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Review of Electromyography Control Systems Based on Pattern Recognition for Prosthesis Control Application

[1]Siti A. Ahmad, [2]Asnor J. Ishak, [3]Sawal H. Ali and [4]Paul H. Chappell

[1,2]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor, Malaysia
[3]Department of Electrical, Electronics and System, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia.
[4]School of Electronics and Computer Science, University of Southampton, Highfield SO17 1BJ Southampton, United Kingdom

Abstract: Electromyographic control is a technique that involve with the detection, processing and classification of the electromyography signal that could be applied in human-assisting robots, prosthesis application or rehabilitation devices. This paper reviews recent research and development electromyographic control systems with an emphasis on pattern recognition control for prosthesis application. Various methods used in the different stages of the pattern recognition based control system are discussed in details.

Key words: electromyography control, prostheses, pattern recognition, feature extraction, classification

INTRODUCTION

The concept of using EMG for prosthesis control started in the 1940s. Electromyographic control is when the signal is used as the input for the control of powered prostheses. The signal is used to select and modulate a function of a multifunction prosthesis Roberto Merletti (2004).

There are two types of EMG; needle and surface EMG. Hargrove *et al.* (2007) had carried out an investigation to compare the performance of these two types of EMG for prostheses control application. In the investigation, both signals were acquired simultaneously and processed using the same methods. They found that both EMG types gave high classification accuracies which are 95% to 99%. Even though there is no significant difference between SEMG and needle EMG in terms of accuracy, SEMG is the most preferred method as it is non-invasive and more convenient to use.

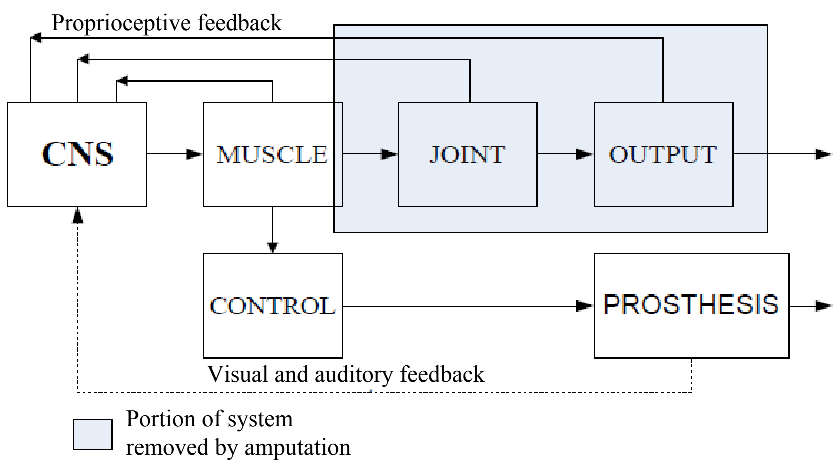

Fig. 1: Block diagram presenting relationship between normal and electromyographic control system (shaded area is removed by amputation) (Parker *et al.,* 2006)

Figure 1 shows the block diagram presenting the relationship between normal and electromyographic control system. For the amputees, the natural motor control system which consist of the joint and the output (the shaded area in the diagram) are replaced with the control mechanism and the prosthesis respectively. The SEMG signal generated from the remnant muscle is used as the control channel of the system.

Corresponding Author: Siti A. Ahmad, Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor, Malaysia
E-mail: sanom@eng.upm.edu.my

Generally, electromyographic control can be divided into two; non-pattern recognition based and pattern recognition based. Non-pattern recognition based control is basically constructed using hierarchical control, threshold control, proportional control or finite state machines. Most of the commercial prosthetic hands use this method which is either amplitude or level coding of the EMG signal generated during an active control muscle of the user to control the prostheses. For example, the Otto Bock two-state system incorporated this technique to assign each prosthetic limb function to a separate control muscle (Roberto Merletti, 2004; Scott and Parker, 1988; Englehart and Hudgins, 2003). The operation of the system is shown in Figure 2 (a), where each muscle is assigned with its threshold value (S1 for muscle 1 and S2 for muscle 2). When the muscle exceeds the cutoff threshold, it is activated and the associated function is selected. Only one function will be activated at one time and this is implemented using appropriate logic circuitry. Figure 2 (b) shows another amplitude coding technique that is based on the different level of muscle contraction. A fixed threshold value is assigned to different level and each level is assigned to different function. The drawback of this method is the function per muscle is limited to two. In proportional control method, the strength of the muscle contraction controls the speed of the performed function. Carrozza et.al have used Finite State Machine (FSM) to control the opening and closing of the hand prosthesis (Carozza *et al.*, 2005). The grasping force during the closure is also controlled using FSM.

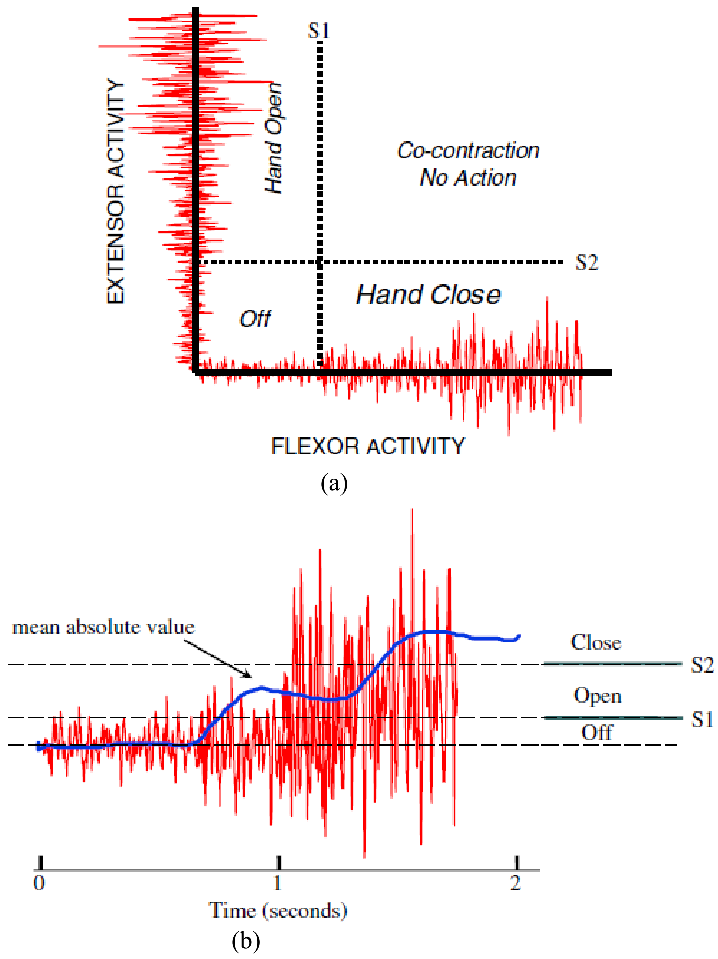

Fig. 2: (a) Two channels amplitude coded; (b) One channel amplitude coded myoelectric control (Parker *et al.*, 2006)

2. Pattern-Recgonition Based Electromyographic Control:

Even though the SEMG signals are stochastic, repeatable EMG patterns can be observed from different muscle contractions and this also can be seen in amputees. They may not have fully functioning muscles but SEMG also has been proven as an effective input for powered upper limb prostheses (Hargrove *et al.*, 2007; Ajiboye and Weir, 2005)

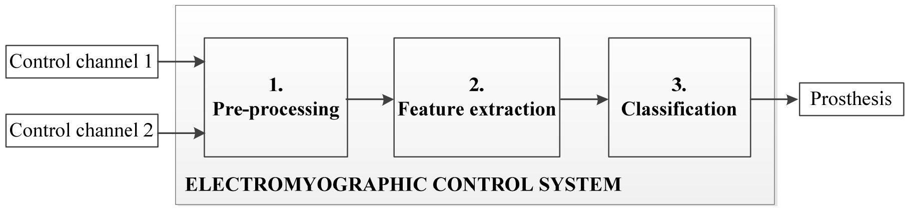

Fig. 3: The block diagram of an electromyographic control system (ECS) based on pattern recognition

Pattern recognition aims to classify data based on statistical information extracted from the patterns and determines the control signal that will select the final output of the device operation. Figure 3 shows the basic components in an ECS based on pattern recognition. Three main modules of ECS are: pre-processing, feature, extraction and classification.

Control channels 1 and 2 labeled in Figure 3, are the SEMG signals. The SEMG data are acquired from the surface of the skin by placing electrodes over the person's muscle. Different muscles responsible on different movement. Therefore, the electrode must be placed on the muscles that are to be investigated. For example, the extensor and flexor muscles are responsible for wrist flexion/extension movement. It is important to place the electrode on the accurate location as correct placement of the electrodes will give strong SEMG signals and gives a good distinction between movements. Inaccurate placement of the electrodes will affect the performance of the classifier (Hargrove *et al.,* 2007; Ajiboye and Weir, 2005). Normally, the electrodes are accompanied by miniature pre-amplifiers. In common practices, the EMG signal will be amplified, usually using an instrumentation amplifier with a gain of 1000 - 5000 (Ajiboye and Weir, 2005; Karlik *et al.,* 2003; Chu *et al.,* 2006; Hudgins *et al.,* 1993; Al-Assaf, 2005). The SEMG signals are then being filtered using band pass filter (low cut-off frequencies, f_{cl} = 450 - 500Hz and high cut-off frequencies, f_{ch} = 10 - 20Hz) to eliminate noise before transferred to the ECS (Ajiboye and Weir, 2005; Karlik *et al.,* 2003; Chu *et al.,* 2006; Hudgins *et al.,* 1993; Al-Assaf, 2005; Chen *et al.,* 2006). The SEMG signal is then sampled digitally, where in common practice the sampling frequency is above 1000Hz

The ECS block diagram shown in Figure 3 is the basic implementation of the control system. Each module plays important role for the success of the system but they can be adjusted (merge or omit) depend on the implementation of the system. Another important factor to consider is the computation time for this control system. Scott *et al.,* (1984) Farina and Merletti, (2000) has reported that 200 to 300 ms is a clinically recognized maximum delay for the response of the prosthesis.

A. Pre-processing:

There have been various techniques in handling the EMG data before feature extraction. Usually, data segmentation will be used and could improve the accuracy and response time of the controller. For each divided segment, a feature set will be computed which will be then fed to the classifier and these processes are continuous. The data length and the windowing technique are two main points that need to be considered. Farina & Merletti [14] showed a segment length that is less than 128ms will leads to high bias and variance of features that will degrade the classifier's performance.

There are two main methods used for the data windowing; adjacent and overlapping. The adjacent windowing technique (Figure 4) is where adjacent disjoint segments with predefined length are used feature extraction and classification after a certain processing delay, τ. The τ depicted in Figure 4 is the time required to calculate the feature and classify the data. The drawback of this technique is that the τ is just a small portion of the segment that will cause the processor to stay at idle condition during the remaining time of the segment length. This matter is overcome with overlapped windowing technique. With this technique, the new segment slides over the current segment and the increment time is less than the segment length. For example, Hudgins *et al.* (2005) processed the signal in every 40 ms in a 240ms adjacent window. Englehart & Hudgins (2003) had reported that shorter segment increment produces a more dense but semi-redundant stream of class decision that could improve response time and accuracy. The overlapping windowing technique is the most common method due to the ability to preserve the important information in the EMG signals where there is limited time for signal processing then the non-overlapping technique is used.

B. Feature extraction:

The feature extraction process is where the raw SEMG signal is represented into a feature vector which is then used to separate the desired output, e.g. different hand grip postures. The success of the ECS based on pattern recognition depends on the selection and extraction of features (Chan *et al.,* 2000). The feature extraction techniques can be grouped into two main categories:

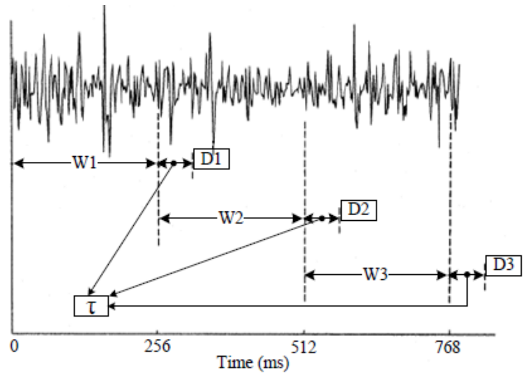

Fig. 4: Adjacent windowing technique. W: Window, D: Delay, τ: time delay [Englehart & Hudgins, 2003]

i. Time Domain Feature:

The time domain (TD) feature is based on the signal amplitude and is the most common method used in ECS for upper limb prosthesis application as the computational complexity is low. The features can be obtained in a short time using a simple algorithm executed in a microprocessor. The amplitude gives an indication of activation level, duration or force of the SEMG signal which is influenced by the following factors: the location of the electrodes, the tissues' thickness, and the system used to acquire the signal and the distribution of motor units in muscle fiber Asghari Oskoei, M., & Hu, H. (2007).

Various methods have been reported for feature extraction of the SEMG. Hudgins *et al.* (1993) used mean absolute value (MAV), mean absolute value slope, slope sign changes (SSC), waveform lengths and zero crossings (ZC). Chan *et al.,* (2000) also used the same features as them except SSC. Other reported features are variance, root mean square (RMS), mean and standard deviation (SD) (Ajiboye and Weir, 2005; Yonghong *et al.,* 2005) Autoregressive (AR) models also have been used for the EMG classification (Karlik, 2003; Zardoshti-Kermani *et al.,* 1995). With AR, the value at the current point of a time series of an EMG signal can be predicted by several previous points. This method can produce high separability between different limb functions; however it requires a more complicated computation process.

ii. Time-Frequency Domain Feature:

The time-frequency domain (TFD) method is to overcome the limitation of the TD method, which is acceptable for a stationary signal. However, the EMG signal is a non-stationary signal which shows high frequency characteristics and with TFD, the performance of the control system could be increased.

Some of the methods used in TFD are short time Fourier transform (STFT), wavelet transform (WT) and wavelet packet transform (WPT). In general, the difference between these methods is the partitioning of the time-scale axis. In short-time Fourier transform (STFT), the EMG signal is mapped into frequency components that present within an interval of time (window). A suitable window size must be determined prior to this as small window will give good time resolution but poor frequency resolution and vice versa. The partitioning ratio of the STFT is fixed: once specified, each cell has an identical aspect ratio. To overcome the resolution problem in STFT, WT was developed.

The WT has a variable partitioning ratio where the aspect ratio of the cells varies such that frequency resolution is proportional to centre frequency. WPT is the generalization of the WT method allows the best adapted analysis of the signal. WPT provides as adaptive partitioning - complete set of partitions are provided as alternatives, and the best for a given application is selected Englehart *et al.* (2001)

Englehart *et al.* (2001) has conducted a comparison between TD features used by Hudgins (1993) and TFD methods. Based on the results of the classification error, WPT was the most effective method. However, he also suggested that there is no clearly superior method between them. Chai *et al.* (1999) had used WT to discriminate between four motions: hand grasp, hand extension, forearm supination and forearm pronation. Their system has an average accuracy 90% by extracting twelve parameters from two channels EMG signals and with the nature of the WT method, the system might have a high computational time.

TFD method may cause high resolution representations and AR model yields high dimensional feature vectors. However, these factors cause long processing time and delays. To avoid these problems, dimensionality reduction was introduced which reduce the dimensionality of the data while maintaining its discrimination capability. This technique also helps to reduce memory requirement, as well as the classifiers' speed (Chu *et al.,* 2006). In general, there are two methods of dimensionality reduction; feature selection and feature projection. There are many strategies for feature selection, such as sequential forward selection, sequential backward selection, simulated annealing and genetic algorithm (Asghari Oskoei and Hu, 2007). Feature projection is mostly used when using the TFD method. WT produces many coefficients to represent time scale features and they need to be mapped into a lower dimension. Principal component analysis (PCA) and linear discriminant analysis (LDA) are the most commonly used method for feature projection (Chu *et al.,* 2006; Englehart *et al.,* 2001).

C. Classifier:

The information obtained during feature extraction will be then fed into a classifier. A classifier should be able to map different patterns and match them appropriately. An efficient classifier should be able to classify patterns in a short duration to meet the real-time constraint of prosthetics device. However, due to the nature of EMG signal it is possible to see a large variation in the value of the feature used. This variation may be due to the electrode placement or sweat. In early EMG control systems, statistical classifiers had been used widely until about the mid-1980s Roberto Merletti, (2004). A statistical classifier also known as linear discriminant analysis (LDA) searches for feature vectors which best discriminate amongst motion classes as opposed to those which best describe the data. The LDA classifier is simpler to implement and has shown high classification accuracies Asghari Oskoei, M., & Hu, (2007). Then, the application of artificial neural network (ANN) began to appear. ANN has been used in most of the EMG classification systems reported in the literature (Englehart and Hudgins, 2003; Al-Assaf 2005). An ANN consists of many simple processing units (neurons) that can be globally programmed for computation. They are trainable and the main advantage of the ANN is its ability to represent both linear and nonlinear relationships. Figure 5 shows one example of ECS that using ANN. A variety of ANN architecture and learning algorithm have been conducted; such as simple feed forward multilayer perceptrons (Hudgins *et al.,* 1993)

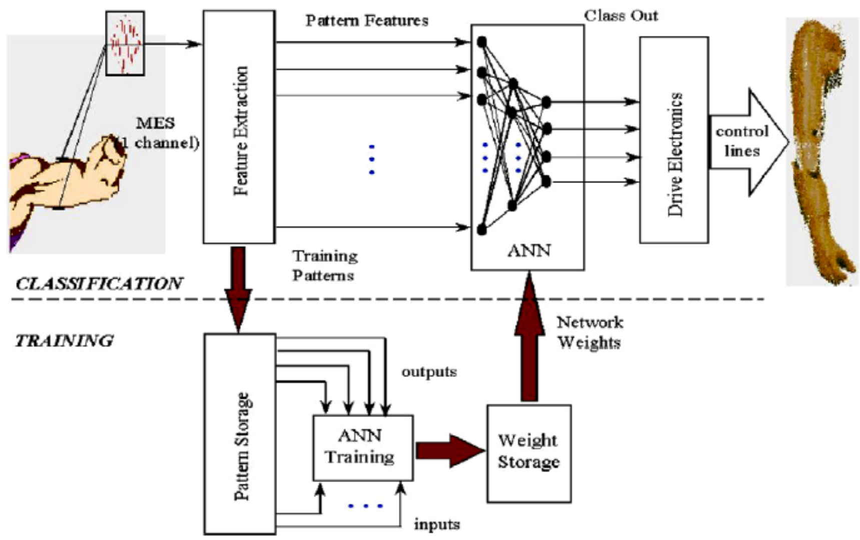

Fig. 5: Electromyographic control system using ANN as the classifier (Parker *et al.,* 2006)

Another technique that has been used for the classification of the SEMG data is fuzzy logic (FL) system. The most useful property of fuzzy logic is that it provides a simple way to arrive at a definite conclusion just based upon imprecise input information which mimics how a person would make a decision. Due to the biomedical signal characteristic, which is not always repeatable, FL is an advantageous control technique in biomedical signal processing and classification.

Basically, FL system consists of three stages: fuzzification, processing and de-fuzzification stages. Weir & Ajiboye (2005). used a heuristic fuzzy logic approach to multiple EMG pattern recognition for multiple prosthesis control. Chan *et al.* (2000) also used FL to classify single channel EMG signal for multifunctional prosthesis control. Some FL systems used in conjunction with a neural network to classify the EMG data. Karlik *et al.* (2003) have reported the used of this method, where the EMG features are clustered using fuzzy c-means algorithm which is then presented to ANN system. All the FL systems reported high classification accuracies which is about 95%.

Conclusions:

Table 1 summarizes some of the methods used for feature extraction and classification processes for the ECS based on pattern recognition for upper-limb prosthesis control. It can be seen that the methods used for the feature extraction are varies between TD and TFD method, and it has been reported that there is no superior method between these two processing techniques. As for the classifier, ANN is the most used method to discriminate the final output of the system.

Table 1: Summary of pattern-recognition based ECS for prosthesis control application

Reference	Feature	Classifier	Accuracy
[8]	Mean. SD	FL	94%
[9]	AR	FC-ANN	96.1%
[10]	WPT	SOFM/ PCA	97%
[11]	MAV, ZC, SSC, waveform length	ANN	90%
[12]	MAV, WT, PCA	ANN	94.9%
[17]	MAV, ZC, waveform length	FL	95%
[18]	AR, RMS	GMM	95%
[20]	STFT, WPT, WT	PCA/ LDA	98%

The most right column of the table shows the accuracy of the electromyographic control systems and the success of the system is depends upon the classification accuracy. It measures the number of correct classification achieved for a number of trials. From the table, it shows that all accuracies are from 90% to 98%.

Continuous research in this field is still needed in order to provide a control system with a high classification rate. From the summary in Table 1, it can be concluded that there are various factor that affect the performance of the electromyogaphic control system. This includes the number of control channel used and also methods used in the feature extraction process. A reasonable number of control channels with good feature extraction method will give a high

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