Limitations of ICA for Artefact Removal

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Abstract— This paper reports analysis of the limitations of using Independent Component Analysis (ICA) for biosignal analysis especially artefact removal. The possible difficulty is that there are limited number of electrodes (recordings) making it an overcomplete problem (non-square ICA). The other difficulty is the distribution of biosignal being close to Gaussian. These two properties of the signals may make these outside the standard ICA application.

This paper reports that ICA is able to successfully separate the biosignals if the number of recordings are not less than the number of sources. If that is not the case, ICA separates artefact component only when the corresponding artefact is predominant. The experiments demonstrate that the results are not reliable and hence the authors recommend that caution should be exercised before using ICA for such applications.

I. INTRODUCTION

BIOELECTRIC activity in the body is a result of the summation of spatially and temporally separated action potentials from number of sources resulting in noise like signals. These signals when recorded from targeted parts of the body, like heart, the brain and specific skeletal muscles, are very useful for clinicians. These signals are studied extensively to identify various physiological conditions. These can generally be recorded non-invasive from the surface of the body and hence are preferred over the other invasive means. But bioelectric signals have a few general problems; (i) presence of noise and (ii) presence of bioelectric signals from other parts of the body (referred to as artefacts).

There is an increasing trend of using independent component analysis (ICA) for removing artefact and noise from recorded biosignals. The first reported application of ICA for removal of artefacts using simulated data [1], [2]. Researchers have also attempted to use ICA to isolate the electrooculography (EOG) artefact from electroenchepalography (EEG) data [3], [4], to identify and remove electrocardiography (ECG) artefact from surface electromyography (SEMG) [5], [6], and for separation of breathing artefacts in ECG signal [7]. Each of these works suggest that ICA has successfully separated or isolated the artefact and noise components.

A review of the published works where ICA has been applied to bioelectric signals (including the earlier work by authors) suggests that most of the authors have not demonstrated that they have established the conditions of the signals for the suitability of applying ICA. This suggests that there is a possibility of that some researchers may have incorrectly used ICA which could have resulted in erroneous results. This paper identifies some of the limitations of using ICA for artefact removal in biosignals. The paper reports theoretical analysis and experimental results.

II. ICA FOR BIOSIGNAL ANALYSIS

ICA is an iterative technique used to estimate statistically independent source signals from a given set of their linear mixtures. If the mixing process is assumed to be linear, it can be expressed as $x = As$, where $x = [x_1(t), ..., x_n(t)]$ is the mixtures, $s = [s_1(t), ..., s_n(t)]$ is the independent sources and A is the $n \times n$ unknown mixing matrix of real number. Then the task is to estimate an unmixing matrix W so that $s = Wx$ becomes as independent as possible.

The success of ICA to estimate independent sources is dependent on the fulfilment of the following conditions.

- The sources must be statistically independent.
- The sources must have non Gaussian distributions. However, ICA can still estimate the sources with small degree of non-Gaussianity.
- The number of available mixtures N must be at least the same as the number of the independent components M.
- The mixtures must be (can be assumed as) linear combination of the independent sources.
- There should be no (little) noise and delay in the recordings.

ICA also suffers from the following unavoidable ambiguities.

- The order of the independent components cannot be determined (it may change each time the estimation starts).
- The exact amplitude and sign of the independent components cannot be determined.

There are several estimations of ICA technique. This paper reports the use of fastICA algorithm that has been developed and proposed by the team at the Helsinki University of Technology [8]. This algorithm uses negentropy as a measure of non-Gaussianity of the signals and uses fixed point iteration scheme that is faster than conventional gradient descent scheme. This algorithm was chosen due to its superiority compared with other algorithms [9], [10].

A. Biosignals characteristics

There are number of bioelectric signals that are commonly studied by clinicans and researchers. The common ones are;

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(i) Electromyogram (EMG), (ii) Electrocardiogram (ECG), (iii) Electro-oculargram (EOG), (iv) Electro-encephlogram (EEG).

There is an overlap of the frequency content of these signals making it difficult to separate these using spectral filtering techniques. Due to this there is a need for new signal separation techniques such as ICA. To determine the efficacy of ICA for these signals, the properties of these signals are analysed below.

First, the EMG and EEG signals have distributions that are close to Gaussian while the EOG and ECG signals have super Gaussian (very spiky) distributions. Second, the ECG and EMG have relatively higher magnitudes than the EOG and EEG. These two properties are important since ICA is only suitable to separate non-Gaussian sources. Also the distributions of the mixtures of these signals will tend to follow the ones that are predominant.

B. Artefact Removal using ICA

ICA has been used for the removal of ocular artefact from EEG [3], [4], [11]. While details differ, the basic technique is that different channels of EEG recordings are the input of ICA algorithm. The outputs of ICA are the temporal independent components u and the estimated unmixing matrix W. The corrected EEG data can then be computed as $x^{'} = (W)^{-1}u^{'}$ where $u^{'}$ is the matrix u with rows containing artefact components set to zero (removing the contribution of the artefact component in the EEG data).

In the above examples, the number of recordings are same as the number of bioelectric signals of interest and there are no extra set of recordings for the atrtefacts. Hence artefact removal using ICA in such a situation can be considered as overcomplete problem because the number of recordings is less than the number of sources (desired and artefacts). This does not satisfy the neccessary conditions of ICA and hence using standard ICA to solve this may be successful only under certain conditions. To prove that, consider two channel recordings x of three independent sources s and express it as:

$$x_1 = a_{11}s_1 + a_{12}s_2 + a_{13}s_3 \qquad (1)$$
$$x_2 = a_{21}s_1 + a_{22}s_2 + a_{23}s_3 \qquad (2)$$

Consider the estimated unmixing matrix $W = [w_{11}w_{12}; w_{21}w_{22}]$ using standard ICA algorithm on that data. The estimated independent components es can be written as:

$$
\begin{aligned}
es_1 &= w_{11}x_1 + w_{12}x_2 \\
&= w_{11}(a_{11}s_1 + a_{12}s_2 + a_{13}s_3) \\
&\quad + w_{12}(a_{21}s_1 + a_{22}s_2 + a_{23}s_3) \\
es_2 &= w_{21}x1 + w_{22}x2 \\
&= w_{21}a_{11}s_1 + a_{12}s_2 + a_{13}s_3 \\
&\quad + w_{22}(a_{21}s_1 + a_{22}s_2 + a_{23}s_3)
\end{aligned}
$$

If none of the coefficient of the mixing matrix A is zero (means that all three sources are present in both mixtures x_1 and x_2) and if A is a full rank matrix (no column

or row dependency), there is no W that will be able to isolate one source from others. It is hypothesized that the one possiblity for the estimated independent component to look very similar to one of the independent sources is when its corresponding magnitude is higher than others. The authors believe that is perhaps the reason why some of the other researchers suggested the separation to have been on good quality. Since the number of actual independent sources of biosignal recorded from electrode is unknown (and is believed to be many), standard ICA may not suitable for all applications except under the condition mentioned above where one of the signals is of greater magnitude than the others. In addition to that, the quality of the corrected signals depends strongly on the quality of the isolated artefact. If the estimated artefact is not good, the corrected signals will be mixtures of any signals from other recording channels.

III. METHODOLOGY AND EXPERIMENT RESULTS

A. Methodology

Two sets of experiments were conducted to test the hypothesis mentioned in the previous section. The first experiment was to determine whether ICA can separate independent sources with small degree of non-Gaussianity in pseudo random signals such as the bioelectric recordings. In this experiment, EMG signals recorded from different muscles (to ensure independence) were considered (Fig. 1). Two signals were chosen in each experiment and were linearly mixed into two mixtures using a mixing matrix that was randomly generated. Then ICA was used to estimate original EMG signals from these mixtures. The quality of the estimated EMG was measured by calculating the mean squared error (MSE) between the original mixing matrix A and its estimate $A^{'}$.

The second experiment was to determine the conditions under which standard ICA could isolate sources in an overcomplete problem (like the case of artefact removal). In this experiment, six independent audio sources symbolic for each type of biosignals discussed in this paper (EEG,EOG, EMG, ECG) with zero mean and peak value of ± 1 were considered.
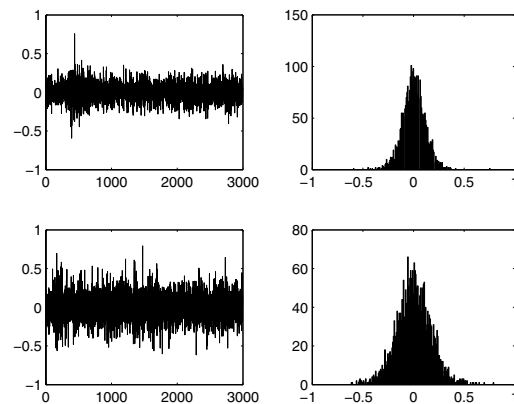

Fig. 1.   Original EMG

These were mixed into four mixtures (representing signals recorded on the scalp) using 6x4 mixing matrix instead of 6x6 as in [1], [2]. This mixing matrix was chosen to mimic the artefact removal problem where the number of sensors is less then the number of sources and artefats. The quality of the isolated component can be verified from the unmixing matrix, the outcome of the experiment.

B. Experiment Results

The first experiment results demonstrate that ICA is capable of separating 'nearly' Gaussian signals such as the bioelectric signals from their mixtures. This can be verified by comparing the graph of the estimated output in Fig. 2 and the original signal in Fig. 1. It is evident that the estimated components look very similar with the original signal.

This can be further verified by comparing the true and the estimated mixing matrix. An example of the true mixing matrix A is

$$\begin{matrix} 0.9979 & 0.0654 \\ 0.2270 & -0.9739 \end{matrix}$$

while the estimated mixing matrix W is

$$\begin{matrix} 0.9979 & -0.0654 \\ 0.1308 & 0.9914 \end{matrix}.$$

To determine the quality of separation using ICA, the difference between the synthesized mixing matrix and the one generated by ICA were computed. Mean square error was used for this to maximize the difference. From the results, it is evident that these two matrices are very similar. The mean square error (MSE) between them is 0.0024. This was repeated 20 times, and the results were similar.

For easier understanding of these results, consider a simple example for the second experiment result when there is only one predominant source. This is similar to the ECG artefact in lower back EMG during static posture [6]. This result can be verified by comparing the original signals, the estimated artefact and the corrected signals as shown in Fig. 3 and Fig. 4 respectively. From these figures it is obvious that
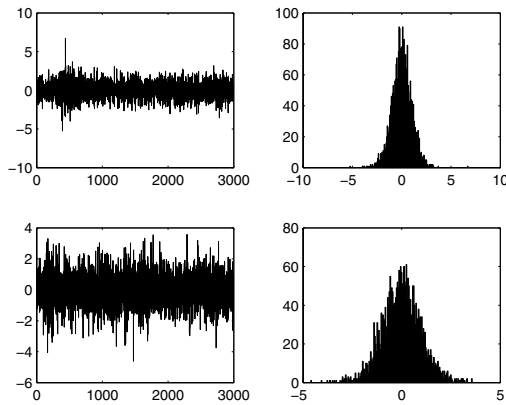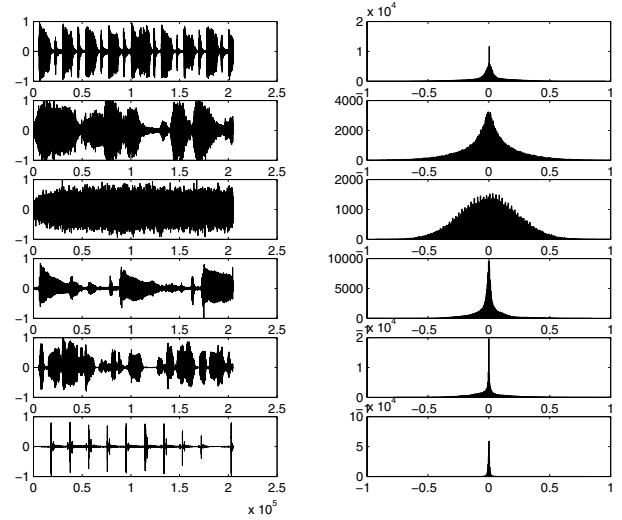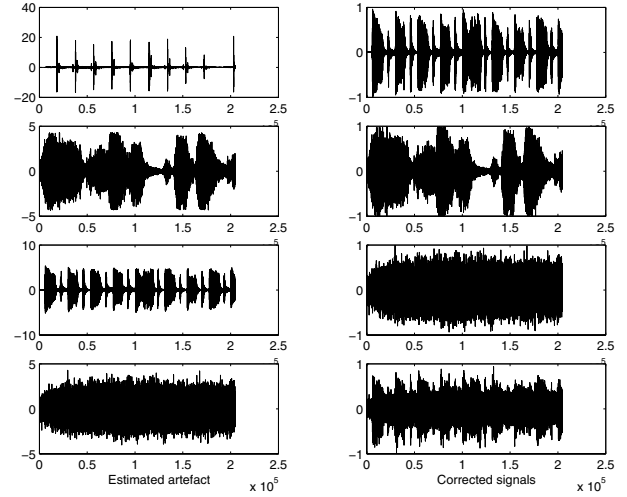

Fig. 3.   Original signals

Fig. 4.   Simulation results

ICA is able to isolate the independent component with high magnitude. However the corrected signals are not as good as expected. This can also be confirmed by listening to these signals.

To explain this observation, consider an example with the mixing matrices A below. The computations are detailed below to show the actual process.

$$\begin{matrix} x_1 \\ x_2 \\ x_2 \\ x_4 \end{matrix} = \begin{matrix} -0.234 & 0 & 0 & 0 & 0 & \mathbf{0.972} \\ 0 & 0.242 & 0 & 0 & 0 & \mathbf{0.970} \\ 0 & 0 & 0.242 & 0 & 0 & \mathbf{0.970} \\ 0 & 0 & 0 & -0.008 & 0 & \mathbf{1.000} \end{matrix} \begin{matrix} s_1 \\ s_2 \\ s_2 \\ s_4 \\ s_5 \\ s_6 \end{matrix}$$

In this example, the artefact (s_6) is predominant in all mixtures. The output of the ICA algorithm is the estimated unmixing matrix W below.

Fig. 2.   Estimated EMG

$$\begin{matrix} -0.1473 & 31.4408 & -0.1299 & -30.1865 \\ -0.0951 & -0.3150 & -22.0286 & 21.7347 \\ -18.2765 & -0.4997 & 0.2248 & 18.0538 \\ -0.1916 & 0.4144 & 0.2372 & -4.7267 \end{matrix}$$

Since $x = As$ and $u = Wx$ then $u = WAs = Us$. In this example A is non square matrix while W is a square matrix estimated by standard ICA and $U = WA$. If the independent components including the artefact are well isolated, each row of the matrix U will have one coefficient equals to ± 1 and the rest are zero. From the above data, matrix U is

$$\begin{matrix} 0.0045 & \mathbf{0.9995} & -0.0041 & 0.0313 & 0 & 0.0062 \\ 0.0042 & -0.0143 & \mathbf{-0.9993} & -0.0322 & 0 & -0.0069 \\ \mathbf{0.9990} & -0.0283 & 0.0127 & -0.0333 & 0 & 0.0041 \\ 0.0105 & 0.0235 & 0.0134 & 0.0087 & 0 & \mathbf{-0.9995} \end{matrix}$$

The last row of matrix U suggests that one of the components of u is the artefact component (s_6) mixed with other signals. It is true that every estimation process will introduce some errors due to the iterative computation. However, in this example the error appears in the estimated non square matrix with square one.

Removing the contribution of this artefact was carried out by making all the elements of the fourth row of u to zero.

$$\begin{matrix} 0.0045 & \mathbf{0.9995} & -0.0041 & 0.0313 & 0 & 0.0062 \\ 0.0042 & -0.0143 & \mathbf{-0.9993} & -0.0322 & 0 & -0.0069 \\ \mathbf{0.9990} & -0.0283 & 0.0127 & -0.0333 & 0 & 0.0041 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{matrix}$$

Following the artefact removal procedure as in [3], the matrix for computing the corrected signals can be found by multiplying this modified U' matrix with the inverse of the estimated mixing matrix W. After normalization, it yields the following matrix:

$$\begin{matrix} \mathbf{-0.9959} & 0.0697 & 0.0442 & 0.0363 & 0 & -0.0034 \\ 0.0644 & \mathbf{0.9948} & 0.0716 & 0.0315 & 0 & 0.0069 \\ 0.0502 & 0.0657 & \mathbf{0.9960} & 0.0319 & 0 & 0.0074 \\ \mathbf{0.5236} & \mathbf{0.6566} & \mathbf{0.5424} & 0.0206 & 0 & 0.0099 \end{matrix}$$

This last matrix demonstrates that the corrected signals are mixtures of several source signals when one or more signals become dominant. The last row of the matrix shows that the last corrected signals is a mixture of all source signals with no dominant magnitude. On the other hand, the other three corrected signals are dominated by one of the sources but still with interference from other signals. It is not possible to determine which of the channels may get corrupted, making this technique unreliable and not suitable for these analysis.

For any other scenarios (more than one source is predominant), the result demonstrates that ICA will isolate those dominant components only. It does not depend on the probability density of the sources because the density distributions of the mixtures tend to follow those with high magnitude. If these isolated artefact components were removed from the mixtures, the corrected signals will be severely distorted.

IV. CONCLUSIONS

The success of ICA to separate EMG signals from their mixtures demonstrates the capability of ICA to separate nearly Gaussian signals. This can be extrapolated for other biosignals with similar properties such as EEG and MEG that also have distributions close to Gaussian. This demonstrates that ICA can be used successfully if the signals have a small degree of non-Gaussianity such as these signals. The authors are currently attempting to identify the limits of this.

The fundamental principle of ICA is estimating the unmixing matrix to estimate the independent components from the mixtures. Thus the estimated independent components are the linear combination of the recorded data. If the number of sources is more than the number of recordings, the estimated independent components must contain some original sources. If some of the original sources are predominant, the estimated independent components will be quite similar to the original sources. Thus, when the number of recordings are less than the total number of signal sources (including artefact sources), ICA is able to separate only thoese components with relatively high magnitude.

V. ACKNOWLEDGEMENTS

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