SURFACE EMG CLASSIFICATION FOR PROSTHESIS CONTROL
Fuzzy Logic vs. Artificial Neural Network

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Abstract: Electromyography control system (ECS) is a well-known technique for prosthesis control application. It consists of two main modules namely feature extraction and classification. This paper presents the investigation of the classification module in the ECS. The surface electromyographic (EMG) signals were recorded from flexor and extensor muscles of the forearm during wrist flexion and extension. Standard deviation and mean absolute value were used to extract information from the raw EMG signals. Two different classifiers, fuzzy logic and artificial neural network were used in investigating the surface EMG signals. The classifier is responsible to determine the movement of the subject's limb during specific moment. The two classifiers were compared in terms of their performance.

1 INTRODUCTION

Prosthetic hand has been designed to provide replacement to people with hand or complete arm amputation. In the USA, there are approximately 40,000 people registered with hand amputation and this number is increasing every year. In the last 30 years, the amputees had been provided with either passive or active prosthetic hands to help them in their daily lives. However, a survey shows that there are 30% to 50% of the handicapped did not use the prosthetic hands regularly (Hardeep and Arora 2010). Among the reasons for the rejection are heavy weight, limited functionality and stiff/robot like movement.

Continuous studies and researches have been carried out in improving the prosthetic hand design with the main aim to have a hand that can best mimic a normal human hand. To improve the functionality of the hand, two main factors have to be considered in the development process. These two factors are the structural design and the control mechanism of the hand. Rapid growth in the structural design of the prosthetic hand can be seen and there is renewed interest in the development of hands with multiple degrees of freedom that lead to multiple grip hand postures (Mitchell, 2008). The control mechanism has become the main concern in the prosthetic hand development process. Various methods have been proposed in controlling the operation of a prosthetic hand and surface electromyography has become the preferred technique for the control mechanism of the prosthesis control application (Hudgins, 1999; Ajiboye, 2005) The concept of using surface electromyography signal for prosthesis control started in the 1940s (Plettenburg, 2006). By using the residual muscles on the amputee's arm, they can be used as the control channel to determine the final movement of the hand. The simplest application is to either open or close hand.

Electromyography (EMG) signal is a technique that is used to describe electrical current produced by skeletal muscles during contractions. In general, EMG can be categorized into two: needle and surface EMG. The later type is the most commonly used in many applications as it is totally non-invasive and low cost. Surface EMG (SEMG) finds application in many areas that include rehabilitation of disabled (Huang, 1999), prosthetics (Nagata, 2004); (Chappell, 2009) and human computer

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interface (Fukuda, 2004). The commonality in these systems is the need to classify SEMG to identify the control commands. These examples and many others (Huang, 1999); (Tsuji, 2000) used multichannel EMG for the purpose of discrimination between classes (Kumar, 2008).

EMG has been used to control the movement of a prosthetic hand and known as EMG control system (ECS). Two main processes involve in the prosthesis control system are feature extraction and classification. 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. Various feature extraction techniques have been reported in this prosthesis control field. Mean absolute value (MAV) has been the most widely used method to extract information from a SEMG signal (Hudgins, 1999); (Chan, 2000). The information obtained in the feature extraction will then be fed to a classifier. A classifier is responsible in mapping different pattern and matches them appropriately to determine the final output. Artificial neural network (ANN) is one of the classification methods and has been used in most of the EMG classification systems reported in the literature (Hudgins, 1999); (Ajiboye, 2005). Another method that has been used for classification is fuzzy logic (FL) (Chan, 2000); (Weir, 2003).

The objective of this work is to compare two classification techniques; ANN and FL in finding the final grip posture of a prosthetic hand. The research will focus on evaluating the performance between these two classifiers in terms of accuracy in classifying the SEMG data. Other aspects of performance are also discussed.

2 METHODOLOGY

The EMG dataset used to test the methods was obtained from the University of Southampton, in UK (Chappell, 2009). The EMG signals were recorded from five participants' forearm muscles, namely flexor carpi ulnaris (FCU) and extensor carpi radialis (ECR) with a reference electrode at the elbow. The participants were asked to do wrist flexion and extension. The signals were recorded using Noraxon Ag/AgCl dual electrodes (diameter 15 mm, centre spacing 20mm). The procedures for surface electrodes placement were referred from SENIAM (Hermans, 1999). Prior to the electrode placement, the electrodes sites were prepared by cleansing the skin surface with rubbing alcohol to reduce the impedance at the surface.

The recorded EMG signals were post-processed for further analysis. Two methods were used in the feature extraction stage are standard deviation (SD) and mean absolute value (MAV).

To preserve the information in the EMG signals, the whole data was divided into overlapping segments. Each segment consists of 200 data points and the current segment overlaps with the previous segment by 50 points. A moving data window was applied to the data sequence and the SD and MAV within the data were calculated repeatedly.

The extracted features were then fed into two types of classifier: ANN and FL. The output from the classifiers will be different postures of hand grips. However, in this work the grip postures are represented in the 'STATE' form. Based on two inputs, SD and MAV, both classifiers will give one final output which is STATE1, STATE2 or STATE3.

For the FL classifier design, a Mamdani type fuzzy logic was used in. The rules were created based on states of contraction and the design process ran over a few cycles of analysis until the most optimum classification system is achieved and it was done manually. The shapes for the inputs in the membership function were the S-type and the output was in triangular shape only. The defuzzification will be set to centroid. Two FL classification systems have been developed, which are with and without solver. Solver is an additional tool in Simulink to smooth the graph by building a time of the next simulation step and applies a numerical method to solve the set of ordinary differential equations that represent the model. Figure 1 shows the Simulink model for the FL classification system without solver.

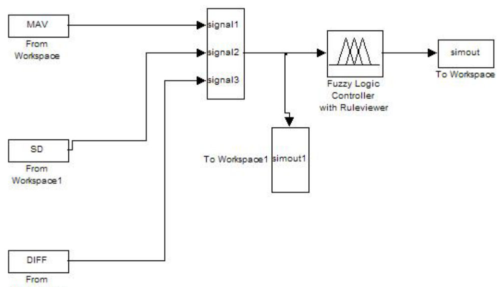

Figure 1: Simulink model for the FL classification system.

Initially, the project was to use only two inputs from SD and MAV. But during the rule building, it is found out that it is difficult to differentiate between State 1 and State 3 for the same amplitude. Thus to solve the problem, another set of input was added. The new input is the difference of current value of SD with the previous value of SD. To simplify the calculation, the sign (positive or negative) was omitted because it also exhibits same results.

For the ANN classifier design shown in Figure 2, two layers feed forward ANN with two hidden layers were used. Feed forward method was chosen instead of feedback due to its simplicity and easily understood algorithm. The number of neurons used was 20 in order to make sure that ANN does not consume too much computational resources. For the validation of the network, two datasets have been created; training and test datasets.

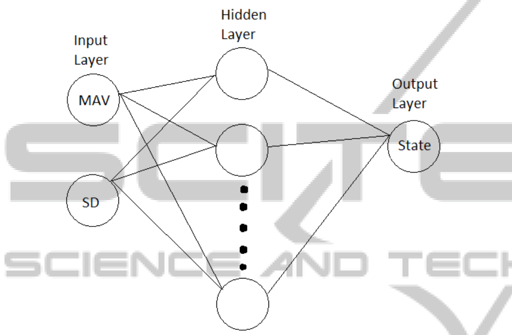

Figure 2: ANN classification system block diagram.

3 RESULTS AND DISCUSSION

Figure 3 show the EMG signals during wrist extension recorded from ECR respectively. The muscles contractions can be seen clearly as there are distinguishable low voltage period between them.

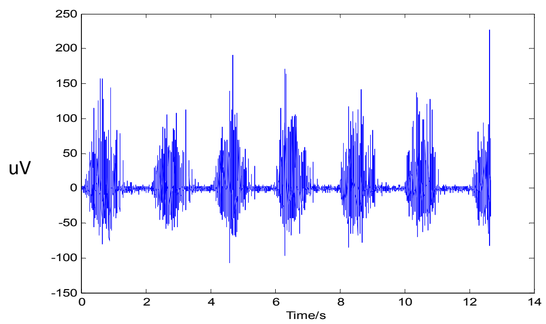

Figure 3: EMG signals during wrist extension from ECR.

The results (SD and MAV) obtained in the feature extraction stage were then used in the rules and membership functions development in fuzzy classifier and algorithm development in ANN.

The classification result for FL and ANN are shown in Figure 4 and Figure 5 respectively. For ANN classifier, the classification results were presented using confusion matrix diagram and one of the results is shown in Figure 5. For the FL classification, the results are based on with and without solver.

The performance of the classifiers was determined by calculating the percentage of accuracy. The accuracy was obtained by calculating the length of the points that not in its desired position. The total misaligned are divided by the total of time are and multiplied with 100%. The ideal graph for each segment is assumed to be linear thus the points that fall off of its threshold are considered misclassified (inaccurate).

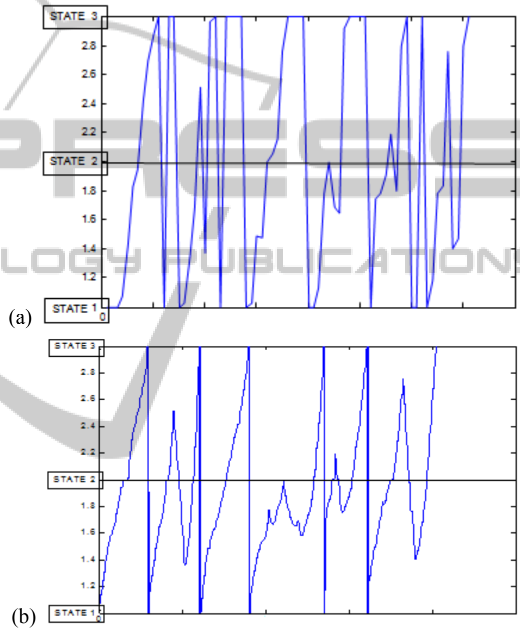

Figure 4: FL classification results (a) without solver and (b) with solver.

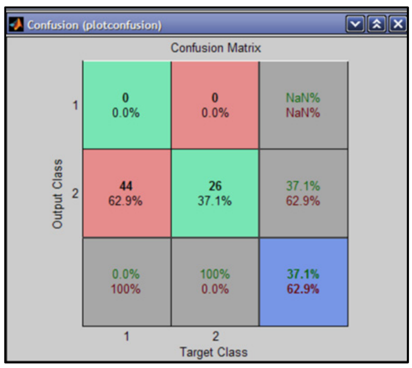

Figure 5: ANN classification result from FCU.

Table I shows the accuracy for both classifiers. In term of accuracy, the fuzzy classifier obviously is the best choice by exhibiting more than 90%

accuracy while the ANN classifier only exhibit around 30% to 60% accuracy. This is due to the fact that the fuzzy classifier has rules that can easily distinguish between states. As for ANN classifier, it needs to build the algorithm based on the training data. This means that if the training data is lacking in some aspects, then the accuracy of study data will also be affected. In this project, the study data size is small thus producing vulgar and incomplete patterns. This affects the accuracy of the result due to the difficulty of the algorithm to recognize the pattern from the data. This can be solved by introducing larger training data set.

Table 1: Classification accuracy.

	FL		ANN
	without Solver	with solver	
FCU	83.0%	97.8%	62.0%
ECR	82.9%	97.1%	37.1%

In term of automation, ease of use and capability to adapt to various samples, the ANN classifier is a better choice than fuzzy classifier. This is due to the fact that the user only needs to introduce the input and the target and the ANN will automatically create an algorithm and network to recognize the study data. On top of that, an accurate network that was produce by ANN can be used on various samples due to its learning capability. As for fuzzy classifier, the user need to determine by them the membership function, rules and need to calculate the accuracy manually thus consuming a lot of time. However, it is not a drawback to FL as automatic tuning is possible (G. Panoutsos, 2010). The main advantage of FL is the data doesn't need to be trained like ANN.

4 CONCLUSIONS

The study is to compare two classification methods namely FL and ANN to determine the final output from the extracted SEMG signals of the forearm. The signals were recorded from FCU and ECR during wrist flexion and extension respectively.

From the classification accuracy, it shows that FL gave higher accuracy (>80%) compared to ANN classifier (60%). This is due to small data size that leads to the difficulty of the ANN model development to recognize the pattern. The performance can be improved by introducing larger training data set.

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