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Limitations and Applications of ICA for Surface Electromyogram

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Abstract— **This paper reports research conducted to evaluate the use of sparse ICA for the separation of muscle activity from SEMG. It discusses some of the conditions that could affect the reliability of the separation and evaluates issues related to the properties of the signals and number of sources. The paper reports tests using Zibulevsky's method of temporal plotting to identify number of independent sources in SEMG recordings. The theoretical analysis and experimental results demonstrate that sparse ICA is not suitable for SEMG signals. The results identify that the technique is unable to identify finite number of active muscles. The work demonstrates that even at extremely low level of muscle contraction, and with filtering using wavelets and band pass filters, it is not possible to get the data sparse enough to identify number of independent sources using Zibulevsky's sparse decomposition technique**

I. INTRODUCTION

In the recent past, there has been an increasing trend of using Blind Source Separation (BSS) or Independent Component Analysis (ICA) algorithm for separation of Biosignals, especially SEMG. Research that isolates MUAP originating from different muscles and motor units has been reported in 2004 [1], where success is reported in the isolation of the different MUAP with applications for decomposing the SEMG at low levels of muscle activation. ICA has also been proposed for unsupervised cross talk removal from SEMG recordings of the muscles of the hand [2]. From literature, ICA appears to be the emerging technology with solutions to most of the requirements for filtering SEMG.

Surface electromyography (SEMG) is the recording of the electrical activity of skeletal muscle from the skin surface. It is a result of the superposition of a large number of transients that have temporal and spatial separation that is semi-random. These transients are the motor unit action potentials (MUAP). SEMG from different muscles that need to be separated often have spectral overlaps and this makes the use of spectral filtering not suitable for separating the signals effectively. The above techniques are suitable only when there is prior information of the signals. ICA is a convenient technique for source separation as it requires very little information of the sources or the signals to be separated. ICA can be employed in unsupervised situations and this makes it very attractive for number of applications. However, the success of using commonly used ICA algorithms for signal separation is dependent on some properties of the signals and the recordings. These include the linearity of the mixing medium, small sensor noise, and the independence of the underlying sources as well as the equity of the number of sources and the number of recordings or sensors. Further, most of the ICA techniques available are based on the assumption that there is no propagation delay. When any one of these is not met, the output of that separation technique is questionable. The other assumption that determines the suitability of ICA is that the number of sources need to be less than or equal to the number of recordings.

When SEMG is recorded, most of the times the number of recording channels correspond to the active muscles being measured, with no spare recording to account for the artefact. If the artefact was to be removed using ICA, the source of the artefacts would be another independent source, and in such a situation, the number of sources would exceed the number of recordings. To overcome the difficulty of separation of signals when the number of sources exceeds the number of recordings, an alternate to the entropy based ICA is the use of blind source separation using clustering. Zibulvesky et al. [3] showed that during the overcomplete case (number of sources exceeds number of recordings) audio recordings can be separated by making the data sparse. It is often the density of the SEMG that carries the information related to the activity of the specific muscle and making it sparse may alter the information content of the signal. In applications where the muscle is weakly active and the signal strength is small, this may provide a solution. This paper uses Zibulvesky's sparse decomposition technique for SEMG to tests by making the data sparse whether it is possible to separate the independent sources.

II. THEORY

A. Surface Electromyogram

SEMG is a non-invasive recording of the muscle activity. There is a near linear relationship between RMS of SEMG and the finger flexion-extension - suggesting the use of SEMG for bio-control for anthropomorphic teleoperators and Virtual Reality entertainment [4]. There is useful information of the posture from the muscle activity of the lumbar muscles. SEMG amplitude and frequency have been investigated as indicators of localized muscular fatigue. Amplitude and spectral information of EMG have also been exploited to estimate force of muscle contraction and torque [5]. These applications require automated analysis and classification of SEMG. SEMG may be affected by various factors such as the muscle anatomy, muscle physiology, nerve factors, nerve contraction, speed of contraction, artefacts and recording apparatus factors. The anatomical/ physiological processes such as properties and dimensions of tissues, and force and duration of contraction of the muscle are known to influence the signal. SEMG is also influenced by onset of muscle fatigue, and contraction of other muscles in the close vicinity. Each of the factors can be used as a criterion to categorise the input signal.One property of the

SEMG is that the signal originating from one muscle can generally be considered to be independent of other bioelectric signals such as electrocardiogram (ECG), electro-oculargram (EOG), and signals from neighbouring muscles. This opens an opportunity of the use of independent component analysis (ICA) for this application.

B. ICA for SEMG applications

Signals from different sources can get mixed during recording. Often it is required to separate the original signals, and there is little information available of the original signals. ICA is an iterative technique that estimates the statistically independent source signals from a given set of their linear combinations. The process involves determining the mixing matrix. The independent sources could be audio signals such as speech, voice, music, or signals such as bioelectric signals.

A number of researchers have reported the use of ICA for separating the desired SEMG from the artefacts and from SEMG from other muscles. While details differ, the basic technique is that different channels of SEMG recordings are the input of ICA algorithm.The fundamental principle of ICA is to determine the un-mixing matrix and use that to separate the mixture into the independent components. The independent components are computed from the linear combination of the recorded data. The success of ICA to separate the independent components from the mixture depends on the properties of the recordings. When examining the various attempted applications of ICA, two properties of SEMG recordings appear important; (i) number of sources exceeding number of recordings and (ii) statistical properties. These two properties of SEMG are examined below.

1) Number of Sources Exceed Number of Recordings: When SEMG is recorded, most of the times the number of recording channels correspond to the active muscles being measured, with no spare recording to account for the artefact. If the artefact was to be removed using ICA, the source of the artefacts would be another independent source, and in such a situation, the number of sources would exceed the number of recordings. It is thus important to determine the conditions under which standard ICA could be used to remove artefacts from biosignal recordings when the number of sources may exceed the number of recordings. To analyse this, consider the set of recordings to be a vector x and the pure signals (unknown) to be a vector s. Then $x = As$, where A is an unknown mixing matrix. The output of ICA algorithm is an estimate of un-mixing matrix W so that

$$s = Wx = WAs$$

It is evident that $WA = I$, identity matrix. If the number of recorded data is less than number of true independent sources (A is not a square matrix), running standard ICA on this kind of data will never give truly independent source. The estimated independent components will be a mixture of those true independent sources with element of W as the scale factor. To prove the same, consider two channel recordings x of three independent sources s and express it as:

$$x_1 = a_{11}s_1 + a_{12}s_2 + a_{13}s_3$$
$$x_2 = a_{21}s_1 + a_{22}s_2 + a_{23}s_3$$

Consider the estimated un-mixing matrix,

$$W = [w_{11}w_{12}; w_{21}w_{22}]$$

generated using standard ICA algorithm on that data. The estimated independent components 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 mixing matrix A is zero means that all three sources are present in both mixtures x_1 and x_2 As A is a full rank matrix, then there is no column or row dependency. Under these conditions, there is no W that will be able to isolate one source from others. The only possible way that the estimated output would look very similar to one of the independent sources is when its corresponding magnitude is higher than others. Since the number of actual independent sources of SEMG signal recorded from electrode is unknown (and is believed to be many), standard ICA will not be suitable for applications except when the magnitude of some of the sources is comparatively much higher.

2) Statistical Properties of SEMG Recordings: Signals from Gaussian sources cannot be separated from their mixtures using ICA [6], making such signals unsuitable for ICA applications. Mathematical manipulation demonstrates that all matrices will transform this kind of mixtures to another Gaussian data. However, a small deviation of density function from Gaussian may make it suitable as it will provide some possible maximization points on the ICA optimization landscape, making Gaussianity based cost function suitable for iteration. If one of the sources has density far from Gaussian, ICA will easily detect this source because it will have a higher measure of non Gaussianity and the maxima point on the optimization landscape will be higher. If more than one of the independent sources has non Gaussian distribution, those with higher magnitude will have the highest maxima point in the optimization landscape. Given a few signals with distinctive density and significant magnitude difference, the densities of their linear combinations will tend to follow the ones with higher amplitude. Since ICA uses density estimation of a signal, the components with dominant density will be found easier.

Signals such as SEMG have probability densities that are close to Gaussian while artefacts such as ECG and motion artefacts have non Gaussian distributions. From the above, it can be suggested that ICA may suitably isolate some of the above signals, while its efficacy for separating the others maybe questionable. It is difficult to identify the quality of separation of EMG from one muscle and the neighbouring muscles, or that of EEG from one channel to the neighbouring recording sites, making it difficult to confirm or negate the above.

C. Sparse ICA

Sparse representation of signals which is modeled by matrix factorisation has been receiving great deal of interest in recent years. The research community has researched many linear transforms that make audio, video and image data sparse, such as the discrete cosine transform (DCT), the Fourier transform, the wavelet transform and their derivatives [7].Chen et al.[8] discussed sparse representations of signals by using large scale linear programming under given over complete basis (e.g., wavelets). But it was Zibulvesky et al. who noticed that in the case of sparse sources, their linear mixtures can be easily separated using very simple ”geometric” algorithms. Sparse representations can be used in blind source separation. When the sources are sparse, smaller coefficients are more likely and thus for a given data point t. if one of the sources is significantly larger, the remaining ones are likely to be close to zero. Thus the density of data in the mixture space, besides decreasing with the distance from the origin shows a clear tendency to cluster along the directions of the basis vectors. Sparsity is good in ICA for two reasons. First the statistical accuracy with which the mixing matrix A can be estimated is a function of how non-Gaussian the source distributions are. Secondly the quality of the source estimates given A, is also better for sparser sources. A signal is considered sparse when values of most of the samples of the signal do not differ significantly from zero. These are from sources that are minimally active. Zibulevsky et al. have demonstrated that when the signals are sparse, and the sources of these are independent, these may be separated even when the number of sources exceeds the number of recordings [3]. The over-complete limitation suffered by normal ICA is no longer a limiting factor for signals that are very sparse. Zibulevsky also demonstrated that when the signals are sparse, it is possible to determine the number of independent sources in a mixture of unknown signal numbers.One application where the use of blind source separation for SEMG is required is when the signal strength is very small, and the sources are minimally active, such as during maintained posture. This leads to the argument of the use of Zibulevsky's ICA technique to separate muscle activity originating from muscles that are minimally active. It also provides the basis for identifying the number of active independent sources in the mixture to validate the use of ICA for SEMG application.

1) Identification of sources using plotting of sparse data: Zibulvesky et al. developed a simple probabilistic method for over determined ICA source separation. For a more general case they used maximum aposteriori approach which includes the situation of over complete dictionary and more sources than sensors. They have also demonstrated the combination of clustering and shortest path decomposition technique to be faster and more robust. This required the estimation of the mixing matrix before hand by clustering and then reconstruction of the sources by shortest path decomposition. They demonstrated the separation of up to six different audio sounds mixed into two mixtures (recordings). During maintained posture of the unloaded hand, muscles are minimally active and the SEMG signal strength is very small. Hence SEMG is expected to be sparse in these conditions. The plotting of the recording against each other would be expected to demonstrate the number of independent sources. As the first stage, it is necessary to suitably linearly transform and filter the signals to ensure the signals are sufficiently sparse. There are number possible methods that are available. Most common one is spectral filtering of the data for the signal to be sparse in the time domain. The filter properties such as frequency and order needs to be selected according to the frequency content of the signal. Typically, while maintaining the properties of the original signal, and desiring to make the signal sparse, filtering is performed where approximately 1 σ or 12% of the signal is removed and 85% to 90% of the energy of the original data is kept. The signal may also be filtered in time domain by applying a threshold function to the signal data.

III. Methodology

A. Experiment

The experiment was conducted where Zibulevsky's technique was applied to SEMG of minimally active muscles to determine the number of distinct independent sources in the mixture, thus establishing whether this test could be used for isolating muscle activity from different muscles.

The experiments were approved by the Human Experiments Ethics Committee of the University. A male subject participated in the experiment. The experiment used 2 channel EMG configurations as per the recommended recording guidelines. A two channel, continuous recording BIO PAC equipment was used for this purpose. Raw signal sampled at 2000 samples/ second was recorded. The target sites were shaved to remove hairs and cleaned with alcohol wet swabs. Ag/AgCl electrodes (AMBU Blue sensors from MEDICOTEST, Denmark) were mounted on appropriate locations close to the selected muscles in the right forearm. The SEMG was recorded from muscles of the right arm while performing simple finger posture (gesture), where the muscles were minimally activated at approximately 5% maximum voluntary contraction (MVC). The aim of the experiment was to determine the effectiveness of using Zibulevsky's technique where the signals (SEMG recordings) in time domain are plotted against each other to identify number of independent sources in the mixture that is the muscle activity.

B. Analysis

The aim of this experiment was to justify the underlying theory of the use of ICA for separation of the EMG signals. This will determine if it is appropriate to assume that the sources of MUAPs can be considered as independent.

For this purpose, the SEMG recordings were first made sparse. The recorded signals were analysed using MATLAB software. The aim was to make the data sparse. The Signals were initially filtered with Butterworth filter of order four so that the energy of the signal after filtering was maintained at 90%. Corresponding histograms were plotted and compared with the original histograms to make sure that they maintain the gaussianity as shown in Figure (1) and Figure (2). Scatter plotting was done by the resultant sparse signals. These were visually observed to identify the number of sources.

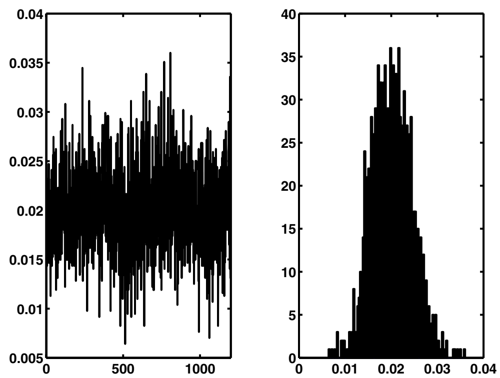

Fig. 1. Example of one Channel EMG Recording of finger movements and the Histograms

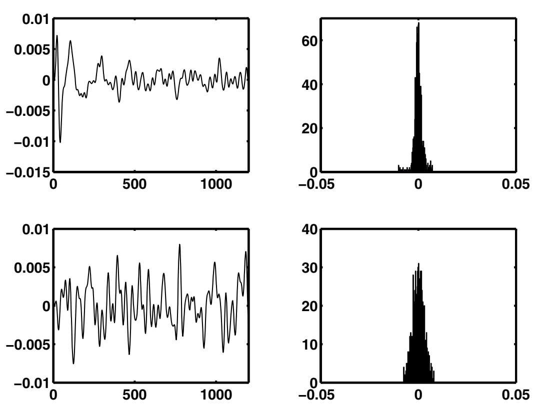

Fig. 2. Two Channel Sparse EMG Recordings and the respective Histograms

IV. RESULTS AND OBSERVATIONS

The SEMG data was made sparse by band pass filter. Figure (1) and Figure (2) shows the histograms for both original and sparse data. Figure.(3) shows the scatter plot of the sparse recorded SEMG signals. From the scatter plot it can be visualised that there are no distinguishable lines in the directions of the basis vectors, which shows that even when SEMG is recorded from minimal contraction and filtered, the data is not suitable to determine the number of independent sources in SEMG recordings.

The sparseness of the SEMG recordings is observed from the histogram plot. While the original data was modestly sparse, the signal was made more sparse after filtering, where nearly 12% of the energy was removed (based on 1 sigma). The results demonstrate that sparse decomposition technique is not able of identifying the independent sources in SEMG recordings. This could suggest that either the signal was not sparse enough even after the filtering, or the sources are not independent, or the number of sources was very large.

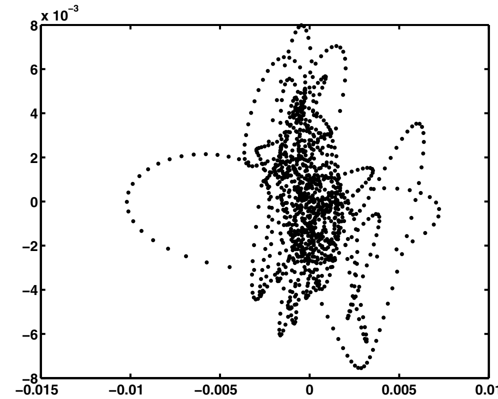

Fig. 3. Scatter plot of Sparse data using Zibulevsky's Sparse Decomposition Technique

V. DISCUSSIONS AND CONCLUSION

The results of the experiments demonstrate that using Zibulvesky's sparse decomposition technique, it is not possible to determine the number of independent sources in SEMG recordings. The reason for this could be either because there are very large numbers of independent sources, or that SEMG signal, even at extremely low levels of contraction and after filtering, is not sparse enough. From the above, it is concluded that Zibulvesky's Sparse Decomposition technique cannot be used for the separation of SEMG signals.

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