An Intelligent Method for Classification of Normal and Aggressive Actions from Electromyography Signals

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***Abstract*— In this paper an intelligent method called adaptive neuro-fuzzy inference system (ANFIS) is proposed for discriminating normal actions from aggressive actions using the features extracted from electromyography (EMG) signals. Classification of normal and aggressive actions are essential for diseases and prosthetic arm controls. But accurate classification of physical actions are sometimes not possible using raw EMG signals. To enhance the classification accuracy feature extraction is an essential criterion. Hence in this work wavelet analysis is used for feature extraction from EMG signals to provide a suitable pattern to the ANFIS based classifier. The EMG signals are decomposed using DB-4 wavelet up to level 5 and approximate coefficients are extracted. Approximate coefficients from the signals are taken as input to the ANFIS module to classify the physical actions. The proposed method is validated using various test cases and it is observed that accuracy of the proposed method is up to 98% from all the tested cases.**

***Keywords*— Artificial Intelligence, ANFIS, Electromyography (EMG),Signal Processing, Wavelet analysis, Physical Action Classification.**

I. *INTRODUCTION*

The Electromyogram (EMG) signals can be analyzed to detect medical abnormalities, activation level, and recruitment order. It also used to analyze the biomechanics of human or animal movement. EMG is used as a diagnostics tool for identifying neuromuscular diseases, assessing low-back pain, kinesiology, and disorders of motor control. EMG signals are also used as a control signal for prosthetic devices such as prosthetic hands, arms, and lower limbs. Various approaches have been suggested by different people to analyze EMG signal. Empirical mode decomposition (EMD) is proposed for analysis of amyotrophic lateral sclerosis (ALS) using EMG signals in [1]. Simple classifier and continuous control scheme based on EMG for an electric-powered wheelchair suggested in [2]. Classification of single channel EMG with Ensemble-Empirical-Mode-Decomposition (EEMD) based on independent component analysis (ICA) for diagnosing neuromuscular disorders proposed and validated with EMG clinical database in [3]. High dimensional biomedical signal classification based on multiscale two directional two-dimensional principal component analysis suggested in [4]. An algorithm used expert rules and time-frequency techniques to find and classify long-term (24h) EMG recordings for muscular spasms analysis is proposed in [5].

Electronic sleep stage classifiers based on VLSI design methodology where classification algorithm uses one EMG and two EEG signals as inputs in order to detect REM (Rapid Eye Movement) sleep is proposed in [6]. A novel post processing algorithm, aiming to detect and remove misclassifications of a pattern recognition system of surface EMG signals for upper limb prosthesis control is proposed in [7]. Neuromuscular disease classification from dominant motor unit action potential of EMG signal based on discrete wavelet transform (DWT) features suggested in [8]. Surface EMG based hand movement classification and movement error rate evolution of machine learning methods is proposed in [9]. Using surface EMG signal and machine learning methods, a supporting diagnosis of amyotrophic lateral sclerosis (ALS) is suggested in [10]. A hand movement recognition system based on multichannel electromyographic activation trajectories feature extraction and classification is proposed in [11]. Motor unit action potentials (MUAPs) classification using EMG signal based on multi-classifier approach for diagnosis of neuromuscular disorders proposed is proposed in [12]. One class support vector machine used for automated bio-signal quality analysis for EMG is proposed in [13].

Using recorded electroencephalogram (EEG), EMG and electrooculogram (EOG) signals based on various entropy and complexity measures for detection and identification of driving fatigue is proposed in [14]. Hand manipulation identification using surface EMG based on nonlinear feature extraction and classification is suggested in [15]. Simultaneous movements classification and pattern recognition using surface EMG (sEMG) is proposed in [16]. EMG patterns recognition classification scheme for robustness enhancement is developed based on boosting and random forest classifiers in [17]. Classification of surface EMG is done by the help of many techniques like KNN, LDA and SVM is described in [18]. A linear regression model to estimate knee joint moment from electromyography (EMG)

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and joint angle is proposed in [19]. Feature extraction from EMG can be done by using signal analysis tools like wavelet are suggested in [20] and higher order spectra are suggested in [21]. In [22] a feature extraction method is proposed for motion recognition based on fuzzy mutual-information. It estimates the required mutual information using a novel approach based on fuzzy membership function.

After studying various literature available it is observed there is still a scope to enhance the performance of the classification of physical actions. In this paper, an ANFIS based classification scheme is proposed. The manuscript is arranged as follows - second section contains a brief description about ANFIS, third section consist of proposed method for physical action classification, fourth section consist of the result and discussion of the method and fifth section of the manuscript contains the conclusion.

II. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS are generally artificial neural network (ANN) work in combination with Takagi-Sugeno fuzzy inference system (FIS). It has features of both ANN and fuzzy system. The neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map. The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure (usually defined by the sum of the squared difference between actual and desired outputs). ANFIS uses either back propagation or a combination of least squares estimation and back-propagation for membership function parameter estimation.

It takes input/output data and build a fuzzy inference model/system that approximate the data. This type of model consists of a number of membership functions and rules with adjustable parameters similarly to that of neural networks. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. ANFIS is used in this work to classify normal action and aggressive action which will be discussed in next section.

III. PROPOSED ANFIS BASED METHOD

Proposed ANFIS based method consists of different stages which are described below. The flow diagram of the proposed ANFIS based method is described in Fig.1.

A. Signal Processing and Feature Extraction

The EMG signals used to test the proposed ANFIS based method are obtained from UCI machine learning repository [23]. Total data used for designing the proposed method are taken from four subjects each with ten normal and ten aggressive action. From all data obtained 70% of the data are used for designing the training module and 30% data are used for testing. In this work EMG signals are analyzed with DB-4 wavelet and decomposed up to 5 levels of detail and approximate coefficients. The approximate coefficients at level 5 are selected as input feature. All the feature extraction works are done using MATLAB software. All the algorithm design works are done using MATLAB 2009a on a 4GB RAM, i7 intel processor.

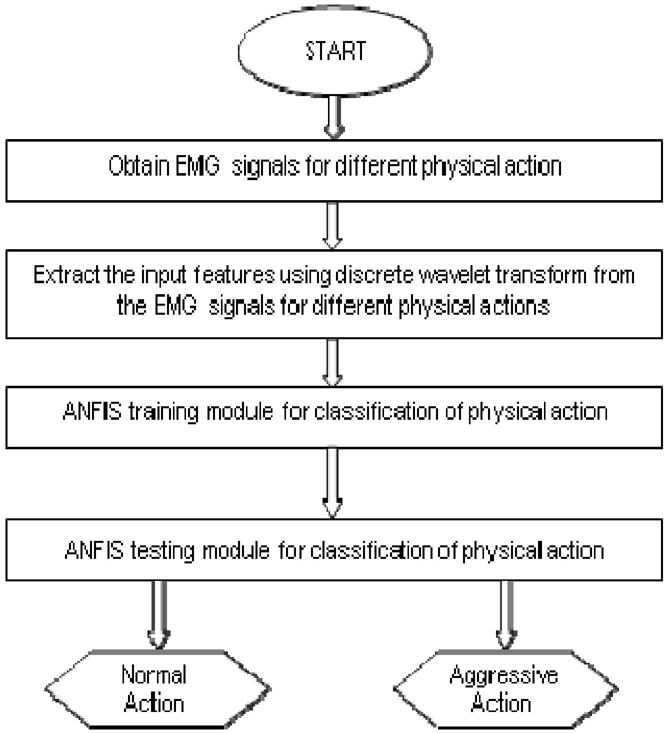

Fig.1 Flow diagram of the proposed ANFIS based technique.

The EMG signal for normal action and aggressive action before and after feature extraction are shown in Fig.2. Fig.2 (a) shows normal action EMG signals before feature extraction of feature using discrete wavelet transform. Fig.2 (b) shows normal action EMG signals after feature extraction using discrete wavelet transform. Fig.2 (c) shows aggressive action EMG signals before feature extraction using discrete

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wavelet transform. Fig.2 (d) shows aggressive action EMG signals after feature extraction using discrete wavelet transform.

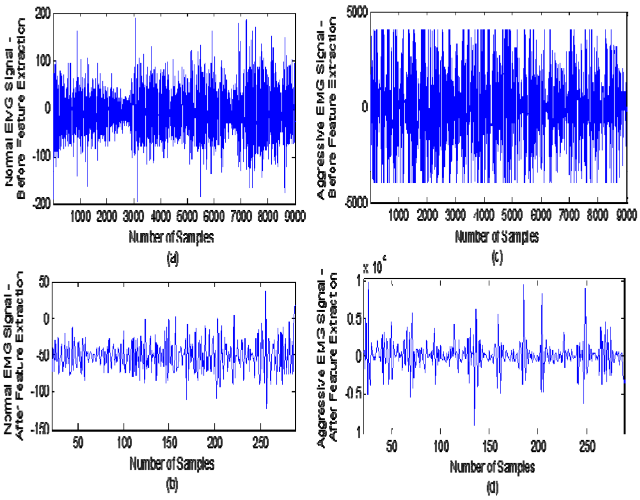

Fig.2 EMG signal recorded for normal action and aggressive action before and after feature extraction.

B. Proposed ANFIS based Method for Physical Action Classification

The features extracted from the EMG signals using wavelets are given as input to ANFIS based network for classification of normal and aggressive actions. The ANFIS based network have 2 output i.e. normal action output and aggressive action output. ANFIS is chosen for classification based on the classification studies carried out in [24]. The corresponding target values for the inputs are set to [1] for normal action and [2] for aggressive action. The network is then trained with various parameters such as triangular member function as input member function, linear membership function as output membership function, back propagation neural network etc. The training output of the proposed ANFIS based method is shown in Fig.3. After designing the ANFIS based training network it is tested with various EMG signals for performance evaluation of the physical action classification module. Test results of proposed method has been discussed in the next section.

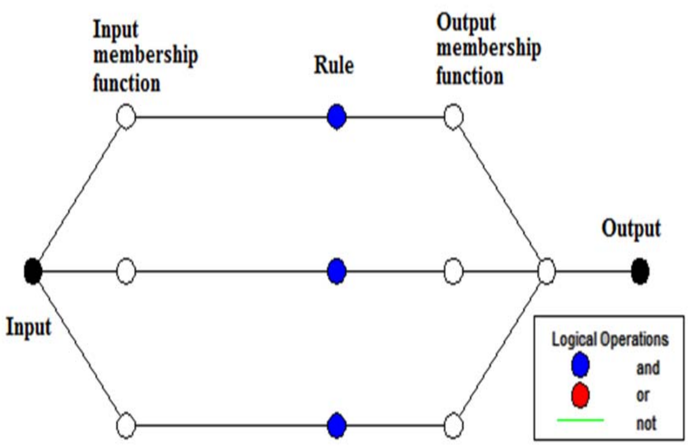

Fig.3 Training ANFIS network.

IV. Test Results

The proposed ANFIS based method is tested with EMG signals to check the efficiency of the physical action classification method. Performance of the method is evaluated in terms of % accuracy, true acceptance rate and false acceptance rate. The results for accuracy of the classification of ANFIS based method is discussed below.

A. Performance without feature extraction

Performance of the ANFIS based method is evaluated without feature extraction. The results of the proposed ANFIS based methods without feature extraction are shown in Table.1. From the Table 1 it can be observed that the maximum accuracy in classification is up to 90% without feature extraction. False acceptance rate of the method is up to 10% without using feature extraction.

Table 1. Accuracy in classification without using discrete wavelet transform

Parameters	Values
Time for Training (s)	57.55
Time for Testing (s)	0.5
Accuracy (%)	90
False acceptance (%)	10
Error	0.0001
Neural network used	Back-propagation
Function used	Least Square
Epochs	30
Fuzzy Inference System Used	Grid Partition
Input Membership Function	Triangular
Output Membership Function	Linear

B. Performance with feature extraction

The performance of the ANFIS based method is also evaluated using features extracted with discrete wavelet transform. Some of the output of the ANFIS based method is shown in Fig.4. Number of test data are shown in x-axis and the output of classifiers is shown in the y-axis.

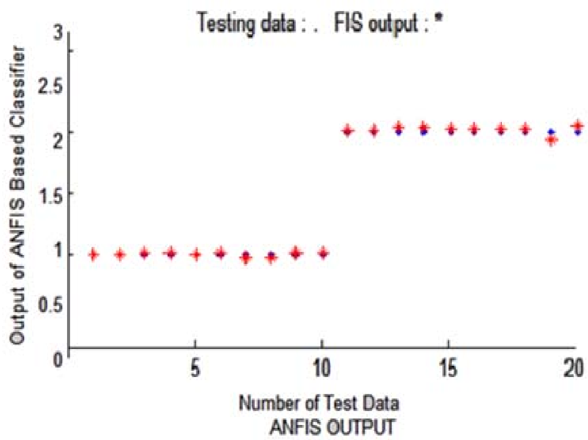

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Fig.4 Output of ANFIS based method.

Test data consist of 10 normal action data and 10 aggressive action data. Blue stars represent the actual target values and the red stars presents the output values. First 10 data are for normal action, so the output is '1' from 1-10. Data from 11-20 are for aggressive action, so the output is '2' from 11-21. From Fig.4 it can be observed that ANFIS based method classifies the physical actions correctly. Test results of the ANFIS based methods are shown in Table 2. Accuracy in classification of physical actions increases after feature extraction with discrete wavelet transform. From Table 2 it can be observed that ANFIS based method have maximum accuracy up to 98%.

Table 2. Accuracy of the ANFIS based method using feature extraction

Parameters	Values
Time for Training (s)	3.5
Time for Testing (s)	0.01
Accuracy (%)	98%
False acceptance (%)	2
Error	0.0001
Neural network used	Back-propagation
Function used	Least square
Epochs	10
Fuzzy Inference System Used	Grid Partition
Input Membership Function	Triangular
Output Membership Function	Linear

C. Comparison with other schemes

Various classifications schemes for EMG signals has been carried out using different classification methods using different data sets and different feature extraction techniques. Comparison of some of the methods along with the proposed method are shown in Table 3. From Table 3 it can be observed that classification accuracy of the methods are lower than the proposed method. Hence proposed method can be used efficiently to for discrimination of normal actions from the aggressive action.

Table 3. Comparison of different methods

Schemes	Accuracy	Feature Extraction	Classification Method
Theodoridis et al [23]	90%	Not mentioned	Distance Classifier
Wang et al [25]	93.75%	Optimal Wavelet Packet	Davies-Bouldin criterion
Zhu et al [26]	90%	Wavelet transform	RBF
Proposed Method	98%	Discrete wavelet transform	ANFIS

V. CONCLUSION

In this work a DWT and ANFIS based method is proposed for discrimination of normal action from the aggressive action. Features extracted using discrete wavelet transform with DB-4 wavelet are given as input to the ANFIS based classifier to distinguish between normal action and aggressive action. Accuracy of the proposed ANFIS based method has been found to be 98%. Test results shows that the physical action classification using ANFIS method is promising and can be used efficiently.

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