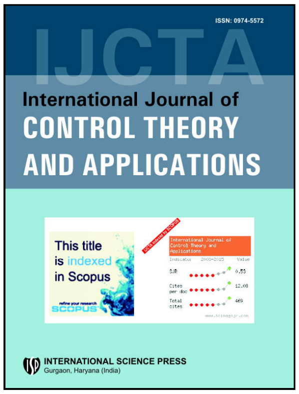


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# sEMG signal classification using Discrete Wavelet Transform and Decision Tree classifier

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***Abstract:*** The surface electromyography (sEMG) signal is a biomedical signal used in various engineering and medical applications. The sEMG signal classification plays the key role in designing assistive devices for amputee and older age person. The present study purposed a Discrete Wavelet Transform (DWT) approach based on Decision Tree (DT) classification of sEMG signals for Elbow movement. DWT was used for de-noising and time scale feature extraction of sEMG signals. Time Domain (TD), Frequency Domain (FD) and Time-Frequency Domain (TFD) features set was used to form a feature vector for classification purpose. An overall classification accuracy of 97.9% was achieved with complex tree and medium tree classifiers whereas simple tree classifiers exhibit the high speed (observation/second). The performance of complex tree and medium tree classifiers was found better as compared to traditional approaches. The result demonstrates that proposed method has a high level of accuracy, fast response and robustness.

***Keywords:*** Decision Tree; Random Forest; Discrete Wavelet Transform; sEMG signal; feature extraction.

## 1. INTRODUCTION

In the recent era, the surface electromyography (sEMG) signal is widely used in biomedical engineering applications. The information provided by the sEMG signal is associated with muscles [1]. A variety of noises and interferences are added automatically into the sEMG signal due to its very low amplitude. Thus, it will create complexities in the analysis of the sEMG signal. Therefore, there are few principal issues that should be carefully addressed including feature selection and classifier designing for improving the efficiency [2]. The sEMG signal is the summation of the electric signal generated from muscles and controlled by the nervous system. The EMG signals are of two types (i) intramuscular EMG and (ii) sEMG. Intramuscular EMG can be recorded by invasive electrodes and the sEMG by non-invasive electrodes. Nowadays, surface-detected signals are most popular for obtaining the desired information of muscle activation [3].

In clinical applications, EMG signals have employed a way for the diagnosis of nervous and muscular systems. The application of EMG signals in rehabilitation and biomedical engineering has been studied for controlling the activities of lower/upper-limb to help the disabled and elderly people for controlling many kinds of assistive devices, notably powered limb prostheses [4]. Most of the researchers have been worked for enhancing the accuracy of the pattern classification of EMG signal. The researchers have achieved above 90% accuracy, but there may be still a chance of further improvement in accuracy [5]. By which one can resolve the problems of Continuous Multifunction Myoelectric Control Systems (MMCS) to deal with real world applications. The accuracy of sEMG classification may be varied according to some factors, such as sampling, selection of a location for electrodes placement, features extraction, sEMG signal acquisition and processing [6]. It will also depend on the type of classification method used. The method of feature extraction was implemented before the classification stage. In the case of noise reduction, Wavelet Transform (WT) plays an important role for the sEMG signal de-noising. The noises like ambient noise, motion artifacts, and inherent instability of sEMG signal can be annihilated by applying bandpass or bandstop filters with proper circuit design and construction techniques. Wavelet de-noising can be used to reduce noise effectively [7]. To get a better performance in the wavelet de-noising algorithm, a proper selection of mother wavelet is very essential. After filtering the various disturbances of the sEMG signal, feature extraction can be done to gather all essential information of the sEMG signal.

This study investigates the different decision tree methods (complex tree, medium tree, and simple tree) with DWT for elbow movement classification of the sEMG signal. DWT is utilized for TFD feature extraction as well as de-noising purpose. The performance of classifiers as critically compared in term of different performance measurement parameters. This paper is divided into four sections, the first section is the introduction of EMG signal classification approaches, the second section explained the material and methods including data acquisition, signal processing, DWT and DT classification methods. The third section discussed the comparative results and the fourth section is the conclusion.

## 2. MATERIALS AND METHODS

### 2.1. Data Acquisition

For sEMG data acquisition, proper selection of acupressure point is essential to generate good classification accuracy. The sEMG signals from 10 subjects within the age group of 20 to 30 years were acquired. Acupressure points are selected on the basis of anatomy defined by Noraxon EMG and sensor system manuals. Through the passive surface electrodes, the sEMG signal was acquired from the simultaneous elbow movement (flexion and extension) by using four different channels. The signal was filtered by a low pass filter at 500 Hz [8]. The Myotrace 400 device is used to acquire the sEMG signal from the subjects in the biomedical laboratory of

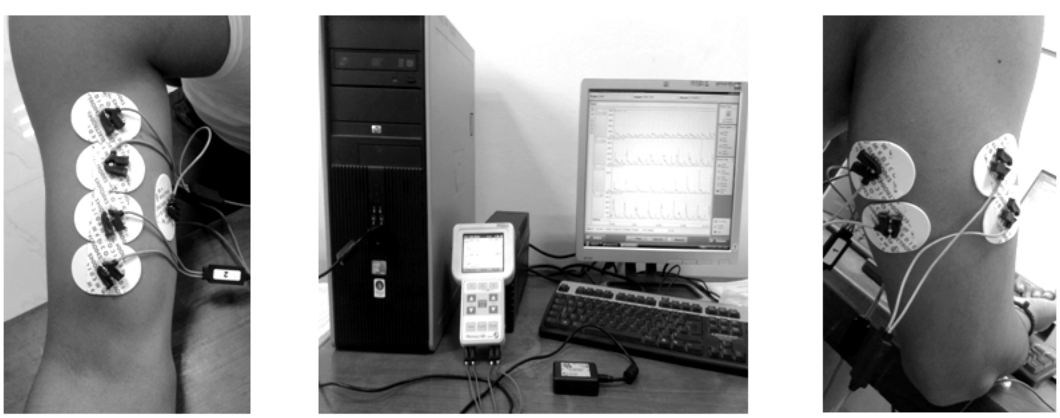

**Figure 1: Placement of electrodes on biceps and triceps muscle with complete setup**

National Institute of Technical Teachers Training & Research (NITTTR). Figure 1 shows the complete setup for sEMG signal acquisition where the electrodes are placed on biceps and triceps muscle.

## 2.2. Signal Processing

To achieve high classification accuracy, Signal processing stage is considered as a necessary step. Various signal processing methods such as rectification, smoothing and normalization have been done to process raw sEMG signals. De-noising was performed by DWT whereas smoothing by RMS algorithm and amplitude normalization by peak value method. Full wave rectification method used to convert the bi-directional signal into the unidirectional signal. In this stage, ECG reduction process is also carried out for better accuracy. Digital smoothing algorithm was utilized to recuperate the explicit shape of the sEMG signal [9]. Instead of using notch filter (50-60 Hz), a digital filter (Butterworth Lowpass filter of 2nd order at 6Hz) was used to generate linear envelope EMG. All channels of Myotrace 400 had a low-pass anti-alias filtering facility with cutoff frequency 500 Hz.

## 2.3. DWT

Wavelet Transform technique is used to represent a signal into two-dimensional functions of time and scale. It splits the signal into a well localize and scales value that permits to utilize long time interims for the low-frequency signal as well as the shorter region for a high-frequency signal. Wavelet transform can be classified into two type: Continuous wavelet transform and discrete wavelet transform [10]. The sEMG signal is decomposed to the fourth level by using DWT, two types of coefficients associated with DWT, one is related to high-frequency with low scale another is related to low-frequency with high scale. Figure 2 shows the fourth level details and approximation coefficient obtained with db2 wavelet with the de-noise signal.

The DWT shows several advantages over the Fourier Transform and Short-Time Fourier Transform (STFT) analysis. While Fourier Transform has better performance for stationary signals, the DWT and STFT use the window technique for mapping the function of time and scale of a signal. DWT performed better for non-stationary signals as compared to Fourier and STFT. In DWT, de-noising is associated with three steps namely,

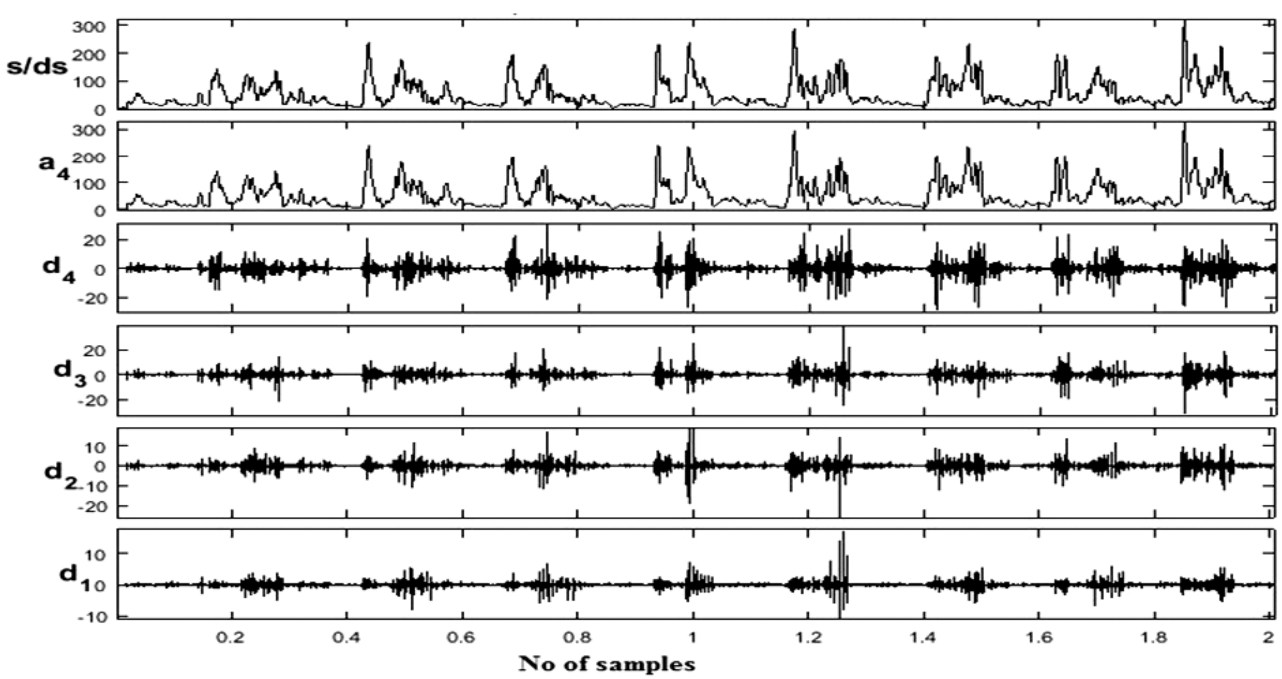


**Figure 2: De-noise sEMG signal with fourth level details and approximation coefficient**

decomposition, modification of detailed coefficient and reconstruction. Before forming the feature vector for the classifier, the selection of feature has an important role [11]. The combination of suitable feature can give a better result and may be used to generate a control signal for controlling of external devices [12]. Figure 3 shows the various steps followed in the classification process. Following feature were extracted to form a feature vector.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{1}$$

$$WL = \sum_{n=1}^{N-1} \left| x_{n+1} - x_n \right| \tag{2}$$

$$SKW = \frac{1}{N}\sum_{n=1}^{N}\left(x_n - \bar{x}\right)^3 / \left(\frac{1}{N}\sum_{n=1}^{N}\left(x_n - \bar{x}\right)^2\right)^{3/2} \tag{3}$$

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2 \tag{4}$$

$$SSC = \Sigma_{n=2}^{N-1}\left[f\left[\left(x_n - x_{n-1}\right)\times\left(x_n - x_{n+1}\right)\right]\right]$$

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases} \tag{5}$$

$$MAV = \frac{1}{N}\Sigma_{n=1}^{N}\left|x_n\right| \tag{6}$$

$$\sigma = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}\left(x_i - \mu\right)^2} \tag{7}$$

Where $$\mu = \frac{1}{N}\Sigma_{i=1}^{N} X_i \tag{8}$$

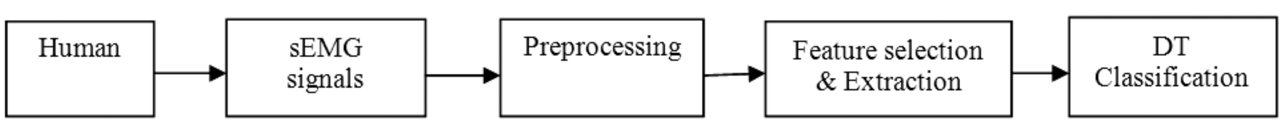


**Figure 3: Flow chart of sEMG signal classification**

## 2.4. Classification using Decision Tree classifier

Classification and regression tree (CART) algorithm is spaciously used for the classification of the signal in the field of biomedical engineering. There are two renowned strategies named as bagging and boosting for the classification purpose. In boosting, progressive trees give additional weight to focuses erroneously anticipated by some indications [13]. At last, a weighted voting system is utilized for the forecasting. In bagging, successive trees don't rely upon prior trees, each is autonomously developed and utilize a bootstrap test of the information set. At last, a straightforward larger part voting is taken for expectation. A Recursive splitting technique is used to create the nodes. Likewise, the tree is constituted using splitting nodes. By applying splitting criteria, the best suitable split node is found. The variance function is processed for achieving these criteria. This function is applied on each split node to find out the best suitable split node. Various criteria may be used to determine the splits $f_i$ namely Gini criteria defined as.

$$Gini(t) = 1 - \sum_i f_i^2 \tag{9}$$

Decision tree algorithm may be considered as a process with four steps. In an initial step, build a tree by using splitting criteria. In the second step, stop the tree building process. Tree pruning is done through cutting important nodes in third step [14]. The selection of optimal tree from the splitting sequence of pruning trees is done in the fourth step. Efficient results are obtained by the appointed least number terminal node as 2 and number of folds in cross-validation are 5 for pruning.

## 2.5. Random Forest

Random forest is a machine learning approach based on decision tree algorithm. It consists of a set of decision trees which is created or developed by the selection of variables arbitrarily. An algorithm is used to create trees independently. After trees formation, the discovery of the most well-known class is based on voting. The algorithm ensures that all trees are distinctive. Randomness may be applied in two steps: In initial step building of each tree is done by utilization of distinctive bootstrap test information. The second step is choosing the best subset of predictor arbitrarily. In bootstrap approach, generalization error reduces while accuracy increases with the random feature. Arbitrary choice of splitting shows better improvement over bagging in terms of generalization error [15]. The quality of individual tree classifier is essential for better classification accuracy. In some cases, this algorithm works superior to other classifiers like Support Vector Machine (SVM), Neural Network (NN) and Discriminant Analysis (DA) etc.

## 3. RESULTS AND DISCUSSION

In the present study, a classification model was proposed based on the complex tree, medium tree, and simple tree classification approach. The sEMG signal was acquired with the help of Myotrace 400 device. The signal is

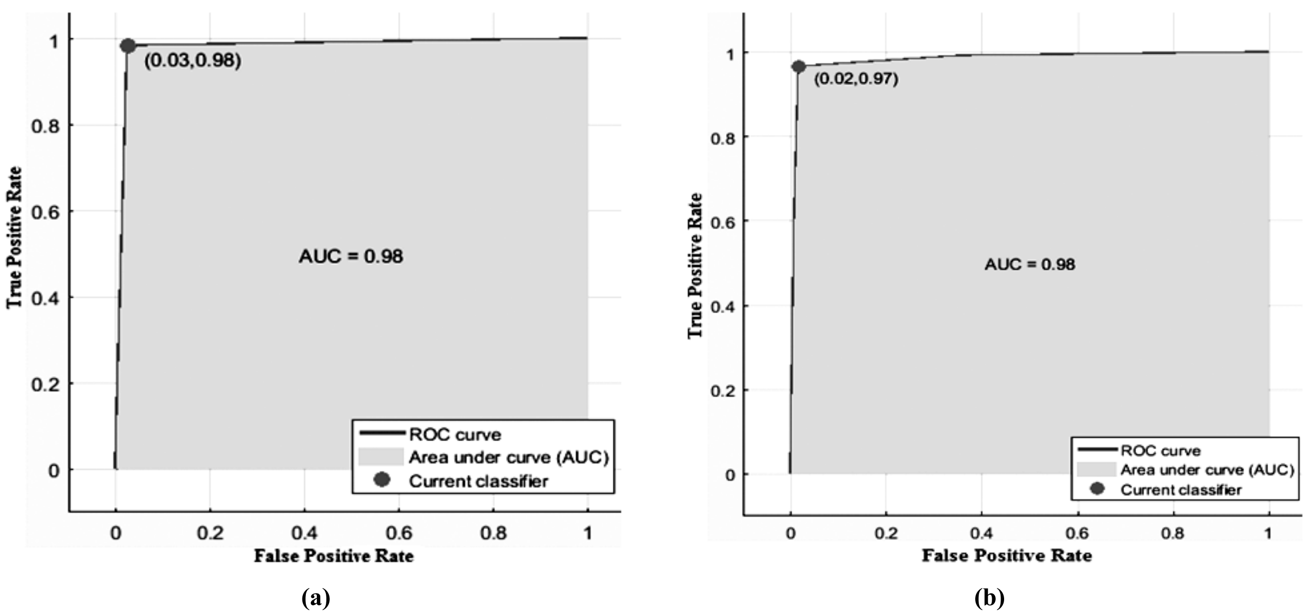


**Figure 4: (a) ROC curve of complex tree and medium tree (b) ROC curve of simple tree**

**Table 1**
**Performance measure of DT classifier**

| *Classifiers* | *SE(%)* | *SP(%)* | *ACC(%)* | *PPV(%)* | *FDR(%)* | *Speed (Obs/sec)* | *Training time (Sec)* |
|---|---|---|---|---|---|---|---|
| Complex Tree | 98.3 | 97.4 | 97.9 | 97.5 | 2.5 | 1000 | 9.5 |
| Medium Tree | 98.3 | 97.4 | 97.9 | 97.5 | 2.5 | 1700 | 1.5 |
| Simple Tree | 96.6 | 98.3 | 97.4 | 98.3 | 1.7 | 10000 | 0.5 |

preprocessed and best feature combinations were calculated. For the present classification model, the best combination of TD, FD, and TFD feature were derived from the sEMG signal to form a feature vector. Feature vector becomes the input to classifiers to give a further response to next stage. Figure 4 (a) show the Receiver Operating Curve (ROC) of the complex and medium tree which is same for both classifiers and Figure 4 (b) shows the ROC of simple tree classifier. In the case of a complex tree, medium tree, and simple tree classifiers Area Under Curve (AUC) is 0.98. ROC is drawn between true positive rate vs false positive rate. The result is compared and computed in term of Sensitivity (SE), Accuracy (AC), False Discovery Rate (FDR), Positive Predictive Value (PPV), speed (observation/second), training time and Specificity (SP) for all classifiers. These parameters are calculated on the basis of confusion matrix obtained in MATLAB© simulation. In the case of the complex tree and medium tree, accuracy was obtained 97.9% whereas simple tree shows 97.4% accuracy. It means complex tree and medium tree classifiers both are better than a simple tree classifier. The simple tree shows fast response as compared to the medium tree and complex tree as well as lowest training time for classification of the sEMG signal for binary movement. Table 1 shows the comparative analysis of all three classifiers used.

## 4. CONCLUSION

The present work proposes the use of DT classifier for elbow movement classification based on discrete wavelet transform and TD, FD & time scale features so that the classification accuracy can be enhanced. The overall classification accuracy was 97.9% in the complex and medium tree with good precision and speed of response. A combination of few selected features like RMS, SKW, VAR, WL and time scale feature (Mean, Median, Standard Deviation, Median Absolute Deviation) was utilized to form the feature vector. The DT method demonstrated the good classification of the sEMG signal with a high level of accuracy and robustness as compared to traditional approach. DT classifier also has the better performance with DWT while communicating and commanding the bidirectional robotic vehicle or arm. Simulationresult shows 97.9% accuracy in the classification of the sEMG signal for elbow movement. DT classifier has low error, less diagnosing time and faster response. Therefore, this classification approach has the various advantages over traditional methods. Future work will be based on ant colony optimization of the best-suited classifier for designing the lower limb. Such optimization method can be useful for improving the overall performance in real world applications.

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