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Fuzzy Logic and Probabilistic Neural Network for EMG Classification – A Comparitive Study

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Abstract

EMG signals are found to show definite patterns for different activities of the muscle and this paved the way for its use in clinical diagnosis, rehabilitation purposes, and also as a source of prosthetic control and control of assistive devices. Identifying these patterns correctly helps to provide better control of assistive devices. This paper presents an attempt for classifying EMG signals based on different speeds of movement of a human elbow, as a part of development of an Assistive Limb. Two different classifiers using Fuzzy logic, and Probabilistic Neural Network are developed and a comparative study is made. Experiments are performed on the biceps brachii muscle of five subjects on their right hand. From the acquired EMG data, two features namely, mean absolute value and variance, are extracted and are applied as inputs to the classifiers. To measure the performance of the classifiers, their classification accuracies are calculated and compared.

1. Introduction

The contraction of the skeletal muscles occurs when the action potential travels down from the brain or spinal cord through an axon to the synapses between the nerves and the muscles, and the graphical record of the electrical activity produced during this contraction is termed Electromyography (EMG). These signals, if properly acquired and analyzed, find applications in biomechanical movement analysis, gait analysis, sport performance, study of neuromuscular diseases, and study of muscular fatigue. Electromyographic signals also have recently gained high importance in the area of prosthetic control, control of assistive devices and in the area of rehabilitation.

Various assistive devices and exoskeletons controlled by EMG signals were developed for supporting people [1-11] with disabilities and for rehabilitation purposes. EMG based exoskeletons primarily require control signals based on the EMG. Kavyan Najarian et al [12] defines EMG as “the signal that records the electrical activities generated by the depolarization of muscle cells during muscle contraction and the nerve impulses that initiate the depolarization of the muscle”. Studies have shown that even in paralyzed people, perceptible quantity of EMG signal is produced through self-effort [13].

In order to utilize EMG as input to control assistive devices or prosthesis, the initial step is the processing of the EMG signal to extract features from it, and classify the signal for different types of desired motions. The features that can be extracted from an EMG signal includes statistical features like mean, variance, standard deviation, RMS EMG amplitude, absolute value, integrated absolute value, mean absolute value, mean absolute value slope, maximum value, zero crossings, slope sign changes, skewness, kurtosis, waveform length, AR model parameters, cepstrum coefficients, wavelet packet transform, frequency parameter of Power Spectral Density of EMG signal, Short-time Fourier Transform (STFT), moving approximate entropy, wavelet transform [2 - 9], [14 - 22] etc. The selected features extracted from the EMG signal, are used for pattern classification. Pattern classification can be defined as the process of assigning one of the *k* discrete classes to an input vector *x*. The different classification techniques include Artificial Neural Network (ANN), Fuzzy classifier, Bayesian classifier, Linear Discriminant analysis, Hidden Markov Model, Gaussian mixture model, and Support Vector Machines [20 - 25].

Our work aims to develop an Assistive Limb for supporting human elbow using surface EMG signals, for helping the disabled and the elderly, and for medical rehabilitation. Several methods have been developed in classifying the flexion/extension of elbow, not much work has been done considering the speed with which the movement occurs, except in a work by Sundaraj [22] in which the classification of four different states namely, rest, slow weak contraction, slow strong contraction, fast weak contraction and fast strong contraction, is done using Artificial Neural Network (ANN) with a classification accuracy of 88%. The present work concentrates on the classification of different speeds of movement of human elbow. For this, EMG signals are acquired from the biceps brachii. The first phase of the work is classification of speed of the elbow motion into rest, slow movement or fast movement. Two types of classifiers are developed and compared namely, Fuzzy Logic Classifier (FLC), and Probabilistic Neural Network Classifier (PNNC).

There are three steps involved in the analysis of EMG (i) Data acquisition and signal processing, (ii) Feature extraction, and (iii) Pattern classification. The organization of the paper is as follows. The next section explains about the signal acquisition and processing. The third section describes about the feature extraction methods adopted. Description of the classifiers and the methodology of classification are discussed in section 4. The results of the experiments conducted are summarized in section 5. The last section gives the major conclusions from the work.

2. Signal acquisition and processing

The EMG signal is a biomedical signal that represents electrical activity generated in the muscles during its contraction. These signals are controlled by the nervous system and are dependent on the anatomical and physiological properties of muscles. EMG signals differ from person to person. Even for the same person, this signal may vary for the same type of motion. There are two methods by which the signal can be acquired: (i) by means of non-invasive surface electrodes and (ii) by means of invasive needle electrodes. Surface electrodes are preferred for the work as it is easy to handle compared to the other, which requires medical expertise for its handling. The EMG signals acquired using surface electrodes are termed surface EMG (sEMG).

The characteristics of EMG signal are: it is stochastic in nature with low amplitude ranging from 0 to 1.5 mV (RMS), its distribution function is Gaussian, and power spectral density ranges from 10 to 500 Hz [26]. The quality of EMG signal depends on timing and intensity of muscle contraction, distance of the electrode from the target muscle area, skin thickness and fatty tissue, properties of electrodes and amplifier, quality of contact between the skin and the electrode etc.

For signal acquisition, Biopac MP100 System, which consists of a data acquisition unit, universal interface module, USB Adapter, Transformer and cables, is used. It has built-in filters, which include a low pass filter of 500/5000 Hz and a high pass filter of 1/10/100 Hz to select the usable energy region of the signal by reducing the noise. A notch filter of 50 dB rejection at 50/60 Hz is also incorporated to avoid the effect of line frequency. The system provides a gain of 500/1000/2000/5000 so that low voltage EMG signals can be amplified and analyzed easily. It provides a high common mode rejection ratio of 110dB. The software used in conjunction with the Biopac system is ACKv3.7 (AcqKnowledge).

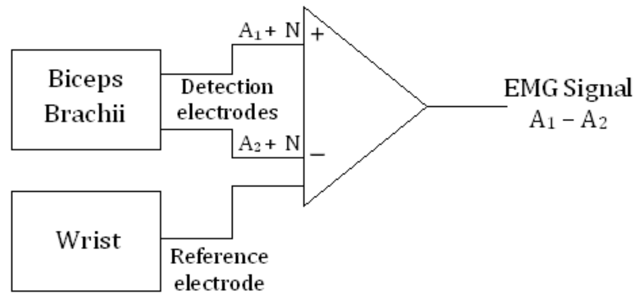

Fig 1: Data acquisition of EMG signals using surface electrodes

The EMG signals are acquired using Ag-AgCl pre-gelled surface electrodes from the biceps brachii of the right hand. The electrode diameter should be 1 cm or smaller. The inter-electrode distance is 2 cm centre point to centre point. Only three electrodes are required for the signal acquisition. Fig. 1 shows the connections of the three leads for the differential amplification of the signal. The following settings are made in the Biopac system before signal acquisition: 500 Hz Low pass filter, 10 Hz High pass filter, 50 Hz Notch filter, and a gain of 2000. The acquisition time, and sampling rate was set using AcqKnowledge software. The sampling frequency used for the work is 2000 Hz.

3. Feature Extraction

As the data acquired from the subjects consists of a large number of readings, it becomes necessary that its dimension needs to be reduced for the ease of handling it, and this is made possible by extracting the features from the signal. For the extraction of features, the available data is first divided into small segments each of 200 ms duration. From each segment, two features are extracted. Since time-domain features are advantageous for real time applications and provide uncomplicated computation, they are extracted in the present work. Let x represent the signals recorded with the surface electrodes, and x_n, the value of the nth

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sample. The features computed from the sEMG segments, each with N samples are:

(i) Mean Absolute Value (MAV):

This is a popular feature used in myoelectric control application. MAV is the average of the absolute value of the signal and is expressed as

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n| \qquad (1)$$

(ii) Variance (VAR):

The variance or second order moment of the EMG is a measure of its power and is given by

$$VAR = \sigma^2 = \frac{1}{N-1}\sum_{n=1}^{N}x_n^2 \qquad (2)$$

4. Pattern Classification

Pattern classification can be defined as the clustering of patterns into groups, which share the same set of properties. Neuro-fuzzy [7, 10], Fuzzy-neuro [3-6, 9], Fuzzy logic [2, 23-28] and Neural Networks [22, 28-30], have been used for pattern recognition as well as control of prosthesis in many of the works. In the present work, Fuzzy Logic and Probabilistic Neural Network (PNN) are used for pattern classification of the acquired sEMG signals. Three modes of movements of the elbow are considered for classification: rest, slow contraction and fast contraction. The classifiers are trained to classify rest, slow contraction and fast contraction as 1, 2 and 3 respectively.

4.1. Fuzzy Logic Classifier (FLC)

Fuzzy Logic Classifier is a Fuzzy Inference System (FIS) [31-32], as shown in Fig. 2.

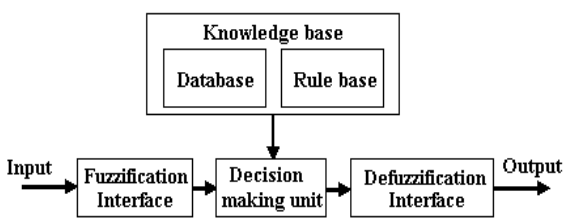

Fig. 2: Fuzzy Inference System

The different blocks of FLC are described briefly below.

- A database defines the membership functions of the fuzzy sets of inputs and output.
- A rule base consists of a number of fuzzy if-then rules, which decides the class to which the respective inputs belong.
- A fuzzification interface fuzzifies the crisp inputs ie, it converts the crisp inputs into the degrees of match with linguistic values.
- A decision making unit performs the implication operations on the rules.
- A defuzzification interface defuzzifies the fuzzy outputs ie, it transforms the fuzzy outputs into crisp outputs.

Fuzzy logic systems are advantageous for bio-signal processing and classification for the following reasons. Bio-signals are not exactly repeatable and sometimes they are even contradictory. Hence, fuzzy logic can be used for bio-signal classification, as they can tolerate considerable contradictions in data. Fuzzy systems have the ability to discover patterns, which are not easily distinguishable. Fuzzy logic also utilizes the tolerance of uncertainty, imprecision, and partial truth, to accomplish tractable, robust and low-cost solutions for classifications.

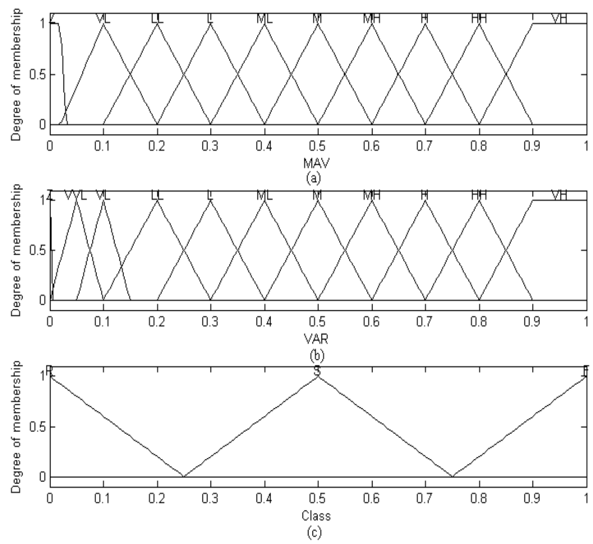

Fig. 3: Membership functions of (a) MAV, (b) VAR and (c) Class

In the present work, a Mamdani type FIS is developed for classification. The FLC receives two inputs namely, Mean Absolute Value (MAV) and Variance (VAR). As the amplitude of the EMG signals vary from person to person, the inputs are normalized in the range of 0 to 1 to obtain a generalized fuzzy inference system. The fuzzifier or fuzzification interface fuzzifies the normalized inputs, using the membership functions defined for them. Ten membership functions (trapezoidal and triangular) are used to describe the different ranges of MAV and eleven membership functions (trapezoidal and triangular) are used for VAR as shown in Fig. 3. The operators used are min-max operators. Triangular membership function is defined by three parameters {a, b, c} [32].

$$triangle(x,a,b,c)=\begin{cases}0, x<a\\ \dfrac{x-a}{b-a}, a\le x\le b\\ \dfrac{c-x}{c-b}, b\le x\le c\\ 0, c\le x\end{cases}$$

or more compactly,

$$triangle(x,a,b,c)=\max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right)$$

Trapezoidal membership function is specified by four parameters {a, b, c, d} [28].

$$trap(x,a,b,c,d)=\begin{cases}0, x<a\\ \dfrac{x-a}{b-a}, a\le x\le b\\ 1, b\le x\le c\\ \dfrac{d-x}{d-c}, c\le x\le d\\ 0, d\le x\end{cases}$$

or more compactly,

$$trap(x,a,b,c,d)=\max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right)$$

The method of defuzzification used is centroid method [31] which is defined as

$$z=\frac{\sum_{i=1}^{n} z_i\mu_c(z_i)}{\sum_{i=1}^{n}\mu_c(z_i)},\quad i=1,2,...,n$$

where $\mu_c(z_i)$ are the sampled values of aggregated output membership function and z is the crisp output of the fuzzy inference system.

The rule base of the FIS classifier is of the form,

Rule R_j: If Input_1 is A_{j1} and Input_2 is A_{j2},
then Class C_j, j = 1, 2, …, N

where R_j is the label of the j-th fuzzy if-then rule, A_{j1} and A_{j2} are antecedent fuzzy sets on the unit interval [0, 1], C_j is the consequent class.

The rule base of the FIS developed is presented in Table I. In this table, the following convention of symbols has been used: (i) Z for Zero, (ii) VVL for Very Very Low, (iii) VL for Very Low, (iv) LL for Low Low, (v) L for Low, (vi) ML for medium Low, (vii) M for Medium, (viii) MH for Medium High, (ix) H for High, (x) HH for High High, (xi) VH for Very High, (xii) R for Rest, (xiii) S for Slow and (xiv) F for Fast.

TABLE I
Rule Base for FLC

Sl.No	MAV	VAR (3)	Class
1	-	Z	R
2	Z	Z	R
3	VL	Z	S
4	VL	VVL (4)	S
5	VL	VL	S
6	LL	VVL	S
7	L	VL	S
8	L	LL	F
9	ML	Z	S
10	ML	VL	F
11	ML	LL (5)	F
12	ML	M	F
13	ML	MH	F
14	M	VL	S
15	M	LL	F
16	M	L	F
17	MH	VL (6)	F
18	MH	L	F
19	MH	ML	F
20	MH	M	F
21	MH	MH	F
22	H	ML	F
23	H	(7)M	F
24	H	MH	F
25	H	H	F
26	H	HH	F
27	H	VH	F
28	HH	ML	F
29	HH	M	F
30	HH	MH	F
31	HH	H	F
32	HH	HH	F
33	HH	VH	F
34	VH	M	F
35	VH	MH	F
36	VH	H	F
37	VH	HH	F
38	VH	VH	F

4.2. Probabilistic Neural Networks

Probabilistic Neural Network was introduced by Donald Specht in 1988. It is a four layer feed forward network which can be used for classification. It has a unique feature that "under certain easily met conditions, the decision boundary implemented by PNN asymptotically approaches Baye's optimal decision surface" [33]. PNN is closely related to Parzen window probability density function (pdf) estimator. A PNN consists of several sub-networks for each of the classes, each of which is a Parzen window pdf estimator. The basic operation performed by PNN is the pdf estimation of the features of each class from the training samples provided, using Gaussian kernel. Then using Baye's decision rule, these estimated densities are classified. The structure of the PNN is shown in Fig. 4.

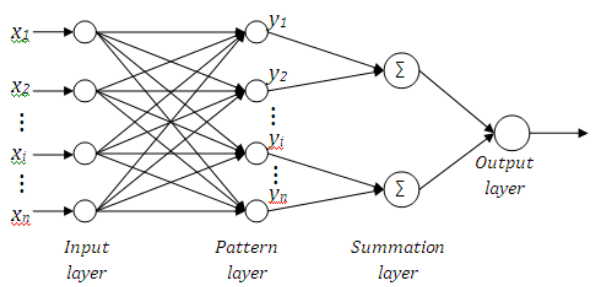

Fig. 4: Structure of Probabilistic Neural Network

The PNN consists of an input layer, pattern layer, summation layer and an output layer. The input layer consists of input units, which are simply distribution units that supply the same input values to the pattern layer. The pattern layer consists of pattern units which receives all the inputs from the input units and each of these units perform the dot product of the input pattern vector x with a weight vector w_i, $y_i = x \cdot w_i$, which actually calculates the vector distances between the input vector and weight vector. It then performs a non-linear operation on y_i before outputting its activation level to the summation layer. The non-linear operation used is $exp\left\{ {-(w_i - x)^t (w_i - x)}/{2\sigma^2} \right\}$, assuming that both x and w_i are normalized to unit length. The summation layer sums the inputs from the pattern layer for each class. The output layer, also called decision layer, which is actually a competitive layer, performs a vote, selecting the largest value in the summation layer. The associated class label is then determined.

5. Experiments and Results obtained

The sEMG signals are acquired from five healthy male subjects in the age group of 21 to 26. The subjects are instructed to do voluntary contraction in slow motion of duration 5 seconds and fast motion of duration 2 seconds, with a weight of around 2 kg on their hand. Signals for rest condition are taken without any movement of the arm for 2 seconds. Five specimens are taken for each class from each subject. The features are extracted using equations (1) and (2) and are given as inputs to the above-mentioned classifiers.

The fuzzification interface of Fuzzy Logic Classifier on receiving the inputs fuzzifies it and is sent to the rule base. The if-then rules in the rule base will generate decisions, which are fuzzified outputs, which are then defuzzified by the defuzzification interface to give crisp outputs. The PNN classifier is a kind of radial basis network suitable for classification. If spread factor or smoothing parameter (σ) is near zero, the network acts as a nearest neighbor classifier. As σ becomes larger, the designed network takes into account several nearby design vectors. The smoothing factor is chosen through experimentation. If the smoothing factor is too large, details can be lost, but if the smoothing factor is too small, the classifier may not generalize well. In this work, the spread factor is chosen to be 0.07. The features from three subjects are used for training PNN, and are tested with the data from the remaining two subjects. The desired response of the classifiers is shown in Table II. For performance evaluation, classification accuracy (CA) is calculated as

$$\%CA = \frac{\text{No. of successful classifications}}{\text{Total no. of classifications}} \times 100$$

TABLE II
Desired Response of Classifiers

Type of movement	Class Output
Rest	1
Slow contraction	2
Fast contraction	3

A comparison of the classification accuracy obtained in each subject for rest, slow and fast movements with FLC and PNNC is shown in Fig. 5. The overall classification accuracy obtained with different classifiers for each subject is shown in Table III.

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Vol. 1 Issue 5, July - 2012

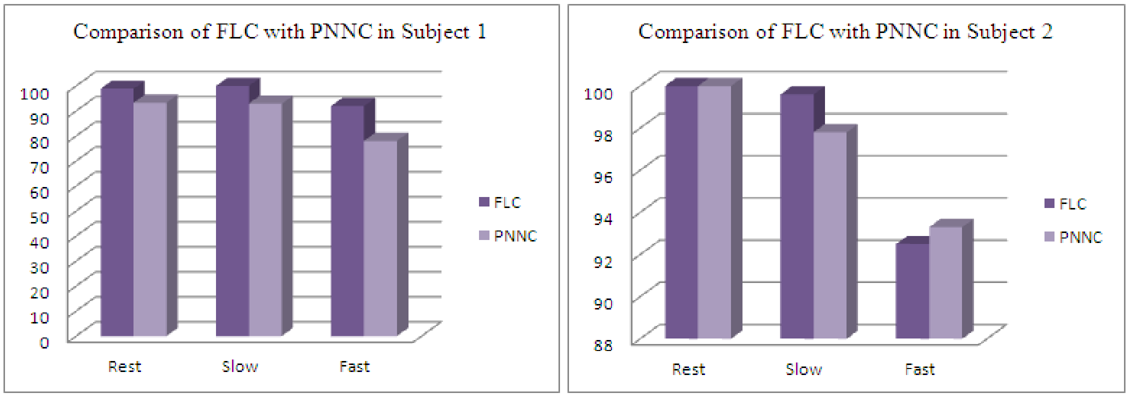

Fig. 5: Comparison of Classification accuracy of different classifiers in Subject 1 and Subject 2.

TABLE III
Classification accuracy obtained with FLC & PNNC

Subject	FLC	PNNC
Subject 1	97.2%	90.3%
Subject 2	97.4%	97%
Average % accuracy	**97.3%**	**93.6%**

6. Conclusion

An attempt to classify the different speeds of movement of a human elbow is done using two different types of classifiers viz, Fuzzy Logic, and PNN. The performance of the classifiers is examined. From Fig. 5 it is evident that Fuzzy Logic Classifier gives better accuracy when compared with Probabilistic Neural Network Classifier, with an average classification accuracy of 97.3 %. This work is conducted as a part of development of an assistive limb. Although the results obtained with two subjects are encouraging, it is decided to test the FLC with more subjects and to implement the developed Fuzzy Logic classifier in real-time for real-time classification. The classifier output obtained is to be used for driving the motor connected to the assistive limb.

References

1. Specialty Materials Handling Products Operation, Research and Development prototype for machine augmentation of human strength and endurance Hardiman I Project, General Electric Company Corporate Research and Development, May 1971.
2. Kazuo Kiguchi, Shingo Kariya, Tomohiko Niwa, Keigo Watanabe, Kiyotaka Izumi, and Toshio Fukuda, Design of an Exoskeletal Robot for Human Elbow Motion Support, *Proceedings of the 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2000, pp: 383 - 388.
3. Kazuo Kiguchi, Koya Iwami, Keigo Watanabe, and Toshio Fukuda, A Study of an EMG based Exoskeletal Robot for Human Shoulder Motion Support, *JSME International Journal, Series C*, Vol. 44, No. 4, 2001, pp: 1133 - 1141.
4. Kazuo Kiguchi, Shingo Kariya, Keigo Watanabe, Kiyotaka Izumi, and Toshio Fukuda, Fuzzy-Neuro Control of an Exoskeletal Robot for Human Elbow Motion, *Proceedings of the 2001 IEEE International Conference on Robotics and Automation*, Korea, May 2001, pp: 3668 - 3673.
5. Kazuo Kiguchi, Shingo Kariya, Keigo Watanabe, Kiyotaka Izumi, and Toshio Fukuda, 'An Exoskeletal Robot for Human Elbow Motion Support—Sensor Fusion, Adaptation, and Control', *IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics*, Vol. 31, No. 3, June 2001, pp: 353 - 361.
6. Kazuo Kiguchi, Shingo Kariya, Keigo Watanabe, and Toshio Fukuda, Application of Multiple Fuzzy-Neuro Controllers of an Exoskeletal Robot for Human Elbow Motion Support, , *Transactions on Control, Automation and Systems Engineering*, Vol. 4, No. 1, March 2002, pp: 49 - 55.
7. Kazuo Kiguchi, Takakazu Tanaka, and Toshio Fukuda, Neuro-Fuzzy Control of a Robotic Exoskeleton with EMG signals, *IEEE Transactions on Fuzzy Systems*, Vol. 12, No. 4, August 2004, pp: 287 - 299.
8. Kazuo Kiguchi, and Toshio Fukuda, Upper-limb Exoskeletons for Physically Weak Persons, *Rehabilitation Robotics*, August 2007, pp: 481 - 490.
9. R.A.R.C. Gopura and Kazuo Kiguchi, Electromyography (EMG)-signal based fuzzy-neuro control of a 3 degrees of freedom (3DO F) exoskeleton robot for human upper-limb motion assist, *Journal of Natn Scientific Foundation*, Sri Lanka, 2009 Vol. 37, No. 4, pp: 241 - 248.
10. Joel C Perry, Jacob Rosen, and Stephen Burns, Upper-Limb Powered Exoskeleton Design,

IEEE/ASME Transactions on Mechatronics, Vol. 12, no. 4, August 2007, pp: 408 – 417.

11. M H Rahman, M. Saad, J P Kenne and P S Archambault, Exoskeleton Robot for Rehabilitation of Elbow and Forearm movements, *18th Mediterranean Conference on Control and Automation*, Morrocco, June 2010, pp: 1567 – 1572.
12. Kavyan Najarian and Robert Splinter, Biomedical Signal and Image Processing, *Taylor and Francis group*.
13. J. B. Walker, B. Scroggins, M. Morse, Are paralyzed people really paralyzed? Probably not according to EMG analysis, *IEEE International conference on Engineering in Medicine and Biology Society*, 1998, pp: 1137.
14. Mahdi Khezri, and Mehran Jahed, 'A Neuro–Fuzzy Inference System for sEMG-Based Identification of Hand Motion Commands', *IEEE Transactions on Industrial Electronics*, Vol. 58, No. 5, May 2011, pp: 1952 - 1960.
15. Hui Yan, Ray P.S. Han, Yu Wang and Jieru Chi, 'Controlling a Powered Exoskeleton System via Electromyographic Signals', *Proceedings of the 2009 IEEE International Conference on Robotics and Biomimetics*, December 19 -23, 2009, pp: 349 - 353.
16. Siti A. Ahmad, Paul H Chappell, Moving Approximate Entropy aaplied to Surface Electromyographic Signals, *Biomedical Signal Processing and Control*, December 2007, Vol. 3, pp: 88 – 93.
17. K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, Classification of the Myoelectric Signal using Time-Frequency based representations, *Special Issue of medical Engineering and Physics on Intelligent Data Analysis in Electromyography and Electroneurography*, Summer 1999.
18. Wen-Juh Kang, Jiue-Rou Shiu, Cheng-Kung Cheng, Jin-Shin Lai, Hen-Wai Tsao, and Te-Son Kuo, The application of Cepstral coefficients and Maximum likelihood method in EMG pattern recognition, *IEEE transactions on Biomedical Engineering*, Vol. 42, No. 8, August 1995, pp:777 – 785.
19. Natalia M. Lopez, Fernando di Sciascio, Carlos M Soria, and Max E valentinuzzi, Robust EMG sensing system based on data fusion for myoelectric control of a robotic arm, *Biomedical Engineering Online*, February 2009.
20. Zeeshan O Kahokhar, Zhen G Xiao, and Carlo Menon, 'Surface EMG pattern recognition for real-time control of a wrist exoskeleton', *Biomedical Engineering Online*, 2010.
21. M. B. I. Reaz, M. S. Hussain and F. Mohd-Yasin, Techniques of EMG signal analysis: detection, processing, classification and applications, *Biological Procedures Online*, 2006, Vol. 8, No. 1, pp: 11-35.
22. Sundaraj, K. Biceps Activity EMG Pattern Recognition using Neural Networks, *Proceedings of the Conference on Advanced Applications of Electrical Engineering*, 2009, pp:25 – 29.
23. Francis H. Y. Chan, Yong-Sheng Yang, F. K. Lam, Yuan-Ting Zhang, and Philip A. Parker, Fuzzy EMG Classification for Prosthesis Control, *IEEE Transactions on Rehabilitation Engineering*, Vol. 8, No. 3, September 2000.
24. Abidemi Bolu Ajiboye and Richard F. ff. Weir, A Heuristic Fuzzy Logic Approach to EMG Pattern Recognition for Multifunctional Prosthesis Control, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 13, No. 3, September 2005.
25. Siti A. Ahmad, Asnor J. Ishak, Sawal Ali, Classification of Surface Electromyographic Signal Using Fuzzy Logic for Prosthesis Control Application, *2010 IEEE EMBS Conference on Biomedical Engineering & Sciences (IECBES 2010)*, Kuala Lumpur, Malaysia, 30th November - 2nd December 2010, pp: 471 - 474.
26. Carlo J. De Luca, Surface Electromyography Detection and Recording (Delsys Inc, 2002).
27. Yang YS, Lam FK, Chan FHY, Zhang YT, and Parker PA, A new fuzzy approach for pattern recognition with application to EMG classification, *International Conference on Neural Networks Proceedings*, Washington DC, USA, 3-6 June 1996, v. 2, p. 1109-1114.
28. Farid Mobasser and Keyvan Hashtrudi-Zaad, A Method for Online Estimation of Human Arm Dynamics, *Proceedings of the 28th IEEE EMBS Annual International Conference New York City*, USA, Aug 30-Sept 3, 2006, pp: 2412 – 2416.
29. Liyu Cai, Zhizhong Wang, Haihong Zhang, An EMG Classification Method Based on Wavelet Transform, *Proceedings of the First Joint BMES/EMBS Conference Serving Humanity, Advancing Technology*, Oct 13-16, '99, Atlanta, USA, pp:565.
30. M.W.JIANG, R.C.WANG, J.Z.WANG, D.W.JIN, A Method of Recognizing Finger Motion Using Wavelet Transform of Surface EMG Signal, *Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai*, China, September 1-4, 2005, pp: 2672 – 2674.
31. S. N. Sivanandan, S. Sumathi, S. N. Deepa, Introduction to Fuzzy logic using Matlab (Springer, 2007).
32. Fuzzy Logic Toolbox User's Guide (The Mathworks Inc, 2009).
33. Donald F Specht, Probabilistic Neural Networks, *Neural Networks*, Vol. 3, 1990, pp: 109-118.