Multi run ICA and surface EMG based signal processing system for recognising hand gestures

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Abstract

Hand gesture identification is a complex problem, where more number of muscles will be involved even for a simple hand movement. Surface electromyography (sEMG) is an indicator of muscle activity and related to body movement and posture. In the recent past sEMG had been used with various statistical signal processing technique to identify different hand gestures, but since the hand actions require simultaneous muscle contractions reliability issues exist. Recently Blind source separation (BSS) techniques like Independent Component Analysis (ICA) had been used to tackle this problem. In this paper, a novel method is proposed to enhance the performance of ICA of sEMG by decomposing the signal into components originating from different muscles. First, we use FastICA algorithm to generate random mixing matrix, and the best mixing matrix is chosen based on the highest Signal to interference ratio(SIR) of mixing matrix. Pattern classification of the separated signal is performed in the second step with a back propagation neural network. The proposed model-based approach is able to overcome the ambiguity problems (order and magnitude problem) of BSS methods by selecting an apriori mixing matrix based on known hand muscle anatomy. Testing was conducted using several single shot experiments conducted with seven subjects. The results indicate that the system is able to classify six different hand gestures with 99% accuracy.

1. Introduction

Hand gestures involve relative flexure of the user's fingers and consist of information that is often too abstract to be interpreted by a machine. An important application of hand gesture recognition is to improve the quality of life of the deaf or non-vocal persons through a hand-gesture to speech system. Another major application is in rehabilitation engineering and in prosthesis. Some of the commonly employed techniques in hand recognition include mechanical sensors [1], vision based systems [2] and the use of electromyogram [3]. Electromyogram has an advantage of being easy to record, and it is non-invasive. Surface electromyography (sEMG) is the electrical manifestation in contracting muscles activity and closely related to the muscle contraction and thus an obvious choice for control of the prosthesis. Many attempts have been made to use sEMG signal as the command to control the prosthesis [4], but none of them takes explicit advantage of its subtlety, the fact that commands can be issued without the generation of strong contraction and observable movements. 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 muscle as well, referred to as cross-talk. The cross-talk problem is more significant when the muscle activation is relatively weak (subtle) because the comparable signal strength is very low. Extraction of the useful information from such kind of sEMG becomes difficult mainly due to the low signal to noise ratio. At low level of contraction, EMG activity is hardly discernible from the background activity. To identify the small movements and gesture of the hand, there is need to identify components of sEMG originating from the different 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) techniques.

Independent component analysis (ICA) has found numerous applications in audio and biosignal processing disciplines. Research that isolates motor unit action potential (MUAP) originating from different muscles and motor units has been reported in 2004 [5]. Recently sEMG with ICA has been proposed for the hand gesture identification [6]. Muscle activity originating from different muscles can be considered to be independent, and this gives an argument to use BSS methods for separation of muscle activity originating from the different muscles. The spatial location of the active muscle activity is the determining factor of the hand action and gesture. One technique that has been reported is the use of prior knowledge of the anatomy. The advantage of this approach is that the model based BSS removes ambiguity of the order and magnitude.

In the previous research ICA had been used for hand gesture identification using constant mixing matrix where the overall accuracy was reported 100% [6], but the number of hand gesture identification was restricted to three. This paper reports improving the identification of various hand gesture using multi run ICA of sEMG. ICA algorithm was performed several times; at each instance mixing matrix was computed. Best mixing matrix was chosen based on the highest Signal to interference ratio (SIR) of global matrix. The processing in this new input system consists of three major stages: At first, hand gestures are sensed from non-invasive surface electromyograms, and in the second step the activities of the involved individual muscles are decomposed by semi-blind ICA. In the last step, the particular hand action is identified with an artificial neural network (ANN).

2. Independent Component Analysis

Independent component analysis is a computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA. It is a special case of blind source separation [7].

ICA assumes the mixing process as linear, so it can be expressed as:

$$x = As \tag{1}$$

where x = $(x_1, x_2, ..., x_n)$ is the recordings, s = $(s_1, s_2, ..., s_n)$ the original signals and A is the n x n mixing matrix of real numbers. 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

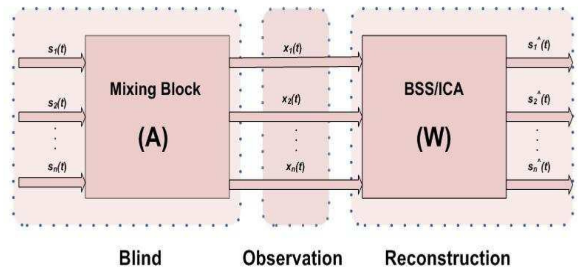

Figure 1. Blind source separation (BSS) block diagram. $s(t)$ are the sources. $x(t)$ are the recordings, $\hat{s}(t)$ are the estimated sources A is mixing matrix and W is un-mixing matrix

$$s = Wx = WAs \tag{2}$$

For this purpose, ICA relies strongly on the statistical independence of the sources s. The ICA source recovering process is shown in Figure 1. For solving the ICA it is assumed that the number of observations is equal to the number of source signals [8].

2.1. Multi run ICA

One of the most effective ways of modeling vector data for unsupervised pattern classification or coding, is to assume that the observations are the result of picking randomly out of a fixed set of different distributions. Independent component analysis is an iterative BSS technique. At each instance original signals are estimated from the mixed data. The estimation quality depends mainly on the mixing matrix A.

Multi run ICA is the process where the ICA algorithm will be computed many times; at each instance different mixing matrices will be obtained. $A_1, A_2, ..., A_n$. Since it is an iterative technique repeat analysis yields similarity matrices at some stage. Hence mixing matrices A_1, A_2 etc, will repeat after certain iterations.Multi run ICA results in several matrices. To estimate the sources from the mixed data ICA requires just one mixing matrix, hence the best matrix has to be selected among the set of these mixing matrices in order to yield better results. There are several methods to compute the quality of the mixing matrices. But SIR is a popular tool to perform this task [9]. This paper uses this unique technique to compute the mixing matrix from the sEMG signals.

3. Methodology

Experiments were conducted to evaluate the performance of the proposed hand gesture recognition system

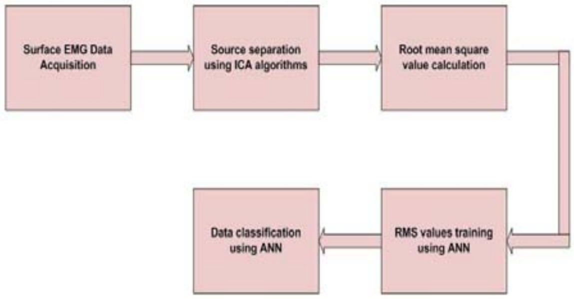

Figure 2. Hand gesture identification methodology block diagram

from hand muscle surface EMG. We have proposed a technique to classify small level of muscle activity to identify hand gesture using a combination of multi run ICA, known muscle anatomy and neural network configured for the individual.The proposed system consists of the following steps which is shown in Figure 2, and explained in the next sections.

3.1. sEMG Data Acquisition

In the hand gesture experiments, seven volunteer subjects between 21 and 32 years participated. For the data acquisition a proprietary sEMG acquisition system from Delsys (Boston, MA, USA) was used. Four electrode channels were placed over four different muscles as indicated in the Table 1. A reference electrode was placed at Epicondylus Medialis.

Each channel is a set of two differential electrodes with a fixed inter-electrode distance of 10mm and a gain of 1000. Before placing the electrodes subject's skin was prepared by lightly abrading with skin exfoliate to remove dead skin that helped 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. Subjects were asked to keep the forearm resting on the table with elbow at an angle of 90 degree in a comfortable position. Six subtle 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 subtle contraction signals during recording. Complex actions were chosen to determine the ability of the system when similar muscles are active simultaneously. The six different hand actions are performed and are listed below:

- Wrist flexion.
- Finger flexion(ring finger and the middle finger together).
- Wrist flexion towards little finger.
- Wrist flexion towards thumb.
- Finger and wrist flexion together but normal along centre line.
- Finger and wrist flexion towards little finger.

These 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

Table 1. Placement of Electrodes

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

3.2. sEMG signal processing

The aim of these experiments was to test the use of BSS algorithm [10] along with known properties of the muscles for separating muscle activity from sEMG recordings for the purpose of identifying subtle hand gestures. BSS methods are 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 subtle hand actions that required not greater than 4 independent muscles. This ensures that the un-mixing matrix is a square matrix of size of 4×4.

The mixing matrix A was computed based on the multi run ICA. ICA algorithm was computed many times, at each instance SIR of mixing matrices were computed. Among them the best mixing matrix was chosen. The SIR computation process is explained next.

3.3. SIR computation

Signal to Interference Ratio (SIR) for the mixing matrix A. This performance index could be used for full-rank or non-full rank analysis. In view of the problem of one component estimation, we have.

$$y_i = w_i^T X = (w_i^T A)S = g_i S = g_{ij} s_j \tag{3}$$

where y_j and s_j are are the estimated component and the j^{th} source, respectively; w_i^T is a row vector of un-mixing matrix W, g_i is a normalized row vector [0 0 g_{ij} 0 0].Because y_i is the estimation of s_j, the ideal normalized vector g_i is the unit vector u_j = [0 0,...,1,...,0]. Therefore, one analysis is successful if and only if its vector g_i is similar to one unit vector u_j.

Actually, vector g_i is one row of matrix G. So, the quality of each estimated component just depends on one row of matrix G. The more different each row of G is to each corresponding unit vector of $R^{N \times N}$, the less quality of output we have. The SIR of each mixing matrix was computed using the following expression which evaluates the success of one component separation [9].

$$SIR_g = -10log10(\|g_i - u_j\|)_2^2 \tag{4}$$

The SIR values for the multi run ICA algorithm for hand gesture experiments are shown in Table 2.

Table 2. SIR values for multi run ICA.

Multi run ICA trials	SIR values (dB)
1	17.7088
2	18.0703
3	**11.4211**
4	25.7227
5	18.4163
6	24.6118
7	31.9806
8	29.8952
9	**44.3187**
10	21.8637

3.4. RMS feature extraction

For hand gesture recognition analysis we selected the mixing matrix with highest SIR (SIR = **44.3187** dB). The selected mixing matrix was 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.

$$s = Wx \tag{5}$$

where, W is the inverse of the mixing matrix A. This process was repeated for each of the four hand gesture experiments. Four sources sa, sb, sc and sd, were computed in each instance. Root Mean Squares (RMS) was computed for each separated sources using the following:

$$s_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} s_i^2} \tag{6}$$

where s are 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 strength of contraction.

3.5. Classification of Hand gesture Data with ANN

The above process was repeated for all six different hand actions 12 times and for each of the participants. These 12 sets of examples were used to train a back-propagation neural network. In the first part of the experiment, RMS values of 4 recordings (sa, sb, sc and sd)for each subject were utilised to train the ANN classifier with back-propagation learning algorithm. The second part of the experiment (testing) was to verify the performance of the network. For that purpose a subset of all the input vectors different from the learning set (an independent data set) was selected. Performance was also monitored during the training phase in order to prevent overtraining of the network. Back propagation gradient descent ANN training algorithm with sigmoid threshold was used for training and testing. During testing, the ANN with weight matrix generated during training was used to classify RMS of the muscle activity. The ability of the network to correctly classify the inputs against known subtle hand actions were used to determine the efficacy of the technique.

4. Results

The results of the experiment demonstrate the performance of the above described system. To compare the performance of the system analysis on raw sEMG and traditional ICA were performed. In traditional ICA method, mixing matrix was computed for each instance. The results demonstrate the ability of the semi-blind multi run ICA in source separation and identification. The following six hand gestures are labelled as below for displaying the results.

- Wrist flexion **(G1)**
- Finger flexion (ring finger and the middle finger together).**(G2)**.
- Wrist flexion towards little finger **(G3)**.
- Wrist flexion towards thumb **(G4)**.
- Finger and wrist flexion together but normal along centre line **(G5)**.
- Finger and wrist flexion towards little finger **(G6)**.

4.1. Hand gesture Identification results on Raw EMG

The results of the experiment on Raw EMG signals on six different hand gestures are shown in Table 3. The accuracy was computed based on the percentage of correctly classified data points to the total number of data points. The results shows an over all efficiency of 60% for all the experiments.

Participants	G1	G2	G3	G4	G5	G6
Subject 1	60%	60%	60%	60%	60%	60%
Subject 2	59%	60%	60%	61%	60%	60%
Subject 3	61%	60%	59%	60%	60%	60%
Subject 4	60%	61%	60%	60%	60%	60%
Subject 5	60%	59%	61%	60%	60%	60%
Subject 6	60%	60%	60%	60%	60%	60%
Subject 7	60%	60%	60%	61%	60%	60%

Table 3. Experimental results for Hand Gesture Identification using Raw EMG (Without using ICA).

4.2. Hand gesture Identification results using traditional ICA

To compare the proposed system with the use of traditional ICA, analysis was performed where RMS of the four channels of sEMG separated using ICA were tabulated for each experiment and classified. The accuracy was observed to be only 65% (Table 4). These results demonstrate that standard (traditional) ICA based separation is not suitable for classifying sEMG.

Participants	G1	G2	G3	G4	G5	G6
Subject 1	65%	64%	65%	65%	65%	65%
Subject 2	65%	65%	65%	66%	65%	65%
Subject 3	64%	65%	65%	65%	65%	65%
Subject 4	65%	65%	65%	65%	65%	65%
Subject 5	65%	65%	66%	65%	65%	65%
Subject 6	65%	65%	65%	65%	65%	65%
Subject 7	65%	65%	65%	65%	65%	65%

Table 4. Experimental results for Hand Gesture Identification using traditional ICA.

4.3. Hand gesture Identification results using semi blind ICA for worst mixing matrix (Lowest SIR)

In order to analyse the performance variations we analysed the mixing matrix with lowest SIR (SIR= **11.4211** dB). The classification of sEMG using multi run ICA for six hand gestures are presented in Table 5. The experiments were repeated for different number of hand gestures to be classified. These results indicate an overall classification accuracy of 62% for all the experiments. The results demonstrate that low SIR matrix gives almost similar results that of raw EMG and is not suitable for Hand gesture identification.

Participants	G1	G2	G3	G4	G5	G6
Subject 1	62%	61%	63%	63%	63%	63%
Subject 2	63%	62%	63%	63%	63%	63%
Subject 3	62%	61%	63%	63%	63%	63%
Subject 4	63%	62%	62%	63%	63%	63%
Subject 5	63%	62%	63%	63%	63%	63%
Subject 6	62%	63%	62%	60%	63%	63%
Subject 7	62%	63%	62%	61%	63%	63%

Table 5. Experimental results for Hand Gesture Identification using multi run ICA for worst mixing matrix (Lowest SIR).

4.4. Hand gesture Identification results using semi blind ICA for best mixing matrix (Highest SIR)

The classification of sEMG after pre-processing using multi run ICA based on best SIR (SIR = **44.3187** dB) for six hand gestures are presented in Table 6. The experiments were repeated for different number of hand gestures to be classified. These results indicate an overall classification accuracy of 99% for all the experiments. The overall performances are shown as bar plot in Figure 3.

The results demonstrate that this technique can be used for the classification of different subtle hand gestures.

4.5. Discussions and conclusions

The proposed technique is capable of classifying small levels of muscle activity to identify six different hand gestures. Its base is using a combination of multi run independent component analysis (ICA), known muscle anatomy and neural network configured for the individual. The technique has been tested with seven volunteer participants and with experiments conducted on different days. The results

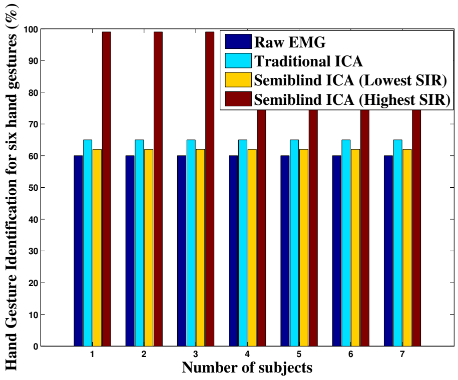

Figure 3. The over all results showing hand gesture identification for 7 subjects

Participant	G1	G2	G3	G4	G5	G6
Subject 1	99%	99%	99%	99%	99%	99%
Subject 2	99%	99%	99%	99%	99%	99%
Subject 3	99%	99%	99%	99%	99%	99%
Subject 4	99%	99%	99%	99%	99%	99%
Subject 5	99%	99%	99%	99%	99%	99%
Subject 6	99%	99%	99%	99%	99%	99%
Subject 7	99%	99%	99%	99%	99%	99%

Table 6. Experimental results for Hand Gesture Identification using multi run ICA for best mixing matrix (Highest SIR).

indicate the ability of the system to perfectly recognise the hand gesture even though the muscle activity is very low and there are number of active muscles for each of the gestures.

There exist numerous papers in literature, which have attempted to identify hand and body gestures from sEMG recordings, but all come with low reliability, perhaps due to low signal to noise ratio and large cross-talk between different simultaneously active muscles. In the recent past, ICA has been applied to separate the muscle activity and to reduce noise to overcome this difficulty, but the order and magnitude ambiguity makes the technique unreliable.

The authors believe that the reason why this technique has succeeded where number of other similar techniques have failed is because the basis of this technique is to estimate the un-mixing matrix during training and maintaining this over the experiment. Which ensured the order and amplitude ambiguity is overcome. Further, other ICA based techniques are not suitable for near Gaussian signals and when signal-to- noise ratio is low and there is large cross-talk between different simultaneously active muscles. Use of ICA alone is not suitable for sEMG due to the nature of sEMG distribution and order ambiguity. Prior knowledge of the muscle anatomy combined with suitable ICA has overcome the above mentioned shortcomings.

This investigation has shown that a combination of the mixing matrix and network weights to classify the sEMG recordings in almost real-time. The results do indicate the ability of the system to work with the set of six different hand gestures selected. We are working on expanding the EMG gesture for increased levels of control. While, further work on the signal processing may make it possible to recognize multiple subtle gestures from a single muscle, it appears more practical to define a more extended interface using different controllers on various muscles (e.g. on both arms). Future work also shall include conducting experiments on inter-day and intra-day variations to verify the stability of the system and also developing a portable model for hand gesture recognition using semi blind multi run ICA technique.

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