Hand gestures for HCI using ICA of EMG

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Abstract

Aiming at the use of hand gestures for human-computer interaction, this paper presents an approach to identify hand gestures using muscle activity separated from electromyogram (EMG) using independent component analysis. While there are a number of previous reported works where EMG has been used to identify movement, 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 paper reports experimental results where the system was accurately able to identify the hand gesture using this technique for all the experiments (100%). The system has been shown not to be sensitive to electrode position as the experiments were repeated on different days. The advantage of such a system is that it is easy to train by a lay user, and can easily be implemented in real time after the initial training.

Keywords: Independent Component Analysis (ICA), Surface Electromyography (SEMG), Root Mean Square (RMS).

1   Introduction

In recent years, hand gesture recognition has become a very active research theme because of its potential use in human- Computer interaction (HCI). Identification of hand gesture has numerous human computer interface (HCI) applications related to controlling machines and computers. Some of the commonly employed modalities include vision based systems (Schlenzig, Hunter & Jain 1997, Rehg & Kanade 1994), mechanical sensors (Pavlovic, Sharma & Huang 1997), and the use of electromyogram, an indicator of muscle activity (Cheron, Draye, Bourgeios & Libert 1996, Koike & Kawato 1996). Surface Electromyogram has an advantage of being easy to record, and is non-invasive.

Surface Electromyogram (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;

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

Hand movement is a result of complex combination of multiple muscles. While Djuwari et al. (Djuwari, Kumar, Polus & Raghupathy 2003) have reported success in the use of multiple channels SEMG recording for the purpose, but the system is sensitive to the location of the electrodes and suitable for five discrete movements only. The cross-talk that exists due to multiple overlapping muscles in the forearm makes the system sensitive to the inter-subject variability and this problem is more significant when the muscle activation is relatively weak.To identify the movement and gesture of the hand more precisely, it is important to identify the muscle activity of each of the muscles responsible for the action. Similarity 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.

Independent component analysis (ICA) is an iterative BSS technique that has been found to be very successful in audio and biosignal applications. ICA has been proposed for unsupervised cross talk removal from SEMG recordings of the muscles of the hand (Greco, Costantino, Morabito & Versaci 2003). Research that isolates MUAP originating from different muscles and motor units has been reported in 2004 (Nakamura, Yoshida, Kotani, Akazawa & Moritani 2004). 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 (Yong, Li, Xie, Pang, Yuzhen & Luk 2005). 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 outcome of ICA 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 while working with muscle activity. The spatial location of the active muscle activity is the determining factor of the hand 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 this approach is the need for well defined location of the electrodes.

2   Hand gesture identification for HCI

In our daily lives we interact with other people and objects to perform a variety of actions that are important to us. Computers and computerised machines have become a new element of our society. They increasingly influence many aspects of our lives. Human-computer interaction is an area concerned with the design, and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them.

The use of hand gesture provides an attractive alternative to cumbersome interface devices for human computer interaction applications. Human hand gestures are a mean of non verbal interactions among people. They range from simple actions of pointing at objects and moving them around to the more complex ones that express our feelings or allow us to communicate with others. The HCI interpretation of gestures requires dynamic and or/static configurations. Of the human hand, arm and sometimes, body be measurable by the machine. Hand gestures are a new mode for HCI. Visual interpretation of hand/arm movements carries a tremendous advantage over other techniques that require the use of mechanical transducers. It is not obstructive. Numerous approaches have been applied to the problem of visual interpretation of gestures for HCI. Many of those approaches have been chosen and implemented so that they focus on one particular aspect of gestures: Hand tracking, pose classification, or hand posture interpretations (Schlenzig, Hunter & Jain 1997, Rehg & Kanade 1994).

Recently a number of approaches based on hand gesture identification have been proposed for human computer interaction. Wheeler et. al. demonstrated that neuroelectric joy sticks and key boards can be used for HCI (Wheeler & Jorgensen 2003). Trejo et. al. (Trejo et. al. 2003)developed a technique for multi modal neuroelctric interface. The most recent work includes the investigation of eleven normally limbed subjects (eight males and four females) for six distinct limb motions: wrist flexion, wrist extension, supination, pronation, hand open, and hand close. Each subject underwent four 60-s sessions, producing continuous contractions (Chan & Englehart 2005).

A number of efficient solutions to gesture input in HCI exist, such as:

- Restrict the recognition situation.
- Use of input devices (e.g. data glove).
- Restrict the object information.
- Restrict the set of gestures.

In traditional HCI, most attempts have used some device, such as an instrumented glove, for incorporating gestures into the interface. If the goal is natural interaction in everyday situations this might not be acceptable. Vision based approach to hand-centered HCI has been proposed in recent years. However, a number of applications of hand gesture recognition for HCI exist, using Computer vision technique. Mostly they require restricted backgrounds and camera positions, and a small set of gestures, performed with one hand (Pavlovic, Sharma & Huang 1997).

In this report we propose Hand gesture identification which uses the prior knowledge of muscle anatomy. This is a model based approach that provides a well defined muscle activity pattern.

3   Surface Electromyogram

SEMG is a non-invasive recording of the muscle activity and finds application in sports training, rehabilitation, machine and computer control, occupational health and safety, and for identifying posture disorders. There is a near linear relationship between RMS of SEMG and the finger flexion-extension - suggesting the use of SEMG for bio-control for anthropomorphic tele-operators and Virtual Reality entertainment (Gupta & Reddy 1996). There is useful information of the posture from the muscle activity of the lumbar muscles. SEMG amplitude and frequency have been investigated as indicators of localized muscular fatigue. Amplitude and spectral information of EMG have also been exploited to estimate force of muscle contraction and torque (Moritani & Muro 1987).These applications require automated analysis and classification of SEMG.

SEMG 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).

- Artefacts (crosstalk between muscle, ECG interference).

- Recording apparatus factors (recording-method, noise, electrode's properties, recording sites).

The anatomical/ physiological processes such as properties and dimensions of tissues, and force and duration of contraction of the muscle are known to influence the signal. SEMG is also influenced by onset of muscle fatigue, and contraction of other muscles in the close vicinity. Each of the factors can be used as a criterion to categorise the input signal.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.

4   Basic Principles of Independent Component Analysis (ICA)

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.

Independent Component Analysis is a technique for extracting statistically independent variables from a mixture of them.ICA searches for a linear transformation to express a set of random variables as linear combinations of statistically independent source variables (Comon 2001). The criterion involves the minimization of the mutual information expressed as a function of high order cumulants. ICA separates signals from different sources into distinct components. The technique is based on unsupervised learning rules where reduction of mutual information and increase in Gaussianity are the cost functions. 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

$$x = As \qquad (1)$$

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

$$s = Wx \qquad (2)$$

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 (Hyvarinen, Karhunen & Oja 2001).

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.

There are several estimation algorithms for the ICA technique. FastICA algorithm is based on negentropy (negative entropy) and has been developed and proposed by the team at the Helsinki University of Technology (FastICA 2005). This algorithm uses negentropy as a measure of non-Gaussianity of the signals and uses fixed point iteration scheme. It is faster than conventional gradient descent scheme. This paper reports the use of FastICA for analysis.

4.1 ICA for SEMG applications

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. ICA has also been used by Heido et al. (Nakamura, Yoshida, Kotani, Akazawa & Moritani 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 how the suitability of their experimental data for ICA application. With the help of 8 channel recordings, the SEMG signal has been decomposed into MUAPs that may have originated from large number of motor units. This could make the number of sources to be more than the number of recordings, making it unsuitable for standard ICA.

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.

4.2 Statistical Properties of SEMG Recordings

ICA uses the Gaussianity of the signals as a cost function to generate the un-mixing matrix and hence signals that have Gaussian distribution are unsuitable for ICA applications (Hyvarinen, Karhunen & Oja 2001). 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, making it difficult to confirm or negate the above. This paper reports the use of ICA to separate EMG from different muscles. As the signal properties of EMG are close to Gaussian, and there is no information available of the original signal, the only measure of quality possible is to determine the accuracy of the system to identify the hand gesture correctly.
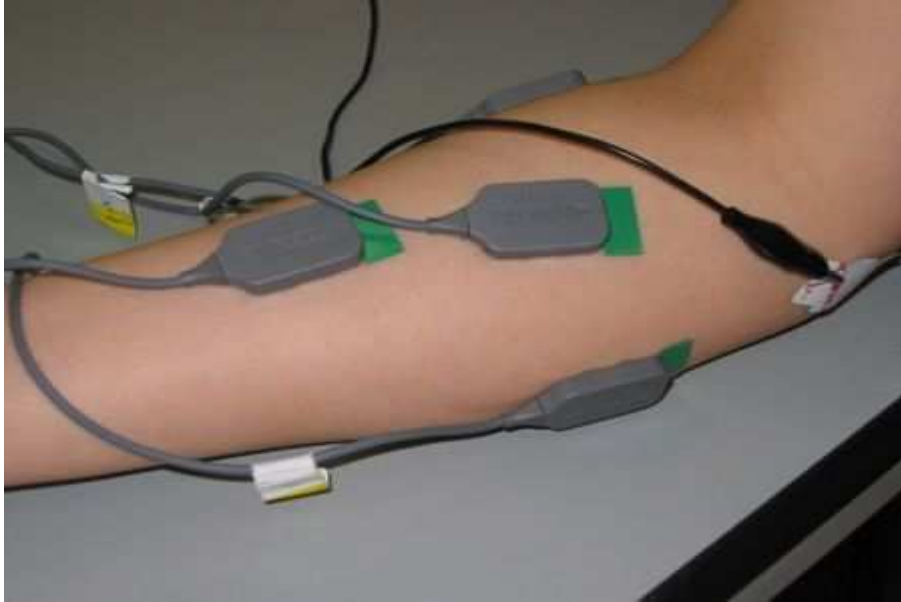
Figure 1: Placement of Electrodes

5 Methodology

5.1 Experimental Procedure

RMIT University ethics committee granted approval to conduct experiments on human subjects and acquire Surface EMG using surface electrodes. For the data acquisition a proprietary SEMG 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 1. Each channel is a set of two differential electrodes with a fixed inter-electrode distance of 10mm and a gain of 1000 which is shown in figure 2. Before placing the electrodes subject's skin was prepared by lightly abrading with skin exfoliator 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.

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 the Electrodes over the skin of the forearm

ICA is suitable when the numbers of recordings are same as or greater than the number of sources. This paper reports using 4 channels of EMG recorded during 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 x 4.

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 actions were complex to determine the ability of the system when similar muscles are active simultaneously and are listed below:

- 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.

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 are the two wrist flexors. 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.

5.2 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 each hand movement we recorded 12 repetitions, lasting approximately 2.5 seconds each. The sampling rate was 1024 samples per second, this gives approximately 2500 samples. For the first set of experiments recorded signals x were analysed using matlab software package. There were four channel (recordings) electrodes and four active muscles associated with the hand gesture, this formed 4X4 mixing matrix. For each set of experiments the EMG data was analyzed using fast ICA matlab package which has been developed and proposed by the team at the Helsinki University of Technology (FastICA 2005). The mixing matrix A was computed for the first set of data only. This was kept constant throughout the experiment.
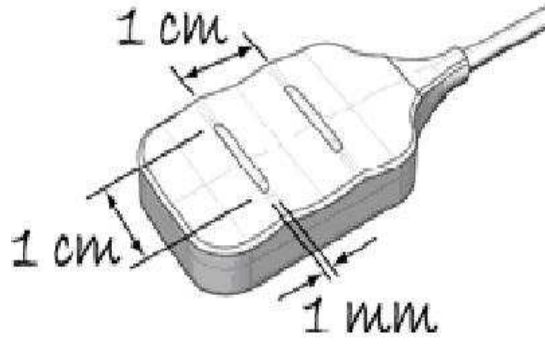
$$x = As \qquad (3)$$

Figure 2: Electrodes. (source: www.delsys.com)

where x is the recorded data, A is the mixing matrix and s is the sources. The independent sources of motor unit action potentials that mix to make the EMG recordings were computed using the following.

$$s = Bx \qquad (4)$$

where B is the inverse of the mixing matrix A. This process was repeated for each of the three hand gesture experiments. Four sources were obtained for each experiment. After separating the four sources s_a, s_b, s_c and s_d each are also 2500 samples long. Root Mean Squares (RMS) was computed for each separated sources using the following formula

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

Where s is the source and N is the number of samples (N = 2500). This resulted in one number representing the muscle activity for each channel for each hand action. Hence we obtained four RMS values every time

The examples of one set of RMS values obtained during wrist flexion experiment are shown in the table 2 below.

Source	RMS(Root Mean Square)values
Source1(s1)	1.2214
Source2(s2)	1.1205
Source3(s3)	1.1846
Source4(s4)	1.2104

Table 2: Example of one set of experiment results showing the RMS (Root Mean Square) values during the wrist flexion action

RMS 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. A combination of the activity from each of these muscles is responsible for the muscle activity (gesture) and has been used to identify the hand gesture. While ICA has the order ambiguity shortcoming, but by using a constant un-mixing matrix (B) for each of the experiments, the data classification can be achieved against the movement.

The above process was repeated for all three different hand actions. The outcome of this was 12 set of examples, each example pertaining to three actions. These 12 sets of examples were used to train a backpropogation neural network with 4 inputs and 3 outputs (The 4 RMS (Root Mean Square) values of the muscles were the input and the 3 RMS (Root Mean Square) values were the output). In the first part of the experiment, RMS values of 3 recordings for subject were used to train the ANN classifier with back propagation learning algorithm. In the second part of the experiment, the neural network was trained using the data from the subject and tested similarly. The architecture of the ANN consisted of two hidden layers and the 20 nodes for the two hidden layers were optimized iteratively during the training of the ANN. 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. In the testing section, the trained ANNs were used to classify the RMS values of recordings that were not used in the training of the ANN to test the performance of the proposed approach. The ability of the network to correctly classify the inputs against known hand actions were used to determine the efficacy of the technique.

6 Results and observations

Backpropagation neural network with 3 inputs and 4 outputs are conducted for three types of hand gestures. The result of the use of these normalized 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. five set of experiments. The accuracy was computed based on the percentage of correct classified data points to the total number of data points. The classification accuracy was 100% for all the experiments.

Action Performed	Action identified for experiments				
Wrist flexion	100%	100%	100%	100%	100%
Finger flexion	100%	100%	100%	100%	100%
Finger flexion & Wrist flexion	100%	100%	100%	100%	100%

Table 3: Neural network testing results

7 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.

8   Acknowledgement

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