SEMG Signals Identification Using DT And LR Classifier by Wavelet-Based Features

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ABSTRACT- In the recent era of technology, biomedical signals have been attracted lots of attention regarding the development of rehabilitation robotic technology. The surface electromyography (SEMG) signals are the fabulous signals utilized in the field of robotics. In this context, SEMG signals have been acquired by twenty-five right-hand dominated healthy human subjects to discriminate the various hand gestures. The placement of SEMG electrodes has been done according to the predefined acupressure point of required hand movements. After the SEMG signal acquisition, pre-processing and noise rejection have been performed. The de-noising and four levels of SEMG signal decomposition have been accomplished by discrete wavelet transform (DWT). In this article, the third and fourth-level detail coefficients have been utilized for time-scale feature extractions. The performance of ten time-scale features has been evaluated and compared to each other with the three-fold cross-validation technique by using a Decision Tree (DT) and Linear Regression (LR) classifier. The results demonstrated that the DT classifier classification accuracy was found superior to the LR classifier. By using the DT classifier technique 96.3% accuracy has been achieved, with all combined features as a feature vector.

Keywords: DT classifier, discrete wavelet transform, LR classifier, SEMG signals.

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1. INTRODUCTION

The human body movement depends on the body structure, which needs very essential information about the human body structure [1], [2]. The smallest functional unit to characterize the neural controlling of the contraction process of muscles is known as a motor unit. It consists of a cell body, axon, dendrites, and muscle fibers [3]. The main objective of studying the SEMG signals is to discriminate between various muscle movements into classes by MUAP during contractions [4]. These signals are detected and recorded using the surface electrodes which are placed adjacent to the skin superimposed on the muscles acupressure point [5]. The signal is generated during the contraction of the electrical activity of muscle fibers and the generated SEMG signals contain some useful feature which can be analyzed by the way of applying Wavelet Transform (WT) and other powerful techniques like Empirical Mode Decomposition (EMD) for multifunctional myoelectric control [6].

The SEMG signal plays a vital role in both engineering and medical applications. SEMG is related to the muscle activation function by critically analyzing the electrical signal which is generated by the muscular contraction and flexion [7], [8]. The muscular contraction can be divided into two types such as voluntary and involuntary. As a result of this contraction, muscle potential is generated in the form of the SEMG signal [9]. So, SEMG signals contained the intentional information of movement performed by the subject [10]. SEMG is the study of the signals generated by muscles. The forearm muscles play a significant role in controlling hand motion [11], [12]. In similar ways, different programmed actions of any robotic arm which can include supination/pronation, opening/closing the hand, extended index, pincer, and a rest position; the muscles of interest are chosen from the desired biceps, triceps, thumb, and wrist movements.

The remaining section of this paper is arranged as follows: In *Section II*, describes the data acquisition as well as the feature extraction process by the DWT technique. Section III shows the proposed experimental results obtained from MATLAB© 20. Finally, the concluded results are given in *Section IV*.

2. MATERIALS AND METHODS

2.1 Data Recording and Pre-processing

The EMG data has been acquired by six different hand movements with the different age groups of 18 to 24 years of 25 subjects. Two channels of passive non-invasive electrodes which have been connected to the Myotrace 400 hardware device are utilized for SEMG data acquisition. The placement of all electrodes has been done by standard Myotrace 400 manual information [13]. Due to the non-invasive characteristic of surface electrodes, the deployment of various surface electrodes has been widely adopted in various engineering as well as medical application-based studies. One advantage of this electrode is the ease of handling moreover it can only explore the surface muscles [14]. But this kind of electrode cannot identify the deeper muscles which can be easily detected

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by fine-wire as well as needle electrodes [15], [16]. In this study, surface electrodes have been employed. The signals pre-processing and data acquisition have been done by exploiting the Myotrace 400 hardware device [17]. *Figure 1* shows the complete EMG signal acquisition setup for six hand movement identification.

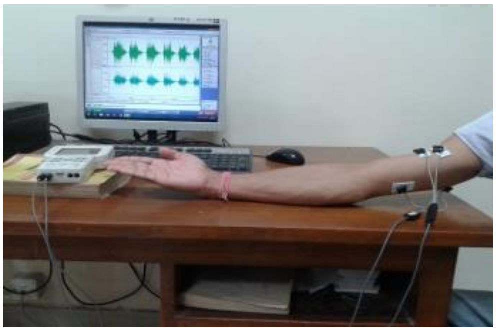

Figure 1: Complete EMG signals acquisition set by Myo-Trace 400 device

The first step of SEMG signals is pre-processing. In these steps, SEMG signals go through various operations like filtering, smoothing, amplitude normalization, and full-wave rectification [18]. The RMS method has been utilized for smoothing the whole SEMG signals dataset [19]. The Maximal Voluntary Contraction (MVC) has employed for carrying out the amplitude normalization in which normalization is done to the signal peak value.

The EMG recording of the heart is also called ECG. So the EMG signal acquired from the upper limb gets contaminated by the ECG spikes. It is because electrical synchronization gets stronger by a factor of 1000mV and hence, it can easily move through the body tissues and reach the site of the electrodes on the upper body. Upper trunk muscles and muscles of the nearby heart-like shoulder are risky regions. This biological artifact cannot be avoided and even the filters cannot eliminate it [20], [21]. *Figure 2* shows that the block diagram of the complete workflow.

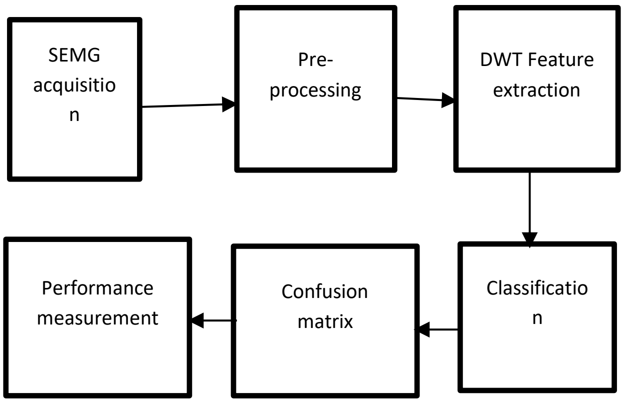

Figure 2: Complete workflow for EMG signal classification

2.2 EMG Feature Extractions

After the EMG data acquisition, the suitable feature must be selected so that EMG signal classification can be done to discriminant different hand movements. The selection of a suitable feature and feature extraction method can play a major role to increase classifiers accuracy. Feature extraction has been performed thereafter, the segmentation of data and pre-processing steps. To improve accuracy, the dimension of the feature vector must be minimized without eliminating the necessary information. The DWT is a popular approach having a great role in the time-frequency scale feature extraction. Some other types of wavelet transform such as wavelet packet transform can also be utilized for EEG and SEMG signals. Mallat has been proposed as an algorithm for multi-resolution analysis of the signal which decomposes them rapidly. The key feature of this technique provides sufficient information for both synthesis and analysis of the original signal.

1.3 Classifier

The decision tree (DT) classifier has an easy and widely accepted technique of classification. It implemented a straight and clear idea to resolve the classification problem. This method puts the series of questions related to the features of the test record. As soon as it gets an answer, it again poses a question and this process continues till the inference is reached [22], [23].

Figure 3: Myo-Trace 400 EMG data acquisition Device

The tree uses the predictive model for mapping the observations for concluding the target value used in machine learning, data mining, and statistics. In this study, DT and linear regression (LR) classifier has compared to each other for different feature evaluations. *Figure 3* shows the Myo-Trace 400 device employed to acquire the SEMG signals from healthy human subjects.

3. RESULTS AND DISCUSSIONS

The performance of different time-frequency domain features was evaluated by using DT and LR classifiers. The extraction of time scale or time-frequency domain (TFD) features was carried out on the detail's coefficients obtained from the SEMG signal decomposition. Daubechies 4 (db4) wavelet-based DWT technique was utilized for de-noising and four-level SEMG signal decomposition into approximations and details

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coefficients. Finally, the details coefficient from the third and fourth levels was employed for the features extraction process of SEMG signals. *Table 1* exhibits the performance of ten different TFD features extracted from SEMG signal details coefficients by using the wavelet technique. C_i represents the detailed coefficients of EMG signals obtained by DWT.

Table 1: TFD Features definitions employed in this work

Features Equations	Definition
$ARC_{nC} = -\sum_{i=1}^{p} a_i c_{n-p} + w_n$	6th order ARC_{nC} of the coefficients
$WL_C = \sum_{i=1}^{M-1} \lvert c_{i-1} - c_i \rvert$	Waveform length (WL_C) of the coefficients
$SSI_C = \sum {c_i}^2$	Simple Square Integral (SSI_C) of the coefficients
$TM_{kC} = \left\lvert \frac{1}{N} \sum_{i=1}^{N} {c_i}^k \right\rvert$	Temporal Moment (TM_{kC}) up to 7th order of the coefficients
$MSR_c = \frac{1}{k} \sum_{i=1}^{k} (c_i)^{\frac{1}{2}}$	Mean value of the Square Root of the coefficients (MSR_c)
$MYOP_{25vC} = \frac{1}{N} \sum_{i=1}^{N} [f(c_i)]$; where $f(c) = \begin{cases} 1 \text{ if } c \geq threshold \\ 0 \text{ otherwise} \end{cases}$	Myo-Pulse ($MYOP_{25vC}$) with 25mV threshold of the coefficients
$ASS_C = \left\lvert \sum_{i=1}^{k} (c_i)^{\frac{1}{2}} \right\rvert$	The absolute value of the Summation of the Square root of the coefficients (ASS_C)
$WAMP_{25VC} = \sum_{i=1}^{N-1} [f(\lvert c_i - c_{i+1} \rvert)]$; where $f(c) = \begin{cases} 1 \text{ if } c \geq threshold \\ 0 \text{ otherwise} \end{cases}$	Willison Amplitude ($WAMP_{25vC}$) with 25mV threshold of the coefficients
$ASM_C = \left\lvert \frac{\sum_{n=1}^{k} (c_n)^{exp}}{k} \right\rvert$; where $exp = \begin{cases} 0.5 \text{ if } 0.75 \geq n \geq 0.25*k \\ 0.75 \text{ otherwise} \end{cases}$	The absolute value of the Summation of the exp^th root of coefficient and its Mean (ASM_C)
$SSC_C = \sum_{n=2}^{N-1} [f[(c_n - c_{n-1})*(c_n - c_{n+1})]]$; $\begin{cases} 1 \text{ if } c \geq threshold \\ 0 \text{ otherwise} \end{cases}$	slope sign change (SSC_C) of the coefficients

The performance evaluation of ten TFD features has been represented in *table 2*. The SEMG dataset has acquired for six different hand movements which had been discriminated by using DT and LR classifiers. The performance has measured by classification accuracy computed by the confusion matrix of the corresponding classifier. The ratio of a truly predicted sample against the whole sample size can be narrated as Classification accuracy in any particular dataset. A three-fold cross-validation technique has been adopted for dividing the dataset into training and testing purposes. In the three-fold cross-validation method, the whole dataset has been divided into three equal parts in which two parts of the dataset are used for training whereas one part has been considered for testing purposes.

Table 2 exhibits the ranks-wise classification accuracy of 10-TFD features for identifying the six different hand movements by employing the DT and LR classifier. The performance of WL_C feature has been found best whereas, ASS_C performs least among all ten features. Top five best-performing features were WLC, WAMPC, SSCC, MYOPC, and ARCnC with the classification accuracy of 58.5% 53.2% 49.7% 47.4% and 44.2% respectively with DT classifier. DT classifier performed better than the LR classifier with the session 1 EMG dataset.

Table 2: Classification accuracy of DT and LR classifier for session 1

Rank	Feature	DT classifier	LR classifier
1	WL_C	58.5	56.7
2	$WAMP_C$	53.2	50.4
3	SSC_C	49.7	47.9
4	$MYOP_C$	47.4	45.8
5	ARC_{nC}	44.2	41.5
6	TM_{kC}	43.9	40.7
7	SSI_C	41.1	39.5
8	MSR_C	39.8	37.5
9	ASM_C	39.2	36.9
10	ASS_C	38.7	36.8

Table 3 shows the classification accuracy of the session 2 SEMG dataset acquired for six different motion classes with DT and LR classifiers. The top five best-performing features were WL_C, $WAMP_C$, SSC_C, $MYOP_C$, and ARC_{nC} with a classification accuracy of 59.8% 55.6% 50.7%, 48.9%, and 45.4% respectively with DT classifier. It is clear from the above discussion that the DT classifier performed better than the LR classifier in all session SEMG datasets using a three-fold cross-validation approach. Top-performing features could be combined for yielding higher classification accuracy. But in this study, we combined all ten features to form the final feature vector for the classification of six different hand movements of SEMG signals.

Table 3: Classification accuracy of DT and LR classifier for session 2

Sr. No.	Feature	DT classifier	LR classifier
1	WL_C	59.8	57.7
2	$WAMP_C$	55.6	54.5
3	SSC_C	50.7	47.9
4	$MYOP_C$	48.9	46.8
5	ARC_{nC}	45.4	43.5
6	TM_{kC}	44.8	42.7
7	SSI_C	43.2	40.6
8	MSR_C	41.5	38.7
9	ASM_C	40.7	38.6
10	ASS_C	40.4	37.9

Figure 4 shows the confusion matrix for the DT classifier with each class classification accuracy in percentage. Motion classes 1, 2, 3, 4, 5 and 6 was achieved the classification accuracy of 99.3% 100%, 94.0%, 98.8%, 96.4% and 89.9% respectively. The confusion matrix also indicated the positive predictive value (PPV) and false descriptive rate (FDR). The PPV for six different classes was of 99.3% 100%, 94.0%, 98.8%, 96.4% and 89.9% respectively which has the classification accuracy whereas, FDR has 0.7%, 0%, 6.0%, 1.2%, 3.6% and 10.1% for classes 1 to 6 respectively. The overall classification accuracy with combined feature vector has 96.3% for DT classifier.

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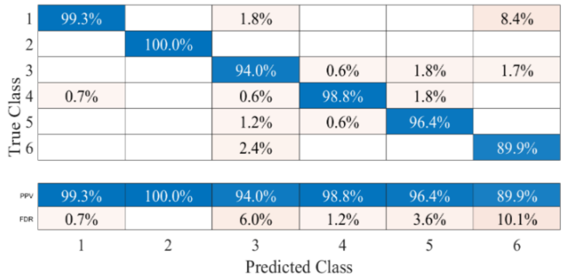

Figure 4: Confusion matrix with positive predictive value and false descriptive rate of DT classifier

4. CONCLUSION

In this study, six different hand movements have been identified by using SEMG signals classification with DT and LR classifiers. The acquisition of the SEMG dataset has performed by employing Myo-Trace 400 device with 25 healthy humans in two data recording sessions. After completing the recording of the SEMG dataset, pre-processing steps are executed followed by the feature extraction by db_4 DWT technique. The performance of all ten features has been individually evaluated and finally, a combined feature vector consisting of all features is tested. The results showed that the best five features were WL_C, $WAMP_C$, SSC_C, $MYOP_C$, and ARC_{nC}. The results also demonstrated that the performance of the DT classifier was found superior to the LR classifier. Furthermore, the accuracy of the DT classifier was 96.3% which could be further improved by optimizing the classifier internal parameters. The finding of this study could be beneficial for different robotic system development. In the future, we will acquire more than six degrees of movement classes EMG dataset from healthy subjects.

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