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Enhancing Prediction of Prosthetic Fingers Movement Based on sEMG using Mixtures of Features and Random Forest

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Abstract: As the recent development of the prosthetic control systems, it is necessary to develop the sub-components such as myoelectric control system. This sub-system is used to acquire electromyogram (EMG) signals from a person's muscles and convert it to movements to control prosthetic hands or fingers. Recently, researchers started focusing on providing feature extraction methods for both time domain and frequency domain for predicting either hand or finger movements. This paper proposes a new mixed feature set for both time and frequency domain for the classification of surface EMG (sEMG) into ten classes for controlling prosthetic finger movements. The features are based on enhanced statistical features extracted directly from a non-overlapped window with a predefined length which was selected carefully from the sEMG directly. Ten classes of individual and combined finger movements are to be recognized by using two sEMG channels from two electrodes are fixed on the human forearm to employ effective knowledge discovery and pattern recognition algorithms to enhance the recognition and classification accuracy. and the other features are statistical features extracted from Instantaneous frequency of the signal to utilize a suitable classifier helps detecting and recognizing the pattern from sEMG signals of different classes of the fingers movements either combined or single movement to enhance the classifier performances and to find the whole class of all extracted window ,a majority voting technique was applied.The method used the random forest as a classifier to build the classifier model which achieved an accuracy of 93.75% and sensitivity of 93.73% and specificity of 99.31%.

Keywords: sEMG, Statistical Features, Instantaneous Frequency, Mixed Features, Random Forest.

I. INTRODUCTION

Human loss or amputation of forearm is one of the most widely occurred disabilities that extremely cause limitation on the everyday routine, capabilities, and interactions of people with such kind of amputation [1, 2]. A full or part of the interaction of people with such amputation can be restored by signal collected or recorded from muscles that are responsible for the movement of the hand or fingers and prosthetics arms and/or fingers.

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These signals are called Electromyogram (EMG) signals and controlling the prosthetics fingers or hand is called myoelectric control [3].

EMG signals generated by the human muscles are collected using surface electrodes and called surface EMG (sEMG) and are used to derive control commands for powered prostheses [4, 5].

Usually, a combination between signal processing and machine learning framework is used and implemented to extract a set of features and to classify the acquired sEMG signals into one of a predefined type of forearm or fingers movements [6]. Recently, a different set of features and types of classifiers have been applied and used in the literature demonstrating the feasibility of myoelectric control [7]. These set of features contain features from time domain and statistical features are the most widely used, the second domain is the frequency domain and especially the Fourier transform (FT) based feature extraction [8, 9]. Also, a combination of Time-Frequency (TF) analysis is used and the most widely used feature extraction method is wavelet analysis using the discrete wavelet transform (DWT) [10]. In the available literature, most of the studies focus on extracting a set of features using the wavelet features only without providing a new feature extraction methodology or by using a combination of time-domain features with wavelet features which are fed into different types of machine learning techniques.

In this paper, we focus on proposing a new methodology for extracting features from an sEMG based individual and combined finger movement recognition system that employs only two sEMG channels using two electrodes which are situated on the human forearm. The goal here is to employ effective knowledge discovery and pattern recognition algorithms to enhance the recognition and classification accuracy where ten classes of individual and combined finger movements are to be recognized. The block diagram of the proposed system is shown in Figure 1.

The extraction was done using a non-overlapped moving window with a predefined length which was selected carefully. Also, a suitable classifier is then utilized to detect and recognize the pattern from sEMG signals of different classes of the fingers movements either combined or single movement. This is followed by a majority voting technique was applied to enhance the classifier performances and to find the whole class of all extracted windows and find the final class of sEMG signal. The organization of this paper is as follows: Section 2 describes the used methodology starting from used dataset until the majority voting technique for the final class of sEMG.

Section 3 presents the experimental results and finally, conclusions are provided in Section 5.

II. METHODOLOGY

In this section, full details about the methodology proposed in this paper containing the used dataset, the feature extraction, and the classifier used are explained. Figure 1 shows the block diagram of the proposed methodology.

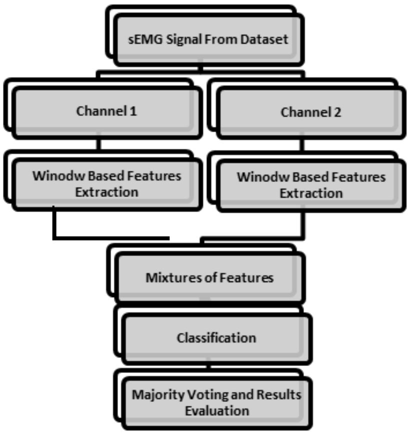

Fig. 1. Block Diagram of Proposed Methodology.

A. Used Dataset

In this research, the used dataset is a two channels sEMG signals with a duration of 5 seconds by electrodes located as shown in Figure 2 below. The dataset was recorded by Khushaba et al. [1] and contains eight volunteers consisting of 6 males and 2 females with age group between 20 and 35 years with 10 different movements of hand fingers. The signals were collected using BNC-2090 which a 12-bit analog-to-digital converter by National Instruments (NI) with bandpass between 20 and 450 Hz and notch filter at 50 Hz for power line interference pre-processing applied [1].

Fig. 2. Position of Recording Electrodes (Black) and Reference Electrode (White) [1].

Ten different classes of fingers movement for both individual and combined were implemented as shown in Figure 3. The finger movements with their labels used in classification are Thumb (T), Index (I), Middle (M), Ring (R), Little (L) while the combined movements are Thumb–Index (T–I), Thumb–Middle (T–M), Thumb–Ring (T–R), Thumb–Little (T–L), and finally the hand–close (HC). Each movement for each subject a folder is created and each trial signals are saved as CSV file.

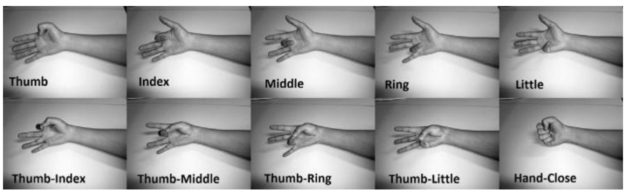

Fig. 3. The Ten Different Movements used in the Dataset [1].

B. Non-Overlapped Moving Window

In the sliding window technique for signal processing, a window of a predefined number of samples L is chosen to move over the sEMG signal [11]. The chosen length must be adequate for the length of the signal and do not require zero-padding. In general, applying such technique ensures that the feature extraction method will focus on every detail and changes on the signal. In addition, it is used to increase the number of instances that used to build the classifier model [11].

C. Features Extraction

In this section, the extracted features from each sEMG channel are discussed in detail. Features from both time domain and using instantaneous frequency are explained. In the following sub-sections.

Time Domain Features

For time-domain features extraction, twelve statistical features were extracted from each extracted window of sEMG channels [12-14]. These features are:

- Mean Absolute Value (MAV)

MAV is a widely used sEMG feature that has been widely applied in EMG pattern recognition. MAV is defined as the average of absolute signal value, and it can be expressed as:

$$\text{MAV}=\frac{1}{L}\sum_{i=1}^{L}|X_i| \tag{1}$$

Where X_i is the wavelet coefficient and L is the total length of the coefficients.

- Wavelength

Wavelength (WL) is a widely used sEMG feature, which deputizes for the cumulative length of the waveform over a certain time. WL can be formulated as:

$$\text{WL}=\sum_{i=1}^{L}|X_i - X_{i-1}| \tag{2}$$

Where X_i is the wavelet coefficient and L is the total length of coefficients.

- Average Amplitude Change (AAC)

AAC is one of the most widely used and popular sEMG features, and it can be formulated as:

$$\text{AAC}=\sum_{i=1}^{L-1}|X_{i+1} - X_i| \tag{3}$$

- Log Detector (LD)

LD is a good feature that is used to estimate the exerted force, and it can be defined as [25]:

$$\text{LD}=\exp\left(\frac{1}{L}\sum_{i=1}^{L}\log|X_i|\right) \tag{4}$$

- Root Mean Square (RMS)

RMS is one of the widely used statistical features, mathematically, RMS can be expressed as:

$$\text{RMS}=\sqrt{\frac{1}{L}\sum_{i=1}^{L}(X_i)^2} \tag{5}$$

- Difference Absolute Standard Deviation (DASD)

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DASD is a frequently used biomedical signals feature, and it can be calculated as:

$$\mathrm{DASD}=\sqrt{\frac{\sum_{i=1}^{L-1}(X_{i+1}-X_i)^2}{L-1}} \quad (6)$$

- Myopulse Percentage Rate (MYOP)

MYOP is a specialized feature for the sEMG signals which is defined as the average of myopulse signal output and it defined as the absolute value of the sEMG signal which exceeds a predefined threshold value. MYOP can be calculated as follows:

$$\mathrm{MYOP}=\frac{1}{L}\sum_{i=1}^{L} f(X_i) \quad (7)$$

$$f(X_i)=\begin{cases}1 & X_i \geq T\\ 0 & otherwise\end{cases} \quad (8)$$

- Willison Amplitude (WA)

WA is one of the most widely used sEMG features which works as an indicator for the firing of motor unit potentials, and it can be calculated as:

$$\mathrm{WA}=\sum_{i=1}^{L-1} f(X_i) \quad (9)$$

$$f(X_i)=\begin{cases}1 & |X_i - X_{i+1}| \geq T\\ 0 & otherwise\end{cases} \quad (10)$$

- Simple Square Integral (SSI)

SSI is simply identified as the summation of the squared values of any signal samples amplitude and in our case the sEMG signal samples amplitude, and it can be computed as:

$$\mathrm{SSI}=\sum_{i=1}^{L}(X_i)^2 \quad (11)$$

- The variance of Signal (VAR)

VAR is the measurement of the signal power, and it can be expressed as:

$$\mathrm{VAR}=\frac{1}{L\text{-}1}\sum_{i=1}^{L}(X_i)^2 \quad (12)$$

- Modified Mean Absolute Value (MMAV)

MMAV is an enhanced extension of the mean absolute value feature by conveying the weight window function. Mathematically, MMAV can be computed as:

$$\mathrm{MMAV}=\frac{1}{L}\sum_{i=1}^{L} W_i|X_i| \quad (13)$$

$$W_i=\begin{cases}1 & 0.25L \leq i \leq 0.75L\\ 0.5 & otherwise\end{cases} \quad (14)$$

- Modified Mean Absolute Value 2 (MMAV2)

MMAV2 is an enhanced extension of the mean absolute value feature which is done by conveying the continuous weight window function, and it can be expressed as:

$$\mathrm{MMAV2}=\frac{1}{L}\sum_{i=1}^{L} W_i|X_i| \quad (15)$$

$$W_i=\begin{cases}1 & 0.25L \leq i \leq 0.75L\\ \frac{4i}{L} & i < 0.25L\\ \frac{4(i-L)}{L} & \text{otherwise}\end{cases} \quad (16)$$

Instantaneous Frequency Estimation Based Features

Instantaneous frequency estimation (IFE) has a wide and high important application especially in signal processing and motion recognition [15, 16], IFE is a widely used Time-Frequency (TF) analysis method in the biomedical signal processing field since most of the signals in this field are non-stationary and frequency methods such as Fourier transform cannot provide valuable information about such signals [17]. The basic definition of instantaneous frequency for a nonstationary signal that it is a time-varying parameter related to the mean of the frequencies available in the signal as it develops [16, 17]. Using this definition let the signal to be analyzed be $X(t)$ then the IFE of it can be calculated using the first conditional spectral moment of the power spectrum as follows:

1. Computes the power spectrum (time-frequency distribution) $P_s(t,f)$ of $X(t)$.
2. Estimates the instantaneous frequency of $X(t)$ using the following equation

$$F_{instantaneous}\,(t)=\frac{\int_0^{\infty} f P_s(t,f)df}{\int_0^{\infty} P_s(t,f)df} \quad (17)$$

Figure 4 shows an example of IFE for sEMG signal.

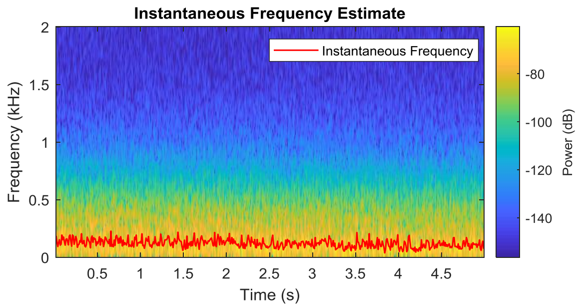

Fig. 4. IFE of an sEMG Signal.

After generating the IFE of an sEMG signal a set of nine statistical features are extracted. These features are maximum by mean, maximum by a median, standard deviation by mean, mean, standard deviation, maximum, minimum, median, and a1 features [12-14].

$$\text{Max by Mean}=\frac{\mathrm{Max}\,(inst_{freq})}{\mu(inst_{freq})} \quad (18)$$

$$\text{Max by Median}=\frac{\mathrm{Max}\,(inst_{freq})}{\mathrm{Median}\,(inst_{freq})} \quad (19)$$

$$\text{Max by Median}=\frac{\mathrm{Max}\,(inst_{freq})}{\mathrm{Median}\,(inst_{freq})} \quad (20)$$

$$\mu=\frac{1}{L}\sum_{i=1}^{L} X(i) \quad (21)$$

$$\sigma=\sqrt{\frac{1}{L-1}\sum_{i=1}^{L}(X(i)-\mu)^2} \quad (22)$$

$$a1=\frac{N_{Features>\mu}}{N_{Features}} \quad (23)$$

D. Random Forest Classifier

Random Forests (RF) classifier is one of the most popular classification tools and excellent ensemble machine learning techniques. It was first proposed by Breiman [18]. The RF was proved that it is efficient more than other available classifications methods. RF is a classification technique that is based on building a tree from random samples by selecting random features using bagging strategy that enables the built trees to vote for a given input vector to get a class label.

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RF classifier is basically constructed using a combination of base learners, where each base learner is an independent binary tree adopting recursive partitioning. The main advantages of RF are: it achieves higher accuracy than other classifiers, very efficient tool on large-scale data, does not overfit, and can be easily applied in multi-class inputs [19].

E. Majority Voting Technique

After getting out the non-overlapped moving windows features and passing them into the random forest classifier, the classifier is trained, and the resultant model is saved. The predicted class of each single windows related to the same signal are assembled, and the most repeated value of the class is selected. This method is effective for the prediction of window level and signal level [11]. Figure 5 shows the majority voting technique process.

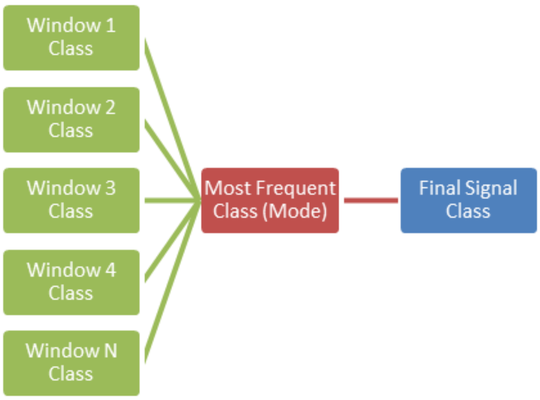

Fig. 5. Majority Voting Technique Process.

F. Classifier Performance Evaluation

For the purpose of evaluating the performance of the used classifier in classifying the finger movement using the proposed methodology, the confusion matrix was generated. This matrix provides a comparison between the classifier outputs with the corresponding original label of [19, 20]. Using the generated confusion matrix, accuracy, sensitivity, specificity, and specificity are computed. These metrics are calculated as follows:

$$Accuracy = \frac{TP}{TP+FP+TN+FN} \quad (24)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (25)$$

$$Specificity = \frac{TN}{FP+FN} \quad (26)$$

$$Precision = \frac{TP}{TP+FP} \quad (27)$$

III. RESULTS AND DISCUSSION

In this section, the experimental results of the proposed methodology are shown and discussed. At first, the used dataset is divided into main subsets training and testing. Training takes 70% of the dataset and the rest (30%) is for testing purpose. After that, the length of moving window is selected based on two variables time and accuracy, based on that Figure 6 shows the variation of time and accuracy over different window lengths.

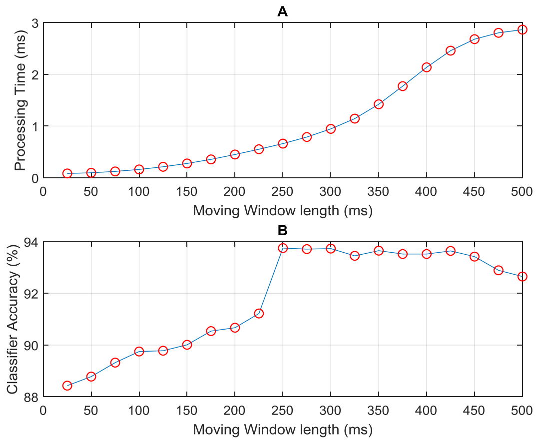

Fig. 6. Variation of the moving window length and the Processing Time (A) and the Classifier Accuracy (B); These results are for a 2.4 GHz Intel Core i5 CPU based Desktop Computer.

Based on Figure 5 above the most suitable moving window length that gives the highest accuracy and good processing time was 250 ms and this length was selected and the result on this section is for this length.

After selecting the moving window length (250 ms) the features are extracted and based on the window length and each signal length (5 seconds), each signal will contain 20 nonoverlapped windows. The features of non-overlapped windows are fed into RF classifier to build the classifier model. After extracting the features comparison is done to study the effect of combining these features on the performance of the RF classifier was done. Figure 7 shows a comparison between the classifier performance for IFE features, statistical features, and combination of them.

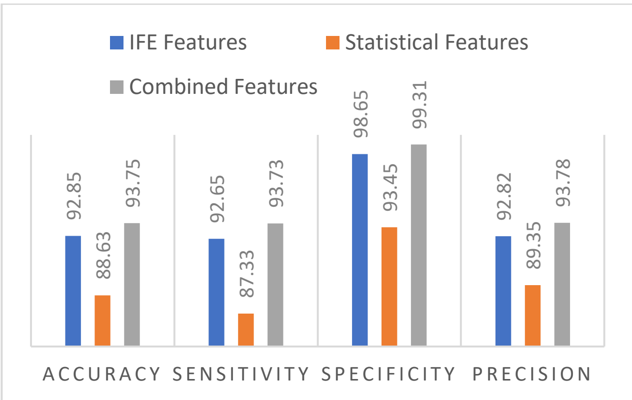

Fig. 7. Compassion Between Different Set of Features Effect on the Classifier Performance.

Based on Figure 7 we can see that the mixtures of these features generate a good classification results that outperform both of single features set. The Confusion matrix of the RF classifier for classifying 10 types of finger movement using the proposed methodology is shown in Figure 8 below.

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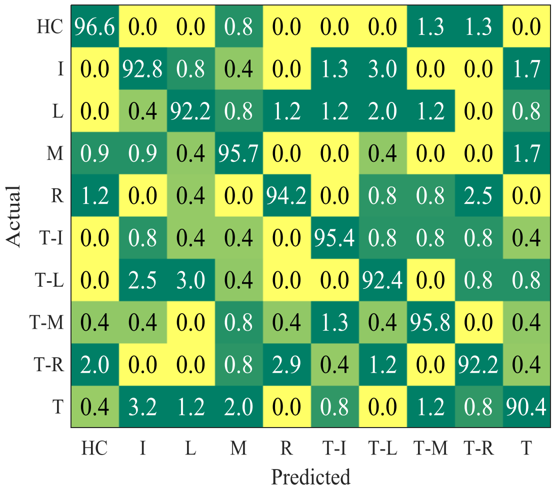

Fig. 8. Confusion Matrix of the used Classifier.

While Table 1 shows the full performance evaluation metrics of the proposed methodology. Based on these results, the proposed methodology shows a promising performance for classifying ten movements of hand finger using data from two channels of sEMG and can be used for controlling prosthetic fingers.

TABLE I. PERFORMANCE EVALUATION OF THE PROPOSED METHOD.

Performance Metric	Performance Metric Value (%)
Accuracy	93.75
Sensitivity	93.73
Specificity	99.31
Precision	93.78

Finally, based on the results above the proposed methodology succeeds with a high rate on classifying the two sEMG for controlling prosthetic hand fingers.

IV. CONCLUSION

In this research, we proposed a simple two channels sEMG based machine learning system for pattern recognition and classifying of ten types of individual and combined finger movements which can be used for prosthetic fingers controlling. Various features from both time and time-frequency domains were extracted from the two channels. In order to enhance the output classification decisions and enlarging the used data that fed into the sEMG pattern recognition system, a non-overlapped moving window with a length of 250 ms is used that is selected according to achieving highest accuracy to extract a sub-window which results on 20 sub-windows from each sEMG channel. Experiments were performed on sEMG datasets that containing ten different combined and individual finger movements which were collected from different eight subjects and it was proved the stability and feasibility of the proposed system using RF classifiers achieving 93.75% classification accuracy, sensitivity of 93.73% and specificity of 99.31%.

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