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Source Separation and Identification issues in bio signals: A solution using Blind source separation

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1. Introduction

The problem of source separation is an inductive inference problem. There is not enough information to deduce the solution, so one must use any available information to infer the most probable solution. The aim is to process these observations in such a way that the original source signals are extracted by the adaptive system. The problem of separating and estimating the original source waveforms from the sensor array, without knowing the transmission channel characteristics and the source can be briefly expressed as problems related to blind source separation (BSS). Independent component analysis (ICA) is one of the widely used BSS techniques for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA is essentially a method for extracting individual signals from mixtures of signals. Its power resides in the physical assumptions that the different physical processes generate unrelated signals. The simple and generic nature of this assumption ensures that ICA is being successfully applied in diverse range of research fields.

Source separation and identification can be used in a variety of signal processing applications, ranging from speech processing to medical image analysis. The separation of a superposition of multiple signals is accomplished by taking into account the structure of the mixing process and by making assumptions about the sources. When the information about the mixing process and sources is limited, the problem is called "blind". ICA is a technique suitable for blind source separation - to separate signals from different sources from the mixture. ICA is a method for finding underlying factors or components from multidimensional (multivariate) statistical data or signals (Hyvarinen et al., 2001; Hyvarinen and Oja, 2000).

ICA builds a generative model for the measured multivariate data, in which the data are assumed to be linear or nonlinear mixtures of some unknown hidden variables (sources); the mixing system is also unknown. In order to overcome the under determination of the algorithm, it is assumed that the hidden sources have the properties of non-Gaussianity and statistical independence. These sources are named Independent Components (ICs). ICA algorithms have been considered to be information theory based unsupervised learning rules. Given a set of multidimensional observations, which are assumed to be linear mixtures of unknown independent sources through an unknown mixing source, an ICA algorithm performs a search of the unmixing matrix by which observations can be linearly translated to form independent output components. When regarding ICA, the basic framework for most researchers has been to assume that the mixing is instantaneous and linear, as in Infomax. ICA is often described as an extension to Principal Component Analysis (PCA) that uncorrelates the signals for higher order moments and produces a non-orthogonal basis. More complex models assume for example, noisy mixtures (Hansen, 2000; Mackay, 1996), nontrivial source distributions (Kaban, 2000; Sorenson, 2002), convolutive mixtures (Attias and Schreiner, 1998; Lee, 1997), time dependency, underdetermined sources (Hyvarinen et al., 1999; Lewicki and Sejnowski, 2000), mixture and classification of independent component (Kolenda, 2000; Lee et al., 1999). A general introduction and overview can be found in (Lee, 1998).

2. Challenges of source separation in Bio signal processing

In biomedical data processing, the aim is to extract clinically, biochemically or pharmaceutically relevant information (e.g metabolite concentrations in the brain) in terms of parameters out of low quality measurements in order to enable an improved medical diagnosis (Niedermeyer and Da Silva, 1999; Rajapakse et al., 2002). Typically, biomedical data are affected by large measurement errors, largely due to the noninvasive nature of the measurement process or the severe constraints to keep the input signal as low as possible for safety and bio-ethical reasons. Accurate and automated quantification of this information requires an ingenious combination of the following four issues:

- An adequate pre-treatment of the data,
- The design of an appropriate model and model validation,
- A fast and numerically robust model parameter quantification method and
- An extensive evaluation and performance study, using in-vivo and patient data, up to the embedding of the advanced tools into user friendly user interfaces to be used by clinicians

A great challenge in biomedical engineering is to non-invasively asses the physiological changes occurring in different internal organs of the human body. These variations can be modeled and measured often as biomedical source signals that indicate the function or malfunction of various physiological systems. To extract the relevant information for diagnosis and therapy, expert knowledge in medicine and engineering is also required.

Biomedical source signals are usually weak, geostationary signals and distorted by noise and interference. Moreover, they are usually mutually superimposed. Besides classical signal analysis tools (such as adaptive supervised filtering, parametric or non parametric spectral estimation, time frequency analysis, and higher order statistics), Intelligent Blind Signal Processing (IBSP) techniques can be used for pre-processing, noise and artefact reduction, enhancement, detection and estimation of biomedical signals by taking into account their spatio-temporal correlation and mutual statistical dependence.

Exemplary ICA applications in biomedical problems include the following:

- Fetal Electrocardiogram extraction, i.e removing/filtering maternal electrocardiogram signals and noise from fetal electrocardiogram signals (Niedermeyer and Da Silva, 1999; Rajapakse et al., 2002).
- Enhancement of low level Electrocardiogram components (Niedermeyer and Da Silva, 1999; Rajapakse et al., 2002)
- Separation of transplanted heart signals from residual original heart signals (Wisbeck et al., 1998)
- Separation of low level myoelectric muscle activities to identify various gestures (Calinon and Billard, 2005; Kato et al., 2006; Naik et al., 2006, 2007)

One successful and promising application domain of blind signal processing includes those biomedical signals acquired using multi-electrode devices: Electrocardiography (ECG) (Niedermeyer and Da Silva, 1999; Rajapakse et al., 2002; Scherg and Von Cramon, 1985; Wisbeck et al., 1998), Electroencephalography (EEG)(Niedermeyer and Da Silva, 1999; Rajapakse et al., 2002; Vig´ario et al., 2000;Wisbeck et al., 1998), Magnetoencephalography (MEG) (H¨am¨al¨ainen et al., 1993; Mosher et al., 1992; Parra et al., 2004; Petersen et al., 2000; Tang and Pearlmutter, 2003; Vig´ario et al., 2000) and Surface Electromyography (sEMG). sEMG is an indicator of muscle activity and related to body movement and posture. It has major applications in biosignal processing; next section explains sEMG and its applications.

3. BSS and Surface Electromyography

Surface EMG is the electrical recording of the spatial and temporal integration of the Motor Unit Action Potential (MUAP) originating from different motor units. It can be recorded non-invasively and used for dynamic measurement of muscular function. It is typically the only in vivo functional examination of muscle activity used in the clinical environment. The signal contains the information that is related to the anatomy and physiology of the muscle. In clinical application, the signal is used for the diagnosis of neuro-muscular disease or disorder. Another application of sEMG is for device control application where the signal is used for controlling devices such as prosthetic devices, robots, and human-machine interface. sEMG is a quick and easy process that facilitates sampling of a large number of MUAPs (Basmajian and Deluca, 1985; Enderle et al., 2005). In sEMG recordings multiple sensors are used to record some physiological phenomena. Often these sensors are located close to each other, so that they simultaneously record signals that are highly correlated with each other. Therefore, the sensors not only record the muscle activity transmitted by volume conduction from a few dynamic muscles but also from artificial signals, such as noise independent of muscle activities, that overlap with actual muscle activity which may be present in all sensors. Extraction of the useful information from such kind of sEMG becomes more difficult for low level of contraction mainly due to the low signal-to-noise ratio. At low level of contraction, sEMG activity is hardly discernible from the background activity. Therefore to correctly identify the number of individual muscles (sources) sEMG 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 BSS (James and Hesse, 2005;Jung et al., 2000). ICA is a statistical technique for obtaining independent sources, s from their linear mixtures, x when neither the original sources nor the actual mixing matrix, A are unknown. This is achieved by exploiting higher order signal statistics and optimization techniques.

For independent component analysis we assume that the observed signals x consists of n underlying sources $s = (s_1, s_2, \ldots, s_n)$, that are unknown, but mutually statistically independent and that these sources were mixed by an unknown (linear) mixing process A

$$x = As(t) \tag{1}$$

with $x = (x_1, x_2, \ldots, x_n)$, $m > n$ where each component s_i has zero mean. The crucial assumption is statistical independence of these source components, which can be expressed mathematically by the joint probability density function as

$$p(s_1, s_2, \ldots, s_n) = \prod_{i=1}^{n} p_i(s_i) \tag{2}$$

Given these assumptions it is possible to separate the recorded data x *through* the linear transformation

$$u(t) = Wx(t) \tag{3}$$

into independent components by applying statistical independence on the output u of this un mixing process and recover the original sources from the observed mixtures. Here both the mixing matrix A and the sources s are unknown, therefore these techniques are called *blind source separation* (Hyvarinen et al., 2001; Hyvarinen and Oja, 2000). The block diagram approach of ICA for source separation is shown in figure 1.

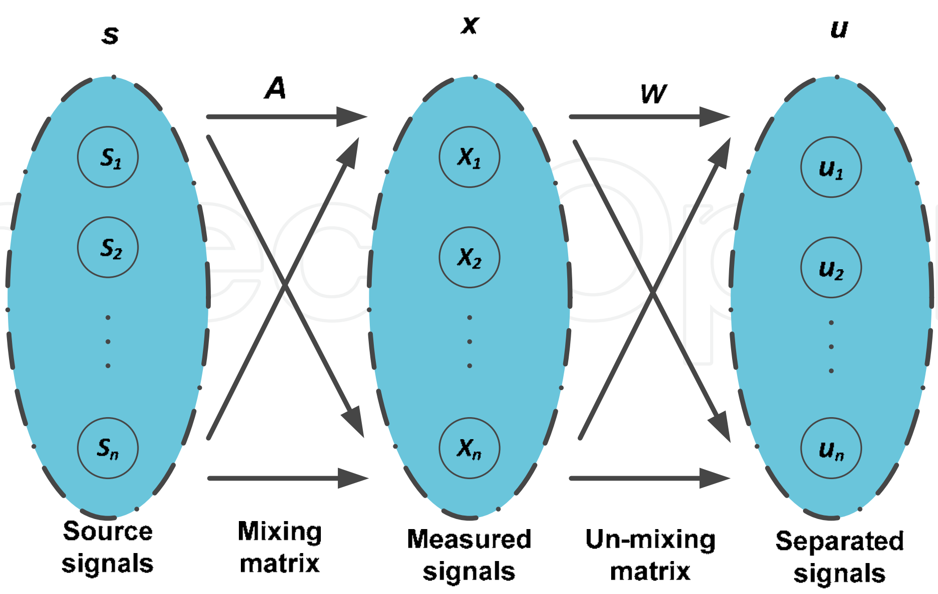

Fig. 1. Flowchart of the Independent Component Analysis (ICA). Here *s(t)* are the sources. *x(t)* are the mixtures, A is mixing matrix and W is un-mixing matrix.

As mentioned above, the signals that can be separated need to be non-Gaussian and independent. For the purpose of applying ICA to sEMG recordings, 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.

3.1 Source separation of sEMG

MUAP separation is a new biomedical application of ICA. In previous applications of ICA to sEMG, researchers have treated the sEMG activity from entire muscles as ICs. Each muscle contains up to 100 individual motor units and the sEMG activity from an entire muscle is the superposition of the activity from each motor unit within the muscle. It has been shown that it is possible to apply ICA to isolate sEMG signals from individual muscles (Azzerboni et al., 2002; Mckeown et al., 2002). Treating sEMG activity from entire muscles as ICs is useful in some applications, especially when studying muscle activity in performing movements. For example, ICA has been used to determine the exact sequence of muscle contractions in swallowing by McKeown et al. (Mckeown et al., 2002) in order to diagnose dysphagia (disorder of swallowing). The focus on treating sEMG activity from entire muscles as ICs arises from a desire to analyse human movement. The most important application of sEMG is as a clinical tool for neuromuscular disease diagnosis. In clinical applications physicians seek to analyse individual motor units. BSS techniques such as ICA is proposed as a novel approach for isolating individual MUAPs from sEMG interference patterns by treating individual motor units as independent sources. This is relevant to clinical sEMG as motor unit crosstalk can make it difficult to study individual MUAPs (Kimura, 2001).

During the sEMG recordings of the digitas muscles to identify the hand gestures for human computer interface, the cross talk due to the different muscles can result in unreliable recordings. The simplest and most commonly used method to improve the quality of the recording is rejection (Barlow, 1979). This is done by discarding a section of the recording that has artefact exceeding a threshold. This method is simple, but causes a significant loss of data and its reliability is questionable since it is predominantly based on visual examination. There is little safeguard that prevents the removal of some small but important features of the signal. It is also very dependent on the technician making it less dependable, and very expensive.

The other commonly used techniques to improve the quality of bio signals recordings include spectral filtering, gating and cross-correlation subtraction (Bartolo et al., 1996). Spectral filtering is often not useful due to the overlap of the frequency spectrum of the desired signals and the artefact component. On the other hand, gating and subtraction may introduce discontinuity in the reconstructed signal. In the recent past, techniques such as time domain (Hillyard and Galambos, 1970; Verleger et al., 1982), and frequency domain regression (Whitton et al., 1978; Woestenburg et al., 1983), have been attempted. However, simple regression in time domain can over-compensate the artefacts (Peters, 1967; Weerts and Lang, 1973). The regression techniques depend on the availability of a good regressing channel - a separate channel to record the corresponding artefact as a reference. This is often not possible when recording sEMG. Therefore, better artefact removal techniques are necessary to overcome the disadvantages of the previous methods. 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 ECG, EOG, and signals from neighbouring muscles. This opens an opportunity of the use of ICA for this application.

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 outputs of ICA are the ICs and the estimated unmixing matrix W. He et al. (He et al., 2006) have used ICA to remove ECG artefact from sEMG data. A variation of the same has been attempted by the Djuwari et al. (Djuwari et al., 2003), for removing ECG artefact from sEMG of the lumbar muscles. They attempted to overcome the limitation of the number of signals to be equal to the number of recordings and remove the ambiguity of the order. Their work utilized ICA in two sequential steps. In the first step, ICA with multichannel sEMG recordings that was corrupted with ECG artefact as the input gave one pure ECG signal in one of its row. In the next step, vector z found by concatenating the row of the output matrix $u = Wx$ contained the ECG artefact and each single row of x in turn was used as its input. The output of this step is a matrix $y = Bz$ that contains ECG artefact in row and the 'cleaned' sEMG of corresponding channel in its other row. While in both cases, the visual inspection suggested the successful removal of the artefact, and statistical analysis seem to suggest an improvement compared to other techniques, because of the unknown properties of the signal, the quality of the signal before and after could not be compared in a better way. Similar work is also reported by Yong et al. (Hu et al., 2007) where ICA has been employed to filter the sEMG of the lumbar muscles. Azzerboni et al. (Azzerboni et al., 2004) demonstrated the artefacts removal in sEMG using ICA and Discrete Wavelet Transform (DWT). ICA has also been used by Nakamura et al. (Nakamura et al., 2004), to decompose the sEMG recordings in terms of the MUAPs. In their paper, they have acknowledged the drawbacks and the necessary conditions required for the success of the ICA, but have not demonstrated the suitability of their experimental data for ICA application. The earlier work done by the researchers have mainly focused on sEMG source separation and identification. However further source separation issues need to be investigated.

3.2 Validity of the basic ICA model for sEMG applications

The application of ICA to the study of sEMG and other bio signals assumes that several conditions are verified, at least approximately: the existence of statistically independent source signals, their instantaneous linear mixing at the sensors, and the stationarity of the mixing and the ICs. The independence criterion considers solely the statistical relations between the amplitude distributions of the signals involved, and not the morphology or physiology of neural structures. Thus, its validity depends on the experimental situation, and cannot be considered in general. There are however, two other practical issues that must be considered:

1. 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 to sEMG is much simpler than in other biomedical signal processing applications such as EEG or fMRI in which the sources can move (Jung et al., 2001).

2. Secondly, in order to use ICA it is essential to assume that signal propagation time is negligible. Signals from Gaussian sources cannot be separated from their mixtures using ICA (Mckeown et al., 1999) because Gaussianity is a measure of independence. 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 maximum 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 maximum 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 easily. The fundamental principle of ICA is to determine the unmixing matrix and use that to separate the mixture into the ICs. The ICs 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. However there are few issues involved in ICA for sEMG applications. Three main problems that need to be addressed:

- issue related to identifying dependency and independency nature of the
- sources
- order of the separated signals and
- normalisation of the estimated ICs

This research proposes the imposition of sEMG conditions on ICA to overcome these limitations, resulting in semi-blind ICA. In order to validate the above mentioned theory two types of sEMG (bio signals) were analysed. First one is to identification of various complex gestures based on decomposition of myo electric signal and the second one is to identification of different vowel utterances based on facial sEMG signals. The experimental methodology, results and discussion related to above mentioned experiments are explained next.

4. Methodology

Experiments were conducted to evaluate the performance of the hand gesture recognition and facial muscle activity using surface EMG. Experiments were performed to determine the reliability of the use of facial sEMG to identify the unspoken vowel of an individual. The study focused on inter-experimental variations, to determine whether the person repeated the same set of muscle activation strategies for the same speech patterns. This was done with the aim of determining the reliability of the use of facial sEMG for identifying unspoken vowels, and for human computer interface. It was also done to establish whether normal people speak with the same muscle activation strategy.

4.1 Hand gesture sEMG and Facial sEMG recording procedure

For the hand gesture experiments five subjects whose ages ranging from 21 to 32 years (four males and one female) were chosen. The experiments were conducted on two different days on all five subjects. 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.

Channel	Muscle	Function
1	Brachioradialis	Flexion of forearm
2	Flexor Carpi radialis (FCR)	Abduction and flexion of wrist
3	Flexor Carpi Ulnaris (FCU)	Adduction and flexion of wrist
4	Flexor digitorum superficialis (FDS)	Finger flexion while avoiding wrist flexion

Table 1. Placement of electrodes over the skin of the forearm

Before placing the electrodes subject's skin was prepared by lightly abrading with skin exfoliate to remove dead skin that helps in reducing the skin impedance to less than 60 Kilo Ohm. Skin was also cleaned with 70% v/v alcohol swab to remove any oil or dust on the skin surface. The experiments were repeated on two different days. Subject was asked to keep the forearm resting on the table with elbow at an angle of 90 degree in a comfortable position. Three hand actions were performed and repeated 12 times at each instance. Each time raw signal sampled at 1024 samples/second was recorded. A suitable resting time was given between each experiment. There was no external load. The gesture used for the experiments are listed below and details have been provided in table 1:

- Wrist flexion (without flexing the fingers).
- Finger flexion (ring finger and the middle finger together without any wrist flexion).
- Finger and wrist flexion together but normal along centre line

The hand actions and gestures represented low level of muscle activity. The hand actions were selected based on small variations between the muscle activities of the different digitas 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. Experiments were conducted on the single subject on two different days to test the inter day variations. A male subject is participated in the experiment. The experiment used 4 channel EMG configurations as per the recommended recording guidelines (Fridlund and Cacioppo, 1986). A four channel, portable, continuous recording MEGAWIN equipment (from MEGA Electronics, Finland) was used for this purpose. Raw signal sampled at 2000 samples/ second was recorded. Prior to the recording, the male participant was requested to shave his facial hair. The target sites were cleaned with alcohol wet swabs. Ag/AgCl electrodes (AMBU Blue sensors from MEDICOTEST, Denmark) were mounted on appropriate locations close to the selected facial muscles: the right side *Zygomaticus Major, Masseter & Mentalis* and left side *Depressor anguli oris*. The inter electrode distance was kept constant at 1cm for all the channels and the experiments.

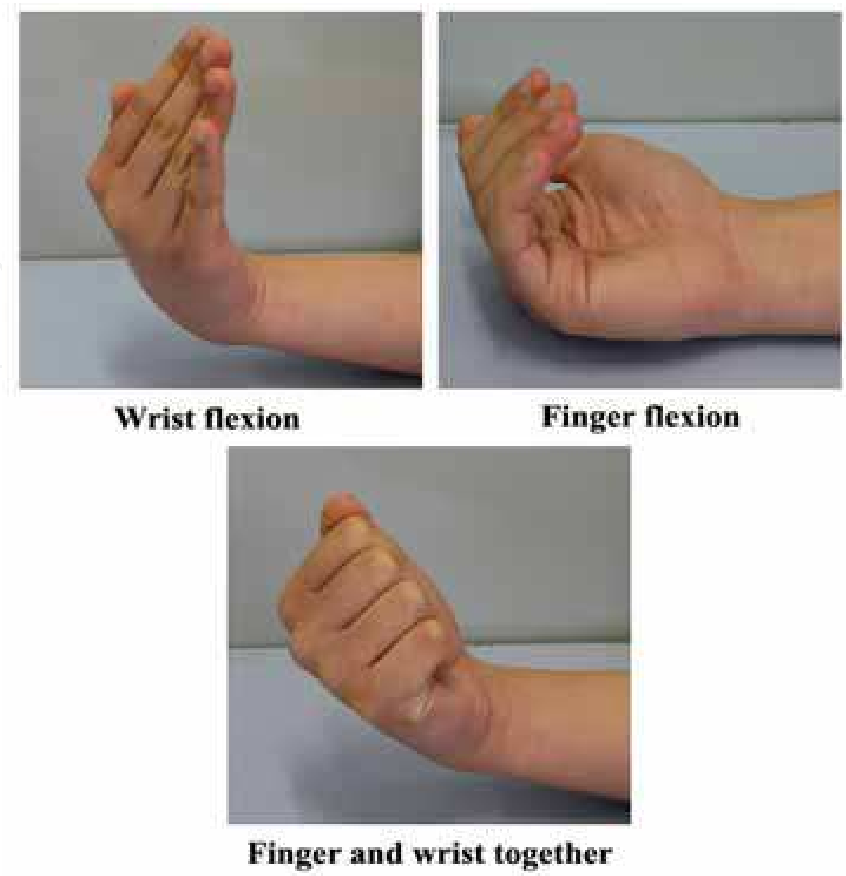

Fig. 2. Three hand gestures during the hand gesture experiment

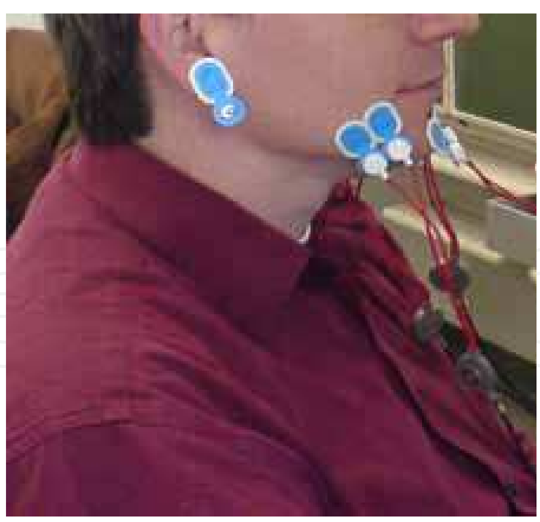

Fig. 3. Facial vowel utterance during the experiment

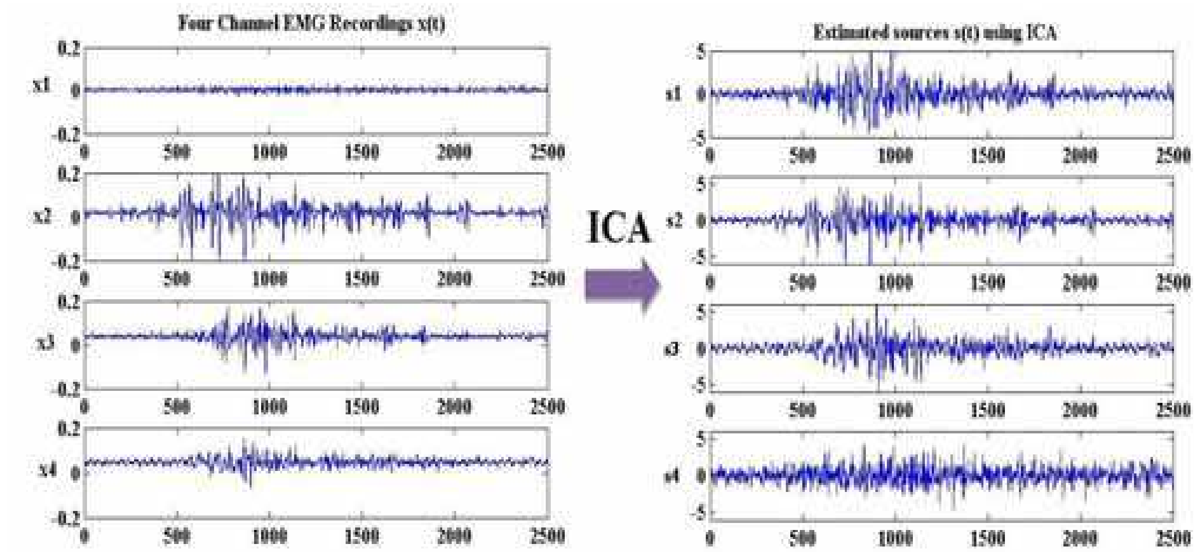

Fig. 4. Estimated four channel source signals $s(t)$ from a four channel Hand sEMG recording $x(t)$ for one of the hand gesture actions using fast ICA algorithm

Controlled experiments were conducted where the subject was asked to speak 5 English vowels (/a/, /e/, /i, /o, /u/). Each vowel was spoken separately such that there was a clear start and ends of the utterance. During this utterance, facial sEMG from the muscles was recorded. sEMG from four channels were recorded simultaneously. The recordings were visually observed, and the recordings with any artifacts -typically due to loose electrodes or movement, were discarded. The experiment was repeated for ten times. A suitable resting time was given between each experiment.

4.2 Data Analysis

The aim of these experiments were to test the use of ICA along with known properties of the muscles for separation of sEMG signals for the purpose of identifying hand gestures and to test the use of ICA on the facial sEMG signals for identifying speakers. Similar data analysis was performed to test the reliability of the ICA on facial sEMG and hand gesture sEMG.

For hand gesture actions each experiment was repeated 12 times and each experiment lasted approximately 2.5 seconds. The sampling rate was 1024 samples per second. There were four channel (recordings) electrodes and four active muscles associated with the hand gesture, forming a square 4×4 mixing matrix. For facial muscle experiments, there were approximately 5000 samples of the data for each utterance of vowels (a/e/i/o/u). 10 set of these recording were considered. Since there were four channel recordings electrodes and four active muscles associated with each utterance of vowel, this formed 4×4 mixing matrix

For both experimental datasets, the sEMG recordings were separated using fast ICA matlab algorithm which has been developed and proposed by the team at the Helsinki University of Technology (Hyvarinen and Oja 1997). The mixing matrix A was computed for the first set of data only. The independent sources of motor unit action potentials that mix to make the EMG recordings were computed using the following.

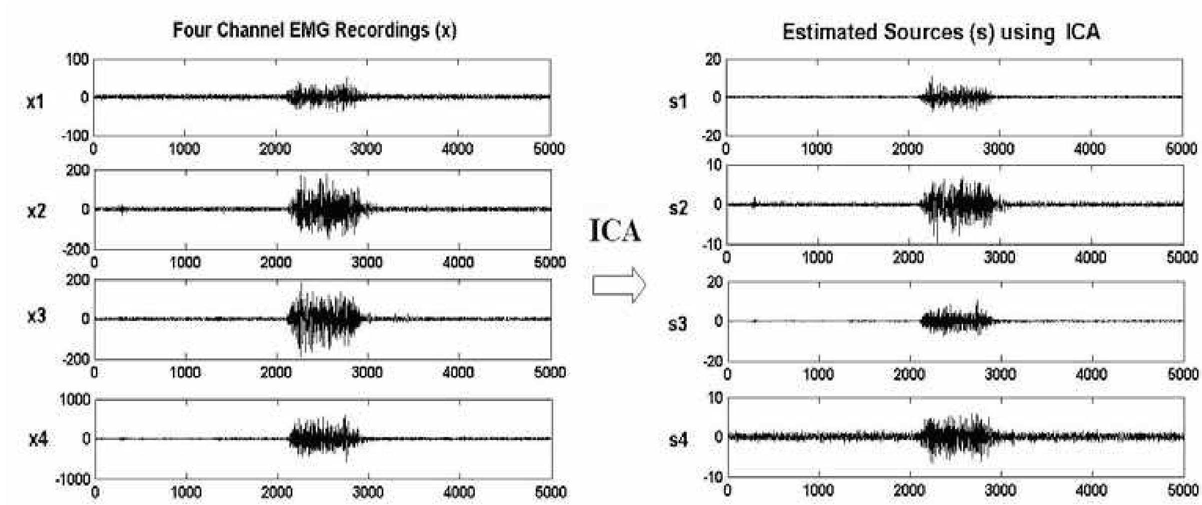

Fig. 5. Estimated four channel source signals $s(t)$ from a four channel Facial sEMG recording $x(t)$ for one of the hand gesture actions using fast ICA algorithm

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

where, W is the inverse of the mixing matrix A. This process was repeated for each of the three hand gesture experiments. Four sources were estimated for each experiment. Samples of four channels of muscle activity for hand gesture and facial muscle activity, after source separation using Fast ICA are shown in figures 4 and 5. After separating the four sources *sa, sb, sc* and *sd,* each of these was segmented to sample length. Root Mean Squares (RMS) was computed for each separated sources using the following.

$$S_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{n} s_i^2} \tag{5}$$

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 and muscle activity for facial muscle. Our analysis demonstrates that this is a simple yet very efficient measure of the muscle activity when the muscle activity for each of the muscles has been separated from the sEMG recordings.

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 responsible for the muscle activity. 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.

The above process was repeated for all three different hand actions 12 times and for each of the participants. The process had been repeated for the facial muscle sEMG for the five vowels (a/e/i/o/u). The outcome of this was 10 set of examples, each example pertaining to speech of five vowels. These results were used further for neural network analysis.

4.3 Neural Network analysis

As a first step, the networks were trained using the randomly chosen training data. Performances were also monitored during the training phase in order to prevent overtraining of the network. The similar ANN architecture was used to test the reliability of Hand gesture sEMG and facial sEMG. The ANN consisted of two hidden layers with a total of 20 nodes. Sigmoid function was the threshold function and the type of training algorithm for the ANN was gradient descent and adaptive learning with momentum with a learning rate of 0.05 to reduce chances of local minima.

The systems were tested using data that was not the training data. During testing, the ANN with weight matrix generated during training was used to classify RMS of the muscle activity separated using un-mixing matrix generated during training. The ability of the network to correctly classify the inputs against known data's was used to determine the efficacy of the technique.

For hand gesture actions 12 sets of examples were used to train a back-propagation neural network. The inputs to the network were the 4 RMS values for each gesture and the output of the network were the three gestures. A back propagation neural network was then trained with the RMS values as the inputs and the gesture numbers as the targets. This network was then tested for the test data. For facial sEMG we used 10 sets with 4 inputs and 3 outputs by taking different combinations of vowels (a/i/u), (i/o/u), (a/o/u), (e/i/u) etc. The inputs to the network were the 4 RMS values for each vowel utterance and the output of the network were the three vowels. Similar to the hand gesture analysis, a back propagation neural network was trained with the RMS values as the inputs and the vowel utterance numbers as the targets. This network was then tested for the test data.

5. Results and observations

The aim of this research was to test the reliability and to determine the efficacy of the semi-blind ICA technique to decompose sEMG into muscle activity from individual muscles and classify the activity from these muscles to identify the hand gestures and speakers. The ability of the system to accurately classify the decomposed sEMG against the known hand gestures has been tabulated in table 2. For comparative purposes and to evaluate the ability of the system, the classification of different vowels has been tabulated in table 3.

5.1 Hand gesture Identification using decomposed sEMG

This is the result of classification of RMS of the decomposed sEMG using ICA generated un-mixing matrix from the training data and classified using a neural network trained with the help of the training data. The accuracy was computed based on the percentage of correct classified data points to the total number of data points. These results indicate an over all classification accuracy of 100% for all the experiments. The results demonstrate that this technique can be used for the classification of different hand gesture actions when the muscle activity is low. The results also indicate that the system is resilient to differences in subjects and inter-day variations.

Number of participants	Wrist flexion		Finger Flexion		Finger flexion and wrist flexion	
	Day one	Day two	Day one	Day two	Day one	Day two
Subject 1	100%	100%	100%	100%	100%	100%
Subject 2	100%	100%	100%	100%	100%	100%
Subject 3	100%	100%	100%	100%	100%	100%
Subject 4	100%	100%	100%	100%	100%	100%
Subject 5	100%	100%	100%	100%	100%	100%

Table 2. Experimental results for Hand Gesture Identification using muscle activity separated from sEMG using ICA

5.2 Vowel classification using decomposed sEMG

The result of the experiment demonstrates the performance of the subject for different days in classifying the RMS values of the 3 vowels.

	Correctly Classified Vowels	
	Day 1	Day 2
/a/	(60%)	(60%)
/o/	(55%)	(65%)
/u/	(65%)	(60%)

	Correctly Classified Vowels	
	Day 1	Day 2
/e/	(60%)	(60%)
/i/	(55%)	(65%)
/u/	(65%)	(60%)

Table 3. Experimental results for vowel classification using muscle activity separated from facial sEMG using ICA

The result of the use of these RMS values to train the ANN using data from individual subjects showed easy convergence. The results of testing the ANN to correctly classify the test data based on the weight matrix generated using the training data is tabulated in table 3 for two different set of vowels. The accuracy was computed based on the percentage of correct classified data points to the total number of data points. The results indicate an overall average accuracy of about 60%.

5.3 Comparative evaluation of hand sEMG with facial sEMG applications

Independent Component Analysis with back propagation neural network was successfully classified the hand gesture surface EMG signals. To measure the efficiency of ICA for source separation, similar analysis was performed on facial sEMG signals. In order to measure the quality of the separation of hand gesture muscle activities in comparison to facial muscle activities, we used the mixing matrix analysis. The surface EMG signals (wide-band source signals) are a linear decomposition of several narrow-band sub components: $s(t) = s_1(t) + s_2(t) + s_3(t) + \ldots + s_n(t)$ where $s_1(t)$, $s_2(t), \ldots, s_n(t)$ are 2500 samples in length each, which are obtained from the recorded signals $x_1(t)$, $x_2(t), \ldots, x_n(t)$ by using ICA. 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: $W_1, W_2, \ldots, W_n$ where W_1 is the un-mixing matrix for sEMG sensor data $x_1(t)$ and W_n is the un-mixing matrix for sEMG 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

$$G_{pq} = W_p \times W_q^{-1} = P \tag{6}$$

will be a sparse generalized permutation matrix *P* with special structure and only one non-zero (or strongly dominating) element in each row and each column (Cichocki and Amari, 2003). This follows from the simple mathematical observation that in such case both matrices W_p and W_q represents 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 (Cichocki and Amari, 2003). The above assumption is applied for different hand gestures, and some convincing results were derived, which demonstrate that ICA is clearly able to isolate the four independent sources from hand muscle sEMG recordings. The results of two un-mixing matrices which are obtained from one of the hand gesture are given below, which satisfies the equation (6):

$$G = W_1 * W_2^{-1} = \begin{bmatrix} 0.0800 & \mathbf{-1.0094} & 0.0271 & 0.0927 \\ 0.0670 & -0.0046 & 0.0307 & \mathbf{-1.2610} \\ 0.0143 & 0.0295 & \mathbf{0.8062} & 0.0273 \\ \mathbf{2.1595} & 0.3787 & -0.0729 & 0.0686 \end{bmatrix}$$

Determinant (G) = 2.2588

In this example the dominant values in each row (ICA does have order and sign ambiguity, hence only absolute values will be taken into consideration) demonstrate that ICA is able to isolate the four sources (*s1, s2, s3* and *s4)* from four sEMG recordings (*x1, x2, x3* and *x4)* successfully. To justify this hypothesis, the determinant of the matrix *G* was computed. From the mathematical point of view, *n* vectors in R_n are linearly dependent if and only if the determinant of the matrix formed by the vectors is zero (Meyer, 2000). In each instance, results which are higher than one were obtained. These results clearly justified that ICA is able to isolate four independent sources from the four channel hand muscle recordings.

Similar analyses were performed on facial muscles: Four sources (*s1, s2, s3* and *s4)* were decomposed from four recordings (*x1, x2, x3* and *x4)* using fastICA algorithm. In order to check the quality of the source separation, the global matrices for each narrow-band components was computed. The following results show one of the examples of facial sEMG signals, which also satisfy the equation (6).

$$G = W_1 * W_2^{-1} = \begin{bmatrix} 0.0485 & \mathbf{-1.1738} & 0.0891 & \mathbf{-1.1105} \\ \mathbf{-0.8019} & \mathbf{1.0171} & \mathbf{0.7873} & 0.1669 \\ \mathbf{-0.8377} & 0.0142 & \mathbf{1.1837} & \mathbf{-1.0169} \\ \mathbf{-1.4905} & 0.0192 & \mathbf{-1.3557} & 0.4750 \end{bmatrix}$$

Determinant (G) = 0.0013 (Which is very close to Zero)

By inspecting the above matrix we are certain that the values are dependent (sources are dependent), cause in each row there are more than one dominant value. To clarify this we computed the determinant of the global matrix *G* and the result are very close to zero which from matrix theory explains that the sources are dependent (Meyer, 2000).

The above analysis demonstrates the importance of mixing matrix analysis for source separation and identification of surface EMG signals. For the results it is evident that the above analysis could be used as a pre-requisite tool to measure the reliability of SEMG-based systems, especially those classifying recorded such bio-signals.

6. Discussion

The results demonstrated the applications and limitations of ICA for Hand gesture sEMG and facial sEMG. Similar data analysis on both hand gesture sEMG and Facial sEMG has helped to verify the reliability of ICA.

6.1 Applications

In this chapter, a new system to classify small level of muscle activity to identify hand gesture using a combination of independent component analysis (ICA), known anatomy and neural network configured for the individual has been proposed. It has been tested with 5 volunteer participants and the experiments were repeated on different days. The results indicate the ability of the system to perfectly recognise the hand gesture even though the muscle activity was very low and there were number of muscles simultaneously active for each of the gesture.

There are number of researchers who have reported attempts to identify hand and body gestures from sEMG recordings but with low reliability. This may be attributed to low signal to noise ratio and large cross-talk between different simultaneously active muscles. ICA is a recently developed signal processing and source separation tool and has been employed to separate the muscle activity and remove artefacts to overcome this difficulty. While ICA has been extremely useful for audio based source separation, its application for sEMG is questionable due to the random order of the separated signals and magnitude normalisation. This paper reports research that overcomes this shortcoming by using prior knowledge of the anatomy of muscles along with blind source separation. Using a combination of the model and ICA approaches with a neural network configured for the individual overcomes the order and magnitude ambiguity. The results indicate that the classification of the muscle activity estimated from sEMG using ICA gave 100% accuracy. These results indicate that muscle activity separated from sEMG recordings using ICA is a good measure of the subtle muscle activity that results in the hand gestures.

6.2 Limitations

The results on facial sEMG analysis demonstrated that, the proposed method provides interesting result for inter experimental variations in facial muscle activity during different vowel utterance. The accuracy of recognition is poor when the system is used for testing the training network for all subjects. This shows large variations between subjects (inter-subject variation) because of different style and speed of speaking. This method has only been tested for limited vowels. This is because the muscle contraction during the utterance of vowels is relatively stationary while during consonants there are greater temporal variations.

The results demonstrate that for such a system to succeed, the system needs to be improved. Some of the possible improvements that the authors suggest will include improved electrodes, site preparation, electrode location, and signal segmentation. This current method also has to be enhanced for large set of data with many subjects in future. The authors would like to use this method for checking the inter day and inter experimental variations of facial muscle activity for speech recognition in near future to test the reliability of ICA for facial SEMG

7. Conclusions

BSS technique has been considered for decomposing sEMG to obtain the individual muscle activities. This paper has proposed the applications and limitations of ICA on hand gesture actions and vowel utterance.

A semi blind source separation using the prior knowledge of the biological model of sEMG had been used to test the reliability of the system. The technique is based on separating the muscle activity from sEMG recordings, saving the estimated mixing matrix, training the neural network based classifier for the gestures based on the separated muscle activity, and subsequently using the combination of the mixing matrix and network weights to classify the sEMG recordings in near real-time.

The results on hand gesture identification indicate that the system is able to perfectly (100% accuracy) identify the set of selected complex hand gestures for each of the subjects. These gestures represent a complex set of muscle activation and can be extrapolated for a larger number of gestures. Nevertheless, it is important to test the technique for more actions and gestures, and for a large group of people.

The results on vowel classification using facial sEMG indicate that while there is a similarity between the muscle activities, there are inter-experimental variations. There are two possible reasons; (i) people use different muscles even when they make the same sound and (ii) cross talk due to different muscles makes the signal quality difficult to classify Normalisation of the data reduced the variation of magnitude of facial SEMG between different experiments. The work indicates that people use same set of muscles for same utterances, but there is a variation in muscle activities. It can be used a preliminary analysis for using Facial SEMG based speech recognition in applications in Human Computer Interface (HCI).

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The field of biomedical engineering has expanded markedly in the past ten years. This growth is supported by advances in biological science, which have created new opportunities for development of tools for diagnosis and therapy for human disease. The discipline focuses both on development of new biomaterials, analytical methodologies and on the application of concepts drawn from engineering, computing, mathematics, chemical and physical sciences to advance biomedical knowledge while improving the effectiveness and delivery of clinical medicine. Biomedical engineering now encompasses a range of fields of specialization including bioinstrumentation, bioimaging, biomechanics, biomaterials, and biomolecular engineering. Biomedical engineering covers recent advances in the growing field of biomedical technology, instrumentation, and administration. Contributions focus on theoretical and practical problems associated with the development of medical technology; the introduction of new engineering methods into public health; hospitals and patient care; the improvement of diagnosis and therapy; and biomedical information storage and retrieval. The book is directed at engineering students in their final year of undergraduate studies or in their graduate studies. Most undergraduate students majoring in biomedical engineering are faced with a decision, early in their program of study, regarding the field in which they would like to specialize. Each chosen specialty has a specific set of course requirements and is supplemented by wise selection of elective and supporting coursework. Also, many young students of biomedical engineering use independent research projects as a source of inspiration and preparation but have difficulty identifying research areas that are right for them. Therefore, a second goal of this book is to link knowledge of basic science and engineering to fields of specialization and current research. The editor would like to thank the authors, who have committed so much effort to the publication of this work.

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