An Exploration of Eliminating Cross-Talk in Surface Electromyography using Independent Component Analysis

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Abstract— the purpose of this study was to explore the use of Independent Component Analysis (ICA) on surface Electromyography (EMG) data to distinguish between individual muscle activations due to its capabilities for signal separation. EMG data was gathered on seven participants using the Delsys Trigno Wireless EMG system. Participants performed specific movements which targeted the calves muscle group of the lower leg. EMG sensors were attached according to SENIAM recommendations and extra sensors were attached in non-recommended locations to achieve crosstalk. Signals were acquired using proprietary Delsys software and processed using the ICA algorithm in Matlab to explore crosstalk. Integrated EMG was calculated for all results using custom Matlab code. The results showed moderate levels of agreement between the ideal EMG locations and the original signals (p < 0.01). However, further work is needed to determine the usefulness of the independent components.

Keywords—ICA, EMG, data analysis, signal processing

I. INTRODUCTION

Cross talk is a common problem associated with surface Electromyography (sEMG). Due to the non-invasive nature of surface mount sensors their use is limited to superficial muscles; isolation of the activity of just one muscle is difficult. Multiple muscles contribute to a movement which may cause electrical activity from adjacent muscles to be picked up and “mixed-in” by the sEMG sensor over the muscle of interest. The combined signal is gathered and analyzed, with the user being unaware if cross talk is contained and how much [1].

EMG data is non-Gaussian and statistically independent; fitting the criteria for ICA [2] and therefore has been used in studies to isolate EMG data from other electrical activity. ICA has been used on the removal of artifacts due to ECG [3], and EKG [4], along with signal classification [2] are some examples. In [5], a novel blind source separation algorithm to remove electrical cross-talk in EMG activity from hand and forearm muscles was proposed. ICA can also be used in signal decomposition [6, 7].

The aim of this study is to explore the use of ICA on EMG signals to reduce cross talk from the gathered data, isolating individual muscle contributions. The integrated EMG was calculated for both ideal EMG locations and for outputs of the ICA algorithm. This was used for statistical analysis. Descriptive statistics, Student t-tests, Bland-Altman limits of agreement and interclass correlation coefficients (ICC) with 95% Confidence Intervals (CI) were calculated.

II. BACKGROUND

A. Theory of Independent Component Analysis

ICA is a dimension reduction technique which can return data that was originally hidden from the larger data set. Components or factors are found in multi-dimensional statistical data. The data should be non-Gaussian and components should be statistically independent. Principal Component Analysis (PCA) and Blind Source Separation (BSS) preceded ICA; they have many uses such as reducing the data set by extracting features and separating signals using weighted sums [8].

The “cocktail party problem” is the common analogy used when describing the use of ICA [9]. Take for example a group people speaking simultaneously at one side of the room and two people listening in two separate locations at the opposite side of the room. Both of the listeners are receiving a mixture of the speech signals from the group of speakers, denoted as $x_1(t)$ and $x_2(t)$. The emitted speech signals from two of the group can be denoted as $s_1(t)$ and $s_2(t)$. The received signals can be expressed as a weighted sum of the speech signals, shown as linear equations [10]:

$$x_1(t) = a_{11}s_1 + a_{12}s_2$$  \hspace{0.5cm} (1)

$$x_2(t) = a_{21}s_1 + a_{22}s_2$$  \hspace{0.5cm} (2)
Where, $a_{ij}$ can be denoted by the matrix $A$, $a_i$ are parameters that depend on the distance of the listeners from the speakers $(a_{i1}, a_{i2}, a_{i3}, a_{i4})$. By using matrix notation, $x$ can be the random vector of the mixtures $x_1$ and $x_2$ and $s$ the random vector with the speech signal $s_1$ and $s_2$. The mixing model for ICA can thus be written as [10]:

$$x = As \tag{3}$$

To solve this problem, the assumption that $s_1(t)$ and $s_2(t)$ are statistically independent must be made. The estimation of $a_{ij}$ based on their independence allows the separation of the two original source signals $s_1(t)$ and $s_2(t)$ from their mixtures $x_1(t)$ and $x_2(t)$ using ICA.

### B. Suitability of EMG signals for use with ICA algorithm

The criteria necessary to satisfy the conditions of ICA as are as follows:

- Components must be statistically independent
- Independent components must be non-Gaussian

Kurtosis, the normalized version of the fourth moment $E[y^4]$ is the classical measure of non-Gaussianity. The kurtosis of $y$ is defined by [10]:

$$kurt(y) = E[y^4] - 3E[(y^2)^2] \tag{4}$$

For a non-Gaussian random variable kurtosis is non zero; random variables with negative kurtosis are called subgaussian and with positive kurtosis are called supergaussian [10].

The muscle electrical activity of muscle contraction satisfies each of the criteria for ICA. Each muscle can be assumed to be an independent source, as the set of motor units in each muscle are well separated from the other muscles. Similarly, the muscle activity can be assumed to be made of independent motor unit action potentials (MUAP). These MUAPs are individual pulses and the finite sum of these is non-Gaussian [11].

### C. Limitations

There are certain limitations to this paper. The first is that the mixing matrix is assumed to be fixed throughout the exercise. Analysis needs to be done on the variation of the mixing matrix. The possibility to reduce the EMG data for processing might result in less chance of variation in the mixing matrix, but is not addressed in this work. The second limitation, again to do with the mixing matrix, is the fact that the scaling factor is unknown. The resultant outputs of the ICA algorithm return the original sources but scale, sign and order are not preserved.

### D. Related Work

ICA was originally developed to deal with the “cocktail party problem”; isolating electrical activity shares many similarities [12]. ICA has many different applications in interesting areas such as audio processing, image processing, biomedical signal processing and telecommunications. The area of biomedical signal processing has a variety of examples where ICA can be of use [13], including the following.

One particular study gathers scalp Electroencephalogram (EEG) recordings of seizures from epileptic patients [14]. By making use of ICA to remove a significant portion of artefacts obscuring the EEG activity, the interpretability of seizures recorded on scalp EEG was improved. A noise reduction procedure is proposed in another study for magnetoencephalography (MEG) signals using ICA [15]. Good performances were shown for both the simulated and real MEG data, which suggests that separation of different cerebral activity sources may be possible. Similarly, another noise reduction study using independent component analysis (ICA) is presented [16]. Once the noise is removed the enhanced independent components are reconstructed to obtain clean original signals. To show the validity and effectiveness of the proposed approach simulations and real EEG data are used.

Image processing is another interesting application of ICA. Studies have looked at a new perspective on image processing using ICA [17] and mixture models [18]. The method was effective in classifying complex image textures and useful for removing noise and filling in missing pixels in images. Another study uses ICA to remove a reflection from an image [19]. The reflective image is extracted from the mixed image.

The use of ICA in audio processing is another application of this algorithm [20]. One paper makes use of ICA and BSS to separate a mixture of audio signals [21]. Results are shown to be effective for this application. Another study uses ICA to separate audio signals [22]. The method can isolate two or three independent signals from the mixed audio signal.

### III. METHODOLOGY

#### A. Test Protocol

Seven volunteers, four males (mean age ±standard deviation, 23.25 ±3.14 years) and three females (mean age ±standard deviation, 23.67 ±3.4 years), who were injury free at the time of testing, participated in this study. Ethical approval was granted by the local University Research Ethics Committee and all participants provided informed consent in writing before testing. All participants were familiar with variations of the calf raise exercise.

Participants performed a standardized warm-up, consisting of 2 minutes of running at a self-selected, comfortable pace followed by short dynamic stretches and drills (forward and sideways skips with arm swings, high
knees, hamstring stretch, bodyweight squats, and lunges). EMG electrodes were attached after the warm-up. Skin was prepared and electrodes were positioned according to SENIAM recommendations [23, 24]. Data was gathered while participants performed five repetitions of sitting calf raises and five repetitions of standing calf raises; which isolate the calves muscle group of the lower leg.

B. Hardware
EMG signals were obtained using the Delsys Trigno™ Wireless EMG System [25]. Electrodes were attached to the Lateral Gastrocnemius (LG), Medial Gastrocnemius (MG) and Soleus (SOL) on the dominant leg according to SENIAM guidelines. Two extra electrodes were attached in non-ideal locations so as to purposefully gather cross talk data. Figure 1 shows an example of the electrode placement on the lower leg.

C. Data Analysis
EMG data was gathered using proprietary Delsys software. All signal processing was performed offline. After acquisition, the data was exported and custom Matlab code was used to analyze the results. EMG data was sampled at 1925.93 Hz, the fixed rate for this system. The built-in kurtosis function was used to check the suitability of EMG signals for ICA. An average kurtosis value of 18.94 was returned. The ICA algorithm used in this process was the fastICA package [26]. A mixed signal matrix was created with data from three of the combination of sensors for each movement, in multiple combinations. Each mixed matrix was then analyzed using the fastICA package and subsequently compared to the signals gathered from the sensors in recommended locations. Figure 2 shows this process.

Figure 1: Electrode placement on the lower leg

Figure 2: The ICA analysis model

Five EMG signals were gathered, a matrix of three signals was created from multiple combinations of these gathered signals. The inputs into the fastICA algorithm above use the following notation: \(m(x, y, z)\) is one signal from the matrix created, \(x\) is the participants’ number, \(y\) is matrix number and \(z\) is the signal number from that matrix. The output arguments returned are three EMG signals which have a similarity to the ideal signal placements. These are denoted with the muscle name with a bar to show that they are not the ideal signals.

The integrated EMG (iEMG) was calculated for each signal. To calculate the iEMG first the DC offset of the raw EMG had to be removed, full wave rectification was then performed and finally a linear envelope was created. The integral of the linear envelope is the iEMG. An example of the full post processing of the raw EMG signal can be seen in Figure 3. Limitations in the calculation of iEMG for ICA outputs exist due to the fact that ICA does not preserve scale. It is assumed that a scaling factor of \(10^{-4}\) exists on all outputs of the ICA algorithm. To counteract this all iEMG values were multiplied by \(10^4\).
D. Statistical Analysis

All statistical analysis was done using SPSS for Windows. The iEMG of the analyzed signals and the original ideal signals were compared using Bland-Altman limits of agreement and ICC with 95% CI. Student t-tests were performed to analyze the significance of the differences between the iEMG in both the mixed signal and the original ideal signals.

IV. RESULTS

Table 1 shows the mean muscle activations (±SD) for the LG, MG and SOL for the sitting calf raises exercise.

<table>
<thead>
<tr>
<th></th>
<th>Lateral Gastrocnemius</th>
<th>Medial Gastrocnemius</th>
<th>Soleus</th>
</tr>
</thead>
<tbody>
<tr>
<td>iEMG ideal ± SD (mV)</td>
<td>0.731 ±0.654</td>
<td>0.502 ±0.340*</td>
<td>0.634 ±0.387*</td>
</tr>
<tr>
<td>iEMG of ICA output ± SD (mV)</td>
<td>1.268 ±0.336</td>
<td>1.260 ±0.348*</td>
<td>1.449 ±0.396*</td>
</tr>
<tr>
<td>% Difference</td>
<td>73.45</td>
<td>151.23</td>
<td>128.57</td>
</tr>
<tr>
<td>Systematic Bias</td>
<td>-0.537</td>
<td>-0.759</td>
<td>-0.815</td>
</tr>
<tr>
<td>ICC (between ideal &amp; ICA outputs)</td>
<td>0.249</td>
<td>0.221</td>
<td>0.723</td>
</tr>
<tr>
<td>(95% CI)</td>
<td>(-3.368 - .871)</td>
<td>(-3.532 - .866)</td>
<td>(-0.612 - .952)</td>
</tr>
<tr>
<td>ICC (on all outputs of ICA)</td>
<td>0.968</td>
<td>0.973</td>
<td>0.981</td>
</tr>
<tr>
<td>(95% CI)</td>
<td>(0.880 - 0.994)</td>
<td>(0.898 - 0.995)</td>
<td>(0.928 - 0.996)</td>
</tr>
</tbody>
</table>

*<p<0.01

The LG returned an ICC of 0.249 when compared with iEMG from the EMG signal gathered at the ideal sensor location and the iEMG of the average output from the ICA algorithm for the LG using sensors from other locations on the calves. Similarly the MG returned an ICC of 0.221 and the SOL returned an ICC of 0.723. In a comparison of iEMG on all the outputs from the ICA algorithm, the LG returned an ICC 0.968, the MG returned an ICC of 0.973 and the SOL returned an ICC of 0.981. Student t-tests returned a p value less than 0.01 for both the MG and SOL; the results were not significant for LG.

Table 2 shows the mean muscle activations (±SD) for the LG, MG and SOL for the standing calf raises exercise. The LG returned an ICC of 0.985 when compared with iEMG from the EMG signal gathered at the ideal sensor location and the iEMG of the average output from the ICA algorithm for the LG using sensors from other locations on the calves. Similarly the MG returned an ICC of 0.237 and the SOL returned an ICC of 0.525. In a comparison of iEMG on all the outputs from the ICA algorithm, the LG returned an ICC 0.898, the MG returned an ICC of 0.920 and the SOL returned an ICC of 0.998. Student t-tests returned a p value of less than 0.01 for the LG, results were not significant for the MG and SOL.

Table II. Comparison of Integrated EMG (iEMG) for ideal EMG signals and outputs from the ICA algorithm for standing calf raises

<table>
<thead>
<tr>
<th></th>
<th>Lateral Gastrocnemius</th>
<th>Medial Gastrocnemius</th>
<th>Soleus</th>
</tr>
</thead>
<tbody>
<tr>
<td>iEMG ideal ± SD (mV)</td>
<td>0.891 ±0.356*</td>
<td>2.446 ±1.68</td>
<td>1.529 ±1.056</td>
</tr>
<tr>
<td>iEMG of ICA output ± SD (mV)</td>
<td>1.232 ±0.350*</td>
<td>1.271 ±0.404</td>
<td>1.372 ±0.405</td>
</tr>
<tr>
<td>% Difference</td>
<td>38.19</td>
<td>-48.04</td>
<td>-10.31</td>
</tr>
<tr>
<td>Systematic Bias</td>
<td>-0.34</td>
<td>1.18</td>
<td>0.16</td>
</tr>
<tr>
<td>ICC (between ideal &amp; ICA outputs)</td>
<td>0.985</td>
<td>0.237</td>
<td>0.525</td>
</tr>
<tr>
<td>(95% CI)</td>
<td>(0.910 – 0.997)</td>
<td>(-3.440 – 0.869)</td>
<td>(-1.763 – 0.918)</td>
</tr>
<tr>
<td>ICC (on all outputs of ICA)</td>
<td>0.898</td>
<td>0.920</td>
<td>0.998</td>
</tr>
<tr>
<td>(95% CI)</td>
<td>(0.621 – 0.981)</td>
<td>(0.702 – 0.985)</td>
<td>(0.994 – 1.000)</td>
</tr>
</tbody>
</table>

*p<0.01

V. DISCUSSION

Results of this investigation identified that the ICA algorithm is a successful tool which can be used to distinguish between individual muscle activations. Results showed moderate agreement between the output from the ICA algorithm and the ideal EMG signals. However, these
ideal EMG signals may still be picking up cross talk from neighboring muscles groups. With sEMG we have no way of knowing if these ideal placements are picking up the isolated signal from that muscle or if we are still receiving cross talk from other muscle groups as well. Therefore for this study we are making the assumption that the ideal sensor placements are returning the ideal signals with minimal crosstalk.

The sitting calf raises exercise predominately used the SOL muscle which sits underneath the MG and LG. It is clear from the results that by isolating the SOL we receive crosstalk on the electrodes from the SOL into the neighboring muscles i.e. LG and MG. Similarly in the standing calf raises we are predominately using the MG and LG. The SOL has less work to do in this exercise and therefore from the results we can see that crosstalk from the LG can be seen in the signal picked up by the electrodes at the SOL. Using the ICA algorithm on these signals resulted in the original SOL, LG and MG muscle activity. The algorithm was able to isolate the true signal from each of these muscles and return the actual signal without the interference of crosstalk.

A moderate to high agreement was found between them which lead to the conclusion that the results of the ICA algorithm may be returning the actual ideal EMG signals for the specific muscle groups. Highlighting that in fact maybe the ideal sensor placements will still pick up crosstalk no matter how careful you are with electrode placement. Further research into the use of this algorithm needs to be done to make results more accurate and reliable and to look into what the actual muscle activations are for each muscle during specific exercises. It is necessary to note that true EMG signals may not be possible with sEMG and indwelling electrodes may need to be explored for more accurate results.

VI. CONCLUSION
This study clearly identifies ICA can be used in the removal of crosstalk from sEMG signals. ICA is an algorithm used for signal separation in many other areas and this study showed that it is possible to use it from sEMG measures of lower leg activity also. The one major area of limitation is the fact that with surface measures it is not known if the signals gathered are actually the ideal. Further work making use of indwelling electrodes may be necessary to find out the true signal from the individual muscles. This could then be used as the control when comparing outputs from various ICA algorithms to find out which methods if any can be used to minimize crosstalk in surface measurements.

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REFERENCES


