Neuro-Fuzzy Surface EMG Pattern Recognition For Multifunctional Hand Prosthesis Control

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Abstract— **Electromyogram (EMG) signal is an electrical manifestation of muscle contractions. EMG signal collected from surface of the skin, a non-invasive bioelectric signal, can be used in different rehabilitation applications and artificial extremities control. This study has proposed to utilize the surface EMG (SEMG) signal to recognize patterns of hand prosthesis movements. It suggests using an adaptive neuro-fuzzy inference system (ANFIS) to identify motion commands for the control of a prosthetic hand. In this work a hybrid method for training fuzzy system, consisting of back-propagation (BP) and least mean square (LMS) is utilized. Also in order to optimize the number of fuzzy rules, a subtractive clustering algorithm has been developed. The myoelectric signals utilized to classify, were six hand movements. Features chosen for SEMG signal were time and time-frequency domain. Neuro-fuzzy systems designed and utilized in this study were tested independently and in a combined manner for both time and time-frequency features. The results showed that the combined feature implementation was the best in regard to identification of required movement tasks. The average accuracy of system for the combined approach was 96%.**

I. INTRODUCTION

The myoelectric signal (MES), recorded at the skin surface, has become an important tool in rehabilitation for amputees. The MES gives us information about the neuromuscular activity from which it originates, and this has been fundamental to its use in clinical diagnosis, and as a source of control for assistive devices and schemes of functional electrical stimulation. It has been proposed that the electromyographic signals from upper limb musculature can be used to identify motion commands for the control of an externally powered prosthesis hand [1]. Extracted information from EMG signals which are represented in a feature vector is chosen to minimize the control error [2],[3]. In order to achieve this goal, a feature set must be chosen which maximally separates the desired output classes. Extraction of accurate features from EMG signals is the main kernel of classification systems and is essential to the motion command identification. SEMG signal for prosthesis application is generally acquired by placing one or more differential electrode on the skin of the user. The non-stationary nature of SEMG signal makes it difficult to extract feature parameters precisely with the block processing stationary model such as autoregressive (AR) model [4]. Also it is very difficult for one feature parameter to reflect the unique feature of the measured SEMG signals to a motion command perfectly. Therefore in order to increase recognition rate of this system, two types of features which are time domain and time-frequency representations have been used. In time domain we use three major feature of SEMG signal such as mean absolute value (MAV), slope sign changes (SSC) and autoregressive (AR) model coefficients of signal and in time-frequency domain, zero crossing (ZC) of wavelet transform have been used [3]. Therefore our feature set composed of four features. Once a feature set has been constructed, they are fed to a classifier for discriminating among six motion commands of human hand. The movements that we apply are Hand opening and closing, wrist radial flexion and extension, pinch, and thumb flexion. The system presented in this work is based on a new approach, namely a neuro-fuzzy classifier. For training this system, a hybrid method including backpropagation and least mean square will be utilized. Also we use subtractive clustering method to specify fuzzy system rules. After implementing SEMG pattern recognition system, we acquire classification rate of this system which varies from 88% to100%. In the first case only time domain features and in another case compound features have been used. This fuzzy algorithm demonstrated success in pattern recognition of SEMG signal and allows for suitable control in multifunctional prosthesis hands.

II. SEMG ACQUISITION AND PREPROCESSING

The EMG signal is the electrical manifestation of the neuromuscular activation associated with a contracting muscle. It is a complicated signal influenced by various factors such as physiological and anatomical properties and characteristics of instrumentation. This signal differs from one person to another. A good acquisition of the SEMG signal is a prerequisite for good signal processing. In this work we use two channels of differential surface electrodes for collecting SEMG signal [1]. This Signal is easily affected by undesired signal that come from different sources such as 50/60 Hz electromagnetic interference from power lines. In addition, for surface electrode instrumentation, complicating issues may arise due to its coupling with skin (e.g. impedance of the skin may vary as function of the moisture of the skin, the superficial skin oil content and the density of dead cell layer).We place differential electrodes on the forearm under the elbow and place reference electrode on the wrist. After the acquisition, SEMG signal is filtered generally using a band-pass filter and amplified by

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using amplifier with high CMRR and gain (band- pass filter consists of a high-pass filter with 500 Hz cut off frequency to reduce motion artifacts and a low pass filter with 20 Hz cut off frequency to reduce noise) [5].Also we exert a notch filter at 60 Hz for eliminating power line noise. Afterward signal is sampled with 1 KHz and converted into a digital stream of data.

A roster of four healthy subjects participated for collecting SEMG signals. Six movements of hands have been considered and SEMG signal for each movement have been extracted. These movements are Hand opening and closing, pinch, thumb flexion and wrist radial flexion and extension. These movements have been shown in Fig.1. For each class of movements 100 signals collected. We divided our acquired signals into two categories. First category was utilized as train set data and second was employed as a test set, in the manner that each of them included 50 signals

III. SEMG PATTERN CLASSIFICATION USING NEURO- FUZZY SYSTEM

Fuzzy inference system was developed in 1965 by professor lotfizadeh [6], [7]. Fuzzy logic systems can emulate human decision-making more closely than many other classifiers, because of the possibility of introducing the knowledge of an expert in the fu fuzzy rules of the form IF-THEN [8],[9],[10],[11]. The non-stationary nature of SEMG signal like other biological signal makes the problem of classification more difficult. But the characteristics of Fuzzy inference system make it as a suitable tool for pattern recognition problem [12].The fuzzy system, initially fuzzifies inputs to values at interval [0,1] using a set of membership functions (MF). Next it is inferred by fuzzy logic through rules in the form of IF-THEN. The basic part of fuzzy system is the fuzzy inference engine that can be used for creating fuzzy rules. The example of fuzzy rules is:

$$\mathbb{R}^i : \text{If } x_1 \text{ is } MF_1^i \text{ and/or } x_2 \text{ is } MF_2^i \text{ and/or} \ldots x_j \text{ is } MF_j^i \quad \text{Then } z^i \text{ is } MFo^i \tag{1}$$

where $\mathbb{R}^i$ (i=1,2,..,l) denotes the i^{th} fuzzy rules, x_j (j=1,2,..,n) is the j^{th} input and z^i is the output of i^{th} fuzzy rule, finally MF_j^i, MFo^i are fuzzy membership function of antecedents and consequents for i^{th} rules (this rule is in the Mamdani form).

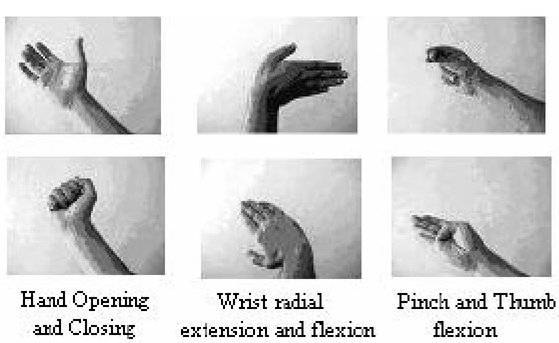

Figure1. The six classes of movements used in this work

In this work we apply neuro-fuzzy approach for recognizing SEMG patterns. Neuro-fuzzy computing enables us to build more intelligent decision making systems by combining the advantage of artificial neural network with the fuzzy modeling of imprecise and qualitative knowledge. Fig.2 briefly shows the ANFIS structure with n inputs and one output. The output of this system can be described by the following function:

$$y = \sum_{i=1}^{L} \left\{ \frac{\left(\prod_{j=1}^{n} MF_j^i(x_j) \right) . \left(z^i \right)}{\sum_{i=1}^{L} \left(\prod_{j=1}^{n} MF_j^i(x_j) \right)} \right\} \tag{2}$$

Where MF is the bell membership function. This membership function depends on three parameters a, b, c as given by:

$$MF(x) = \frac{1}{1 + \left| \frac{x - c}{a} \right|^{2b}} \tag{3}$$

The basic problem of fuzzy system is, adjusting membership function parameters, output of each fuzzy rule and estimating number of rules that should be minimum and precise enough. Adaptive neuro-fuzzy inference system adapts the parameters of Sugeno type inference system using neural network [13]. (For Sugeno type systems, output is a crisp number computed by multiplying each input by a constant and then adding up the results. Indeed the resultant output is in the form of $z^1 = s_0^1 + s_1^1 x_1 + \ldots + s_j^1 x_j$).

For training fuzzy system, ANFIS employs backpropagation for the parameters associated with the input membership functions, and LMS estimation for the parameters associated with the output membership functions.

In order to optimize the FIS system and increase its ability for SEMG pattern recognition problem, the method called subtractive clustering is used for determining the best number of fuzzy rules. This method partitions the data into groups called clusters, and generates a FIS with the minimum number of rules required to distinguish the fuzzy qualities associated with each of the clusters. In the next section we introduce these methods and describe their application in implementing neuro-fuzzy system.

A. *Hybrid method (BP and LMS):*

The ANFIS structure can be used for training fuzzy inference system. One of the most useful algorithms that can be used for this purpose is backpropagation. BP adjusts membership function parameters. For neuro-fuzzy system usually the bell function is applied as membership function. In this function a, b and c are variables and must be adjusted. The BP algorithm may be used to train these parameters.

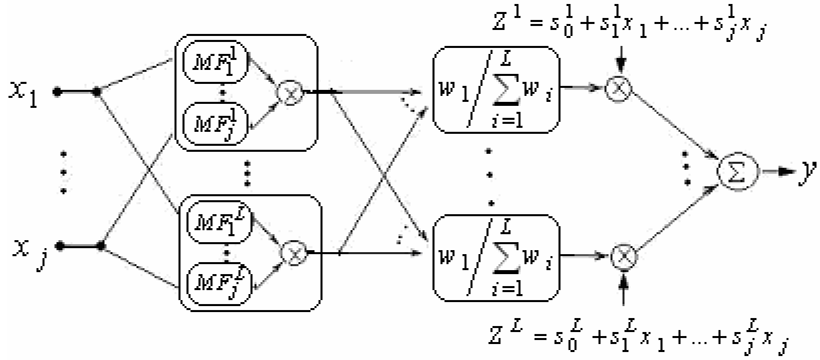

Figure 2. Network representing ANFIS structure. (MFs are bell membership functions)

Suppose that we are given an input-output pair (x, y), $x = [x_1, x_2, ... x_n]$, our goal is, minimizing the cost function:

$$e = \frac{1}{2}[y_{des} - y]^2 \tag{4}$$

The output of each rule z^i defined by:

$$z^i(t+1) = z^i(t) - k_z \frac{\partial e}{\partial z^i} \tag{5}$$

Where k_z is a step size. Now three parameters a, b, c must to be adjusted. For this Sugeno system, if we specify output as follows:

$$w^i = \prod_{j=1}^{n} MF_j \ , \quad y = \frac{\sum_{i=1}^{L} w^i z^i}{\sum_{i=1}^{L} w^i} \tag{6}$$

And if we compute derivative in equation (4), we will have:

$$\frac{\partial e}{\partial z^i} = \frac{\partial e}{\partial y} \cdot \frac{\partial y}{\partial z^i} \ , \quad \frac{\partial y}{\partial z^i} = \frac{w^i}{\sum_{i=1}^{L} w^i} \quad \text{and} \ \frac{\partial e}{\partial y} = (y_{des} - y) \tag{7}$$

Then for output of each rule we will define the following equations:

$$z^i(t+1) = z^i(t) - k_z \left(\frac{w^i}{\sum_{i=1}^{L} w^i}\right)(y_{des} - y) \tag{8}$$

Similarly way for j^{th} membership function of i^{th} fuzzy rule the parameters are calculated:

$$a_j^i(t+1) = a_j^i(t) - k_a \frac{\partial e}{\partial a_j^i} \tag{9}$$

$$b_j^i(t+1) = b_j^i(t) - k_b \frac{\partial e}{\partial b_j^i} \tag{10}$$

$$c_j^i(t+1) = c_j^i(t) - k_b \frac{\partial e}{\partial c_j^i} \tag{11}$$

In order to specify the number of rules in fuzzy system we utilize subtractive clustering approach. This method is introduced bellow:

B-*subtractive clustering:*

Subtractive clustering is based on a measure of the density of data points in the feature space. The idea behind this approach is to find regions in the feature space with high densities of data points. The point with the highest number of neighbors is selected as the center for a cluster. The data points within a prespecified fuzzy radius are then removed (subtracted), and the algorithm looks for a new point with the highest number of neighbors. This continues until all data points are examined. Consider a collection of K data points specified by m-dimensional vectors u_k, k =1, 2, …, K. Since each data point is a candidate for a cluster centre, a density measure at data point u_k is defined as:

$$D_k = \sum_{j=1}^{K} \exp\left(-\frac{\|u_k - u_j\|}{(r_a/2)^2}\right) \tag{12}$$

Where r_a is a positive constant. Hence, a data point will have a high density value if it has many neighbouring data points. Only the fuzzy neighbourhood within the radius r_a contributes to the density measure .After calculating the density measure for each data point, the point with the highest density is selected as the first cluster center. Let u_{c1} be the point selected and D_{c1} its density measure. Next, the density measure for each data point u_k is revised by the formula:

$$D_k^{'} = D_k - D_{c1} \exp\left(-\frac{\|u_k - u_{c_1}\|}{(r_b/2)^2}\right) \tag{13}$$

Where r_b is a positive constant. Therefore, the data points near the first cluster centre u_{c1} will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster center. The constant r_b defines a neighborhood to be reduced in density measure and It is normally larger than r_a to prevent closely spaced cluster centers, where Typically $r_b = 1.5 \times r_a$.

After the density measure for each point is revised, the next cluster center u_{c2} is selected and all the density measures are revised again. The process is repeated until a sufficient number of cluster centers are generated. When applying subtractive clustering to a set of input-output data, each of the cluster centers represents a rule. To generate rules, the cluster centres are used as the centres for the premise sets in a singleton type of rule base (or the radial basis functions in a radial basis function neural network).

IV. FEATURE SELECTION

A. *Time domain features*

Time domain features extracts time structures in EMG signal. EMG signal has a number of irregular structures in the temporal waveform due to deterministic components but despite this there is a great deal of intra class variability due to random component in this signal. In the case of time domain features, various features of signal have been considered. If we use sampled waveform for classifying SEMG pattern, we will lose temporal structure of signal that in not desirable for us. On the other hand, in this case high variability of features and high dimension of feature space would result in very poor classification performance.

To overcome these problems we segment SEMG signal and extract favorite features from each segment. In this work, we used a time domain window of 300 (ms) for collecting SEMG signal. For classification problem, appropriate length of SEMG signal should be considered. Hudgins experimented with different segment lengths in attempt to reduce classification error. He decided upon a scheme of five 40 (ms) segment plus an extra segment [1]. Fig.3 represents wavelength size for SEMG pattern recognition based on correctness percentage.

In this work, 200 (ms) segmented signal was shown to be suitable for classification problem (similar to Hudgins results). We decided on four 50 (ms) SEMG sub-segment for better accuracy. In the case of real time application, the system should not have perceivable delay.

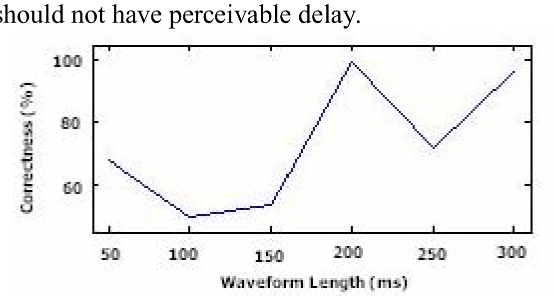

Figure 3. Wavelength size for SEMG Pattern recognition

EMG features must be calculated over all four segments. In this work we used, MAV, SSC and AR model coefficients as time features of SEMG signal [1].

B. *Time Frequency domain features.*

Time-frequency domain representations (TFRs) combine time and frequency features for extracting more information of signal. TFRs have received considerable attention in the case of pattern recognition problem especially EMG pattern recognition [3].

The major incentive for using these representations as a feature for the application of SEMG pattern recognition is our need to gain more information about this signal in order to better discriminate among various movements. Discrete wavelet transform (DWT) is a famous type of these representations. Wavelet analysis, similar to Fourier transform that breaks up a signal into sine waves of various frequencies, is utilized to split a signal into shifted and scaled versions of the original (or mother) wavelet.

The wavelet coefficients can constitute a very effective feature set but there is a fundamental drawback for the DWT, namely, lack of shift invariance. If the signal to be analyzed is shifted, the coefficients of wavelet transform vary in complex manner. This matter presents significant problem in the of pattern recognition. To overcome this problem, we can use shift invariant features of DWT such as zero crossing (ZC) [14].

For constructing feature set by using DWT, we needed to determine the parameters that affected it. For this reason we consider these parameters and calculate accuracy of the SEMG pattern recognition system then we chose the best parameters. For DWT two parameters must be determined, namely choice of mother wavelet and depth of decomposition. The best mother wavelet for SEMG pattern recognition was determined empirically. Basically, the selection of mother wavelet must be based on best correlation with the EMG signal.

The DWT decomposition can be terminated prior to a full decomposition. If signal have been length of N sample, then the maximum depth of decomposition is $J = \log_2^N$ .The SEMG signal in this work have 500 sample thus the maximum depth of decomposition will be 9. Fig.4 shows the effect of mother wavelet and depth of decomposition on SEMG pattern recognition system.

To obtain these results, we used different mother wavelet types such as haar, daubechies, symlet,coiflet and biorthogonal. The mother wavelet shown in Fig.4 depicts the best accuracy. The results indicate that biorthogonal3.5 as a mother wavelet with 9 level of decomposition, presents the best performance to recognize SEMG patterns.

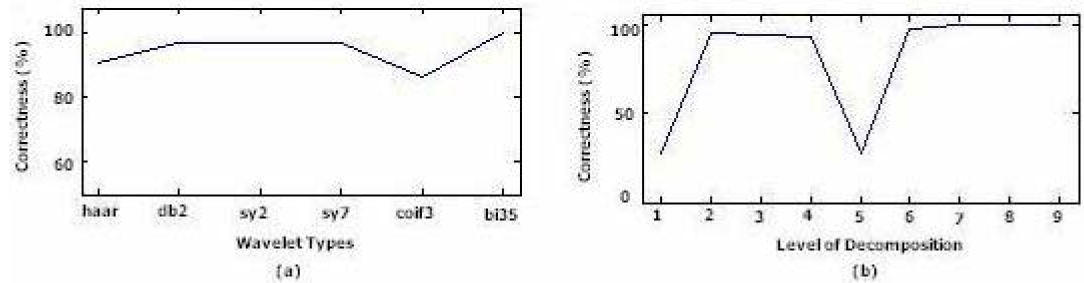

Figure 4. (a) Comparison of mother wavelet's accuracy, (b) the effects of depth of decomposition in SEMG pattern recognition system

V. DESIGNING NEURO FUZZY SYSTEM STRUCTURE

As shown before, four features of SEMG signal for the application of pattern recognition in this study, namely MAV, SSC, and AR model were applied as time domain features and ZC of wavelet coefficients was employed as time-frequency features.

We designed three SEMG pattern recognition systems. These system use time domain features, time-frequency feature, and compound features, a combination of time and time-frequency features. Therefore these systems have three, one and four inputs respectively. Due to similarity between the structures of these systems, here we have presented a neuro-fuzzy system for only compound features. In this work we used subtractive clustering method to determine the number of fuzzy rules and BP and LMS for membership function parameters and outputs of each rules. By implementing subtractive clustering, for each of the designed systems, rule characteristics are determined. The characteristics of these systems are briefly shown in Table I.

For system that was designed with compound features, six fuzzy rules have been obtained. Table II, depicts these rules and their respective outputs. In this table, the used membership functions are represented with linguistic expression. For this purpose we applied these expressions from lower range to upper range of inputs as low, middle-low, average-low, average-high, middle-high and high, respectively. The output for each rule have been shown with Z_i , (for i=1, 2, 3, 4, 5, 6). Each output obtains by combining all inputs.

TABLE I
CHARACTERISTIC OF NEURO FUZZY SYSTEM FOR EACH TYPE OF APPLIED FEATURES

ANFIS information	Three time features	One Time-frequency feature	Four Compound Features
Number of rules	6	3	6
Number of input parameters (MF parameters)	54	9	72
Number of output parameters (output coefficients)	24	6	30

As shown before this system is of Sugeno-type with order four and the output for each rule is determined by LMS method. If we consider Z_i in the form of:

$$Z_i = \alpha_{i1}(in1) + \alpha_{i2}(in2) + \alpha_{i3}(in3) + \alpha_{i4}(in4) + \alpha_{i5} \qquad (14)$$

Where in1 is the first input and so on for other inputs. In Table III, adjusted coefficients for each output with LMS algorithm have been shown. Fig.5 shows the structure of this fuzzy system, our system has four inputs (which are SEMG compound selected features), one output and six fuzzy rules. To design this system, we used "prod" as AND method, "probor" as OR method, and "weigh average" as deffuzification method.

TABLE II
REPRESENTATION OF FUZZY RULES TO DESIGN SEMG PATTERN RECONITION SYSTEM USING COMPOUND FEATURES

IF				THEN
EMG Input_1	EMG Input_2	EMG Input_3	EMG Input_4	Output Z_i
average- low	average- high	average- high	average- low	Z_1
middle-high	high	middle-low	middle-high	Z_2
low	Middle-low	high	low	Z_3
average- high	low	average- low	average-high	Z_4
middle-low	average- low	middle-high	middle-low	Z_5
high	middle-high	low	high	Z_6

TABLE III
THE COEFFICIENTS OF EACH OUTPUT FOR SYTEM WITH COMPOUND FEATURES

i	Z_1	Z_1	Z_3	Z_4	Z_5	Z_6
α_{i1}	-0.3749	-0.3294	-0.0155	-0.1377	0.6832	-0.3413
α_{i2}	0.0489	0.0913	0.0002	0.0678	0.0427	0.0851
α_{i3}	-0.0055	-0.0774	0.0006	-0.0057	-0.0022	-0.0743
α_{i4}	1.2330	1..9875	0.0354	0.1737	0.0374	2.4382
α_{i5}	3.7759	5.7210	0.0113	4.5509	2.8117	5.3324

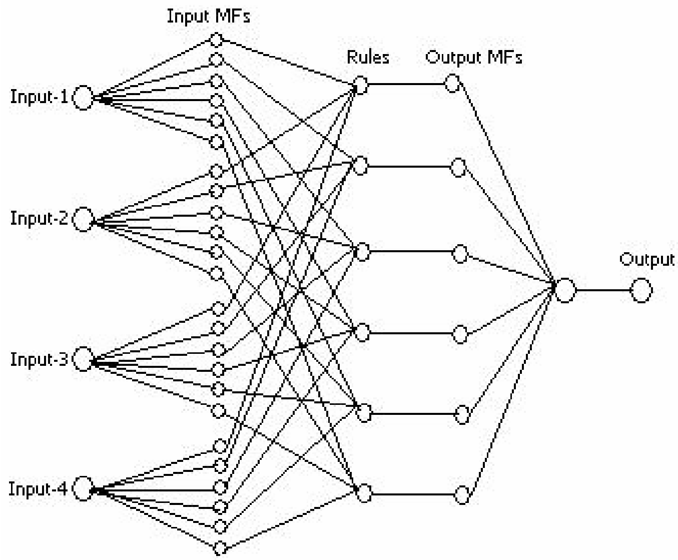

Figure 5. Structure of fuzzy system with four inputs and one output.

VI. EXPERIMENTAL RESULTS

In order to obtain best results for recognizing SEMG patterns in the application of hand prosthesis control, we applied a neuro-fuzzy based system. To achieve this goal we considered time domain features, time-frequency feature and compound features, constructed by combining time and time frequency features. For compound analysis, we used four features of SEMG signal, in which three were in time domain and in time-frequency domain.

For extraction of these features we considered 100 signals for each class (movement type), and divided this signal in two groups, 50 signals as train set and 50 signals for test set. For training set, arbitrary outputs were chosen for each motion of hand. After training these systems and obtaining estimated outputs for each class, we were able to determine the correctness of systems in recognizing each motion. Table IV, presents the results of implementing such systems. These results have been extracted by three types of that SEMG features. As shown in Table IV, the results associated to compound features were better and all of the movements were recognized with correctness of more than 90%. In Table V the average results for three state of this system have been shown.

TABLE IV
COMARING THE EFFECTIVENESS OF FEATURE TYPE FOR RECOGNIZING EMG PATTERNS

Feature types	Movements					
	opening	closing	Wrist flexion	Wrist extension	pinch	Thumb flexion
Time domain	90%	100%	88%	84%	84%	%80
Time–frequency domain	94%	98%	92%	92%	88%	%84
compound features	98%	100%	96%	98%	94%	%90

TABLE V
AVERAGE ACCURACY OF FUZZY SYSTEM IN SEMG CLASSIFICATION

	Time domain features	Time frequency features	Compound features
Average Correctness	87.7 %	91. 33 %	96 %

VII. CONCLUSION

In this work, we introduced a new approach for recognizing SEMG pattern based on neuro-fuzzy system with high degree of correctness. Three types of SEMG features were used, namely time, time-frequency and compound features. When compound features were utilized, a high degree of correctness for recognizing each of the six selected movements of hand was obtained. The proposed neuro-fuzzy system exhibited very good results as the minimum accuracy obtained of this system by using compound features was 90% (TABLE IV). Therefore the presented method can be effectively utilized in the pattern recognition of hand motions and prosthesis hand control.

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