational runners adopt comparable stride parameters when undertaking half and full marathon events. Furthermore, walking periods during marathon distances may allow runners to retain dynamic stride time variability similar to that in a half marathon. Lastly, despite a 6-week extended training period, increased running training does not induce stride time and stride rate characteristics similar to trained distance runners, outlining the importance of specialised training.

9.2 Introduction
Participation in distance running events, such as full and half-marathons, has increased dramatically over the last number of decades; with these events now mass sporting events which attract participants of varying fitness levels (Murphy and Bauman 2007). In the US alone the number of race finishers has increased by just under 300% over a thirteen year period from 1990 to 2013, with recreational
runners accounting for a considerable proportion of race finishers (indicated by a median time of US marathon finishers > 4 hours) (Running USA 2015). However, whilst increased participation of recreational runners within running events indicates a positive shift in attitude toward physical activity and running, previous literature also identifies that recreational runners are increasingly susceptible to incurring a running related injury (RRI) (Junior et al. 2013). Less than 3 years running experience and running greater than 64 km per week have been identified as increasing risk of RRI in recreational runners, whilst in a male cohort of recreational runners performing the Rotterdam Marathon the 1 year prevalence of RRI was 54.8% (van Middelkoop et al. 2008). Therefore, this growing population of recreational runners competing in distance running events, and combined increased RRI risk has led to an increased necessity for research investigating how this group performs.

While much of the previous research surrounding distance road running has focused around elite runners (Saunders et al. 2004 & Hasegawa et al. 2007), recreational runners are not as optimally coordinated for endurance running performance (Hreljac and Marshall 2000 & Eriksson et al. 2011). Firstly, elite marathon runners perform with a higher stride rate during marathon races compared to recreational runners (Kasmer et al. 2013). Also, recreational runners may incur alterations to foot strike patterns during marathon running (Larson et al. 2011), lower limb joint angles (Dierks et al. 2010), stride rate and tibial acceleration (Mizrahi et al. 2000), during periods of prolonged running. Therefore, due to these differences, it may not be appropriate to infer equivalent kinematic changes between elite and recreational athletes during distance and prolonged running.

Stride time and stride rate are major contributing factors to running economy and overall run outcome (Mercer et al. 2008). Traditionally these variables were assessed using statistical measurement techniques of variability, such as standard deviation (SD) and coefficient of variance (CV) (Mercer et al. 2002 & Gottschall and Kram 2005). While these techniques provide us with insight into the magnitude of stride fluctuations, SD and CV values are typically associated with "noise" added to
a system and therefore do not inform us about any temporal structure which these fluctuations may possess (Buzzi et al. 2003).

However, studies investigating running using detrended fluctuation analysis (DFA) have reported that stride time fluctuations are not inherently random, but exhibit self-similarity and long range correlations (Hausdorff 2007). DFA, explained comprehensively elsewhere (Chapter 2 and Peng et al. 1995), calculates long range correlations which are then quantified using the scaling exponent, $\alpha$. $\alpha$ values closer to 1 indicate increased dependency of a stride to a previous stride at any given time, $\alpha$ values closer to 0.5 indicating decreased dependency of a stride to a previous stride at any given time, and $\alpha$ values of less than 0.5 indicating a lack of correlation among different time scales (Meardon et al. 2011). To date, changes in stride time $\alpha$ have identified limited information regarding the stride time variability of recreational runners. Jordan et al. (2006) identified that recreational runners exhibited decreased $\alpha$ values at their preferred treadmill running speed (PRS), compared to faster and slower speeds, suggesting they were most adaptable at PRS. Also, Meardon et al. (2011) identified that previously non-injured runners (no history of overuse injury) exhibited increased $\alpha$ values throughout a prolonged over ground run compared to their previously injured counterparts. This, along with decreasing $\alpha$ values displayed by both groups at the end of the run (previously injured and previously non-injured), indicates stride time predictability may be increased in a non-fatigued state and perhaps provide a protective mechanism against injury.

While these studies have contributed vital information to the area surrounding recreational runners’ stride time variability there are limitations. Firstly, Jordan et al. (2006) utilised a treadmill protocol when investigating long range correlations in recreational runners, however Lindsay et al. (2014) found that treadmill running does not accurately portray over ground gait dynamics. Secondly, recreational runners participate in both full and half marathon races and yet little is known about their continuous running mechanics across these events. Recently, progress has been made within the field as Hoos et al. (2014) investigated pacing and long range correlations for stride length, frequency and mean speed during a half marathon race. Whilst Hoos et al. (2014) found that stride rate fluctuations in
elite runners are generally as a result of tactical strategies, such as fast - slow – fast, recreational runners’ stride rate fluctuations are more likely to be a representation of running ability and may provide information as to ability levels and mechanical coping alterations undertaken during distance running. Also, Hoos et al. (2014) did not investigate stride time long range correlations. As such, the current authors believe there is a gap in current research to accurately portray the gait characteristics of the recreational distance runner.

Lastly, whilst we examine the larger recreational distance running cohort it is also important to distinguish between full and half marathon recreational runners. Previous research (Zillmann et al. 2013 & Poppel et al. 2016) has identified that recreational half marathon runners run significantly less mileage per week ($p < 0.001$), run for significantly less time per week ($p < 0.01$) and have significantly less experience than their comparative marathon runners ($p < 0.05$). Additionally, anthropometric differences were identified between half and full marathon runners, with half marathon runners having a thicker sum of skinfolds and a higher body fat percentage, with the latter negatively correlated to training running speed (Zillmann et al. 2013). These factors are important to understand when comparing half and full marathon recreational runners as they may impact on the interpretation of biomechanical differences between the groups.

Therefore, the purpose of this study was to investigate recreational runners’ stride time and stride rate variability whilst undertaking 21.1 km, during both half and full marathon competitive races. Firstly, it was hypothesised that runners completing the marathon would display decreased stride time α values and no difference in stride rate for the first half of the full marathon race compared to half marathon race values. A decreased α value, along with a similar stride rate, would indicate ability by full marathon runners to perceive and adapt to their surroundings, perhaps due to increased training volumes compared to their half marathon counterparts. Secondly, we hypothesised a further decrease in stride time α values, combined with an increase in stride rate, in the second half of the full marathon race, compared to both the first half of the marathon and half marathon values. A decrease in stride time α value and combined increase in stride
rate may be indicative of fatigue onset being imposed on the runner in the latter half of the marathon.

9.3 Methods

9.3.1 Participants
Accelerometry running data collected within Chapter 4 from four recreational runners partaking in a half-marathon (age: 32.5 ± 6.1 years, stature: 1.68 ± 0.90 m, mass: 68.4 ± 14.0 kg, personal best 10 km time: 52.2 ± 4.9 min) and three recreational runners partaking in a full marathon (age: 39.7 ± 3.1 years, stature: 1.68 ± 0.13, mass: 67.0 ± 18.4 kg, personal best 10 km time: 50.7 ± 4.2 min) were utilised. As before, prior to half marathon completion participants undertook a self-led 12 week Hal Higdon Novice Half Marathon (Hal Higdon 2011a) running training programme. Prior to full marathon completion participants undertook a self-led 18 week Hal Higdon Novice Marathon (Hal Higdon 2011b) running training programme. As the competitive running events did not occur concurrently one participant (age: 37.0 years, stature: 1.82 m, mass: 87.0 kg) completed both half and full marathon distances. Whilst one participant was diagnosed with patellar tendinopathy in the lead up the full marathon all remaining participants were free from injury when undertaking their competitive distance running events, as confirmed via training logs outlined in Chapter 4.

9.3.2 Instrumentation
Following guidelines outlined in Chapter 2, Chapter 3 and Chapter 4, participants were required to attach a triaxial Shimmer 2r™ accelerometer (SHIMMER Ltd, Dublin, Ireland) to their anteromedial distal tibia bi-laterally for their distance running event. All accelerometer parameters, including accelerometer attachment, weight, calibration and orientation were as described in Chapter 3. Participants also completed a rate of perceived exertion (RPE) for their competitive run, within their weekly running log (Appendix B). RPE was measured utilising the Borg 15-grade RPE scale (Borg 1982), with 6 indicating very, very light perceived exertion and 20 indicating maximum exertion. Accelerometers were collected by the investigator within 7 days of race completion.
9.3.3 Data analysis
Preliminary data processing was performed for all right leg tibial accelerometry race files using custom built MATLAB™ (MathWorks, Cambridge, UK) and LabVIEW™ (National Instruments, Newbury, UK) algorithms. Estimated running time was identified via participant’s pre- and post-race standing periods. Accelerometer race data were corrected for static tilt as outlined in Chapter 3. Stride time series was as outlined in Chapter 6. As running stride time was of interest any stride above one second duration was excluded as this was designated to be a walking step (Rowe et al. 2007 & Rowe et al. 2011). Additionally a lower stride time threshold of 0.6 s were implemented, based on previous literature investigating both runners and non-runners (Nakayama et al. 2010). For stride rate, run time was broken into 1% epochs and stride rate (strides min^{-1}) was calculated for each epoch. To analyse stride variables the complete full marathon race stride time series were split into full marathon (1st half) and full marathon (2nd half) groupings via race chip timing information. Full marathon (1st half) and full marathon (2nd half) groupings will hereon be referred to as FM1 and FM2, whilst the half marathon grouping will be referred to as HM. For overall half marathon values the stride time series were analysed in their entirety. Completion time (CT) (mins) was collected via chip timing, whilst running time (mins) and average running speed (m·s^{-1}) were calculated using the stride time series minus walking periods. Stride time long range correlations were calculated using DFA (Peng et al. 1995).

9.3.4 Statistical analysis
DFA exponents, \( \alpha \), were calculated using the PhysioNet Toolkit (Goldberger et al. 2000). Descriptive statistics including mean, standard deviation, coefficient of variation and range were calculated for stride time (s) and stride rate (strides min^{-1}). The mean and range was also calculated for ground contact time CT (mins). Group averages were calculated for all stride variables with individual results graphed for stride time \( \alpha \) and stride rate. Effect sizes for \( \alpha \) values were calculated both between groupings (HM, FM1 and FM2) and across time splits (FM1 and FM2). Due to small sample size Hedge's G, a modified version of Cohen's D, was employed (Hedges 1981). Siegal et al. (1956) identified that traditional parametric tests should not be utilised on small sample sizes as parametric tests have many
assumptions within them which will be violated due to the sample size (De Winter 2013). Therefore, non-parametric statistical tests were utilised to explore all gait variables. Mann-Whitney U tests were used to identify statistical significance between groupings (HM, FM1 and FM2). Wilcoxon-Signed Rank test was used to identify statistical significance between full marathon splits (FM1 and FM2). An alpha value of 0.05 was used to identify statistical significance.

9.4 Results
A total of 102,906 running stride times were analysed, of which 39,488 stride times were HM values, 31,154 stride times were FM1 values and 32,264 stride times were FM2 values (Figure 9.1). These data sets were considerably larger than previously reported for DFA analysis (Nakayama et al. 2010 & Meardon et al. 2011).

![Figure 9.1 Number of stride times analysed for half marathon (HM) and full marathon (FM1 and FM2) groupings.](image)

Mean stride time was comparable across groupings (HM = 0.70 s, FM1 = 0.68 s and FM2 = 0.68 s). However, FM1 displayed increased results for stride time SD and CV (0.017 s and 2.43 %) compared to both HM (0.013 s and 1.90 %) and FM2 (0.015 s and 2.27 %). A similar pattern was seen for stride rate with mean stride rate comparable across groupings (HM = 86.2 strides min\(^{-1}\), FM1 = 88.4 strides min\(^{-1}\) and FM2 = 88.6 strides min\(^{-1}\)). However, FM1 displayed increased results for stride rate SD and CV (1.5 strides min\(^{-1}\) and 2.1 %) compared to both HM (1.0 strides min\(^{-1}\) and 1.2 %) and FM2 (1.4 strides min\(^{-1}\) and 1.6 %) (Table 9.1). For individual
stride rate values one full marathon participant (participant six) displayed a stride rate value (99.2 strides min\(^{-1}\)) which exceeded the half marathon range of 83.3 - 89.7 strides min\(^{-1}\). Participant 6 was also the only runner to decrease stride rate across full marathon time splits (-1.8 strides min\(^{-1}\)) (Figure 9.2). Statistically there was no significant difference for stride rate variables (mean, SD and CV) across groupings (p > 0.05). The difference in completion time (CT) was minimal when comparing HM with FM1 (114.5 mins and 118.4 mins, +3.3%) (Table 9.1). However, this CT difference increased between HM and FM2 (114.5 mins and 133.7 mins, +16.7%). There was no significant difference for CT across groupings (p >0.05).

Previously, magnitudes of ≥40% of average stride time has been identified to effect interpretation of DFA in longitudinal time series (Chapter 8, 8.4). The mean stride time across all groupings (HM, FM1 and FM2) was 0.68 s, with 40% of this equal to 0.27 s. Therefore, stride time values of 0.96 s (0.68 s + 0.27 s) and or 0.41 (0.68 s – 0.27 s) may have affected subsequent DFA interpretation. Due to the implementation of higher (1.0 s) and lower (0.6 s) thresholds stride time values with a 40% magnitude reduction (0.41 s) would not have been included in the stride time series. However, stride time values with a 40% magnitude increase (0.96 s) may be included, therefore visual inspection of the data was undertaken prior to DFA analysis to ensure high magnitude outliers did not effect DFA calculation. DFA analysis displayed increased mean α values for FM1 and FM2 groupings compared to HM, however α decreased across FM1 and FM2 time splits (HM α = 0.93, FM1 α = 0.97 and FM2 α = 0.95) (Table 9.1). Within this only one full marathon participant (participant five) exhibited α values in both FM1 and FM2 (FM1 α = 0.91 and FM2 α = 0.94) within the α range displayed by half marathon participants (0.87 - 0.98) (Figure 9.2). The remaining full marathon participants (participants 6 and 7) each displayed one α value above this range (0.99 and 1.18). There was no significant difference in α values across groupings (p > 0.05). Hedge’s G values indicated a medium effect size difference of 0.66 between HM α values and FM1 α values. Small effect size differences were found between HM and FM2 α values (ES = 0.35) and between FM1 and FM2 α values (ES = 0.46) (Table 9.1).
**Table 9.1** Group stride interval and stride rate characteristics for half marathon and full marathon splits. Mean values presented with range in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Half Marathon (HM)</th>
<th>Full Marathon (1st Half) (FM1)</th>
<th>Full Marathon (2nd Half) (FM2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stride interval (s)</strong></td>
<td>0.70 (0.67 - 0.72)</td>
<td>0.68 (0.65 – 0.71)</td>
<td>0.67 (0.66 – 0.70)</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td>0.013 (0.010 - 0.015)</td>
<td>0.017 (0.014 – 0.022)</td>
<td>0.015 (0.013 – 0.019)</td>
</tr>
<tr>
<td><strong>CV</strong></td>
<td>1.90 (1.48 - 2.15)</td>
<td>2.43 (1.98 – 3.21)</td>
<td>2.27 (1.93 – 2.87)</td>
</tr>
<tr>
<td><strong>α</strong></td>
<td>0.93 (0.87 - 0.98)</td>
<td>0.97 (0.93 – 0.99)</td>
<td>0.95 (0.93 – 0.99)</td>
</tr>
<tr>
<td><strong>Effect Size</strong></td>
<td></td>
<td>0.66&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.35&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td><strong>Stride rate (strides min&lt;sup&gt;-1&lt;/sup&gt;)</strong></td>
<td>86.2 (83.3 – 89.7)</td>
<td>88.4 (84.8 – 92.7)</td>
<td>88.6 (85.9 – 90.9)</td>
</tr>
<tr>
<td><strong>SD</strong></td>
<td>1.0 (0.7 - 1.3)</td>
<td>1.5 (1.2 – 1.9)</td>
<td>1.4 (1.1 – 1.7)</td>
</tr>
<tr>
<td><strong>CV</strong></td>
<td>1.2 (0.8 - 1.6)</td>
<td>2.1 (1.4 – 2.2)</td>
<td>1.6 (1.2 – 2.0)</td>
</tr>
<tr>
<td><strong>Running time (mins)</strong></td>
<td>114.5 (98.8 – 130.1)</td>
<td>117.0 (102.0 – 134.0)</td>
<td>121.3 (113.8 – 133.3)</td>
</tr>
<tr>
<td><strong>Time to completion (mins)</strong></td>
<td>114.5 (99.0 – 130.1)</td>
<td>118.4 (102.0 – 134.0)</td>
<td>133.7 (114.0 – 169.0)</td>
</tr>
<tr>
<td><strong>Average running speed (m·s&lt;sup&gt;-1&lt;/sup&gt;)</strong></td>
<td>3.06 (2.69 – 3.54)</td>
<td>3.00 (2.61 – 3.43)</td>
<td>2.89 (2.63 – 3.08)</td>
</tr>
</tbody>
</table>

<sup>a</sup> = between Half Marathon (HM) group α values and Full Marathon group (1st Half) (FM1) α values. <sup>b</sup> = between Half Marathon (HM) group α values and Full Marathon group (2nd Half) (FM2) α values. <sup>c</sup> = between Full Marathon time splits (1st and 2nd half) (FM1 and FM2).
9.5 Discussion

The purpose of this study was to compare stride time and stride rate variability of recreational runners when completing a 21.1 km distance, both in half and full marathon events. Additionally, alterations which occurred over the course of the full marathon race were examined. Firstly, it was hypothesised that full marathon runners would display decreased stride time $\alpha$ values along with no difference in
stride rate in the first half of the marathon race (FM1) compared to half marathon (HM) runners. Secondly, it was hypothesised that full marathon runners would display further decreased stride time α values and increased stride rate in the latter half of the marathon (FM2), compared to both the half marathon (HM) and full marathon first half (FM1). Contrary to both hypotheses no significant differences were found either between groupings (HM, FM1 and FM2) or across time splits (FM1 and FM2) for stride time α or stride rate. This may indicate that recreational marathon runners adopt similar stride dynamics to half marathon runners during race events.

9.5.1 Distributional measures
This is the first study to compare stride time and stride rate variability in recreational runners undertaking a 21.1 km distance in half and full marathon road races. Stride time CV results in HM (1.90 %) and FM1 (2.43 %) and FM2 (2.27 %) were higher than those previously reported in healthy recreational runners (1.29 %, Meardon et al. 2011; < 1.3 % Jordan et al. 2006) and healthy non- runners (1.00 - 2.00 %, Nakayama et al. 2010). While CV values were lower than in the current study, Jordan et al. (2006) recreational runners displayed increased stride time CV when running at 80% and 90% of PRS. Both half and full marathon runners here ran for an extended time compared to Jordan et al. (2006) participants (8 min trials, 2 - 10 min rest between each). This extended running period, along with decreased running velocity across full marathon time splits, FM1 and FM2, (indicated by increased running time and CT), may have resulted in a negative shift from PRS, accounting for increased stride time CV values. Whilst no significant differences were found for stride time measures across groupings, increased stride time SD and CV were displayed in FM1 (0.017 s and 2.43 %) compared to HM (0.013 s and 1.90 %), despite comparable average running speeds (3.00 m·s⁻¹ and 3.06 m·s⁻¹). Mann et al. (2015) previously suggested that at lower running speeds, runners have more freedom to make changes or alterations to their running style, resulting in increased CV values. However, this was not identified within the current study. Conversely, Nakayama et al. (2010) identified decreased stride time CV values in university level trained distance runners compared to non-runners and suggested this may be due increased stability of the running gait pattern, gained through increased repetition with practise. Within the current study
neither group undertook specialised training (any training in which participants were committed solely to their specified running distance, fully committed to intense training and aiming for competitive success, Baker et al. 2005), however full marathon participants completed an extra six weeks running in their training programme, along with training runs of greater distance, prior to the completion of the full marathon. Despite increased running volume the full marathon group displayed increased stride time SD and CV when compared to half marathon stride results. This may indicate that increased running volume alone, and by default increased stride time repetition, is not enough to increase stride time distributional variability and the "trained" level of a recreational runner. To stabilise running patterns, specialised running training may be required, such as that which Nakayama et al.’s (2010) trained runners would have completed.

9.5.2 Stride-to-stride variability

Stride time mean α values for the groupings, HM α = 0.93, FM1 α = 0.97 and FM2 α = 0.95, were within the white to pink noise range (α = 0.5 to α = 1.0) and comparable to those found in previous research (Jordan et al. 2006; Nakayama et al. 2010; Meardon et al. 2011). This represents a healthy movement system within the participants in which stride time is not completely random but possesses a dynamic structure (Kiefer et al. 2009). Whilst no significant difference in α values were identified across groupings, a medium effect size difference (ES = 0.66) was identified between HM (0.93) and full FM1 (0.97) α values. Whilst the HM and FM1 runners differed in terms of training programme length undertaken it is unlikely that the medium effect size observed is attributed to the extended training period of the full marathon group. Nakayama et al. (2010) identified that trained runners displayed decreased α values compared to their non-running counterparts, however the current study observed an increase in α with increased training status (FM1 α = 0.97 and HM α = 0.93). Nakayama et al. (2010) stated that a decrease in α was due to an increased ability to perceive and adapt to sensory information by trained runners during running. However, it appears that, as before, increased running volume alone is not enough to develop this skill to the extent of a trained runner, and that specialised training is required. Interestingly, FM1 had the widest range of stride rate values of all the groupings and it is possible that this may have attributed to the medium effect size observed between HM and FM1 group α.
Jordan et al. (2006) has identified that a negative shift away from PRS (decrease in running speed) elicits a "biological stressor" on the body, leading to strengthened stride time long range correlations. Participant six displayed the highest stride rate of all participants (92.7 strides min\(^{-1}\), FM1), which, when combined with an overall decreased running velocity compared to half marathon (3.00 m·s\(^{-1}\) and 3.06 m·s\(^{-1}\)), may indicate a shift away from PRS and contribute to the medium effect size difference. It could then be argued that across marathon time splits further increasing α values, and perhaps a larger effect size then identified (ES = 0.46), should be present, due a further decrease in running velocity (-0.11 m·s\(^{-1}\)). However, it is clear when comparing average running time (121.3 mins) and completion time (133.7 mins) of FM2 that sizeable periods of rest and walking were taken by participants in the marathon latter half. This may have prevented "biological stressors" being imposed on participants, and therefore preserved stride time long range correlations across the full marathon, despite the overall decrease in running speed.

### 9.5.3 Stride rate

Lastly, stride rate was examined, with the highest average stride rate found during FM2 (88.6 strides min\(^{-1}\)) compared to HM (86.2 strides min\(^{-1}\)) and FM1 (88.4 strides min\(^{-1}\)). It was expected that runners would display increased stride rate (possibly along with decreased step length) as an attempt to offset fatigue onset during the latter half of the full marathon. Furthermore, Morin et al. (2011) and Degache et al. (2016) both identified increases in step frequency during the running of an ultramarathon with a suggestion that this is an adaptive mechanism to decrease impact forces on the body (Reenalda et al. 2015). When examining alterations in stride rate, in terms of mean, SD and CV, we must explain the role which stride rate provides in running. Traditionally in running, increases in velocity up to 4.0 m·s\(^{-1}\) are primarily brought on due to increases in stride length (Hoos et al. 2014), with stride rate increase playing a role in top end velocity. As the average running speeds seen here were HM = 3.06 m·s\(^{-1}\), FM1 = 3.00 m·s\(^{-1}\) and FM2 = 2.89 m·s\(^{-1}\) respectively, we can assume that alterations in stride rate, were due to an inability to maintain a given stride rate, and not an attempt to increase velocity. Also, interestingly, all stride rate values, except participant four, were within the newly suggested "optimal" stride rate zone of 85 - 97.5 strides min\(^{-1}\).
(Kasmer et al. 2013). This method has yet to be conclusive in terms of running economy and appears here that it may be due to lack of specialised or coached training, as opposed to a selected running gait technique. Stride rate CV values for HM (1.2 %), FM1(2.1 %) and FM2 (1.6 %) were consistent to those found in previous literature using experienced runners (Hoos et al. 2014).

9.5.4 Limitations

Whilst this study investigated recreational runners’ stride dynamics over periods of prolong running, there were limitations to this study. Non-parametric methods were utilised to analyse the small sample size, thus can be problematic to infer occurrences here to the wider recreational running population. A larger sample size would have provided further detail into fluctuations of recreational running gait during distance road running and should be investigated in the future.

9.6 Conclusion

Research investigating recreational runners’ gait techniques is increasing and the current research further adds to a growing body of literature. The current results indicate that recreational half marathon and full marathon runners may adopt similar stride dynamics whilst undertaking distance road events. Participants who undertook an 18-week running training programme appear to exhibit similar stride time characteristics compared to those who undertook a shorter 12-week programme, when completing a 21.1 km distance. The extended programme does not elicit characteristics in gait comparable to that of a "trained runner" and perhaps identifies the importance of specialised training for these adaptions. Also, whilst the ability to alter running velocity and stride rate in a natural environment may result in a move away from PRS and strengthen stride time long range correlations in recreational runners, the presence of extended stationary and walking periods may preserve already present correlations.

DFA is underutilised in longitudinal running due to extensive processing and analysis times. Therefore, future research should investigate methods of utilising DFA in real-time, allowing researchers to investigate efficiently the effect of running alterations, such as running terrain and speed, on recreational runners running patterns.
9.7 Thesis context
Half and full marathon distances provide a strenuous task to complete for all running abilities. Whilst previous research has focused on fatiguing acute running protocols to investigate changing temporal gait parameters this is one of the first studies to apply gait analysis over continuous, longitudinal running data. Within the thesis, Chapter 9 encapsulates all the methods utilised within the thesis so far, stride time calculation, stride rate analysis and DFA application, and successfully applies this to runners DFA as a method of analysis distance running data.
Chapter 10. Design, verification and validation of an advanced running analysis system
10.1 Abstract

As running has become more popular there has also been a concurrent increase in the focus on running analysis techniques. Many techniques have enhanced our knowledge of running, laboratory analysis often utilise treadmill protocols, whilst commercial consumer products often provide basic feedback such as running speed and distance. This leads to a multitude of analysis techniques which may not be ecologically valid as they do not reflect a natural running environment, and/or do not inform runners about their individual running technique. Detrended fluctuation analysis (DFA) is a technique utilised for the detection of long range correlations in non-stationary time series and has recently been applied to running gait stride time analysis. DFA reports an $\alpha$ value which has been shown to differentiate trained runners from non-trained runners, and previously injured runners from injury free runners. DFA $\alpha$ values therefore provide researchers with succinct information about the coordination of stride time over extended periods of running. However, DFA requires a large number of running strides (>400), which requires increased data processing time. This may limit its use within feedback and analysis environments. The current study aims to validate a developmental running analysis system incorporating over ground real-time data collection, individualised derivation of stride time series and output of reoccurring, real-time DFA $\alpha$ values in a rapid manner, during prolonged running. Data are collected utilising a triaxial Shimmer 2r™ accelerometer, attached to a participant’s lower tibia. Triaxial accelerometry data is transmitted, via Bluetooth, to custom built analysis software. This analysis software permits real-time visual identification of gait patterns and researcher input for custom filtering and stride time derivation parameters. Along with this, DFA $\alpha$ values are calculated during real-time at reoccurring, researcher defined, running time periods. Preliminary investigation of the advanced running analysis system indicates output of DFA $\alpha$ values within 5 seconds of these predetermined running time periods, enabling researchers to give rapid real-time DFA feedback, during a prolonged run. Further analysis will aim to confirm reliability of the running gait analysis system, taking
into account individual running styles. Development of this system will enhance sports engineering capabilities, in terms of rapid advanced running gait analysis techniques.

10.2 Introduction

Advances in motion capture, force platforms, pressure sensors, electromyography, accelerometers and gyroscopes mean there are now numerous measurement methods available which provide participants, coaches and researchers with quantitative data during running (Higginson 2009). While many of these methods, such as motion capture and force platforms, may be more commonly restricted to use within a laboratory, accelerometers are not, and have therefore become increasingly popular in running gait analysis (Norris et al. 2014). Due to their wireless and lightweight nature accelerometers are an integral part of research and consumer-led wearable running devices such as sports bracelets, smartwatches and smart clothing (Wang 2015). Accelerometers are commonly embedded within these devices to provide feedback to consumers and/or research participants on parameters such as distance and speed (Conger et al. 2005), and stride frequency (Hausswirth et al. 2009) during running.

While distance, speed and stride frequency are some of the primary running parameters of distance running (Nelson and Gregor, 1976), recently there has been increased interest in measuring running variability by investigating long range correlations in stride time series using the advanced statistical analysis, Detrended Fluctuation Analysis (DFA) (Jordan et al. 2006; Nakayama et al. 2010; Meardon et al. 2011). DFA investigates the intrinsic dynamics of physical and biological systems (Hu et al. 2001 & Chen et al. 2002), as outlined in Chapter 8 and is quantified through output of an α value. Briefly, when applied to stride time series an α value of 0.5 indicate a random walk, where one stride is uncorrelated to previous strides, whilst an α value of between 0.5 and 1 indicate the presence of long range correlations, where stride time patterning continues over a number of strides resulting in predictable pattern (Meardon et al. 2011). Previously, DFA α values have been found to distinguish the training status of runners (Nakayama et al. 2010), and identify previously injured runners from their previously non-injured counterparts (Meardon et al. 2011). DFA may therefore provide vital
information to researchers and recreational runners alike, as to changes in their stride time variability due to training and/or onset of injury. However, DFA requires extended data collection, due to its investigation into long range correlations (Damouras et al. 2010), and studies investigating DFA on running populations have typically collected >400 strides (Nakayama et al. 2010 & Meardon et al. 2011). Therefore, to complete DFA increased post-processing capabilities are needed along with advanced statistical knowledge for correct implementation. This has led to DFA being underutilised within laboratory settings, and never utilised in consumer wearable running devices.

Whilst real-time feedback in sports technology has been described as “a method that allows participants to observe their movements for the purpose of making immediate biomechanical adjustments” (Ericksen et al. 2015, pg. 112), DFA does not investigate discrete values which are susceptible to immediate adjustments. Therefore, longer periods of data collection prior to result output is more appropriate within this system when referring to “real-time” DFA \( \alpha \) value output. Additionally, the availability of DFA within a real-time setting may increase the use of this analysis within research. To date there is limited research utilising DFA within running (Jordan et al. 2006; Nakayama et al. 2010; Meardon et al. 2011; Fuller et al. 2016a; Fuller et al. 2016b), however results indicate that DFA may identify changes in running patterns which may aid injury diagnosis (Meardon et al. 2011), and/or changes in training status (Nakayama et al. 2010). Further investigation is required for researchers to gain a comprehensive understanding of how DFA can benefit the running population, and when performed in real-time this can occur quickly and efficiently. Thus, the aim of this research was to develop an advanced running analysis system, which will provide real-time DFA \( \alpha \) values. If verified this system could enhance researcher and coach data collection alike, in terms of rapid data output and statistically advanced running variability information.

10.3 System description
The advanced running analysis system is comprised of a Shimmer 2r™ accelerometer (range ± 6 g, sensitivity = 200 mV/g) (SHIMMER™, Dublin, Ireland) and a laptop equipped with Bluetooth capability, MATLAB™ (MathWorks,
Cambridge, UK) and the PhysioNet C+ DFA programme (Goldberger et al. 2000) (Figure 10.1).

10.3.1 Pre-data collection process
The system is designed to be adaptable to different research interests, along with the individual running styles of the participants and therefore there are a number user inputs which can be varied prior to data collection to enhance the accuracy of data output (Table 10.1). Prior to data collection the Shimmer 2r™ accelerometer should be programmed with Bluetooth streaming capability and paired with the laptops appropriate comport, to ensure real-time data streaming via the Shimmer MATLAB™ Instrument Driver.
Table 10.1 Pre-data collection user input parameters.

<table>
<thead>
<tr>
<th>Parameter Title</th>
<th>Parameter Explanation</th>
<th>Input Example or Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name_</td>
<td>Enter name of subject or experiment bordered by apostrophes.</td>
<td>Any input eg, 'John'</td>
</tr>
<tr>
<td>comPort</td>
<td>Designated comPort due to Shimmer bluetooth pairing, enter number bordered by apostrophes.</td>
<td>Number designated by pairing eg, '9'</td>
</tr>
<tr>
<td>Epoch_1</td>
<td>Enter length of 1st running Epoch in seconds. *Must be a long enough period to collect &gt; 400 running strides for valid DFA result for Epoch 1.</td>
<td>Any number of seconds eg, 480</td>
</tr>
<tr>
<td>Trials</td>
<td>Enter number of DFA values and/or number of overlapping windows, maximum 10.</td>
<td>Any value 1-10 eg, 10</td>
</tr>
<tr>
<td>TrialPeriod</td>
<td>Enter length of each overlapping window in seconds.</td>
<td>Any value eg, 60</td>
</tr>
<tr>
<td>fs</td>
<td>Enter sampling frequency of Shimmer 2r™. Must be a multiple of 51.2 and ≤ 1024 eg, 51.2 OR 102.4 ... 1024.</td>
<td>Any value eg, 51.2</td>
</tr>
<tr>
<td>fc</td>
<td>Filtering cutoff for butterworth lowpass filter</td>
<td>Any value, eg 2</td>
</tr>
<tr>
<td>Order</td>
<td>Enter butterworth lowpass filter order</td>
<td>2 OR 4</td>
</tr>
<tr>
<td>SignalAnalysis</td>
<td>Axis which strides will be derived from (bordered by apostrophes)</td>
<td>'Filtered_X' OR 'Filtered_Y' OR 'Filtered_Z'</td>
</tr>
<tr>
<td>FolderName</td>
<td>Enter folder pathway (ending in \ and bordered by apostrophes) to save pre-processed files in.</td>
<td>Any folder pathway eg, 'C:\Users\John\Documents\MATLAB\data'</td>
</tr>
<tr>
<td>SaveFolderName</td>
<td>Enter folder pathway (ending in \ and bordered by apostrophes) to save post-processed files in.</td>
<td>Any folder pathway eg, 'C:\Users\John\Documents\MATLAB\data'</td>
</tr>
</tbody>
</table>
10.3.2 Data collection initiation

Firstly, a Shimmer 2r™ accelerometer is turned on and attached to the participants’ right distal anteromedial tibia (Figure 10.1, A). Participants are then given a treadmill warm-up period in which they are allowed to reach the required running speed. On having reached their running speed the system user\researcher then runs the custom developed ‘DFA_running_analysis.m’ script ( ). This script contains the Shimmer MATLAB™ Instrument Driver streaming, plotting and text writing capabilities (provided by the manufacturer), along with a data analysis function to perform data processing to create a stride time series and run the PhysioNet DFA C+ Programme to calculate a DFA α value (Figure 10.1, B), at user specific time intervals (defined in pre-data collection user input). The Shimmer 2r™ accelerometer then starts logging triaxial data which it transmits, via Bluetooth, to a laptop situated within 5 m of the treadmill, for a designated capture period, (Figure 10.1, A and B). When accelerometry data begins streaming to MATLAB™ a timer is automatically generated incrementing elapsed time.

![Figure 10.1 System image](image)

The participant runs continuously for the designated capture period (Eq. 2),

\[
\text{capture period} = \left(\text{Trials} \times \text{TrialPeriod} \right) + \text{Epoch} - 1
\]  

(2)
10.3.3 Accelerometry text file generation.

During this capture period accelerometry data is written to 11 text files, 'Epoch_1' + 10 trials named 'Epoch_2', 'Epoch_3' etc. The end of each Epoch period is defined as (Eq. 3),

\[
\text{Epoch}_2 = \text{Epoch}_1 + \text{TrialPeriod}, \\
\text{Epoch}_3 = \text{Epoch}_2 + \text{TrialPeriod etc.} 
\]  

(3)

As previously stated, when the user runs the 'DFA_running_analysis.m' script there is an inbuilt data analysis function to perform data processing and DFA. This data analysis function requires 2 - 3 s to perform data analysis, calculate and display the DFA $\alpha$ value on a message dialog box. To allow for this, variables $A1 - A11$ are created automatically to identify the point of at which each Epoch ceases writing to text file (Eq. 4).

\[
A1 = \text{Epoch}_1 - 2, \\
A2 = \text{Epoch}_2 - 2 etc. 
\]  

(4)

Therefore, the first data file containing accelerometry data, 'Epoch_1', is generated and continuously appended to whilst (Eq. 5),

\[
'\text{Epoch}_1' = 0 \leq \text{elapsed time} < A1 
\]  

(5)

The period in which the remaining text files are written to, 'Epoch_2', 'Epoch_3' etc., are defined by (Eq. 6),

\[
'\text{Epoch}_2' = \text{Epoch}_1 \leq \text{elapsed time} < A2, \\
'\text{Epoch}_3' = \text{Epoch}_2 \leq \text{elapsed time} < A3 etc. 
\]  

(6)

Therefore, there is a 2 s period within each Epoch in which accelerometry data are streamed, but not written to file and therefore not included in the subsequent analyses. The effect of this 2 s loss of recorded data is minimal as, using the
example of the minimal suggested Epoch length of Epoch_1 = 8 minutes (Figure 10.3), it results in a 0.4 - 3.3 % loss of data within an 8 minute Epoch, and a 2 % loss of data in an overall capture period of 18 minutes.

When elapsed time ≥ capture period acceleration data collection ceases.

**10.3.4 Data processing and DFA calculation.**

Data processing and DFA initiates 1 second post variables A1 – A11, allowing for sufficient accelerometry collection time and text files to cease writing prior to processing. Therefore, data analysis occurs at (Eq. 7),

\[
A_1 \leq \text{elapsed time} < (A_1 + 1),
\]

\[
A_2 \leq \text{elapsed time} < (A_2 + 1) \text{ etc.} \quad (7)
\]

At each data analysis initiation, firstly all accelerometry text files are concatenated to previous accelerometry files. This merged file is then cut from the beginning down to mirror ‘Epoch_1’, using Fraction = TrialPeriod / Epoch_1, multiplied by the length of Epoch_1. At each data analysis initiation this creates overlapping accelerometry data files, which all contain an acceleration collection period equal to Epoch_1 (Figure 10.2).

![Figure 10.2 Process of data merging and cutting.](image)

This merged file undergoes filtering, using a Butterworth Filter, with pre-data collection user input defined frequency cut off and filter order. Then, a stride time series is produced using peak identification in the axis chosen through pre-data collection user input. Due to the process of merging multiple acceleration files which contain 2 seconds of missing data, and therefore not continuous data, there
is the possible creation of stride times not representative of actual strides. Therefore, within the data analysis there are stride time threshold boundaries, which can be altered by the user, to eliminate stride time outliers. Lastly, the PhysioNet DFA C+ programme generates a DFA $\alpha$ value from the calculated stride time series, which is displayed automatically in a message dialog window (Figure 10.1, C).

### 10.4 System verification experimental protocol

To verify the advanced running analysis system generates real-time DFA $\alpha$ values in an efficient manner, and in line with expected $\alpha$ results, a healthy active participant (female, age: 26.6 years, stature: 1.80 m, mass: 70.1 kg) performed a running protocol whilst completing the advanced analysis system. Firstly, an 8-minute period for Epoch_1 was selected, as is suggested by the current researchers as the minimum length of time required to allow enough time within you are guaranteed to collect over 500 strides, regardless of running speed. Previous research has investigated DFA during running using 512 strides (Nakayama et al. 2010), 661 strides (Meardon et al. 2011) and 659 strides (Jordan et al. 2006) and therefore the recommended 500 + strides is in line with previous research. Further pre-data collection user input parameters were as follows, Trials = 11, TrialPeriod = 1 min, fs = 102.4, fc = 2, Order = 4, SignalAnalysis = ‘Filtered_Z’ (Figure 10.3). Utilizing a 2 Hz filter cut off to derive stride time has previously been validated (Norris et al. 2016 & Chapter 5). Along with this a stride time upper threshold of 0.8 s and a lower stride time threshold of 0.6 s were implemented, based on previous literature investigating both runners and non-runners (Nakayama et al. 2010). Previously magnitudes of $\leq 30\%$ of the average stride time, added to 10 $\%$ of strides within a stride series length of 600, has been found to alter DFA interpretation (Chapter 8, 8.4). However, within the current protocol the participant ran at three steady state speeds (80% PRS, PRS and 120% PRS), with upper and lower stride time thresholds applied. Therefore, it is believed no “outlier” stride time values, which may have affected DFA calculation, were within the outputted stride time series.

The running protocol implemented within the current study also aimed to verify the successful use of the advanced analysis system over a range of running speeds.
For this, the participant was required to run at their preferred running speed (PRS), 80% of their PRS and 120% of their PRS. To establish the participant’s PRS the same protocol as that used by Nakayama et al. (2010) and Jordan et al. (2006) was employed. In short, the participant ran at a range of speeds which they indicated to the researcher were “comfortable” or “uncomfortable”. The participant was blinded to the speeds at which they were running, as the console on the treadmill utilised was covered. The average speed of the “comfortable” speeds was estimated as the participant’s PRS. From the participant’s PRS, 120% and 80% of their PRS were calculated. The participant was then required to run for 18 minutes at 80% PRS, 100% PRS and 120% PRS in randomized order. This 18-minute running period was composed of an 8-minute period to allow for primary collection of the necessary 500 strides for DFA calculation and an additional ten, 1-minute periods (Figure 10.3). The participant was allowed a necessary resting period between runs, to mitigate the effect of fatigue. This resting period was further supported by a return to resting heart rate as confirmed by a heart rate monitor.

Figure 10.3 Data collection, analysis and output timeline of the running analysis system. Visuals A1 – A12 indicate automatic data analysis initiation.
To verify the system met the specified requirement, real-time output of repeated DFA $\alpha$ values, the time difference in seconds ($\Delta t$) between the end of each Epoch and the related $\alpha$ value display time were calculated, via a record of the MATLAB™ Command Window displaying elapsed time and each data analysis. To verify the system produced reliable $\alpha$ values over a range of running speeds $\alpha$ values were also recorded and compared to previous literature.

10.5 Results
The participant’s PRS was 2.8 m·s$^{-1}$, with 80 % of PRS 2.2 m·s$^{-1}$ and 120 % of PRS 3.3 m·s$^{-1}$ (Table 10.2). The running analysis system resulted in the collection of 653 – 711 stride times within a data analysis epoch (A1- A11) across all running speeds (average 663 ± 6 stride times for 80 % of PRS, average of 677 ± 3 stride times for 100 % of PRS and average of 704 ± 3 for 120 % PRS). Within each 18-minute run (A12) >1,000 stride times were collected (1,490 for 80 % of PRS, 1,526 for 100% of PRS and 1,591 for 120 % of PRS).

All $\alpha$ values were displayed to the researcher within 0.83 – 2.19 s of Epoch completion time (average of 1.49 ± 0.41 s for 80 % of PRS, average of 1.55 ± 0.34 s for 100 % of PRS, and average of 1.28 ± 0.32 s for 120 % PRS). Post overall run, or at cessation of the capture period, DFA $\alpha$ value output occurred within 5 s, across all running speeds (average 3.61 ± 1.03 s). DFA $\alpha$ values ranged 0.70 – 0.86, within the data analyses epochs (A1- A11), across all running speeds. The participants overall run $\alpha$ was lowest at 100 % of PRS (0.80, compared to 0.85 at 80 % of PRS and 0.92 at 120 % of PRS).
Table 10.2 Number of strides (n), difference in elapsed time $\Delta t$ (s) and $\alpha$ value output time, and DFA $\alpha$ values over three running conditions at 80 \% PRS, PRS and 120 \% PRS.

<table>
<thead>
<tr>
<th>Analysis No.</th>
<th>Strides (n)</th>
<th>$\Delta t$ (s)</th>
<th>$\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>80% PRS</td>
<td>PRS</td>
<td>120% PRS</td>
</tr>
<tr>
<td>A1</td>
<td>669</td>
<td>679</td>
<td>711</td>
</tr>
<tr>
<td>A2</td>
<td>671</td>
<td>679</td>
<td>709</td>
</tr>
<tr>
<td>A3</td>
<td>669</td>
<td>680</td>
<td>706</td>
</tr>
<tr>
<td>A4</td>
<td>668</td>
<td>680</td>
<td>704</td>
</tr>
<tr>
<td>A5</td>
<td>665</td>
<td>679</td>
<td>703</td>
</tr>
<tr>
<td>A6</td>
<td>663</td>
<td>679</td>
<td>702</td>
</tr>
<tr>
<td>A7</td>
<td>661</td>
<td>678</td>
<td>702</td>
</tr>
<tr>
<td>A8</td>
<td>658</td>
<td>677</td>
<td>701</td>
</tr>
<tr>
<td>A9</td>
<td>656</td>
<td>676</td>
<td>702</td>
</tr>
<tr>
<td>A10</td>
<td>656</td>
<td>673</td>
<td>702</td>
</tr>
<tr>
<td>A11</td>
<td>653</td>
<td>672</td>
<td>701</td>
</tr>
<tr>
<td>Average (± stdev)</td>
<td>663 (± 6)</td>
<td>677 (± 3)</td>
<td>704 (± 3)</td>
</tr>
<tr>
<td>Overall Run</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A12</td>
<td>1490</td>
<td>1526</td>
<td>1591</td>
</tr>
</tbody>
</table>
10.6 Discussion
Recently there has been a move toward integrating gait kinematics into smartphone technology, or useable real-time streaming (Barrios et al. 2010), to develop user friendly methods which are efficient and effective at delivering gait information. This should not be limited to descriptive gait values such as the absolute angle of the knee (Barrios et al. 2010), or stride length (Ferrari et al. 2016) and should integrate advanced methods of non-linear gait analysis to increase both research output and available gait information. Real-time advanced stride time variability information may aid researchers in investigating the acute effects of interventions such as auditory stimulation (Hove et al. 2012) and visual cues (Kastavelis et al. 2010) in an efficient, timely manner. While previously this analysis was primarily used within post-processing in running (Meardon et al. 2010 & Jordan et al. 2006) the current system may now bridge this gap to allow for DFA in a real-time environment.

Firstly, the participant’s PRS (2.8 m·s⁻¹), 80% of PRS (2.2 m·s⁻¹) and 120% of PRS (3.3 m·s⁻¹) were similar to that previously seen in trained runners (PRS of 3.0 m·s⁻¹) (Nakayama et al. 2010). Furthermore, the running analysis system resulted in the collection of 653 – 711 stride times within a data analysis epoch (A1- A11) across all running speeds. This is similar to the number of stride times collected by both Nakayama et al. (2010) (512 stride times) and Meardon et al. (2011) (661 stride times) when investigating running variability using DFA. The number of overall stride times (A12) collected within the capture period (> 1000) are greater than any represented in the current literature of DFA in running (Jordan et al. 2006; Nakayama et al. 2010; Meardon et al. 2011; Fuller et al. 2016a; Fuller et al. 2016b) and may be more representative of running periods which runners undertake. Additionally, using an increased number of stride times retains important information regarding the intrinsic dynamics of locomotion, as Hausdorff et al. (1997) previously identified long range correlations with power-law decay in walking stride time series with 1,000 strides.

In relation to the real-time output of DFA α values, all α values were displayed to the researcher within 2 s of Epoch completion time. For 80% of PRS and PRS average stride times of 0.71 s and 0.70 s were identified, which indicates DFA α
value output occurred within 3 running strides of the next successive Epoch, at these running speeds. For 120% of PRS an average stride time of 0.67 s was identified, which indicates DFA α value output also within 2 running strides of the next successive Epoch. Post overall run, or at cessation of the capture period, DFA α value output occurred within 5 s, across all running speeds. To the current authors knowledge, all previous literature investigating running DFA (Jordan et al. 2006; Nakayama et al. 2010; Meardon et al. 2011; Fuller et al. 2016a; Fuller et al. 2016b) indicated that DFA calculation occurred within a post processing environment. Therefore, whilst there is an offset time delay (explained within 10.3) the current system represents a way researchers may now generate efficient DFA results.

Lastly, DFA α values identified by the current running analysis system (0.70 – 0.86) are similar to those found by Jordan et al. (2006), who identified α values of 0.70 – 0.90 whilst participants ran with an identical running protocol (PRS, 80% of PRS and 120% of PRS). Interestingly, the running analysis system further identified that the participants overall run α was lowest at their PRS. This was previously identified by Jordan et al. (2006), and is explained as a runner being most adaptable, and therefore less predictable in their stride time, at their PRS. Whilst using a single participant protocol, the current analyses may verify our advanced running analysis system generates valid DFA α values over a range of running speeds. Further research is needed with a larger sample size to investigate the current system within a training and skill level identification setting; however it appears the system can detect stride time α values identified previously within the literature.

10.7 Conclusion

The running analysis system presented within the current study provides real-time output (< 2 s post Epoch, < 5 s post overall run) of advanced variability information, which previously required extensive data processing and analysis. This provides access to further feedback information, important in both a training and injury prevention context, for coaches and researchers alike. Due to the limited research on DFA during running (Jordan et al. 2006; Nakayama et al. 2010; Meardon et al. 2011; Fuller et al. 2016a; Fuller et al. 2016b), there is a required
need for further research to provide us with definite answers regarding stride patterning and injury and/or training. The current analysis system will allow researchers to efficiently investigate acute and longitudinal interventions on running DFA providing us with a better understanding of DFA in running. Furthermore, the system also supports the future use of inertial sensors in a sports engineering context, as advances in Bluetooth technology will lead to further development of the system, with an aim of performing advanced stride variability analysis in an outdoor, ecological environment.

10.8 Thesis context
DFA provides invaluable variability information related to both running injury and running performance level, however it can be time consuming in both the collection of the required data to perform the analysis, and the application of the analysis. Chapter 10 provides a proof of concept incorporating DFA within real-time gait analysis, therefore advancing the ability to apply this analysis efficiently. Within the thesis Chapter 10 displays the natural progression from developing methods of stride time calculation, to applying DFA retrospectively to data, to now applying it in real-time.
Chapter 11. Thesis conclusions and implications
11.1 General discussion

As outlined in Chapter 1 distance running has become increasingly popular in the last number of years, with recreational runners accounting for the majority of this increase. Recreational runners provide an intriguing cohort as they undertake half and full marathon distances which are known to induce physiological and biomechanical alterations due to their strenuous nature, whilst having no specialised training such as their trained and elite counterparts have. However, much of the running related research focuses around elite and/or trained runners (Mooses et al. 2014 & Tanji et al. 2017) as they provide a more invariant cohort (in terms of training habits), and/or is undertaken within a laboratory (Kernozek et al. 2014 & Beck et al. 2016), over an acute period (Di Michele et al. 2014 & Garcia-Perez et al. 2014), again providing very controlled conditions. Recently the use of inertial sensors, such as accelerometers, as measurement techniques which can utilised external to the lab has increased (Norris et al. 2014), with researchers now acknowledging the importance of collecting data in an environment akin to where the participants regularly performs. However, there are numerous technical challenges with using accelerometry, such as data volume and the calculation of meaningful parameters from within these data. When utilised correctly during running gait analysis accelerometers can provide information related to gait patterns, shock attenuation, stride length, stride rate and stride time (Norris et al. 2014). Of these, stride time and stride rate are increasingly important given their links with run outcome, runner performance (Nakayama et al. 2011) level and injury onset (Meardon et al. 2010).

Therefore, the aims of this thesis as outlined in Chapter 1 were threefold. Firstly, we aimed to develop efficient and accurate methods of acquiring large accelerometry files during running. Secondly, we aimed to apply these methods, and knowledge gained through a review of the literature, to a population of recreational runners training for and competing in distance running events, investigating coaching (stride rate) and research (stride time variability) orientated parameters. Lastly, we aimed to develop a real-time advanced running analysis system focusing on stride time variability.
11.2 Delimitations and limitations

Whilst this body of work comprises of extensive, novel investigations into longitudinal temporal gait parameters, it is not without its delimitations and limitations. Delimitations have been defined as “characteristics that arise from limitations in the scope of the study (defining the boundaries) and by the conscious exclusionary and inclusionary decisions made during the development of the study plan” (Simon and Goes 2013, pg. 2). Limitations have been defined as “matters and occurrences that arise in a study which are out of the researcher’s control” (Simon and Goes 2013, pg. 1).

11.2.1 Focus on temporal gait parameters

The first delimitation within this thesis is the choice to focus on solely temporal gait parameters (stride time and stride frequency). Accelerometers and gyroscopes provide a method of collection of a number of research (2.2.5.1) and coaching orientated (tibial acceleration, shock attenuation etc., section 2.2.5.8) parameters during distance running, as identified within the literature review (Chapter 2). However, whilst some of the parameters were beyond the current research due to equipment availability, a choice was made early within the research to focus purely on temporal parameters, with accelerometers placed on the tibia. This choice was made based on the understanding of the importance which stride time and stride rate play in overall run outcome (Morgan et al. 1989), recommendations within previous literature to further the availability of literature based around stride time variability (Meardon et al. 2011) and intriguing connections between stride time variability and injury and performance level (Meardon et al. 2011 & Nakayama et al. 2010). Furthermore, by concentrating on stride time calculation methods (Chapter 5 and Chapter 6) the thesis was able to divulge information related to both coaching and research orientated parameters (stride rate and stride time). Davis (1988) outlined that sports biomechanists look for fine alterations in neuromuscular performance which enhance the athlete or performer away from normalcy, however to practically apply this knowledge coach interpretation is key. The work completed within this thesis provide comprehensive analysis understandable by both researchers and coaches, and this was primarily due to careful parameter (stride time and stride rate) selection.
11.2.2 Selection of recreational runners

A second delimitation within the thesis was the selection of recreational runners, undertaking their novice half or full marathon. The reason for this selection was firstly, recreational runners have long been identified to be at risk of running related injury occurrence, depending on running experience (some recreational runners are more akin to novice runners depending on study definitions) (Videbaek et al. 2015). Furthermore, running related injuries impose a significant cost on public health systems and efforts should be made to lessen this, through investigation of how and why these injuries occur (Junior et al. 2016). Secondly, the number of recreational runners has increased dramatically in the last number of years, due to race availability (park-run etc.) and increased knowledge of the health benefits associated with running, with 36% of 15 – 65 year olds in Europe identifying themselves as recreational runners (Poppel et al. 2016). Therefore, this cohort represents a population in which developments of our understanding of how they perform, can impact many people. However, there were risks associated with recruiting this specific population. As these participants had limited running experience (previously completed a 10-km distance) there was increased risk of poor adherence to the training programme or possible dropout (Havenar and Lochbaum 2007). To combat this, during recruitment and inclusion criteria was included which required participants to have already expressed interest (registered for or registering in the near future) for completing their chosen distance race. Furthermore, runners were required to have previously completed a 10-km race, which therefore meant they were not novice runners and also had experience running for a mid to long period, and within a competitive, organised event. This resulted in no voluntary pre-race drop out despite previous research (Havenar and Lochbaum 2007) identifying a drop-out rate of 70%, in recreational runners training for and completing their first marathon.

11.2.3 Equipment availability

In regards to limitations, equipment availability impacted the variety of parameters (i.e. acceleration, orientation etc.) collected within this study, along with the amount of data collected. Firstly, whilst this thesis utilised accelerometers for data collection methods, the literature review identified the use of integrated accelerometer and gyroscope sensors along with IMU's within running gait
analysis (Chapter 2). Prior to developing the research protocol for data collection within Chapter 4 an investigation into the collection of both accelerometer and gyroscope was undertaken. Unfortunately, due to excessive drainage of battery life, and as sensors were given to participants on a weekly basis with no battery charger provided, it was not feasible to combine gyroscopes or further sensors (GPS would have provided similar demand on battery life) with the accelerometer units provided. Furthermore, during data collection periods the accelerometers provided to participants intermittently became faulty, despite efforts to prevent this. Before accelerometer distribution the sensors were calibrated, waterproofed and placed within a purpose built plastic clip located on an elasticated attachment band. Additionally, to prevent any confusion by participants regarding the turning off and on of the accelerometers which may lead to sensor breakages, manuals were provided to participants clearly outlining usage instructions. Lastly, a small number of participants were initially recruited (6 for the first data collection period and 6 for the second data collection period) to ensure surplus accelerometers were available for distribution throughout the training programmes, to quickly replace any faulty sensors. Despite this, accelerometer failure contributed to the number of unrecorded runs indicated in 4.4.1 and 4.4.2

11.2.4 Sample size
Another limitation was the sample size utilised, which was limited due to the availability, and functionality, of equipment. As outlined in 11.2.3 it was decided when outlining the research protocol to recruit a smaller sample size to allow for surplus accelerometers in case of sensor failure. This resulted in a sample size of 6 people who completed the half marathon training programme and competitive events, and a sample size of 4 people who completed the full marathon training programme and competitive event (6 were recruited however 2 incurred a running related injury and dropped out, Chapter 4). To counter this, additional efforts were made to ensure adherence to training programmes and completion of the distance running event (11.2.2) and non-parametric analysis were utilised when required (9.3.4). However, due to the longitudinal data collection periods employed within this thesis (4.3.3), whilst sample size was lower, the number of accelerometry data points collected within participants was extensive, with the number of stride time values utilised within Chapter 9 alone greater than 100,000.
Also, the sample size achieved was appropriate given the timeframe of the doctoral thesis and the resources available.

### 11.3 Key findings and implications of this thesis

The key outcomes of this work were the development of novel methods of stride time calculation, which can be utilised by future researchers when collecting and analysing longitudinal accelerometry data. Furthermore, the measurement of recreational runners’ stride variability during half and full marathon events has made noteworthy strides within the field of longitudinal running gait analysis, as similar investigation had previously been only undertaken within acute testing sessions (Meardon et al. 2011 & Nakayama et al. 2010). Lastly, the developed advanced running analysis system represents a user- and researcher-friendly method of performing DFA in both running and walking in an efficient manner.

Results indicated that:

- Inertial sensors provide a popular method for collecting longitudinal gait data, divulging information related to both research (shock attenuation, tibial accelerometry etc.) and coaching related parameters (stride rate, gait pattern).

- A novel method of stride time calculation, utilising 2 Hz filtering, was derived indicating good comparability to previous methods (ICCs > 0.95 and coefficient of variance values < 1.5%), whilst being more efficient and robust when applied to longitudinal running accelerometry data.

- Performing with a comparable or decreased stride rate (compared to a similar training run) within a competitive distance running event may result in an optimal running style in relation to overall run outcome.

- No significant differences ($p > 0.05$), and small (ES = 0.35) and medium (ES = 0.46) effect sizes, occur between recreational runner's half marathon and full marathon DFA $\alpha$ values and stride rate, indicating that recreational runners adopt similar stride parameters when undertaking half and full marathon events despite extended training periods.
• A novel running analysis system results in the output of reoccurring, real-time DFA α values in a rapid manner, during prolonged running. Preliminary investigation of the advanced running analysis system indicated output of DFA α values within 5 seconds of predetermined running time periods, enabling researchers to give rapid real-time DFA feedback, during a prolonged run.

Key implications to runners, coaches, researchers and clinicians include:

• Methods which were developed within this thesis, such as the novel stride time calculation method (Chapter 6) and the development of the running gait analysis system (Chapter 10), were created to allow for the efficient and accurate processing of longitudinal gait data. This may further encourage coaches, researchers and clinicians as to the practical application of accelerometers within running gait analysis, and increase data collected within an ecological environment (external to the lab).

• The stride rate analysis performed within this thesis emphasises the importance of increasing knowledge surrounding optimal stride rate strategies for recreational runners. Based off these results runners utilising fitness trackers with stride rate analysis should focus on stride rate when completing their training programmes and competitive run.

• Lastly the development of the real-time running analysis system will now allow for advanced stride variability to be relayed efficiently to runners, coaches, researchers and clinicians, whereas before this required extensive post processing. For runners, coaches and researchers this will allow for the swift identification of alterations in running linked to both injury and performance (Meardon et al. 2010 & Nakayama et al. 2011). With swift identification, interventions can be rapidly introduced which may be able to offset alterations which may lead to poor performance or possible injury. Overall the development of this system may help retain runners within running, for longer periods, in an efficient manner. Additionally, the premise of this system allows for running data collection at any required
speed of movement, also taking walking into account. Given the confirmed links between DFA α values identified in walking gait and disease progression (more random walking stride time variability in those with Huntington’s and Parkinson’s, than healthy comparisons, Hausdorff 2009; Hausdorff et al. 1997) this system has definite applicability to clinical diagnosis of disease and disease progression.

11.4 Future direction
The overall scope of this thesis resulted in numerous methodological development sections and also the development of a real-time feedback system, previously unavailable. Therefore, future direction of this research should focus on the application of these methods.

- The development of the running analysis system within this thesis was purely as a proof of concept and was therefore applied to one participant over a range of running speeds. However, there are numerous other factors (than speed) which have yet to be explored in relation to stride variability and running. For example, previous research has indicated that step frequency manipulation during uphill running alters subsequent level running kinematics, resulting in running kinematics similar to that of better runners and increased running efficiency (Padulo et al. 2012). However, there is currently no research available outlining how gradients affect stride variability and possibly run performance, despite many half and full marathon courses containing numerous gradient changes. Additionally, Meardon et al. (2010) currently provide the only research investigating stride variability DFA in relation to running injury. Whilst numerous research (Saragiotto et al. 2014; Junior et al. 2013; Buist et al. 2010) has identified factors related to running related injury (e.g. past running related injury, speed training, running experience), this is mainly performed using follow-up surveys in prospective studies and therefore does not provide a quantitative, kinematic parameter related to injury. The current running analysis system developed could be easily applied to large groups of runners over long time periods, to provide further kinematic analysis which may relate to injury onset.
Additionally, based on the findings provided within Chapter 7, the integration of the running analysis system, developed in Chapter 10, into a wearable technology, along with the advancement of the system to output real-time stride frequency information may improve recreational runners’ performance in future distance running events. Whilst research indicates that novice marathon runners perform their first marathon mainly motivated by health and weight concerns, mid-level runners are more highly motivated by performance enhancement (Masters and Ogles 1995). Therefore, by increasing running performance outcomes, possibly using an integrated stride time variability/stride rate wearable technology this may enhance retention within distance running, particularly after completion of a first marathon. These running performance outcomes need not necessarily be only completing the race within your desired time, but may also be completing the training programme and competitive run without incurring injury or maintaining consistent stride rate during times of fatigue.
References


Hottenrott, K., Ludyga, S., Schulze, S., Gronwald, T. and Jäger, F.-S. (2016) 'Does a run/walk strategy decrease cardiac stress during a marathon in non-elite runners?', *Journal of Science and Medicine in Sport, 19*(1), 64-68.


definition on injury surveillance in novice runners', *Journal of Science and Medicine in Sport*, 19(6), 470-475.


Murphy, N.M. and Bauman, A. (2007) ‘Mass sporting and physical activity events—are they “bread and circuses” or public health interventions to increase population levels of physical activity?’, *Journal of Physical Activity and Health*, 4(2), 193-202.


Reenalda, J., Maartens, E., Homan, L. and Buurke, J.J. (2016) 'Continuous three dimensional analysis of running mechanics during a marathon by means of inertial magnetic measurement units to objectify changes in running mechanics', *Journal of Biomechanics*, 49(14), 3362-3367.


Appendices
Appendix A: Ethical Approval

Dear Ian,

Thank you for your amended Research Ethics application which was recently reviewed by the Education and Health Sciences Research Ethics Committee. The recommendation of the Committee is outlined below:

Project Title: 2013_04_07_EHS Investigating running patterns, over longitudinal training and competitive running phases, using inertial sensors.  
Principal Investigator: Ian Kenny  
Other Investigators: Ross Anderson, Michelle Norris  
Recommendation: Approved until March 2018

Please note:

- EHSREC do not object to the student phone number being given out once participant is recruited to study as long as it is felt necessary to the research.
- The identifier codes need to be kept securely away from the main data files and destroyed when no longer required.

Yours Sincerely,
Appendix B: Subject Manual Sample

Subject Manual

Limerick Great Run

Name: _______________________________________________________
ID Number: ________________________________________________
Table of Contents

Hal Higdon’s Training Programme

Half Marathon Training Guide - Novice 1 Programme Breakdown

Terms used in the training schedule

Equipment Utilisation

Necessary equipment

Parts of the SHIMMER Device

What do I need to do?

Step by Step Picture Guide

Quick Notes

Training Log and Discomfort Questionnaire Guide

Training Log and Discomfort Questionnaire
Half Marathon Training Programme for the Great Limerick Run 4th May 2014

Half Marathon Training: Novice 1

- Have the ability to run 3 miles, three to four times a week

<table>
<thead>
<tr>
<th>Week</th>
<th>Beginning</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
<th>Sat</th>
<th>Sun</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>10th Feb</td>
<td>Stretch and Strengthen</td>
<td>5km run</td>
<td>3km run or cross</td>
<td>5km run + strength</td>
<td>Rest</td>
<td>30 min cross</td>
<td>6.5km run</td>
</tr>
<tr>
<td>2.</td>
<td>17th Feb</td>
<td>Stretch and Strengthen</td>
<td>5km run</td>
<td>3km run or cross</td>
<td>5km run + strength</td>
<td>Rest</td>
<td>30 min cross</td>
<td>6.5km run</td>
</tr>
<tr>
<td>3.</td>
<td>24th Feb</td>
<td>Stretch and Strengthen</td>
<td>5.5km run</td>
<td>3km run or cross</td>
<td>5.5km run + strength</td>
<td>Rest</td>
<td>40 min cross</td>
<td>8km run</td>
</tr>
<tr>
<td>4.</td>
<td>3rd Mar</td>
<td>Stretch and Strengthen</td>
<td>5.5km run</td>
<td>3km run or cross</td>
<td>5km run + strength</td>
<td>Rest</td>
<td>40 min cross</td>
<td>8km run</td>
</tr>
<tr>
<td>5.</td>
<td>10th Mar</td>
<td>Stretch and Strengthen</td>
<td>6.5km run</td>
<td>3km run or cross</td>
<td>6.5km run + strength</td>
<td>Rest</td>
<td>40 min cross</td>
<td>9.5km run</td>
</tr>
<tr>
<td>6.</td>
<td>17th Mar</td>
<td>Stretch and Strengthen</td>
<td>6.5km run</td>
<td>3km run or cross</td>
<td>6.5km run + strength</td>
<td>Rest or easy run</td>
<td>Rest</td>
<td>5k Race</td>
</tr>
<tr>
<td>7.</td>
<td>24th Mar</td>
<td>Stretch and Strengthen</td>
<td>7km run</td>
<td>5km run or cross</td>
<td>7km run + strength</td>
<td>Rest</td>
<td>50 min cross</td>
<td>11km run</td>
</tr>
<tr>
<td>8.</td>
<td>31st Mar</td>
<td>Stretch and Strengthen</td>
<td>7km run</td>
<td>5km run or cross</td>
<td>7km run + strength</td>
<td>Rest</td>
<td>50 min cross</td>
<td>13km run</td>
</tr>
<tr>
<td>9.</td>
<td>7th Apr</td>
<td>Stretch and Strengthen</td>
<td>8km run</td>
<td>5km run or cross</td>
<td>8km run + strength</td>
<td>Rest or easy run</td>
<td>Rest</td>
<td>10k Race</td>
</tr>
<tr>
<td>10.</td>
<td>14th Apr</td>
<td>Stretch and Strengthen</td>
<td>8km run</td>
<td>5km run or cross</td>
<td>8km run + strength</td>
<td>Rest</td>
<td>60 min cross</td>
<td>14.5km run</td>
</tr>
<tr>
<td>11.</td>
<td>21st Apr</td>
<td>Stretch and Strengthen</td>
<td>8km run</td>
<td>5km run or cross</td>
<td>8km run + strength</td>
<td>Rest</td>
<td>60 min cross</td>
<td>16km run</td>
</tr>
<tr>
<td>12.</td>
<td>28th Apr</td>
<td>Stretch and Strengthen</td>
<td>6.5km run</td>
<td>5km run or cross</td>
<td>3km run</td>
<td>Rest</td>
<td>Rest</td>
<td>Great Limerick Run Half Marathon</td>
</tr>
</tbody>
</table>
**Half Marathon Training Guide - Novice 1 Programme**

**Breakdown**

(All information from [www.halhigdon.com](http://www.halhigdon.com))

**BEFORE STARTING TO TRAIN FOR A HALF MARATHON**, you need to possess a basic fitness level. And if you are over age 35, you probably should see your doctor for a physical examination. But assuming no major problems, most healthy people can train themselves to complete a 21.1km race.

The following schedule assumes you have the ability to run 3 miles, three to four times a week. If that seems difficult, consider a shorter distance for your first race—or take more time to develop an endurance base.

**Terms used in the training schedule**

- **Pace:** Don't worry about how fast you run your regular workouts. Run at a comfortable pace. If you're training with a friend, the two of you should be able to hold a conversation. If you can't do that, you're running too fast. (For those wearing heart rate monitors, your target zone should be between 65 and 75 percent of your maximum pulse rate.)

- **Distance:** The training schedule dictates workouts at distances, from 5 to 16 km. Don't worry about running precisely those distances, but you should come close. Pick a course through the neighbourhood, or in some scenic area where you think you might enjoy running. Then measure the course either by car or bicycle. In deciding where to train, talk to other runners. They probably can point you to some accurately measured courses for your workouts. GPS watches seemingly make measuring courses easily, but trees and tall buildings sometimes can interfere with their accuracy.

- **Rest:** Rest is as important a part of your training as the runs. You will be able to run the long runs on the weekend better—and limit your risk of injury—if you rest before, and rest after.
Long Runs: The key to getting ready to finish a Half Marathon is the long run, progressively increasing in distance each weekend. Over a period of 12 weeks, your longest run will increase from 5 to 16 km. Don’t worry about making the final jump from 16 kms in practice to 21kms in the race. Inspiration will carry you to the finish line, particularly if you taper the final week. The schedule below suggests doing your long runs on Sundays, but you can do them Saturdays, or any other convenient day, as long as you are consistent. (See "Juggling," below.)

Cross-Train: On the schedule above, this is identified simply as "cross." What form of cross-training works best? It could be swimming, cycling, walking (see below), cross-country skiing, snowshoeing, or even some combination that could include strength training if you choose to do it on Wednesdays and Saturdays instead of as indicated on the schedule. And feel free to throw in some jogging as well if you’re feeling good. In fact, on Wednesdays I offer you the option to run or cross-train. What cross-training you select depends on your personal preference. But don’t make the mistake of cross-training too vigorously. Sports such as basketball or volleyball that involve sideways motions or sudden stops and starts do not qualify as cross-training. In fact, you may increase your risk of injury if you double up on these sports, particularly as the mileage builds. Cross-training days should be considered easy days that allow you to recover from the running you do the rest of the week.

Walking: Walking is an excellent exercise that a lot of runners overlook in their training. I don’t specify walking breaks, but feel free to walk during your running workouts any time you feel tired or need to shift gears. When you go to the starting line in your twelfth week, nobody will care whether you run the full Half Marathon; they’re more concerned that you finish! If this means walking every step in practice and in the race, do it! Be aware that I also offer a separate half marathon training program for those who plan to walk all the way.
Stretch & Strength: Mondays are the days on which I advise you to spend extra time stretching—and do some strength training too. This is actually a day of "rest" following your long run on the weekends, so don’t overdo it. It’s wise to stretch every day, particularly after you finish your run, but spend more time stretching on Mondays. Strength training could consist of push-ups, pull-ups, use of free weights or working out with various machines at a health club. Runners generally benefit if they combine light weights with a high number of repetitions, rather than pumping very heavy iron. I also suggest that you strength train following your Thursday workouts, however you can schedule strength training on any two convenient days. If you have not strength trained before beginning this program, you may want to postpone starting that activity until after your race.

Racing: It’s not obligatory, but you might want to run a 5-K or 10-K to see how you’re doing—and also to experience a road race, if you have not run one before. You will be able to use your times to predict your finishing time in the half marathon, and what pace to run that race. I have suggested a 5-K race at the end of Week 6 and a 10-K race at the end of Week 9. If you can’t find races at those distances on the weeks suggested, feel free to modify the schedule.

Juggling: Don’t be afraid to juggle the workouts from day to day and week to week. If you have an important business meeting on Thursday, do that workout on Wednesday instead. If your family is going to be on vacation one week when you will have more or less time to train, adjust the schedule accordingly. Be consistent with your training, and the overall details won’t matter.

Running 21 km is not easy. If it were easy, there would be little challenge to an event such as the Half Marathon.

Whether you plan your Half as a singular accomplishment or as a stepping stone to the even more challenging full marathon, crossing the finish line will give you a feeling of great accomplishment.
Equipment Utilisation

Necessary equipment

(a) And (b) 2 Waterproofed SHIMMER devices – (c) 1 labelled RMAS (right leg, master), the other labelled LSLVE (left leg, slave) each on a black ankle strap,

(d) 10 rolls of Powerflex cohesive bandage,
Parts of the SHIMMER Device

**Pin Hole Button** – Compress this for 8 seconds.

**LED** – Will indicate whether the sensor is turned on/off,

**Exterior Push Button** – Press this to start/stop logging data.

---

**What do I need to do?**

For each running training session and the final marathon you are required to do the following:

**BEFORE EACH RUN**

1. Turn both SHIMMER on by using a paper clip or pen to compress that pin button for 8 seconds.
   
   *You will know SHIMMER are turned on when*

   **MASTER**
   - This will flash green quickly (50ms on/2 secs off) 4 times and then pause for a long flash of green.
   - It will then resume flashing green quickly (50ms on/2 secs off)

   **SLAVE**
   - This will flash green quickly (50ms on/2 secs off) 4 times and then pause for a long flash of green.
   - This will then flash orange and remain a steady orange flash

2. Wrap 1 layer of Powerflex tape around the circumference of both your lower shins (10cms up from ankle joint centre).
(3) Press the exterior push button on the MASTER SHIMMER to begin data logging

You will know data is logging when

**MASTER**
- This will begin to flash at a rate of 1 second on, 1 second off.

**SLAVE**
- This will remain orange for a few seconds (varies) and then will begin to flash green at a rate of 1 second on, 1 second off. Every 120 seconds it will also flash orange- don't worry about this.

(4) Strap the SHIMMER labelled **RMAS** to the **FLAT INSIDE** part of your **RIGHT** lower shin above the layer of Powerflex.

(5) Do this so that the **SHIMMER is placed against your shin** (facing inwards) and the label **RMAS** is toward the inside of the leg.

(6) The arrow should also be pointing up (see image)

(7) Strap the SHIMMER labelled **LSLVE** to the **FLAT INSIDE** part of your **LEFT** lower shin following the same manner

(8) Do this so that the **SHIMMER is placed against your shin** (facing inwards) and the label **LSLVE** is toward the inside of the leg.

(9) The arrow should also be pointing up (see image)

**ONCE YOU HAVE REACHED THE BEGINNING OF YOUR RUN DESTINATION**

(10) Stand still for 10 seconds before beginning your run.

**ON COMPLETION OF EACH RUN**

(1) Stand still for 10 seconds to indicate the end of the run,

(2) Press the exterior push button on the MASTER SHIMMER to stop logging

You will know data has stopped logging when

**MASTER**
- This will flash green and orange quickly for up to two minutes.
- It will then repeatedly flash green quickly (50ms on/2 secs off).

**SLAVE**
- This will flash green for up to two minutes before turning orange constantly.

(3) Turn both SHIMMER off by using paper clip or pen to compress and hold the pin button for 8 seconds (must be done individually for each SHIMMER)

*You will know SHIMMER are turned off when*

Both SHIMMER will cease to flash any colour.

**ONCE A WEEK**

The investigator will meet you to take both SHIMMER away overnight. These will then be returned to you the following day prior to your run.

*Please note: Place and time of location to arrange the SHIMMER handover will be determined by you so as to have as little impact on your day to day routine as possible.*

If it ever arises that the electronic devices will not work or that you wish to talk to the investigator for any reason related to the study please do not hesitate to get in contact. The details are as follows:

**Name:** Michelle Norris  
**Email Address:** michelle.norris@ul.ie  
**Phone Number:**
Step by Step Attachment Picture Guide

BEFORE EACH RUN

RIGHT LEG (MASTER)   LEFT LEG (SLAVE)

(1) Mark 10 cm up from the inside of the centre of the ankle joint

(2) Place one layer of the Powerflex around the shin so that the 10 cm mark falls in the centre
(3) Place the sensors so that the flashing LEDS are placed toward the Powerflex and the sensor is placed on the flat part of the tibia.

NOTE - The RMAS or LSLVE writing should be towards the inside of the leg and the arrow pointing upward.

(4) Frontal view of sensor location on both limbs

NOTE – Sensors should be slightly off centre at the front and not placed on the inside of the legs
LED guide to starting the Sensors.

Quick Notes

SHIMMER are **TURNED ON** and **NOT LOGGING DATA** when:
- The master is flashing green quickly (50ms on/ 2 secs off),
- The slave has a steady orange flash.

SHIMMER are **TURNED ON** and **LOGGING DATA** when:
- The master is flashing green at a rate of 1 sec on/1 sec off,
- The slave is flashing green at a rate of 1 sec on/1 sec off and flash quickly orange every 10 secs.

SHIMMER are **TURNED OFF**:
- When both the master and slave are not flashing any colour

**LED Indicators**

The Shimmer has three LEDs (green, yellow1 and red), which are used to indicate operation according to Table 5.

<table>
<thead>
<tr>
<th>Sequence</th>
<th>ON</th>
<th>OFF</th>
<th>50 ms ON/2 s OFF</th>
<th>1 s ON/1 s OFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>Configuring*</td>
<td>Shimmer OFF</td>
<td>Shimmer ON (standby)</td>
<td>Logging†</td>
</tr>
<tr>
<td>Yellow</td>
<td>802.15.4 radio on</td>
<td>802.15.4 radio off</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Red</td>
<td>File-system error</td>
<td>File-system OK</td>
<td>Error in sdlog.cfg file</td>
<td>N/A</td>
</tr>
</tbody>
</table>

If SHIMMER flashes red please inform the investigator.
Training Log and Discomfort Questionnaire Guide

You have previously indicated to the investigator that you preferred mode of training log and discomfort survey collection is

(1) Notebook training log, paper and pen discomfort questionnaire completion  
(   )

(2) Notebook training log entered into online survey, online discomfort questionnaire completion  
(   )

IF YOU CHOSE (1) Notebook training log, paper and pen survey completion:

AFTER EACH RUN
- Please fill in the notebook training log as accurately as possible (identify km OR miles)

AFTER THE LONG RUN
- Please select an RPE which represents how you felt during that run and note it in the notebook.

AT THE END OF EACH RUNNING WEEK (having completed all short runs and long run for the week)
- Please fill out the discomfort questionnaire in relation to that week.

ONCE A WEEK
- The investigator will arrange a suitable time and place to meet at your discretion.
- Here the investigator will collect the completed training log and discomfort survey (From tear out log book).
- This will also be the time of the SHIMMER swap over.

IF YOU CHOSE (2) Notebook training log entered into online survey, online discomfort survey:

AFTER EACH RUN

- Please fill in the notebook training log as accurately as possible (identify km OR miles)

**AFTER THE LONG RUN**

- Please select an RPE which represents how you felt *during that run* and note it in the notebook.

**AT THE END OF EACH RUNNING WEEK** *(having completed all short runs and long run for the week)*

- A link to the online training log and questionnaire will be mailed out (on Facebook, email etc.) each week.
- This link will remain the same throughout the collection period but the email will serve as a reminder to the online survey.
- Within this please enter the training log data collected during the week and also please fill out the discomfort questionnaire *in relation to the week just past*.

**ONCE A WEEK**

- The investigator will arrange a suitable time and place to meet at your discretion.
- This will be the time of the SHIMMER swap over so that the devices can be recharged for your next week.
This questionnaire will ask you to complete sections related to your training, any aches, pain or discomfort felt and your general health over the last week. This questionnaire is COMPLETELY CONFIDENTIAL. Please ANSWER ALL QUESTIONS.

**TRAINING**

Please complete the table below in reference to training over the last week.

<table>
<thead>
<tr>
<th></th>
<th>Distance (miles)</th>
<th>Time of Day (00:00:00)</th>
<th>Run Completion Time (hr/min)</th>
<th>Additional Info</th>
<th>Did Shimmer devices record run?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mon</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
<tr>
<td>Tues</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
<tr>
<td>Weds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
<tr>
<td>Thurs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
<tr>
<td>Fri</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
<tr>
<td>Sat</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
<tr>
<td>Sun</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>YES/NO</td>
</tr>
</tbody>
</table>

Please circle a Rate of Perceived Exertion (RPE) which best describes how you felt during your LONG RUN. (Please fill in 30 minutes after run)
Please fill the sections below (ACHE, PAIN OF DISCOMFORT and GENERAL HEALTH) at the end of the running week.

**ACHE, PAIN OR DISCOMFORT**
Did you suffer from any ache, pains or discomfort felt during the last week? **YES/NO**

**IF NO** please skip to the section entitled **GENERAL HEALTH**

**IF YES** was this ache, pain or discomfort diagnosed by a healthcare professional? **YES/NO**

**IF YES** please outline what the diagnosis and line of treatment is

<table>
<thead>
<tr>
<th>Rating</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>No exertion at all</td>
</tr>
<tr>
<td>7</td>
<td>Extremely light</td>
</tr>
<tr>
<td>8</td>
<td>Very light</td>
</tr>
<tr>
<td>9</td>
<td>Light</td>
</tr>
<tr>
<td>10</td>
<td>Somewhat hard</td>
</tr>
<tr>
<td>11</td>
<td>Hard (heavy)</td>
</tr>
<tr>
<td>12</td>
<td>Very hard</td>
</tr>
<tr>
<td>13</td>
<td>Extremely hard</td>
</tr>
<tr>
<td>14</td>
<td>Maximal exertion</td>
</tr>
</tbody>
</table>

232
Please fill out the survey below.

<table>
<thead>
<tr>
<th>Section</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>During the last work week, how often did you experience ache, pain, discomfort in:</td>
<td>If you experienced ache, pain, discomfort, how uncomfortable was this?</td>
<td>If you experienced ache, pain, discomfort, did this interfere with your ability to run?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Never</td>
<td>1-2 times</td>
<td>3-4 times</td>
</tr>
<tr>
<td>Neck</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Shoulder</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Upper Back</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Upper Arm</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Lower Back</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Forearm</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Wrist</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Hip/Buttocks</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Thigh</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Knee</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Lower Leg</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
<tr>
<td>Foot</td>
<td></td>
<td>□□□□□</td>
<td>□□□□□</td>
<td>□□□□□</td>
</tr>
</tbody>
</table>

**IF** you answered *SLIGHTLY INTERFERED* or *SUBSTANTIALLY INTERFERED* in section 4 please outline

(a) How many scheduled training sessions were missed  ________________

(b) Did ache, pain or discomfort occur most

IN THE MORNING  YES/NO

DURING RUNNING  YES/NO

AFTER RUNNING  YES/NO

**GENERAL HEALTH**

**SLEEP**

On average, how many hours per night do you sleep? ______
How well does each of the following statements apply over the past week? (CIRCLE ONE)

I have nightmares:     Never                      Sometimes                        Often
I am too tired:            Never                      Sometimes                        Often
I have sleep problems: Never                    Sometimes                       Often.

MOOD

Below is a list of words that describe feelings people have. Please read each one carefully and circle the answer which best describes how you feel over the past week. Please answer all questions.

<table>
<thead>
<tr>
<th>Not at all</th>
<th>A Little</th>
<th>Moderately</th>
<th>Quite a bit</th>
<th>Extremely</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panicky</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Confused</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Annoyed</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Mixed-up</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Bitter</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Anxious</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Worried</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Muddled</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Nervous</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Angry</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Bad tempered</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

STRESS

Please read each statement and tick a number 0, 1, 2 or 3 which indicates how much the statement applied to you over the past week.

0 Did not apply to me at all.

1 Applied to me to some degree, or some of the time
2 Applied to me to a considerable degree, or a good part of time
3 Applied to me very much, or most of the time

<table>
<thead>
<tr>
<th>Situation</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>I found it hard to wind down</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I tended to over-react to situations</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I felt that I was using a lot of nervous energy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I found myself getting agitated</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I found it difficult to relax</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I was intolerant of anything that kept me from getting on with what I was doing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I felt that I was rather touchy</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Please tear this training log and discomfort questionnaire out of the manual and present to the investigator at your next encounter.**
Appendix C: Participant Recruitment Email

Title: “Investigating running patterns, over longitudinal training and competitive running phases, using inertial sensors.”

- Are you 18-65 and have previously run a competitive 10 kilometre race?
- Are you a NOVICE half marathon/marathon runner?
- Are you registered/training/planning to take part in the Great Limerick Run half/full marathon this year?
- Are you looking for a proven training programme suited to your running goals?
- Are you located around the greater Limerick area?

If you answered yes to all the above please read below!

Project: Whilst running continues to increase in popularity so too does the number of people suffering from Running Related Injuries (RRI). We are researching the use of inertial sensors in collecting running
gait in an effort to see if this equipment can be utilised in detecting possible running patterns linked to RRI. We will use the sensors to monitor your training leading up to, and competing in, the race.

**Who are we looking for?** 10 male or female recreational runners, currently registered/training/planning to take part in their first Great Limerick Run full/half marathon and having previously completed a competitive 10km).

**Where and when:** December 2013 – May 2014

**Further Information:** Please contact

Michelle Norris,  
PhD researcher,  
Biomechanics Research Unit,  
Department of Physical Education and Sport Sciences,  
University of Limerick,  

Phone: 061 234715  
michelle.norris@ul.ie

---

*This study has been approved by the ethics committee of the faculty of Education and Health Sciences. If you have any concerns about this study and wish to contact someone independent, you may contact The EHS Research Ethics Contact Point of the Education and Health Sciences Research Ethics Committee,*  

*Room E1003, University of Limerick, Limerick.*  

*Tel: (061) 234101 / Email: ehsresearchethics@ul.ie*
Appendix D: Hal Higdon Half Marathon Novice 2 Training Programme

Hal Higdon's
(www.halhigdon.com)

Half Marathon Training Programme for the Great Limerick Run 4th May 2014

Half Marathon Training: Novice 2

- People moving up from 5/10km
- **Pace** = at the pace which you wish to complete the marathon at
- **Cross** training can be swimming, cycling, rowing or any other form of aerobic exercise

<table>
<thead>
<tr>
<th>Week</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
<th>Sat</th>
<th>Sun</th>
</tr>
</thead>
<tbody>
<tr>
<td>1)</td>
<td>10thFeb</td>
<td>Rest</td>
<td>5km run</td>
<td>5km run</td>
<td>5km run</td>
<td>Rest 6.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>2)</td>
<td>17thFeb</td>
<td>Rest</td>
<td>5km run</td>
<td>5km pace</td>
<td>5km run</td>
<td>Rest 8km run</td>
<td>Cross</td>
</tr>
<tr>
<td>3)</td>
<td>24thFeb</td>
<td>Rest</td>
<td>5km run</td>
<td>6.5km run</td>
<td>5km run</td>
<td>Rest 9.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>4)</td>
<td>3rdMar</td>
<td>Rest</td>
<td>5km run</td>
<td>6.5km pace</td>
<td>5km run</td>
<td>Rest 11km run</td>
<td>Cross</td>
</tr>
<tr>
<td>5)</td>
<td>10thMar</td>
<td>Rest</td>
<td>5km run</td>
<td>6.5km run</td>
<td>5km run</td>
<td>Rest 13km run</td>
<td>Cross</td>
</tr>
<tr>
<td>6)</td>
<td>17thMar</td>
<td>Rest</td>
<td>5km run</td>
<td>6.5km pace</td>
<td>5km run</td>
<td>Rest <strong>5K race</strong></td>
<td>Cross</td>
</tr>
<tr>
<td>7)</td>
<td>24thMar</td>
<td>Rest</td>
<td>5km run</td>
<td>8km run</td>
<td>5km run</td>
<td>Rest 14.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>8)</td>
<td>31stMar</td>
<td>Rest</td>
<td>5km run</td>
<td>8km pace</td>
<td>5km run</td>
<td>Rest 16km run</td>
<td>Cross</td>
</tr>
<tr>
<td>9)</td>
<td>7thApr</td>
<td>Rest</td>
<td>5km run</td>
<td>8km run</td>
<td>5km run</td>
<td>Rest <strong>10k Race</strong></td>
<td>Cross</td>
</tr>
<tr>
<td>10)</td>
<td>14thApr</td>
<td>Rest</td>
<td>5km</td>
<td>8km pace</td>
<td>5km run</td>
<td>Rest 18km</td>
<td>Cross</td>
</tr>
</tbody>
</table>
Half Marathon Training Guide - Novice 2 Programme

Breakdown

(All information from www.halhigdon.com)

Terms used in the training schedule

✓ **Long runs:** The key to the program is the long run on weekends, which builds from 6.5kms in Week 1 to 19.5kms in the climactic Week 11. (After that, you taper a week to get ready for the half marathon.) You can skip an occasional workout, or juggle the schedule depending on other commitments, but do not cheat on the long runs. Although the schedule suggests long runs on Saturdays, you can switch to Sundays or even other days of the week to suit your schedule. On two of the weeks, I suggest a 5-K or 10-K race as an option to that week’s long run. Notice that I just said “option.” See “Races” below for more on the subject.

✓ **Run slow:** For experienced runners, I recommend that they do their long runs anywhere from 30 to 90 or more seconds per km slower than their half marathon pace. You may have done enough races, so that you can predict your race pace. If not, don't worry. Simply do your long runs at a comfortable pace, one that allows you to converse with your training partners, at least during the beginning of the run. Toward the end, you may need to abandon conversation and concentrate on the act of putting one foot in front of the other to finish. Or, feeling inspired, you may decide to pick up the pace, converting your workout into what I describe as a 3/1 Run, the first three-quarters at an easy pace, the final one-quarter at a faster pace. One important point: If you find yourself finishing at a pace significantly slower than your early pace, you probably need to start much slower, or include regular walking breaks. It's better to run too slow during these long runs, than too fast. The important point is that you cover the prescribed distance; how fast you cover it doesn't matter.

✓ **Walking breaks:** Walking is a perfectly acceptable strategy in trying to finish a half marathon. It works during training runs too. While some coaches recommend walking 1
minute out of every 10, or walking 1 minute every km, in I suggest that runners walk when they come to an aid station. This serves a double function: 1) you can drink more easily while walking as opposed to running, and 2) since many other runners slow or walk through aid stations, you'll be less likely to collide with someone. It's a good idea to follow this strategy in training as well.

**Cross-training:** Sundays in this training program are devoted to cross-training. What is cross-training? It is any other form of aerobic exercise that allows you to use slightly different muscles the day after your long run. In this program, we run long on Saturdays and cross-train on Sundays, although it certainly is possible to reverse that order. The best cross-training exercises are swimming, cycling or even walking. What about sports such as tennis or basketball? Activities requiring sideways movements are not always a good choice. Particularly as the mileage builds toward the end of the program, you raise your risk of injury if you choose to play a sport that requires sudden stopping and starting. One tip: You don't have to cross-train the same each weekend. And you could even combine two or more exercises: walking and easy jogging or swimming and riding an exercise bike in a health club. Cross-training for an hour on Sunday will help you recover after your Saturday long runs.

**Midweek training:** Training during the week also should be done at a comparatively easy pace. As the weekend mileage builds, the Tuesday and Thursday mileage stays the same: 5 kms. Run these kms at an easy, or comfortable, pace. How fast is “easy?” That can vary from day to day. On Tuesdays after two days of comparative rest, you might even find yourself running faster than race pace. On Thursdays after two days of training, your “easy” might be a slower pace. Don’t get trapped by numbers. Listen to your body signals as much as the signals coming from your GPS watch. Wednesdays feature a mini-build-up from 5 to 8 kms with some of those workouts done at race pace. More on that below. If you strength train, Tuesdays and Thursdays would be the best days to combine lifting with running. Usually it’s a good idea to run before you lift rather than the reverse.

**Race Pace:** What do I mean by "race pace?" It's a frequently asked question, so let me explain. Race pace is the pace you plan to run in the race you're training for. If you're training for a 2:00 half marathon, your average pace per km is 5:41. So you would run that same pace when asked to run race pace (sometimes stated simply as "pace" on the training charts). If you were training for a 5-K or 10-K, "race pace" would be the pace you planned to run in those races. Sometimes in prescribing speedwork, I define paces for different workouts as 5-K pace or 10-K pace, but you won't be asked to run this fast in the Novice 2 program.
✓ **Races:** What about races, since I suggest running a 5-K race in Week 6 and a 10-K race in Week 9. As stated earlier, consider races as an “option.” Doing at least some racing in a training program can be a valuable experience, because you can learn how races operate: everything from where to pin your number (the front) to how to drink at the aid stations (walking works well). You can also use races to determine your level of fitness and predict how fast you might run in your goal race (using various charts on the Internet). But too much racing can wear you out and distract from your training, so embrace this option cautiously. Finally, there is nothing magic about 5-K or 10-K as distances or Week 6 or Week 9 for when to race. Seek races in your area convenient to your schedule.

✓ **Rest:** Despite my listing it near the end, rest is an important component of this or any training program. Scientists will tell you that it is during the rest period (the 24 to 72 hours between hard bouts of exercise) that the muscles actually regenerate and get stronger. Coaches also will tell you that you can't run hard unless you are well rested. And it is hard running (such as the long runs) that allows you to improve. If you're constantly fatigued, you will fail to reach your potential. This is why I include two days of rest each week for Novice 2 runners. If you need to take more rest days--because of a cold or a late night at the office or a sick child--do so. The secret to success in any training program is consistency, so as long as you are consistent with your training during the full 12 weeks of the program, you can afford--and may benefit from--extra rest.
Appendix E: Hal Higdon Full Marathon Novice 2 Training Programme

Hal Higdon's (www.halhigdon.com)

Marathon Training Programme for the Dublin City

Marathon Monday 27th October 2014

Marathon Training: Novice 2

- People with a running background/have been running a year, run occasional 5/10k
- Able to comfortably run 3-6 miles, training 3-5 days a week and covering 15-25 miles a week
- **Pace** = at the pace which you wish to complete the marathon at
- **Cross** training can be swimming, cycling, rowing or any other form of aerobic exercise

<table>
<thead>
<tr>
<th>Week</th>
<th>Mon</th>
<th>Tue</th>
<th>Wed</th>
<th>Thu</th>
<th>Fri</th>
<th>Sat</th>
<th>Sun</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) 23rd Jun</td>
<td>Rest</td>
<td>5km run</td>
<td>8km pace</td>
<td>5km run</td>
<td>Rest</td>
<td>13km run</td>
<td>Cross</td>
</tr>
<tr>
<td>2) 30th Jun</td>
<td>Rest</td>
<td>5km run</td>
<td>8km run</td>
<td>Pace</td>
<td>5km run</td>
<td>Rest</td>
<td>14.5km run</td>
</tr>
<tr>
<td>3) 7th Jul</td>
<td>Rest</td>
<td>5km run</td>
<td>8km run</td>
<td>5km run</td>
<td>Rest</td>
<td>9.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>4) 14th Jul</td>
<td>Rest</td>
<td>5km run</td>
<td>9.5km pace</td>
<td>5km run</td>
<td>Rest</td>
<td>17.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>5) 21st Jul</td>
<td>Rest</td>
<td>5km run</td>
<td>9.5km run</td>
<td>5km run</td>
<td>Rest</td>
<td>19km run</td>
<td>Cross</td>
</tr>
<tr>
<td>6) 28th Jul</td>
<td>Rest</td>
<td>5km run</td>
<td>9.5km pace</td>
<td>5km run</td>
<td>Rest</td>
<td>14.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>7) 4th Aug</td>
<td>Rest</td>
<td>6.5km run</td>
<td>11km pace</td>
<td>6.5km run</td>
<td>Rest</td>
<td>22.5km run</td>
<td>Cross</td>
</tr>
<tr>
<td>8) 11th Aug</td>
<td>Rest</td>
<td>6.5km run</td>
<td>11km run</td>
<td>6.5km run</td>
<td>Rest</td>
<td>24km run</td>
<td>Cross</td>
</tr>
<tr>
<td>9) 18th Aug</td>
<td>Rest</td>
<td>6.5km run</td>
<td>11km pace</td>
<td>6.5km run</td>
<td>Rest</td>
<td>Rest</td>
<td><strong>Half Marathon</strong></td>
</tr>
<tr>
<td>10) 25th Aug</td>
<td>Rest</td>
<td>6.5km run</td>
<td>13km pace</td>
<td>6.5km run</td>
<td>Rest</td>
<td>27.5km run</td>
<td>Cross</td>
</tr>
</tbody>
</table>
**Marathon Training Guide - Novice 2 Programme Breakdown**

(All information from [www.halhigdon.com](http://www.halhigdon.com))

**HERE IS MY NOVICE 2 PROGRAM**, It is designed for people with some background as a runner, whether or not they have run a marathon before. Runners differ greatly in ability, but ideally before starting a marathon program, you should have been running about a year. You should be able to comfortably run distances between 3 and 6 miles. You should be training 3-5 days a week, averaging 15-25 miles a week. You should have run an occasional 5-K or half marathon race.

**Terms used in the training schedule**

- **Long runs**: The key to the program is the long run on weekends, which builds from 13kms in Week 1 to 32kms in the climactic Week 15. (After that, you taper to get ready for the marathon.) Starting at 13kms, you get up over 24kms sooner than in Novice 1 and have an additional run above that distance. You can skip an occasional workout, or juggle the schedule depending on other commitments, but do not cheat on the long runs. Notice that although the weekly long runs get progressively longer, every third week is a "stepback" week, where we reduce mileage to allow you to gather strength for the next push upward. Rest is an important component of any training program.

<table>
<thead>
<tr>
<th>Date</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
<th>Run 5</th>
<th>Run 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>11) 1st Sept</td>
<td>Rest</td>
<td>8km</td>
<td>13km</td>
<td>8km</td>
<td>Rest</td>
<td>29km</td>
</tr>
<tr>
<td>12) 8th Sept</td>
<td>Rest</td>
<td>8km</td>
<td>13km</td>
<td>8km</td>
<td>Rest</td>
<td>21km</td>
</tr>
<tr>
<td>13) 15th Sept</td>
<td>Rest</td>
<td>8km</td>
<td>8km</td>
<td>8km</td>
<td>Rest</td>
<td>30.5km</td>
</tr>
<tr>
<td>14) 22nd Sept</td>
<td>Rest</td>
<td>8km</td>
<td>13km</td>
<td>8km</td>
<td>Rest</td>
<td>19.5km</td>
</tr>
<tr>
<td>15) 29th Sept</td>
<td>Rest</td>
<td>8km</td>
<td>8km</td>
<td>8km</td>
<td>Rest</td>
<td>32km</td>
</tr>
<tr>
<td>16) 6th Oct</td>
<td>Rest</td>
<td>8km</td>
<td>6.5km</td>
<td>8km</td>
<td>Rest</td>
<td>19.5km</td>
</tr>
<tr>
<td>17) 13th Oct</td>
<td>Rest</td>
<td>6.5km</td>
<td>5km</td>
<td>6.5km</td>
<td>Rest</td>
<td>13km</td>
</tr>
<tr>
<td>18) 20th Oct</td>
<td>Rest</td>
<td>5km</td>
<td>3km</td>
<td>Rest</td>
<td>Rest</td>
<td>3km</td>
</tr>
</tbody>
</table>

DUBLIN CITY MARATHON
Run slow: For experienced marathoners, I recommend that runners do their long runs anywhere from 30 to 90 seconds or more per km slower than their marathon pace. The problem with offering this advice to many novice runners, however, is that they probably don't know what their marathon pace is, because they never have run a marathon before! If not, don't worry. Simply do your long runs at a comfortable pace, one that allows you to converse with your training partners, at least during the beginning of the run. Toward the end, you may need to abandon conversation and concentrate on the act of putting one foot in front of the other to finish. However, if you find yourself finishing at a pace significantly slower than your pace in the first few miles, you probably need to start much slower, or include regular walking breaks. It's better to run too slow during these long runs, than too fast. The important point is that you cover the prescribed distance; how fast you cover it doesn't matter.

Walking breaks: Walking is a perfectly acceptable strategy in trying to finish a marathon. It works during training runs too. While some coaches recommend walking 1 minute out of every 10, or even alternating running and walking as frequently as every 30 seconds, I teach runners to walk when they come to an aid station. This serves a double function: 1) you can drink more easily while walking as opposed to running, and 2) since many other runners slow or walk through aid stations, you'll be less likely to block those behind. It's a good idea to follow this strategy in training as well. You will lose less time walking than you think. Walking gives your body a chance to rest, and you'll be able to continue running more comfortably. It's best to walk when you want to, not when your (fatigued) body forces you too.

Cross-training: Sundays in this training program are devoted to cross-training. What is cross-training? It is any other form of aerobic exercise that allows you to use slightly different muscles while resting (usually) after your long run. In this program, we run long on Saturdays and cross-train on Sundays, although it certainly is possible to reverse that order. The best cross-training exercises are swimming, cycling or even walking. What about sports such as tennis or basketball? Activities requiring sideways movements are not always a good choice. Particularly as the mileage builds up toward the end of the program, you raise your risk of injury if you choose to play a sport that requires sudden stopping and starting. One tip: You don't have to cross-train the same each weekend. And you could even combine two or more exercises: walking and easy jogging or swimming and riding an exercise bike in a health club. Cross-training for an hour on Sunday will help you recover after your Saturday long runs.
Strength Training: A frequently asked question is: "Should I add strength training to my marathon program?" If you have to ask, you probably should not. I strongly endorse strength training for maximum fitness and long life, but if you never have pumped iron before, now is probably not the time to start. Wait until after you have that medal around your neck. For gym rats, continue to work out, but you might want to cut back on the weights as the long run mileage moves into the double digits. Tuesdays and Thursdays work well for strength training--after you finish your runs on those days.

Midweek training: Training on Tuesdays and Thursdays should be done at a comparatively easy pace. As the weekend mileage builds, the weekday mileage also builds. Add up the numbers, and you'll see that you run roughly the same mileage during the week as you do during long runs on the weekends. Midweek workouts on Wednesdays build from 8 to 13 kms, many of them done at race pace. (I call these my Sorta-Long Runs.) There are similar slight advances on Tuesdays and Thursdays. The program is built on the concept that you do more toward the end than at the start. How fast is "comfortably easy?" That might vary from day to day. On Tuesday after a day's rest, you might find yourself running faster than race pace. On Thursday after two days of running, your pace might be significantly slower.

Race Pace: What do I mean by "race pace?" It's a frequently asked question, so let me explain. Race pace is the pace you plan to run in the race you're training for. If you're training for a 4:00 marathon, your average pace per km is 5.41. So you would run that same pace when asked to run race pace (sometimes stated simply as "pace" on the training charts). If you were training for a 5-K or 10-K, "race pace" would be the pace you planned to run in those races.

Rest: Despite my listing it at the end, rest is an important component of this or any training program. Scientists will tell you that it is during the rest period (the 24 to 72 hours between hard bouts of exercise) that the muscles actually regenerate and get stronger. Coaches also will tell you that you can't run hard unless you are well rested. And it is hard running (such as the long runs) that allows you to improve. If you're constantly fatigued, you will fail to reach your potential. This is why I include two days of rest each week for novice runners. The secret to success in any training program is consistency, so as long as you are consistent with your training during the full 18 weeks of the program, you can afford--and may benefit from—extra rest.

Good luck with your training!
Appendix F: LabView™ Screenshot
function void = dataanalysis4(FolderName,FolderName2,Fraction,SignalAnalysis,fc,fs,order)
filetype = '*.txt';
d = dir(fullfile(FolderName,filetype));
d2 = dir(fullfile(FolderName2,filetype));
d(1:0) = [];
for k = 1:numel(d);
    filename{k} = fullfile(FolderName,d(k).name);
end
% Runs the program through each data file that is in the directory 'Data'.
lenn1 = length(filename);
if lenn1 >= 1;
    S = dir(fullfile(FolderName,filetype));
    fnm = natsortfiles({S.name});
    [Pathstr,Name,Ext] = fileparts(filename(1));
    filename2 = fullfile(Pathstr,Name);
    t1 = '.txt';
    filename3 = strcat(filename2,t1);
    fid = dlmread(filename3,'\t',1,0);
    fid(:,1) = fid(:,1)./1000;
    lenn_original = length(fid(:,1));
    location = lenn_original*Fraction;
    for r = 1:numel(S);
        title = strcat(FolderName,(fnm(r)));
        title = char(title);
        a{r} = textread(title);
    end
    if r == 1;
        if SignalAnalysis == 'Filtered_X';
            NewFile_filt = lopass_butterworth(a{1,1},fc,fs,order); % cut off at fc Hz
            [pks,locs] = findpeaks((NewFile_filt(:,2)),'MINPEAKHEIGHT',0);
            R1 = locs(2:end);
            R2 = locs(1:end-1);
            Rstridesec = R1-R2;
            Rstridesec = Rstridesec';
            Strides = Rstridesec*(1/fs);
            Strides(any(Ext<0.6 | Strides>0.8,2),:)=[];
            HighOutliers = Strides>0.8;
            LowOutliers = Strides<0.6;
            TotalOutliers = Sum(HighOutliers + LowOutliers);
            Strides(1,:) = [];
            Strides(2,:) = [];
            Strides(end-1) = [];
            Strides(end)= [];
            fileID = fopen(((strcat(Name,'_Filtered_X_Strides','.txt')),'w');
            formatSpec = '%1.8f\n';
            fprintf(fileID,formatSpec,Strides);
        end
    end
end
fclose(fileID);

elseif SignalAnalysis == 'Filtered_Y';
    NewFile_filt = lopass_butterworth(a{1,1},fc,fs,order); % cut off at fc Hz
    [pks,locs] = findpeaks((NewFile_filt(:,3)),'MINPEAKHEIGHT',0);
    R1 = locs(2:end);
    R2 = locs(1:(end-1));
    Rstridesec = R1-R2;
    Rstridesec = Rstridesec';
    Strides = Rstridesec*(1/fs);
    Strides(any(Strides<0.6 | Strides>0.8,2),:)=[];
    HighOutliers = Strides>0.8;
    LowOutliers = Strides<0.6;
    Outliers = sum(HighOutliers + LowOutliers);
    Strides(1,:) = [];
    Strides(2,:) = [];
    Strides(end-1) = [];
    Strides(end)= [];
    fileID = fopen((strcat(Name,'_Filtered_Y_Strides','.txt')),'w');
    formatSpec = '%1.8f
';
    fprintf(fileID,formatSpec,Strides);
    fclose(fileID);

elseif SignalAnalysis == 'Filtered_Z';
    NewFile_filt = lopass_butterworth(a{1,1},fc,fs,order); % cut off at fc Hz
    [pks,locs] = findpeaks((NewFile_filt(:,4)),'MINPEAKHEIGHT',0);
    R1 = locs(2:end);
    R2 = locs(1:(end-1));
    Rstridesec = R1-R2;
    Rstridesec = Rstridesec';
    Strides = Rstridesec*(1/fs);
    Strides(any(Strides<0.6 | Strides>0.8,2),:)=[];
    HighOutliers = Strides>0.8;
    LowOutliers = Strides<0.6;
    Outliers = sum(HighOutliers + LowOutliers);
    Strides(1,:) = [];
    Strides(2,:) = [];
    Strides(end-1) = [];
    Strides(end)= [];
    fileID = fopen((strcat(Name,'_Filtered_Z_Strides','.txt')),'w');
    formatSpec = '%1.8f
';
    fprintf(fileID,formatSpec,Strides);
    fclose(fileID);
else
    [pks,locs] = findpeaks((a{1,1}(:,3)),'MINPEAKHEIGHT',0);
    R1 = locs(2:end);
    R2 = locs(1:(end-1));
    Rstridesec = R1-R2;
    Rstridesec = Rstridesec';
    Strides = Rstridesec*(1/fs);
    Strides(any(Strides<0.6 | Strides>0.8,2),:)=[];
    HighOutliers = Strides>0.8;
    LowOutliers = Strides<0.6;
    Outliers = sum(HighOutliers + LowOutliers);
    Strides(1,:) = [];
    Strides(2,:) = [];
    Strides(end-1) = [];
    Strides(end)= [];
end
fileID = fopen([strcat(Name,'_Original_Strides','.txt')],'w');
formatSpec = '%1.8f\n';
fprintf(fileID,formatSpec,Strides);
fclose(fileID);
end

[Pathstr] = fileparts(FolderName2);
h = strcat(Name,'_',SignalAnalysis,'_Strides','.txt');
fname = fullfile(Pathstr, h);
[status, cmdout] = system(['C:\Users\Michelle\Documents\dfa\dfa.exe< ' fname,'-echo']);
H = strcat(Name, '_', SignalAnalysis,'_DFA', '.txt');
output = str2num(cmdout);
dlmwrite(H,output,'delimiter','\t','precision','%6f');

LogN = output(:,1);
LogFN = output(:,2);
coefficients = polyfit(LogN,LogFN,1);
DFAalpha = coefficients(:,1);
Message = sprintf('The alpha value for Epoch_1 is %5.2f',DFAalpha);
h = msgbox(Message);
end
Method analysis of accelerometers and gyroscopes in running gait: A systematic review

Michelle Norris, Ross Anderson and Ian C Kenny
Biomechanics Research Unit, University of Limerick, Ireland

Abstract
Purpose: To review articles utilising accelerometers and gyroscopes to measure running gait and assess various methodology utilised when doing so. To identify research and coaching orientated parameters which have been previously investigated and offer evidence based recommendations as to future methodology employed when investigating these parameters.

Methods: Electronic databases were searched using key related terminology such as accelerometer(s) and gyroscope(s) and/or running gait. Articles returned were then visually inspected and subjected to an inclusion and exclusion criteria after which citations were inspected for further relevance. Thirty-eight articles were then included in the review.

Results: Accelerometers, gyroscopes plus combined units have been successfully utilised in the generation of research orientated parameters such as head/tibial acceleration, vertical parameters and angular velocity and also coach orientated parameters such as stride parameters and gait pattern. Placement of sensors closest to the area of interest along with the use of bi/triaxial accelerometers appear to provide the most accurate results.

Conclusion: Accelerometers and gyroscopes have proven to provide accurate and reliable results in running gait measurement. The temporal and spatial running parameters require sensor placement close to the area of interest and the use of bi/triaxial sensors. Post data analysis is critical for generating valid results.

Key Words
Accelerometry, gyroscopes, inertial measurement unit, kinematics, variability.

1. Introduction
While running continues to increase in popularity so too does the number of people suffering from Running Related Injuries (RRI). Injury incidence levels amongst runners have reached as high as 85% in recent research. In an effort to combat RRI levels there has been increasing demand for running gait research. While previous methods of analysis have generally required well equipped research labs, recently there has been a move to produce low cost, portable equipment. This allows researchers to remove participants from an artificial laboratory environment, to measure participants in a more natural environment and uncover longitudinal information perhaps more applicable to real life practice. With this the use of accelerometers and gyroscopes has increased. These devices exploit the property of inertia, i.e. resistance to a change in motion, to sense angular motion in the case of the gyroscope, and changes in linear motion in the case of the accelerometer. Scientists have also discovered their potential in assessing gait analysis without the restrictions of laboratory technology. In addition, research has shown that typical observational kinematic measurement systems, such as video analysis techniques often employed by coaches are wholly subjective and based on the knowledge of the coach and that coaches accuracy at scoring the same movement recorded using video analysis changes over time. Therefore accelerometers and gyroscopes are also bridging a
gap between coaching and science performance measures providing research orientated parameters (acceleration, velocity) and coach orientated parameters (stride length, stride frequency). These parameters, both alone and combined, have in the past been linked to RRI. The evolution of these sensors for biomechanical analysis has gathered pace as they provide direct contact with the subject in question, whilst also becoming smaller in size and more wearable, allowing for use during more dynamic movement. MEMS (microelectromechanical systems) accelerometers have led the way in technology for direct measurement of acceleration. While previous optical measurement systems allow for acceleration calculation error, during the differentiation of displacement and velocity measurements (such as 2D image analysis), accelerometers avoid this while also having the benefit of utilising one or multiple axes. This has led to accelerometers being successfully validated for identifying a number of parameters when measuring running gait including centre of mass (COM) vertical displacement, stride parameters and running speed, and angular velocity. Similar to accelerometers, gyroscopes are portable, lightweight and provide direct measurement, in this case, of angular velocity. Gyroscopes when combined with accelerometers form a very useful, compact measurement system, an inertial measurement unit (IMU), which have also been successfully validated in identifying parameters when measuring running gait including stride times, vertical displacement and speed. While there has been much evidence to support the validity of accelerometers and gyroscopes in measuring running gait there is still debate regarding the techniques used while utilising these systems. A previous systematic review focused on the implementation and data processing of the sensors (i.e. study design, fixation) however that review focused only on lower limb kinematics and also included a range of activities including walking, sitting and tennis serving. While that review may aid researchers in considering implementing this analysis method across a range of activities it does not divulge critical information as to the direct methodology when performing movement at high velocity, as done in running. It is also necessary that this information is made accessible both to the science community and to running coaches, so it can be accessed by the running population. Therefore a systematic review is necessary so that a summary of information will be collated from which biomechanists and coaches alike will be able to make educated decisions about the appropriate methods of the application of accelerometers and/or gyroscopes to assess running gait. While in this review accelerometers, gyroscopes or combined units (IMU) will be included accelerometers will feature more heavily due to their greater popularity in running gait analysis. Regardless, from the information gathered here it is hoped in the future that scientists and coaches alike will be able to successfully identify kinematic parameters from sensor data, which may be linked with RRI.

2. Research Methods
PubMed, ScienceDirect, Web of Knowledge and Google Scholar were searched to identify studies which utilised accelerometers and/or gyroscopes for running gait kinematic analysis. Searches consisted of a combination of the following keywords (1) inertial sensors or accelerometer/s or acceleration or gyroscopes or wearable sensors or sensing technology or inertial measurement unit and (2) gait or locomotion or running or running gait. Due to recent technology advances articles within the last decade were preferentially considered.

The inclusion criteria for study selection were (1) the literature was written in English (2) participants were human (3) sensors consisted of accelerometers or gyroscopes individually or when combined within one unit (IMU) (4) participants performed running gait whilst wearing the sensors and (5) clearly defined outcome measures were kinematic parameters. Articles which did not meet the inclusion criteria after inspection of the title and abstract were omitted. Reference lists of articles which met the inclusion criteria were then physically searched to identify any potentially relevant articles which may not have been identified in the previous search. A total of 38 articles were identified (See Figure 1).
3. Results
In the 38 articles 385 participants (166 distance runners, 12 sprinters, 144 recreational runners and 63 mixed sport or unknown) were tested with a mean of 10.1 ± 7.8 participants per study. These participants performed on average 3.8 ± 3.9 trials from which accelerometer and/or gyroscope data were used, with a total of 1488 trials completed. Of the 38 articles only 10 articles\textsuperscript{13-15, 17-23} utilised IMU’s, with combined accelerometer and gyroscope capabilities, while the remaining 28 utilised either accelerometers or gyroscopes individually.

3.1 Research orientated kinematic output parameters
Of the 38 articles included in the review 23 utilised accelerometers and/or gyroscopes during running gait to derive research orientated kinematic parameters (See Table 1.1).

Table 1.1 Research orientated kinematic output article details.

<table>
<thead>
<tr>
<th>Tibial/Shank Acceleration</th>
<th>Head Acceleration</th>
<th>Shock Attenuation</th>
<th>Vertical Parameters</th>
<th>Angular Velocity</th>
<th>Stride Regularity/Symmetry</th>
<th>Accelerometry relative to V̇o2 and speed</th>
<th>Total Acceleration and Kinematic Patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.1.1 Tibial/shank acceleration. Firstly shank/tibial acceleration was identified in 12 of the 23 articles (See Table 1.1). Peak tibial acceleration after impact was identified in all 12 studies which may be due to its links with overuse injury such as tibial stress fractures\textsuperscript{28, 39}. All but 1 of the 12 studies generated peak tibial acceleration data by attaching the accelerometer to the distal anteromedial portion of the tibia. Clark et al.\textsuperscript{27} placed their accelerometer on the proximal tibial tuberosity. Although research has indicated that the distal anteromedial portion of the tibia is chosen as a placement site to reduce the effect of angular acceleration and rotational movement\textsuperscript{30}, Clark et al.\textsuperscript{27} were not incorrect in their placement. Clark et al.\textsuperscript{27} were interested in tibial acceleration at the knee, of most importance in the mediolateral plane, as they investigated varus/valgus knee motion during running. By placing the accelerometer at the proximal end of the tibia Clark et al.\textsuperscript{27} were following protocol in line with Mathie et al.\textsuperscript{40} which states that accelerometer placement is key to providing accurate output and should be placed on the area of interest. Clark et al.’s\textsuperscript{27} study also led them to being the only study of the twelve which identified tibial acceleration in all three planes, vertical, mediolateral and anteroposterior, which has
been previously identified as an area to be investigated due to high acceleration rates within these planes. While their study may provide important information on knee movement one flaw can be identified, which is the size of the accelerometer used. When comparing bone and skin mounted accelerometers, while bone was found to be more accurate skin mounted were found to be acceptable as long as the mass of the accelerometer was kept minimal, <3g suggested. The accelerometer used by Clark et al. weighed 25g, over eight times the suggested mass, which may have led to spurious data, in all planes. For the remaining articles six utilised accelerometers weighing more than 3g which question the validity of their results. Three studies utilised accelerometers weighing less than 3g and one did not outline the mass of the accelerometer used. It is also important to note that the majority of the 12 studies identified peak tibial acceleration utilising uni-axial accelerometers (n=8) which, despite producing sufficient peak tibial acceleration data, has limitations.

Mercer et al. reported that when the subject was standing the axis of the accelerometer was aligned with the longitudinal axis of the tibia however with any manipulation of stride length, as can happen in fatiguing long distance running, the axis alignment became distorted. Although previous research has stated that this misalignment leads to minimal differences in acceleration values (1-2% impact peak magnitude) the risk of this affecting data could be minimised with the use of bi-axial and tri-axial accelerometers. Four studies also analysed tibial acceleration across the stance phase using the Fast Fourier transformation function to calculate power spectral density (PSD) using a previously published method. Using the aforementioned methods tibial acceleration has been successfully identified to be reduced in high arched runners when running in cushion trainers shoes compared to motion control shoes and also decrease when provided as visual feedback to those running on treadmills. Tibial acceleration was also found to be increased in fore-foot strikers opposed to rear foot strikers and identified to increase mediolaterally in women during menstruation compared to ovulation. Lastly it has been found to increase with increases in preferred stride length and showed mixed increases when investigated in relation to fatiguing runs (dependent on run length and training status of runner).

3.1.2 Head acceleration. A second variable of interest was head acceleration which was successfully identified in all of the 23 articles which examined research orientated kinematic parameters. Head acceleration has been identified due to its role in understanding shock absorption as the body attempts to combat the repetitive forces being applied to it during running. All seven studies outline that to acquire head acceleration data the accelerometer was placed on the anterior aspect of the forehead or the frontal bone of the skull whilst all seven also provided extra strapping or adhesive to ensure attachment. Head peak impact acceleration was the key parameter investigated in all 7 studies with 4 of the studies also generating the PSD value for head acceleration during stance. Head acceleration values were successfully acquired within all seven studies with no limitations identified (as regards to attachment point or output data). Using accelerometry to analyse head movement has therefore led to information being derived such as knowledge that PSD remains between a narrow magnitude when stride length or frequency is adapted, without inducing fatigue. Also accelerometry data has found that PSD and peak impact head accelerations can significantly increase or remain relatively consistent after fatiguing runs. This, as before, may be due to varying conditions within the different studies such as test design (i.e. length of run) and training status of runners playing a role, with Hamill et al. believing that at high speed constant head acceleration is needed to maintain visual field. Alternatively longer fatiguing runs that altered joint mechanics due to increased fatigue can have a greater impact, perhaps even in more highly trained athletes.
3.1.3 Shock attenuation. Shock attenuation is the process of decreasing the magnitude of impact force between the leg and head and is derived from the accelerations of these segments. It was another variable commonly looked at within the 12 articles containing research orientated kinematic parameters. It was identified in 6 of the 12 articles and is important considering the repetitive nature of running thus any alteration of the body's ability to absorb shock could lead to additional stresses being placed on joints and the onset of overuse injury. Four of the six articles calculated shock attenuation using the same transfer function utilising frequency domain analysis. All of these articles identified shock attenuation as the average transfer function across similar impact frequencies ranges (10-20 Hz for Abt et al., Derrick et al. and Mercer et al., 11-18 Hz for Mercer et al.). This method resulted in a shock attenuation value in decibels, with positive values indicating a gain in the acceleration signal from leg to head and negative values indicating attenuation of the signal. Of the two remaining articles, however, while one study utilised a simplified frequency domain analysis of ratio of PSD<sub>head</sub> to PSD<sub>leg</sub> (with a low ratio indicative of greater attenuation) the other utilised time domain analysis using averaged peak head and tibial accelerations, shown in Equation 1.

\[
\text{Shock attenuation} = \left(1 - \frac{\text{peak head acceleration}}{\text{peak tibial acceleration}}\right) \times 100 \tag{1}
\]

Although these methods generate a numeric value representative of shock attenuation it is thought the preferred method is using the PSD and Fourier technique followed by the average transfer function. This analysis of the frequency domain allows us to attain greater understanding of the distribution of the energy in the signal, in this case acceleration, and also can let us see how quickly shock attenuation can occur. Within the 6 articles, 3 articles identified shock attenuation increases, all utilising the average transfer function value at similar running impact frequencies. Whilst Derrick et al.'s study was based on an exhaustive run Mercer et al. and Mercer et al. altered running conditions (stride length and frequency and speed), but commonly all three articles found an increase in stride length as well as shock attenuation. This link between shock attenuation and stride length is supported by Mercer et al. who found decreases in shock attenuation post fatigue, but also consistent stride length pre and post. Similarly, Abt et al. and Clansey and Hanlon also found decreases in shock attenuation following fatiguing runs and indicate this is due to a highly trained population, who perhaps do not adapt stride length when facing fatigue due to enhanced coping strategies.

3.1.4 Vertical parameters. Vertical acceleration, displacement or vertical oscillation was also identified in 6 of the 23 articles. When measuring vertical oscillation 5 of the 6 articles located the accelerometer or IMU in proximity to the centre of mass, placing it either on/near the sacrum or located on the hip in order to give a true reflection of vertical displacement. On the other hand Tan et al. attached their GPS/IMU system to the top of a cyclist's helmet which was worn by the runner. This GPS/IMU unit combined GPS (global positioning systems) capabilities of determining speed over ground and an IMU (inertial measurement unit) comprised of an accelerometer, gyroscope, 3D magnetometer and temperature sensor. Placement on top of the helmet was for convenience as the system was bulky and required the mounting of an antenna, as did the GPS system it was being compared to. Also in Tan et al.'s study when compared to the GPS system (OEM4) the combined GPS/IMU system achieved a reliability of 0.02 m in vertical displacement. Given this relatively large systematic error and the author's statement that the error was as a result of both measurements containing error neither of these two systems would be recommended for future measurement of vertical displacement. Of the remaining articles Lee et al. found accelerometry acceptable in generating vertical acceleration in a transtibial amputee sprinter and Lee et al. also found near perfect correlations and very small error between COM vertical acceleration when derived from an accelerometer and compared to 3D motion capture. This would indicate accelerometry as a highly valid
method of deriving vertical COM parameters. However, while this level of validity is supported by Gullstrand et al., when compared to three-dimensional infra-red motion capture and position transducers the reliability of the accelerometer is seen to be very poor as it produces a large amount of random error (5, 7 and 11 mm). Gullstrand et al. however put this error down to changes in the orientation of the uniaxial accelerometers used. Although this was assumed to be constant the orientation was most likely altered at each step. Their suggestion for more complex sensors to be used to avoid this is supported by Lee et al. as they used a triaxial accelerometer and their data did not suffer from this orientation alteration and therefore had small typical error (1.84 m/s²). Of the studies which chose to analyse vertical displacement as opposed to acceleration, all studies double integrated the vertical acceleration component derived at the hip/sacrum. By using the above methods previous research has identified symmetry in running gait and shown that there is little difference between vertical acceleration in anatomical and prosthetic strides. Previous studies have also found conflicting results as to levels of vertical oscillation, dependent on running ability.

3.1.5 Angular velocity. While most of the variables identified within this review so far have been linked to acceleration patterns of the 28 articles identified also looked at angular velocity whilst running. Bergamini et al. utilised an IMU consisting of a tri-axial accelerometer and a tri-axial gyroscope placed on the lower back (L1) to provide analysis of amateur and elite sprinters. They found that acceleration and angular velocity profiles provided no consistent features which could be linked to foot strike and toe off, which is in contrast to previous research using lumbar based sensors. It is thought Bergamini et al.'s results may be due to utilising sprint trials in their study, which due to forefoot striking causes increased damping of impact forces, making identifiable markers harder to distinguish. This raises the question whether lower back attached sensors are suitable for measuring sprint parameters. In contrast to this however Bergamini et al. was able to identify consistent events on the second derivative of angular velocity wavelet, which verified that not only is trunk rotation present in sprinting, as had been previously found in walking and long distance running, but also that this feature could be found across different levels of athletes (amateur and elite) and could be utilised to identify stride duration. Negative and positive peaks related to time of heel strike and toe-off were also found on this wavelet. While Bergamini et al. utilised gyroscopes within an IMU to identify angular velocity patterns, Channells et al. utilised accelerometry data which were then integrated. They placed an acceleration measurement unit (AMU) consisting of 2 bi-axial accelerometers (one measuring mediolateral and anteroposterior accelerations - x and y axis, the second measuring vertical accelerations - z axis) on the athlete’s shin with which they then performed a series of walking, jogging and running trials. Angular velocity data were then generated through integration which were compared to angular velocity derived through the same calculation using motion capture. They found that the AMU resulted in comparable angular velocity patterns when compared to the motion capture and this was not affected by running technique. It was, however, affected by running speed; results indicating that as speed increased so did error (percentage error ranges from 2.31% in walking to 9.76% at higher speeds). This increase in error could be due to increasing noise induced integration error due to poor attachment at increased speeds. Both papers found increased problems when looking at angular velocity during sprinting and so may raise the question as to techniques used by both studies. Perhaps combining the equipment used by Bergamini et al. based on its high validity and gyroscope utilisation, and the tibial attachment site (used by Channells et al.) should be further investigated when analysing angular velocity in sprinting.

3.1.6 Remaining parameters. Having identified the common themes within the 38 articles investigating research orientated kinematic parameters there were 3 papers which identified unique variables utilising accelerometers. Le Bris et al. investigated the effect of fatigue on middle distance runner’s stride patterns using
Locometrix system (Locometrix™, Centaure Metrix, France) located on the lower back. While they looked at stride regularity (similarity of cranial-caudal acceleration over successive strides) and stride symmetry (similarity of cranial-caudal acceleration over left and right strides) through autocorrelation, these variables are similar to those found by papers looking at vertical acceleration\textsuperscript{5, 10, 14, 22, 23, 32}. Of greater interest however was their use of accelerometry in the investigation into medio-lateral axis acceleration patterns. While this is similar to that done by Clark et al.\textsuperscript{27} in their investigation of knee varus/valgus movement, Le Bris et al.\textsuperscript{31} located their accelerometer on the centre of the lower back, close to the COM, which gives a better indicator of whole body movement as affected by fatigue. From this they found that fatigue increased the medio-lateral impulse significantly in sub-elite middle distance runners, perhaps indicating they cannot combat fatigue as effectively as elite, leading to increasing energy expenditure in an axis (mediolateral) not conducive to propulsion. McGregor et al.\textsuperscript{33} also investigated kinematic accelerometry patterns by locating an accelerometer on the lower back of their participants; however they wished to investigate the validity of using the accelerometer relative to Vo\textsubscript{2} and speed by comparing the root mean square of the three axes and the Euclidean resultant (RES) to Vo\textsubscript{2}. They not only found that the accelerometer was highly valid and reliable in predicting Vo\textsubscript{2} but also looked to investigate the differences between trained and untrained runners in regards to acceleration at certain speeds, economy of acceleration relative to speed and ratio of accelerations relative to RES in all axes. By using the acceleration data derived from their trials in this manner McGregor et al.\textsuperscript{33} were able to divulge a wealth of information regarding acceleration pattern differences between trained and untrained runners performing to fatigue. They found that nearly all acceleration parameters were lower in trained than untrained runners perhaps indicating enhanced running economy when reaching fatigue (through positive adaptions), which is supported through much of the research\textsuperscript{1, 26}, supporting the validity of their study. Lastly Patterson et al.\textsuperscript{30} looked at acceleration of the lower limb by placing a tri-axial accelerometer on the shoe laces of their subject. From this they wished to investigate the relationship between the total acceleration, x and y axis accelerations and kinematic gait movements such as knee and ankle angle at various parts of the gait cycle (initial swing, mid-swing) during fatiguing runs. They were able to identify certain relationships existed, such as accelerometer variables during mid-swing being predictive of dorsi-flexor fatigue. However their study was only performed on one subject and so these results are not necessarily generalizable to a larger population, given that gait has such individual characteristics.

\subsection*{3.2 Coach orientated kinematic output parameters}

Having investigated research orientated kinematic parameters identified using accelerometers and/or gyroscopes it was also important to investigate coach orientated parameters. This is to ensure that these sensors were able to generate information accessible to audiences of different scientific knowledge backgrounds. Of the 38 articles included in this review 23 articles utilised accelerometers and/or gyroscopes during running gait to identify coach orientated kinematic parameters (See Table 1.2).

<table>
<thead>
<tr>
<th>Table 1.2 Coach orientated kinematic output parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auvinet et al.\textsuperscript{18}</td>
</tr>
</tbody>
</table>

256
3.2.1 Step/Stride frequency/rate. Firstly frequency or rate of step and stride, was commonly identified in 10 of the 38 articles\textsuperscript{11, 14, 18, 23, 31, 35, 36, 50-52}. Stride frequency is important as increased stride frequency means increased repetitive impacts on the body which can lead to a higher risk of injury and degenerative disease due to increased stress on the structure of the body\textsuperscript{45}. Of the 10 articles 4 articles did not define how they identified step/stride frequency\textsuperscript{11, 14, 31, 50} with some only identifying that it was analysed using the Fast Fourier Transform via MATLAB\textsuperscript{31}. Of the remaining 6 articles however 5 identified stride frequency using similar methods. Mercer et al.\textsuperscript{35} and Mercer et al.\textsuperscript{36} identified the peak in vertical acceleration associated with foot impact and calculated stride frequency as a result of the time, whilst Stohrmann et al.\textsuperscript{23} identified peak impact by not only looking at the anterior-posterior acceleration curve but combining the three planes of acceleration to calculate the magnitude. All three studies chose lower limb sensor attachment and whilst Stohrmann\textsuperscript{23} utilised an IMU all three papers identified results through accelerometer generated data. Neville et al.\textsuperscript{51} and Neville et al.\textsuperscript{52} again utilised accelerometer sensors combined with a zero crossing method in MATLAB (not dissimilar to the previously mentioned method). Here every zero crossing in the anterior-posterior plane was identified as a foot impact, which was then divided by the time between first and last impact to derive stride frequency. As there would be minimal time difference in the time of zero crossing and impact peak and both methods successfully derived stride frequency both methods could be used. However, the zero crossing method was successfully compared to speed as measured using a stopwatch (stride frequency showing a linear trend as speed increase, $r^2=0.896$) and GPS ($r^2=0.901$)\textsuperscript{52} and against various speeds as measured by GPS (walking $r^2=0.820$, running $r^2=0.838$)\textsuperscript{51}. This supports its position as the method with proven validity. It is important to note, however, the use of a stopwatch as a comparison speed measurement device. This method is highly subjective and has been found to be a valid method in assessing speed only when used by a trained tester\textsuperscript{55}. It is not stated in Neville et al.\textsuperscript{52} whether the tester is trained or not, which may question the derived speed accuracy. While it could be argued that Neville et al.\textsuperscript{51, 52} placed their accelerometers on the lower back, against that recommended by Mathie et al.\textsuperscript{40}, foot strike here created easily identifiable markers in large peak acceleration changes and so was identifiable regardless of position. This is in contrast to that found by Bergamini et al.\textsuperscript{17} who utilising an IMU were unable to identify a regular pattern on the acceleration curve using the same sensor placement. However, in Bergamini et al.\textsuperscript{17} the subjects sprinted, which is thought to have hindered pattern identification. Lastly, in terms of identifying stride frequency, Bichler et al.\textsuperscript{18} utilised an IMU, however unlike Bergamini et al.\textsuperscript{17} and Stohrmann et al.\textsuperscript{23} they utilised the gyroscope data available to identify stride frequency. They expanded the "pedestrian dead reckoning" method (a method used to give position and orientation of a subject using integration of acceleration and angular velocity – Torres-Solis and Chau\textsuperscript{56}) to provide greater accuracy during running. This method identified the rotation of the foot prior to, during and after stance in order to derive stride parameters such as stride frequency. From this stance could be identified due to rotation below a certain threshold (<1 rad/s) and also with combined accelerometer key markers (peak at impact)\textsuperscript{18}. When this method was compared to video
analysis it was found to show a more regular pattern in terms of stride frequency but also that increases in speed increased parameter failure rate. However these differences between measurement systems (IMU/GPS and video) overall were minimal and most lay within 95% limits of agreement. Any differences could also be due to the weak comparison method of 2D analysis and also stance would have been identified here as ground contact time, as opposed to with the sensor data where it was identified by level of rotational movement. By using the above methods, the use of accelerometers and/or gyroscopes to derive stride frequency has been validated\textsuperscript{11, 14, 51, 52} and also been successfully used to derive stride frequency changes with speed\textsuperscript{36}, fatigue\textsuperscript{23, 31} and its relationship to jump performance\textsuperscript{50}.

\section*{3.2.2 Temporal parameters.} Secondary coach orientated kinematic parameters which were identified were temporal and covered a multitude of smaller parameters. Parameters which included foot/ground interface (foot contact time, step, stance and stride duration) and also airborne parameters such as swing time were identified through use of accelerometers and/or gyroscopes in 10 of the 24 articles\textsuperscript{13, 17, 18, 20-23, 32, 47, 53}. In order to identify these parameters all the studies required identification of when the foot was in contact with the ground through knowledge of when foot strike occurred and toe-off occurred. Utilising an IMU Stohrmann et al.\textsuperscript{21, 22} identified foot/ground contact through an acceleration threshold, where below 2g (g=gravity) represented stance time with values increasing above this representing swing time. This use of a threshold is commonly seen in comparison analysis when using force plates\textsuperscript{17, 53} but Stohrmann et al.\textsuperscript{21, 22} is the only identified study to utilise it with accelerometry data. A more commonly identified method to generate foot contact times was by analysis of the anterior-posterior accelerometry data with positive peaks identifying foot strike and smaller peaks identifying toe-off\textsuperscript{17, 32, 47}. This method can provide information easily as it can be generated through visual observation of acceleration patterns, as done in Lee et al.\textsuperscript{32}. The validity of this method has also been tested over differing conditions including a Paralympic sprinter using a prosthetic limb, and at varying running speeds with similar results\textsuperscript{47, 53}. Lee et al.\textsuperscript{47} found that an accelerometer based sensor placed on the lower back had strong agreement and near perfect correlations ($r=0.90+$) to 3D motion capture, for most parameters (step, stride and stance times) at varying running speeds (low, medium and high). This was similar to Purcell et al.'s\textsuperscript{53} findings when comparing tibial accelerometry contact time measures to force plate data ($r=0.89+$). Gyroscope data derived from IMU units were also utilised to measure temporal parameters with O'Donovan et al.\textsuperscript{20}, Bichler et al.\textsuperscript{18} and McGrath et al.\textsuperscript{13} all identifying foot/ground interface using angular velocity. All three studies identified different methods to analyse angular velocity for ground contact. O'Donovan et al.\textsuperscript{20} used a method by Aminian et al.\textsuperscript{57} which utilised medio-lateral angular velocity. Bichler et al.\textsuperscript{18} stated that foot contact occurred between the first and last samples of angular velocity below 1rad in the respective foot and McGrath et al.\textsuperscript{13} utilised an algorithm which calculated thresholds based on angular velocity about the y-axis (mediolateral) and also incorporated an artefact rejection routine. Two of the 3 studies validated their methods in comparison to 3D motion capture with Bichler et al.\textsuperscript{18} identifying their 2D camera analysis as a limitation to their study, perhaps being too weak for a comparison method and leading to poorer results with Intra-class coefficient (ICC) results here (averaged 0.4) being lower than both O'Donovan et al.\textsuperscript{20} (0.86) and McGrath et al.'s\textsuperscript{13} (0.53 +) findings. When looking at the individual parameter findings McGrath et al.\textsuperscript{13} showed poor to moderate ICC (0.24 -0.66) for stance and swing times across all speeds when comparing gyroscope data to motion capture. This is in contrast to O'Donovan et al.\textsuperscript{20} who found high ICC values (0.85 and 0.99) for these parameters, although a major difference here is that O'Donovan et al.\textsuperscript{20} utilised both walking and jogging and did not differentiate the results of both or state the speeds utilised. Therefore the higher values represented by O'Donovan et al.\textsuperscript{20} could be due to slower speeds, which is supported by the fact that ICC values at the top of McGrath et al.'s\textsuperscript{13} range for swing and stance time utilising gyroscopes were closer to O'Donovan et al.'s\textsuperscript{20} values (0.66 compared to 0.99 for stance time). Overall, studies which utilised gyroscopes all demonstrated limitations or
require further study in the validation of this method so accelerometer data may be a more valid method of analysis in temporal parameters. In general studies which have utilised the above methods have investigated changing temporal parameters regarding fatigue\textsuperscript{23}, in sprinting kinematics with the use of a prosthetics limb\textsuperscript{32} and in the validity of accelerometers and/or gyroscopes as a measurement technique\textsuperscript{17, 18, 53}.

### 3.2.3 Gait pattern

Gait pattern was also identified in 3 of the 24 articles which examined coach orientated parameters\textsuperscript{48, 49, 54}. All three studies utilised accelerometers and wished to identify key markers of gait pattern such as the acceleration peaks at foot strike and toe off to confirm that accelerometry was feasible for gait pattern analysis. Two of the studies compared accelerometric measures to force measures, with Heiden et al.\textsuperscript{49} using force plate data as a comparison and Wixted et al.\textsuperscript{54} using insole shoe sensors. While Heiden et al.\textsuperscript{49} did not discuss comparison results, Wixted et al.\textsuperscript{54} found by visual observation that accelerometer data showed a significant negative peak in the anterior-posterior plane which occurred at the approximate same time as heel strike, as shown by the insole shoe sensors. The end of foot contact, the period directly after toe off, was then characterised by vertical acceleration crossing zero positively, as foot contact and sensor pressure data ceased. Unfortunately no analysis was done on the timing of these events relative to one another and so it is not possible to compare these data to previous validation studies. Auvinet et al.\textsuperscript{48} also employed visual comparison of gait pattern derived from accelerometer data (peaks in anterior-posterior and vertical planes) and, in this case, 2D motion capture data and once more found a deceleration trough in the anterior-posterior plane at foot strike with loading (zero crossing) at toe-off, same as Wixted et al.\textsuperscript{54} found. Of most interest in these three articles was Heiden et al.’s\textsuperscript{49} investigation as to whether the hip sensor or ankle sensor presented the most accurate data for gait pattern markers (heel strike and toe off). They reported that the hip sensor resulted in gait pattern data that could not lead to accurate and easily identifiable gait markers whereas the ankle sensor generated replicable and identifiable data. This supports Mathie et al.’s\textsuperscript{40} thoughts on sensor location but contrasts with findings by Lee et al.\textsuperscript{47} and Bergamini et al.\textsuperscript{17}. Both Lee et al.\textsuperscript{47} and Bergamini et al.\textsuperscript{17} utilised lower back placement and successfully identified gait pattern. Although Bergamini et al.\textsuperscript{17} did so using the second derivative of angular velocity and it is possible Lee et al.\textsuperscript{47} did so at increased running speeds compared to Heiden et al.\textsuperscript{49}, which they identified led to increased accelerometer peaks and easier identification. When using a lumbar sensor to derive gait pattern perhaps Lee et al.\textsuperscript{47} utilised the best running speed (range 2.8-5.3 m/s) as they successfully validated this method in comparison to Heiden et al.\textsuperscript{49} (unknown speed) and Bergamini et al.\textsuperscript{17} (range 5.7-10.8 m/s) who at increased speeds found signal was dampened and markers on the accelerometer curve were unidentifiable. Easily recognised identification of gait pattern, as seen in these three studies, provides information on basic running pattern important to coaches.

### 3.2.4 Stride/step length

Another parameter identified via accelerometers and/or gyroscopes was stride/step length, identified in 4 of the 23 articles\textsuperscript{18, 35, 36, 50}. Stride length is a key parameter for coaches as it provides information on fatigue and also has been linked with RRI in relation to lower limb stiffness\textsuperscript{58}. While McCurdy et al.\textsuperscript{50} did not discuss how stride length values were obtained, only that it was done so using an accelerometer attached to a waist belt, both Mercer et al.\textsuperscript{36} and Mercer et al.\textsuperscript{35} utilised the same method, dividing treadmill speed by already attained stride frequency (as previously discussed). All 3\textsuperscript{35, 36, 50} of these articles utilised accelerometers in attaining stride/step length whilst Bichler et al.\textsuperscript{18} utilised IMU derived gyroscope data also. Whilst outlining the advanced pedestrian dead reckoning method which Bichler et al.\textsuperscript{18} used to derive kinematic parameters, does not specifically outline the method for calculating stride length, although results show that when compared to 2D camera analysis the mean stride length calculated by the IMU differed by only 0.01 m. This parameter was most sensitive to difference at higher speeds. Within these studies accelerometers and/or gyroscopes have uncovered stride length increases with increased velocity\textsuperscript{36}, unchanged stride length values after a graded exercise test\textsuperscript{35}, the relationship between stride length and jump performance in
soccer players and has also been validated to derive stride length at lower speeds. However, as Bichler et al. was the only author to test the validity of stride length results generated, and this was from gyroscope data, this is an area requiring further study.

3.2.5 Various remaining parameters. Other parameters identified are foot strike type, heel lift, running speed, knee angle, sprint time and arm movement, trunk forward lean and shoulder rotation. Although measurements such as angle derivation and speed may not be commonly identified using accelerometers and/or gyroscopes this information does provide insight into advancing capabilities of these low cost transducers whilst also providing support for their validity within this research.

4. Recommendations for future research

4.1 Parameter specific recommendations

For researchers who intend to utilise accelerometers and/or gyroscopes for research and coach orientated kinematic parameters for running gait there are several recommendations. Firstly regarding research orientated kinematics there are recommendations when investigating tibial acceleration, head acceleration, shock attenuation, vertical parameters and angular velocity among some parameters. In terms of tibial acceleration it is recommended to follow guidelines as suggested by Mathie et al., with accelerometer placement at the anterior/distal aspect of the tibia if tibia acceleration or running patterns derived from acceleration curves are of interest. It is also recommended that a bi-axial or tri-axial accelerometer is used as axial alignment has been found to become distorted during testing and by having multiple axes to analyse this may have less of a negative effect on data collection. Sensor/device weight also plays an important role and it is recommended for accurate data collection to keep weight to <3g. This may be of vital importance especially in collecting tibial acceleration data as the sensor will be placed in a body segment of small surface area (distal tibia compared to lower back placement) and by keeping sensor weight low this will maximise the unobtrusive method of data collection. Secondly, in terms of head acceleration, recommendations on placement follow those of Mathie et al. and so anterior aspect of the forehead is suggested and has been proven to be successful. This placement however can be the most obtrusive as the attachment of a foreign object onto the centre of a subject's forehead may be uncomfortable and unwanted during running. It is therefore suggested that this placement may be of the least value, as it obtains information only on shock attenuation and head acceleration and also may have the greatest effect on running efficiency and economy depending on the subject.

Recommendations in terms of collecting vertical parameter data using accelerometers and/or gyroscopes were also generated and again sensor location was recommended closest to the area of interest, the subject's centre of mass (lower back) for valid results. Also bi-axial or tri-axial accelerometers were recommended as altered orientation had again been observed and stated as a limitation using uni-axial accelerometers. For angular velocity both accelerometers and gyroscopes have been utilised successfully however placement has proven to be vital as lumbar placed sensors were found to produce inconsistent patterns in relation to acceleration and angular velocity peaks and dips associated with gait, making it difficult to identify parameters in subjects performing a sprint. In contrast when accelerometers on their own were utilised, while attached to the distal tibia, consistent patterns were found, although error within these patterns increased with speed. It is therefore recommended that a combination of methods is utilised in the future to generate angular velocity data, especially for sprinting analysis. The utilisation of gyroscopes, as used by Bergamini et al., to provide reliable data, followed with placement used by Channells et al. is therefore recommended for future study. While these are the main research orientated kinematic parameters, accelerometers have also been proven to generate reliable data in the mediolateral planes when located at various attachment points. When attached to the proximal tibia, accelerometers have been found
to generate knee valgus/varus data and when attached to the lower back have generated running efficiency data. This provides support for future studies not only investigating cranial-caudal and anteroposterior planes but also mediolateral to divulge important information.

In terms of generating coach orientated kinematic parameters through accelerometer and/or gyroscope utilisation there are also a number of recommendations. With stride frequency, identification has been successful using both the zero crossing method and identifying the peak in the anteroposterior acceleration curves. Also, whilst stride frequency has been successfully generated on accelerometers and/or gyroscopes attached to both lumbar and lower limb attachment points, research has shown that sprinting analysis can lead to diminished acceleration patterns with lumbar attachment and so lower limb and tibia attachment are recommended. Whilst gyroscopes alone were also utilised to derive stride frequency, they were validated against a subjective comparison method (2D video analysis) and have been found to provide greater complications than accelerometers (drift etc.) and so accelerometers are recommended in terms of the sensor utilised. For temporal parameters a common technique utilised which has also been validated at different speeds and with various subjects (i.e. paralympian) is identifying foot contact through examination of the acceleration curves. Again this would be recommended with tibial or lower limb attachment for distinct patterns and also to minimise time lag between accelerometer data and actual foot contact. While gyroscopes have also previously been utilised it was found that those that validated against 3D motion capture generated less accurate parameter output as speed increased. This would again lead to the recommendation of accelerometer utilisation for temporal parameter collection. For gait pattern research visual inspection of the acceleration curve (and the key gait markers associated with it) generated via accelerometers has been validated against both in-shoe sensors and 2D motion capture. Research here has also shown that lower limb (ankle) attachment has provided greater accuracy in providing gait pattern analysis than hip placement which is consistent in previous research. However it is suggested that if lower limb attachment is not possible, perhaps due to limitation of sensor quantity availability, but gait information is still desired that running speed be maintained between 2.8-5.3 m/s. This speed, along with lumbar sensor attachment, has been previously validated in gait pattern analysis whilst higher speeds (5.7-10.8 m/s) have been found to dampen gait pattern acceleration curves. For stride length limited information in the derivation of results has been outlined with only the advanced pedestrian dead reckoning method utilised by Bichler et al. and dividing treadmill speed by stride frequency being stated in the literature. Of these methods Bichler et al. is the only author to have provided validation and so this method may be the preferred. Again though this parameter, stride length, was most sensitive to error at higher speeds and so perhaps following similar guidelines and speeds suggested for the derivation of gait pattern (previously mentioned) should be followed to control this risk of error. Accelerometers and/or gyroscopes have also been utilised in deriving other lower body parameters such as foot strike type and heel lift and upper body parameters (arm movement, trunk forward lean etc.) however due to limited research on these parameters it is difficult to make future guidelines as to the most accurate methodology to be employed when these are of interest. However by utilising general guidelines as to the placement and weight of these sensors and by following recommendations on the derivation of similar parameters this may lead to greater accuracy in data collection.

### 4.2 General recommendations

Overall, research utilising gyroscopes (individually) in the analysis of running gait has proven to be limited. Whilst ten of the articles within this review utilised IMU’s some did not utilise the gyroscope capabilities of these units and most focused on the acceleration data generated. There therefore remains a question whether future research should focus on the use of gyroscopes. From the information collected within this systematic review gyroscopes have demonstrated greater limitations (i.e. drift) than accelerometers, while
Accelerometers have been successfully utilised to ascertain valid data, gyroscopes are primarily utilised for angular velocity, whilst also being easier to work with. Finally, to our knowledge, while previous studies have regularly investigated short distance running trials and sprints, no authors have addressed longitudinal running gait analysis, in terms of over an extended period of time and over longer distances, using accelerometers and/or gyroscopes. This is an important area which should be addressed as information gathered over an extended period could divulge important data related to overuse injury.

5. Conclusion
Based on the evidence provided we are able to support the use of accelerometer and/or gyroscopes in the analysis of running gait, as it is clear they have been utilised, and validated, in the use of deriving research and coach orientated kinematic parameters. Within this however it is important to point out that many different methodologies have been utilised by previous researchers in areas such as attachment site, type of sensor and different calculation methods to generate kinematic data. As to which methodology is correct it is important for future scientists and coaches to clearly identify what parameters they wish to investigate and to then let this lead the methodology. The importance of accelerometers and/or gyroscopes in combating increasing levels of RRI is valid as by accurate generation of kinematic data they may provide a wealth of information on ever-changing running patterns in an unobtrusive and natural environment.

6. Acknowledgement
Funding for this research was provided by an Education and Health Sciences Faculty, University of Limerick.


47. Lee JB, Mellifont RB and Burkett BJ. The use of a single inertial sensor to identify stride, step, and
49. Heiden T, and Burnett A. Determination of heel strike and toe-off in the running stride using an
accelerometer: Application to field-based gait studies. *2004 International Society of Biomechanics in
jump and sprint performance in division I women soccer players. *J Strength Cond Res*. 2010; 24:
3200-8.
monitoring. *2010 Sixth International Conference on Intelligent Sensors, Sensor Networks and
Information Processing (ISSNIP)*. 2010; 7-10 Dec, Brisbane, Australia.: 287-90.
53. Purcell B, Channells J, James D, et al. Use of accelerometers for detecting foot-ground contact time
during running. *Proceeding of SPIE, BioMEMS and Nanotechnology II SPIE*. 2006; Brisbane, Australia,
11th Dec, 2005.
54. Wixted AJ, Billing DC, and James DA. Validation of trunk mounted inertial sensors for analysing
running biomechanics under field conditions, using synchronously collected foot contact data. *Sports
56. Torres-Solis J, and Chau T. Wearable indoor pedestrian dead reckoning system. *Pervasive Mob
58. Butler RJ, Crowell HP 3rd and Davis IM. Lower extremity stiffness: implications for performance

264
Development of an advanced running analysis system; possibilities for real-time injury and skill level differentiation.

M. Norris, I.C. Kenny, R. Healy & R. Anderson

Biomechanics Research Unit, University of Limerick, Ireland.

Abstract

Detrended fluctuation analysis (DFA) has been applied to running stride time series for the detection of long range correlations. However, DFA requires extended data collection which may limit its use. We aimed to verify a running analysis system for production of real-time DFA α values. Data were collected utilising an accelerometer, attached to the tibia. The accelerometer data were transmitted to MATLAB for processing. Results demonstrated DFA α value output < 2 seconds post individual running Epochs, and < 5 seconds post run completion. Our running analysis system provides rapid advanced variability information, important in both training, and injury prevention.

© 2016 The Authors. Published by Elsevier Ltd.

Keywords: Feedback; gait; locomotion; variability; stride.

1. Introduction

Advances in motion capture, force platforms, pressure sensors, electromyography, accelerometers and gyroscopes mean there are now numerous measurement methods available which provide participants, coaches and researchers with quantitative data during running [1]. While some of these methods, such as motion capture and force platforms, are limited to use within a laboratory, accelerometers are not, and so have become increasingly popular in running gait analysis [2]. Due to their wireless and lightweight nature accelerometers are an integral part of research and consumer-led wearable running devices such as sports bracelets, smartwatches and smart clothing [3]. Accelerometers are commonly embedded within these devices to provide feedback to consumers on parameters such as distance and speed [4], and stride frequency [5] during running.

While these are basic running parameters recently there has been increased interest in measuring running variability through investigating long range correlations in stride time series using the advanced statistical analysis, Detrended Fluctuation Analysis (DFA) [6]. DFA is quantified through output of an α value. When applied to stride time series α values of 0.5 indicate a random walk, where one stride is uncorrelated to previous strides, whilst α values of between 0.5 and 1 indicate the presence of long range correlations, where stride time patterning continues over a number of strides resulting in predictable pattern [7]. Previously, DFA α values have been found to distinguish training status of runners [8], and identify previously injured runners from their previously non-injured counterparts [7]. It could therefore provide vital information to researchers and recreational runners alike as to changes in their stride time variability due to training or perhaps onset of injury.

However, DFA requires extended data collection due to its investigation into long range correlations, and studies investigating DFA on running populations have typically collected greater than 500 strides [7],[8]. Therefore, to complete DFA increased post-processing capabilities are needed along with advanced statistical knowledge for correct
implementation. This has led to DFA being underutilised within laboratory settings, and never utilised in consumer wearable running devices.

Whilst real-time feedback in sporting technology has been described as “a method that allows participants to observe their movements for the purpose of making immediate biomechanical adjustments” [9], DFA does not investigate discrete values which are susceptible to immediate adjustments. Therefore, longer periods of data collection prior to result output is more appropriate within this system when referring to “real-time” DFA α value output.

Thus, the aim of this research is to develop an advanced running analysis system, which will provide real-time DFA α values. If verified this system could enhance researcher and coach data collection alike, in terms of rapid data output and statistically advanced running variability information.

Table 1. Pre-data collection user input parameters.

<table>
<thead>
<tr>
<th>Parameter Title</th>
<th>Parameter Explanation</th>
<th>Input Example or Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>Enter name of subject or experiment bordered by apostrophes.</td>
<td>Any input eg, 'John'</td>
</tr>
<tr>
<td>comPort</td>
<td>Designated comPort due to Shimmer bluetooth pairing, enter number bordered by apostrophes.</td>
<td>Number designated by pairing eg ‘9’</td>
</tr>
<tr>
<td>Epoch_1</td>
<td>Enter length of 1st running Epoch in seconds. *Must be a long enough period to collect &gt; 400 running strides for valid DFA result for Epoch 1.</td>
<td>Any number of seconds eg, 480</td>
</tr>
<tr>
<td>Trials</td>
<td>Enter number of DFA values and/or number of overlapping windows, maximum 10.</td>
<td>Any value 1-10 eg, 10</td>
</tr>
<tr>
<td>TrialPeriod</td>
<td>Enter length of each overlapping window in seconds.</td>
<td>Any value eg, 60</td>
</tr>
<tr>
<td>fs</td>
<td>Enter sampling frequency of Shimmer 2r. Must be a multiple of 51.2 and ≤ 1024 eg, 51.2 OR 102.4 ... 1024</td>
<td></td>
</tr>
<tr>
<td>fc</td>
<td>Filtering cutoff for butterworth lowpass filter</td>
<td>Any value, eg 2</td>
</tr>
<tr>
<td>Order</td>
<td>Enter butterworth lowpass filter order</td>
<td>2 OR 4</td>
</tr>
<tr>
<td>SignalAnalysis</td>
<td>Axis which strides will be derived from (bordered by apostrophes)</td>
<td>'Filtered_X' OR 'Filtered_Y' OR 'Filtered_Z'</td>
</tr>
<tr>
<td>FolderName</td>
<td>Enter folder pathway (ending in \ and bordered by apostrophes) to save pre-processed files in.</td>
<td>Any folder pathway eg, ‘C:\Users\John\Documents\MATLAB\data’</td>
</tr>
<tr>
<td>SaveFolderName</td>
<td>Enter folder pathway (ending in \ and bordered by apostrophes) to save post-processed files in.</td>
<td>Any folder pathway eg, ‘C:\Users\John\Documents\MATLAB\data’</td>
</tr>
</tbody>
</table>

2. System Description

The advanced running analysis system is comprised of a Shimmer 2r accelerometer (range ± 6 g, sensitivity = 200 mV/g) (SHIMMER™, Dublin, Ireland) and a laptop equipped
with Bluetooth capability, MATLAB (Mathworks, Cambridge, UK) and the PhysioNet C+ DFA programme [10] (Fig 1).

2.1 Pre-data collection process

The system is designed to be adapted to research interests, along with the individual running styles of the participants and therefore there are a number user inputs which can be varied prior to data collection to enhance the accuracy of data output (Table 1). Prior to data collection the Shimmer 2r accelerometer should be programmed with Bluetooth streaming capability and paired with the laptops appropriate comport, to ensure real-time data streaming via the Shimmer MATLAB Instrument Driver.

2.2 Data collection initiation

Firstly, a Shimmer 2r accelerometer is turned on and attached to the participants’ right distal antero-medial tibia (Fig. 1, A). Participants are then given a treadmill warm-up period in which they are allowed to reach the required running speed. On having reached their running speed the system user\researcher then runs the custom developed ‘DFA_running_analysis.m’ script. This script contains the Shimmer MATLAB Instrument Driver streaming, plotting and text writing capabilities, along with a data analysis function to perform data processing to create a stride time series and run the PhysioNet DFA C+ Programme to calculate a DFA α value (Fig. 1, B), at user specific time intervals (defined in pre-data collection user input). The Shimmer accelerometer then starts logging tri-axial data which it transmits, via Bluetooth, to a laptop situated within 5m of the treadmill, for a designated capture period, (Fig. 1, A and B). When accelerometry data begins streaming to MATLAB a timer is automatically generated incrementing elapsed time.

\[ \text{capture period} = ((\text{Trials} \times \text{TrialPeriod}) + \text{Epoch}_1) \]  

(1)

2.3 Accelerometry text file generation

During this capture period accelerometry data is written to 11 text files, 'Epoch_1' + 10 trials named 'Epoch_2', 'Epoch_3' etc. The end of each Epoch period is defined as,

\[ \text{Epoch}_2 = \text{Epoch}_1 + \text{TrialPeriod}, \]
\[ \text{Epoch}_3 = \text{Epoch}_2 + \text{TrialPeriod} \text{ etc.} \]  

(2)

As previously stated, when the user runs the ‘DFA_running_analysis.m’ script there is an inbuilt data analysis function to perform data processing and DFA. This data analysis
function requires 2 - 3 seconds to perform data analysis, calculate and display the DFA α value on a message dialog box. To allow for this, variables A1 – A11 are created automatically to identify the point of at which each Epoch ceases writing to text file.

\[
A_1 = \text{Epoch}_1 - 2, \\
A_2 = \text{Epoch}_2 - 2 \ etc.
\]  

(3)

Therefore, the first data file containing accelerometry data, ‘Epoch_1’, is generated and continuously appended to whilst,

‘Epoch_1’ = 0 \leq \text{elapsed time} < A_1 \]  

(4)

The period in which the remaining text files are written to, ‘Epoch_2’, ‘Epoch_3’ etc, are defined by,

‘\text{Epoch}_2’ = \text{Epoch}_1 \leq \text{elapsed time} < A_2, \\
‘\text{Epoch}_3’ = \text{Epoch}_2 \leq \text{elapsed time} < A_3 \ etc.
\]  

(5)

Therefore, there is a 2 second period within each Epoch in which accelerometry data are streamed, but not written to file and therefore will not be included in subsequent analyses. The effect of this 2 second loss of recorded data is minimal, since using the example of the minimal suggested Epoch length of \(\text{Epoch}_1 = 8\) minutes (Fig 3.), it results in a 0.4 – 3.3% loss of data within an 8 minute Epoch and a 2% loss of data in an overall capture period of 18 minutes.

When elapsed time \(\geq\) capture period acceleration data collection ceases.

2.4 Data processing and DFA calculation.

The data analysis and DFA initiates 1 second post variables A1 – A11 allowing for sufficient accelerometry collection time and text files to cease writing before processing. Therefore data analysis occurs at,

\[
A_\_1 \leq \text{elapsed time} < (A_\_1 + 1), \\
A_\_2 \leq \text{elapsed time} < (A_\_2 + 1) \ etc.
\]  

(6)

At each data analysis initiation, firstly all accelerometry text files are concatenated to previous accelerometry files. This merged file is then cut from the beginning down to mirror ‘Epoch_1’, using Fraction = \(\text{TrialPeriod} / \text{Epoch}_1\), multiplied by the length of \(\text{Epoch}_1\). At each data analysis initiation this creates overlapping accelerometry data files, which all contain an acceleration collection period equal to \(\text{Epoch}_1\) (Fig.2).

![Fig 2. Process of data merging and cutting.](image)

This merged file undergoes filtering, using a Butterworth Filter, with pre-data collection user input defined frequency cut off and filter order. Then, a stride time series is produced using peak identification in the axis chosen through pre-data collection user input. Due to the process of merging multiple acceleration files which contain 2 seconds of missing data
and therefore not continuous data there is the possible creation of stride times not representative of actual strides. Therefore within the data analysis there are stride time threshold boundaries, which can be altered by the user, to eliminate stride time outliers. Lastly, the PhysioNet DFA C+ programme generates a DFA $\alpha$ value from the calculated stride time series, which is displayed automatically in a message dialog window (Fig. 1, C).

3. Programme verification experimental protocol

To verify the advanced running analysis programme generates real-time DFA $\alpha$ values in an efficient manner and in line with expected $\alpha$ results, a healthy active subject (female, age: 26.6 years, height: 1.80 m, mass: 70.1 kg) performed a running protocol whilst completing the advanced analysis programme. Firstly, an 8 minute period for Epoch_1 was selected, as it suggested by the current researchers as the minimum length of time required to allow enough time within you are guaranteed to collect over 500 strides, regardless of running speed. Further pre-data collection user input parameters were as follows, Trials = 11, TrialPeriod = 1 min, $fs = 102.4$, $fc = 2$, Order = 4, SignalAnalysis = ‘Filtered Z’ (Fig. 3). Utilizing a 2 Hz filter cut off to derive stride time has previously been validated [11]. Along with this a stride time upper threshold was identified as 0.8 seconds with a lower threshold of 0.6 seconds, based on previous literature investigating both runners and non-runners [8].

The running protocol used aimed to verify the analysis programme over a range of running speeds. For this, the participant ran at their preferred running speed (PRS), 80% of their PRS and 120% of their PRS. To establish the participant’s PRS the same protocol as that used by Nakayama et al. [8] and Jordan et al. [6] was employed. In short, the participant ran at a range of speeds which they indicated were “comfortable” or “uncomfortable”. The average speed of the “comfortable” speeds was estimated as the participant’s PRS. From the participant’s PRS, 120% and 80% of their PRS were calculated. The participant was then required to run for 18 minutes at 80% PRS, 100% PRS and 120% PRS in randomized order. The participant was allowed as long as necessary to rest between runs to mitigate the effect of fatigue. This resting period was further supported by a return to resting heart rate as confirmed by a heart rate monitor.

Fig 3. Data collection, analysis and output timeline of the running analysis system. Visuals A1 – A12 indicate automatic data analysis initiation.

To verify the system met the specified requirement, real-time output of repeated DFA $\alpha$ values, the time difference in seconds ($\Delta t$) between the end of each Epoch and the related $\alpha$ value display time were calculated, via a record of the MATLAB Command Window.
displaying elapsed time and each data analysis. To verify the system produced reliable $\alpha$ values over a range of running speeds $\alpha$ values were also recorded and compared to previous literature.

4. Results & Discussion

The participant’s PRS was 2.8 m/s, with 80% of PRS 2.2 m/s and 120% of PRS 3.3 m/s, similar to that previously seen in trained runners (PRS of 3.0 m/s) [8]. The running analysis programme resulted in collection of 653 – 711 stride time values within a data analysis epoch (A1- A11) across all running speeds (average 663 ± 6 for 80% of PRS, average of 677 ± 3 for 100% of PRS and average of 704 ± 3 for 120% PRS). This is similar to the amount of stride time values collected by both Nakayama et al. [8] (512 strides time values) and Meardon et al. [7] (661 stride time values) when investigating running DFA. The number of overall stride time values (A12) collected within the capture period (1,490 for 80% of PRS, 1,526 for 100% of PRS and 1,591 for 120% of PRS) are greater amounts than any represented in the current literature of DFA in running.

In relation to the real-time output of DFA $\alpha$ values, all $\alpha$ values were displayed to the researcher within 0.83 – 2.19 seconds of Epoch completion time (average of 1.49 ± 0.41 seconds for 80% of PRS, average of 1.55 ± 0.34 seconds for 100% of PRS, and average of 1.28 ± 0.32 seconds for 120% PRS). For 80% of PRS and 100% of PRS average stride intervals of 0.71 seconds and 0.70 seconds were identified, which indicates DFA $\alpha$ value output within 3 running strides of the next successive Epoch, at these running speeds. For 120% of PRS an average stride interval of 0.67 was identified, which indicates DFA $\alpha$ value output also within 2 running strides of the next successive Epoch. Post overall run, or at cessation of the capture period, DFA $\alpha$ value output occurred within 5 seconds, across all running speeds (average 3.61 ± 1.03 seconds). All previous literature around running DFA [6] [7] [8] appears to indicate that DFA occurred within a post processing environment and therefore the current author believes this may be the first running analysis system to produce real-time DFA output.

Lastly, DFA $\alpha$ values ranged 0.70 – 0.86, within the data analyses epochs (A1- A11), across all running speeds. Whilst our results are similar to those found in previously injured runners (average $\alpha$ values of 0.68 – 0.92) [7], Meardon et al. [7] were unable to determine that previous injury and the $\alpha$ values they reported were explicity linked. They suggest further investigation into the clinical interpretation of DFA $\alpha$ values, which this system may provide. However, these results are similar to those found by Jordan et al. [6], who identified $\alpha$ values of 0.70 – 0.90 whilst running at various percentages of PRS. This may verify our advanced running analysis system generates valid DFA $\alpha$ values over a range of running speeds. Interestingly, we also found that the participants overall run $\alpha$ was lowest at 100% of PRS (0.80, compared to 0.85 at 80% of PRS and 0.92 at 120% of PRS). This was previously identified by Jordan et al. [6], and is explained as a runner being most adaptable, and therefore less predictable in their stride time, at their PRS. This further supports our system within a training and skill level identification setting, as it appears the system is able to detect $\alpha$ value differences previously identified within the literature.
Table 2. Number of strides (n), difference in \textit{elapsed time} and \(\alpha\) value output time (secs) \(\Delta t\), and DFA \(\alpha\) values over three running conditions at 80\% PRS, PRS and 120\% PRS.

<table>
<thead>
<tr>
<th>Analysis No.</th>
<th>Strides (n)</th>
<th>(\Delta t)</th>
<th>(\alpha)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>80% PRS</td>
<td>PRS</td>
<td>120% PRS</td>
</tr>
<tr>
<td>A1</td>
<td>669</td>
<td>679</td>
<td>711</td>
</tr>
<tr>
<td>A2</td>
<td>671</td>
<td>679</td>
<td>709</td>
</tr>
<tr>
<td>A3</td>
<td>669</td>
<td>680</td>
<td>706</td>
</tr>
<tr>
<td>A4</td>
<td>668</td>
<td>680</td>
<td>704</td>
</tr>
<tr>
<td>A5</td>
<td>665</td>
<td>679</td>
<td>703</td>
</tr>
<tr>
<td>A6</td>
<td>663</td>
<td>679</td>
<td>702</td>
</tr>
<tr>
<td>A7</td>
<td>661</td>
<td>678</td>
<td>702</td>
</tr>
<tr>
<td>A8</td>
<td>658</td>
<td>677</td>
<td>701</td>
</tr>
<tr>
<td>A9</td>
<td>656</td>
<td>676</td>
<td>702</td>
</tr>
<tr>
<td>A10</td>
<td>656</td>
<td>673</td>
<td>702</td>
</tr>
<tr>
<td>A11</td>
<td>653</td>
<td>672</td>
<td>701</td>
</tr>
<tr>
<td>Average</td>
<td>663</td>
<td>677</td>
<td>704</td>
</tr>
<tr>
<td>(± stdev)</td>
<td>(± 6)</td>
<td>(± 3)</td>
<td>(± 3)</td>
</tr>
</tbody>
</table>

Overall Run

<table>
<thead>
<tr>
<th>Analysis No.</th>
<th>Strides (n)</th>
<th>(\Delta t)</th>
<th>(\alpha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A12</td>
<td>1490</td>
<td>1526</td>
<td>1591</td>
</tr>
</tbody>
</table>

5. Conclusion

The running analysis system provides real-time output (< 2 secs post Epoch, < 5 seconds post overall run) of advanced variability information, which previously required extensive data processing and analysis. This provides access to further feedback information important in both a training and injury prevention context, for coaches and researchers alike. The programme also supports the future use of inertial sensors in a sports engineering context, as advances in Bluetooth technology will lead to further development of the system, with an aim of performing advanced stride variability analysis in an outdoor, ecological environment.

Acknowledgements

This work was supported by the Education and Health Sciences Faculty, University of Limerick.

References


Short Communication

Comparison of Accelerometry Stride Time Calculation Methods.

Michelle Norris, Ian C Kenny and Ross Anderson

Biomechanics Research Unit, University of Limerick, Ireland

Abstract

Inertial sensors such as accelerometers and gyroscopes can provide a multitude of information on running gait. Running parameters such as stride time and ground contact time can all be identified within tibial accelerometer data. Within this, stride time is a popular parameter of interest, possibly due to its role in running economy. However, there are multiple methods utilised to derive stride time from tibial accelerometer data, some of which may offer complications when implemented on larger data files. Therefore, the purpose of this study was to compare previously utilised methods of stride time derivation to an original proposed method, utilising medio-lateral tibial acceleration data filtered at 2 Hz, allowing for greater efficiency in stride time output. Tibial accelerometry data from six participants training for a half marathon were utilised. One right leg run was randomly selected for each participant, in which five consecutive running stride times were calculated. Four calculation methods were employed to derive stride time. A repeated measures analysis of variance (ANOVA) identified no significant difference in stride time between stride time calculation methods (p=1.00), whilst intra-class coefficient values (all > 0.95) and coefficient of variance values (all < 1.5%) indicate good reliability. Results indicate that the proposed method possibly offers a simplified technique for stride time output during running gait analysis. This method may be less influenced by "double peak" error and minor fluctuations within the data, allowing for accurate and efficient automated data output in both real time and post processing.

Key Words: Accelerometry, analysis, gait, inertial sensor, performance.

1. Introduction

The use of low cost portable sensors, such as accelerometers and gyroscopes, has become increasingly popular in running gait analysis over the last number of years (Higginson, 2009). Their decreased size and lightweight nature allows easy, ecologically valid attachment whilst still uncovering a multitude of information in a natural environment. Within running gait analysis tibial sensor attachment has been identified as superior in identifying lower limb acceleration patterns as it is close to the area of interest, this being the lower limb (Mathie et al., 2004). This attachment allows for identification of running gait parameters such as stride frequency (Mercer et al., 2002) and ground contact time (Purcell et al., 2006). Of these parameters, stride frequency, and therefore stride time, has been identified as a major contributing factor to running economy and overall run outcome, making it a parameter of great interest (Mercer et al., 2008). Stride time is defined as “time elapsed between the first contacts of two consecutive foot falls of the same foot expressed in milliseconds” (Beauchet et al., 2011), and numerous methods have been previously utilised to identify initial ground contact during running within tibial accelerometer data. Mercer et al. (2003) identified the minimum value before the absolute maximum value in the longitudinal axis as the beginning of foot strike. Mizrahi et al. (2000) identified the absolute maximum value in the longitudinal axis as the point of heel strike. However, there are numerous factors which may affect the ability to accurately and efficiently identify stride time from longitudinal accelerometer data streams utilising these, and similar, methods. Firstly, many studies which have utilised previous stride time calculation methods have done so during treadmill running protocols (Mercer et al., 2003;
Mizrahi et al., 2000), taking out any possible effect of alternate terrains on foot strike pattern and stride time calculation. Secondly, previous research (Mizrahi et al., 2000) has used secondary manual confirmation of heel strike through visual observation of data to avoid the inclusion of any "bad" data. These "bad data" may be representative of a stumble or fall, or may be due to sensor movement causing a "double peak" at heel strike. Manual confirmation to confirm the time of heel strike would be inefficient on longitudinal data sets, and where there are "double peak" error it is not possible to correctly distinguish the impact peak from the rebound peak, even using automated processes (Panther and Bradshaw, 2013). Thirdly, running patterns have been found to vary between individuals with different striking patterns, rearfoot and forefoot (Laughton et al., 2003), and may be altered by gait retraining programmes and shoe variation (Giandolini et al., 2013). This may affect the validity of using stride time calculation methods utilising heel strike (Mizrahi et al., 2000), across groups of runners. Lastly, peak tibial acceleration during impact has been found to reach up to 147.2 m/s^2 in running studies (Crowell et al., 2010; Flynn et al., 2004), and this may vary during self-paced running on various terrains (Giandolini et al., 2015). This may affect stride time calculation methods using thresholds (Meardon et al., 2011) in tibial acceleration peaks. The current study sought to investigate if stride time derived from 2 Hz filtered, medio-lateral tibial accelerometry data is comparable to previous methods. It is proposed 2 Hz filtered data may produce accurate and comparable results to previous methods, whilst being more efficient due to lack of manual intervention in producing stride time series in expansive, longitudinal data sets. It is also proposed that filtering running data at 2 Hz will retain the dynamics of stride time, whilst being less influenced by "double peak" error, individual foot strike patterns or various running terrains. The proposed method is not reliant on distinct peak acceleration values or individualised acceleration value threshold selection, associated with individual running styles. Lastly, the use of the medio-lateral axis to derive the beginning of ground contact has been previously validated (Purcell et al., 2006) and therefore the current authors wish to ascertain if, when filtered at 2 Hz, it provides comparable results. If valid, our novel method would provide an efficient, robust method of stride time calculation in longitudinal accelerometry data, without the need for manual intervention and/or stride time confirmation, or individualised acceleration thresholds. This would allow for efficient stride time calculation across groups of runners, providing valid results regardless of running style, terrain or pace.

2. Methods
2.1 Participants and instrumentation
Accelerometry data from six (one male, five female) recreational runners (age: 33.5 ± 5.8 years, stature: 1.66 ± 0.08 m, mass: 71.1 ± 12.2 kg) undertaking a half marathon training programme were utilised. During this half marathon training programme participants ran at a self-paced speed, which they could alter as they wished through alterations in stride time and stride frequency. Participants also ran on freely chosen terrain. This resulted in the extracted accelerometry data representing recreational running in its most natural, uncontrolled form, with variance between participants providing a range of tibial accelerometry data. Informed consent was collected prior to data collection. Participants were required to attach a tri-axial Shimmer 2r sensor (SHIMMER, Dublin, Ireland) to their antero-medial distal tibia bi-laterally for each training run (n= 48), and the event itself (total distance covered +340km) (Figure 1). Accelerometers were self-attached by the participants via a purpose built elastic strap (accelerometer mass: 28 g, combined accelerometer and strap mass: 48 g) with the sensor placed inward, toward the tibia, to prevent further movement. Prior to distribution a demonstration of sensor attachment was provided and sensors underwent static calibration every three weeks, following manufacturer 9DOF application methods. As sensor attachment is medial on the anterior tibia, the static calibration resulted in a local sensor coordinate system not directly aligned with the global coordinate system of the lower limb. Therefore, when attached the sensor allowed for the collection of an approximate estimate of tibial medio-lateral acceleration in the x axis, tibial vertical acceleration in the y axis and tibial anterior-posterior
acceleration in the z axis. When attached to the tibia a positive vertical acceleration was
directed proximally, positive medio-lateral acceleration was directed laterally and positive
anterio-posterior acceleration directed posteriorly. Data were sampled at 204.8 Hz (± 6 g,
sensitivity = 200 mV/g). Training comprised of four runs per week for twelve weeks of a
popular Hal Higdon (Hal Higdon 2014) half marathon 'novice' programme.

(Figure 1 Here)

2.2 Data analysis

For this analysis accelerometry data collected from the Shimmer 2r sensor attached to
each participants right leg were chosen from one randomly selected run (containing up to
7 million data points). Standing periods performed by the participants pre- and post each
run indicated run start and completion. Accelerometer run data were corrected for static
tilt, calculated during the standing period, with x and z axis corrected to 0 m/s² and y
corrected to +9.81 m/s². Preliminary data processing was performed for all files using a
custom built LabView (National Instruments, Newbury, UK) programme. Data containing
six consecutive impact peaks were chosen at random from the file, resulting in the
calculation of 5 strides for each participant. The number of strides derived was chosen due
to manual calculation of strides in methods 2, 3 and 4, and also as previous research
(Wixted et al., 2010) has utilised similar amounts of running data in accelerometer
validation studies. A total of four stride time calculation methods were compared; the
proposed method (M1) and three previously utilised methods, (Figure 2). M1 was custom
designed and proposed that medio-lateral accelerometer data were filtered at 2 Hz using a
Butterworth low-pass 4th order reverse filter. A 2 Hz filter cut-off was chosen as this cut off
will still retain the gross tibial acceleration pattern created due to swing, impact and
stance phases, however will negate any minor fluctuations which may be present and
could result in incorrect stride time calculation when automated. Filter order was the
same as that previously utilised to derive stride duration in accelerometry data (Mearon
et al., 2011; Mercer et al., 2002). Beginning and end of stride time was identified via a
positive zero crossing via a custom built LabView programme. Method 2 (M2) identified
heel contact as the minimum acceleration value before the absolute maximum (peak
impact) in the vertical axis of the tibia (Mercer et al., 2003). Method 3 (M3) identified the
peak or transient in the vertical axis of the tibia as heel strike occurrence (Mizrahi et al.,
2000). Method 4 (M4) identified the beginning of contact time as the maximum value in
the medio-lateral axis (Purcell et al., 2006). Accelerometer placement with previously
employed methods, M2 and M4, was the same as that utilised to collect the accelerometry
data in the present investigation, the anterio-medial distal tibia. However, M3 employed
accelerometer placement at the tibial tuberosity. Stride time data for M1 were calculated
via LabView whilst M2, M3 and M4 were calculated via Excel. Both single subject and
group analyses were undertaken. For single subject analysis distributional variability due
to method type was investigated in individual strides, using standard deviation. For group
analysis all stride times were grouped via method type (4 methods each containing 30
strides) and statistical analysis, in the form of a repeated measures analysis of variance
(ANOVA), was performed across the four methods. Furthermore, to investigate reliability
between M1 and the remaining three methods (M2, M3 and M4), within the group analysis
standard error (SEM), coefficient of variance represented as a percentage (CV %) and
intra-class correlation coefficients (ICC) were calculated using methods by Hopkins
(2015), previously outlined elsewhere (Gindre et al., 2016).

(Figure 2 Here)

3. Results

Results illustrated that there was no significant difference between methods to derive
stride time $F(3,87) = 0.03, p = 1.00$. To further uncover the practical applicability of our
method a comparison of individual stride times across methods was also undertaken
(Table 1). The minimum stride time across all participants was 0.677 seconds, whilst the
maximum stride time was 0.957 seconds, resulting in a stride frequency range of 1.04 –
1.48 Hz. All methods employed compared favourably to each other resulting in low standard deviations (0.002 – 0.017 seconds).

All ICC values were > 0.95, whilst all CV values were < 1.5% when comparing M1 and the remaining three methods (M2, M3, M4) (Table 2).

4. Discussion and Conclusion
Of the methods compared, M2 and M4 have been previously validated for heel strike occurrence (LaFortune 1991; Purcell et al., 2006). Therefore, using these methods to derive stride time represents a valid, accurate and accepted depiction of stride time, as defined by Beauchet et al. (2011). When compared to these methods, the method proposed here (M1) offers an accurate technique to derive stride time during running gait analysis. ICC and CV values reported (mean ICC = 0.99, mean CV = 1.12%) all indicate close agreement between the proposed method (M1) and the remaining 3 methods of stride time calculation (M2, M3 and M4). Also, current ICC and CV values are all in agreement with those previously found when deriving step frequency using three different methods (Myotest®, Optojump Next® and high speed video cameras) (mean ICC = 0.90, mean CV = 4%). Lastly, the stride frequencies present (1.04 – 1.48 Hz) represented a wider range of running stride frequencies than those found previously whilst investigating healthy recreational runners performing self-paced running (Zdziarski et al., 2015). Previous research (Purcell et al., 2006) indicates stride frequency rates above the present range, such as maximal sprint, retain the presence of a medio-lateral zero crossing and therefore indicates our novel method would also result in valid stride time calculation at higher stride frequency rates. Overall the proposed method offers an accurate and reliable method of stride time calculation. Whilst previous stride time calculation methods can be automated via the reoccurring detection of a maxima (Mizrahi et al., 2000), minima (Mercer et al., 2003) or threshold value (Meardon et al., 2011), these detection points can be highly variable, dependent on running style and terrain. Also, fluctuations surrounding maxima, minima and threshold values, such as double peaks containing two similar high magnitude values closely placed, may lead to incorrect stride time identification during automated processing (Sinclair et al., 2013). Therefore, using specific data point detection methods researchers may attempt to confirm detection points post data collection (Mizrahi et al., 2000). However, the current proposed method can be automated without manual intervention and utilised accurately across a variety of running styles and/or terrains, as minor fluctuations are significantly reduced and the data do not contain “double peak” error, due to the smoothing associated with 2 Hz filtering. Also, within these filtered data a medio-lateral zero crossing is a consistent reoccurring feature. This ability to output running stride parameters accurately and promptly may allow for the development of an automated feedback system based on the consistency or fluctuation of these parameters. This type of system may be useful for the recreational runner, high level athletes and researchers alike as it could output information related to both health and performance. Further research should investigate our proposed method when applied to a clinical field.

Acknowledgement
Funding for this research was provided by an Education and Health Sciences Faculty bursary, University of Limerick.

Conflict of interest statement
There is no conflict of interest.
References
<table>
<thead>
<tr>
<th>Participant</th>
<th>Method</th>
<th>Stride</th>
<th>M1 (s)</th>
<th>M2 (s)</th>
<th>M3 (s)</th>
<th>M4 (s)</th>
<th>Average (s)</th>
<th>SD (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td>0.728</td>
<td>0.718</td>
<td>0.708</td>
<td>0.713</td>
<td>0.717</td>
<td>0.009</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>0.718</td>
<td>0.723</td>
<td>0.728</td>
<td>0.722</td>
<td>0.723</td>
<td>0.004</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>0.722</td>
<td>0.717</td>
<td>0.717</td>
<td>0.723</td>
<td>0.720</td>
<td>0.003</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td>0.703</td>
<td>0.718</td>
<td>0.713</td>
<td>0.713</td>
<td>0.712</td>
<td>0.006</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>0.723</td>
<td>0.718</td>
<td>0.728</td>
<td>0.722</td>
<td>0.723</td>
<td>0.004</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td>0.693</td>
<td>0.684</td>
<td>0.683</td>
<td>0.689</td>
<td>0.687</td>
<td>0.005</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>0.689</td>
<td>0.688</td>
<td>0.694</td>
<td>0.688</td>
<td>0.690</td>
<td>0.003</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>0.693</td>
<td>0.698</td>
<td>0.693</td>
<td>0.694</td>
<td>0.694</td>
<td>0.002</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td>0.689</td>
<td>0.679</td>
<td>0.683</td>
<td>0.683</td>
<td>0.684</td>
<td>0.004</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>0.693</td>
<td>0.703</td>
<td>0.699</td>
<td>0.698</td>
<td>0.698</td>
<td>0.004</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td>0.708</td>
<td>0.708</td>
<td>0.708</td>
<td>0.703</td>
<td>0.707</td>
<td>0.002</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>0.698</td>
<td>0.684</td>
<td>0.693</td>
<td>0.688</td>
<td>0.691</td>
<td>0.006</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>0.708</td>
<td>0.718</td>
<td>0.713</td>
<td>0.713</td>
<td>0.713</td>
<td>0.004</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td>0.703</td>
<td>0.703</td>
<td>0.698</td>
<td>0.703</td>
<td>0.702</td>
<td>0.002</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>0.698</td>
<td>0.698</td>
<td>0.698</td>
<td>0.703</td>
<td>0.699</td>
<td>0.002</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td>0.708</td>
<td>0.703</td>
<td>0.718</td>
<td>0.737</td>
<td>0.717</td>
<td>0.015</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>0.708</td>
<td>0.719</td>
<td>0.703</td>
<td>0.679</td>
<td>0.702</td>
<td>0.017</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>0.713</td>
<td>0.688</td>
<td>0.703</td>
<td>0.703</td>
<td>0.702</td>
<td>0.010</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td>0.703</td>
<td>0.728</td>
<td>0.718</td>
<td>0.742</td>
<td>0.723</td>
<td>0.016</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>0.708</td>
<td>0.693</td>
<td>0.689</td>
<td>0.669</td>
<td>0.690</td>
<td>0.016</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td>0.718</td>
<td>0.698</td>
<td>0.708</td>
<td>0.708</td>
<td>0.708</td>
<td>0.008</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>0.698</td>
<td>0.708</td>
<td>0.698</td>
<td>0.693</td>
<td>0.699</td>
<td>0.006</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>0.703</td>
<td>0.688</td>
<td>0.703</td>
<td>0.703</td>
<td>0.699</td>
<td>0.007</td>
</tr>
<tr>
<td>Participant</td>
<td>Stride</td>
<td>Method</td>
<td>M1 (s)</td>
<td>M2 (s)</td>
<td>M3 (s)</td>
<td>M4 (s)</td>
<td>Average (s)</td>
<td>SD (s)</td>
</tr>
<tr>
<td>-------------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>-------------</td>
<td>--------</td>
</tr>
<tr>
<td>1</td>
<td>0.923</td>
<td>0.957</td>
<td>0.938</td>
<td>0.942</td>
<td>0.940</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.942</td>
<td>0.913</td>
<td>0.913</td>
<td>0.908</td>
<td>0.919</td>
<td>0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.938</td>
<td>0.952</td>
<td>0.952</td>
<td>0.947</td>
<td>0.947</td>
<td>0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.933</td>
<td>0.938</td>
<td>0.938</td>
<td>0.938</td>
<td>0.936</td>
<td>0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.942b</td>
<td>0.947</td>
<td>0.942b</td>
<td>0.952</td>
<td>0.946</td>
<td>0.005</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Stride time (s) calculations for all participants. a indicates the greatest difference in stride time, whilst b indicates no difference in stride time, compared to proposed M1. The greatest and least SD values are also denoted in bold.

<table>
<thead>
<tr>
<th>Method</th>
<th>M2</th>
<th>M3</th>
<th>M4</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEM</td>
<td>0.008</td>
<td>0.007</td>
<td>0.010</td>
</tr>
<tr>
<td>CV%</td>
<td>1.077</td>
<td>0.942</td>
<td>1.346</td>
</tr>
<tr>
<td>ICC</td>
<td>0.994</td>
<td>0.996</td>
<td>0.992</td>
</tr>
</tbody>
</table>

Table 2. Reliability statistics (standard error, coefficient of variance (%) and intra-class correlation coefficients) calculated using the proposed method (M1) against the remaining three methods (M2, M3 and M4).

Figure 1.
Figure 1. Bi-lateral accelerometer attachment to the anterio-medial distal tibia. Only data collected from the accelerometer attached to the right tibia was used in this investigation. On a concentrated section of the right tibia, positive axial directions of the accelerometer local coordinate system when attached are superimposed in bold arrows, with vertical and lateral directions of the lower limb global coordinate system superimposed in dashed arrows.

Figure 2. Acceleration patterns (m/s^2) for a representative two second running trial. Identification of beginning/end of stride times for M1, M2, M3 and M4 as identified by the circle.

Figure Caption List

Figure 1. Bi-lateral accelerometer attachment to the anterio-medial distal tibia. Only data collected from the accelerometer attached to the right tibia was used in this investigation. On a concentrated section of the right tibia, positive axial directions of the accelerometer local coordinate system when attached are superimposed in bold arrows, with vertical and lateral directions of the lower limb global coordinate system superimposed in dashed arrows.

Figure 2. Acceleration patterns (m/s^2) for a representative two second running trial. Identification of beginning/end of stride times for M1, M2, M3 and M4 as identified by the circle.