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Blind Source Separation Based Classification Scheme for Myoelectric Prosthesis Hand

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1. Introduction

For over three decades, researchers have been working on using surface electromyography (sEMG) as a means for amputees to use remaining muscles to control prosthetic limbs (Baker, Scheme, Englehart, Hutcinson, & Greger, 2010; Hamdi, Dweiri, Al-Abdallat, & Haneya, 2010; Kiguchi, Tanaka, & Fukuda, 2004). Most research in this domain has focused on using the muscles of the upper arms and shoulders to control the gross orientation and grasp of a low-degree-of-freedom prosthetic device for manipulating objects (Jacobsen & Jerard, 1974). Each measured upper arm muscle is typically mapped directly to one degree of freedom of the prosthetic. For example, tricep contraction could be used for rotation while bicep flexion might close or open the prosthetic. More recently, researchers have begun to look at the potential of using the forearm muscles in hand amputees to control a multi-fingered prosthetic hand. While we know of no fully functional hand prosthetic, this is clearly a promising new area of EMG research. One of the challenges for creating hand prosthetics is that there is not a trivial mapping of individual muscles to finger movements. Instead, many of the same muscles are used for several different fingers (Schieber, 1995).

To identify hand gestures and actions that are a result of multiple active muscles, relative muscle activity from the different muscles in the forearm has to be identified. For this purpose, the sEMG needs to be recorded using multiple electrodes. However due to the close proximity of the different active muscles, each of these electrodes record muscle activity from multiple muscles, referred to as cross talk. In case of the hand there are number of muscles in the close proximity and often crossing over each other and cross talk is a major cause of low reliability in identifying the action. This is further exaggerated when the muscle activity is weak such as during maintained isometric gestures due to the relative low signal to the background noise. Spectral and temporal overlap makes the use of conventional filtering quite useless. Differences between people make accurate modeling and generalization of the sEMG not possible. To overcome this, number of researchers have used generalization pattern recognition tools and some of these works have got good results (Cheron, Draye, Bourgeios, & Libert, 1996; Koike & Kawato, 1996; Meyer, 2000). However these require manual intervention and it is obvious that such techniques are not suitable for reliable operations that can be automated.

Numbers of researchers have attempted to use sEMG for controlling the prosthetic devices (Doerschuk, Gustafon, & Willsky, 1983;Zardoshti-Kermani, Wheeler, Badie, & Hashemi, 1995). While the current techniques to classify sEMG are suitable for identifying gross

actions that are the result of the contraction of a single muscle, these are unable to accurately identify actions that have multiple active muscles or where the strength of contraction is weak. Previous EMG-based input methods have classified gross movements such as wrist flexion or bicep activation, and hand prosthetics research has placed sensors on the forearm to detect finger movements. However, these approaches involve a restrictive setup procedure including fixing the hand to a board or placing sensors at many places on the arm in order to recognize only a few finger movements.

Recently, blind source separation (BSS) by independent component analysis (ICA) has received attention because of its potential in many signal processing fields. In this research, we present results demonstrating accurate gesture classification with an off-the-shelf electromyography (EMG) device. Here ICA is applied to the electromyography (sEMG) signal analysis. The experiment shows that ICA can decompose sEMG signal and separate source and noise effectively. A unique classification scheme is adopted using ICA and neural network to control the adjustment of myoelectric prosthetic hand's movement. Many experiments show that some steady independent components always appear when muscle does the same tasks. This result will provide us with a promising method in the classification of muscle pattern recognition and the research on the Human-Computer Interface (HCI) technology.

2. Related work

There are two broad approaches that have been used for classification of the sEMG to obtain command signals for controlling a prosthetic device. The first approach is to use the amplitude of the *steady state* electromyography (EMG) signal where the subject exerts constant force with a chosen muscle. A single recording site or channel on this muscle is then used to control in a manner proportional to the amplitude. Many commercially available prosthetics fall into this category, but generally afford the use of only a single degree of freedom such as a gripper for grasping and releasing objects due to the inability of such a system to identify small changes in muscle activity. The second approach uses the initiation of an action as a trigger, coding of which produces functional movements.

(Graupe & Cline, 1975) were one of the pioneers to classify sEMG signals for prosthetic control. They obtained 85% accuracy in classifying magnitude data from a single channel with autoregressive coefficients as features. While their work is impressive, it is neither suitable for automation nor for identifying number of complex actions. (Englehart & Hudgins, 2003) identified four discrete elbow and forearm movements using the transient structure in the signal by using time-frequency representations of the signal. They achieved accuracy up to 93.7% with four channels of EMG data from the biceps and triceps. Such a scheme is suitable when there are single prime movers but not for hand gestures where there are number of multiple active muscles. (Nishikawa, Yu, Yokoi, & Kakazu, 1999) classified ten discrete movements of the wrist and fingers using four electrodes placed on the forearm. They proposed an online learning scheme, and obtained an average accuracy of 85.1%. The shortcoming in this approach is the large inter-group variations with accuracy of identifying the correct action ranging from 75.2% to 91.7%. (Ju, et al., 2000) report finger action identification for consumer electronics applications and their technique achieved 85% accuracy in classifying four finger movements with the aid of two pair of electrodes placed close to the wrist. Such accuracy may be suitable for consumer electronics but is unsuitable

for rehabilitation and aged care applications. Further, this system requires the user to train the system for each experiment limiting the suitability of this approach.

Numerous approaches have been applied to solve the problem of visual interpretation of gestures. Many of these approaches have been chosen and implemented to focus on a particular aspect of gestures: Hand tracking, pose classification, or hand posture interpretations (Rehg & Kanade, 1993; Schlenzig, Hunter, & Jain, 1994). (Farry & Walker, 1993) presented myoelectric control of NASM Johnson Space Center's sixteen degree-of-freedom Utah/MIT Dextrous Hand for two grasping (key and chuck) options and three thumb motions (abduction, extension, and flexion). Their work discussed myoelectric signal processing approaches, data collection apparatus, and a real-time teleoperation implementation. They also demonstrated results in real-time discrimination of key and chuck grasps and offline discrimination of thumb motions. Their research outcome included a 90% correct grasp selection rate and an 87% correct thumb motion selection, both using the myoelectric spectrum. (Peleg, Braiman, Yom-Tov, & Inbar, 2002) used a combination of a K-nearest neighbour (KNN) classifier and a genetic algorithm (GA) for feature selection which results in an average error rate of approximately 2%, thereby making it feasible to operate a robotic replacement arm with relatively few errors using only two pairs of electrodes. Four subjects were participated in the experiment.

Most recent work includes the investigation of hand gestures for six distinct actions (Chan & Englehart, 2005) and a framework where myoelectric signals from natural hand and finger movements can be decoded with a high accuracy. (Chan & Englehart, 2005) presented the work related to prosthetic applications. Their work includes the investigation of twelve 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. They used short time Fourier transform and a linear discriminant analysis (LDA) classifier to classify the data. (Tenore et al., 2007) presented a hand gesture identification device using 32 surface-EMG electrodes were placed on the forearm of an able-bodied subject while performing individual finger movements. Using time-domain feature extraction methods as inputs to a neural network classifier, they showed that 12 individuated flexion and extension movements of the fingers can be decoded with accuracy higher than 98%. While this approach has the merits of reliability, the difficulty with this approach is that it requires multiple actions, leading to an unnatural and slow system. There is a need for systems that can recognize a range of hand actions that are more subtle and that are a result of multiple active muscles. Such a technique will allow the user to give natural control commands and would not require learning to make a series of actions for a specific command. To reliably identify actions that are based on contraction of multiple muscles requires identifying the level of muscle activity of the different muscles. This chapter reports a paradigm that is based on identifying activity from the different muscles by separating sEMG and the results indicate that the system is successful in identifying different complex hand actions. It is a combination of model based approach with blind source separation technique.

3. Myoelectric signal

Surface electromyogram (sEMG) is a non-invasive recording of muscle activity. It requires relatively simple equipment, and is suitable for numerous control applications. The close relationship of sEMG with the force of contraction of the muscle is useful for number of

applications such as sports training, urinary incontinence and for machine control. The relationship of sEMG spectrum with muscle fatigue is also very useful for occupational health and sports training. While there are numerous applications for sEMG, these are limited due to reliability issues arising due to the complexity of the signal. 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 muscles, ECG interference).
- Recording apparatus factors (recording-method, noise, electrode's properties and 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. Peripheral factors such as spacing, type and size of electrodes may also have an influence on the signal (Basmajian & Deluca, 1985), and to obtain reliable information, considering such factors is critical. Some of these factors may be handled through careful skin preparation, and by selecting proper anatomical landmarks for the placement of electrodes. While these factors influence Surface EMG in general, these factors are more apparent when the sEMG signal strength is very small, such as during static posture.

The complexity of the human body along with the high level of environmental noise results in the bioelectric signal recordings getting corrupted. Environmental noise and electrical activity from parts of the body other than the target muscles gets super-imposed on the recordings. There are number of techniques that are employed to reduce the environmental noise and artefacts from other organs such as by careful selection of the electrode location and with suitably designed acquiring equipment. But there are number of conditions where the artefacts may be very strong and prevent the useful interpretation of the desired signals. Examples of such situations include EMG recordings from the back and thorax region that have ECG and breathing artefacts, and the artefacts maybe of much greater magnitude than the signal. The other example is during the sEMG recordings of the digitas muscles to identify the hand gestures where the cross talk due to the different muscles can result in unreliable recordings. 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 blind source separation (BSS) for this application.

4. Basic principles of BSS techniques

Signals from different sources can get mixed during recording. Often it is required to separate the original signals, and there is little information available of the original signals. An example is the cocktail party problem. Even if there is no (limited) information available of the original signals or the mixing matrix, it is possible to separate the original signals using independent component analysis (ICA) under certain conditions. ICA is an iterative technique that estimates the statistically independent source signals from a given set of their

linear combinations. The process involves determining the mixing matrix. The independent sources could be audio signals such as speech, voice, music, or signals such as bioelectric signals (Bell & Sejnowski, 1995; Aapo Hyvärinen, Karhunen, & Oja, 2001).

Independent Component Analysis (ICA) is a new statistical technique that aims at transforming an input vector into a signal space in which the signals are statistically independent. The drawback of ICA, namely the need of high order statistics in order to determine ICA expansion, is counterbalanced by its performances, which are more meaningful compared with other methods like PCA -Principal Component Analysis

ICA assumes the mixing process as linear, so it can be expressed as:

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

Where $x = [x_1(t), .x_2(t), \ldots, x_n(t)]$ are the recordings, $s = [s_1(t), .s_2(t), \ldots, s_n(t)]$ the original signals and A is the mixing matrix of real numbers. 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 so that:

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

For this purpose, ICA relies strongly on the statistical independence of the sources s. The block diagram approach of ICA for source separation is shown in figure 1.
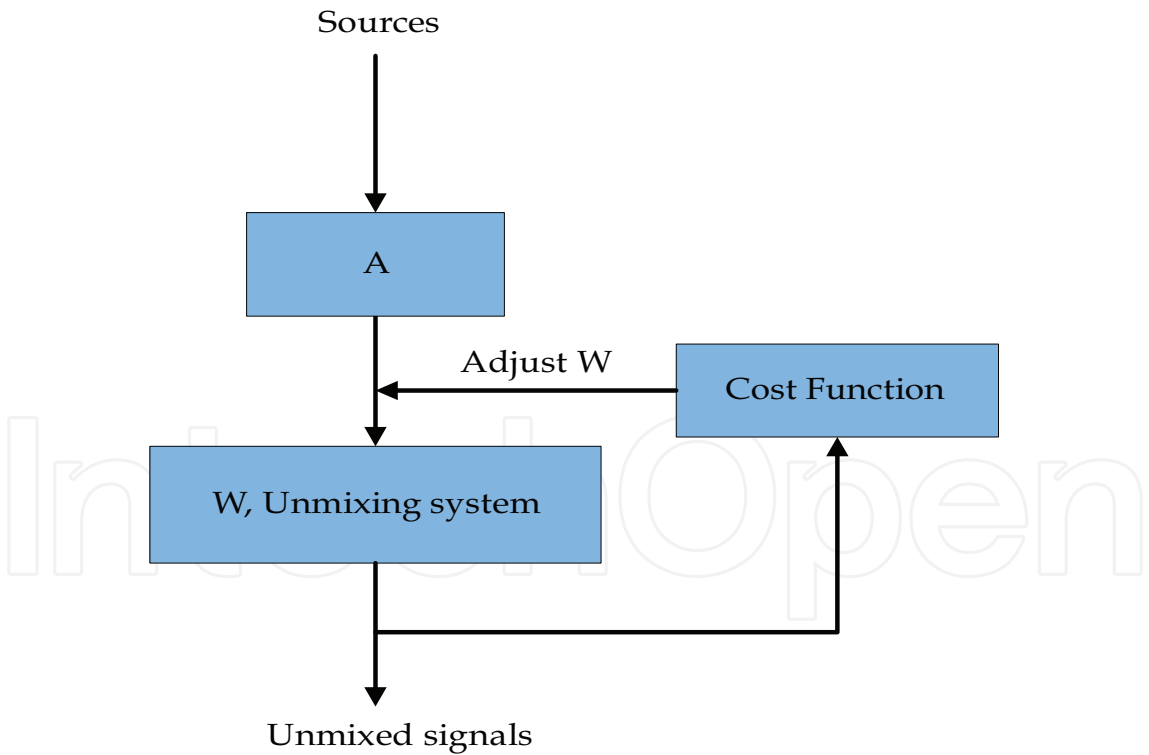

Fig. 1. An example of ICA source separation system

The ICA technique iteratively estimates the un-mixing matrix using the maximisation of independence of the unmixed signals as the cost function. Signals are statistically independent if the joint probability density of those components can be expressed as a multiplication of their marginal probability density. It is important to observe the distinction

between independence and uncorrelatedness, since decorrelation can always be performed by transforming the signals with a whitening matrix to get the identity covariance matrix I. Independent signals are always uncorrelated but uncorrelated signals are not always independent. But in case of Gaussian signals, uncorrelatedness implies independence. Transforming of a Gaussian signal with any orthogonal un-mixing matrix or transform results in another Gaussian signal, and thus the original signals cannot be separated. Hence Gaussian signals are forbidden for ICA. Thus the key of independent component estimation is measuring the non-Gaussianity of the signals (Bell & Sejnowski, 1995; Comon, 1994; Aapo Hyvärinen, et al., 2001; Lee, 1998).

To summarise from the above, the signals that can be separated need to be non-Gaussian and independent. For the purpose of applying ICA to sEMG recordings, there is a need to determine the conditions under which these signals can be considered as independent and non-Gaussian, and the mixing matrix can be considered to be stationary and linear. This chapter analyses and tests these conditions using a stationary mixing matrix.

The ICA technique iteratively estimates the unmixing matrix using the maximisation of independence of the unmixed signals as the cost function. Substantial research has been conducted on algorithms using higher order statistics for estimation of ICA. One of the widely used techniques among these is FastICA. FastICA is a fixed point algorithm that employs higher order statistics for the recovery of independent sources (A. Hyvärinen, 2000; Aapo Hyvärinen, et al., 2001; Aapo Hyvärinen & Oja, 1997a, 1997b). Separation is performed to obtain uncorrelated and independent sources whose amplitude distributions are as non-Gaussian as possible are obtained. The non Gaussianity is measured with the differential entropy J, called negentropy, which is defined as the difference between the entropy of a Gaussian random variable y_{Gauss} (having the same mean and variance of the observed random variable y) and the entropy y (Aapo Hyvärinen, et al., 2001; Aapo Hyvärinen & Oja, 1997b).

$$J(y) = H(y_{Gauss}) - H(y) \qquad (3)$$

Where the entropy H is given by

$$H(y) = -\int f(y) \log(f(y)) dy \qquad (4)$$

Since Gaussian random variables have the largest entropy H among all random variables having equal variance, maximizing the negantropy, $J(y)$ leads to the separation of independent source signals.

FastICA can estimate independent components (ICs) one by one (deflation approach) or simultaneously (symmetric approach), and the extracted number of ICs can be lower than the number of mixtures so that the unmixing matrix W can be rectangular. FastICA uses simple estimates of negentropy based on the maximum entropy principle (Aapo Hyvärinen, et al., 2001; Aapo Hyvärinen & Oja, 1997b).

4.1 Relevance of ICA for sEMG

This section establishes the relevance of the application of ICA for sEMG. The first step is test sEMG against the assumptions that underpin the theory of ICA. ICA is suitable for source separation when;

- The sources are statistically independent

- Independent components have non-Gaussian distribution
- The mixing matrix is invertible
- Sources and sensors are fixed.
- Signal transmission delays are negligible.

These assumptions are satisfied by sEMG because; (i) the MUAPs are statistically independent, (ii) have non-Gaussian distributions, (iii) if the number of recordings is same as the number of sources, the mixing matrix will be square and invertible, (iv) the sources and electrodes are fixed and (v) volume conduction in the tissue is essentially instantaneous (T. P. Jung et al., 1998; T. P. Jung et al., 2000; Makeig, Bell, Jung, & Sejnowski, 1996). Based on the above, ICA is suitable for separating sEMG recordings to obtain muscle activity if the number of channels is same as the number of active muscles.

One measure to test the quality of separation is to determine the dominant values and sparseness in the global matrix. Global matrix for ICA are generated by multiplying un-mixing matrix of signals from one time window, Wp, with the inverse un-mixing matrix of the other time window, Wq. If the separated signals are independent, each of the un-mixing matrices should be the inverse of the mixing matrix but for the ambiguity due to the order and arbitrary scaling (Cichocki & Amari, 2002; Aapo Hyvärinen, et al., 2001; T.-P. Jung, et al., 1998; T. P. Jung, et al., 2000; Makeig, et al., 1996), and the product of these, the global matrix should be sparse with typically one dominant cell in each row and column while the other cells should be close to zero (Meyer, 2000).

To test the efficacy of the use of ICA for sEMG, preliminary experiments were conducted where the global matrix was computed for the recordings. Four channels of sEMG that had been recorded during finger and wrist flexion experiments were separated using Fast ICA and the unmixing matrices were estimated for a series of time windows. Below are two matrices corresponding to two set of time frames. From these, it is observed that in each of these matrices, there is only one dominant cell in each row and column and the others are close to zero, and thus the matrix is sparse. This indicates that the quality of separation of the signals is good.

Trial 1:

$$G_{hand} = \begin{bmatrix} -0.0126 & -0.0519 & -0.0670 & 1.2294 \\ 0.0701 & -1.5252 & -0.0699 & 0.0263 \\ -1.4221 & -0.0233 & -0.0144 & -0.1761 \\ -0.0266 & -0.0045 & 0.6180 & 0.0100 \end{bmatrix}$$

$$\mathrm{Det}\left(G_{semi\_blind\_ICA\_Hand}\right) = 1.6533$$

Trial 2:

$$G_{hand} = \begin{bmatrix} 0.0800 & -1.0094 & 0.0271 & 0.0927 \\ 0.0670 & -0.0046 & 0.0307 & -1.2610 \\ 0.0143 & 0.0295 & 0.8062 & 0.0273 \\ 2.1595 & 0.3787 & -0.0729 & 0.0686 \end{bmatrix}$$

$$\mathrm{Det}\left(G_{semi\_blind\_ICA\_Hand}\right) = 2.2588$$

From these trials, it is also evident that one shortcoming with the use of ICA is the ambiguity related to the order of the outputs. The other ambiguity is due to the arbitrary scaling making the absolute value of the output arbitrary. To overcome these issues, this research has proposed to estimate the unmixing matrix only once for an individual and with the help of this, to train a supervised neural network with the targets being the known actions. It is proposed that this unmixing matrix and the trained network be used for identifying the hand actions. Such a scheme would be extremely fast and would not need supervision because during operations the computations would only require the pre-estimated unmixing matrix and pre-trained neural network weight matrix.

Wrist flexion   **Index and Middle finger flexion**

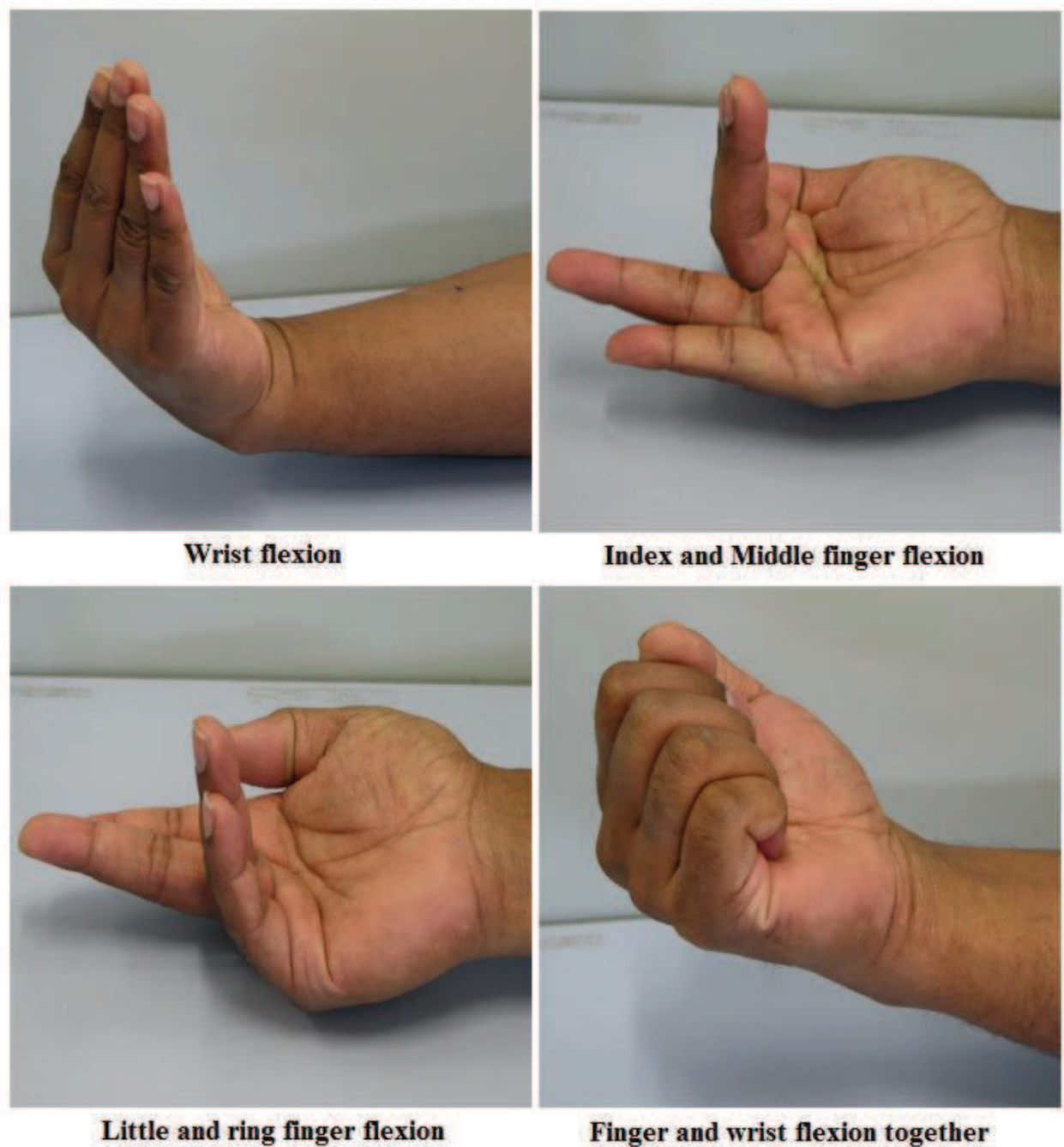**Little and ring finger flexion**   **Finger and wrist flexion together**

Fig. 2. Four Isometric Hand gestures performed during the experiment.

Experiments were conducted to evaluate the performance of the proposed ICA based technique. sEMG was recorded while the participant maintained four isometric finger flexions (fig. 2). The recordings were statistically tested to evaluate the reliability of separation and then tested using a backpropogation neural network. Overall methodology approach is shown in fig. 3.
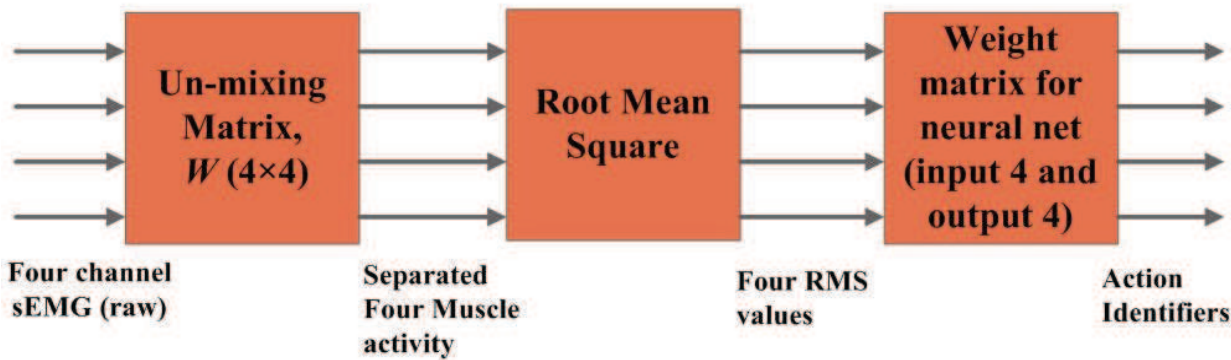

Fig. 3. Flowchart of the system.

4.2 sEMG recording

Experiments were conducted after obtaining approval from RMIT University human experiments ethics committee. Five able subjects, ages ranging from 21 to 32 years (four males and one female) and one amputee subject are volunteered for the experiments. Surface EMG was recorded using a Delysis eight channel sEMG acquisition system (Boston, MA, USA). Each channel has a pair of electrodes mounted together with a fixed inter-electrode distance of 10mm and a gain of 1000. Four electrode channels were placed over four different muscles. A reference electrode was placed at Epicondylus Medialis. Before placing the electrodes, the subject's skin was prepared by lightly abrading with skin exfoliate to remove dead skin. This was done to reduce the skin impedance to less than 60 kOhm. Skin was also cleaned with 70% v/v alcohol swab to remove any oil or dust on the skin surface.

The experiments were repeated on two different days. The forearm was resting on the table with elbow at an angle of approximately 90 degree and in a comfortable position. Four isometric wrist and finger flexions were performed and each was repeated for a total of 24 times for each action over the two sessions. The signal was sampled at 1024 samples/second. The actions were selected because these required four multiple muscles to be contracting at the same time and thus could test the ability of the system and this ensured that the estimated unmixing matrix was square. 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.

4.3 Data analysis

As a first step, sEMG recordings were segmented to remove the start and end of each recording. This was done based on the temporal location of the markers. FastICA was then used to separate the four channels of sEMG using 4×4 matrix structures for the first day experiments. The estimated unmixing matrix, W, was saved and corresponded to the

participant. Root mean square (RMS) was computed for the four estimated separated signals to obtain one number corresponding to each muscle for each action. The above was repeated for each of the five participants.

The unmixing matrix, W, was then multiplied with the recordings of the experiments of the test data corresponding to the balance twenty experiments (not used for training). RMS was computed for each of the separated signals and this resulted in a set of four RMS values for each of experiment.

4.4 Classification of data

A neural network with four inputs, four outputs, and twenty hidden neurones was used to classify the data. Four RMS values of the muscles were the inputs and numbers identifying the four actions were the target. For each participant and for each action, there were 24 recordings. Data from four randomly selected recordings were used to train the network. The weight matrix obtained at the end of the training and the unmixing matrix generated by ICA was saved to correspond to the participant. The training was repeated for each participant.

The system was tested using the balance twenty experiments data that had not been used for training. The input to the neural network was the set of four RMS values of the separated sEMG signal using the unmixing matrix corresponding to each participant. The weight matrix for each participant was used for the testing of the data of that participant. The output of the network was recorded and compared with the known corresponding actions and accuracy of identifying the action was estimated as a percentage. This was repeated for the five participants.

To compare the technique, data classification was also repeated for raw sEMG corresponding to the sEMG without separation, and the sEMG separated using ICA based technique reported in literature, where the unmixing matrix was generated for each experiment, similar to the technique used for separating audio and similar data.

5. Results and observations

The experiments have compared the accuracy of identifying the hand actions based on the RMS of sEMG recordings using raw sEMG, sEMG separated using standard ICA and using the unmixing matrix and weight matrix corresponding to the individual. These results have been tabulated in Table 1 in the following form:

- Method 1: Experimental results for Hand Gesture Identification using Raw sEMG (without using ICA)
- Method 2: Experimental results for Hand Gesture Identification using muscle activity separated from sEMG using traditional (matrix repeated) ICA
- Method 3: Experimental results for Hand Gesture Identification using muscle activity separated from sEMG (using fixed matrix) ICA
- Method 4: Experimental results for Hand Gesture Identification using muscle activity for amputee data from sEMG (using fixed matrix) ICA

From this table, it is observed that classification of sEMG after pre-processing using the unmixing matrix and corresponding weight matrix has 97% accuracy. This accuracy is only 65% when the unmixing matrix is generated for each set of experiments. When RMS from unseparated sEMG was used (referred to as raw sEMG), the accuracy of classification was

only 60%. This indicates that using the set of unmixing matrix and weight matrix corresponding to each participant improves the system accuracy dramatically, from 60% to 97%. Similar analysis was performed for amputee data, where the classification accuracy was 90%. The discrepancy between able and amputee data could be due to more cross-talk among the amputee data, as compared to that of able bodied subjects.

Methods	Wrist flexion		Index and Middle Finger flexion		Little and ring finger flexion		Finger and wrist flexion together.	
	Day one	Day two	Day one	Day two	Day one	Day two	Day one	Day two
Method 1	60%	60%	60%	60%	60%	60%	60%	60%
Method 2	65%	65%	65%	65%	65%	65%	65%	65%
Method 3	97%	97%	97%	97%	97%	97%	97%	97%
Method 4	90%	90%	90%	90%	90%	90%	90%	90%

Table 1. Over all Experimental results (average) for Hand Gesture Identification

6. Myo electric prosthetic control using robotic hand

Most prosthetic hands, available in current market, utilize at best take sensory feedback and are dependent on muscle rather than neural control. They require an extensive training before the patients can properly use the prosthetic hand and are bounded with limited functionality. Many organizations, Defense Advanced Research Projects Agency (DARPA), for instance have set an agenda and envision of advanced prosthetic arm with various functional properties. Whereby, the data glove can be used in the training to help the end users in controlling the robotic hand. Also it would be useful for the rehabilitation program i.e. for amputees who lost the sensation of their fingers movement. The development of Robotic hand system shall provide an option for both doctors and patients (amputees and those of weak upper-limbs) to monitor their finger movements. Furthermore, the designed system 'Command for Robotic Hand' may be able to assist the elder people who are facing decrepitude; the users may be able to control the robotic hand to do the work for them which required similar training i.e. wirelessly or embedding the robotic hand on the wheel chair.

Prosthetic hand controlled by EMG has the ability to control more joints than other conventional prosthetic hands, such as functional upper extremity prostheses, which can control no more than two joints. Development of EMG prosthetic hands that can perform more humanlike and inherent movements is desired in rehabilitation engineering and welfare work, especially by amputee patients. However, the majority of the EMG prosthetic hands on the market cannot meet the demand of doctors and amputees because those products can control only one joint and perform hand-opening/closing. Current EMG prosthetic hands use two dry-type electrodes; which applied to skin surface under two types of muscles –i.e. extensor digitorum muscle and flexor digitorum superficial muscle- during EMG signals detection. The control of prosthetic hands required the amputees to generate EMG patterns which are different from the patterns before amputation. This task is quite

difficult for most patients; hence the training for certain period of time is essential before the amputees can adapt themselves with the prosthetic hand.

6.1 On-line learning method for EMG prosthetic hand control

On-Line Learning Method for EMG Prosthetic Hand control enumerated their problems blocking the realization of multi-degree-of-freedom EMG prosthetic hands as follows:

- Problem of developing an effective analysis method, which can discriminate multiple motions. It is feasible because EMG is the superimposed complex signal of the electromyograms from multiple muscles.
- Problem of adapting to an operator's individual variation, which is caused by differences of physical properties, such as impedance generated by the amount of muscles and fat, and differences of the results of motor learning, that is, personal habits of motion, which result in different EMG even if in the same motion.
- Problem of developing a robotic hand which will be light enough, with high power and durability, and the same size as the human hand.
- Problem of reducing noise, which results form the fact that the EMG is a physiological signal with small amplitude (about 1mV), while the dry-type electrode has high impedances.
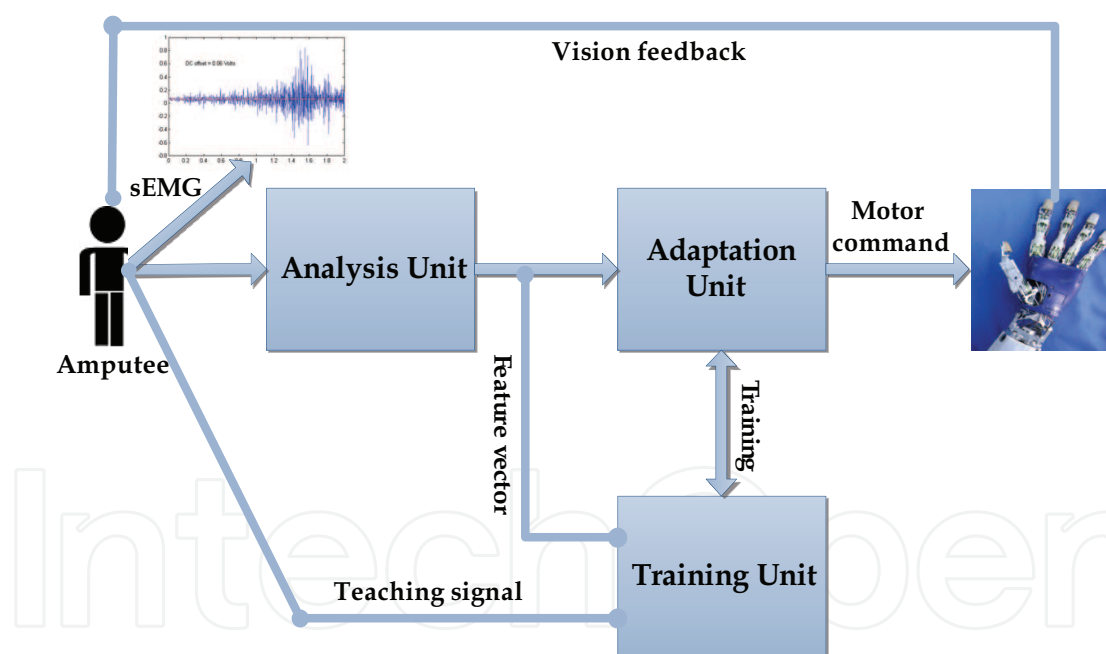

Fig. 4. A schematic diagram of the proposed prosthetic hand control system using electromyogram.

The research work of *Real-time control of a virtual hand* has been integrated a myoelectric control system for prostheses and evaluated on six healthy subjects; the system were able to control a computer-animated hand in real time with a 20Hz refresh rate. The schematic block diagram of the entire process is shown in Fig. 4. A data glove, equipped with joint angle sensors, was used to train the system and to evaluate the continuous joint predictions –prediction error. A linear envelop filter was used for EMG signal preprocessing and the recognition of muscle patterns.

EMG recognition, in nature, is indeed a complex task and the variation between different subjects is often large; one reason being for this is reported in their demographic data, but rarely been reported in related publications, is tissue thickness that heavily affect the capability to record deeply located muscles. Their purpose of the experiments was to investigate the performance of the proposed real time control system and the advantages of on-line training on a healthy homogenous study group. Different parameters that are important for practical use of hand prosthesis were calculated such as the delay between the prediction and measured hand joints and the accuracy of 4 basic hand movements.

7. Discussion and conclusions

The poor results when using raw sEMG is attributed to the closeness of the multiple active muscles resulting in high level of cross-talk. The poor accuracy in the use of ICA is attributable to the ambiguity associated with ICA and these results in inaccurate classification of the data. The proposed technique has overcome the above mentioned shortcomings of the earlier methods by having a set of unmixing matrix and weight matrix corresponding to each participant. The result is that the ambiguity associated with ICA does not affect the outcomes because while the order is not known, this remains the same during the unmixing and classification stages. The result is that the system identifies the actions accurately.

The presented work has demonstrated that use of the RMS of sEMG recorded from four channels from the forearm is not suitable to accurately identify finger and wrist flexions. The experiments have also demonstrated that if ICA is used to separate the signal to obtain muscle activity from individual muscles, there is the problem of order and scale ambiguity. To mitigate these shortcomings, the proposed system uses a set of unmixing and weight matrices that separate and classify the signal. This set is built for each individual and is referred to as ICANN. Because the ambiguities are the same during the testing and during the training phases, the test results indicate that the system accuracy is markedly better than the earlier techniques. While the results for raw sEMG was 60%, and for sEMG separated using ICA was only 65%, the method reported in this paper gives an accuracy of 97% for the same set of recordings, and classified by similar methods.

The other benefit of this technique is that it offers a system that is suitable for real time operations. During regular operations, the pre-trained system would only require two multiplication steps of 4×4 matrix to obtain the classification. While the training requires supervision, the regular operation does not require any supervision and is suitable for a lay user. The experimental results demonstrate that the system is resilient to inter-experimental variations. One of the possible shortcomings of such the proposed technique is that even after separation, background noise can make the segmentation difficult to automate and hence there is need for identifying a non-linear feature set that can replace RMS of the signal. The other shortcoming of such a technique is that while it has made a set of unmixing and classification matrices, there is the randomness associated with genetic algorithms and this set is not optimized. There is a need for optimizing such a system.

This research also proposes a visual training method for prosthetic hand control; in particular, it had succeeded in generating a command control for the Robotic hand. The success included the ability in discriminating distinct finger movements (per channel) with respect to time. As the training design aimed to assist people in the rehabilitation who have

weaken limbs, encountered lost of sensation and amputees by delivering output as visual feedbacks. It is a crucial contribution to those who lost their sensation after the amputation. This experiment represents a modest foray into using supervised learning to control a prosthetic hand. It was a proof-of-concept and needs to be extended before being considered proven. To be useful, a prosthetic hand must be capable of executing considerably more than six gestures. It may not be possible to recognize directly the large number of gestures used in every day life. A better approach might be to build a small vocabulary of gesture components from which the larger set of everyday gestures can be built. Based on this paper, an intelligent EMG control scheme can be implemented to recognize the hand's gesture and grasping force simultaneously. That makes a big improvement to current multi-DOF prosthetic hands' myocontrol. Future work will concentrated on validating this method on patients.

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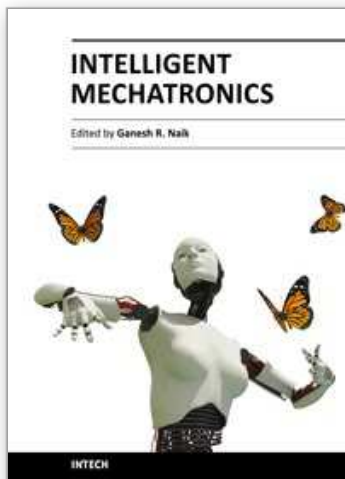
Intelligent Mechatronics

Edited by Prof. Ganesh Naik

This book is intended for both mechanical and electronics engineers (researchers and graduate students) who wish to get some training in smart electronics devices embedded in mechanical systems. The book is partly a textbook and partly a monograph. It is a textbook as it provides a focused interdisciplinary experience for undergraduates that encompass important elements from traditional courses as well as contemporary developments in Mechtronics. It is simultaneously a monograph because it presents several new results and ideas and further developments and explanation of existing algorithms which are brought together and published in the book for the first time.

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