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Artificial Neural Network based Body Posture Classification from EMG Signal Analysis

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Abstract

This paper deals with the body posture Classification from EMG signal analysis using artificial neural network (ANN). The various statistical features extracted from each EMG signal corresponding to different muscles associated with the different body postures are framed using LABVIEW software. Further-more, these features are taken as the input towards the ANN classifier and thus the corresponding output for the respective classifier predicts the postures like Bowing, Handshaking, and Hugging. The performance of the classifier is determined by the classification rate (CR). The outcome of result indicates that the CR of Multilayer Feed Forward Neural Network (MFNN) type of ANN is rounded up to a percentage of 71.02%.

Keywords: *EMG, statistical features, LABVIEW, ANN, MFNN, CR*

1. Introduction

Electromyography (EMG) is a technique for recording the electrical activity of muscles in our body [1]. This operation is performed using an instrument known as electromyograph. The process of recording the signals by electromyograph instrument is called as an electromyogram. An electromyograph detects the electrical activity generated by muscle cells when these cells are mechanically activated [2]. The signals can further be analyzed to detect medical abnormalities, activation level in order to analyze certain various mechanical activities of human movement. In this present study the EMG signals are taken from different muscles with respect to different body postures at different time. The muscles are Right bicep, Right Triceps, Left Bicep and Left Triceps.

For handling various complexities and non-linear problems Artificial Neural Networks (ANNs) has gained lot of interest towards this aspect [3]. These are massively parallel-interconnected networks of simple elements intended to interact with the real world as the same way as that of biological nervous system of human body. ANNs offers an unusual scheme based on the programming and exhibit higher computing speeds compared to other methods like fuzzy rule based approach [4]. ANN is characterized by their topology, that is, the number of interconnections, the node characteristics which are classified by the type of nonlinear elements used and the kind of learning rules employed. The ANN is composed of Processing Elements called neurons, which are arranged in layers namely input, hidden and output layers [5].

In this research we use LABVIEW based statistical feature extraction technique to extract the features from each EMG signal corresponding to different body postures. Then, we implement the MFNN as classifier to classify these postures as bowing, clapping and handshaking.

2. Materials and Methods

In this present study the EMG signals are obtained during different body postures from the EMG physical action datasheet [6]. These data sheet contains the pre-defined EMG signals which are collected from different muscles like right bicep, right triceps, left bicep, left triceps, right thigh, right hamstring, left thigh and left hamstring during different body postures with the help of Delsys wireless EMG apparatus. Here we are implementing the gesture classification by considering the signals for only four different muscles which are right bicep, right triceps, left

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bicep and left triceps for classifying the body postures such as bowing, clapping and handshaking of a normal person. The bicep is the muscle which lies on the upper arm between shoulder and elbow. The triceps are the large muscles on the back of the upper limb of vertebrates. This muscle is mainly responsible for extension of the elbow joints while strengthening the arm. Here we only classify the different body postures such as Bowing, Clapping and Handshaking which are assigned as class-1, class-2 and class-3 respectively. The detail flow chart for this classification is focused in Figure 1. The EMG signals (in Figure 2) in the physical action data sheet contains each of 10000 samples for which we have to segment each signal into 1000 samples for better classification and effective analysis purpose.

After segmentation we have extracted various statistical features like the arithmetic mean, root mean square value (RMS), standard deviation, variance, kurtosis, median, mode, summation and Skewness from each EMG signals using LABVIEW corresponding to the different body postures class of a normal person, which is shown in Figure 2. These statistical features extracted from each signal as:

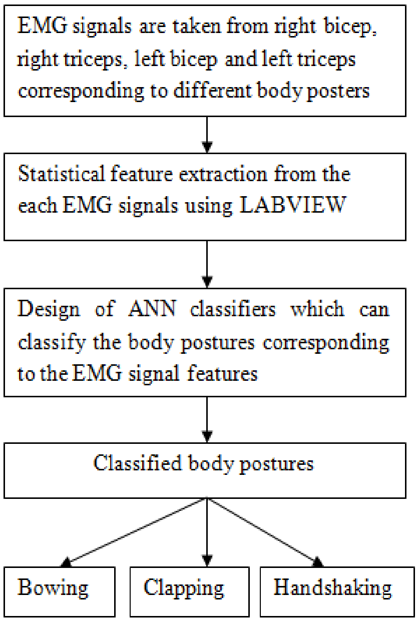

Figure 1. Flowchart for the Body Posture Classification

Arithmetic Mean-The mean of raw signals given by:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_n \tag{1}$$

Root Mean Square Value-The root mean square value of the signals given as:

$$RMSV = (\frac{1}{N}\sum_{i=1}^{N} x_n)^{\frac{1}{2}} \tag{2}$$

Standard Deviation-The standard deviation of the raw signals given as:

$$\sigma = (\frac{1}{N-1}\sum_{n=1}^{N} (x_n - \mu)^2)^{\frac{1}{2}} \tag{3}$$

Variance-The variance of the signal is given as:

$$\sigma = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu)^2 \tag{4}$$

Kurtosis- The kurtosis of the signal given as:

$$ku = \frac{\sum_{n=1}^{N}(x_n - \mu)^4}{\sigma^4} \tag{5}$$

Skewness-The Skewness of the signal given as:

$$sn = \frac{\sum_{n=1}^{N}(x_n - \mu)^3}{\sigma^3} \tag{6}$$

Among various number of neural network structures, the MFNN is widely used for both classification and regression tasks. The general architecture of MFNN is given in Figure 3; the theory behind the working of the MFNN is given by the back propagation algorithm which is used to adjust the weights during training phase.

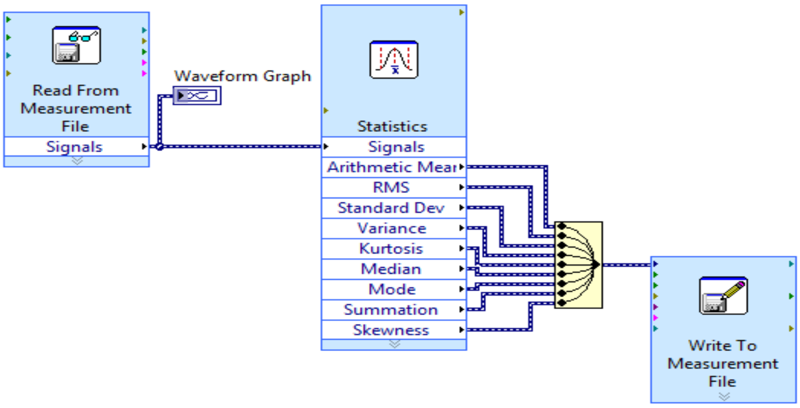

Figure 2. Statistical Feature Extraction using LABVIEW

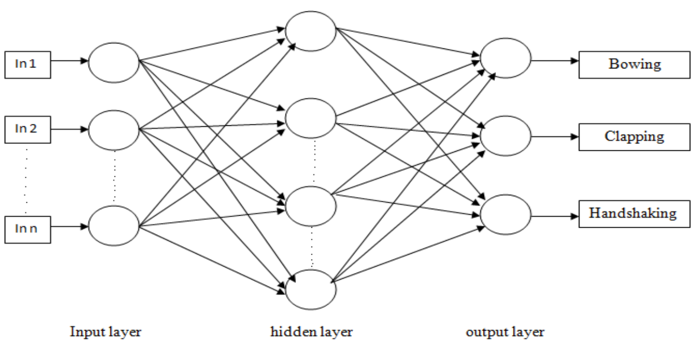

Figure 3. Architecture of MFNN for Body Posture Classification

3. MFNN as classifier

The MFNN shown in architecture diagram shown in Figure 3 has three layers namely input layer, hidden layer and output layer. The input layer mainly consists of ‘m’ nodes in the ‘m’ dimensional feature vector. The input layer sends the data to the next layer which is called as the hidden layer. Each input node is fully connected with hidden layer nodes by a set of weights V_{ji}. Similarly the data propagation from hidden layer to output layer can be done by setting the weight V_{kj}.

The main aim of MFNN is to minimize the cost function which can be defined as the mean square value of the error between actual output (Y_k) and predicted output (P_k). The cost function given by:

$$C(V) = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{m}(Y_k - P_k)^2 \quad (7)$$

The back propagation algorithm is used to update the weights for the minimization of the cost function [7]. This weight minimization corresponds to:

$$V(t+1) = V(t) + \Delta V(t) \quad (8)$$

This implies:

$$\Delta V(t) = -\eta \frac{\partial}{\partial V} C(V) \quad (9)$$

As the actual output and predicted output present in the output layer, that’s why the change in weight is given as:

$$\Delta V_{kj} = \eta(Y_k - P_k)F'(net_k)x_j = \eta\delta_k x_j \quad (10)$$

Where $F'(net_k)$ is the derivative of the activation function. Generally sigmoid activation function is used for both hidden and output layers of MFNN.

Likewise the change in weights obtained in input to hidden layer is determined by the formula:

$$\Delta V_{ji} = -\eta \frac{\partial}{\partial V_{ji}}(C) = \eta\left[\sum_{k=1}^{m}\partial_k V_{kj}\right]F'(net_j)x_i \quad (11)$$

Hence:

$$\Delta V_{ji} = \eta\partial_j x_i \quad (12)$$

Where ∂_j and ∂_k are sensitivity of hidden and output layer respectively.

4. Results and Discussion

Here the proposed classification model is carried out by taking 216 numbers of segmented EMG signal during different body postures. Using LABVIEW software, the various statistical features like Arithmetic Mean, Root Mean Square Value, Standard Deviation, Kurtosis, Median, Mode, Summation, Skewness and Variance are extracted from each EMG signal corresponding to different body postures.

Out of this 216 number of examples 50 % are taken as training and 50% are taken as testing purpose for MFNN. During training of MFNN we assume the parameters given as in Table 1.

Table-1.Optimised Neural Network Parameters during Training Phase

Different parameters taken for training of MFNN classifier	Values
Number of hidden neurons	8
Learning rate	0.9
Momentum factor	0.9
Number of iterations	3000

After training operation the optimized training performance is found to be 74% in terms of accuracy and 0.08 in terms of mean square error (MSE).After the training the testing data is evaluated. The measured accuracy of the testing data is given in terms of confusion matrix which is given in Table 2. From Table 2 we calculate the CR.

Table 2. Confusion Matrix for Testing Features

Predicted / True	Class-1	Class-2	Class-3
Class-1	28	6	8
Class-2	5	25	2
Class-3	7	3	23

Hence the (CR) = $\dfrac{(28+25+23)}{(28+25+23+6+8+2+5+4+6)}$ =71.02%

5. Conclusion

Here, the various statistical features were successfully extracted from the each class of EMG signal corresponding to different postures. After extracting these features the MFNN classifier was implemented to classify the postures as Bowing, Clapping and Handshaking. Our result confirms that the desired MFNN classifier able to classify the EMG signal features handsomely with a CR of 71.02%. Further this work can be extended by considering more number of body postures corresponding the signals from other muscles of the body. Also the SVM and Ensemble and fuzzy based classifiers can be used to improve the accuracy for the classification.

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