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An Ensemble Classifier for Finger Movement Recognition using EMG Signals

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Abstract: Electromyography (EMG) signals that obtained by electrodes connected to the forearm are the monitoring of the muscles by the electrical method. These signals are quite useful during the use of prosthesis as a source signal to the moving prosthesis. Therefore, it is essential that classifying the EMG signals with high accuracy by analyzing. This study aims that classifying the individual and combined finger movements using surface EMG signals taken from the surface of the human forearm. EMG signals that belong to 10 different finger movements obtained from eight subjects were used. Firstly, EMG signals have been split into segments by the windowing process, and temporal feature vectors are formed by applying various feature extraction methods to these segments. Feature vectors have been classified with the ensemble bagged tree algorithm, which is a combination of classifiers, to obtain the correct classification decision. As a result of 10-fold cross-validation, with the proposed method, 96.6% overall classification accuracy was achieved. The results obtained show that the ensemble classifier can be used successfully in determining finger movements when compared with similar studies.

Keywords: *Ensemble Classifier, Bagged Tree, Electromyography, Feature Extraction, Finger Movement*

1. Introduction

Electromyogram (EMG) is a biopotential signals generated by muscle contraction [1]. Various electrochemical events in the body generate these signals. The transmitted stimulating potentials from the brain through the nerves constitute the Motor Unit Action Potentials (MUAP). Muscle contraction occurs due to MUAP electrical potential Motor neurons are linked to one or several muscle fiber groups. Contraction or relaxation occurs depending on the level of potential change in muscles triggered by MUAP [2]. The amount of muscle contraction increases with the increase in the number and frequency of MUAPs. The examination of MUAPs in cases of muscle fiber contraction and relaxation is used to determine muscular problems. Electrical changes occur in muscles as a result of MUAPs [3].

In EMG, the signals can be received by two different methods, either invasive or non-invasive, depending on the electrodes used [4]. In the invasive method that is used needle electrodes, the signals received from the muscles have higher amplitude and therefore, more reliable. Accordingly, more detailed analysis of muscles can be performed by the invasive method. However, this method has significant disadvantages such as long processing time and the lack of safe sterilization of the electrodes as well as being painful for the patient. Nevertheless, in the non-invasive method that using surface electrodes, the activities of localized muscles very close to the skin can be determined. Also, this method is easy to apply, painless for the patient and suitable for on-the-go analysis. [5], [6].

The bioelectric activity that occurs during muscle contraction is recorded as a function of time. By examining the frequency and amplitude characteristics of the EMG signal, it is obtained that critical information about the physiological activity and function of the muscle. This method is a frequently used technique for the detection of medical anomalies, muscle-nerve examination and investigation of the biomechanics of mammalian movement. According to the standards, the EMG signal has an amplitude of 50μV ~ 5mV and a frequency range of 2 ~ 500 Hz [7].

Classification of EMG signals is of great interest in the fields of biomedical and robotics. Mostly, it has been widely used as a command signal to identify individual motions for the control of prostheses. In order to realize this purpose, individual movements need to be extracted from existing EMG signal patterns. Pattern recognition systems are used to classify existing EMG signals into one of the predefined movements [8], [9].

In the literature, many methods used to classify hand and finger movements have been presented, and the researchers use different feature extraction techniques. Lucas et al. (2007) classified six different hand movements with eight electrodes attached to the forearm in their studies. Discrete wavelet transformations were applied to EMG signals, and then classification was completed by the SVM method. In their study, they obtained a 5% inaccurate classification rate [10]. Khezri and Sadati (2007) classified six hand-based movements using surface EMG to recognize patterns of hand prosthesis movements in their study. Using both time and frequency domain features, they achieved a 96% classification performance with a hybrid classifier that uses ANN and ANFIS together [11]. Cerci et al. (2018) done classification by using EMG signals containing eight different hand movement data. After the feature extraction, they achieved 89%, 92% classification success, respectively, in the classification with kNN and ANN [12].

Ensemble methods are learning algorithms that combine machine learning techniques to obtain a better prediction model [13]. Multiple classifiers are combining at the last stage, and the overall result is obtained. Bagging (Boostrap Aggregating) and Boosting techniques are commonly used to create an ensemble. Bagging is a simple, usable method for decreasing variance for machine learning techniques that have high variance. It also prevents

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overfitting [14].
This study aims to determine the different finger movements from EMG signals. In the study, a publicly available EMG dataset of finger movements was used. The time-domain feature set was obtained from these EMG signals. The extracted feature set was classified with the ensemble bagged tree method to recognize different finger movements.

2. MATERIAL METHODS

In this study, it is aimed to classify ten different finger movements by using surface EMG signals. Ensemble bagged tree method was used in the classification. The proposed method consists of five steps. Firstly, data were obtained from the EMG finger movement dataset. Segments were formed with 10% overlap on the dataset. Then, the features used in the classification were obtained in the time domain. The obtained features were classified using the ensemble classifier. Lastly, decision making was carried out according to classification results. The flow diagram that describes these steps, in general, is given in Figure 1.

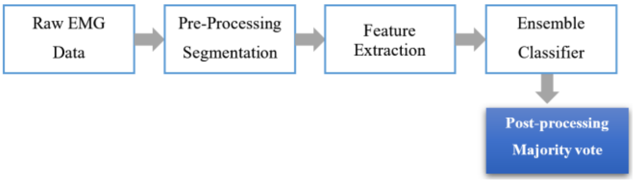

Fig 1. General flow diagram of the proposed method

2.1. EMG Dataset

In this study, publicly available EMG finger movements dataset was used [15]. In this dataset, finger movements were taken from 8 subjects (six males and two females). The EMG signal data were obtained with the help of two surface electrodes, as shown in Figure 2. Each channel contains 20,000 samples. There are six samples of each movement class. The arms of the subjects were fixed to the chair to reduce the noise from other muscles. Using the Delsys Bagnoli-8 amplifier, EMG signals were amplified 1000-fold. The EMG signal was sampled at 4000 Hz with a 12-bit analogue-to-digital converter (National Instruments, BNC-2090). The data set was obtained using Delsys EMGWorks software. The obtained signals were applied with a bandpass filter between 20 and 450 Hz [15].

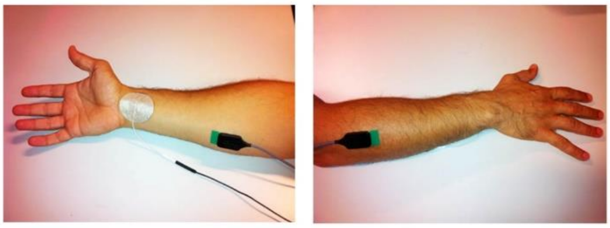

Fig 2. Surface electrodes placement in obtaining the EMG signals [15]

In the data set, the classes formed by using individual and combined fingers were determined. There are a total of 10 different classes: Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the pinching of combined Thumb–Index (T–I), Thumb–Middle (T–M), Thumb–Ring (T–R), Thumb–Little (T–L), and finally the hand close (HC). The screenshots of 10 different finger movements are given in Figure 3.

2.2. Feature Extraction

Data windowing is an important point in data segmentation. Each segment with a predefined length is used for feature extraction [16,17]. There are two window approaches, overlapping windowing and disjoint windowing. It is stated that the windowing technique, which overlaps with the studies, gives better results [15, 18]. In this study, overlapping windowing is applied. A window length of 150 ms to 250 ms was recommended in the studies with the EMG signals [19, 20]. The window length was chosen as 200 ms. Most of the features used in EMG signals are time-domain (TD) features. TD features give good results in both clinical and pattern recognition-based applications. In this study, time-domain characteristics were extracted from each segment for the proposed method. The extracted temporal features are as follows [21, 22]:

Mean absolute value (MAV) is one of the commonly used features, mainly as it provides information with amplitude levels of muscles.

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \qquad (1)$$

Root mean square (RMS) is modelled as amplitude modulated Gaussian random process.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \qquad (2)$$

Waveform length (WL) is found through the measurement of cumulative amplitude variations between samples over a full period.

$$\mathrm{WL} = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \qquad (3)$$

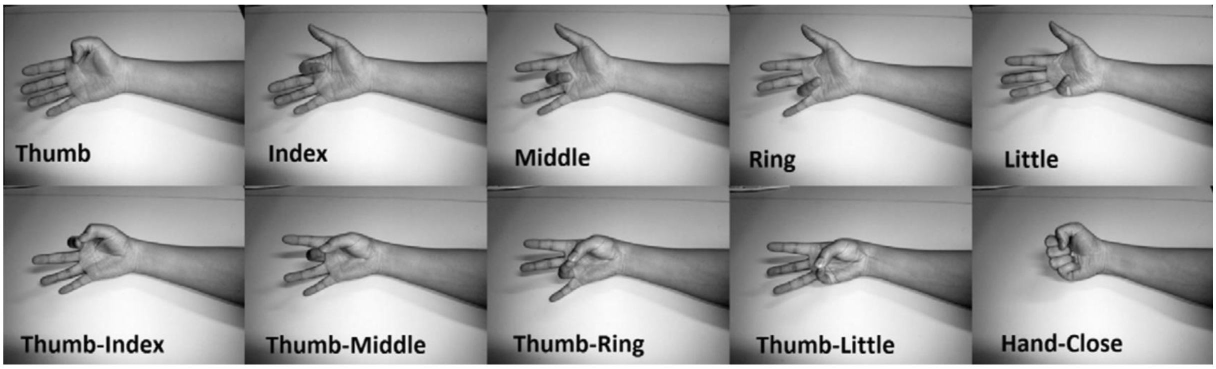

Fig 3. Types of finger movement [15]

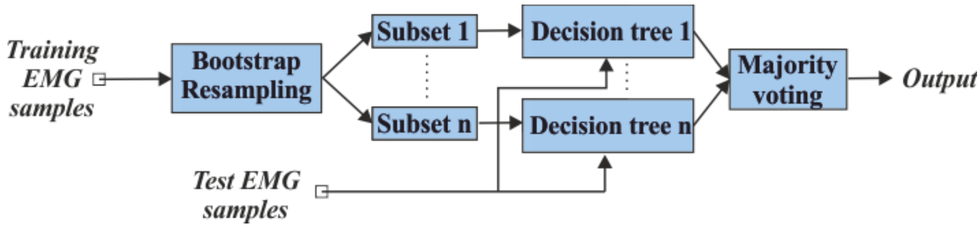

Fig 4. A schematic illustration of ensemble bagged tree classifier [23]

Varyans (VAR) gives information about the strength of the EMG signal and is, therefore, a widely used feature. In the equation, $\bar{x}$ refers to the mean of the signal.

$$VAR = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 \tag{4}$$

Slope Sign Change (SSC) is a method based on counting transitions from positive to negative or negative to positive on the EMG signal. Noise immunity of the property can be increased by enabling it to count the changes above a specified threshold level.

$$SSC = \sum_{i=2}^{N-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]; \tag{5}$$

$$f(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

Zero Crossing (ZC) parameter calculates the number of times the signal has passed through the zero points. This feature is noise sensitive, so it is necessary to determine a specified threshold level.

$$ZC = \sum_{i=1}^{N-1}[\mathrm{sgn}(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geqslant \text{threshold}]; \tag{6}$$

$$\mathrm{sgn}(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

Myopulse percentage rate (MPR) is the average of the number of times the EMG signal exceeds a predefined threshold.

$$MYOP = \frac{1}{N}\sum_{i=1}^{N}[f(x_i)] \tag{7}$$

$$f(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

2.3. Classification

In this study, ensemble bagged tree learning technique was used. In the bagging ensemble algorithm, the N-dimensional training set is generated randomly and repeatedly from the same size training set. Each generated training set is trained with the decision tree algorithm, and its results are combined by majority voting. The number of bootstrap samples determines the number of trees to be created, and the majority vote is applied to the results of decision trees trained by different subsets [23]. This process reduces the problem of overfitting of decision trees and improves generalization. The bagged tree block diagram is given in Figure 4.

Classification accuracy is calculated by the average of the confusion matrices of classifiers in each case. The overall classification accuracy is expressed as a ratio between the correctly classified samples to the total number of samples [24].

3. RESULTS and DISCUSSION

In this study, 14 temporal features obtained from a two-channel surface EMG signal were used in the classification. A 10-fold cross-validation technique was used to train the classifier and to avoid overfitting. In 10-fold cross-validation, the dataset is randomly divided into ten subsets of equal size. One of the subsets is taken as the test set, and the remaining sets are used as the training set. By repeating this process ten times, it is performed in a form that the test set will have a different algorithm in each repeat. The results are obtained by averaging the performance values of the test sets obtained.

In this study, the effect of the change in the number of decision trees on the ensemble bagged tree was evaluated (Figure 5). When 30 tree base learners are used, the bagged tree classifier has an overall classification accuracy of 96.6%. In addition, 75.3% classification performance was obtained with a single decision tree. These results show that the proposed method provides a good improvement in classification accuracy.

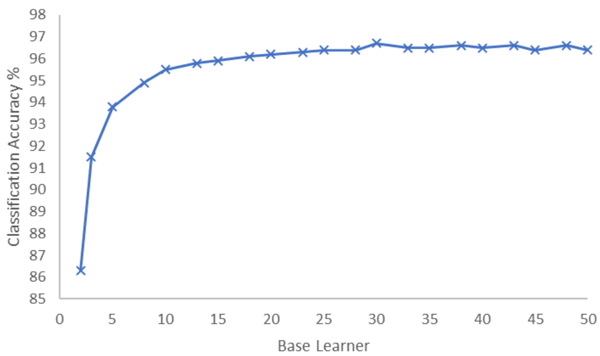

Fig 5. The classification accuracy of bagged tree classifier

The accuracy rates obtained for each class with the bagged tree classifier are given in Figure 6. At the determining of the Thumb Class (TI) finger movement, it seems that the proposed classifier shows a 99% classification performance. The lowest classification performance is obtained with a 95% classification rate for determining Ring (R) and Little (L) movements.

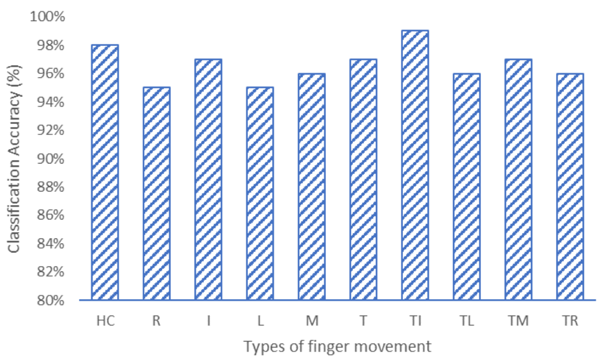

Fig 6. Classification accuracy for each type of finger movement

In literature, for ten classes an average of 91.40% classification accuracy with the SVM based classifier [18], for eight classes an average of 88% and 92% classification accuracy with kNN and ANN-based classifiers respectively [12], for ten classes approximately 92% classification success with SVM and kNN based classifiers [15] were obtained on the EMG finger movements dataset. On the other hand, the classification success for ten classes is 96.6% with the ensemble bagged tree classifier which was proposed in this study.

In this study, it was aimed to determine ten different finger movements obtained from eight different subjects by using EMG signals. Features have been extracted by performing the segmentation process on the EMG signals. The applied bagged tree classification method can be considered as successful, and the classification rates are over 95% for each type of finger movement. The result shows that the proposed classifier can be used successfully to determine finger movements. Classification accuracy can be increased by different feature extraction methods and segmentation methods.

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