Subtle Hand gesture identification for HCI using Temporal Decorrelation Source Separation BSS of surface EMG

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Abstract

Hand gesture identification has various human computer interaction (HCI) applications. 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 temporal decorrelation source separation (TDSEP) based blind source separation 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 prosthesis and other HCI based devices. The proposed model based approach is able to overcome the ambiguity problems (order and magnitude problem) of BSS methods by selecting an a priori mixing matrix based on known hand muscle anatomy. The paper reports experimental results, where the system was able to reliably recognize different subtle hand gesture with an overall accuracy of 97%. 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. The paper also highlights the importance of mixing matrix analysis in BSS technique.

1. Introduction

Human communication comes in many modalities. They include speech, gestures, facial and bodily expressions which appear to implement in close cooperation parts or all of the aspects of the expression, such as temporo-spatial, visual, structural and emotional aspects. Hand gesture identification is one of the major techniques used in Human computer interaction (HCI). Applications of hand gesture recognition widely range from tele-operated control to medicine or to entertainment. 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], [3] and the use of electromyogram [4]. Electromyogram has an advantage of being easy to record, and it is non-invasive. Surface Electromyography (EMG) is the electrical manifestation in the contracting muscles activity and closely related to the muscle contraction and thus an obvious choice for control of the prosthesis. While there are number of possible applications of EMG, one common shortcoming is the difficulty to identify small and subtle muscle contraction related to actions or maintained gestures and postures. Many attempts have been made to use surface EMG signal as the command to control the prosthesis [5], 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, 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 when the muscle activation is relatively weak (subtle). Extraction of the useful information from such kind of surface EMG becomes difficult mainly due to the low signal to noise ratio. At low level of contraction, EMG activity is hardly discernible

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from the 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 the muscle activity, and the signals have temporal and spectral overlap, making the problem suitable for blind source separation (BSS).

BSS techniques, especially Independent component analysis (ICA) has found numerous applications in audio and biosignal processing disciplines. ICA has been proposed for unsupervised cross-talk removal from Surface EMG recordings of the muscles of the hand [6]. Research that isolates motor unit action potential (MUAP) originating from different muscles and motor units has been reported in 2004 [7]. 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 approach removes ambiguity of the order and magnitude. This paper proposes the use of semi blind BSS technique for separation of muscle activity from the different muscles in the forearm to identify the subtle hand gesture where a pre-trained neural network classifier is used to identify the hand gestures.

2. Hand gesture identification for HCI

The use of hand gestures provides an attractive alternative to cumbersome interface devices for human-computer interaction (HCI). 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 devices. 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. 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 of the examples of applications include:

- Control of consumer electronics.
- Interaction with visualization systems.
- Control of mechanical systems.
- Computer games.

Apart from these hand gesture also has useful applications in rehabilitation and prosthetic control.

2.1. Existing work

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], [3]. Trejo et al developed a technique for multi modal neuroelectric interface [8]. The most recent work includes the investigation of hand gestures for six distinct actions [9]. Recent studies focus on the use of EMG for the recognition of an alphabet of discrete gestures. Fistre and Tanaka [10] 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 [11] reported the development and successful testing of a neuroelectric joystick and a neuroelectric keypad. They recognize the movement corresponding to the use of a virtual joystick and virtual numeric keypad by using EMG signals collected from four and eight channels on the forearm. Gestures mimicking the use of physical devices are successfully recognized 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 technique.

3. Surface Electromyography (sEMG)

Surface Electromyography (sEMG) 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 analysis of EMG can be broadly categorised into two:

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

The close relationship of surface EMG with the force of contraction of the muscle is useful for number of applications such as sports training, prosthesis 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 and have numerous applications such as sports training, 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 originate from. 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 for using Blind source separation methods for this application.

4. Blind source separation model

Blind source separation 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 BSS technique aims at transforming an input vector into a signal space in which the signals are statistically independent [12].

The simplest BSS model assumes that the mixing process as linear, so it can be expressed as:

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

Where $x(t) = [x_1(t), x_2(t), ..., x_n(t)]$ are the recordings, $s(t) = [s_1(t), s_2(t), ..., s_n(t)]$, 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 $\hat{s(t)}$), the task is to estimate an un-mixing matrix W so that:

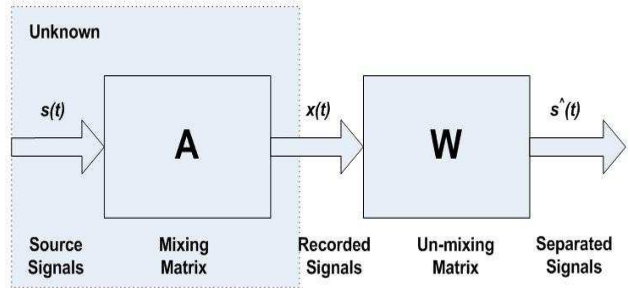

Figure 1. Block diagram describing the BSS: $s(t)$ are the sources, $x(t)$ are the recordings, A is the mixing matrix, W is the estimated un-mixing matrix and $\hat{s}(t)$ are the estimated separated signals.

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

BSS source recovering process is shown in Figure 1. BSS is a difficult task because we do not have any information about the sources and the mixing process. BSS is a method to tackle this problem and is based on the assumption that the sources are independent from each other [12]. BSS iteratively determines the un-mixing matrix W and thus estimates the corresponding independent signals $\hat{s(t)}$ from the observations $x(t)$. There are number of possible cost-functions that may be considered for making the separated signals as independent as possible. The fundamental of these is based on the statistical independence of the sources $s(t)$. This paper reports the use of temporal decorrelation source separation (TDSEP) method which is explained in detail next.

4.1. Details of TDSEP

Temporal decorrelation source separation (TDSEP) is one of the BSS technique, based on the simultaneous diagonalisation of several time-delayed correlation matrices [13]. The TDSEP algorithm uses the property that the cross-correlation functions vanish for mutually independent signals. It assumes that the signals $s(t)$ have temporal structure ("non delta" autocorrelation function). All time delayed correlation matrices $R_{\tau(s)}$ should be diagonal. This knowledge is used to calculate the unknown mixing matrix A in(1) by a simultaneous diagonalisation of a set of correlated matrices $R_{\tau(x)} = [x(t)x^T(t-\tau)]^1$ for different choices of τ. Since the mixing model in (1) is just linear transformation we can substitute $x(t)$ by $As(t)$ and get

$$R_{\tau(x)} = [As(t)(As(t-\tau))^T] = AR_{\tau(s)}A^T \tag{3}$$

where the source cross-covariance functions $R_{\tau(x)}$ are a set of diagonal matrices due to the statistical independence of the sources [13].

In order to estimate a square mixing matrix W, TDSEP uses whitening and rotation of the mixtures. This method requires a set of time delays τ, which can be arbitrarily selected or manually given. The advantage of second order methods is their computational simplicity and efficiency. Furthermore for a reliable estimate of covariances only comparatively few samples are needed.

4.2. Relevance of BSS methods for sEMG signals

The aim of this section is to demonstrate that there is a strong theoretical basis for applying BSS to sEMG signals. The assumptions that underpin the theory of instantaneous BSS - discussed in the previous section - indicate that BSS methods are 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 to 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 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 BSS methods to sEMG is much simpler than in other biomedical signal processing applications such as EEG or fMRI in which the sources can move [14]. Secondly, in order to use BSS technique it is essential to assume that signal propagation time is negligible. Volume conduction in tissue is essentially instantaneous [15]. Hence this assumption is also well satisfied.

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

5. Methodology

Experiments were conducted to evaluate the performance of the proposed subtle hand gesture recognition system from hand muscle surface EMG. We have proposed a

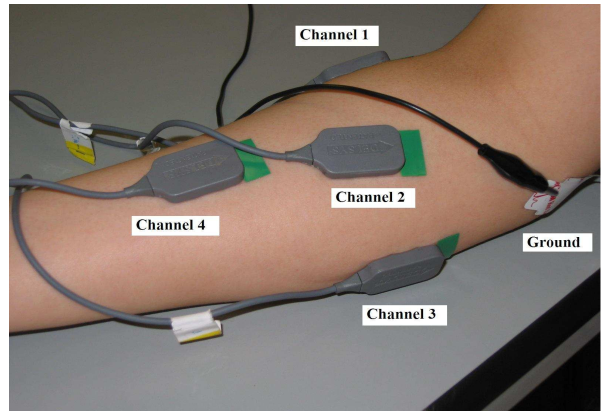

Figure 2. Placement of the Electrodes over the skin of the forearm

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

Table 1. Placement of Electrodes for Hand gesture Experiment

technique to classify small level of muscle activity to identify hand gesture using a combination of Blind source separation (BSS), known muscle anatomy and neural network configured for the individual.

5.1. Data Acquisition

In the hand gesture experiments, seven subjects between 21 and 32 years participated. For the 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 the Table 1 and Figure 2. 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. Four subtle hand actions were performed and repeated 12 times at each instance. Each time raw sEMG signal 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 are performed and are listed below:

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

These hand actions and gestures represented low level 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 TDSEP BSS algorithm.

5.2. Data analysis

The aim of these experiments was to test the use of TDSEP BSS algorithm [9] along with known properties of the muscles for separation 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.

Each experiment lasted approximately 2.5 seconds and was repeated 12 times. The sampling rate was 1024 samples per second, and this gives 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 TDSEP 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 the following equation.

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

where, B is the inverse of the mixing matrix A. This process was repeated for each of the four hand gesture experiments. Four sources were estimated for each experiment. After separating the four sources $s1$, $s2$, $s3$ and $s4$, RMS (root mean square) was computed for each of the separated sources using the following relation:

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

where s is the source and N is the number of samples. 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 its contraction.

5.3. Classification of Data

The above process was repeated for all four different hand actions 12 times and for each of the participants. In the first part of the experiment, RMS values of 4 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 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. Sigmoid function was the threshold function and the type of training algorithm for the ANN was gradient descent. 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.

6. 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 BSS were performed. In traditional BSS method, mixing matrix was computed for each instance. The results demonstrate the ability of the semi-blind BSS in source separation and identification. The following four subtle hand gestures are labelled as below for displaying results:

- Middle and index finger flexion **(G1)**.
- Little and ring finger flexion**(G2)**.
- All finger flexion **(G3)**.
- Finger and wrist flexion together**(G4)**.

6.1. Hand gesture Identification results using semi blind TDSEP BSS

The classification of sEMG after pre-processing using BSS based separation for four subtle hand gestures are presented in Table 2. The accuracy was computed based on the percentage of correct classified data points to the total number of data points. The experiments were repeated for different number of hand gestures to be classified. The accuracy was computed based on the percentage of correctly classified data points to the total number of data points. These results indicate an overall classification accuracy of 97% for all the experiments. The results demonstrate that this technique can be used for the classification of different subtle hand gestures.

Participants	G1	G2	G3	G4
Subject 1	97%	96%	97%	96%
Subject 2	96%	96%	96%	96%
Subject 3	97%	96%	96%	96%
Subject 4	97%	97%	96%	97%
Subject 5	97%	97%	96%	97%
Subject 6	97%	97%	96%	97%
Subject 7	97%	97%	96%	97%

Table 2. Hand gesture Identification results using semi blind TDSEP BSS.

6.2. Hand gesture Identification results using traditional TDSEP BSS

To compare the proposed system with the use of traditional BSS, analysis was performed where RMS of the four channels of sEMG separated using BSS 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.

6.3. Hand gesture Identification results on Raw EMG

The results of the experiment on Raw EMG signals on four different subtle hand gestures are shown in Table 4. The accuracy was computed based on the percentage of correct classified data points to the total number of data points. The results shows an over all efficiency of 60% for all the experiments. Authors believe that more cross-talk from the adjacent channels is the cause of this low discrimination rate.

The overall results are shown in Figure 3.

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

Table 3. Experimental results for Hand gesture Identification using traditional TDSEP BSS.

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

Table 4. Experimental results for Hand Gesture Identification without using TDSEP Blind source separation (Raw EMG).

7. Discussions

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 human computer interaction, even when the actions are very small that may not be observable by other people. The basis for the technique is source separation using BSS based on temporal decorrelation source separation (TDSEP), knowledge of muscle anatomy and a neural network configured for the individual.

The authors believe that the reason why this technique has succeeded where number of other similar techniques have failed is because other techniques are not suitable when signal-to- noise ratio is low and there is large cross-talk between different simultaneously active muscles. Use of BSS 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 BSS has overcome the above mentioned shortcomings.

This technique can be used for real-time applications because of easy to use algorithms like TDSEP and back propagation neural network. Quick computation time of these algorithms makes it suitable for day to day applications.

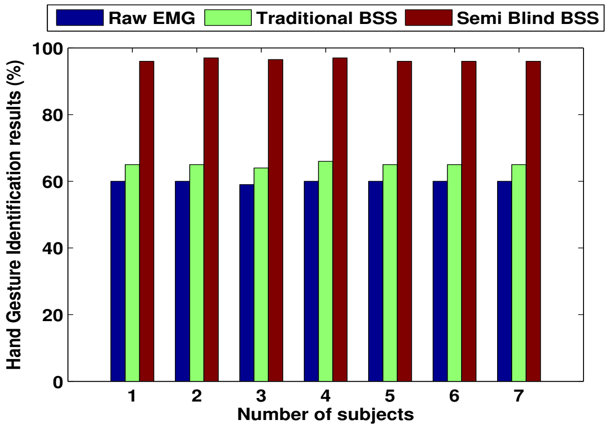

Figure 3. The over all results showing hand gesture identification for 7 subjects.

7.1. Mixing matrix analysis

In order to measure the quality of the separation of hand gesture muscle activities, we used the mixing matrix analysis for semi blind TDSEP technique.

The surface EMG signals (wide-band source signals) are a linear decomposition of several narrow-band sub components:$s(t) = [s_1(t) + s_2(t) + s_3(t), \ldots, s_n(t)]^T$ where $s_1(t)$,$s_2(t)$,...,$s_n(t)$ each are approximately 2500 samples in length which are obtained from recorded signals $x_1(t)$,$x_2(t)$,...,$x_n(t)$ using BSS. Such decomposition can be modelled in the time, frequency or time frequency domains using any suitable linear transform. We obtain a set of un-mixing or separating matrices: W_1,W_2,W_3,...,W_n where W_1 is the un-mixing matrix for sensor data $x_1(t)$ and W_n is the un-mixing matrix for sensor data $x_n(t)$. If the specific sub-components of interest are mutually independent for at least two sub-bands, or more generally two subsets of multi-band, say for the sub band "p" and sub band "q" then the global matrix

$$G_{pq} = W_p \times W_q^{-1} \tag{6}$$

will be a sparse generalized permutation matrix P with special structure with only one non-zero (or strongly dominating) element in each row and each column [16]. This follows from the simple mathematical observation that in such case both matrices W_p and W_q represent pseudo-inverses (or true inverse in the case of square matrix) of the same true mixing matrix A (ignoring non-essential and unavoidable arbitrary scaling and permutation of the columns) and by making an assumption that sources for two multi-frequency sub-bands are independent.

The above assumption is applied for different hand gestures, and some convincing results were derived, which demonstrate that BSS technique is clearly able to isolate the four independent sources from hand muscle sEMG recordings. For explaining this, we have shown the results of two un-mixing matrices which are obtained from one of the hand gesture, which satisfies equation (6).

$$G = \begin{pmatrix} \mathbf{-1.7555} & -0.1522 & -0.0608 & -0.0665 \\ -0.0806 & 0.1189 & -0.0201 & \mathbf{1.2224} \\ -0.0760 & \mathbf{0.9003} & 0.0124 & 0.0538 \\ -0.1653 & -0.0046 & \mathbf{0.8451} & -0.0054 \end{pmatrix}$$

Determinant(G) = **-1.6490**

In this example the dominant values in each row (BSS does have order and sign ambiguity, hence only absolute values are considered) demonstrate that BSS is able to separate the four sources. The semi blind BSS technique isolated the four sources ($s1$, $s2$, $s3$ and $s4$) from four sEMG recordings ($x1$, $x2$, $x3$ and $x4$) successfully. To justify this hypothesis, the determinant of the matrix G was computed. From the mathematical point of view, n vectors in R_n are linearly dependent if and only if the determinant of the matrix formed by the vectors is zero [17]. In each instance, results which are higher than one were obtained. These results clearly showed that semi blind BSS technique is able to isolate four independent sources from the four channel hand muscle recordings, which in turn provided the higher classification results (97% overall accuracy)using back propagation neural network.

The above analysis demonstrates the importance of mixing matrix analysis for source separation and identification of surface EMG signals. Our strong guess is the above analysis could be used as a pre-requisite tool to measure the reliability of the system. The analysis is also useful to test the requirement of further analysis, like classification of signals.

8. Conclusions and future work

This paper has shown that a combination of a known biological model with TDSEP BSS (semi-blind) along with neural networks for classification can effectively be applied to classify small muscle activities for identifying subtle hand actions and gestures. The experimental results of this investigation also demonstrate that TDSEP is highly efficient in performing classification of subtle, motionless gestures. These results indicate that TDSEP can be successfully employed for the separation of highly correlated low level muscle activity.

The results indicate that the system is able to perfectly (97% accuracy) identify the set of selected complex hand gestures for each of the subjects. These gestures represent a complex set of muscle activation 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 make recognition of gestures on large number of people and for variety of hand actions to increase the performance of the system.

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 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). An important component of the work is to perform continuous user studies in close connection with the development work. The goal is to explore hand gestures suitable for various control tasks in human-machine interaction. 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 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. Quicker computation of TDSEP BSS and neural network processing makes it suitable for real-time applications.

One important benefit of such an HCI approach is that visual information makes it possible to communicate with computerized equipment at a distance, without need for physical contact with the equipment to be controlled. Compared to speech commands, hand gestures are advantageous in noisy environments, in situations where speech commands would be disturbing, 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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