Multi-step Independent Component Analysis for Removing Cardiac Artefacts from Back SEMG Signals

D Djuwari
SECE, RMIT University
RMIT City Campus, Swanston Street
Melbourne - Australia
s3001068@student.rmit.edu.au

D K Kumar
SECE, RMIT University
RMIT City Campus, Swanston Street
Melbourne - Australia
dinesh@rmit.edu.au

SC Ragupathy
SECE, RMIT University
RMIT City Campus, Swanston Street
Melbourne - Australia
s2116958@student.rmit.edu.au

B Polus
LS, RMIT University
RMIT Bundoora West Campus
Melbourne - Australia
barbara.polus@rmit.edu.au

Abstract

The Electromyogram (EMG) signals recorded from the back muscles often contain large electrocardiogram (ECG) artefacts. For better interpretation of these SEMG signals, it is essential to remove ECG artefacts. This paper reports research conducted to address the problem of removing ECG artefacts from SEMG recordings using new approach of Independent Component Analysis (ICA) called Multi-step ICA. The technique isolates the ECG artefact first and then removes the ECG artefact from each channel and solves permutation problem simultaneously. The results have been validated using standard deviation reduction of the normalised RMS amplitude of the data after separation process. The results demonstrate that this new proposed technique is successful in removing ECG artefacts from SEMG signals.

1. Introduction

Electromyogram (EMG) is the recording of the electrical activity of muscles. The EMG is usually recorded using monopolar or bipolar needle electrodes or surface electrodes. With needle EMG, it is possible to examine the activity of individual motor units while surface EMG (SEMG) is useful for examining the gross activity of a muscle or a group of muscles [6]. SEMG is a non-invasive technique and provides knowledge of the activation of the muscle of interest for a specific activity or posture and the relative strength of contraction [10]. One difficulty with SEMG is cross talk among the signals from adjacent electrodes and the recording of electrical activity from other sources. For accurate information of the activity of muscles it is important to ensure that SEMG is noise and artefact free and the recording represents the activity of the selected muscles.

SEMG of lumbar erector spine muscles (LESM) has been used frequently in applied physiology for the assessment of back muscle function during various activities [9]. Researchers have attempted to use the magnitude of the SEMG for the analysis of the relative strength of contraction of the paraspinal muscles for the diagnosis of lumbar back ailments [1]. However, SEMG of lumbar paraspinal muscles may record the activity from several different muscles during static postures. Before the clinical and research utility of the SEMG for this task can be assessed, it is essential that issues of reliability and validity of the SEMG of lumbar paraspinal muscles be addressed. The ability of the SEMG to reliably record the relative strength of contraction of specific lumbar paraspinal muscles during the maintenance of a specific static posture is an important preliminary step in the validation procedure.

During SEMG recordings of multifidus muscle activity in different static postures the reliability of the SEMG signal is a major concern with issues such as electrode placement and high noise content in the recordings needing to be addressed. The development of a reliable objective measure of muscle activity would allow investigation into treatment outcomes and the role of muscle dysfunction in the maintenance or generation of LBP [9]. Recordings of SEMG from the back and abdomen muscles are contaminated by strong ECG signals making the raw signal unsuitable for analysis, confirming the findings of other researchers [11]. Therefore a technique to remove ECG artefact from SEMG recordings of the back is essential.

The commonly used techniques to remove noise such as high-pass filtering [13], spectral filtering [8], gating and cross-correlation subtraction [3] are not suitable. Each of these techniques has drawbacks that make them unsuitable for this application. Due to spectral overlap between ECG and SEMG, frequency filtering is unsuitable for this purpose. Gating, removing or deleting part of the SEMG that contains ECG adds discontinuities and makes the output unreliable since there must be some discontinuity in the joint point. Further, this technique is based on removing the QRS complex from the signal, often not the only source of contamination.

ECG and SEMG are statistically independent signals. Thus Independent Component Analysis (ICA) can be used to remove ECG artefact from SEMG recordings. ICA is a technique used to estimate two independent signals from a mixture of the two signals based on their independence to each other. It has been used to estimate and separate breathing artefacts from ECG recordings and results demonstrate the enhancement of cardiac signal quality with the use of ICA technique [16]. It has also been used to estimate and separate ECG artefact, noise and pure SEMG signal from synthetic mixture signals (one pure ECG signal and any two EMG signals that were linearly combined using 3x3 mixing matrix) using fixed-point algorithm but not with the real raw EMG signals from the recording [15]. A recently published paper reports success in the application of ICA to detect the underlying functional muscle activations during swallowing and successfully detect the presence of ECG and exclude it from the analysis. ICA was used to separate the 8 largest principle components of raw SEMG to obtain the signals representing each of the independent sources [11].

The ICA techniques described above were used in situations where the number of sources and recordings were the same. These methods are suitable where the prior knowledge of the type of independent component is known (such as pure ECG, abrupt signal and white noise) [14]. The other shortcoming of ICA is the ambiguity in permutation and amplitude [5]. Thus, ICA in the conventional form is not suitable for removing the ECG artefact from pre-recorded data where there is no extra channel that has simultaneously recorded ECG along with SEMG.

This paper presents a modification of ICA to overcome the shortcomings mentioned above. This technique successfully removes the ECG artefact from SEMG recordings from the muscles of the lumbar back. It overcomes the ambiguity of the permutation and amplitude and does not require an extra channel recording of ECG in parallel with SEMG. This is important for the analysis of the muscle activation for posture control.

1.1 Independent Component Analysis (a brief)

ICA was originally developed to deal with problems that are similar to the cocktail party problem. In a simplified situation, imagine 4 people are sitting together and talking to each other in a room that is equipped with 4 randomly distributed microphones. Each microphone will record a mixture of the 4 voices but with a different composition based on the relative location. The objective of ICA is to estimate the individual voice of each person, given only the recorded signals from those 4 microphones without having any knowledge about their location or their speech properties. Using ICA, the four recordings are separated to provide four sound signals that are independent to each other and thus are from each of the four speakers by suitably remixing the recordings.

ICA is based on some fundamental assumptions. Some of these have been listed below:

The first assumption is that the number of mixtures is greater than or equal to the number of independent sources.

The mixtures are linear combinations of the sources and there is no delay or external noise included.

The sources are stationary and are not moving during the recording process.

There is a constant effort by research groups to overcome the limitations of these assumptions.

A basic formulation of ICA can be expressed mathematically as [5]:

$$\begin{aligned} x_1(t) &= a_{11}s_1(t) + a_{12}s_2(t) \\ x_2(t) &= a_{21}s_1(t) + a_{22}s_2(t) \end{aligned} \tag{1}$$

or in general form (matrix notation)

$$\boldsymbol{x} = \boldsymbol{A}^*\boldsymbol{s}, \tag{2}$$

where $\boldsymbol{x}$ is the vector of the mixtures, $\boldsymbol{A}$ is the unknown mixing matrix, and $\boldsymbol{s}$ is the vector of unknown independent components. The goal of ICA is finding an unmixing matrix $\boldsymbol{W}=\boldsymbol{A}^{-1}$ using neural networks.

Bell and Sejnowski have proposed a simple ICA algorithm based on an information maximization approach or minimization of mutual information among the outputs of neural network [4]. Mutual information is a natural measure of the dependence between random variables. The greater the mutual information, the more dependent are the variables. For this purpose, it is important to determine a suitable contrast function ***g(u)*** for the neurones of the network because the high density part of the probability density function (*pdf*) of $\boldsymbol{x}$ should be aligned with highly sloping part of ***g(u)***. Mutual information of the output vector **y** is defined as [5]:

$$I(y_1, y_2, \ldots, y_n) = \sum_{i=1}^{n} H(y_i) - H(y) \tag{3}$$

Bell and Sejnowski have shown that minimizing mutual information $\boldsymbol{I}(\boldsymbol{y})$ among the output components is equal to maximizing their joint entropy $\boldsymbol{H}(\boldsymbol{y})$ with respect to the weighting matrix, $\boldsymbol{W}$. The learning ruled derived by maximizing this joint entropy with respect to $\boldsymbol{W}$ is [7]:

$$\Delta W \propto \frac{\partial H(y)}{\partial W} W^T W = [I + \dot{p}u^T]W \tag{4}$$

where $\dot{p} = \frac{\partial}{\partial u_i} \ln\left(\frac{\partial y_i}{\partial u_i}\right)$ and $\boldsymbol{u} = \boldsymbol{W}^*\boldsymbol{x}$.

If the contrast function $\boldsymbol{g}(\boldsymbol{u}) = \tanh(\boldsymbol{u})$ then:

$$\Delta W \propto \frac{\partial H(y)}{\partial W} W^T W = [I + 2\tanh(u)u^T]W \tag{5}$$

This is the learning rule used in the ICA algorithm to separate different sources from mixed recordings.

1.2 Multi-step ICA

The ICA technique has certain limitations such as lack of certainty of permutation and amplitude of the independent components. When applied to remove biosignal artefacts, the need for ICA to have as many channels as sources becomes a major limitation, as it requires an extra recording channel that would provide the information of the artefact. Thus it is not possible to apply ICA directly to remove the ECG artefact from 4 raw SEMG signals with the goal to obtain 4 clean SEMG signals. If the input of ICA algorithm is 4 raw EMG signals, the output will be 4 independent components where one of them is the ECG component while the other three are mixtures of the 4 EMG signals and are unsuitable for further analysis. Therefore, a new approach is needed in this situation to solve the problem.

The technique proposed here is called Multi-step ICA since it uses more than one step to get the clean EMG signals. The rationale of this is based on the fact that ECG is an independent signal that appears in each channel and identifying this would provide us information for the fifth channel. The detail description of this method is shown in figure 1. In the first step, the four raw SEMG signals from each channel are given as the input of ICA algorithm. The output of this separation process is 1 pure ECG signal and 3 SEMG mixture signals. Because of permutation problem of ICA, a short algorithm was used to get the pure ECG part for further processing. This algorithm discards the peak amplitude of abrupt noise by applying a 10-point moving average filter, detects the *R-S* value of the ECG that is much higher than any other part of the separated signals and gets the index of ECG signal. The ECG now becomes the first independent component that obtained from this ICA step.

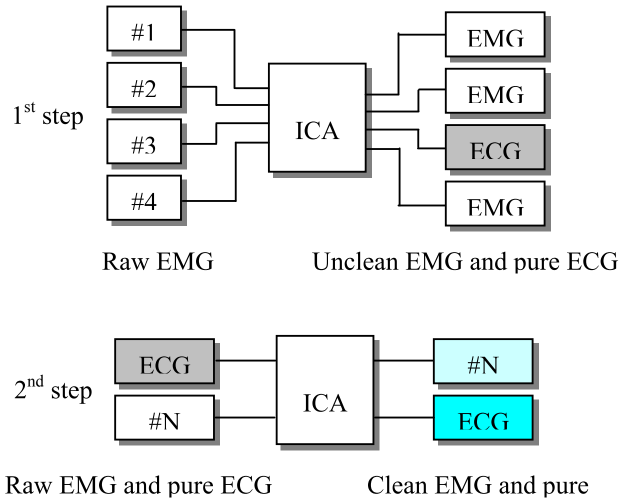

Figure 1: Cardiac artefact removal procedure by Multi-step ICA

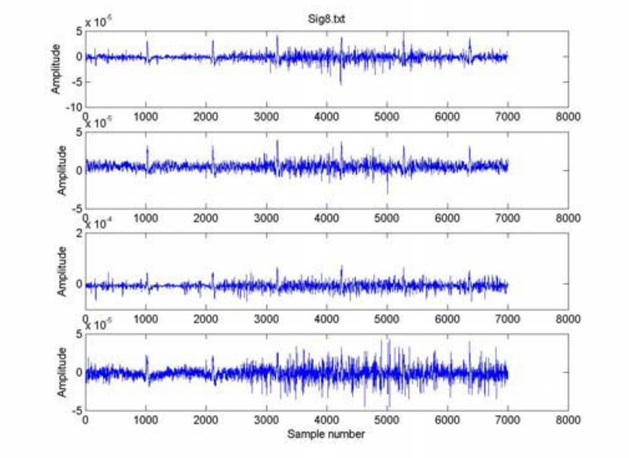

Figure 2: Four raw SEMG signals as an input to the first step ICA

The second step has one raw SEMG signal from a single channel and the ECG signal obtained from the previous process as the input to the ICA algorithm. The output of this process is 1 pure ECG and 1 clean SEMG for the particular channel. A similar algorithm as used in the previous step was used to detect the clean SEMG signal. This process is repeated for all the channels. Figure 2, 3 and 4 illustrate the waveform of the raw signals, first and second step ICA outputs respectively.

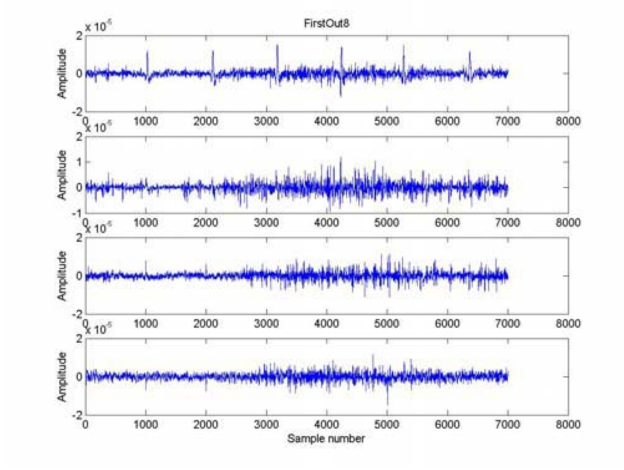

Figure 3: One ECG and three mixed SEMGs as the output of the first step ICA

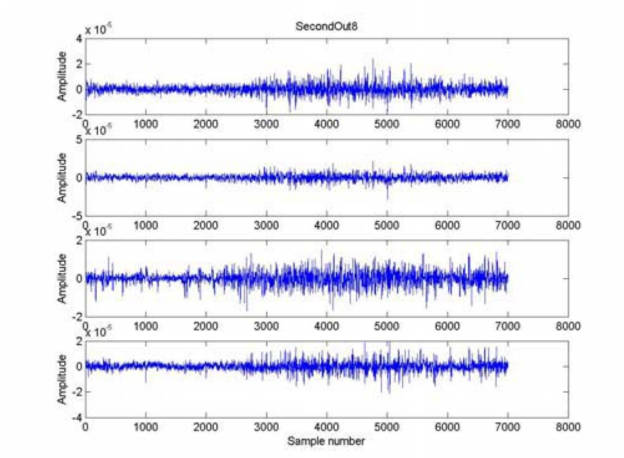

Figure 4: Four clean SEMGs as the output of the second step ICA

2. Materials And Methods

2.1 SEMG Recordings

SEMG recording was done using a 4-channel PowerLab data acquisition system (ADInstrument, Castle Hill, NSW, Australia) on 11 subjects on 2 days. The subjects were healthy males and females with ages ranging from 20 to 60 years old. The sampling rate was selected at 1000 sample/second and with antialiasing, high pass and notch filters having cut-off at 200 Hz, 3 Hz and 50 Hz respectively. The 4 channels were connected to 4 surface electrodes attached on the back muscles located on the left (ch.#3 and ch.#4) and right (ch.#1 and ch.#2) sides of the spinal cord. The recording was done while the subjects were in specified normal sitting and standing positions. It was observed that most of the SEMG recordings were a mixture of SEMG and ECG. It was also observed that often the ECG (the artefact) strength was much greater than SEMG signal. A total of 31 recordings (containing 4 channels) were used for this experiment.

2.2 Signal Analysis

All SEMG recordings were saved in a *.txt format and then transferred to Matlab (Mathworks.Inc) for further processing. The ICA algorithm developed by Bell and Sejnowski [4] was used in the first and second step ICA calculation. The proposed technique Multi-step ICA explained above was applied to each SEMG recording to remove the ECG artefact. The outputs of this artefact removal process were saved again in the text format for further statistical analysis.

2.3 Validation of Results

SEMG, based on changes in amplitude and frequency, is a useful indicator for the strength of muscle contraction and muscle status. Comparison of SEMG magnitude from different locations of the back has been considered as a useful indicator of the relative contraction of the lumbar muscles and for information regarding posture control of the subject. Root Mean Square (RMS) is considered to be a good indicator of the strength of contraction of the muscles.

The RMS amplitude (energy) of a signal ***x(n)*** is defined as [2]:

$$RMS\{x(n)\} = \sqrt{\left(\frac{1}{N-1}\sum_{0}^{N-1} x^2(n)\right)} \qquad (6)$$

With the presence of ECG in the SEMG, the RMS of SEMG may have a very strong dependence on ECG and the information from this may not be reliable. But Melaku and Kumar have demonstrated that the RMS magnitude of the SEMG varies between subjects and between different recordings for the same subject and hence is not a suitable measure for improved reliability [12]. Thus, to determine any improvement in the reliability of the recordings using modified ICA for ECG removal, the reduction in the inter-recording variation is a suitable measure.

3. Results And Discussion

3.1 Results

RMS values of all raw SEMG recordings and clean SEMG signals after ECG artefact removal were calculated using (6). These values were then normalised by the value of the first channel of each recording to observe the relative muscles contraction for different postures. The mean, standard deviation and the ratio between standard deviation and mean of those normalised values were calculated. These are displayed in table 1 and tabel 2.

Table 1. Mean, STD and STD/mean values of the normalised data before and after separation for standing posture

	Raw SEMG signals				Multi-step ICA output			
	Ch1	Ch2	Ch3	Ch4	Ch1	Ch2	Ch3	Ch4
μ	*1.0000*	*0.5425*	*0.7342*	*0.4225*	*1.0000*	*1.0100*	*1.0169*	*1.0562*
σ	*0.0000*	*0.0870*	*0.2207*	*0.1299*	*0.0000*	*0.0558*	*0.1141*	*0.1077*
σ/μ	*0.0000*	*0.1603*	*0.3006*	*0.3075*	*0.0000*	*0.0552*	*0.1122*	*0.1019*

Table 2. Mean, STD and STD/mean values of the normalised data before and after separation for sitting posture

	Raw SEMG signals				Multi-step ICA output			
	Ch1	Ch2	Ch3	Ch4	Ch1	Ch2	Ch3	Ch4
μ	*1.0000*	*0.5698*	*0.9199*	*0.5593*	*1.0000*	*1.0111*	*0.9895*	*1.0041*
σ	*0.0000*	*0.3806*	*0.4459*	*0.2686*	*0.0000*	*0.0580*	*0.0502*	*0.1004*
σ/μ	*0.0000*	*0.6680*	*0.4848*	*0.4803*	*0.0000*	*0.0573*	*0.0507*	*0.1000*

3.2 Discussion

The analysis above provides evidence that ECG artefact removal using this new approach of ICA gives a convincing result. The decrease of standard deviation shows that after ECG artefact removal the variance of the signal is less then the raw SEMG. The ratio between standard deviation and mean demonstrates that the output of the separation has less Gaussian distribution. This means that the output signals are independent to each other.

This approach of ICA is suitable when there are fewer channels than sources and in situations where the signal / artefact that needs to be removed appears in all channels. The permutation ambiguity was also solved by applying ICA to each channel in turn while the magnitude ambiguity was equalised by a post processing step that makes the separated sources have unit variance. Thus, this technique gives more reliable SEMG signals for quality interpretation. With raw SEMG signals, it is hard to determine which muscles contribute more or less during a certain static posture.

The disadvantage of this technique is the increased computational time required to accomplish the separation task because of multi-step processing. Further, this technique is dependent on the artefact having a distribution that differs from the rest in the mixtures. The extension of this technique is to estimate a greater number of sources than the number of sensing channels.

4. Conclusion

From visual inspection of the output signals (Figure 4) and from the statistical analysis result, it is clear that this new approach of Multi-step ICA is able to remove the cardiac artefact from SEMG recording and give more reliable signal for clinical interpretation.

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