Improving Isometric Hand Gesture Identification for HCI based on Independent Component Analysis in Bio-signal Processing

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Abstract. Hand gesture identification has various human computer interaction (HCI) applications. There is an urgent need for establishing a simple yet robust system that can be used to identify subtle complex hand actions and gestures for control of prosthesis and other computer assisted devices. Here, an approach is explained to demonstrate how hand gestures can be identified from isometric muscular activity, where signal level is low and changes are very subtle. Obvious difficulties arise from a very poor signal to noise ratio in the recorded electromyograms (EMG). Independent component analysis (ICA) is applied to separate these low-level muscle activities. The order and magnitude ambiguity of ICA have been overcome by using a priori knowledge of the hand muscle anatomy and a fixed un-mixing matrix. The classification is achieved using a back-propagation neural network. Experimental results are shown, where the system was able to reliably recognize motionless gestures. The system was tested across users to investigate the impact of inter-subject variation. The experimental results demonstrate an overall accuracy of 96%, and the system was shown being insensitive against electrode positions, since these successful experiments were repeated on different days. The advantage of such a system is, that it is easy to train by a lay user, and that it can easily be implemented as real-time processing after an initial training. Hence, EMG-based input devices can provide an effective solution for designing mobile interfaces that are subtle and intimate, and there exist a range of applications for communication, emotive machines and human computer interface.

1 Introduction

Hand gesture identification has numerous human computer interface (HCI) applications related to controlling machines and computers. Some of the commonly employed techniques include mechanical sensors [1], vision-based systems [2] and the

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use of electromyogram [3]. Electromyogram has an advantage of being easy to record, and is non-invasive. The Electromyogram is an electrical signal generated by muscular contraction [4]. It 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 using surface electrodes in different pairs, each pair constituting a channel.

In previous research, gestures are typically sensed by accelerometers [5], capacitive techniques [6] or proximity sensors worn on different parts of the body [7]. These techniques require the users to noticeably move their limbs, which can be inconvenient and socially unacceptable. On the contrary, electromyographic (EMG) signals can convey information about isometric muscular activity: activity related to very subtle or no movement at all. Hence it allows the definition of a class of "subtle" or "motionless gestures" that can be used to design discreet, intimate mobile interfaces.

EMG is a biosignal related to muscle contraction. Studies on the use of EMG for gesture recognition have been reported, but none of them takes explicit advantage of its subtlety, the fact that commands can be issued without the generation of observable movements.

Any hand movement is a result of a complex combination of many flexors and extensors present in the forearm. Since all these muscles present in the forearm are close to each other, myo-electric activity observed from any muscle site comprises the activity from the neighbouring muscles as well, referred to as cross-talk. When the muscle activity is small (subtle), the signal strength is small and the impact of cross talk and noise is very high. This is further exaggerated when considering different subjects, since the size of the muscles, presence of subcutaneous fat layer and also the training level is different for different people. Therefore this mixing of electrical activity from different muscles to result in the surface EMG (sEMG) signal can not be easily modelled or generalized. Extraction of the useful information from such kind of surface EMG becomes even more difficult for low level of contraction mainly due to the low signal – to – noise ratio. At low level of contraction, EMG activity is hardly discernible from the background activity. Therefore to correctly classify the movement and gesture of the hand more precisely, EMG needs to be decomposed to identify activities of individual 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) or ICA for the separation of muscle activities.

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 about 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 muscle anatomy. The advantage of this approach is the model based approach that provides a well defined muscle activity pattern.

In the current technology any mobile device should be as natural and conceptually as un noticeable as possible. Hence our research extends this concept: we believe that not only the devices should be unnoticeable and natural, but also the interaction with them needs to be subtle and discreet. Therefore, we promote the idea of subtle gestures (isometric hand gesture identification).

2 Hand Gesture Identification for HCI and Related Work

Computers and computerised machines have become a new element of our society. Human-computer interaction requires the design, and implementation of interactive computing systems for human use. The intent is to provide seamless and natural interface that allows the human user to control and interact with computers and computer based machines.

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 interaction among people. They range from simple actions of pointing at objects to the more complex ones that express our feelings and communicate with others. Numerous approaches have been applied to the problem of visual interpretation of gestures for HCI. Many of those approaches have been chosen and implemented to focus on a particular aspect of gestures: Hand tracking, pose classification, or hand posture interpretations [2].

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 keyboards can be used for HCI [8]. Trejo et al [9] 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-seconds sessions, producing continuous contractions [10]. Recent studies focus on the use of EMG for the recognition of an alphabet of discrete gestures. Fistre and Tanaka [11] propose a system that can recognize six different hand gestures using two EMG channels on the forearm. The device is designed to control consumer electronics and is described as portable.

Wheeler and Jorgensen [8] report the development and successful testing of a neuroelectric joystick and a neuroelectric keypad. By using EMG signals collected from four and eight channels on the forearm they successfully recognise the movement corresponding to the use of a virtual joystick and virtual numeric keypad. Gestures mimicking the use of physical devices are successfully recognised using hidden Markov models.

To improve the reliability, 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 external mechanical device such as an instrumented glove. 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 vision based techniques require restricted backgrounds and camera positions and are suitable for a small set of gestures performed with only one hand [1]. In this report we propose the identification of maintained hand gesture based on the muscle activity using the decomposition of surface EMG. It is a combination of model based approach with blind source separation

3 Foundation of Semg Bio-signal Processing

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

sEMG is a non-invasive recording, requires relatively simple equipment, and this opens it for numerous applications. The close relationship of surface EMG with the force of contraction of the muscle is useful for number of applications such as sports training and for machine control. The relationship of surface EMG spectrum with muscle fatigue is also very useful for occupational health and sports training.

One property of the surface EMG 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.

3.1 Independent Component Analysis

Independent component analysis one of the Blind source separation (BSS) technique, aims at recovering the sources from a set of observations. Applications include separating individual voices in cocktail party. In BSS problem, it contains two processes. They are the mixing process and un-mixing process. First, we observe a set of multivariate signals $x = [x_1(t), x_2(t),\ldots,x_n(t)]^T$ that are assumed to be linearly mixed with a set of source signals $s = [s_1(t), s_2(t),\ldots, s_n(t)]$ The mixing process is hidden so we can only observe the mixed signals. The task is to recover the original source signals from the observations through a un-mixing process. Equation 1 and 2 describe the mixing and un-mixing processes mathematically.

$$\textit{Mixing} \qquad x = As \tag{1}$$

$$\textit{Un-mixing} \qquad Wx = WAs \tag{2}$$

For solving the BSS it is assumed that the number of observations is equal to the number of source signals. Matrix s contains the original source signals driving the observations, whereas the separated signals are stored in matrix u. They are both $[n\times t]$ matrices. A and W are both $[n\times n]$ matrices, called mixing and un-mixing matrix respectively. If the separated signals are the same as the original sources, the mixing matrix is the inverse of the un-mixing matrix, i.e. $A = W^{-1}$

ICA is an iterative method that is able to separate independent sources from the mixture [12]. ICA estimates the mixing matrix W using 'independence' based cost function. Various ICA algorithms have been proposed. Most of them use higher order statistics to obtain the independent components [12].

3.2 Relevance of ICA for Surface EMG Signal Evaluation

The goal of this section is to demonstrate that there is a strong theoretical basis for applying ICA to sEMG. The assumptions that underpin the theory of instantaneous ICA, indicate that ICA is ideally suited to separating sources when

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

These assumptions are well satisfied by sEMG data as MUAPs are statistically independent, have non-Gaussian distributions and we can be (virtually) certain that the mixing matrix will be invertible. There are, however, two other practical issues that must be considered. Firstly, to ensure that the mixing matrix is constant the sources must be fixed in space (this is an implied assumption as only the case of a constant mixing matrix is 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 [13]. Secondly, in order to use ICA it is essential to assume that signal propagation time is negligible. Volume conduction in tissue is essentially instantaneous [14]. Hence this assumption is also well satisfied.

Based on the above discussion of the ICA assumptions as they apply to sEMG, it is reasonable to be confident that ICA can be effectively applied to EMG data. The validity of using ICA on sEMG is examined later in the experimental and analysis section.

4 Methodology

4.1 Experimental Procedure

University ethics committee granted approval to conduct experiments on human subjects and acquire Surface EMG using surface electrodes. For the hand gesture experiments four subjects whose ages ranging from 21 to 32 years (three males and one female) were chosen. 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 Fig. 1. A reference electrode was placed at Epicondylus Medialis.

Table 1: Muscle Electrode Configuration.

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

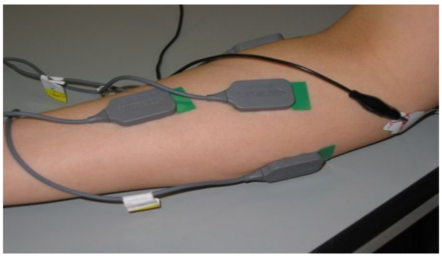

Fig. 2. Hand gesture experimental set up with four electrodes.

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 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.
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 unmixing matrix is a square matrix of size of 4×4. The experiments were repeated on two different days. Subjects were asked to keep the forearm resting on the table with elbow at an angle of 90 degree in a comfortable position. Four isometric hand actions were performed and repeated 12 to 14 times at each instance. Each time raw signal sampled at 1024 samples/second was recorded. Markers were used to obtain the Isometric contraction signals during recording. 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 were active simultaneously. The four different hand actions were performed and are listed below:

- Middle and index finger flexion.
- Little and ring finger flexion
- All finger flexion
- Finger & wrist flexion together.

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

4.2 Data Analysis

The aim of this experiment was to test the use of ICA along with known properties of the muscles for separation of sEMG signals for the purpose of identifying stationary hand gestures and finger movement actions. Each action was repeated 12 to 14 times and each contraction lasted approximately 2.5 seconds. The sampling rate was 1024 samples per second, and this gives approximately 2500 samples during the contraction. There were four channel (recordings) electrodes over the four active muscles associated with the different hand gestures, forming a square 4×4 mixing matrix. The sEMG recordings were then separated using fast ICA algorithm which is developed by the team at the Helsinki University of Technology [15]. The mixing matrix A was computed for the first set of data only and kept constant throughout the experiment. The independent sources of motor unit action potentials that mix to make the EMG recordings were computed using the following equation:

$$s = Bx \tag{3}$$

where B is the inverse of the mixing matrix A. This process was repeated for each of the hand gestures. Four sources were estimated for each experiment. The example of four channel source separation using Fast ICA matlab package is depicted in Fig. 3.

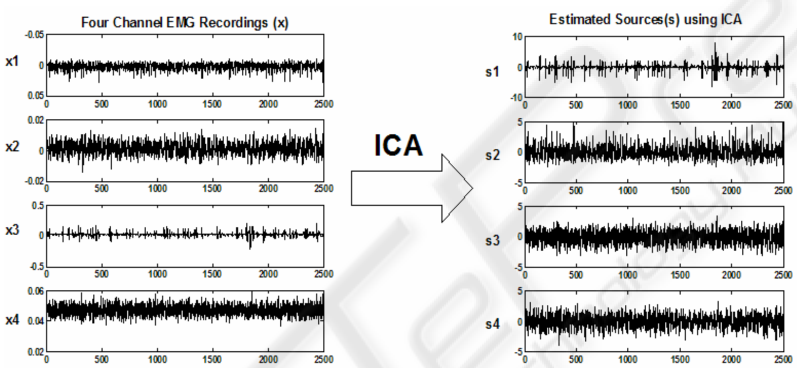

Fig. 3. Estimated four channel source signals s(t) from a four channel recording *x(t)*-1024 sampling rate using fast ICA.

After separating the four sources *sa*, *sb, sc* and *sd,* each of these was segmented to 2500 samples length. Root Mean Squares (RMS) was computed for each separated sources using the following relation:

$$Srms = \sqrt{\frac{\sum_{i=1}^{n} s_i^2}{N}} \tag{4}$$

where s is the source and N is the number of samples ($N = 2500$). 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 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 and has been used to identify the hand gesture. A constant mixing matrix A and set of weight matrix for neural networks were used for each subject making the system configured for each individual.

The above process was repeated for all four different hand actions 12 to 14 times and for each of the participants. These 12 to 14 sets of examples were used to train a back-propagation 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 recordings for each subject were used to train the ANN classifier with back-propagation learning algorithm. The second part of the experiment (testing) was to verify the training results. For that the set of data's which were not used for the training purpose (an independent data set) was selected. During the training, ANN consisted of two hidden layers with a total of 20 nodes and a sigmoid function as threshold function. The gradient descent algorithm with a learning rate of 0.05 was used to avoid any chances of local minima. 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 hand actions were used to determine the efficacy of the technique.

4.3 Results and Observations

The results of the experiment demonstrate the performance of the above described system. The results of testing the back propagation ANN to correctly classify the test data based on the weight matrix generated using the training data is tabulated in Table 2. 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 96% for all the experiments. The results demonstrate that this technique can be used for the classification of different types of isometric muscular activity. This feature makes it possible to define a class of *subtle motionless gestures* to control an interface without being noticed and without disrupting the surrounding environment.

Table 2. Experimental results for Isometric Hand Gesture Identification.

Number of participants	Middle and index finger flexion	Little and ring finger flexion	All finger flexion	Finger and wrist flexion together
Subject 1	97%	96%	97%	96%
Subject 2	96%	96%	96%	96%
Subject 3	97%	96%	96%	96%
Subject 4	97%	97%	96%	97%

5 Discussion

The proposed technique is capable of classifying small levels of muscle activity to identify Isometric hand gesture. Its base is using a combination of independent component analysis (ICA), known muscle anatomy and neural network configured for the individual. The results indicate the ability of the system to perfectly recognize 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.

This research overcomes these issues by using a priori knowledge of the anatomy of muscles in combination with blind source separation technique. Using a combination of the model, and ICA approaches with a neural network configured for the individual overcomes the order and magnitude ambiguity.

6 Conclusions and Future Work

This investigation has shown that a combination of a known biological model used in a semi-blind ICA combined with neural networks for classification can effectively be employed to detect small muscle activities, and by that to identify subtle hand actions and gestures. The presented experimental methods are able to reliably recognize a motionless gesture for different muscle volumes.

A new approach that combines semi-blind ICA and a back-propagation neural network was used to separate and identify subtle hand gestures, and subsequently using the combination of the mixing matrix and network weights to classify the sEMG recordings in almost real-time.

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 gestures have been chosen, because each of these represents a complex combination of muscle activations 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. In parallel, there is ongoing work to investigate recognition of gestures on a larger number of people and for a greater variety of hand actions to increase the performance of the system.

We are working on expanding the EMG gesture for extended 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 to develop a portable model for hand gesture recognition using semi-blind ICA technique.

Overall, the purpose of this project is to develop new perceptual interfaces for human computer interaction based on hand gesture identification, and to investigate how such interfaces can complement or replace traditional interfaces based on keyboards, mice, remote controls, data gloves and speech. Application fields for hand gestures analysis include control of consumer electronics, interaction with visualization systems, control of mechanical systems, and computer games.

One important benefit of such an HCI approach is that visual information makes it possible to communicate with computerized equipment at a distance, without a need for physical contact to the controlled target. Compared to speech commands, hand gestures are especially advantageous in noisy environments –particularly in situations where speech commands would be disturbed – as well as for communicating quantitative information and spatial relationships. Furthermore, the human user shall be enabled to control electronic systems in a quite natural manner, without requiring specialized external equipment.

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