Identification of number of independent sources in surface EMG recordings using over complete ICA

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Abstract

Artifacts in bioelectric signals can make bioelectric signals unreliable. Spectral and temporal overlap can make the removal of artifact or separation of different bioelectric signals extremely difficult. Often, the sources of the bioelectric signals may be considered as independent at the local level and this makes an argument for separating the signals using independent component analysis (ICA). This paper reports research conducted to evaluate the use of ICA for the separation of bioelectric signals when the number of sources exceed number of sensors. The paper proposes the use of value of the determinant of the global matrix generated using subband ICA for identifying the number of active sources. The results indicate that the technique is successful in identifying the number of active muscles for complex hand gestures. The results support the applications such as human computer interface.

1. INTRODUCTION

Independent component analysis (ICA) [1],[15] has been a widely accepted technique to solve the BSS problem. Although the BSS problem involves two implications: source number estimation and source separation, for conceptual and computational simplicity, most ICA algorithms employ the linear instantaneous mixture model and assume that the number of sources equals to the number of observations (so that the mixing/un mixing matrix is square and can be easily estimated). However, this equality assumption is in general not the case in bio signal processing applications where number of muscles can be activated for a simple hand gesture and the number of sources (muscles) can easily exceed the number of sensors. Hence, the number of sources has to be estimated before any further calculation can be done.

Independent component analysis (ICA) is an important method for blind source separation and unsupervised learning. Recently, the method has been extended to the overcomplete situation where the number of sources is greater than the number of receivers. Most ICA algorithms assume that at least as many sensor signals as there are underlying source signals are provided. In overcomplete ICA however, more sources are mixed to less signals. The ideas used in overcomplete ICA originally came from coding theory, where the task is to find a representation of some signals in a given set of generators which often are more numerous than the signals, hence the term overcomplete basis. Sometimes this representation is advantageous as it uses as few 'basis' elements as possible, which is then called sparse coding. Olshausen and Fields [2] first put these ideas into an information theoretic context decomposing natural images into an overcomplete basis. Later Olshausen [3] presented a connection between sparse coding and ICA in the quadratic case. Lewicki and Sejnowski [4] then were the first to apply these terms to overcomplete ICA, which was further studied and applied by Lee et al [5]. Bofill and Zibulevsky [6] treated delta-like source distributions for overcomplete case of source signals after Fourier transformation.

ICA has been successfully used for signal extraction tasks in sound, bio medical and image processing [7],[8],[14]. A more recent biomedical application of ICA concerns the processing of Surface EMG signals. ICA has been proposed for unsupervised cross talk removal from Surface EMG recordings of the muscles of the hand [9]. Recently surface EMG with ICA has been proposed for the Hand gesture identification [10].

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 identify number of individual muscles (sources) the EMG needs to be decomposed. 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. There are several muscles get activated at the same time during the hand movement which makes it typical overcomplete ICA problem $(n > m)$.

Despite the success of using standard ICA in many applications, the basic assumptions of ICA may not hold for some kind of signals hence some caution should be taken when using standard ICA to analyse real world problems, especially in biomedical signal processing. Hence in this paper sub-band ICA approach has been used to estimate the number of sources in overcomplete ICA.

The aim of this research is to determine suitable signal processing techniques where the system identifies muscles as independent sources and extracts suitable features to classify the recordings based on these features. This paper reports the identification of number of sources (muscles) from the various hand gestures using sub-band ICA. The paper also explains the various issues involved in source separation problem in biomedical applications.

2. Related work

A. Sub-band decomposition ICA

ICA uses higher-order statistics of the data to minimize the dependence between the components of the system output. However, classical ICA algorithms do not work well for separation in the presence of noise or when performed online especially with bio-medical signal processing. In fact, by definition, the standard ICA algorithms are not able to estimate statistically dependent original sources, that is, when the independence assumption is violated. The key idea in this approach is the assumption that the unknown wide-band source signals can be dependent, however some their narrow band sub-components are independent. In other words, we assume that each unknown source can be modelled or represented as a sum (or linear combinations) of narrow-band sub-signals. Sub-band decomposition ICA (SDICA), an extension of ICA, assumes that each source is represented as the sum of some independent subcomponents and dependent subcomponents, which have different frequency bands.

Wide-band source signals are a linear decomposition of several narrow-band sub components:

$$s(t) = s_1(t) + s_2(t) + s_3(t), \ldots, s_n(t) \quad (1)$$

Such decomposition can be modeled in the time, frequency or time frequency domains using any suitable linear transform. We obtain a set of un-mixing or separating matrices: W_1,W_2,W_3,…,W_n where W_1 is the un-mixing matrix for sensor data $x_1(t)$ and W_n is the un-mixing matrix for sensor data $x_n(t)$. If the specific sub-components of interest are mutually independent for at least two sub-bands, or more generally two subsets of multi-band, say for the sub band "p" and sub band "q" then the global matrix

$$G_{pq} = W_p \times W_q^{-1} \quad (2)$$

will be a sparse generalized permutation matrix P with special structure with only one non-zero (or strongly dominating) element in each row and each column [11]. This follows from the simple mathematical observation that in such case both matrices W_p and W_q represent pseudo-inverses (or true inverse in the case of square matrix) of the same true mixing matrix A (ignoring non-essential and unavoidable arbitrary scaling and permutation of the columns) and by making an assumption that sources for two multi-frequency sub-bands are independent [11]. This provides the basis for separation of dependent sources using narrow bandpass filtered sub-band signals for ICA.

This paper reports the use of sub-band ICA to separate the signals from different sources which may have a level of dependency such as for biosignals. This paper also reports a novel research conducted to identify the number of independent and dependent sources. The work has been conducted on sEMG of the forearm during hand actions to identify the number of active muscles during each action.

3. THEORY

A. Bio sensors

To accurately and reliably capture clinically relevant episodes in a pervasive health care monitoring system, multiple sensors are required to measure both physiological and contextual information. Since both intrinsic and extrinsic factors can affect the sensor readings, it is important to perform source separation before data. For example, typical ECG (Electrocardiogram) sensors can pick up not only the ECG signal, but also respiration, motion artefact, and noise induced signal changes. For Bio Sensor Network (BSN), the same physiological information can also spread across a number of different sensing channels. For instance, the heart beat signal can be sensed by ECG sensors, pulse oximetry sensors, accelerometers, and audio sensors. In other words, for a patient wearing these sensors, it is necessary to extract the common sources of these signals such that the derived signal characteristics are immune to noise and artifacts. Similar scenario arises when conducting the experiments with sEMG signals where the adjacent muscles(sources) can be mixed during the recording. Hence there is a need for identifying number of sources involved in the bio signal experiments.

B. Surface Electromyogram

Surface EMG (sEMG) is a result of the superposition of a large number of transients (muscle action potentials) that have temporal and spatial separation that is pseudo-random. The origin of each of the MUAP is inherently random and the electrical characteristics of the surrounding tissues are nonlinear. Due to the nature of this signal the amplitude of the EMG signal is pseudo-random and the shape of the probability distribution function (PDF) resembles a Gaussian function.

Surface EMG is a non-invasive recording, requires relatively simple equipment, and this opens it for numerous applications. This technique has clear advantages over needle EMG. Most importantly it avoids the use of needles and as a result is painless for patients and avoids health hazards for patient and doctor. Furthermore, sEMG is a quick and easy process that facilitates sampling of a large number of MUPs. The close relationship of surface EMG with the force of contraction of the muscle is useful for number of applications such as sports training and for machine control. The relationship of surface EMG spectrum with muscle fatigue is also very useful for occupational health and sports training. Unfortunately due to a number of factors [12] sEMG is currently of limited use in clinical testing.

Surface EMG may be affected by various factors such as:

- The muscle anatomy (number of active motor units, size of the motor units, the spatial distribution of motor units).
- Muscle physiology (trained or untrained, disorder, fatigue).
- Nerve factors (disorder, neuromuscular junction).
- Contraction (level of contraction, speed of contraction, isometric/non-isometric, force generated).
- Artifacts (crosstalk between muscle, ECG interference).
- Recording apparatus factors (recording-method, noise, electrode's properties, recording sites).

Surface EMG recordings provide a practical means to record from several muscles simultaneously but tend to be unreliable, i.e. recordings from a subject performing the same movement repetitively tend to have considerable trial-to-trial variability. sEMG recordings are also affected by"cross-talk" whereby several muscles may contribute to the recording of a given electrode, making the source of the signal difficult to be identified. Recently, Independent Component Analysis (ICA) has been proposed as a method to analyze sEMG recordings, which addresses many of these concerns. 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.

C. ICA model

It is often required to separate the original signals from the mixture of signals, when there is little information available of the original signals and there is an overlap of the signals in time and frequency domain. Even if there is no or limited information available of the original signals or the mixing matrix, it is possible to separate the original signals using independent component analysis (ICA) under certain conditions. 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.

The aim of source separation is to recover unobserved signals or sources from temporally and spatially correlated observations. Generally, a Blind Source Separation (BSS) problem can be formulated as finding an inverse system that recovers the original signal sources given an observed number of sensor signals $x(t)$ = $[x_1(t)$+$x_2(t)$+$x_3(t)$,. . .,$x_n(t)]$. The mathematical formulation of BSS is typically given in the form of a statistical estimation problem. This model is generative, which means that it describes how the observed data is generated by a process of mixing the source components. By assuming $s(t) = [s_1(t) + s_2(t) + s_3(t), \dots, s_n(t)]^T$ as the unknown signal sources mixed according to a vector valued non-linear function f [1],[13],[15].

For linear mixing models, ICA is a valuable tool for BSS, and the mathematical formulation of the classical ICA is a simplified form of the BSS problem

$$x(t) = As(t) \tag{3}$$

where A is an $N \times M$ scalar matrix representing the unknown mixing coefficients and it is called transfer or mixing matrix. For most ICA applications, noise is either assumed to be white Gaussian with variance σ^2 or negligible. Apart from the source signals, noise can also be assumed to be part of the sources. In this case, the noise is assumed to be statistically independent of other source components. The goal of ICA is to find a linear transformation W of the dependent sensor signals $x(t)$ that makes the outputs as independent as possible:

$$\hat{s}(t) = Wx(t) = WAs(t) \tag{4}$$

where $\hat{s(t)}$ is an estimate of the sources. The sources are exactly recovered when W is the inverse of A up to a permutation and scale change. Since both the sources and the mixing coefficients are unknown, it is impossible either to determine the variances or the order of the independent components. The block diagram approach of ICA for source separation is shown in Figure 1.

The success of ICA to estimate independent sources is dependent on the fulfillment 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.

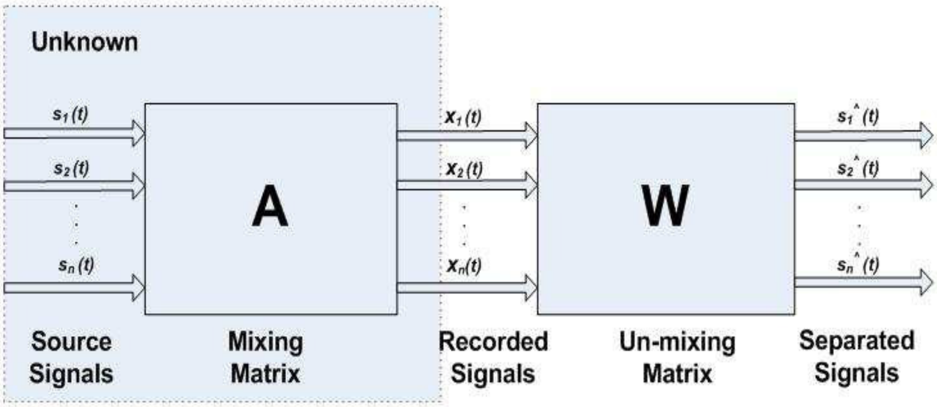

Fig. 1: Source recovery process in Blind source separation (ICA). Here $s(t)$ are the sources. $x(t)$ are the mixtures, A is mixing matrix, W is un-mixing matrix and $\hat{s(t)}$ are the estimated sources.

While standard ICA requires that the number of signals be less than or equal to the number of recordings, number of researchers have attempted to overcome this limitation by developing techniques to separate over-complete (sources are more than recordings) recordings [5],[6]. In some of these papers, the quality of separation has not been objectively measured. The other concern with these techniques is that these are based on the assumption that the signals are sparse. This is not always possible, and in some cases this may require pre-processing of the data.

D. Relevance of ICA methods for sEMG signals

The aim of this section is to demonstrate that there is a strong theoretical basis for applying ICA methods to sEMG signals. The assumptions that underpin the theory of instantaneous ICA - discussed in the previous section - indicate that ICA/BSS methods are ideally suited to separating sources when

- The sources are statistically independent.
- Independent components have non-Gaussian distribution.
- The mixing matrix is invertible.

These assumptions are well satisfied to sEMG data as MUAPs are statistically independent, have non-Gaussian distributions and we can be (virtually) certain that the mixing matrix will be invertible. There are, however, two other practical issues that must be considered. Firstly, to ensure that the mixing matrix is constant, the sources must be fixed in space (this was an implied assumption as only the case of a constant mixing matrix was considered). This is satisfied by sEMG as motor units are in fixed physical locations within a muscle, and in this sense applying ICA/BSS methods to sEMG is much simpler than in other biomedical signal processing applications such as EEG or fMRI in which the sources can move [16]. Secondly, in order to use ICA technique it is essential to assume that signal propagation time is negligible. Volume conduction in tissue is essentially instantaneous [14]. Hence this assumption is also well satisfied.

Based on the above discussion of the ICA assumptions as they apply to sEMG, it is reasonable to be confident that ICA can be effectively applied to sEMG data.

E. Number of Sources Exceed Number of Recordings:

When Surface EMG 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 artifact 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 artifacts 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 $s(t)$. Then $x(t) = As(t)$, where A is an unknown mixing matrix. The output of ICA algorithm is an estimate of un-mixing matrix W so that

$$\begin{aligned} s(t) &= Wx(t) \\ s(t) &= WAs(t) \end{aligned}$$

It is evident that $WA = I$, identity matrix. If the number of recorded data is less than the 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 $x(t)$ of three independent sources $s(t)$ and express it as:

$$\begin{aligned} x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + a_{13}s_3(t) \\ x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) + a_{23}s_3(t) \end{aligned}$$

Consider the estimated un-mixing matrix,

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

generated using standard ICA algorithm on that data. The

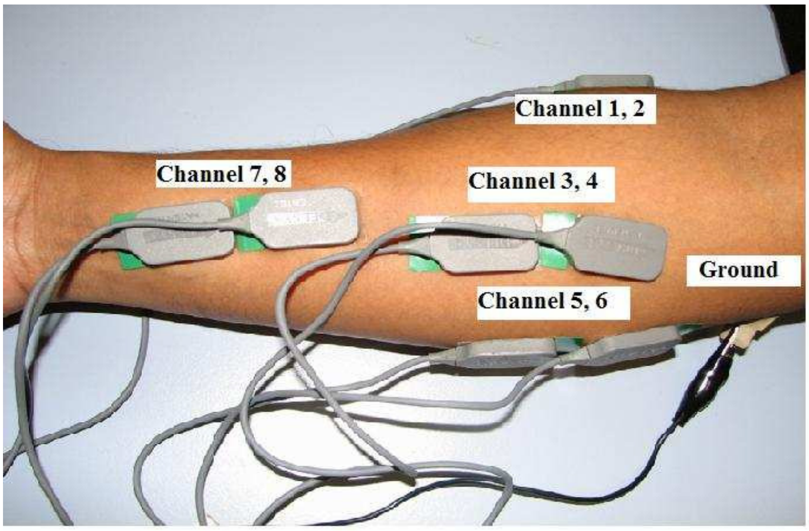

Fig. 2: Placement of Electrodes for Hand gesture Experiment.

estimated independent components can be written as:

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

If none of the coefficient of mixing matrix A is zero means that all three sources are present in both mixtures $x_1(t)$ and $x_2(t)$ 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.

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 sub-band ICA, where normal ICA concept will be applied to various sub-bands to compute the mixing and un-mixing matrices. This paper reports the identification/estimation of number of sources (muscles) involved in different hand actions. The paper explains the concept of dependency and independency to identify number of sources in bio signals like EMG.

4. Methodology

Controlled experiments were conducted, where subjects were asked to perform three different hand actions. Based on the assumption that the muscle contraction is small during the hand actions, ICA algorithm was used to estimate the sources for each sub-band components:

A. EMG Recording

Five subjects (four 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. Eight electrode channels were placed over four different assumed muscles (two electrode channels on each muscle), electrode placement diagram for the hand gesture experiment is shown in 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.

Three different 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 muscle contraction signals during recording. The actions were complex to determine the ability of the system when similar muscles are active simultaneously. The three different hand actions are performed and are listed below:

- Wrist flexion.
- Finger flexion
- Finger and wrist flexion together but normal along centre line.

These hand actions were selected based on small variations between the muscle activities of the different digitas muscles situated in the forearm. The hand actions were selected based on small variations between the muscle activities of the different digitas muscles situated in the forearm.

B. EMG signal processing

The experiments were conducted to obtain three sets of data-independent sources, dependent sources, and double dependent sources. For this purpose, eight channels of sEMG were recorded during three hand actions. These eight channels depicted six independent sources (refer Table 1).During the recording the sensors can pick up the other source information, hence in reality there were at least six or more muscles

TABLE 1: MUSCLES INVOLVED DURING THE HAND GESTURE EXPERIMENT.

Channel	Muscle	Function
1	Brachioradialis	Flexion of forearm
2	Flexor Carpi Ulnaris(FCU)	Abduction and flexion of wrist
3	Flexor Carpi Radialis (FCR)	Abduction and flexion of wrist
4	Flexor Digitorum Superficialis (FDS)	Finger flexion while avoiding wrist flexion
5	Palmer longus	Wristflexor
6	Pronator teres	Pronation of forearm

involved which made it to typical overcomplete ICA problem. The muscles that involved in different hand actions are listed in table 1:

Three classes of recordings were identified using a combination of 4 channels at a time (refer Table 2). These data's were further analyzed using sub-band decomposition ICA.

TABLE 2: CHANNEL SELECTION FOR THREE DIFFERENT CLASSES (INDEPENDENCY, DEPENDENCY AND DOUBLE DEPENDENCY) FOR ICA MATRIX ANALYSIS.

Channel Selection	Classes Involved
(1, 3, 5, 7)	Independent
(2, 4, 6, 8)	Independent
(3, 4, 6, 8)	Dependent
(5, 6, 3, 7)	Dependent
(3, 4, 7, 2)	Dependent
(1, 2, 3, 4)	Double Dependent
(5, 6, 7, 8)	Double Dependent

C. Analysis of mixing matrix

In order to measure the quality of the separation of hand gesture muscle activities and to estimate number of sources, we used the mixing matrix analysis.The surface EMG signals (wide-band source signals) are a linear decomposition of several narrow-band sub components:$s(t) = [s_1(t) + s_2(t) + s_3(t), \ldots, s_n(t)]^T$ where $s_1(t)$,$s_2(t)$,...,$s_n(t)$ each are 2500 samples in length which are obtained from recorded signals $x_1(t)$,$x_2(t)$,...,$x_n(t)$ using ICA. Such decomposition can be modelled in the time, frequency or time frequency domains using any suitable linear transform. We obtain a set of unmixing or separating matrices, then the global matrix

$$G_{pq} = W_p \times W_q^{-1} \tag{5}$$

will be a sparse generalized permutation matrix P with special structure with only one non-zero (or strongly dominating) element in each row and each column [11]. We investigated mathematical properties of ICA mixing and un-mixing matrices to estimate number of sources using the dependency and independency of the sources.

D. Mathematical Methods

Mathematical properties of matrices were investigated to check the linear dependency and independency of global matrices (Permutation matrix P)

- Rank of the matrix

Rank of the matrix will be less than the matrix size for linear dependency and rank will be size of matrix for linear independency, but this couldn't be assured yet due to noise in the signal. Hence determinant is the key factor for estimating number of sources.

- Determinant of the matrix

In real time Determinant should be zero for linear independency (In our case the real time data gives the answer very close to zero for the case, double dependency of hand gesture experiments). Determinant value should be more than zero for linear independency (Valid for hand gesture signals).

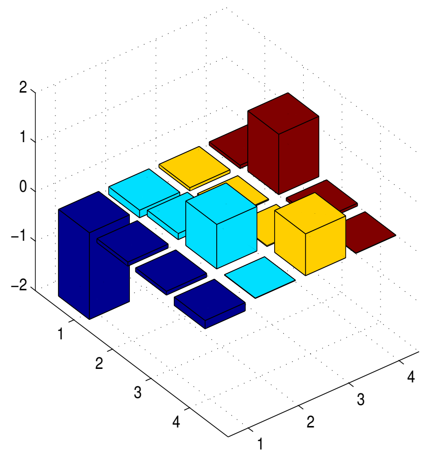

Fig. 3: Three dimensional plot showing the individual matrix elements for Global matrix (G) during Independent test case.

5. RESULTS AND OBSERVATIONS

The above mathematical analysis was performed for all the cases. The determinant results were normalized using Frobe-

TABLE 3: FROBENIUS NORM DETERMINANT RESULTS OF FOUR CHANNELS USING ICA MATRIX ANALYSIS

Independency	Dependency	Double Dependency
0.6628	0.0678	0.0242
0.4475	0.0992	0.0195
0.6591	0.06397	0.0086
0.7937	0.07081	0.0077
0.6328	0.0632	0.0142
0.6071	0.0932	0.0195
0.6891	0.08397	0.0086
0.7992	0.06081	0.0077
0.7891	0.08397	0.0142
0.7292	0.04081	0.0132
Mean = 0.68096	**Mean = 0.072774**	**Mean = 0.01374**
StD = 0.107427	**StD = 0.017413**	**StD = 0.005795**

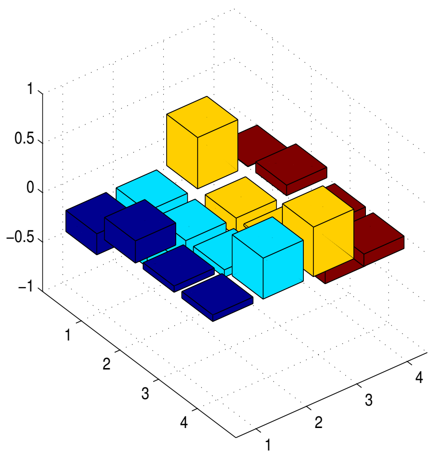

Fig. 4: Three dimensional plot showing the individual matrix elements for Global matrix (G) during Dependent test case.

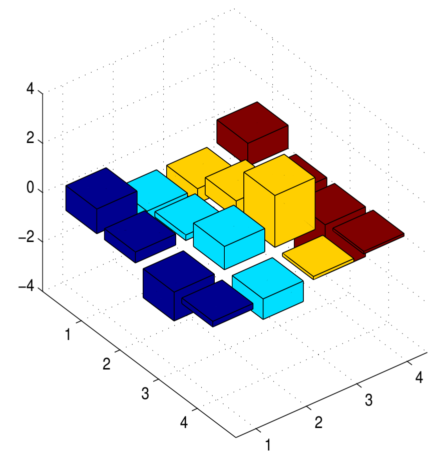

Fig. 5: Three dimensional plot showing the individual matrix elements for Global matrix (G) during Double dependent case.

nius Norm. For hand gesture analysis we considered three different classes of results.

- Independency
- Dependency
- Double dependency

A. *Independency*

The independent results were evident from the global matrix (G). The matrix results confirms with one of the dominant values in each row and column. From the resultant matrix G it is observed that there is clear source separation when the sources are totally independent.

$$G = \begin{pmatrix} \mathbf{-1.7555} & -0.1522 & -0.0608 & -0.0665 \\ -0.0806 & 0.1189 & -0.0201 & \mathbf{1.2224} \\ -0.0760 & \mathbf{0.9003} & 0.0124 & 0.0538 \\ -0.1653 & -0.0046 & \mathbf{0.8451} & -0.0054 \end{pmatrix}$$

Determinant (G) = -1.6490, Det. FrobeniusNorm = **-0.6628**

The Matrix results are clearly shown using 3 dimensional plot (refer Figure 3).

B. *Dependency*

From the global matrix (G) it appears confirmed that there exists more dependent values in the matrix. The matrix shown the results with more than one dependent value in each row and column. More dominant values can be seen in matrix G, which shows the trend of dependency. The results also demonstrate that there could be influence of sources (muscles) from the adjacent channels during the sEMG recordings.

$$G = \begin{pmatrix} -0.2130 & \mathbf{-0.5643} & \mathbf{0.5196} & -0.0028 \\ \mathbf{0.2245} & \mathbf{-0.2497} & \mathbf{-0.1832} & 0.1062 \\ 0.0621 & -0.0753 & -0.0213 & \mathbf{-0.5959} \\ 0.0660 & \mathbf{0.4147} & \mathbf{0.5015} & -0.1231 \end{pmatrix}$$

Determinant (G) = 0.0858, Det. FrobeniusNorm = **0.0678**

The dependent values are shown using 3 dimensional plot (refer Figure 4).

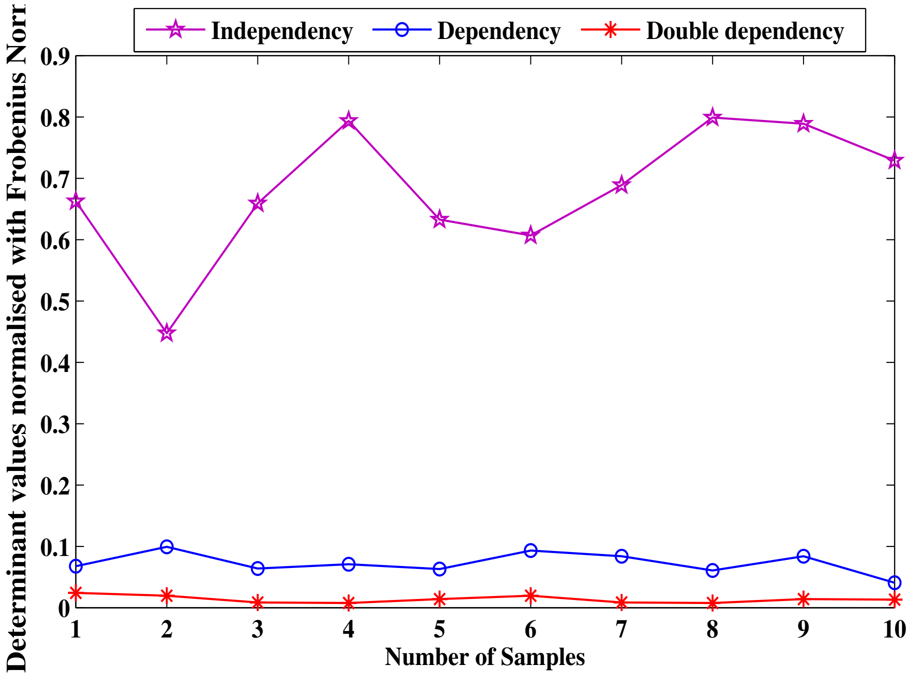

Fig. 6: Plots showing the Frobenius norm determinant results for dependency, double dependency and independency case

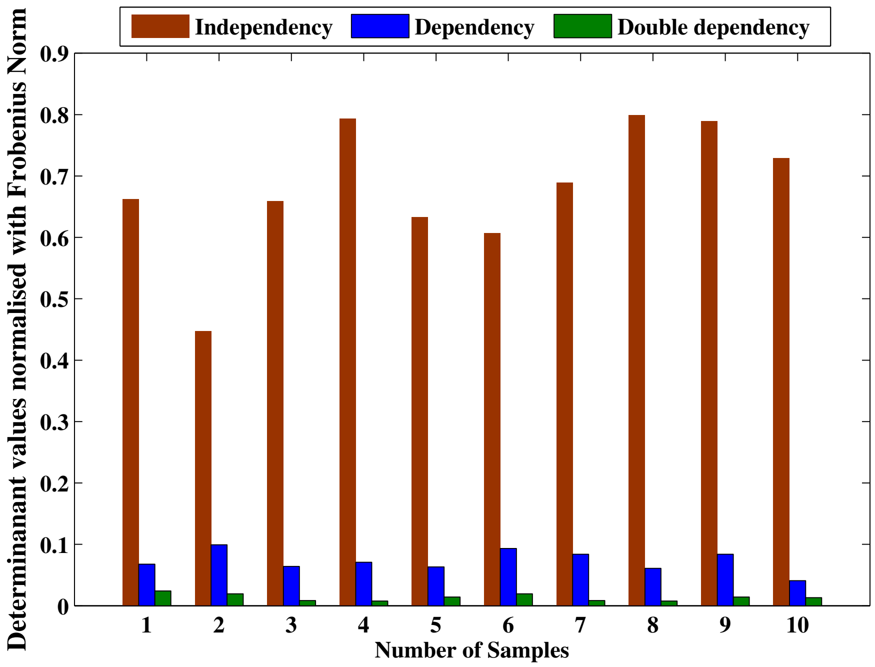

Fig. 7: Bar Plot showing the Frobenius norm determinant results for dependency, double dependency and independency case

C. Double Dependency

In this case, the global matrix (G) shown the results with more than two dependent values in each row and column of the matrix. The results indicates that there could be more cross-talk between adjacent sources. The low determinant results normalized with Frobenius norm justifies the argument.

$$G = \begin{pmatrix} \mathbf{0.9955} & \mathbf{-1.2131} & -0.5903 & \mathbf{0.9328} \\ \mathbf{0.4400} & 0.2165 & \mathbf{0.6893} & \mathbf{-0.3979} \\ \mathbf{-1.1664} & \mathbf{0.9400} & \mathbf{2.0976} & \mathbf{-2.0100} \\ -0.2226 & \mathbf{-0.8282} & -0.1252 & 0.1048 \end{pmatrix}$$

Determinant(G) = -0.0967, Det. FrobeniusNorm = **-0.0242**

The Matrix results for Double dependency are clearly shown using 3 dimensional plot, which is shown in Figure 5.

The overall results for the above analysis are shown in Table 3. The same is well explained with line plot in Figure 6 and using bar plot in Figure 7. Where the plot shows the low determinant values for dependency and double dependency which are well below the independency value results.

Hence if we consider threshold value of 0.4 for Frobenius norm, we can clearly distinguish between independent and dependent sources. A threshold of 0.04 separates between dependent and double dependent sources.

6. Discussion and Conclusion

The overall results were summarized as follows:

- With the use of combination of 4 channels (from 8 recordings) representing three different classes of sources; dependent, double dependent and independent sources it is possible to determine the number of active sources using sub-band ICA.
- The rank of the global matrix is an indicator of the dependency within the matrix and did not indicate the dependent or independent nature of the sources, and was always 4 in the above examples making this unsuitable for deciding dependency and independency of the sources.
- Determinant of the global matrix has been found to be a reliable measure of identifying the linear dependency and independency (refer Table 3).
- The value of the determinant is a good measure to identify the number of dependent sources in the mixture. This provides a measure of the number of active muscles from sEMG.
- There are number of possible applications for such a technique for biosignal applications such as identifying the number of active muscles in overlapping muscles during complex actions and gestures.

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