Journal & Proceedings of the Royal Society of New South Wales, Vol. 140, p. 55–62, 2007
ISSN 0035-9173/07/020055–8 $4.00/1

Subtle Hand Gesture Identification for Human-Computer Interaction using Independent Component Analysis of Surface Electromyography

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Abstract: Surface electromyography (sEMG) is an indicator of muscle activity and is related to body movement and posture. One common shortcoming in the use of sEMG is to distinguish between small actions that require simultaneous contraction of number of adjoining muscles. This paper presents a method for subtle hand gesture identification from sEMG of the forearm by decomposing the signal into components originating from different muscles. The processing requires the decomposition of the surface EMG by independent component analysis (ICA) technique. Pattern classification of the separated signal is performed in the second step with a back propagation neural network. The focus of this work is to establish a simple, yet robust system that can be used to identify subtle complex hand actions and gestures for control of prostheses and other computer-assisted devices. The proposed model-based approach is able to overcome the ambiguity problems (order and magnitude problems) of ICA methods by selecting an *a priori* mixing matrix based on known hand muscle anatomy. Testing was conducted using several single shot experiments conducted with five subjects. The results indicate that the system is able to classify the data with 97% accuracy.

Keywords: Independent component analysis, surface electromyogram, motor unit action potentials, human-computer interaction, blind source separation

INTRODUCTION

Surface electromyography (EMG) is the electrical manifestation of contracting muscle activity and is thus an obvious choice for control of prostheses and other control applications. While there are number of possible applications of EMG, one common shortcoming is the difficulty in identifying small and subtle muscle contractions related to actions or maintained gestures and postures. Many attempts have been made to use the surface EMG signal as the command to control a prosthesis (Doerschuk et al. 1983, Kermani et al. 1995), but none of them takes explicit advantage of its subtlety, the fact that commands can be issued without the generation of observable movements. Hand actions and maintained gestures are a result of complex combination of contraction of multiple muscles in the forearm. Since all these muscles present in the forearm are close to each other, myoelectric activity observed from any muscle site comprises the activity from neighbouring muscle as well, referred to as cross-talk. The cross-talk problem is greater when muscle activation is relatively weak (subtle). Extraction of useful information from such surface EMG becomes difficult mainly due to the low signal to noise ratio. At low levels of contraction, EMG activity is hardly discernible from background activity. Therefore to correctly classify the movement and gesture of the hand more precisely, EMG needs to be decomposed to identify contraction of individual muscles. There is little or no prior information of muscle activity, and signals have temporal and spectral overlap, making the problem suitable for independent component analysis (ICA).

Blind source separation (BSS) techniques, especially in ICA, have found numerous applications in audio- and bio-signal processing. ICA has been proposed for unsupervised cross-talk removal from surface EMG recordings of muscles of the hand (Greco et al. 2003). Research that isolates motor unit action potential (MUAP) originating from different muscles and motor units was reported in 2004 (Nakamura et al. 2004). Muscle activity originating from different muscles can be considered to be independent, and this gives suggests the use of

BSS methods for separation of muscle activity. 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 method removes ambiguity of the order and magnitude. This paper proposes the use of ICA for separation of muscle activity from the different muscles of the forearm to identify subtle hand gesture where a pre-trained neural network classifier is used to identify hand gestures.

HAND GESTURE IDENTIFICATION FOR HCI

The use of hand gestures provides an attractive alternative to cumbersome interface devices for human-computer interaction (HCI). HCI requires the design and implementation of interactive computing systems for human use. The intent is to provide a seamless and natural interface that allows the human user to control and interact with computers and computer-based devices. Human hand gestures are a mean of non-verbal interaction. They range from simple actions like pointing at objects to more complex ones that express feelings and communicate ideas. The main applications of gesture recognition are communicative (e.g., sign language recognition) and manipulative (e.g., controlling robots without any physical contact between human and computer). Some examples of applications include control of consumer electronics, interaction with visualization systems, control of mechanical systems and computer games. Numerous approaches have been applied to the problem of visual interpretation of gestures for HCI. Many have focussed on a particular aspect of gesturessuch as hand tracking, pose classification, or hand posture interpretations (Rehg and Kanade 1996). Trejo et al. (2003) developed a technique for a multimodal neuroelctric interface. Recent studies focus on the use of EMG for the recognition of an alphabet of discrete gestures. To improve reliability, a number of efficient solutions to gesture input in HCI exist, such as restricting the recognition situation, use of input devices (e.g. a data glove), restricting the object information and restricting 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. A 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 (Pavlovic et al. 1997). In this report we propose the identification of maintained hand gesture based on muscle activity using the decomposition of surface EMG. It is a combination of a model-based approach with the BSS technique.

SURFACE ELECTROMYOGRAPHY

Surface electromyography is the electrical recording of the spatial and temporal integration of the 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 close relationship of surface EMG with the force of contraction of the muscle is useful for number of applications such as sports training, prostheses and for machine control. The EMG signals contain a lot of important information such as muscle force, operator's intended motion, and muscle impedance. Gross properties of sEMG such as magnitude and spectrum parameters are a good indicator of the overall magnitude of contraction, but these are unable to differentiate between muscle activities originating from different adjoining muscles.

Decomposition of sEMG has been attempted with the aim of determining the number of MUAP. Such methods are designed to identify the MUAP based on the shape, and are not suitable for determining the closely located muscles from where the MUAP originates.

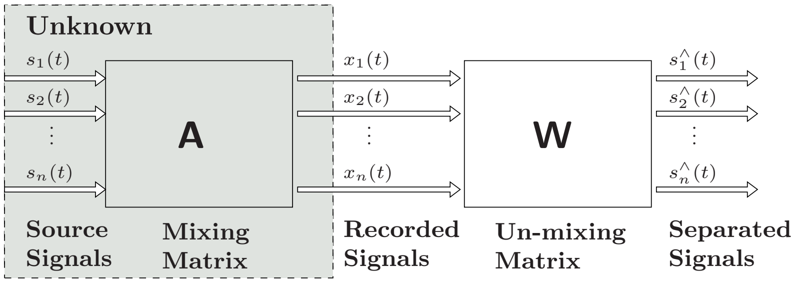

Figure 1. Block diagram describing the system concept; $s(t)$ are the sources, $x(t)$ are the recordings, A is the mixing matrix, W is the estimated un-mixing matrix and $u(t)$ are the estimated separated signals.

One property of the surface EMG is that the signal 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 the opportunity for using BSS methods.

INDEPENDENT COMPONENT ANALYSIS

ICA consists in recovering unobserved signals or 'sources' from several observed mixtures. Typically the observations are obtained at the output of a set of sensors, each sensor receiving the different combination of source signals. The simplest ICA technique aims at transforming an input vector into a signal space in which the signals are statistically independent (Hyvarinen et al. 2001). The simplest ICA model assumes that the mixing process as linear, so it can be expressed as in equation (1),

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

where $x(t) = [x_1(t), \ldots, x_n(t)]^T$ are the recordings, $s(t) = [s_1(t), \ldots, s_n(t)]$ the original signals, and A is the $n \times n$ mixing matrix. This mixing matrix and each of the original signals are unknown. To separate the recordings to the original signals (estimated original signals, u), the task is to estimate an un-mixing matrix W as in equation (2).

$$s = Wx(t) = WAs(t) \tag{2}$$

The ICA source recovering process is shown schematically in Figure 1. ICA is a difficult task because we do not have any information about the sources and the mixing process. ICA is a method to tackle this problem and is based on the assumption that the sources are independent from each other (Hyvarinen 1999, Comon 2001). BSS iteratively determines the un-mixing matrix W and thus estimates the corresponding independent signals u from the observations x. There are numbers of possible functions that may be considered for making the separated signals as independent as possible. The choice is based on the statistical independence of the sources s.

Relevance of ICA for sEMG Signal Evaluation

The aim of this section is to demonstrate that there is a strong theoretical basis for applying BSS techniques especially using ICA to sEMG signals. The assumptions that underpin the theory of ICA discussed in the previous section and indicate that BSS methods are ideally suited to separating sources when the sources are statistically independent, independent components have non-Gaussian distributions and the mixing matrix is invertible. These assumptions are well satisfied for 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. First, 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. 2000). Secondly, in order to use ICA techniques it is essential to assume that the signal propagation time is negligible. Volume conduction in tissue is essentially instantaneous (Makeig et al. 1997) and hence this assumption is also well satisfied. Based on the, it is reasonable to be confident that ICA can be effectively applied to EMG data. The validity of using ICA is examined below.

METHODOLOGY

Experiments were conducted to evaluate the performance of the proposed subtle hand gesture recognition system from hand muscle surface EMG. We propose a technique to classify small levels of muscle activity to identify hand gestures using a combination of ICA, known muscle anatomy and a neural network configured for the individual.

Data Acquisition

In the hand gesture experiments, seven subjects participated. For data acquisition a proprietary surface EMG acquisition system from Delsys (Boston, MA, USA) was used. Four electrode channels were placed over four different muscles as indicated in Table 1 and Figure 2. Subjects were asked to keep the forearm resting on the table with the elbow at an angle of 90 degree in a comfortable position. Four subtle hand actions were performed and repeated 12 times in each instance. Each time the 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 four different hand actions performed weremiddle and index finger flexion, little and ring finger flexion, all finger flexion and finger and wrist flexion together. These hand actions and gestures represented low levels of muscle activity (subtle hand gestures). The hand actions were selected based on small variations between the muscle activities of the different digitas muscles situated in the forearm. The subtle hand muscle recordings were separated using the Fast ICA algorithm.

Data Analysis

The aim of these experiments was to test the use of an ICA algorithm (Hyvarinen and Oja 1997) along with known properties of the muscles for separation of muscle activity from sEMG recordings for the purpose of identifying subtle hand gestures. These require no more than 4 independent muscles. Each experiment lasted approximately 2.5 seconds and was repeated 12 times. The sampling rate was 1024 samples per second to give approximately 2500 samples. There were four channel (recordings) electrodes and four active muscles associated with the hand gesture, forming a square 4×4 mixing matrix. The mixing matrix A was computed using the Fast ICA, BSS algorithm 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 estimated using equation (3),

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

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. Muscle electrode configuration.

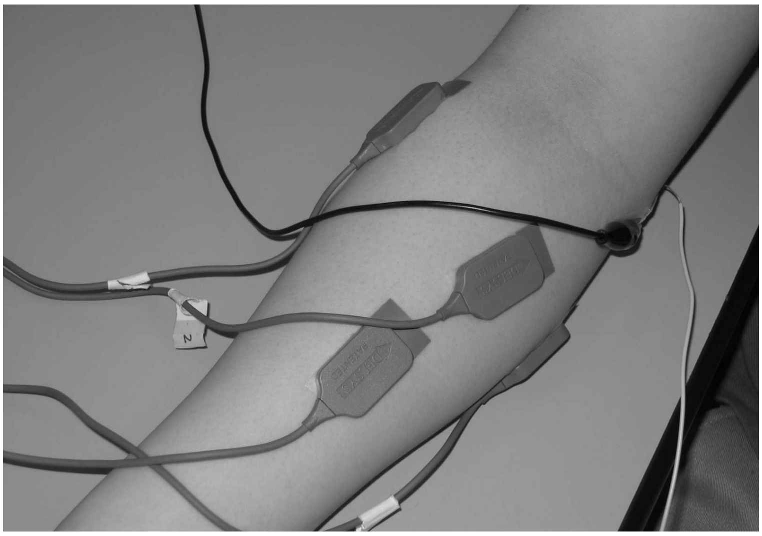

Figure 2. Hand gesture experimental set up with four electrodes.

where, B 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 estimated for each experiment. Root mean squares (RMS) was computed for each of the separated sources using equation (4),

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

where s are the estimated sources and N is the number of samples. This results in one number representing the muscle activity for each channel for each hand action. RMS values of muscle activity of each source represent the muscle activity of that muscle and are indicative of the strength of contraction.

Classification of Data

The above process was repeated for all four 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 with 4 inputs and 4 outputs. The 4 RMS values of the muscles were the input and the 4 RMS values were the output. In the first part of the experiment, RMS values of 4 recordings for each subject were used to train the artificial neural network (ANN) classifier with a 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. The ANN consisted of two hidden layers with a total of 20 nodes. A sigmoid function was the threshold function and the type of training algorithm for the ANN was gradient descent. During testing, the ANN with a weight matrix generated during training was used to classify the RMS of the muscle activity. The ability of the network to correctly classify the inputs against known subtle hand actions was used to determine the efficacy of the technique.

RESULTS AND DISCUSSION

The results of the experiment demonstrate the performance of the described system. To compare the performance of the system analysis of RAW sEMG and traditional ICA were performed. In the traditional ICA method, a mixing matrix was computed for each instance. Results demonstrate the ability of the semi-blind ICA method in source separation and identification.

Hand Gesture Identification Results on Raw sEMG

The results of the experiment on raw EMG signals for three different hand gestures are shown in Table 2. The accuracy was computed based on the percentage of correctly classified data points with respect to the total number of data points. Results shows an overall efficiency of 60% for all experiments.

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. This experiment was conducted for four hand gestures where the accuracy was observed to be only 65% (Table 3). These results demonstrate that standard BSS-based separation is not suitable for classifying sEMG.

Hand Gesture Identification Results using Semi-blind ICA

The classification of sEMG after pre-processing using ICA-based separation for four subtle hand gestures are presented in Table 4. The accuracy was computed based on the percentage of correct classified data points with respect to the total number of data points. The experiments were repeated for different numbers of hand gestures to be classified. Results indicate an overall classification accuracy of 97% for all experiments and demonstrate that this technique can be used for the classification of different subtle hand gestures.

The proposed technique is suitable for classify small levels of muscle activity even when there are multiple, simultaneously active muscles. Such a system may be suitable for being used for HCI, even when the actions are so slight that they may not be observable by other people. The technique has been tested with 7 volunteer participants and with experiments repeated on different days, thus indicating the robustness of the system. We believe that the reason the technique succeeded where others have failed is because the other techniques are not suitable when the signal-to- noise ratio is low and there is significant 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 muscle anatomy combined with suitable semi-blind ICA has overcome the abovementioned shortcomings.

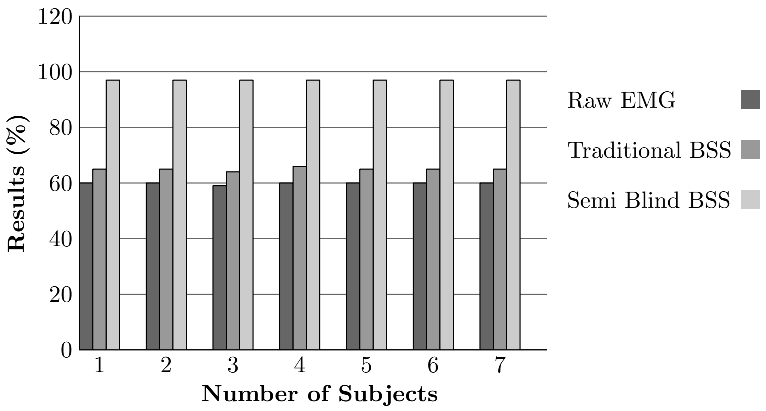

Figure 3. Results showing hand gesture identification results for 7 subjects.

Number of participants	Middle and index finger flexion	Little and ring finger flexion	All finger flexion	Finger and wrist flexion together
Subject 1	60%	60%	61%	60%
Subject 2	60%	62%	60%	60%
Subject 3	58%	60%	60%	60%
Subject 4	60%	60%	60%	60%
Subject 5	60%	60%	60%	60%
Subject 6	60%	60%	60%	60%
Subject 7	60%	60%	60%	60%

Table 2. Experimental results for hand gesture identification without using independent component analysis.

Number of participants	Middle and index finger flexion	Little and ring finger flexion	All finger flexion	Finger and wrist flexion together
Subject 1	66%	65%	65%	65%
Subject 2	64%	65%	64%	65%
Subject 3	65%	65%	65%	66%
Subject 4	65%	66%	65%	66%
Subject 5	66%	64%	66%	64%
Subject 6	66%	64%	66%	64%
Subject 7	66%	64%	66%	64%

Table 3. Experimental results for hand gesture identification using traditional independent component analysis.

Number of participants	Middle and index finger flexion	Little and ring finger flexion	All finger flexion	Finger and wrist flexion together
Subject 1	97%	97%	97%	97%
Subject 2	96%	97%	96%	97%
Subject 3	97%	98%	97%	97%
Subject 4	98%	97%	98%	98%
Subject 5	97%	97%	97%	98%
Subject 6	97%	97%	97%	98%
Subject 7	97%	97%	97%	98%

Table 4. Experimental results for isometric hand gesture identification using the semi-blind ICA algorithm.

CONCLUSIONS

We have shown that a combination of a known biological model with ICA along with neural networks for classification can effectively be applied to classify small muscle activities for identifying subtle hand actions and gestures. Experimental results demonstrate that ICA is highly efficient in performing classification of subtle, motionless gestures. Results indicate that ICA can be successfully employed for the separation of highly correlated, low level muscle activity. 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 ones. Possible applications include rehabilitation, prostheses, control of consumer electronics, interaction with visualization systems, control of mechanical systems and computer games.

ACKNOWLEDGEMENTS

The authors would like to thank ISSNIP, Melbourne, and the Biomedical Signal Processing Group at RMIT for their support.

REFERENCES

Doerschuk, P.C., Gustafson., D.E. and Willsky, A.S. 1983. Upper extremity limb function discrimination using EMG Signal analysis, *IEEE Transactions on Biomedical Engineering*, **30**, 18–28.

Greco, A., Costantino, D., Morabito, F.C. and Versaci, M.A. 2003. Morlet wavelet classification technique for ICA filtered SEMG experimental data. *Neural Networks*, **1**, 166–171.

Hyvarinen, A., Karhunen, J. and Oja, E. 2001. Independent Component Analysis. John Wiley, New York.

Hyvarinen, A. 1999. A fast and robust fixed-point algorithm for independent component analysis. *IEEE Transaction on Neural Networks*, **10**, 626–634.

Hyvarinen, A. and Oja, E. 1997. Fast fixed-point algorithm for ICA. The Fast ICA matlab software package. `http://www.cis.hut.fi/projects/ica/fastica/index.shtml`

Jung, T., Makeig, S., Lee, T., McKeon, M., Brown, G., Bell, A. and Sejnowski, T. 2000. Independent component analysis of biomedical signals. Proceedings of the Second International Workshop on Independent Component Analysis and Blind Signal Separation, pp. 633–644.

Kermani., M.Z., Wheeler, B.C., Badie K. and Hashemi, R.M. 1995. EMG feature evaluation for movement control of upper extremity prostheses. *IEEE Transactions on Rehabilitation Engineering*, **2**, 1267–1271.

Makeig, S., Jung, T., Bell, A. and Sejnowski, T. 1996. Independent component analysis of electroencephalographic data. *Advances in Neural Information Processing*, **8**, 145–151.

Nakamura, H., Yoshida, M., Kotani, M., Akazawa K. and Moritani, T. 2004. The application of independent component analysis to the multi-channel surface electromyographic signals for separation of motor unit action potential trains. *Journal of Electromyography and Kinesiology*, **14**, 423–432.

Pavlovic, V.I., Sharma, R. and Huang, T.S. 1997. Visual interpretation of hand gestures for human computer interaction: a review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **19**, 677–695

Rehg, J.M. and Kanade, T. 1994. Vision-based hand tracking for human-computer interaction. Proceedings of the IEEE Workshop on Motion of Non-Rigid and Articulated Objects, pp. 16–22

Trejo, L.J., Wheeler, K.R., Jorgensen, C.C., Rosipal, R., Clanton, S.T., Matthews, B., Hibbs, A.D., Matthews, R. and Krupka, M. 2003. Multimodal neuroelectric interface development, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **11**, 199–204.

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(Manuscript received 30.08.07, accepted 17.12.2007)