Effects of Forearm Muscle Fatigue on Classification Performance in sEMG-Based Hand Gesture Recognition

Şeyma Yol
Health Institutes of Türkiye
İstanbul, Türkiye
seyma.yol@tuseb.gov.tr

Müberra Aydın
Faculty of Engineering
FSMVU
İstanbul, Türkiye
muberraaydin@fsm.edu.tr

Şayeste Söyünmezoğlu, Ulvi Başpınar, Cengiz Şafak
Institute of Pure and Applied Sciences, Faculty of Technology, Institute of Pure and Applied Sciences
Marmara University
İstanbul, Türkiye
sayeste37@gmail.com; ubaspinar@marmara.edu.tr; csaf@gmail.com

***Abstract*—Hand gestures can be identified by using surface electromyography (sEMG) of the upper limb, which measures the electrical activity of skeletal muscles. Hand gesture recognition has recently become most commonly used methods in many applications, such as brain computer interfaces, orthosis and prosthesis control etc. However, there are many factors affecting this recognition in the experimental staps and muscle fatigue is one of these factors. In this study, the effect of forearm muscle fatigue on the performance of hand gesture recognition is investigated using sEMG signals. Four healthy subjects perform six hand motions (fist, hold cup, pointing, pinch, open hand, and rest position). Signals were collected under two conditions: with and without muscle fatigue, and the classification performance of each condition was compared. The four statistical features, including mean frequency, wavelength, mean absolute value, and Willison amplitude are extracted from the sEMG signals. Three classification algorithms have been used, which are the Random Forest, the Support Vector Machine, and the Artificial Neural Network. The results show that in sEMG-based classification applications, data collection steps should be performed by considering the fatigue levels of the muscles.**

Keywords—hand gesture recognition; surface electromyography; muscle fatigue; machine learning

I. INTRODUCTION

Surface electromyography (sEMG) based hand gesture recognition is an emerging and promising area of research with far-reaching applications in prosthetics, human-computer interaction, and rehabilitation (1),(2),(3). The capability to accurately differentiating hand gestures from sEMG signals is essential for creating systems that are both intuitive and responsive, facilitating natural integration with the user's movements.

The effectiveness of sEMG in detecting the electrical activity of muscles during various hand movements has been reported in the literature. However, one of the major challenges faced by researchers and practitioners is the impact of muscle fatigue on the reliability and accuracy of sEMG-based gesture recognition systems. Muscle fatigue, characterized by decreased muscle performance and increased perceived effort, changes sEMG signal patterns. These changes represemt as alterations in signal amplitude, frequency content, and variability, which can reduce the performance of classification algorithms used for gesture recognition (4), (5), (6), and (7).

Understanding and minimising the effects of muscle fatigue is crucial for improving the robustness and reliability of sEMG-based systems. This is particularly important in real-world applications where prolonged use and repetitive movements are common, making muscle fatigue unavoidable. The literature indicates that muscle fatigue leads to significant changes in sEMG characteristics, such as a decrease in median frequency and an increase in signal amplitude, which complicates the gesture recognition process (4), (5), (6), (7), (8). These findings highlight the importance of considering muscle fatigue in sEMG-based gesture recognition systems and propose potential alternatives or complementary technologies to improve performance. The main contribution of this work is to analyze the effect of muscle fatigue on accuracy of hand gesture recognition.

Biosignals are inherently unpredictable and non-stationary which show highly irregular fluctuations. For all these reasons, it is essential to use effective methods to analyze EMG signals. In this study, nonlinear dynamic methods are utilized, such as Empiricial Mode Decomposition (EMD), Ensemble Empiricial Mode Decomposition (EEMD) and Complete Ensemble Empiricial Mode Decomposition (CEEMD). The extracted features obtained from EMD, EEMD and CEEMD are fed into the classifiers, that includes Random Forest, Support Vector Machine, Artificial Neural Network).

II. MATERIALS AND METHODS

The general overview of the study is given in Figure 1. Initially, the raw sEMG signals are filtered by using band-pass

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filter and then decomposed into Intrinsic Mode Functions (IMFs) using EMD, EEMD, and CEEMD algorithms. Features are extracted from each IMF and utilized as training and test data for machine learning. ANN, Random Forest, and SVM are chosen as the machine learning algorithms.

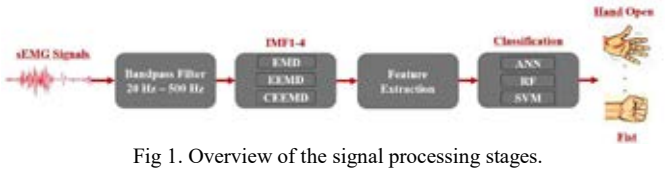


Fig 1. Overview of the signal processing stages.

A. Data Acquisition

The EMG data is obtained from 4 healthy males using surface electrodes from the following four muscles, namely Flexor Pollicis Longus, Flexor Digitorium Superficialis, Extensor Digitorium and Extensor Pollicis Longus. Data acquisition was performed at a sampling rate of 1000 Hz using the LiveAmp model amplifier from Brain Products®. The recording process involved four channels, with the high pass and low pass cut-off frequencies set to 20 Hz and 500 Hz, respectively. All subjects had no history of neuromuscular disease. The subjects were instructed to perform the following six different hand movements (fist, hold cup, pointing, pinch, open hand, and rest position). Additionally, every movement was performed ten times both under fatigued and non-fatigued conditions. The participants were asked to repeat the hand-opening and closing process until they could not close the adjustable hand grip strengthening tool they used, and fatigue was caused in the hand and finger muscles. In Figure 2, a picture is given during the recording step of raw sEMG data.

B. Signal Processing

Nonstationary signals were analysed in the frequency domain by using EMD, EEMD, CEEMD.

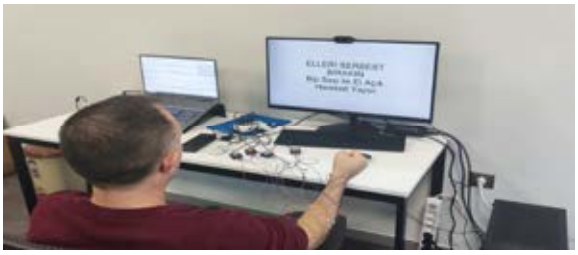


Fig 2. An image from a participant during the recording of the data.

The EMD algorithm is a method used to decompose a signal into its fundamental waveforms (9). This method divides the signal into IMFs of different frequencies and a residual component. EMD is effective in analysing instantaneous frequency variations of the signal and can perform on both nonlinear and non-stationary data. The EMD algorithm is not able to correctly decompose the very low or very high frequency components of some signals and may cause mode mixing problems (10).

EEMD is an advanced signal processing technique used to decompose a signal into its IMFs. EEMD improves upon the original EMD by addressing the mode mixing problem, which can occur in traditional EMD (11). The features of each IMF were then analyzed to provide significant information about the muscle activity during different hand gestures. In this study, the EEMD algorithm was applied with the following parameters: a relative noise standard deviation of 0.3, an ensemble size of 50, and a maximum of 4 IMFs.

CEEMD is an advanced signal processing technique that addresses the limitations of earlier methods like EMD and EEMD (10). CEEMD decomposes signals into oscillatory components with positive, smoothly varying instantaneous frequencies, solving the mode mixing problem of EMD. It offers improved spectral separation and reduced computational cost compared to EEMD (12).

C. Feature Extraction

After decomposing the sEMG signals into IMFs using EMD, EEMD, and CEMD methods several features were extracted from each IMF to analyze the muscle activity during different hand gestures. These features include mean frequency (MF), which provides insight into the dominant frequency components of the signal; wavelength (WL) is a feature that is calculated by the cumulative length of waveform summation over the time period (13), (14) Mean Absolute Value (MAV) is known as average of the summation of absolute value of EMG signal amplitude (13), (15) Willison Amplitude (WAMP) is defined as a measure of the frequency information of the EMG signals (14) and acts as an indicator of the firing of motor unit potentials (16).

D. Classification

In this study, three classification algorithms—Artificial Neural Network (ANN), Support Vector Machine (SVM), and Random Forest (RF) are utilized to classify sEMG signals based on extracted features.

ANN is a computational model inspired by the structure and functionality of biological nervous systems. In EMG signal processing, ANNs are used in systems that record and analyse muscle activity. EMG signals provide information about muscle movements and functions. In this study, the ANN model consist of 64 neurons in the input layer, a fully connected hidden layer, which has 35 neurons, and 6 neurons in the output layer. The activation function of the ANN model is ReLu.

SVM is a supervised machine learning algorithm used for classification and regression tasks. It finds an optimal hyperplane that maximizes the margin between classes in a high-dimensional feature space. This hyperplane separates different classes of data points, effectively handling complex decision boundaries. The cross-validation value was set to 10 at the SVM stage.

Random forest is another supervised learning algorithm that outperforms many methods for both regression and classification. It has gained popularity in various classification tasks which is preferred with ease of use, high accuracy rate, ability of anti-noising and robust against overfitting (17). It grows multiple decision trees on bootstrapped samples of

training data, with each tree considering a random subset of features at each node (18).

III. Results

The results were analysed in 2 groups: the effects of muscle fatigue on power spectrum density and the comparison of classifier performances.

A. The Effect of Fatigue On The Power Spectrum Density

The power spectrum densities of the sEMG signals recorded from 4 channels during fist movement are shown in Figure 3.

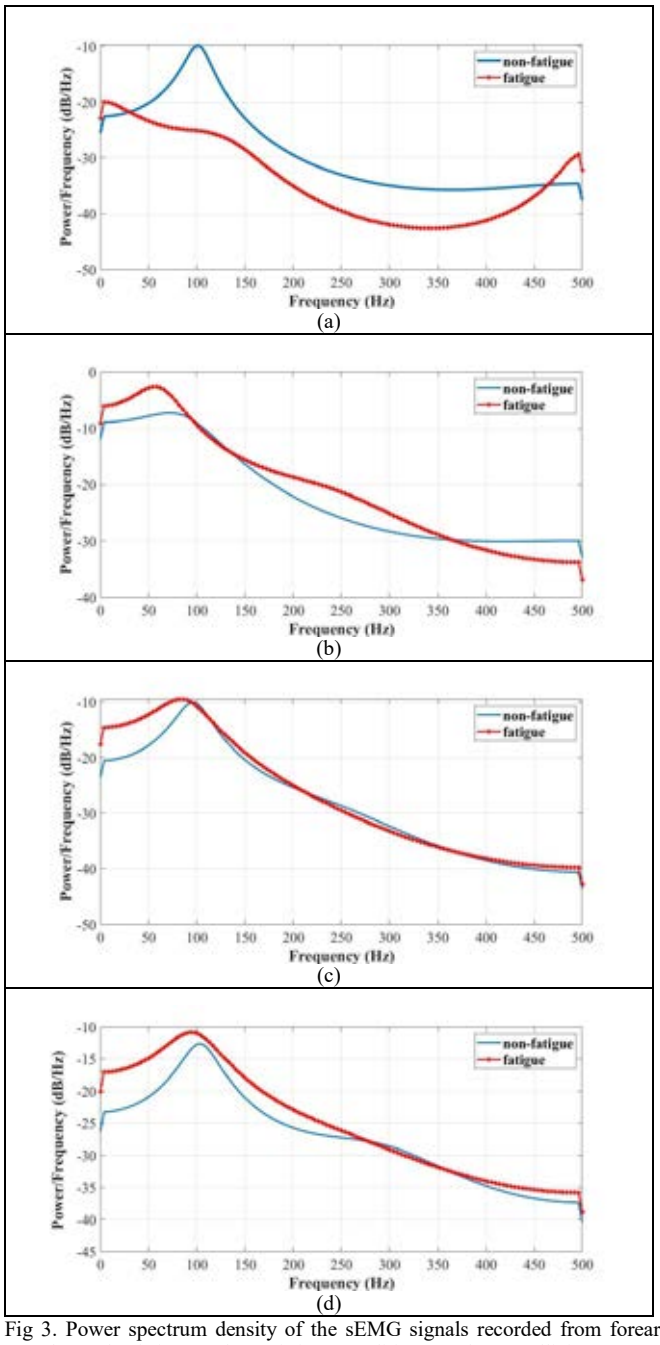


Fig 3. Power spectrum density of the sEMG signals recorded from forearm muscles under fatigue and non-fatigue conditions. a Flexor Pollicis Longus, b. Flexor Digitorium Superficialis, c. Extensor Digitorium, d. Extensor Pollicis Longus

The change in spectrum is more obvious in the signals from the flexor muscles, which are used more actively during the fist movement. It is observed as an increase in amplitude towards low frequencies in the power densities.

B. The Performances of Classifiers

A total of 64 features were extracted for each trial from 4 channels. These features were then divided, with 75% used to train machine learning algorithms and the remaining 25% were used as test. As machine learning algorithms, ANN, Random Forest, and SVM classifiers, which are commonly used in sEMG classification in the literature, were utilized. To analyse the effects of fatigue on classification, 7 different scenarios were planned.

TABLE I. Detailed information of scenarios.

Scenario	Train	Test
1	Non-fatigue	Non-fatigue
2	Non-fatigue	Fatigue
3	Fatigue	Non-fatigue
4	Fatigue	Fatigue
5	Non-fatigue & Fatigue	Non-fatigue & Fatigue
6	Non-fatigue & Fatigue	Non-fatigue
7	Non-fatigue & Fatigue	Fatigue

In this respect, the data were grouped as train/test for machine learning and results of each group were compared. These groups are shown in Table I.

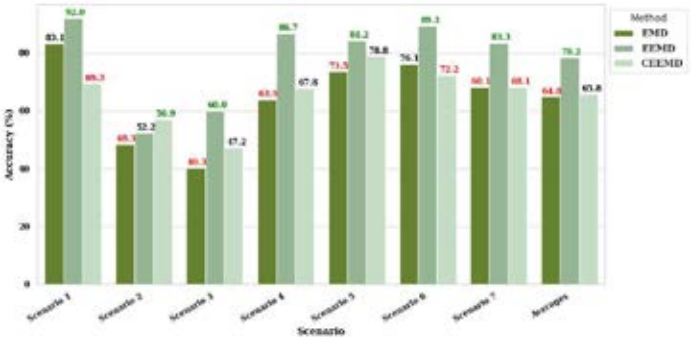


Fig 4. The classification accuracies of ANN classifier.

In the ANN classifier, the highest classification rate was achieved using signals processing by the EEMD algorithm. The highest classification accuracy of 92% was obtained when non-fatigue data was used for both training and testing. In contrast, the lowest classification accuracy of 52.2% was observed when non-fatigue data was used for training and fatigue data for testing observed in Fig. 4.

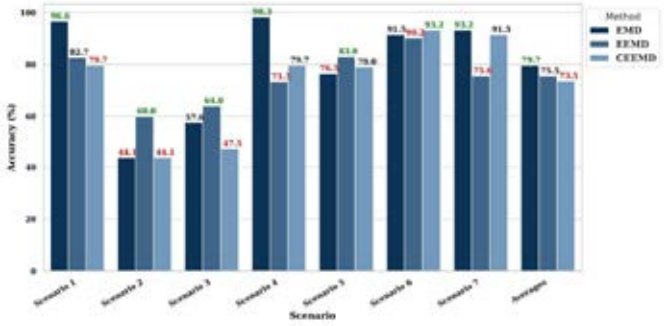


Fig 5. The classification accuracies of Random Forest classifier.

The combination of EEMD algorithm and RF classifier achieved best classification performance (Figure 5). The highest classification success with 98.3% accuracy was obtained in the data labelled as fatigued, while the lowest classification was obtained in the non-fatigue/fatigue (train/test) group.

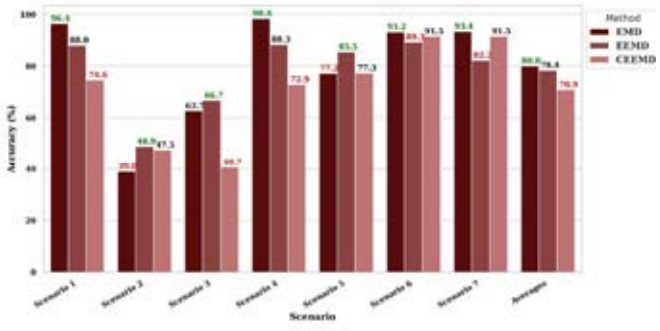


Fig 6. The classification accuracies of SVM classifier.

In the comparison of SVM performance with different scenarios, EMD algorithm give the best result with ACC of 98.4% under the condition that fatigue data is used as test and train. This is followed by the combination of the EMD algorithm with the condition where non-fatigue data is used as training and test with a ratio of 96.4 %. The lowest accuracy of 39.0% was obtained from the EMD algorithm in which non fatigue data was used as train and fatigue data was used as test.

IV. Conclusion

It is important to increase the robustness of EMG signals, which are becoming more widely used in applications such as brain computer interface, active prosthesis control, etc. In this study, it has been clearly shown that classification performance is adversely affected when recordings of muscle fatigue are not used in machine learning. This study is meaningful in terms of demonstrating that effects such as muscle fatigue should be taken into consideration, especially in long-term use during the day. In this research, RF and SVM classifiers outperformed ANN in hand motion classification.

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