Performance comparison of ICA algorithms for Isometric Hand gesture identification using Surface EMG

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Abstract

There is an urgent need for developing a robust technique that can identify small and subtle hand and other body movements with applications in health, rehabilitation and defence. Surface electromyogram (sEMG) is a measure of the electrical activity of the muscles and a measure of the strength of muscle contraction. While this may be a good measure of the actions and gestures, this is unable to identify small variations in the muscle activity, especially when there are number of simultaneously active muscles. Independent component analysis (ICA) is a statistical based source separation technique that has been shown to be suitable for the decomposition of signals such as sEMG and been shown to improve the ability of sEMG to identify small variations in muscle activity.

ICA algorithms using multivariate statistical data analysis technique have been successfully used for signal extraction and source separation in the field of biomedical and statistical signal processing. Recent research has resulted in the development of number of different ICA technique. While there are some researchers who have compared their techniques with the existing methods for audio examples, there is no comparison of performance between ICA algorithms for biosignal applications such as surface electromyography (sEMG) applications. With ICA being the feasible method for source separation and decomposition of biosignals, it is important to compare the different techniques and determine the most suitable method for the applications. This paper has studied the performance of four ICA algorithms (FastICA, JADE, Infomax and TDSEP) for decomposition of sEMG to identify subtle hand gestures. Comparing several ICA algorithms, it is observed that an algorithm based on temporal decorrelation method (TDSEP) which is based on the second order statistics gives the best performance.

1. INTRODUCTION

The task of separating two or more sources from a set of mixtures when the signals have temporal and spectral overlap and there is no information about the sources is referred to as Blind Source Separation (BSS). Independent component analysis (ICA) has gained momentum in the last few years as a solution to BSS problems. The fundamental principle of ICA consists, estimating the set of independent signals from the mixture of the given signals by estimating the un-mixing matrix. ICA has been successfully used for signal extraction tasks in sound, bio-medical and image processing [1],[2],[3]. Analysis of signals such as surface electromyogram (sEMG) and electro-encephalogram (EEG) often have required separation of signals emerging from various independent sources, and there is spectral and temporal overlap. This makes such signals suitable candidates for ICA based estimation. ICA has been proposed for unsupervised cross talk removal from Surface EMG recordings of the muscles of the hand [4]. ICA based analysis and classification of sEMG has been proposed for the hand gesture identification [5].

Hand gesture identification has various human computer interface (HCI) applications related to controlling machines and computers, for rehabilitation, prosthesis and defence applications. There are number of methods to identify the hand gestures and actions. The traditional techniques rely on movement or position sensed by accelerometers [6], capacitive techniques [7] or proximity sensors worn on different parts of the body [8]. These techniques require the users to noticeably move their limbs. On the contrary, electromyographic (EMG) signals can convey information about isometric muscular activity: activity related to very subtle or no movement at all. EMG is a biosignal related to muscle contraction. Studies on the use of EMG for gesture recognition have been reported, but none of them takes explicit advantage of its subtlety, the fact that commands can be issued without the generation of observable movements.

Any hand movement is a result of a complex combination of many flexors and extensors present in the forearm. Since all these muscles present in the forearm are close to each other, myo-electric activity observed from any muscle site comprises the activity from the neighbouring muscles as well, referred to as cross-talk. When the muscle activity is small (subtle), the signal strength is small and the impact of cross talk and noise...
is very high. This is further exaggerated when considering different subjects since the size of the muscles, presence of subcutaneous fat layer and also the training level is different for different people. Extraction of the useful information from such kind of surface EMG becomes more difficult for low level of contraction mainly due to the low signal-to-noise ratio. At low level of contraction, EMG activity is hardly discernible from the background activity. Therefore to correctly classify the movement and gesture of the hand more precisely, EMG needs to be decomposed to identify activities of individual muscles. There is little or no prior information of the muscle activity, and the signals have temporal and spectral overlap, making the problem suitable for blind source separation (BSS) or ICA for the separation of muscle activities. The present study involves the evaluation of four ICA algorithms commonly used for biomedical analysis. Their performances in the specific task of separating Surface EMG source signals were quantified, with particular attention to subtle Hand gesture (Isometric) identification.

2. BACKGROUND

A. Surface Electromyography

The electromyogram (EMG) is an electrical signal generated by muscle contraction. It can be recorded noninvasively using surface electrodes in differential pairs, each pair constituting a channel. Methods for effective recording and computer aided analysis of EMG signals have been the object of study in the field of biomedical engineering for the last three decades.

The analysis of EMG can be broadly categorized into two:

- Gross and global parameters.
- Decomposition of EMG into MUAP.

The close relationship of surface EMG with the force of contraction of the muscle is useful for number of applications such as sports training, prosthesis and for machine control. The EMG signals contain a lot of important information such as muscle force, operator’s intended motion, and muscle impedance. Gross properties of sEMG such as magnitude and spectrum parameters are a good indicator of the overall magnitude of contraction and have numerous applications such as sports training, but these are unable to differentiate between muscle activities originating from different adjoining muscles.

Decomposition of sEMG has been attempted with the aim of determining the number of MUAP. Such methods are designed to identify the MUAP based on the shape, and are not suitable for determining the closely located muscles from where the MUAP originate from. One property of the surface EMG 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 neighboring muscles. This opens an opportunity for using independent component analysis (ICA) for this application.

B. ICA model and algorithms

Independent Component Analysis (ICA) is a new statistical technique that aims at transforming an input vector into a signal space in which the signals are statistically independent. ICA assumes that the mixing process as linear, so it can be expressed as:

\[ x(t) = As(t) \]  

where \( x = [x_1(t), x_2(t), \ldots, x_n(t)] \) are the recordings, \( s = [s_1(t), s_2(t), \ldots, s_n(t)]^T \) are the original signals, and \( A \) is the \( n \times n \) mixing matrix. This mixing matrix and each of the original signals are unknown. To separate the recordings to the original signals, an ICA algorithm performs a search of the un-mixing matrix \( W \) by which observations can be linearly translated to form Independent output components so that:

\[ s(t) = Wx(t) = WAs(t) \]
In order to successfully apply ICA for EMG analysis, the assumption on which the operation of ICA is based must be fulfilled. In standard ICA it is assumed that

- The recoded signals are a result of linear mixing.
- The artifacts are statistically independent from the EMG signals.
- The sources must have non-Gaussian distributions.
- The number of sources is the same as the number of mixtures.
- The recorded signals must be (approximately) linear combination of the independent sources.
- There should be no (little) noise common to the sources and there should be no (minimal) delay between the signals of the different sources in the recordings.

While ICA has demonstrated success in the ability to separate signals, the output of ICA suffers from the following 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.

As mentioned above, the signals that can be separated need to be non-Gaussian and independent. For the purpose of applying ICA to Surface EMG recordings, there is a need to determine the conditions under which these signals can be considered as independent and non-Gaussian, and the mixing matrix can be considered to be stationary and linear. Hence this paper analyses the conditions using a stationary mixing matrix.

There are several ICA algorithms available in literature. How ever the following four algorithms are widely used in numerous signal processing applications. These included FastICA [9],[10], JADE [11], TDSEP [12], and Infomax [1]. Each algorithm used a different approach to solve equation.

1) FastICA: FastICA is a fixed point ICA algorithm that employs higher order statistics for the recovery of independent sources [9]. FastICA can estimate ICs one by one (deflation approach) or simultaneously (symmetric approach). FastICA uses simple estimates of negentropy based on the maximum entropy principle [9],[10], which requires the use of appropriate nonlinearities for the learning rule of the neural network.

Separation is performed by minimization of negentropy of the mixture such that uncorrelated and independent sources whose amplitude distributions as non Gaussian as possible are obtained. The non Gaussianity is measured with the differential entropy $J$, called negentropy [13], which is defined as the difference between the entropy of a Gaussian random variable $y_{gauss}$.

$$J(y) = H(y_{gauss}) - H(y) \quad (3)$$

Where the entropy $H$ is given by

$$H(y) = - \int f(y) \log(f(y))dy \quad (4)$$

Since Gaussian random variables have the largest entropy $H$ among all random variables having equal variance, maximizing $J(y)$ leads to the separation of independent source signals.

2) TDSEP: Temporal decorrelation source separation (TDSEP) is one of the ICA algorithms, based on the simultaneous diagonalisation of several time-delayed correlation matrices [12]. It can even separate signals whose amplitude distribution is near Gaussian which makes it suitable for sEMG separation which is a very noisy and Gaussian like signal.

The TDSEP algorithm uses the property that the cross-correlation functions vanish for mutually independent signals. It assumes that the signals $s(t)$ have temporal structure ("non delta" autocorrelation function). All time delayed correlation matrices $R_{\tau(s)}$ should be diagonal. This knowledge is used to calculate the unknown mixing matrix $A$ in(1) by a simultaneous diagonalisation of a set of correlated matrices $R_{\tau(x)} = [x(t)x^T(t-\tau)]$ for different choices of $\tau$. Since the mixing model in (1) is just linear transformation we can substitute $x(t)$ by $As(t)$ and get

$$R_{\tau(x)} = [As(t)(As(t-\tau))^T] = AR_{\tau(s)}A^T \quad (5)$$

where the source cross-covariance functions $R_{\tau(x)}$ are a set of diagonal matrices due to the statistical independence of the sources [12].

In order to estimate a square mixing matrix $W$, TDSEP uses whitening and rotation of the mixtures. This method requires a set of time delays $\tau$, which can be arbitrarily selected or manually given. The advantage of second order methods is their computational simplicity and efficiency. Furthermore for a reliable estimate of covariances only comparatively few samples are needed.

3) JADE: The Joint Approximate Diagonalization of Eigen-matrices (JADE) is an algorithm based on the joint diagonalization of cumulant matrices under the assumption that the sources have non-Gaussian distributions [11]. After whitening and possible dimension reduction, a set of matrices obtained from Eigen matrices of the fourth-order cumulant tensor is approximately diagonalized with a single orthogonal transformation [11].

The JADE algorithm uses second and fourth order cumulants. JADE measures the mutual information between cross cumulants. Second order cumulant is used to decorrelate the data, i.e., to obtain a whitening matrix $W$. The separation matrix is estimated as $V'W$, where $V'$ is a rotation matrix used to make the cumulant matrices as diagonal as possible according to specific contrast function, which is the sum of squared fourth order cross cumulants from the cumulants matrix. To make the cumulants diagonal as possible is the same that makes the data as independent as possible, so the matrix that performs the diagonalisation of cumulants can be used to perform the separation on the mixed data. Usually JADE provides excellent results on low dimensional data if succiently many sample points are available.

4) Infomax: The information maximization algorithm (often referred as infomax) is another ICA algorithm widely
used to separate super-Gaussian sources [1]. Infomax is a gradient-based neural network algorithm, with a learning rule for information maximization. Infomax uses higher order statistics for the information maximization. The information maximization is attained by maximizing the joint entropy of a transformed vector, \( z = g(Wx) \), where \( g \) is a point wise sigmoidal nonlinear function. The learning rule for a single layer feed forward neural network to implement the separation is

\[
\Delta W \propto [W^T]^{-1} + (1 - 2y)x^T \tag{6}
\]

\[
\Delta w_0 \propto (1 - 2y) \tag{7}
\]

Where \( y = f(Wx + w_0) \) and \( f(u) \) is a sigmoid contrast function, usually \( f(u) = 1 + e^{-u^{-1}} \) or \( f(u) = \tanh(u) \).

ICA is suitable when the numbers of recordings are same as or greater than the number of sources. This paper reports using 4 channels of EMG recorded during isometric hand actions that required not greater than 4 independent muscles. This ensures that the un-mixing matrix is a square matrix of size of \( 4 \times 4 \).

### 3. Methodology

This paper reports conducting controlled experiments where subjects were asked to perform four different isometric hand actions. Based on the assumption that the muscle contraction is stationary during the isometric hand actions, different ICA algorithms were used to estimate the sources. Later the root mean square (RMS) of each of the signals for the duration of the contraction was computed and used for the purpose of training and testing the neural network. This is detailed below:

#### A. Surface EMG Recording and processing

Eight subjects (seven males and one female) participated in the investigation. For the data acquisition a proprietary Surface EMG acquisition system by Delsys (Boston, MA, USA) was used. Four electrode channels were placed over four different muscles as indicated in the Table 1 and Figure 2. A reference electrode was placed at Epicondylus Medialis.

Before placing the electrodes subject’s skin was prepared by lightly abrading with skin exfoliate cleaned with 70% v/v alcohol swab.

Four different subtle (isometric) hand actions were performed and repeated 12 times at each instance. Each time raw signal sampled at 1024 samples/second was recorded. Markers were used to obtain the Isometric contraction signals during recording. The actions were complex to determine the ability of the system when similar muscles are active simultaneously. The four different hand actions are performed and are listed below:

- Middle and index finger flexion.
- Little and ring finger flexion.
- All finger flexion.
- Finger and wrist flexion together.

The hand actions and gestures represented low level of muscle activity (subtle hand gestures). The hand actions were selected based on small variations between the muscle activities of the different digits muscles situated in the forearm. The recordings were separated using ICA to separate activity originating from different muscles and used to classify against the hand actions.

#### B. Signal Processing of surface EMG

In order to have a better insight into ICA (BSS) algorithms, high quality implementations written by members of the research groups that originally produced the algorithms were utilized for these experiments. The specific algorithms evaluated are Hyvärinen’s fixed point algorithm (FastICA) [9], [10], Bell and Sejnowski’s infomax algorithm [1], J. F Cardoso’s JADE algorithm [11] and Andreas Ziehe’s TDSEP algorithms [12].

The aim of these experiments was to test the use of ICA along with known properties of the muscles for separation of sEMG signals for the purpose of identifying isometric (subtle) hand gestures. Similar analysis was performed for all the four ICA algorithms by keeping the mixing matrix constant at each instance.

The wide band EMG signal was broken into 12 narrow band signals each of length approximately 2500 samples. The mixing matrix \( A \) was computed for the first set of data only and kept constant throughout the experiment. The independent sources of motor unit action potentials that mix to make the EMG recordings were estimated using the following equation.

### Table 1: Placement of Electrodes

<table>
<thead>
<tr>
<th>Channel</th>
<th>Muscle</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Brachioradialis</td>
<td>Flexion of forearm</td>
</tr>
<tr>
<td>2</td>
<td>Flexor Carpi Ulnaris(FCU)</td>
<td>Abduction and flexion of wrist</td>
</tr>
<tr>
<td>3</td>
<td>Flexor Carpi Radialis (FCR)</td>
<td>Abduction and flexion of wrist</td>
</tr>
<tr>
<td>4</td>
<td>Flexor Digitorum Superficialis (FDS)</td>
<td>Finger flexion while avoiding wrist flexion</td>
</tr>
</tbody>
</table>

Fig. 2: Placement of Electrodes for Hand gesture Experiment
\[ s = Bx \]  

where, \( B \) is the inverse of the mixing matrix \( A \). This process was repeated for each of the four hand gesture experiments. Four sources \( s_a, s_b, s_c \) and \( s_d \) were computed in each instance. Root Mean Squares (RMS) was computed for each separated sources using the following:

\[ s_{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} s_i^2} \]

where \( s \) is the source and \( N \) is the number of samples. This results in one number representing the muscle activity for each channel for each hand action.

RMS value of muscle activity of each source represents the muscle activity of that muscle and is indicative of the force of contraction generated by each muscle. Taking a ratio of these activities gives a relative combination of the activity from each of these muscles is responsible for the muscle activity (gesture) and has been used to identify the isometric (subtle) hand gesture. A constant mixing matrix \( A \) and set of weight matrix for neural networks was used for each subject making the system configured for each individual.

C. Hand gesture identification from sEMG

This paper presents the use of Back Propagation (BPN) type Artificial Neural Network. The advantage of choosing BPN learning algorithm architecture is to overcome the drawback of the standard ANN architecture by augmenting the input by hidden context units, which give feedback to the hidden layer, thus giving the network an ability of extracting features of the data from the training events. The size of the hidden layer and other parameters of the network were chosen iteratively after experimentation with the back-propagation algorithm. There is an inherent trade off to be made. More hidden units results in more time required for each iteration of training; fewer hidden units results in faster update rate. These experiments used sigmoid as the threshold function and gradient descent and adaptive learning with momentum as training algorithm. A learning rate of 0.05 and the default momentum rate were found to be suitable for stable learning of the network. The training stopped when the network converged and the network was found to be suitable for stable learning of the network. The weights and biases of the network were saved and used for testing the network. The data was divided into subsets of training data, validation, and test subsets. One fourth of the data was used for the validation set, one-fourth for the test set, and one half for the training set. The four RMS EMG values were the inputs to the ANN. The outputs of the ANN were the different isometric hand action RMS values. The above process was performed for all the four ICA algorithms. In order to measure the efficacy of the above ICA techniques, the Raw EMG signals were also analyzed. In the analysis, the RMS values of all the four channels were computed. A back propagation neural network was then trained and tested with these RMS values taken as feature vector.

### 4. Results

The results of the experiments demonstrated the performance of the different ICA algorithms on sEMG in classifying the four different subtle hand gestures using back propagation ANN learning algorithm. The results of testing the back propagation ANN to correctly classify the test data based on the weight matrix generated using the training data for each ICA algorithm are shown in Table 2. The accuracy was computed based on the percentage ratio of correctly classified data points to the total number of data points.

The performance of all four algorithms and Raw EMG signals are plotted as bar graph as shown in Figure 3. The overall performance of different ICA algorithms on isometric hand gesture experiments for 8 different subjects are explained in Figure 4.

### 5. Discussions and Conclusion

The results of the experiments demonstrate:

- The results demonstrate that TDSEP (based on second order statistics) is more efficient in performing classification of subtle motionless gestures as compared to other higher order statistical ICA methods. The TDSEP which uses correlation method to perform separation gave an overall efficiency of 97%, whereas FastICA and other higher order ICA methods fail to provide good results for this specific task.
- Based on the higher order statistics techniques, it is evident that subtle hand gesture sEMG signals of different channels are correlated making these not suitable for separation using higher order statistics.
- One possible explanation for the higher order statistics are not performing well may be due to need for larger number of sample points while in these applications the number of sample points was limited.
- The low SNR would have an impact on the PDF shape of the signal resulting in change of the Kurtosis making it less suitable for higher order ICA methods.

From the above it is evident that the TDSEP which is based on the second order statistics is more efficient and robust.
### Table 2: Experimental results for Isometric Hand Gesture Identification

<table>
<thead>
<tr>
<th>Number of participants</th>
<th>Middle and index finger flexion</th>
<th>Little and ring finger flexion</th>
<th>All finger flexion</th>
<th>Finger and wrist flexion together</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw sEMG</td>
<td>60%</td>
<td>60%</td>
<td>60%</td>
<td>60%</td>
</tr>
<tr>
<td>Infomax</td>
<td>80%</td>
<td>80%</td>
<td>80%</td>
<td>80%</td>
</tr>
<tr>
<td>JADE</td>
<td>85%</td>
<td>85%</td>
<td>85%</td>
<td>85%</td>
</tr>
<tr>
<td>FastICA</td>
<td>90%</td>
<td>90%</td>
<td>90%</td>
<td>90%</td>
</tr>
<tr>
<td>TDESP</td>
<td>97%</td>
<td>97%</td>
<td>97%</td>
<td>97%</td>
</tr>
</tbody>
</table>

![Graph showing Isometric hand gesture identification results](image)

**Fig. 4:** Over all performance of different subjects on various ICA algorithms (Percentage) for Isometric hand gesture identification.

for the separation of electrical activities from subtle hand gestures. Furthermore, there are other advantages of using second order methods such as computational simplicity and efficiency. Such a method for a reliable estimate of covariances only comparatively few samples are needed which makes it very efficient to implement.

### References


