Simple and Computationally Efficient Movement Classification Approach for EMG-controlled Prosthetic Hand: ANFIS vs. Artificial Neural Network

Hessam Jahani Fariman*, Siti A. Ahmad, M. Hamiruce Marhaban, M. Ali Jan Ghasab, Paul H. Chappell,

Department of Electrical & Electronic Engineering, Faculty of Engineering, University Putra Malaysia, 43400 Serdang, Selangor, Malaysia.

* Corresponding author email: ee.hessam.jahani@gmail.com , h.jahanifariman.1988@ieee.org

Institutional mailing address: H. Jahani Fariman is with the Control System and Signal Processing Research Group, Department of Electrical & Electronic Engineering, Faculty of Engineering, University Putra Malaysia 43400 UPM Serdang, Selangor, Malaysia.

Simple and Computationally Efficient Movement Classification Approach for EMG-controlled Prosthetic Hand: ANFIS vs. Artificial Neural Network

Abstract— The aim of this paper is to propose an exploratory study on simple, accurate and computationally efficient movement classification technique for prosthetic hand application. The surface myoelectric signals were acquired from 2 muscles – Flexor Carpi Ulnaris and Extensor Carpi Radialis of 4 normal-limb subjects. These signals were segmented and the features extracted using a new combined time-domain method of feature extraction. The fuzzy C-mean clustering method and scatter plots were used to evaluate the performance of the proposed multi-feature versus other accurate multi-features. Finally, the movements were classified using the adaptive neuro-fuzzy inference system (ANFIS) and the artificial neural network. Comparison results indicate that ANFIS not only displays higher classification accuracy (88.90%) than the artificial neural network, but it also improves computation time significantly.

Keywords: Pattern Recognition; EMG; ANFIS; Neural Network; prosthetic hand

1. INTRODUCTION

Despite the significant development of the prosthetic hand industry over the past decade, high-accuracy commercial prosthetic hands are still quite expensive (Ottobock, 2013). In fact, the complicated control algorithm and exclusive hardware that are incorporated into hand prostheses render them unaffordable for amputees, most of whom are from the working class of society or from below middle-class. Moreover, available cheap prostheses are either not accurate enough or are slow to perform control actions. Thus, an affordable prosthetic hand should be developed in consideration of the tradeoff between accuracy and price.

The first step is designing an effective yet simple control system for prosthetic devices. The desired system should be capable of performing the essential movements efficiently in terms of both movement classification accuracy and computational time. It should also be simple enough for non-exclusive and cheap real-time implementation. Over the past decade, the concept of integrating human body signals into designed prosthetic control system devices as a control mechanism has attracted much interest (Ajiboye & Weir, 2005; Clement, Bugler, & Oliver, 2011; Favieiro & Balbinot, 2011; Guangying, 2007; Losier, Englehart, & Hudgins, 2007), especially the brain waves detected in electroencephalograms and the muscle activity detected in electromyograms (EMGs).

In myoelectric control systems (MCSs), myoelectric signals (from EMGs) are acquired to operate external devices, such as prosthetic or orthotic devices for people who have been subject to some level of limb amputation (Castellini & van der Smagt, 2009). Myoelectric control typically uses a pattern recognition scheme (Liu & Yu, 2005). This approach recognizes one of several predetermined classes, which represent certain motions including elbow flexion and extension. The pattern recognition approach either defines a specific motion that is relative to the current position or an entire range of motion to be performed. Once it is activated, it cannot be altered. Figure 1 depicts the different steps in pattern recognition-based MCS.

To improve the functionality of the prosthesis control system, two important factors should be considered in development: feature extraction accuracy and classification performance. Several feature extraction approaches are specifically relevant to EMG data [16]. In line with the main objective of the current research, which is to develop a simple and accurate MCS for affordable prosthetic hands, time-domain (TD) features are applied.

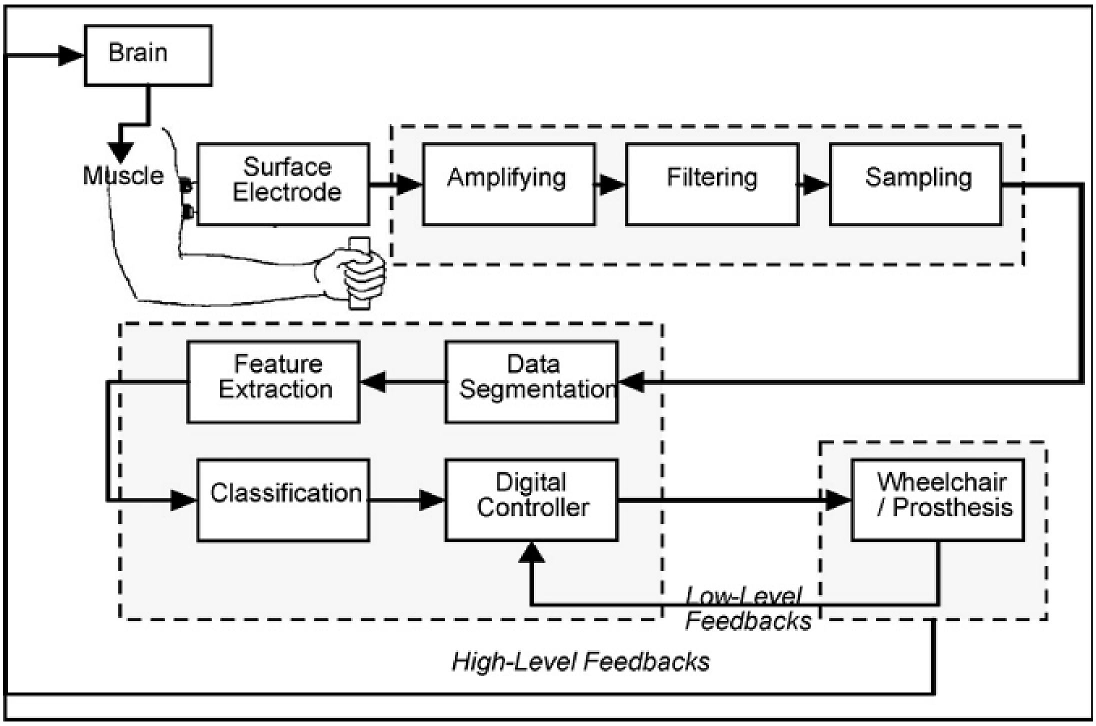

Figure 1. A pattern-recognition based myoelectric control system for prosthesis from (Asghari Oskoei & Hu, 2007) .

The time-domain methods to extract features have mainly simple implementation and efficient calculation because in these features, despite the frequency-domain, no transformation is needed, and are analyzed based on raw EMG time series. This makes them to have good potential for real-time feature extraction (Hudgins, Parker, & Scott, 1993; A Rezaee Jordehi, 2014; Oskoei & Hu, 2008; Tkach, Huang, & Kuiken, 2010).

A considerable amount of literature has been published on soft computing techniques especially fuzzy logic systems and neural networks for bio-signal classification in many biomedical applications (Ajiboye & Weir, 2005; Khushaba, Al-Ani, & Al-Jumaily, 2010; Khushaba, Al-Jumaily, & Al-Ani, 2007). The Artificial Neural Network (ANN) was presented as the signal classifier in numerous works (Y.-C. Du, Lin, Shyu, & Chen, 2010; Jordehi; Ahmad Rezaee Jordehi, 2014; Wojtczak, Amaral, Dias, Wolczowski, & Kurzynski, 2009). Their main advantage is the ability to learn linear and nonlinear relationships directly from the data and to adapt to real-time implementations. One of the pioneers of the development of real-time multifunction myoelectric control, Hudgins' group implemented an ANN to classify four different limb motions with an average accuracy of around 90% (Englehart & Hudgins, 2003; Hudgins et al., 1993) .On their way to develop a new generation of prosthetic arm/hand, a group of researchers from John Hopkins University employed feed-forward ANN to decode movements of the hand (Soares, Andrade, Lamounier, & Carrijo, 2003). Other works utilized ANN of classifiers to identify limb movements produced by the subjects (Al-Assaf & Al-Nashash, 2005; Au & Kirsch, 2000; Luo, Wang, & Ma, 2006; Rezaee Jordehi & Jasni, 2013).

Fuzzy logic can also be applied to improve the MCS system classification algorithm given the contradictory nature of bio-signals, the linguistic characteristics of fuzzy systems, and their reasoning style. In other words, adding fuzzy logic to ANN can cause classification approaches to be capable of tolerating imprecision, partial truth, and uncertainty, as well as of obtaining robust, low-cost, and precise solutions for problem classification (Asghari Oskoei & Hu, 2007).

With regard to the combination of fuzzy logic and ANN in EMG systems, a neuro-fuzzy modifier was proposed by Khushaba et al. (Khushaba et al., 2010) to realize proper elbow motion. In addition to the high classification accuracy, this neuro-fuzzy approach also significantly improved the robustness and stability of the algorithm. Moreover, Khezri and Jahed (Khezri & Jahed, 2007, 2009) developed an exploratory robust MCS that uses an adaptive neuro-fuzzy inference system (ANFIS) as a classifier and compounds FD features to improve feature extraction. (Favieiro & Balbinot, 2011) contributed a MCS for a multifunctional prosthesis. This system employs the ANFIS Sugeno-type inference system as a classification technique.

As for other soft computing methods for MCS, Rasheed et al. (Rasheed, Stashuk, & Kamel, 2006) also introduced an adaptive fuzzy k-nearest neighbor (k-NN) classifier for EMG decomposition. This classifier significantly outperformed adaptive certainty classifiers. The same researchers also presented another approach that uses fuzzy logic and k-NN in (Rasheed, Stashuk, & Kamel, 2008) and developed a MATLAB-based software program that can be applied as a potential motor unit classifier. Kim et al. (Kim, Choi, Moon, & Mun, 2011) compared k-NN with linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). They concluded that classification improved significantly with k-NN; however, the classification performance of the neuro-fuzzy approach was superior to other soft computing methods, such as k-NN (Rasheed et al., 2006), LDA, and QDA (Khushaba et al., 2010; Kiguchi & Hayashi, 2011; Phinyomark et al., 2013).

Nonetheless, fuzzy logic does not always improve ANN classification performance, according to the comparative studies conducted by (Karlik, Osman Tokhi, & Alci, 2003) and (Ren, Huang, & Deng, 2009). As per the research presented by (Ren et al., 2009) on MCS classification accuracy with ANN, conic section function NN, and new fuzzy clustering NNs (FCNNs), the fuzzy clustering approach improved EMG decomposition accuracy and processing time but did not affect the classification performance of NNs. Thus, ANN outperforms FCNN in terms of classification accuracy. Based on previous literature and given the theoretical advantages of ANN and fuzzy logic over other recent approaches, neuro-fuzzy- and ANN-based classifiers are potential solutions for establishing simple and accurate MCS given their high accuracy and short processing times. Nonetheless, their application requires further investigation and analysis.

This study, intends to propose a comparative pattern-recognition approach for the classification of hand movements in a manner in which the functionality and accuracy of a myoelectric prosthetic hand control system can be improved. Investigation and evaluation are first conducted on the feature extraction methods for the proposed simple and accurate multi-feature(Hudgins et al., 1993). An optimal multi-feature method through doing a comparative study using scatter plots and Fuzzy C-mean clustering will be investigated. These features are then inputted into ANFIS and ANN classifiers. Furthermore, the classification outcome is evaluated based on classification accuracy, learning time, and classification time. The superior classifier is determined and confirmed by a statistical analysis using T-test. Finally, a simple, computationally efficient MCS for a multifunctional prosthetic hand is recommended. Figure 2 shows the methodology scheme of this research.

2. METHODS AND MATERIALS

2.1 Subjects and data acquisition

The EMG datasets applied in this work were obtained from the University of Southampton, UK (Ahmad, 2009). This investigation focused on wrist muscles, and participants were asked to perform movements related to these particular muscles. The surface EMG (SEMG) signals were obtained with Noraxon Ag/AgC1 dual electrodes (diameter 15 mm; center spacing 20 mm). These electrodes were placed on the forearm above the flexor carpi ulnaris (FCU) and the extensor carpi radialis (ECR). A reference electrode was positioned at the elbow. The SEMG data were recorded during the performance of four tasks, namely, wrist flexion, wrist extension, co-contraction, and isometric contraction. One trial was conducted for each movement at a speed of 60 bpm (beat per minute), as controlled by a metronome.

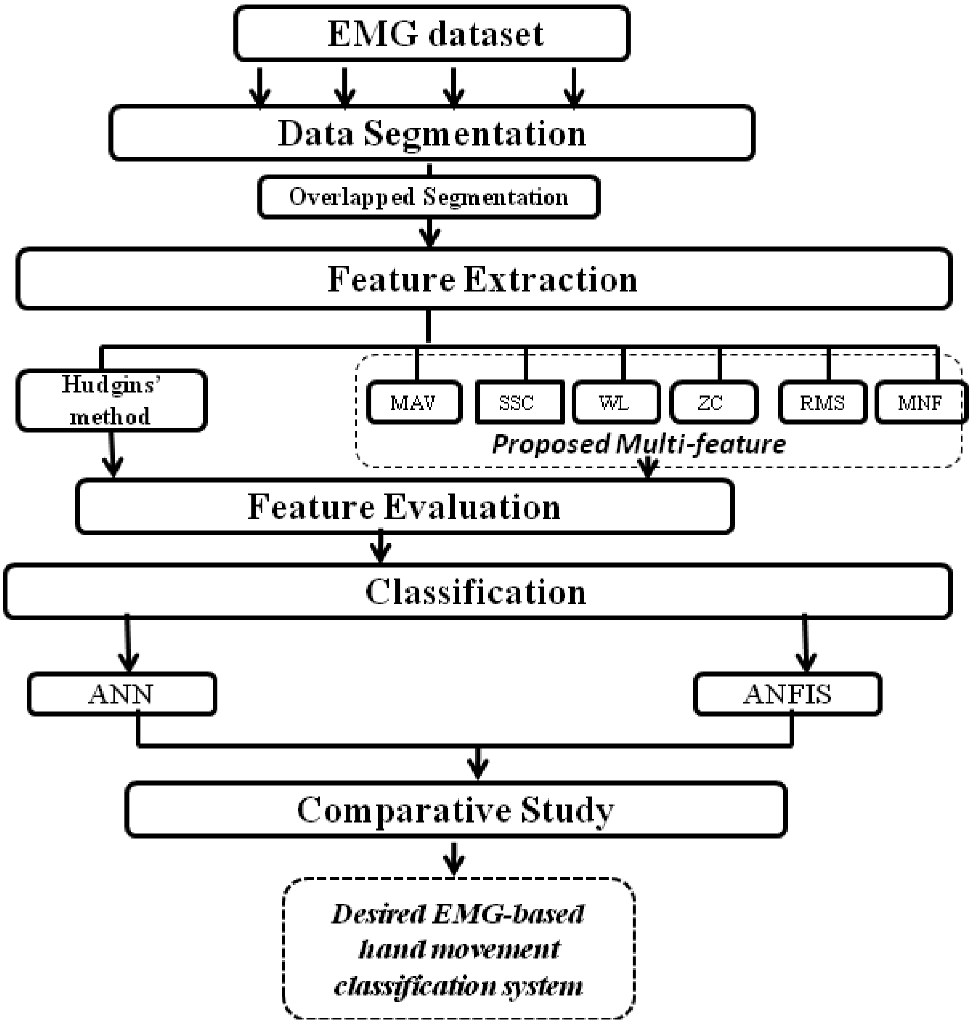

Figure 2. Pattern recognition methodology scheme applied in this study.

In this study, data were gathered from four normal-limb subjects. Two SEMG channels were used to discriminate four hand movements from each subject.

2.2 Data Segmentation

Prior to feature extraction, data should be handled such that accuracy and response time are improved because the use of data as feature extractor inputs is impractical. Therefore, these data are segmented. Two methods of segmentation have been established: Adjacent and overlapping (Figure 3). Given real-time constraints (Ren et al., 2009), the segment length is 200 points (140 ms) when overlapping segmentation is employed. Furthermore, the overlapping time should be less than the segment length and greater than the processing time because the processor must compute the feature set and generate a decision before the next segment arrives. The processing time for most microprocessors is less than 50 ms; thus, the increment time should be 70 ms to meet this requirement.

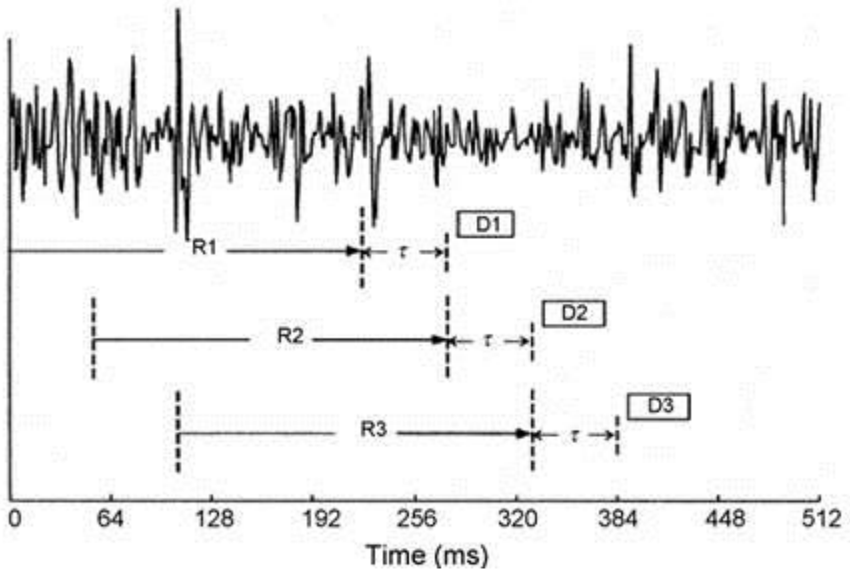

Figure 3. Overlapping segmentation of data (Asghari Oskoei & Hu, 2007).

2.3 Feature Extraction

For a classifier to be computationally efficient, it must employ a feature extraction method that quantifies large datasets into a small number of features that optimally distinguish a certain set of data from other sets. A classifier can then group that dataset with related ones. A wide spectrum of features has been introduced in literature for myoelectric classification. These features fall into one of three categories: TD, FD, and time-scale (time–frequency) domain (Zecca, Micera, Carrozza, & Dario, 2002). The TD feature extraction method was chosen as the main feature extraction method for this research, and the multi-feature was modified slightly by adding mean frequency (MNF). The objective of this study is to investigate a simple and accurate multi-feature using a TD-based feature extraction method and to evaluate the extraction performance in comparison with the Hudgins multi-feature, which is the best-known one (Hudgins et al., 1993). According to (Asghari Oskoei & Hu, 2007), the results for classification accuracy and computational simplicity obtained by combining TD features may compete with those derived from FD features. The proposed multi-feature consists of mean absolute value (MAV), zero crossing (ZC), slope sign change (SSC), waveform length (WL), root mean square (RMS), and MNF.

2.3.1 Mean Absolute Value (MAV)

MAV feature is an average of absolute value of the EMG signal amplitude in a segment, which can be defined as (Hudgins et al., 1993)

$$\mathrm{MAV} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{x_i}| \qquad (1)$$

2.3.2 Zero Crossing (ZC)

Zero crossing (ZC) is a measure of frequency information of the EMG signal that is defined in time domain (Hudgins et al., 1993); the calculation is defined as

$$\mathrm{ZC} = \sum_{\mathrm{i}=1}^{\mathrm{N}-1} \left[\mathrm{sgn}\,(\mathrm{x_i} \times \mathrm{x_{i+1}}) \cap \left|\mathrm{x_i} - \mathrm{x_{i+1}}\right| \right] \geq \mathrm{threshold} \quad (2)$$

$$\mathrm{sgn}\,(\mathrm{x}) = \begin{cases} 1\,, & \text{if x} \geq \text{threshold} \\ 0\,, & \text{otherwise} \end{cases} \qquad (3)$$

2.3.3 Slope Sign Change (SSC)

It is defined as the number of times slope of the EMG signal changes sign. There is a threshold for avoiding the background noise.

$$SSC = \sum_{i=2}^{N-1} f[(x_i - x_{i-1}) \times (x_i - x_{i+1})] \qquad (4)$$

$$f(x) = \begin{cases} 1\,, & if\ x \geq threshold \\ 0\,, & otherwise. \end{cases} \qquad (5)$$

2.3.4 Waveform Length (WL)

It is expressed as cumulative length of the EMG waveform over the time segment (Hudgins et al., 1993).

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \quad (6)$$

2.3.5 Root Mean Square (RMS)

Root mean square is again a well-known feature analysis regarding EMG signal (Boostani & Moradi, 2003; Kim et al., 2011). It is also alike to the standard deviation method. The mathematical definition of RMS feature can be expressed as:

$$\mathrm{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2} \quad (7)$$

2.3.6 Mean Frequency (MNF)

Mean Frequency (MNF) is an average frequency which is calculated as sum of the product of the EMG power spectrum and the frequency divided by the total sum of the spectrum intensity e.g. (Oskoei & Hu, 2008). Central frequency (fc) and spectral center of gravity are other calling names of the MNF feature (S. Du & Vuskovic, 2004). It can be calculated as

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j \quad (8)$$

2.4 Fuzzy C-mean Clustering Method

Fuzzy c-means (FCM) is an iterative data clustering technique in which a dataset is grouped into n clusters with every data point in the dataset belonging to every cluster to a certain degree. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster centre weighted by that data point's membership grade. It starts with an initial guess for the cluster centers, and then FCM iteratively moves the cluster centers to the right location within a data (Figure 4). Formally, clustering an unlabeled data $X = \{x1, x2, \ldots, xN\} \subset R^{h}$, where N represents the number of data vectors and h the dimension of each data vector, is the assignment c of partition labels to the vectors in X. c-Partition of X constitutes sets of (c . N) membership values that can be conveniently arranged as a (c . N) matrix $U = [u_{ik}]$.

The problem of fuzzy clustering is to find the optimum membership matrix U (Karlik et al., 2003).

2.5 Neural network clustering

The nctool in MATLAB© is employed to solve a clustering problem using a self-organizing map. The map generates a compressed representation of the input space, thus reflecting the relative density of the input vectors in that space. It also provides a two-dimensional compressed representation of the input-space topology.

2.6 Classification of Hand Movement

To recognize four hand movements, the output of FCM is inputted into the ANFIS. In parallel, NN clustering and ANN are employed as the second and comparative classifiers, respectively.

2.6.1 ANFIS

ANFIS was first introduced by (Jang, 1993). It is composed of three abstract components: a fuzzy rule base that includes a set of fuzzy if–then rules, a database that identifies the membership functions used in the fuzzy rules, and a reasoning mechanism that conducts an inference procedure on the rules to obtain a reasonable output or conclusion (Kandel, 1992). The ANFIS applies a Sugeno-type inference system. A typical rule in Sugeno is expressed in the form:

$$R^1\text{: IF } x1 \text{ is } MF1 \text{ AND } x2 \text{ is } MF2 \text{ AND } \ldots xj \text{ is } MFj$$

$$\text{THEN} \quad z^1 = s0^{\,1} + s1^{\,1}x1 + s2^{\,1}x2 + \ldots + sj^1xj\,. \qquad (9)$$

In this work, we chose the generalized bell function as the membership function. This function depends on three parameters, namely, a, b, and c, as given in:

$$\mathrm{MF}(x) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \quad . (10)$$

The basic problem of fuzzy system involves adjusting the membership function parameters, the output of each fuzzy rule, and estimating the minimum number of rules that should be adequately precise. Given a training fuzzy system, ANFIS employs the back propagation (BP) scheme and the least mean square (LMS) estimation (hybrid method) for the parameters associated with the output membership functions.

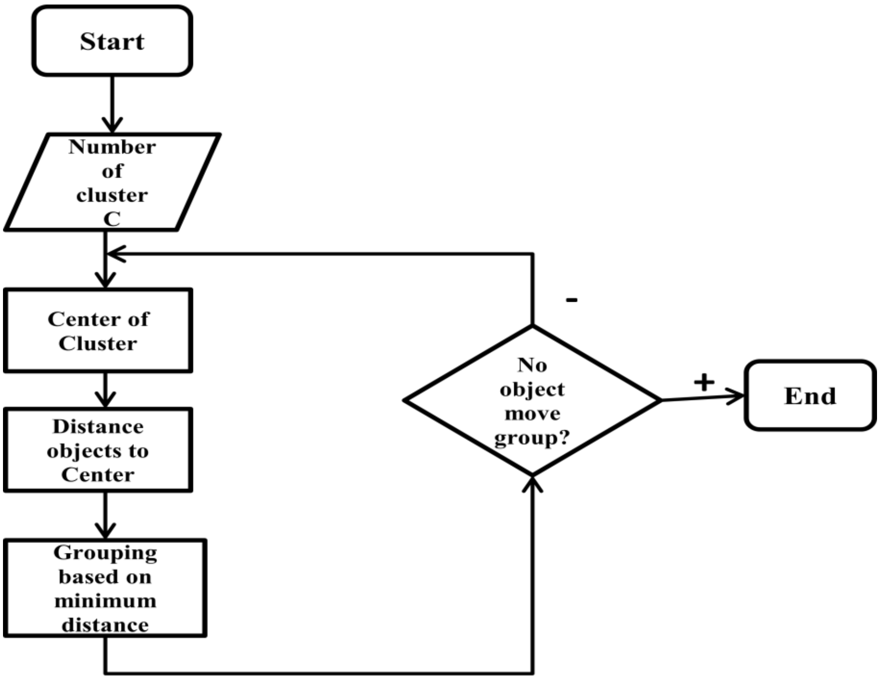

Figure 4. Flowchart of the fuzzy C-mean clustering process.

According to the cross-validation information presented in (Braga-Neto & Dougherty, 2004) for this research, threefold cross validation was applied to examine ARTMAP networks, LDA, and k-NN classifiers because the dataset is large enough. Moreover, the potential computational time is minimized. ANFIS is implemented with four subjects. Furthermore, a subtractive clustering method is employed to determine the number of fuzzy system rules. BP and LMS algorithms are also utilized for membership function parameters and rule outputs, respectively. Nine fuzzy rules are set for the recognition system that is designed with compound features. As shown in Equation (9), this system is an order 2 Sugeno-type system; that is, two SEMG channels are considered inputs for each subject. In addition, the output for each rule is determined using the LMS method.

2.6.2 Design of the ANN Classifier

ANNs were first studied by Rosenblatt, who applied single-layer perceptrons to pattern classification learning (Rosenblatt, 1962). A typical ANN is also known as a multi-layer perceptron neural network (MLPNN) and has been presented as a signal classifier in numerous works. Its main advantage lies in its capabilities to model (learn) linear and nonlinear relationships directly from the data and to adapt to real-time implementations. The use of a NN as a classifier aims to divide a feature space into different regions according to the various classes. Given a set of features from an unknown sample as an input, the output of the NN determines the class to which the sample belongs.

An ANN paradigm consists of a structure, a training algorithm, and an activation function. The structure describes the connectivity and functionality among neurons, and the training algorithm indicates the method used to determine the weights associated with each link. BP is one of the most commonly used algorithms to implement this training (Fielding, 2007). A BP MLPNN is an adaptive network whose nodes (neurons) perform the same function on incoming signals. The typical activation functions are nonlinear, and a hyperbolic tangent sigmoid transfer function was applied in this study.

The MLPNN was designed with a combination of features: the MAV, ZC, WL, SSC, RMS, and MNF of EMG signals were integrated into the input layer, and the output layer consisted of the outcome of NN clustering. The training procedure started with a hidden node in the hidden layer, followed by the training of the training data (600 distinct datasets), and then by the testing of the test data (600 distinct datasets) to determine the prediction performance of the network. The same procedure was repeated each time the network was expanded by adding another node to the hidden layer until the ideal architecture and set of connection weights were obtained. The optimal network was selected by monitoring the variation in the mean squared error of the network. This error represents the mean of the squared deviations of the MLPNN solution (output) from the true (target) values for both the training and test sets, and it is used to determine the optimal network.

3. RESULTS AND DISCUSSION

3.1 Evaluation of Feature Extraction Methods

The previous section describes the features employed in this research. As mentioned in the Introduction section, the purpose of this research is to investigate a necessary, efficient, and easily implemented feature extraction method for hand movement classification. Thus, an evaluation method should be developed to compare the proposed multi-feature against the Hudgins multi-feature. This study mainly discusses how separable and distinct the former can be from the latter considering the discrimination performance of multi-features and according to the scatter plot observations in Figures 5 and 6. The proposed multi-feature consists of MAV, ZC, WL, SSC, RMS, and MNF, whereas the Hudgins multi-feature includes MAV, ZC, WL, and SSC (Hudgins et al., 1993). The proposed multi-feature outperforms the Hudgins multi-feature in terms of discriminating patterns between class#1 and class#3; in the proposed multi-feature (Figure 5), these two classes are separate from each other whereas they overlap in the Hudgins multi-feature (Figure 6), based on a close examination of the borders of class#1, class#2, and class#3. In addition, the Hudgins multi-feature erroneously discriminates class#3 and clusters it near class#1, whereas the proposed multi-feature method discriminates class#3 in the vicinity of an almost similar neighborhood. In conclusion, clustering and scatter plots are both useful as visual techniques to evaluate feature performance. They also suggest the superiority of the proposed multi-feature over the Hudgins multi-feature.

3.2 Evaluation of Classification Performance

Signal processing was implemented in MATLAB, and the accuracy of the system was verified for four distinct movements, namely, wrist flexion, wrist extension, co-contraction and isometric contraction. All four subjects participated in the threefold cross-validation process. To validate the proposed ANFIS classification method, the same database was used to build a NN clustering classifier and then a MLPNN classifier in parallel for comparison with ANFIS.

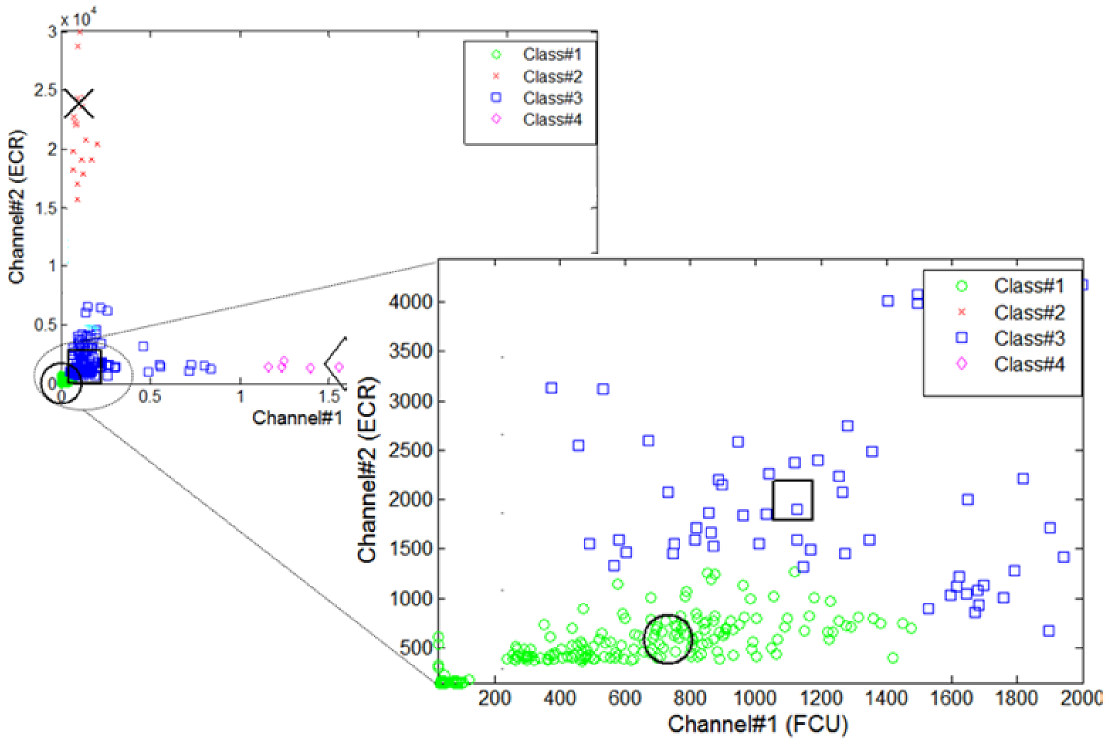

Figure 5. Scatter plots of the proposed multi-feature as a feature extractor for one subject and two channels in consideration of all four movements (classes).

Based on the results summarized in Tables 1 and 2, the average recognition rates for ANFIS and ANN are 88.90% (STD = 0.92) and 84.31% (STD = 2.21), respectively. Moreover, a time-measurement test was conducted on an unoptimized MATLAB prototyping code, which is executed on a Pentium 4 processor, to compare the speed of these two algorithms in both learning and classification. The time measurement results are depicted in Table 3. The ANFIS algorithm based on FCM clustering is more successful than the classical NN approach. In addition, the ANFIS algorithm is approximately five times faster than the NN approach in terms of learning and classification. Specifically, the classification and learning times for ANFIS are 121.5 and 82.2 ms, respectively, whereas those for ANN are 561.9 and 349.4 ms.

The results indicated above are clearly superior to ones achieved with similar classification algorithms under different control systems in (Ajiboye & Weir, 2005), (Khushaba et al., 2010), and (Khezri & Jahed, 2009) in terms of the simplicity of the pattern recognition system when only two EMG channels are applied. Other similar neuro-fuzzy approaches, such as those in (Khezri & Jahed, 2007) and (Favieiro & Balbinot, 2011), employ at least four channels.

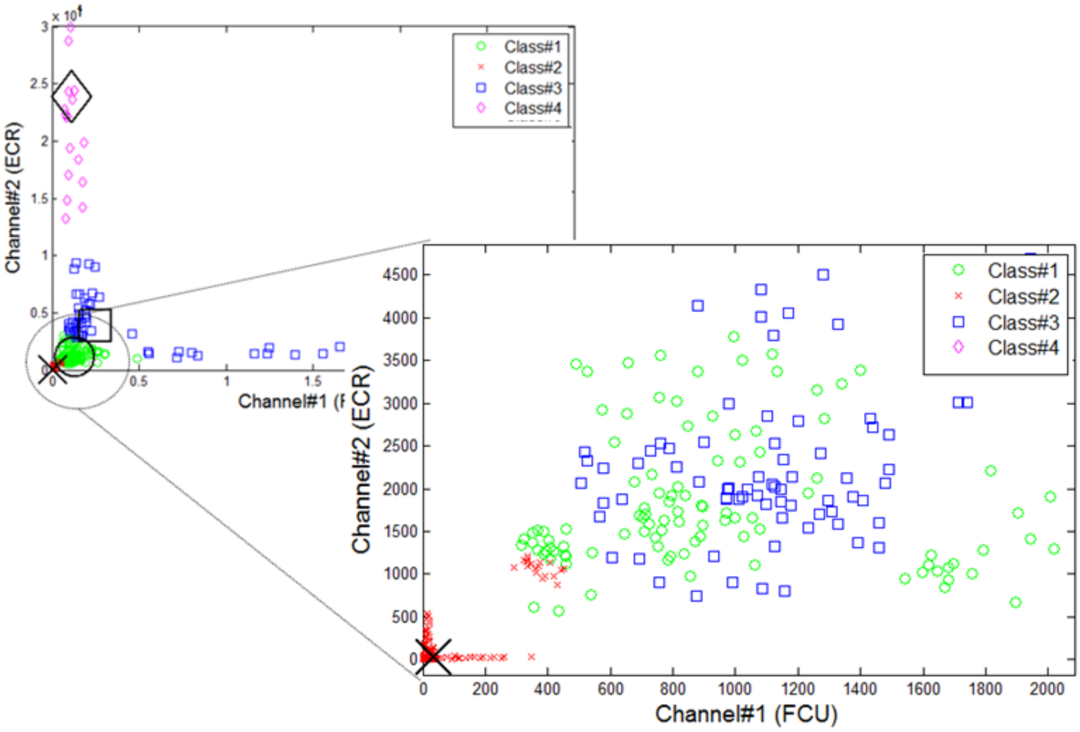

Figure 6. Scatter plot of the Hudgins's multi-feature as feature extractor for one subject, 2 channels and considering all 4 movements (classes).

In addition, the four movements that were verified in this study, including wrist flexion/extension, are more complex than those reported in similar works, such as in (Favieiro & Balbinot, 2011). In these studies, wrist flexion and extension have been applied as two separate classes to simplify classification. Furthermore, large data sequences (normally more than 200 ms) were used in most researches, such as in (Karlik et al., 2003). However, we utilized a 140 ms data segment to enhance the rigorousness of pattern classification based on a review conducted by (Asghari Oskoei & Hu, 2007). According to these comparisons, the ANFIS approach discussed and evaluated in this study can be employed in a simple, computationally efficient MCS for a prosthetic hand.

Table 1. Result of EMG classification accuracy using ANFIS as classifier.

Movements	***Subject#1***	***Subject#2***	***Subject#3***	***Subject#4***	***Mean***	***STD***
Wrist Flexion/Extension	90.50%	88.50%	89.40%	91.15%	89.89%	0.86
Finger Flexion/Extension	87.00%	86.65%	88.50%	92.70%	88.71%	1.01
Co-contraction	88.00%	89.15%	86.00%	90.50%	88.41%	1.25
Isometric	89.00%	87.50%	88.16%	89.70%	88.59%	1.45
4 movements average	88.63%	87.95%	88.02%	91.01%	**88.90%**	**0.92**

Table 2. Result of EMG classification accuracy using ANN as classifier.

Movements	***Subject#1***	***Subject#2***	***Subject#3***	***Subject#4***	***Mean***	***STD***
Wrist Flexion/Extension	83%	86.5%	87%	86%	86%	1.56
Finger Flexion/Extension	82%	85%	89%	83.5%	85%	2.60
Co-contraction	79%	82.5%	84%	81%	82%	1.85
Isometric	81%	82%	86.5%	87.5%	84.25%	2.81
4 movements average	81%	84%	87%	85%	**84.31%**	**2.21**

Table 3. Final result of classification performance (Accuracy and Computation time): ANFIS vs. ANN.

Classifier	**Classification Accuracy (%)**	**Learning Time(ms)**	**Classification Time(ms)**
ANN	84.31±2.21	561.9	349.4
ANFIS	**88.90±0.92**	**121.5**	**82.2**

3.3 Statistical Analysis of Classifiers through T-test

In the final step of classifier evaluation, a T-test is conducted to statistically analyze the difference in the classification accuracies of the proposed algorithms and to validate the significance of the classifier performance; that is, the superiority of ANFIS over ANN. The T-test comparison indicated that the ANFIS (M = 84.31, STD = 2.21) classified movements significantly more accurately (p = 0.0002) than ANN (M = 77.25, STD = 2.18).

4. CONCLUSION

This preliminary study examines the significance of employing ANFIS as the pattern classification method for a MCS. Class separability and distinction are improved in comparison with those of the Hudgins multi-feature by using only four normal-limb subjects, two muscles (FCU and ECR), and a new combination of feature extraction methods (ZC, MAV, SSC, WL, RMS, and MNF) as the multi-feature. As per the results, the performance of the ANFIS system is superior to ANN in terms of both classification accuracy (88.90% ± 0.92) and speed during training and classification (shorter classification and learning times).

5. FUTURE RESEARCH DIRECTION

The results of this research can be improved by incorporating additional subjects and muscles and by combining additional features. Future research on prosthetic hand application can focus on post-processing methods such as heuristic optimization algorithms (A. Rezaee Jordehi, 2014; Ahmad Rezaee Jordehi, 2014; Jordehi & Jasni, 2011) to improve hand movement classification performance.

6. ACKNOWLEDGMENT

This research is supported by "E-Science fund Grant No. 03-01-04871348, Ministry of Science, Technology & Innovation of Malaysia".

7. CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

REFERENCES

Ahmad, S. A. (2009). *Moving approximate entropy and its application to the electromyographic control of an artificial hand.* University of Southampton.

Ajiboye, A. B., & Weir, R. F. (2005). A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 13*(3), 280-291.

Al-Assaf, Y., & Al-Nashash, H. (2005). Surface myoelectric signal classification for prostheses control. *Journal of medical engineering & technology, 29*(5), 203-207.

Asghari Oskoei, M., & Hu, H. (2007). Myoelectric control systems—A survey. *Biomedical Signal Processing and Control, 2*(4), 275-294.

Au, A. T., & Kirsch, R. F. (2000). EMG-based prediction of shoulder and elbow kinematics in able-bodied and spinal cord injured individuals. *Rehabilitation Engineering, IEEE Transactions on, 8*(4), 471-480.

Boostani, R., & Moradi, M. H. (2003). Evaluation of the forearm EMG signal features for the control of a prosthetic hand. *Physiological measurement, 24*(2), 309.

Braga-Neto, U. M., & Dougherty, E. R. (2004). Is cross-validation valid for small-sample microarray classification? *Bioinformatics, 20*(3), 374-380.

Castellini, C., & van der Smagt, P. (2009). Surface EMG in advanced hand prosthetics. *Biological cybernetics, 100*(1), 35-47.

Clement, R., Bugler, K., & Oliver, C. (2011). Bionic prosthetic hands: a review of present technology and future aspirations. *The surgeon, 9*(6), 336-340.

Du, S., & Vuskovic, M. (2004). *Temporal vs. spectral approach to feature extraction from prehensile EMG signals.* Paper presented at the Information Reuse and Integration, 2004. IRI 2004. Proceedings of the 2004 IEEE International Conference on.

Du, Y.-C., Lin, C.-H., Shyu, L.-Y., & Chen, T. (2010). Portable hand motion classifier for multi-channel surface electromyography recognition using grey relational analysis. *Expert Systems with Applications, 37*(6), 4283-4291.

Englehart, K., & Hudgins, B. (2003). A robust, real-time control scheme for multifunction myoelectric control. *Biomedical Engineering, IEEE Transactions on, 50*(7), 848-854.

Favieiro, G. W., & Balbinot, A. (2011). *Adaptive neuro-fuzzy logic analysis based on myoelectric signals for multifunction prosthesis control.* Paper presented at the Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE.

Fielding, A. (2007). *Cluster and classification techniques for the biosciences*: Cambridge University Press.

Guangying, Y. (2007). *Study of myoelectric prostheses hand based on independent component analysis and fuzzy controller.* Paper presented at the Electronic Measurement and Instruments, 2007. ICEMI'07. 8th International Conference on.

Hudgins, B., Parker, P., & Scott, R. N. (1993). A new strategy for multifunction myoelectric control. *Biomedical Engineering, IEEE Transactions on, 40*(1), 82-94.

Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on, 23*(3), 665-685.

Jordehi, A. R. A chaotic artificial immune system optimisation algorithm for solving global continuous optimisation problems. *Neural Computing and Applications*, 1-7.

Jordehi, A. R. (2014). A chaotic-based big bang-big crunch algorithm for solving global optimisation problems. *Neural Computing and Applications*.

Jordehi, A. R. (2014). Enhanced Leader PSO (ELPSO): A new PSO Variant for Solving Global Optimisation Problems. *Applied Soft Computing*.

Jordehi, A. R. (2014). Particle swarm optimisation for dynamic optimisation problems: a review. *Neural Computing and Applications*, 1-10.

Jordehi, A. R., & Jasni, J. (2011). A Comprehensive Review on Methods for Solving FACTS Optimization Problem in Power Systems. *International Review of Electrical Engineering, 6*(4).

Kandel, A. (1992). *Fuzzy expert systems*: CRC press.

Karlik, B., Osman Tokhi, M., & Alci, M. (2003). A fuzzy clustering neural network architecture for multifunction upper-limb prosthesis. *Biomedical Engineering, IEEE Transactions on, 50*(11), 1255-1261.

Khezri, M., & Jahed, M. (2007). Real-time intelligent pattern recognition algorithm for surface EMG signals. *Biomedical engineering online, 6*(1), 45.

Khezri, M., & Jahed, M. (2009). An exploratory study to design a novel hand movement identification system. *Computers in biology and medicine, 39*(5), 433-442.

Khushaba, R. N., Al-Ani, A., & Al-Jumaily, A. (2010). Orthogonal fuzzy neighborhood discriminant analysis for multifunction myoelectric hand control. *Biomedical Engineering, IEEE Transactions on, 57*(6), 1410-1419.

Khushaba, R. N., Al-Jumaily, A., & Al-Ani, A. (2007). *Novel feature extraction method based on fuzzy entropy and wavelet packet transform for myoelectric control.* Paper presented at the Communications and Information Technologies, 2007. ISCIT'07. International Symposium on.

Kiguchi, K., & Hayashi, Y. (2011). *Control of a myoelectric arm considering cooperated motion of elbow and shoulder joints.* Paper presented at the Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE.

Kim, K. S., Choi, H. H., Moon, C. S., & Mun, C. W. (2011). Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions. *Current applied physics, 11*(3), 740-745.

Liu, H., & Yu, L. (2005). Toward integrating feature selection algorithms for classification and clustering. *Knowledge and Data Engineering, IEEE Transactions on, 17*(4), 491-502.

Losier, Y., Englehart, K., & Hudgins, B. (2007). *A control system for a powered prosthesis using positional and myoelectric inputs from the shoulder complex.* Paper presented at the Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE.

Luo, Z., Wang, F., & Ma, W. (2006). *Pattern Classification of Surface Electromyography Based on AR Model and High-order Neural Network.* Paper presented at the Mechatronic and Embedded Systems and Applications, Proceedings of the 2nd IEEE/ASME International Conference on.

Oskoei, M. A., & Hu, H. (2008). Support vector machine-based classification scheme for myoelectric control applied to upper limb. *Biomedical Engineering, IEEE Transactions on, 55*(8), 1956-1965.

Ottobock. (2013). from http://www.ottobockus.com/prosthetics/info-for-new-amputees/prosthetics-101/myoelectric-prosthetics-101/

Phinyomark, A., Quaine, F., Charbonnier, S., Serviere, C., Tarpin-Bernard, F., & Laurillau, Y. (2013). EMG feature evaluation for improving myoelectric pattern recognition robustness. *Expert Systems with Applications*.

Rasheed, S., Stashuk, D., & Kamel, M. (2006). Adaptive fuzzy k-NN classifier for EMG signal decomposition. *Medical engineering & physics, 28*(7), 694-709.

Rasheed, S., Stashuk, D., & Kamel, M. (2008). A software package for interactive motor unit potential classification using fuzzy k-NN classifier. *Computer methods and programs in biomedicine, 89*(1), 56-71.

Ren, X., Huang, H., & Deng, L. (2009). *MUAP Classification Based on Wavelet Packet and Fuzzy Clustering Technique.* Paper presented at the Bioinformatics and Biomedical Engineering, 2009. ICBBE 2009. 3rd International Conference on.

Rezaee Jordehi, A., & Jasni, J. (2013). Parameter selection in particle swarm optimisation: a survey. *Journal of Experimental & Theoretical Artificial Intelligence, 25*(4), 527-542.

Rosenblatt, F. (1962). Principles of neurodynamics.

Soares, A., Andrade, A., Lamounier, E., & Carrijo, R. (2003). The development of a virtual myoelectric prosthesis controlled by an EMG pattern recognition system based on neural networks. *Journal of Intelligent Information Systems, 21*(2), 127-141.

Tkach, D., Huang, H., & Kuiken, T. A. (2010). Research Study of stability of time-domain features for electromyographic pattern recognition.

Wojtczak, P., Amaral, T. G., Dias, O. P., Wolczowski, A., & Kurzynski, M. (2009). Hand movement recognition based on biosignal analysis. *Engineering Applications of Artificial Intelligence, 22*(4), 608-615.

Zecca, M., Micera, S., Carrozza, M., & Dario, P. (2002). Control of multifunctional prosthetic hands by processing the electromyographic signal. *Critical Reviews™ in Biomedical Engineering, 30*(4-6).

AUTHORS BIOGRAPHY:

Hessam Jahani Fariman received his B.Sc. degree in Electrical and Electronic Engineering from Ferdowsi University of Mashhad, Iran in 2011 and M.Sc. in Control and Automation Engineering from the University of Putra Malaysia, Malaysia, in 2014. His areas of interest include Pattern Recognition, Machine Learning, Biomedical Engineering and Rehabilitation.

Siti Anom Ahmad is a senior lecturer at the Department of Electrical and Electronic Engineering, University Putra Malaysia (UPM). She received her first degree in Electronic/Computer Engineering from UPM, and then she obtained her MSc in Microelectronics System Design and PhD in Electronics from University of Southampton UK in 2004 and 2009 respectively. Her research interests are Biomedical Engineering, Signal Processing and Intelligent control system.

Mohammad Hamiruce Marhaban received his degree in Electrical and Electronic engineering from the University of Salford, UK, in 1998 and Ph.D. in Electronic Engineering from the University of Surrey, UK, in 2003. He is an associate professor at the Department of Electrical and Electronic Engineering, UPM. His areas of interest include Intelligent control system and computer vision.

Mohammad Ali Jan Ghasab received his B.Eng. degree in Electrical and Electronic Engineering from Azad University, Iran in 2010 and M.Sc. in Electronic Engineering from the University of Putra Malaysia, Malaysia, in 2014. His areas of interest include Image & Signal Processing, Biomedical Engineering and Rehabilitation, Pattern Recognition, Machine Learning, Control System Design and Optimization.

No Photo

Paul H Chappell is an Associate Professor in the School of Electronics and Computer Science at the University of Southampton 2017 1BJ UK. He is a Chartered Engineer, FIET, FIPEM, SMIEE and MInstP. Paul has published over one hundred and sixty journal articles, conference papers, chapters in books and patents. phc@ecs.soton.ac.uk