SEMG for Identifying Hand Gestures using ICA

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Abstract. There is an urgent need for establishing a simple yet robust system that can be used to identify hand actions and gestures for machine and computer control. Researchers have reported the use of multi-channel electromyogram (EMG) to determine the hand actions and gestures. The limitation of the earlier works is that the systems are suitable for gross actions, and when there is one prime-mover muscle involved. This paper reports overcoming the difficulty by using independent component analysis to separate muscle activity from different muscles and classified using backpropogation neural networks. The system is tested and found to be effective in classifying EMG.

1 Introduction

Identification of hand gesture has numerous applications, primarily related to controlling machines and computers. Some of the commonly employed modalities include vision based systems [1, 2], mechanical sensors [3], and the use of electromyogram, an indicator of muscle activity [4, 5]. Electromyogram has an advantage of being easy to record, and is non-invasive. Electromyography (SEMG) is a result 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 analysis of EMG can be broadly categorised into two; (i) gross and global parameters and (ii) decomposition of EMG into MUAP. Hand movement is a result of complex combination of multiple muscles. While Dinesh et al. [6] have reported success in the use of multiple channels SEMG recording for the purpose, the precise location of the electrodes and multi-channel recordings make the system complex. A single channel system where the location of electrodes is not critical to the results is highly desirable. But the difficulty in the use of single channel when there is a complex group of muscles that control the movement is the very large variation in the magnitude and frequency content of the signal when the distance between the recording electrodes and the muscle fibres is changed. To determine the hand action based on the muscle activity, it is important to identify the muscle activity of the different muscles responsible for the action. When attempting to identify small level of muscle activity such as required for hand gestures, and with simultaneous activation of number of closely spaced muscles, there is considerable cross talk. Similarity

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in the spectrum and other properties of the activity from the different muscles makes the separation of these difficult. There is a need to separate the muscle activity originating from different muscles. With little or no prior information of the muscle activity from the different muscles, this is a blind source separation (BSS) task. Blind separation of independent sources is an important research area. Independent component analysis (ICA) is an iterative BSS technique which has been found to be very successful and has found applications in audio and biosignal applications. ICA has been proposed for unsupervised cross talk removal from SEMG recordings of the muscles of the hand [7]. Research that isolates MUAP originating from different muscles and motor units has been reported in 2004 [8]. A denoising method using ICA and high pass filter banks has been used to suppress the interference of electrocardiogram (ECG) in EMG recorded from trunk muscles [9]. Muscle activity originating from different muscles can be considered to be independent, and this gives an argument to the use of ICA for separation of muscle activity originating from the different muscles. This paper proposes the use of ICA for separation of muscle activity from the different muscles in the forearm to identify the hand action. ICA is an iterative technique where the only model of the signals is the independence, and the distribution. The natural outcome of this is that the signals are separated without there being any information of the order of the sources. While this difficulty is generally not consequential for audio signals, this would be of concern when working with muscle activity. The spatial location of the active muscle activity is the determining factor of the hand action and gesture. To overcome this difficulty, one approach that has been reported is the use of prior knowledge of the anatomy. The advantage of this approach is the model based approach that provides a well defined muscle activity pattern. The difficulty with that approach is the need for well defined location of the electrodes.

2 Basic Principles of Independent Component Analysis (ICA)

ICA separates signals from different sources into distinct components. The fundamentals of ICA rest on information theory. The technique is based unsupervised learning rules where reduction of mutual information and increase in Gaussianity can be considered to be the cost function. Given a set of multidimensional observations, which are a result of linear mixing of unknown independent sources through an unknown mixing source, ICA can be employed to separate the signals from the different sources. The independent sources may be sources for audio signals such as speech, voice, music, or signals such as bioelectric signals. If the mixing process is assumed to be linear, it can be expressed as

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

where x = $(x_1, x_2, \ldots, x_n)$ is the recordings, s = $(s_1, s_2, \ldots, s_n)$ 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 de mixing matrix W by which observations can be linearly translated to form Independent output components so that

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

For this purpose, ICA relies strongly on the statistical independence of the sources s. This technique iteratively estimates the un-mixing matrix using the maximisation of independence of the sources as the cost function [10].

2.1 ICA for SEMG Applications

Signals from different sources can get mixed during recording. Often it is required to separate the original signals, and there is little information available of the original signals. An example is the cocktail party problem. Even if there is no (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.

A number of researchers have reported the use of ICA for separating the desired SEMG from the artefacts and from SEMG from other muscles. While details differ, the basic technique is that different channels of SEMG recordings are the input of ICA algorithm.

The fundamental principle of ICA is to determine the un-mixing matrix and use that to separate the mixture into the independent components. The independent components are computed from the linear combination of the recorded data. The success of ICA to separate the independent components from the mixture depends on the properties of the recordings.

2.2 Statistical Properties of SEMG Recordings

Signals from Gaussian sources cannot be separated from their mixtures using ICA [10], making such signals unsuitable for ICA applications. Mathematical manipulation demonstrates that all matrices will transform this kind of mixtures to another Gaussian data. However, a small deviation of density function from Gaussian may make it suitable as it will provide some possible maximization points on the ICA optimization landscape, making Gaussianity based cost function suitable for iteration. If one of the sources has density far from Gaussian, ICA will easily detect this source because it will have a higher measure of non Gaussianity and the maxima point on the optimization landscape will be higher. If more than one of the independent sources has non Gaussian distribution, those with higher magnitude will have the highest maxima point in the optimization landscape. Given a few signals with distinctive density and significant magnitude difference, the densities of their linear combinations will tend to follow the ones with higher amplitude. Since ICA uses density estimation of a signal, the Components with dominant density will be found easier. Signals such as SEMG have probability densities that are close to Gaussian while artefacts such as ECG and motion artefacts have non Gaussian distributions. From the above, it can be suggested that ICA may suitably isolate some of the above signals, while its efficacy for separating the others maybe questionable. It is difficult to identify the quality of separation of EMG from one muscle and the neighbouring muscles, or that of EEG from one channel to the neighbouring recording sites, making it difficult to confirm or negate the above.

3 Methodology

3.1 Experimental Procedure

Ethics approval by the RMIT university committee of ethics of experiment on human subject was granted to conduct the experiment. One healthy male subject was recruited for the experiment. A written consent was signed by the subject for the above experiment. A proprietary SEMG acquisition system by Delsys (USA) was used for data collection. Four differential electrodes with inter-electrode distance of 10mm and gain of 1000 were placed on the four muscles of the subject's forearm as outlined in the table (1) as shown below.

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

Channel	Muscle	Function
1	Brachioradialis	Flexion of forearm
2	Flexor Carpi Ulnaris (FCU)	Adduction 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

Subjects were 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 15 times. There was no external load. The actions are listed below.

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

While Brachioradialis is an elbow flexor, a very little activity may be recorded in this muscle while finger and/or wrist flexion. FCU and FCR the two wrist flexors that are responsible for adduction and abduction of the wrist respectively and they perform the flexion in the normal direction along the centre line together. FDS performs the flexion of the middle finger and the ring finger.

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.

3.2 Analysis

The aim of this experiment was to test the use of ICA for separation of the EMG signals for the purpose of identifying hand gestures and actions. For the first set of experiments recorded signals x were analysed using matlab software package. There were approximately 30000 samples of the data which was the result of 15 times wrist movements. Since there were four Chanel (x) electrodes it formed 4 x 4 mixing matrix. For each set of experiments the EMG data from 15 repetitions were analysed using fast ICA matlab package. The mixing matrix A was computed for the first set of data. The computed mixing matrix had been kept constant (Same mixing matrix had been used through out the one main experiment) for the remaining set of experiments and in each case the sources had been computed using the following formula

$$x = As \tag{3}$$

Where x is the recorded data, A mixing matrix and s is the sources. The sources are recovered using the following formula

$$s = Bx \tag{4}$$

Where B is the inverse of mixing matrix A. This process was repeated for each of the three experiments.Each experiment resulted in four sources. Root Mean Squares of each experiment were computed using the following formula

$$s_{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} s_i^2} \tag{5}$$

Where s is the source and N is the number of samples.The examples of one set of results and RMS values were shown in the table (2) below.

Table 2. Example of one set of sub experiment results showing the RMS (Root Mean Square) values.

Source	RMS (Root Mean Square) value
Source1(s1)	0.0461
Source2(s2)	0.0366
Source3(s3)	0.0311
Source4(s4)	0.0209

The above set of process had been repeated for the three actions. The outcome of this was a set of 12 set of examples, each example pertaining to three actions. These 12 sets of examples were used to train a backpropogation neural network with 3 inputs and 4 outputs. After training, the network conditions were saved and used to test the network data from experiments not used to train the network. The ability of the network to correctly classify the inputs against known hand actions were used to determine the efficacy of the technique.

4 Results and Observations

A result of testing the network using five set of experiments are tabulated below. The classification accuracy was 100% for all the experiments. The results are outlined in table (3).

Table 3. Neural network testing results.

Action Performed	Action identified for each sub experiments				
Wrist flexion	100%	100%	100%	100%	100%
Finger Flexion	100%	100%	100%	100%	100%
Finger flexion and wrist flexion	100%	100%	100%	100%	100%

5 Discussions and Conclusion

A new approach that combines semi-blind ICA along with neural networks was used to separate and identify hand gestures. The results demonstrate that the technique can be effectively used to identify hand gestures based on surface EMG when the level of activity is very small. The authors would like to mention that this is early stage of the work, and work needs to be done to identify inter-day variations. It is also important to test the technique for different actions, and for a large group of people. Further, there is need to automate the semi-blind operation.

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