ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 5, May 2017

Approach for Classification of Neuromuscular Disorder using EMG Signals

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ABSTRACT: The electromyography (EMG) is an invaluable measurement for the purpose ofassessing muscular activities. In this paper, a new method for classification of EMGsignals is proposed. The proposed method is based on empirical mode decomposition (EMD) process. In this method, features namely mean, standard deviation, variance and Entropy of the intrinsic mode functions (IMFs) generated by EMD process is used to classification of EMGsignals. The features measured from the IMFs have been used as a feature for artificial neural network for classification of EMG signals. The statistical features of IMFs have provided better classification performance. The proposed approach basedon EMD is better other methods in the literature for classification of EMGsignals.

KEYWORDS: Cascaded Kernel Learning Machine (CKLM), Electromyography (EMG), Fractal Dimension (FD) , Generalized Discriminant Analysis (GDA), Relevance Vector Machines (RVM), Intrinsic Mode Functions (IMFs).

I. INTRODUCTION

Electromyography (EMG) is the process for studying electrical activity produced by muscles. Electrical activities produced by the muscles are collected by using intramuscular electrodes. EMG signals include information about the working and status of muscular system, which makes EMG signal a valuable tool for the diagnosis of neuromuscular disorder such as myopathy and neuropathy [1]. Myopathy is a non-progressive muscular disease, which causes abnormalities, inflammatory, standing, holding things, swallowing, and metabolic disorders [2]. Neuropathy is a neuromuscular rapid progressive disorder, which may affect the working of nerves system in the body. It causes the gradual degeneration of neurons and affects the working of upper and lower motor neurons. Improper functioning of nerves is referred as neuropathy and symptoms includes muscle cramps, weakness, burning, pain, muscle twitching, numbness of the feet or hands [3]. Diagnosis of neuromuscular disorder by visual analysis of EMG signals is difficult, time consuming and may be inaccurate. Due to this, a properanalysis using signals processing may improve the understanding and diagnosis performance of neural diseases. Automatic diagnostic systems can be helpful for the clinicians to detect neuromuscular diseases as well as abnormalities in the neuromuscular system.

Multiscale based features estimated at various scales like instantaneous amplitude, instantaneous frequency and instantaneous phase have been used as input to K-nearest neighbor (KNN), self-organizing map (SOM) and support vector machine (SVM). These classifiers are used for classification of normal and abnormal EMG signals [4]. A combination of mutual information based feature combined with SVM technique has been developed to classify EMG signal [5]. Pattern recognition based strategy has been used for classification of EMG signals [6]. Forearm surface EMG signal has been used for real time control of a robotic arm. Signals produced by muscles in different gestures were recorded which help in controlling prosthetic device with the use of SVM classifier for classification of EMG signals [7]. Real time EMG classification of user-selected intentional forearm movement has been demonstrated for multifunction prosthesis control [8].Cascaded kernel learning machine (CKLM) combined with generalized discriminant analysis (GDA) and support vector machine (SVM) has been used to classify EMG signals [9]. The decomposition approach with fuzzy logic has been used for classification of intramuscular EMG signals [10].

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The relevance vector machines (RVM) and fractal dimension (FD) have been used for classification of EMG signals [11]. Hidden Markov model in combination with multivariate autoregressive model (HMM-mAR) based features have been used for classification of EMG signals [12]. EMG signals derived from the neuromuscular system is useful for human-robot interface [13].

Pre-processing, MUAP clustering and detection, feature extraction with radial basis function based artificial neural networks and decision tree have been used for classification of normal, neuropathic and myopathic EMG signals. [14]. Intelligent computing system (ICS) and knowledge-based system (KBS) have been used with ANN for classification of neuromuscular diseases [15]. Euclidean distance measure (EDM), weighted distance measure (WDM) and modified maximum likelihood method (MMLM) have been used to discriminate the motions of neck and shoulder using EMG signals [16]. Improved back propagation network (IBPN), radial basis network (RBN) and learning vector quantization network (LVQN) have been examined for classification of healthy with myopathic and neuropathic disorders [17]. The nonlinear features are used as an input features for classification of normal, myopathy and neuropathy EMG signals [18].

In this paper, a new method for nonlinear and non-stationary EMG signal analysis is proposed. The method is based on features computation of IMFs extracted from EMG signal by using EMD process. The rest of the paper is structured as follows: In section 2, EMG signal dataset, the methodology based on EMD and features have been described. Section 3 provides the simulation results. Finally, some concluding remarks are given in section 4.

II. METHODOLOGY

A. *DATASET:*

The dataset consists signal of a healthy, a neuropathic and a myopathic patient [19]. To collect EMG data from each subject, a 25 mm needle electrode was used into the tibialis anterior muscle. The location of the needle electrode was changed again and again until motor unit action potentials with a brisk rise time were identified. During the mentioned period of time, the data which was digitized at 50 kHz sam-plingrate, was collected for several seconds and then the patients were asked to relax and needle electrodes were removed. The sampling rate was achieved using a high pass filter and a low-pass filter of sampling rate 20 Hz and 5 kHz respectively. In this work, 51 subsets of healthy EMG (H) signal, 111 subsets of myopathy EMG signal (M), and 148 subsets of neuropathy EMG signal (N) with each subset of 1000 samples are used for analysis of EMG signals. Fig. 2 shows EMG signals obtained from the dataset.

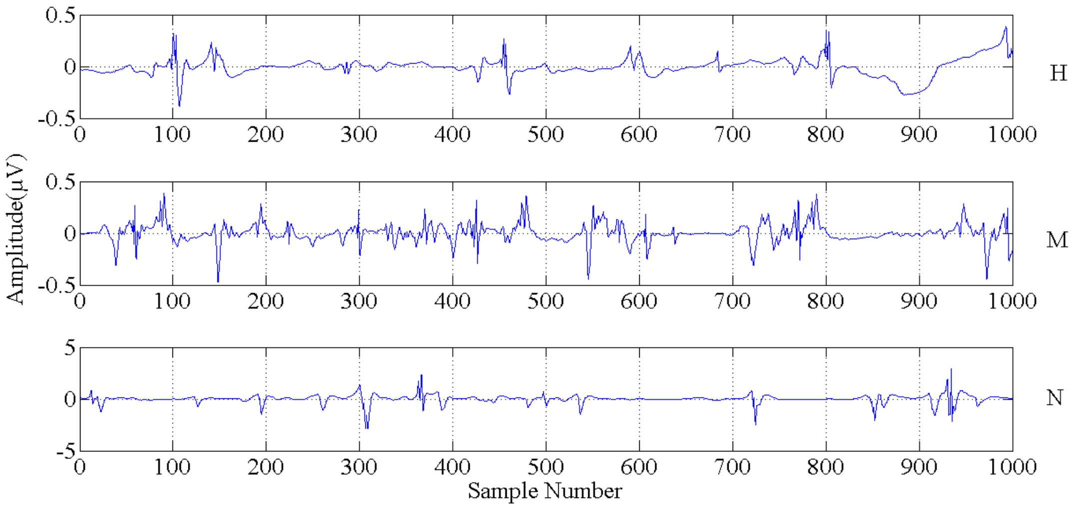

Fig.1 An example of EMG signals from healthy, myopathy and neuropathy EMG signals.

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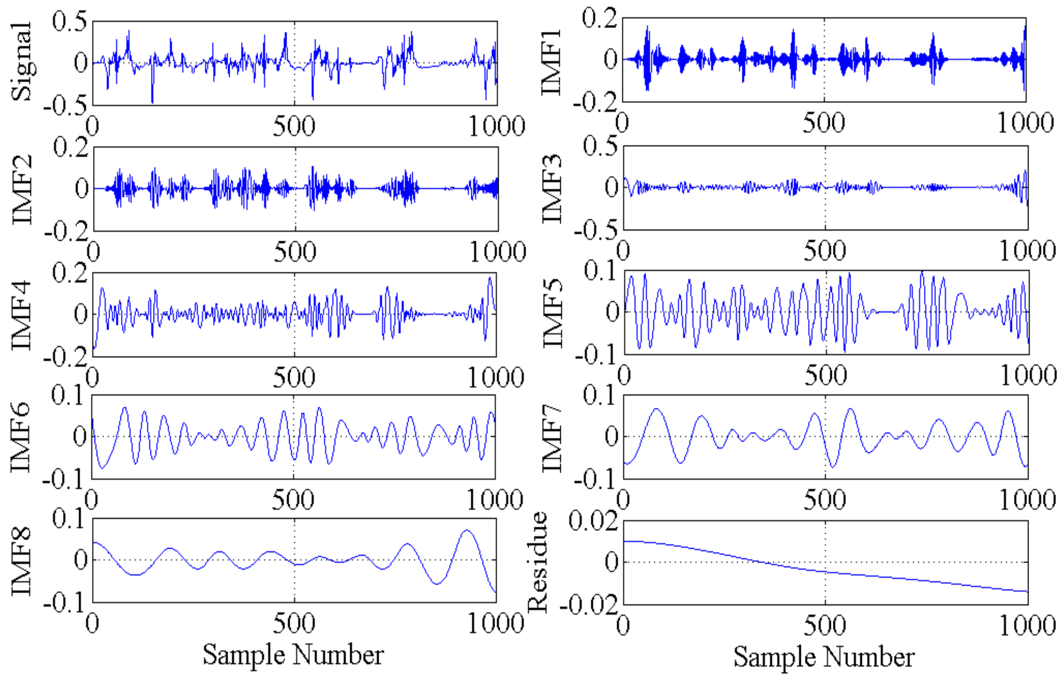
B. *Empirical mode decomposition:*

Empirical mode decomposition is a self adaptive analysis approach which decomposes non-stationary EMG signal into several intrinsic mode functions (IMFs). EMD does not employ an external basis function for decomposition. EMD has a large number of applications such as audio processing, biomedical, denoising, image processing, fault detection etc. IMF must satisfy two basic conditions [20-21]. Firstly, the number of extrema and number of zero crossing must be equal or differ by at most one. Secondly, the mean value of upper and lower envelope is zero.

- Find the number of extrema i.e. local maxima and local minima of the real valued signal s(t).
- Now using cubic spline interpolation, get the upper envelope emax(t) and the lower envelope emin(t) .
- Find the local mean m(t) = {emax(t) + emin(t)}/2 .
- Now subtract the mean from the original signal to get c(t).
- If the resultant satisfies the IMF conditions, it will be the first IMF, else repeat first 3 steps with the resultant signal.

where, M, $c_{m}(t)$, and $r_{M}(t)$ denote number of IMF, m^{th} IMF and final residue respectively. Recently EMD has been used for analysis and classification of physiological signal [22-24]. IMFs generated by EMD process on healthy, myopathy and neuropathy EMG signal are shown in Fig. 2.



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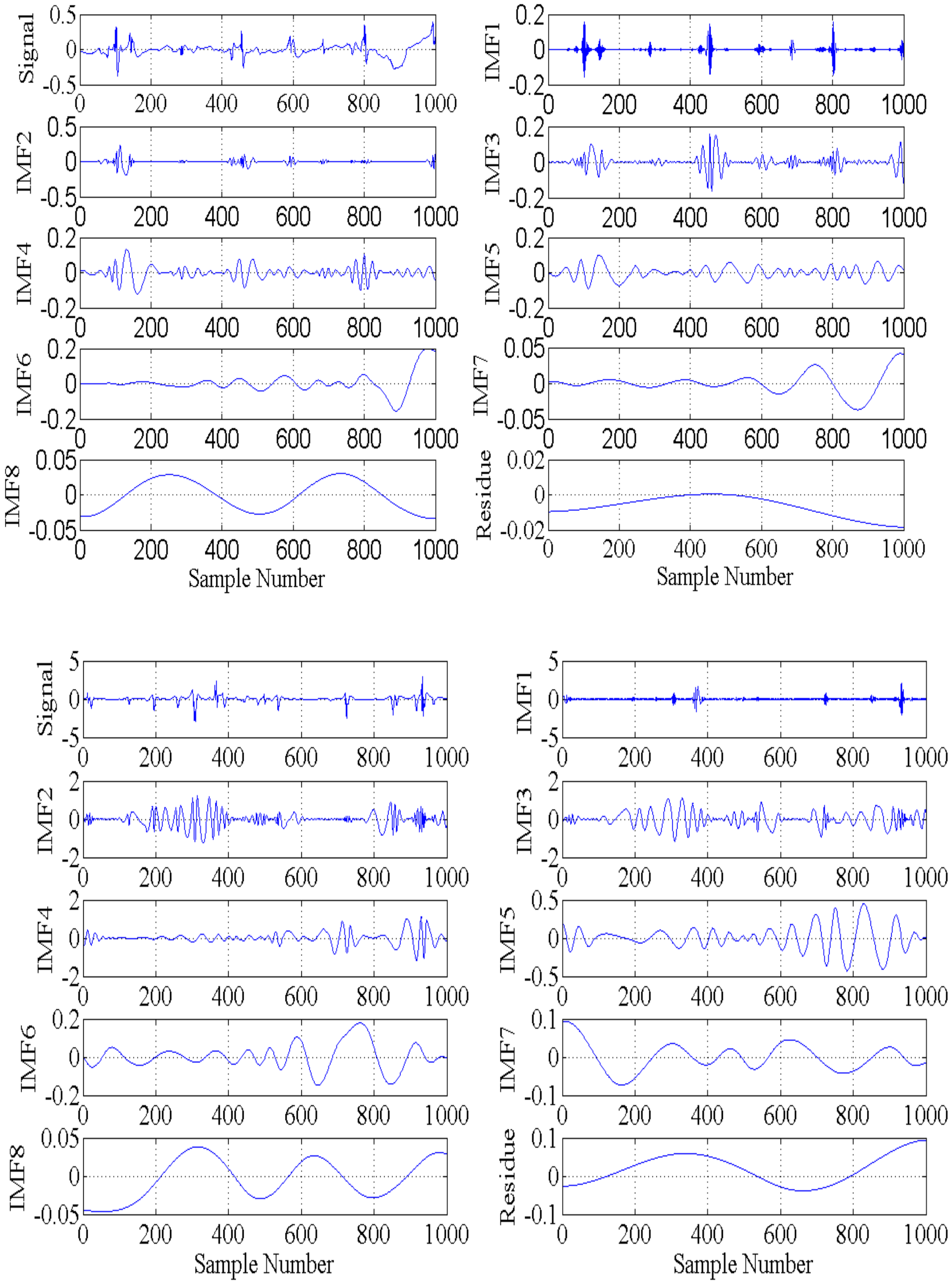

Fig. 2 EMD of healthy, myopathy and neuropathy EMG signals.

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C. *Features extracted from IMFs:*

The statistical features are extracted from IMFs of EMG signals. It can be express as:

Mean: $\mu = \frac{\sum_{1=1}^{N} x_i}{N}$

Standard Deviation: $\sigma = \sqrt{\frac{\sum_{1=1}^{N} (x_i - \mu)^2}{N}}$

Variance: $\sigma = \frac{\sum_{1=1}^{N} (x_i - \mu)^2}{N}$

Entropy: $H(x) = \sum_{i=1}^{L} p_i \log p_i$

D. *Classifier:*

An Artificial Neural Network is a powerful and reliable tool to emulate the complexity of the system with high accuracy and its ability to show linear andnon-linear analogy in input and output data. The information is stored in its processing units by collecting it from an external source and transferred to itsadjacent layers by using transfer functions and connection parameters.Theback propagation (BP) neural network is a type of artificial neural networkwhich has wide applications in pattern recognition and signal processing[25-26]. It is a multi-layer architecture which consists of an input layer, one or morehidden layers and an output layer. The BP neural network is based on errorbackpropagation algorithm. The information is fed to the input layer througha source. The input layer is connected to the hidden layer with weights whichis further connected to output layer with weights. The output layer gives a desired output. If desired output and the actual output contradict then error iscalculated and weights are updated through back propagation algorithm. The process is repeated multiple times until the error at the output is admissible.

III. **RESULTS AND DISCUSSION**

As EMD decomposes EMG signal into narrow-band AM-FM components (IMFs). Features of the IMFs, which has been used as an input to classifier for classification of healthy, myopathy and neuropathy EMG signals. In order to illustrate the effectiveness of features of IMF for time series analysis, the method has been applied to EMG signals. Features of IMFs are computed for classification of myopathy, neuropathy and healthy EMG signals.

Work	Approach Type	Accuracy (%)
Guler et al.(2005) [27]	Feature-based	85.4(3-class)
Katsis et al.(2007)[28]	Feature-based	88.7(3-class)
Istenic et al.(2010)[29]	Multiscale entropy, WT	80.5(2-class) 69.4 (3-class)
Kocer et al.(2010)[30]	AR coefficients	90.0 (3-class)
AnjanaGoen (2014)[31]	Feature-based	91.2(3-class)
Proposed Method	EMD based features	94.0 (3-class)

TABLE I. Comparison of our proposed method with other reported work in the literature

IV. **CONCLUSION**

The We explored the ability of features measurement of intrinsic mode functions for classification of myopathy, neuropathy from healthy EMG signals. The proposed method requires selection of input parameters in the algorithm for neural network classifiers. Therefore, by choosing the parameters which provides better classification, the proposed method may be used as agood dynamical signature to characterize the myopathy and neuropathy in EMG signals. It is

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illustrate from simulation results that the feature of IMFs is statistically significant for classification of healthy, myopathy and neuropathy EMG signals and it also increases the classification efficiency.

REFERENCES

[1] Hu X,Wang Z, Ren X "Classification of surface EMG signal using relative wavelet packet energy". Computer Methods and Programs in Biomedicine 79(3): 189-195,2005.
[2] Rasheed S, Stashuk D, KamelM"A software package for interactive motor unit potential classification using fuzzy k-NN classifier". Computer Methods and Programs in Biomedicine 89(1): 56-71,2008.
[3] Arabadzhiev TI, Dimitrov GV, Dimitrov AG, Chakarov VE, Dimitrova NA"Factors affecting the turns analysis of the interference EMG signal''. Biomedical Signal Processing and Control 3(2): 145-153, 2008.
[4] Christodoulou CI, Kaplanis PA, Murray V, Pattichis MS, Pattichis CS, Kyriakides T " Multi-scale AM-FM analysis for the classification of surface Electromyographic signals". Biomedical Signal Processing and Control 7(3): 265- 269,2012.
[5] Yan Z, Wang Z, XieH " The application of mutual information-based feature selection and fuzzy LS-SVM-based classifier in motion classification", Computer Methods and Programs in Biomedicine, 90(3): 275-284,2008.
[6] Huang H, Kuiken TA, and Lipschutz RD" A strategy for identifying locomotion modes using surface electromyography", IEEE Transactions on Biomedical Engineering, 56(1): 65-73, 2009.
[7] Shenoy P, Miller KJ, Crawford B, Rao RPN" Online electromyography control of a robotic arm". IEEE Transactions on Biomedical Engineering, 55(3): 1128-1135, 2008.
[8] Momen K, Krishnan S, Chau T"Real-time classification of forearm elec-tromyographic signals corresponding to user-selected intentional movements for multifunction prosthesis control".IEEE Transactions on Neural Systems and Rehabilitation Engineering 15(4):535-542,2007.
[9] Liu Y, Huang H, Weng C "Recognition of electromyographic signals using cascaded kernel learning machine". IEEE/ASME Transactions on Mechatronics, 12(3): 253-264,2007.
[10] Erim Z, Lin W," Decomposition of intramuscular EMG signals using a heuristic fuzzy expert system". IEEE Transactions on Biomedical Engineering, 55(9): 2180-2189, 2008.
[11] Lima CAM, Coelho ALV, Madeo RCB, Peres SM "Classification of electromyography signals using relevance vector machines and fractal dimension". Neural Computing and Applications pp 1-14 DOI 10.1007/s00521- 015-1953-5, 2015.
[12] Chiang J, Jane Wang Z, McKeown MJ" A hidden markov, multivariate autoregressive network framework for analysis of surface EMG". IEEE Trans-actions on Biomedical Engineering 56(8): 4069-4081,2008.
[13] Chen Y, Zhao X, Han J "Hierarchical projection regression for online estimation of elbow joint angle using EMG signals Neural" Computing and Applications September (23) Issue 3: 1129-1138 ,2013.
[14] Katsisa CD, Exarchosa TP, Papaloukas C, Goletsis Y, Fotiadise DI, Sarmasg I "A two-stage method for MUAP classification based on EMGdecom-position". Computers in Biology and Medicine 37(9): 1232-1240, 2007.
[15] Pandey B, Mishra RB "An integrated intelligent computing model for the interpretation of EMG based neuromuscular diseases". Expert Systems with Applications 36(5): 9201-9213,2009.
[16] Kang WJ, Cheng CK, Lai JS, Shiu JR, KuoTS " A comparative analysis of various EMG pattern recognition methods". Medical Engineering and Physics 18(5): 390-395,1996.
[17] Abel EW, Zacharia PC, Forster A, Farrow TL " Neural network analysis of the EMG interference pattern", Medical Engineering and Physics, 18(1): 12-l7,1996.
[18] Acharya UR, Ng EYK, Swapna G, Michelle YSL" Classification of normal, neuropathic, and myopathicelectromyograph signals using nonlinear dynamics method". Journal of Medical Imaging and Health Informatics 1(4): 375-380, 2011.
[19] http://physionet.org/physiobank/database/emgdb/
[20] Huang NE " The Empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis". Proc. Roy. Soc.London A, 454: 903-995, 1998.
[21] Flandrin P, Rilling G, GoncalvesP" Empirical mode decomposition as a filter bank". IEEE Signal Processing Letters 11: 112-114,2004.
[22] Hassan AR, Haque MA, "Computer-aided obstructive sleep apnea identification using statistical features in the EMD domain and extreme learning machine", Biomedical Physics and Engineering Express, 2(3):256-266, 2016.
[23] Hassan AR, Bhuiyan MIH, "Automatic sleep scoring using statistical features in the EMD domain and ensemble methods"Biocybernetics and Bio-medical Engineering, 36(1): 248-255,2016.
[24] Hassan AR (2015)," Automatic screening of obstructive sleepapnea from single-lead electrocardiogram", International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), 1-6,2015.
[25] B. Yegnanarayana, Artificial Neural Networks, Prentice-Hallof India, New Delhi, 1999.
[26] D. J. C. MacKay, Bayesian interpolation, Neural Computation 4 415-447,1991.
[27] N. F. Güler and S. Koçer, "Classification of EMG signals using PCA and FFT," Journal of Medical Systems, vol. 29, no. 3, pp. 241-250, June 2005.
[28] C. D. Katsis, T. P. Exarchos, C. Papaloukas, Y. Goletsis, D. I. Fotiadis, and I. Sarmas, "A two-stage method for MUAP classification based on EMG de-composition," Computers in Biology and Medicine, vol. 37, no. 9, pp. 1232-1240, 2007.
[29] R. Istenic, P. A. Kaplanis, C. S. Pattichis, and D. Zazula, "Multiscaleentropyba-sedapproach to automated surface EMG classification of neuromuscular dis-orders," Med BiolEngComput. vol. 48, no. 8, pp. 773-781, August 2010.
[30] S. Kocer, "Classification of EMG signals using neuro-fuzzy system and diagnosis of neuromuscular diseases," Journal of Medical Systems, vol. 34, pp. 321-329, 2010.
[31] AnjanaGoen" Classification of EMG Signals for Assessment of Neuromuscular Disorders "International Journal of Electronics and Electrical Engineering Vol. 2, No. 3, September, 2014.