A hybrid method for classification of physical action using discrete wavelet transform and artificial neural network

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Abstract: This paper proposes a method for physical action classification based on wavelet analysis and artificial neural network (ANN) from electromyography (EMG) signals. The physical action includes the person's normal action as well as aggressive action. During various types of physical actions, the EMG signals are recorded. Discrete wavelet transforms (DWT) with DB-4 wavelet is used for feature extraction from recorded EMG signals. Extracted features are given as input to the ANN-based classifier to distinguish between normal actions and aggressive actions. The hybrid approach using combination of ANN and wavelet shows significance increase in level of accuracy in classifying the physical action. Hence proposed method can be used to discriminate the physical actions ultimately helps in identifying persons mental state.

Keywords: EMG; electromyography; wavelet analysis; DWT; discrete wavelet transform; ANN; artificial neural network; classification.

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1 Introduction

Electromyography (EMG) is a clinical investigative process that diagnosed the healthiness of muscles and the motor neurons, the nerve cells by which muscles controlled. The motor nerve cells communicate with muscles in the form of electrical signals which is the control signal of muscles. Electrodes are put on or into the muscles to transmit or acquired the electrical signals. The signals acquired from muscles called as electromyogram and the complete electroclinical process of muscles diagnosis is called electromyography. EMG signals can be investigated to distinguish biomechanics of muscles movement or activation level, abnormalities and movement behavioural of human or animal. In this investigation electrical potential of EMG signal generated from muscles has a massive impact. Several types of advance investigation process and it applications based on EMG signal have been described by researchers, some of them mentioned below.

An electromyograph detects the electrical potential generated by muscle cells when these cells are electrically or neurologically activated. There are two kinds of EMG in widespread use: surface EMG and intramuscular (needle and fine-wire) EMG where surface electrodes are used to recorder or monitor the general activity of muscle activation by non-invasive process. On the other hand, intramuscular EMG is an invasive EMG signal acquisition process. EMG signals are used in many clinical and biomedical applications (Merletti and Parker, 2004). The signals can be analysed to detect medical abnormalities, activation level, recruitment order or to analyse 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. Classification of surface EMG is done by the help of many techniques like KNN, LDA and SVM (Murugappan, 2011; Oskoei and Hu, 2008). Theodoridis et al. (2009) suggested a rigorous investigation on the synergy of mechanical attributes to engineer tactics for measuring human activity in terms of forces. It provides independency and discrimination clarity of action recognition using linear and non-linear classification methodologies from data mining and evolutionary computation. Sun et al. (2013) suggested a linear regression model to estimate knee joint moment from EMG and joint angle.

For better performance of the classification, feature selection is an important task as suggested by Phinyomark et al. (2009) Feature extraction from EMG is done by using signal analysis tools like wavelet as suggested by Zhu (2008), Wang et al. (2006) and Khushaba et al. (2011) and higher order spectra as suggested by Sezgin (2012).

Li et al. (2005) suggested a fuzzy wavelet packet (WP) based feature extraction method for the classification of high-dimensional biomedical data such as magnetic resonance spectra. Kwak (2012) suggested a feature extraction method for motion recognition based on fuzzy mutual-information. It estimates the required mutual information using a novel approach based on fuzzy membership function. By using the better feature and classification methods, signal can have more accuracy in classification. Al-Assaf (2006) suggested a dynamic method to simultaneously detect and classify surface myocardial signals. Dynamic cumulative sum of local generalised likelihood ratios using wavelet decomposition of the myoelectric signal is used for online detection. Multi-resolution wavelet analysis and autoregressive modelling is used to extract signal features while polynomial classifiers are used for pattern modelling and matching.

After studying various literatures available it is observed there is still a scope to enhance the performance of the classification of physical actions. In this work an EMG-driven model for classification of physical actions is designed using wavelet analysis and ANN. The EMG signals are processed using discrete wavelet transform (DWT) to obtain suitable input features for pattern classification. The input features are then given as input to the ANN classifier for physical action classification. The detail procedure of the proposed method has been described in the sections below.

2 Tools and techniques

In this work discrete wavelet transform and artificial neural network (ANN) techniques has been used to carry out the work. DWT has been used to extract appropriate features from the EMG signals. ANN has been used to classify the physical actions.

2.1 Wavelet transform

Wavelet transform is a linear transform which gives better time-frequency resolution. The wavelet transform has capabilities of providing accurate features for pattern classification. Continuous wavelet transforms (CWT) for a given function $f(t)$ can be calculated as follows:

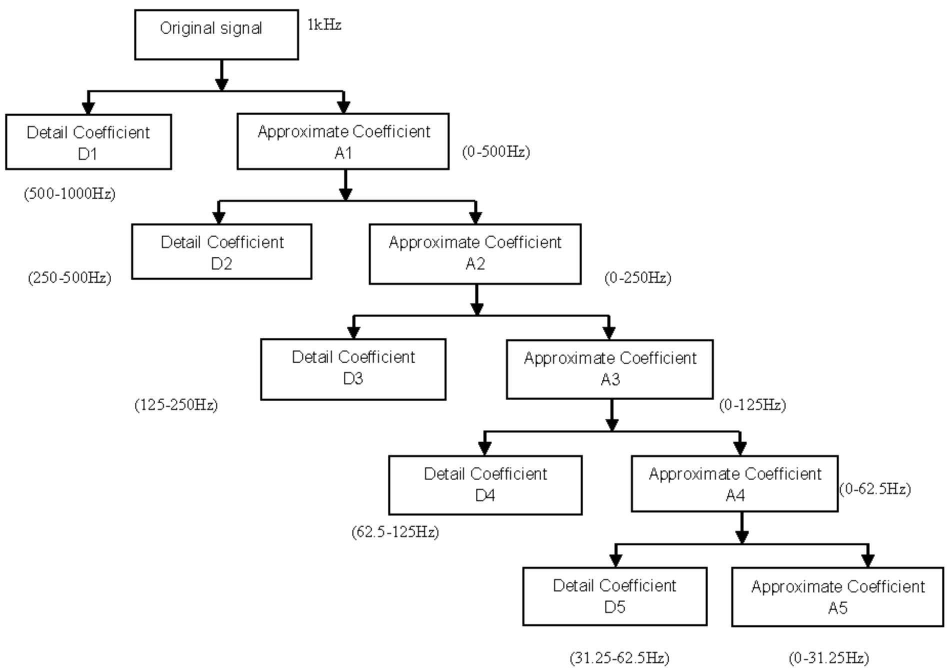
$$CWT(f,a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \Psi^*\left(\frac{t-a}{b}\right) dt \quad (1)$$

where a and b are the scaling (dilation) and translation (time shift) constants, respectively, and Ψ is the mother wavelet function. Further DWT is given by

$$DWT[f,m,n] = \frac{1}{\sqrt{a_o^m}} \sum_k f[k] \Psi^*\left(\frac{n-ka_o^m}{a_o^m}\right) \quad (2)$$

where $f[k]$ is the sampled waveform ($p \times 1$ vector), $a = a_o^m$ and $b = ka_o^m$ are the discretised parameters of scaling and translation, respectively. The discrete wavelet analysis divides the signals into approximate and detail coefficients. Signals analysed using Daubechies wavelet and decomposed up to 5 levels of detail and approximate coefficients using wavelet analysis toolbox of MATLAB software. After many investigations it was found that DB-4 depicts the pattern of the fault more accurately. Number 4 represents the number of wavelet coefficient. The decomposition process can be iterated, with successive approximations being decomposed so that one signal is broken down into many lower-resolution components as shown in Figure 1.

Figure 1 Discrete wavelet transform analysis



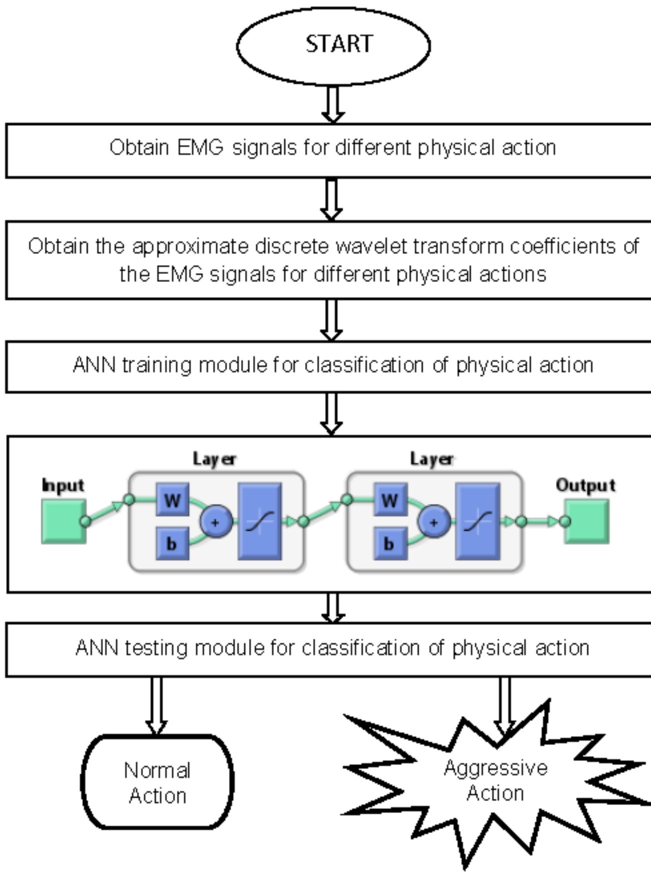
2.2 *Artificial neural network*

Inspired by biological neural networks, ANNs are massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. ANNs are massively parallel adaptive networks of simple nonlinear computing elements called neurons which are intended to abstract and model some of the functionality of the human nervous system in an attempt to partially capture some of its computational strengths. ANNs are used for classification, pattern recognition and functions approximation or mapping problems. Each element of ANN is a node called unit. Units are connected by links. Each link has a numeric weight. Components of neural networks are input layer, hidden layer, output layer, weight, bias, transfer function. In this work ANN has been used for classification of physical actions.

3 Proposed method using wavelet and ANN

Proposed wavelet and ANN based hybrid method consist of different stages which are described below. The flow diagram of the proposed method is described in Figure 2.

Figure 2 Flow diagram of the proposed wavelet and ANN technique (see online version for colours)

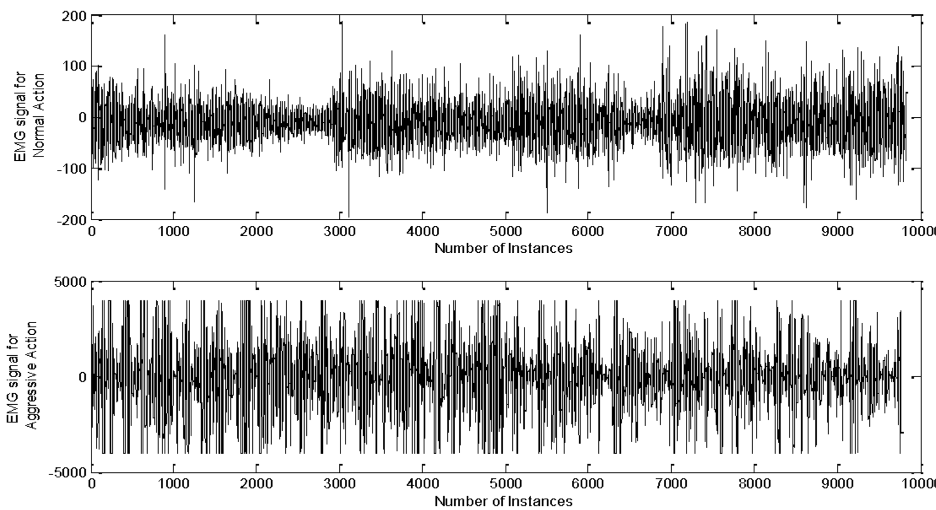


3.1 Input data

The EMG signals used in this work are obtained from UCI machine learning repository (Theodoridis, 2011). Three male and one female subjects (age 25 to 30), who have experienced aggression in scenarios such as physical fighting, took part in the experiment. Throughout 20 individual experiments, each subject had to perform ten normal and ten aggressive activities. The subjects' performance has been recorded by the Delays EMG apparatus, interfacing human activity with myoelectrical contractions. The data acquisition process involved eight skin-surface electrodes placed on the upper arms (biceps and triceps), and upper legs (thighs and hamstrings). The overall number of electrodes is 8, which corresponds to 8 input time series one for a muscle channel (ch1-8).

The dataset consists of ten normal actions bowing, capping, handshaking, hugging, jumping, running, seating, standing, walking and waving. The ten aggressive physical actions are elbowing, frontkicking, hamering, headering, kneeing, pulling, punching, pushing, side kicking and slapping. Total data used are from four subjects each with ten normal and ten aggressive actions. Each of the action has 10,000 instances. For ten normal actions, total number of instances is 100000. For ten aggressive actions, total number of instances is 100000. Hence the dataset consists of 200000 instances in total. From total data, 70% of the data are used in training and 30% are used for testing. Total number of samples used for training is 140000 and testing is 60000. The EMG signal for normal action and aggressive action are shown in Figure 3. Figure 3 shows that the signals recorded during the physical actions are different for aggressive and normal actions. Aggressive actions have more amplitude in EMG recordings than the normal signals.

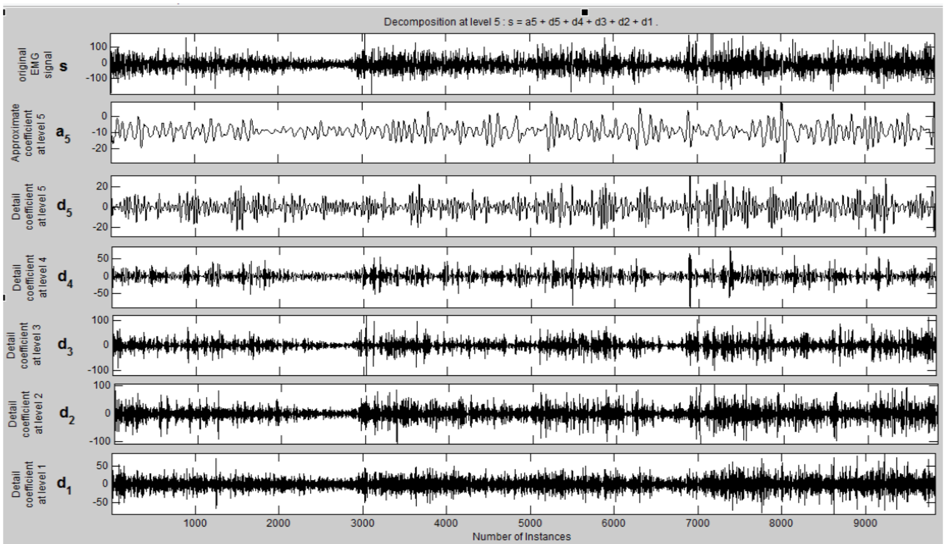
Figure 3 EMG signal recorded for normal action and aggressive action



3.2 Feature extraction using discrete wavelet transform (DWT)

The wavelet transform has emerged as a very effective tool to analyse the non-stationary signals. In this study, the EMG signals are analysed with Daubechies wavelet and decomposed up to 5 levels of detail and approximate coefficients using wavelet analysis toolbox of MATLAB software (MATLAB, 2009a, The MathWorks Inc.). DB wavelets are orthogonal wavelets used for signal discontinuities. The decomposition process can be iterated, with successive approximations being decomposed so that one signal is broken down into many lower-resolution components. Wavelet is used for feature extraction because it provides accurate pattern for classification than by using the EMG signals directly. All the works are done using MATLAB 2009a (MATLAB, 2009a, The MathWorks Inc.) on a 4GB RAM, i3 intel processor. The EMG signals are analysed using DB-4 up to level 5 as shown in Figure 4.

Figure 4 DWT up to 5 level of decomposition of EMG signal



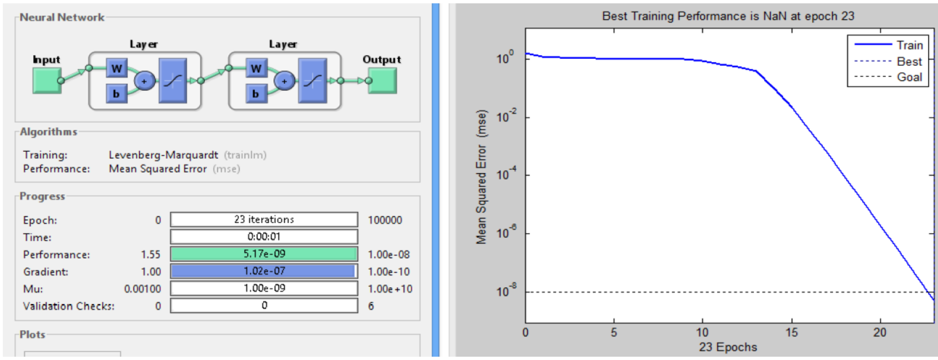
3.3 Classification of physical action using ANN

The pre-processed EMG signals are given as input to ANN based classifier. All the networks have 2 outputs, one output for normal action and another output for aggressive action. The ANN used is feed-forward back-propagation neural network based on the pattern classification carried out by Swetapadma and Yadav (2015a, 2015b) The training patterns that are given to the ANN are the EMG signals of different physical action which are pre-processed using DWT. A variation of back propagation algorithm, called Levenberg-Marquardt (LM) algorithm was used for neural network training, as it is fastest methods for training neural networks. The input given to the ANN for training in a manner that rows contains the attributes and column contain the number of samples. The corresponding target values are set i.e., for normal action target is [1 0] and for aggressive action target is [0 1] as shown in equation (4). If action is normal then N output will be high (1) and other output A will be low (0).

$$T = [N, A]. \tag{4}$$

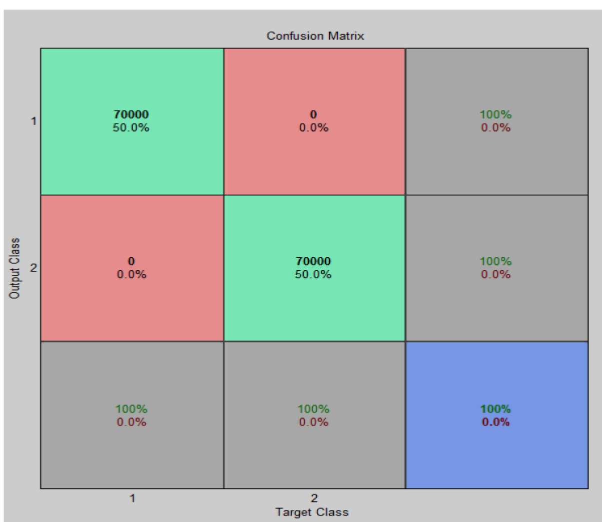
The input and output signals are then normalised in order to make the ANN input level (±1). Neural network toolbox of MATLAB is used to normalise the input signals. The architecture of different ANN modules for classification are selected based on a heuristic approach. The activation function of the hidden layer and output layer is hyperbolic tangent sigmoid function. The number of neurons in the hidden layer is determined empirically by experimenting with various network configurations. Through a series of trials and modifications of the ANN architecture, the best performance is achieved with 1 hidden layer with 8 inputs, 20 numbers of neurons in the hidden layers and 2 neuron output layers. The ANN's were trained by Levenberg-Marquardt training algorithm. The mean squared error is 1.0e-08 in around 0.01s computation time on a PC (i3, 2.4GHz, 4GB RAM). The training output of the proposed ANN based method is shown in Figure 5.

Figure 5 Training diagram for neural network (see online version for colours)



To check the percentage of training data that are correctly trained the confusion matrix is calculated. Confusion matrix is the plot between the target values and the output values. If the output matches with the target then there is no confusion, hence the training is correct. Results for the confusion of classes are shown in diagonal of the matrix. The first output shows the percentage of correctly trained data and second output shows the percentage of incorrectly trained data. Confusion matrix plot of the proposed training module is shown in Figure 6.

Figure 6 Confusion matrix obtained for training module (see online version for colours)



4 Test results and discussion

The physical action classification can be efficient if the feature extractions from the EMG signals are done properly. Here DWT is used which is an effective signal analysis tool. ANN is used for classification of physical actions using EMG. The results for accuracy of the classification of physical datasets are discussed below.

4.1 Performance of the method without using feature extraction

The EMG signals for physical actions can be classified into normal and aggressive actions. But as it is without pre-processing the percentage of accuracy is less. The performance of the proposed methods without feature extraction are shown in Table 1. From Table 1 it can be observed that the sensitivity of the proposed method is found to be 96% and the specificity of the proposed method is found to be 98%. The maximum accuracy in classification is up to 97% if no feature extraction techniques are used. Hence there is a chance that performance of the method can be used enhanced.

Table 1 Accuracy in classification without using discrete wavelet transforms

Parameters	*Values*
Time for training (s)	23.65
Time for testing (s)	0.3
Accuracy (%)	97
False acceptance (%)	3
Error	0.00000001
Neural network used	Back-propagation
Function used	LM algorithm
Epochs	125
Number of layers	2
Number of neurons	40/2
Specificity	98.00%
Sensitivity	96.00%

4.2 Performance of the method using discrete wavelet transform for feature extraction

Proposed wavelet and ANN based method has been tested with various test cases. The proposed method has been tested with varying number of neurons, number of layers, transfer function etc. Table 2 shows the performance varying number of layers. It can be observed that proposed method has same accuracy for two and three layers. But two layers are chosen as the optimal number of layers to for efficient processing. Table 3 shows the performance varying number of neurons. It can be observed that proposed method has same accuracy for 20/2 and 30/2 neurons. Hence 20/2 neurons are chosen as the optimal number of neurons. Table 4 shows the performance varying transfer function. It can be observed that proposed method has highest accuracy for tan-sig transfer function. Hence tan-sig transfer are chosen as the optimal transfer function.

The output of the wavelet and ANN based method is shown in Figure 7. Number of test data are shown in x-axis and the output of classifiers is shown in the y-axis. Test data consist of 1088 normal action data and 1088 aggressive action data. First 1088 data are for normal action, so the output is high (1) from 1-1088 and low(0) for 1089-2176 shown in first plot of Figure 7. Data from 1089-2176 is for aggressive action, so the output is low(0) from 1-1088 and high(1) for

1089-2176 shown in second plot of Figure 7. From Figure 7 it clearly shows that ANN based method classifies the physical actions correctly. Test results for different methods of classification are shown in Table 5. From Table 5, it can be observed that the sensitivity of the proposed method is found to be 98.66% and the specificity of the proposed method is found to be 99.34%. From Table 5 it can be observed that ANN has maximum accuracy i.e., 99%. When feature extraction is carried out with the help of DWT accuracy in classification of physical action increases.

Table 2 Performance varying number of layers

Number of hidden layers	*Training time* (sec)	*Accuracy* (%)	*False acceptance* (%)
1	0.50	91	9
2	0.01	99	1
3	0.02	99	1

Table 3 Performance varying number of neurons

Number of neurons in hidden/output layers	*Training time* (sec)	*Accuracy* (%)	*False acceptance* (%)
5/2	0.06	88	12
10/2	0.03	93	7
20/2	0.01	99	1
30/2	0.01	99	1

Table 4 Performance varying transfer function

Transfer function	*Training time* (s)	*Accuracy* (%)	*False acceptance* (%)
Pure linear	10.0	91	9
Log-sig	540	71	29
Tan-sig	0.01	99	1

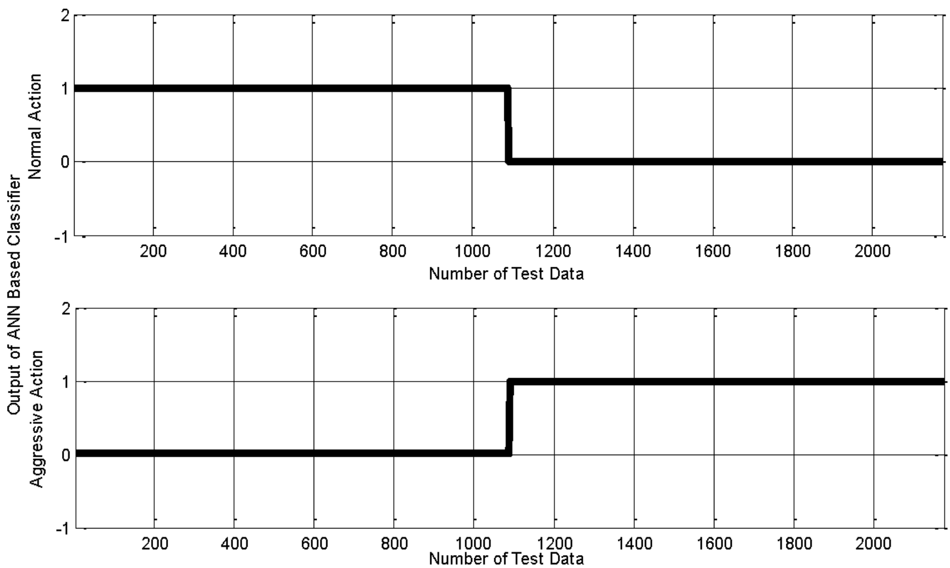
Table 5 Accuracy in classification using discrete wavelet transform for feature extraction

Parameters	*Values*
Time for training (s)	0.01
Time for testing (s)	0.0015
Accuracy (%)	99%
False acceptance (%)	1
Error	0.00000001
Neural network used	Back-propagation
Function used	LM algorithm
Epochs	23
Number of layers	2

Table 5 Accuracy in classification using discrete wavelet transform for feature extraction (continued)

Parameters	*Values*
Number of neurons	20/2
Specificity	99.34%
Sensitivity	98.66%

Figure 7 Output of the wavelet and ANN based scheme



4.3 Comparison of the proposed method with other classification schemes

Various classifications schemes for EMG signals are carried out using different classification methods using different datasets and different feature extraction techniques. Some of the methods for classification are shown in Table 6. Classification accuracy of most of the methods is lower than the proposed method. Hence proposed method can be used efficiently to classify the physical actions.

Table 6 Comparison between methods using different dataset

Schemes	*Dataset*	*Accuracy*	*Feature extraction*	*Classification method*
Oskoei and Hu (2008)	Not UCI	95%	Mean absolute value, root mean square, waveform length, variance, zero crossings, slope sign changes	SVM
Theodoridis (2011)	UCI	90%	Not mentioned	Distance classifier

Table 6 Comparison between methods using different dataset (continued)

Schemes	*Dataset*	*Accuracy*	*Feature extraction*	*Classification method*
Wang et al. (2006)	Not UCI	93.75%	Optimal wavelet packet	Davies-Bouldin criterion
Al-Assaf (2006)	Not UCI	95%	Multi scale wavelet analysis	Autoregressive (AR) models
Zhu (2008)	Not UCI	90%	Wavelet transform	RBF
Proposed method	UCI	99%	Discrete wavelet transform	ANN

5 Conclusion

In this paper a hybrid method using DWT and ANN is used to classify the physical actions. Discrete wavelet transform is used for feature extraction using DB-4 wavelet up to level 5. Extracted features are given as input to the classifier to distinguish between normal action and aggressive action. Accuracy of the proposed method is 99%. Most of the data that are not classified accurately belongs to the jumping, running, pulling and kneeing action of the dataset. Test results shows that the physical action classification using wavelet for feature extraction and ANN for pattern classification is the most appropriate method for EMG signals for this datasets. Limitation of the proposed method is that if the input data contains noise or artefacts the accuracy of the proposed method may decrease. Hence the signals should be recorded carefully for better performance of the algorithm.

References

Al-Assaf, Y. (2006) 'Surface myoelectric signal analysis: dynamic approaches for change detection and classification', *IEEE Trans. on Biomedical Engineering*, Vol. 53, No. 11, pp.2248–2256.

Khushaba, R.N., Kodagoda, S., Lai, S. and Dissanayake, G. (2011) 'Driver drowsiness classification using fuzzy wavelet-packet-based feature extraction algorithm', *IEEE Trans. on Biomedical Engineering*, Vol. 58, No. 1, pp.121–131.

Kwak, K.C. (2012) 'Motion recognition based on fuzzy WP feature extraction approach', *World Academy of Science, Engineering and Technology*, Vol. 71, pp.411–414.

Li, D., Pedrycz, W. and Pizzi, N.J. (2005) 'Fuzzy wavelet packet based feature extraction method and its application to biomedical signal classification', *IEEE Trans. on Biomedical Engineering*, Vol. 52, No. 6, pp.1132–1139.

MATLAB (2009a) *Wavelet Analysis Toolbox and Neural Network Toolbox*, The MathWorks Inc., Natick, Massachusetts, United States.

Merletti, R. and Parker, J.P. (2004) *Electromyography: Physiology, Engineering, and Non-Invasive Applications*, Wiley-IEEE Press, ISBN: 978-0-471-67580-8.

Murugappan, M. (2011) 'Electromyogram signal based human emotion classification using KNN and LDA', *IEEE International Conference on System Engineering and Technology*, pp.106–110.

Oskoei, M.A. and Hu, H. (2008) 'Support vector machine-based classification scheme for myoelectric control applied to upper limb', *IEEE Transactions on Biomedical Engineering*, Vol. 55, No. 8, pp.1956–1965.

Phinyomark, A., Limsakul, C. and Phukpattaranont, P. (2009) 'A novel feature extraction for robust EMG pattern recognition', *Journal of Computing*, Vol. 1, No. 1, pp.71–80.

Sezgin, N. (2012) 'Analysis of EMG Signals in Aggressive and Normal Activities by Using Higher-Order Spectra', *The Scientific World Journal*, Vol. 2012.

Sun, Y.P., Yen, K.T., Liang, Y.C., Wu, L.N. and Lu, K.C. (2013) 'An EMG-driven model to estimate knee joint moment', *Life Science Journal*, Vol. 10, No. 2, pp.249–253.

Swetapadma, A. and Yadav, A. (2015a) 'All shunt fault location including cross-country and evolving faults in transmission lines without fault type classification', *Electric Power Systems Research*, Vol. 123, pp.1–12.

Swetapadma, A. and Yadav, A. (2015b) 'Improved fault location algorithm for multi-location faults, transforming faults and shunt faults in TCSC compensated transmission line', *IET-Generation, Transmission and Distribution*, Vol. 9, No. 13, pp.1597–1607.

Theodoridis, T. (2011) 'EMG physical action data set', *UCI Machine Learning Repository*, 27-Jul-2011, https://archive.ics.uci.edu/ml/datasets/EMG+Physical+Action+Data+Set#

Theodoridis, T., Agapitos, A., Hu, H. and Lucas, S.M. (2009) 'Mechanical feature attributes for modeling and pattern classification of physical activities', *IEEE International Conference in Information and Automation* (*ICIA-2009*), pp.528–533.

Wang, G., Wang, Z., Chen, W. and Zhuang, J. (2006) 'Classification of surface EMG signals using optimal wavelet packet method based on Davies-Bouldin criterion', *Medical and Biological Engineering and Computing*, Vol. 44, No. 10, pp.865–872.

Zhu, X. (2008) 'Study of surface electromyography signal based on wavelet transform and radial basis function neural network', *International Seminar on Future Bio-Medical Information Engineering (FBIE '08)*, pp.160–163.