Automatic Muscle Fatigue and Movement Recognition Based on sEMG Signals

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***Abstract*—This paper explores the potential of wearable technology equipped with surface electromyography (sEMG) sensors to provide real-time monitoring of muscle activity during dynamic contractions. By leveraging sEMG data, the study aims to classify forearm exercises and detect muscle fatigue, contributing to a deeper understanding of physical performance and well-being. Through the implementation of a cost-effective sensor armband in a laboratory setting, the feasibility of using sEMG for quantifying muscle fatigue and recognizing forearm exercises is demonstrated. The acquired sEMG signals are analyzed using a set of features in both time and frequency domains. Indicators such as Root Mean Square (RMS) and Mean Frequency (MNF) are utilized to assess fatigue levels. Classification of signals into fatigue and non-fatigue categories is achieved through linear regression slope analysis, followed by a more nuanced classification into three exercise categories using neural network architecture. We evaluate the proposed methods using an original database of 100 subjects, accessible for free through the provided link. Support Vector Machines (SVM) yield the best results, with a classification accuracy of 74% for both exercise and muscle fatigue.**

***Keywords*—Wearable technology; sEMG; neural networks; muscle fatigue;**

I. INTRODUCTION

The localization of muscle fatigue has been the subject of extensive study in numerous scientific publications, drawing considerable interest for its implications in sports training, ergonomics, and primarily in physical therapy [1–4]. Muscle fatigue is a physiological phenomenon that intermittently reduces the muscles ability to generate force, accompanying intense and repetitive contractions of the myofibrils. This complex process, which is still not fully understood, involves biochemical changes, insufficient oxygen supply, micro-injuries to the contractile apparatus, and alterations in nervous system excitability [5]. The literature describes various methods of determining muscle fatigue. Some of them are based on establishing the onset of muscle fatigue by measuring the time required for a person to perform a specific task. Determining the concentration of lactate in muscles based on blood samples taken at specific intervals during a specific exercise can also be a good measurement for fatigue detection. Lately, methods based continuous monitoring of local muscle fatigue during the performance of a specific task by measuring the myoelectric activity of individual muscles using surface electromyography (sEMG) have shown promising results [2].

Mean Frequency (MNF) was proposed in [6], as a useful indicator for detecting muscle fatigue. The decrease in MNF values following repeated exercises reflects a reduction in the number of power spectral. In [7], considering a limitation regarding the nonlinear relationship between muscle force and characteristic values, especially in the case of cyclic dynamic contractions, the concept of temporal dependency of MNF for muscle contractions (TD-MNF) was introduced. In addition to MNF, Root Mean Square (RMS) is added in the JASA study [8], resulting in four muscle conditions, as follows: if both RMS and MNF values increase, it indicates an increase in force; if they decrease, it indicates a decrease in force; if RMS values increase and MNF values decrease, it indicates muscle fatigue, whereas if MNF values increase and RMS values decrease, it indicates muscle recovery.

Over the years, the advancement of machine learning algorithms has led to the widespread adoption of supervised learning methodologies for tasks such as muscle fatigue classification, gesture recognition, and physical exercise identification. Supervised learning entails the classification of subjects based on discernible features. Notably, various classification algorithms leveraging surface electromyography (sEMG) data have been explored, including k-nearest neighbor (KNN) [9], support vector machine (SVM) [10], and Multi-layered Perceptron Neural Network (MLPNN) [11]. A crucial aspect in accurate fatigue detection lies in the extraction of features from sEMG signals. Existing literature delineates four primary types of feature extraction methods in sEMG-based signal processing: time domain, frequency domain, time-frequency domain, and nonlinear parameters [11], [12].

This paper introduces a real-time method for detecting muscle fatigue and recognizing forearm exercises based on surface electromyography (sEMG) signals. The signals are captured using a laboratory armband equipped with 8 circularly arranged EMG sensors, positioned on the forearm. Muscle fatigue detection is executed through linear regression, while classification is accomplished using a support vector machine (SVM) trained on a newly acquired database obtained with the laboratory armband. We gathered a dataset containing 100 subjects for forearm exercises, unlike other datasets in the literature, such as the one in [10] which includes 40 subjects and [11] with 55 subjects. The remainder of the paper is structured as follows: Section II outlines the proposed method, highlighting the features and architecture employed for classification and detection. Section III delves into the experimental setup and presents the corresponding results. Lastly, Section IV offers concluding remarks.

II. Proposed method

An outline of the proposed method is provided in Figure 1. The signals captured by the armband are transmitted to a computer via Wi-Fi (UDP). The device has a sampling frequency of Fs = 512 Hz. For the analysis, we used a rectangle sliding window with a length of 2 s (30 samples) for classification and a length of 1s (60 samples) for detection.

A. Dataset acquisition

A dataset consisting of surface electromyography (sEMG) signals acquired at forearm level during various flexion exercises was collected using a laboratory armband inspired by the design of the Myo armband [13], [14]. As illustrated in Figure 2, the armband features 8 sEMG sensors, operates at a sampling frequency of 512 Hz, utilizes a Wifi-UDP transmission mode, and offers a three-hour battery life. Subjects, comprising both males and females aged between 20 and 30 years, wore the armband while performing forearm exercises to capture the sEMG signals. The dataset encompasses recordings from 100 subjects, each participating in three distinct forearm exercises outlined in Figure 3. Each exercise session lasted for one minute, punctuated by one-minute rest intervals. The dataset is made available online by the provided link: sEMG dataset[1].

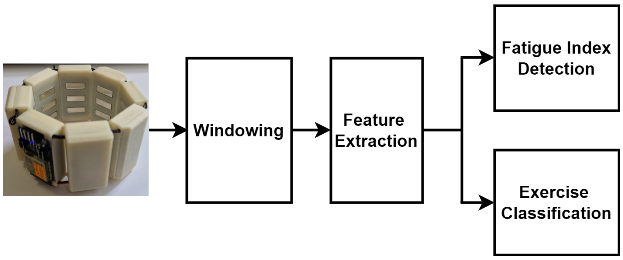

Figure 1. General overview of the system

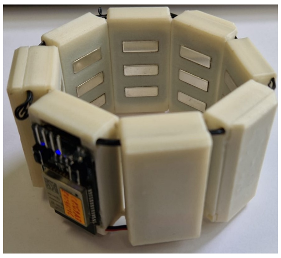

Figure 2. Laboratory armband used for signal acquisition

B. Feature extraction

Feature extraction is essential for recognition systems. In signal processing, a variety of extraction techniques are used to retrieve relevant information. Different feature extraction

[1]https://sharing.speed.pub.ro/owncloud/index.php/s/CcOkNlga5I4xA5R

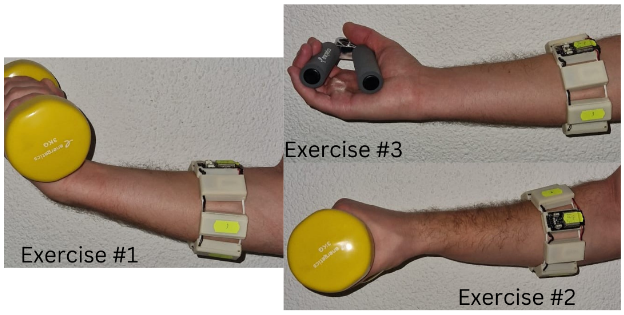

Figure 3. Forearm Exercises (Exercise #1: Palms-up wrist curl, Exercise #2: Palms-down wrist curl, Exercise #3: Forearm squeeze)

methods in the time, frequency, and time-frequency domains are used to sEMG signals for the purposes of muscle fatigue detection and classification. In order to accelerate the classification process, a limited number of time and frequency domain features are utilized. For example, the amplitude of sEMG signals increases and shifts towards lower frequency bands during exercise. RMS and MNF are employed for automatic annotation of fatigue, and ZCR, WL, and SSC in the time domain, as well as $Kurtosis$ and $Skewness$ in the frequency domain, are used for physical exercise recognition.

Considering x to be the analysed signal of length K, the above mentioned features are defined as follows:

1) Slope Sign Change

$$SSC(x) = |k : (x_k - x_{k-1})(x_k - x_{k+1}) \leq \alpha| \tag{1}$$

2) Zero Crossing Rate

$$\begin{aligned} ZCR(x) = |\{k : (|x_k - x_{k-1}| \geq \alpha) \\ \wedge (sgn(x_i) \neg sgn(x_{i-1}))\}| \end{aligned} \tag{2}$$

3) Waveform Length

$$WL(x) = \sum_{k=1}^{K-1} |x_k - x_{k-1}| \tag{3}$$

4) Root Mean Square

$$RMS(x) = \sqrt{\frac{1}{K} \sum_{k=0}^{K-1} (x_k)^2} \tag{4}$$

5) Kurtosis

$$Kurtosis(x) = \frac{1}{K} \sum_{k=0}^{K-1} \left(\frac{x_k - \mu}{\sigma} \right)^4 \tag{5}$$

6) Skewness

$$Skewness(x) = \frac{1}{K} \sum_{k=0}^{K-1} \left(\frac{x_k - \mu}{\sigma} \right)^3 \tag{6}$$

7) Mean spectral frequency

$$MNF = \frac{\sum_{k=1}^{K} f_k P_k}{\sum_{k=1}^{K} P_k} \tag{7}$$

where:

- P_k is Power spectral density in a window

$$P_{XX}(W) = \frac{S(e^{jW})}{2p} \tag{8}$$

- S - Power spectrum using FFT
- p - Estimation of spectrum value using periodogram

C. Classification Module

These days, machine learning algorithms are very helpful since they can handle a wide range of tasks in any industry. Simple regressions or larger neural networks work well for classifying various movements or identifying fatigue based on electromyography (EMG) in the medical and sports domains. The proposed work uses linear regression slope for fatigue threshold detection and algorithms like MLP, SVM, and kNN for classification physical exercises. Using a kernel function to map the input data into a high-dimensional feature space, the SVM method creates the best classification surface within the feature space. The nearest neighbors are used by the k-NN technique to classify or predict new data points. The non-parametric feature of this method makes it appropriate for data with complex or uncertain distributions; however, it suffers from a disadvantage when the dataset is huge. Deep network-based architectures can learn very complex patterns but are vulnarable to overfitting. The $slope$ of the regression line represents the change in the dependent variable for a one-unit change in the independent variable.

$$slope = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2}, \tag{9}$$

where

- x_i and y_i are individual data points
- $\bar{x}$ and $\bar{y}$ are the expected values of the independent and dependent variables respectively.

III. Experiments and results

Next, we validate the dataset that we have acquired in different setups. Our experimental investigations encompass three main components, all centered around surface electromyography (sEMG) signals.

- Firstly, we develop and implement an algorithm for muscle fatigue detection, based on MNF and RMS
- Subsequently, we explore various machine learning methodologies for the recognition of different physical exercises based on sEMG signals,
- Finally, we integrate the two approaches to create an automated system capable of classifying both the type of exercise being performed and determining whether the muscle is fatigued.

Through these multifaceted experiments, we aim to provide a comprehensive understanding of sEMG-based techniques for muscle fatigue detection and exercise recognition, culminating in the development of an advanced system for real-time monitoring and analysis of physical activity and muscle fatigue.

A. Detection of muscle fatigue muscle

To detect muscle fatigue from sEMG signals, it is known that this fatigue occurs when the signal's amplitude increases and the average spectral power decreases during an exercise. In this work, we used linear regression slope to find the threshold where muscle fatigue occurs.

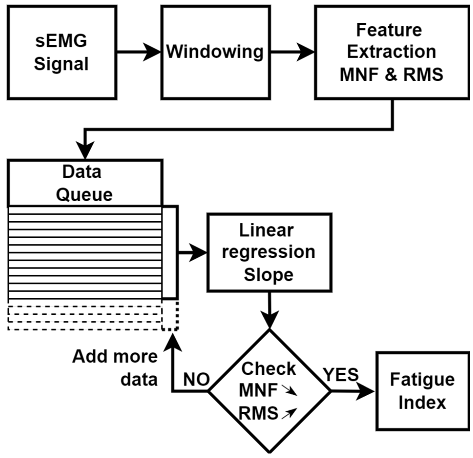

Figure 4. Fatigue Index Detection

The proposed algorithm shown in Figure 4 performs non-overlapping 1-second windowing of the signals for each movement and calculates RMS and MNF on these windows. To find the slope, linear regression was performed on the first $10s$ for RMS values and a similar linear regression for MNF values. We check if the trend for the slope of the RMS values is increasing and for the MNF values is decreasing. If so, muscle fatigue is considered to occur; otherwise, an additional $5s$ of signal are added for a new evaluation according to the algorithm. When the threshold is identified, the total $60s$ signal is divided into two: one signal where the muscle is fatigued and one where the muscle is not fatigued. Since it is possible that after the first $10s$ the muscle may appear fatigued, and then only confused with a decrease in strength, the check is done in multiple stages, adding $5s$ of signal each time. If, after a certain number of checks, the trend for the MNF values remains decreasing and the trend for the RMS values is also decreasing, then it is clear that the muscle is fatigued.

B. Forearm Exercises Recognition

The acquisition of the dataset was undertaken to facilitate the classification of physical activities, wherein each participant completed three one-minute forearm workout sessions. The dataset was partitioned into 60% training data, 30% validation data, and 10% for testing purposes. Following signal extraction, a non-overlapping windowing process of two seconds duration was performed, enabling the extraction of features from both the frequency and time domains, which served as input data for classification purposes. Three distinct classification algorithms, namely Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Multi-layer Perceptron (MLP), were employed in three methodological approaches. In the k-NN algorithm, the number of neighbors was set to 500 because using a large k value reduces the risk of overfitting by averaging out the predictions over a larger set of neighbors, leading to more robust and reliable classification results. For SVM, a radial kernel (RBF) with $C = 10$ was used to handle non-linear data and balance margin maximization with error minimization. Regarding MLP, the architecture yielding optimal performance comprised 4 hidden fully connected layers with 128, 64, 32, and 16 neurons, respectively. Each linear layer was followed by ReLU non-linearity, except for the last layer which used softmax for classification. Through extensive hyperparameter tuning, each method underwent rigorous testing, culminating in the identification of the most effective techniques as detailed herein. The outcomes of this method are delineated in Table I. The results demonstrate that SVM produced the best classification.

TABLE I. Confusion Matrices for Forearm Exercises

True / Pred	k-NN		
	Ex #1	Ex #2	Ex #3
Ex #1	30	0	0
Ex #2	0	30	0
Ex #3	0	21	9

True / Pred	MLP		
	Ex #1	Ex #2	Ex #3
Ex #1	4	2	24
Ex #2	0	30	0
Ex #3	0	10	20

True / Pred	SVM		
	Ex #1	Ex #2	Ex #3
Ex #1	30	0	0
Ex #2	0	30	0
Ex #3	0	6	24

C. Forearm Exercises and Fatigue Classification

To combine the two methods, the data were first passed through the fatigue detection method, resulting in the fatigue index. Using the fatigue index, the data were divided into two categories for each movement. For each of the three movements, the data have two subcategories of muscular fatigue and non-muscular fatigue. The data divided into these six classes are preprocessed according to the second method and prepared for classification using the same algorithms as in the second method. The classification results are highlighted in Table II, where overall accuracy refers to the percentage of correct predictions made by the model compared to the total number of observations. SVM produced the best results even when the number of classes was increased.

TABLE II. Results for forearm exercises and fatigue classification

Method	k-NN	MLP	SVM
Overall Accuracy	62%	73%	74%

IV. Conclusions

In conclusion, this article presents a method for classifying forearm exercises and a fatigue detection approach using sEMG signals. The fatigue detection method can be expanded to represent a standalone real-time muscle state detection system using sEMG signals but requires advanced signal processing and computational resources. In addition to the proposed methods, this article provides a database with over 100 subjects, totaling around 300 recordings of 1-minute each. The following will be taken into account as future directions: extending the dataset for more accurate generalization, performing additional preprocessing for better classification, and acquiring new datasets that includes different physical movements and recuperation procedures.

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