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Muscle Fatigue Analysis in Dynamic Contractions Using Semi-Automatic Segmentation of Muscle Inactivity Areas

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Abstract. Electromyography (EMG) is a technique that registers muscle activity allowing the study of muscle behavior. One such study is the muscle fatigue analysis, which can be defined as the beginning of muscle tiredness and can occur in static or dynamic contractions. There are moments of activity and muscle rest during dynamic contractions, where the latter may not be interesting for some muscle analysis, like muscle fatigue. Therefore, removing muscle inactivity is attractive, but as the signal is not standardized, this process is slower and more individualized. So, this work aims at presenting a muscle fatigue analysis using semi-automatic segmentation of the EMG signal, cutting off the inactivity moments of an electromyography signal obtained during dynamic activity. This analysis consists in calculating the median frequency, a traditional measure to analyze muscle fatigue in static contractions. To assess the efficiency of the proposed method, the median frequency values were compared using manual and semi-automatic segmentation. The result is satisfactory, preserving the desired signal parts for analysis and indicating muscle fatigue as expected.

Keywords. Electromyography, Semi-Automatic Segmentation, Median Frequency.

1 Introduction

The electromyography signal registers muscle activity by electrical pulses responsible for activation of muscle fibers, allowing the visualization of many aspects of muscle behavior. These fibers are grouped and organized into functional units known as motor units (MU), consisting of a neuron and a set of muscle fibers. The muscle is composed of several MUs, and when a contraction starts, the MUs are gradually activated, increasing the action potential, known as MUAP [2, 4].

As a muscle has several motor units, electromyography presents a collection of MUAPs. Since muscle tissue conducts electrical potentials, the EMG signal records information from muscle tissue showing the potential behavior over a period. Thus, the EMG signal amplitude is affected by the number of active MUs, and when the muscle starts to lose strength, more motor units are randomly activated, and the behavior of the signal, in time and frequency domains, is modified [2, 4, 8].

The analysis of EMG signals has applications in sports medicine, rehabilitation medicine, and prosthesis control, among other areas, since they represent the behavior of muscles as activity develops. Despite being the focus of numerous studies, EMG continues to be the subject of recent research, especially in dynamic contractions, which involve moments of muscle contraction and

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relaxation, unlike static contractions, that are simpler exercises since they only involve muscle contraction. An example of the latter is holding an exercise weight for a certain amount of time, causing the muscle to contract [5]. On the other hand, dynamic contractions involve body movement, like running or pedaling. In these activities, muscle fibers change quickly as the exercise demands stretching and shortening of the muscle (contraction and relaxation). There are also changes in the muscle articulation angle and the neural activation pattern, recorded in the EMG signal [3, 4]. More details of muscle fatigue with dynamic contractions are presented in [12–14].

Based on that, this study aims at presenting a muscle fatigue analysis using a semi-automatic method to remove moments of muscle inactivity from an EMG signal recorded during a dynamic exercise. We also estimate the median frequency of the signals in order to assess the efficiency of the proposed method. As shown in [3, 15], there are still some aspects of the EMG signal analysis for dynamic contractions that need to be further developed. Moreover, an efficient strategy for removing inactive muscular areas of these signals is still little explored in the literature.

This paper is divided as follows: the next section presents information regarding one of the most common EMG signal measurements used for fatigue analysis, the median frequency. After that, in Materials and Methods, we describe the signal database and the semi-automatic segmentation method. In Section 4, we present and discuss the results with the conclusions in the last section.

2 EMG Signal Measurements

As mentioned before, in studies related to muscle fatigue, the signal parts corresponding to the muscle relaxation may not be interesting for the analysis, as they are parts that record no muscle activity. Therefore, removing these moments is interesting, as areas of muscle inactivity can impair the EMG analysis. Figure 1 presents a part of an EMG signal recorded during pedaling, where it is possible to observe the moments of muscle contraction and relaxation.

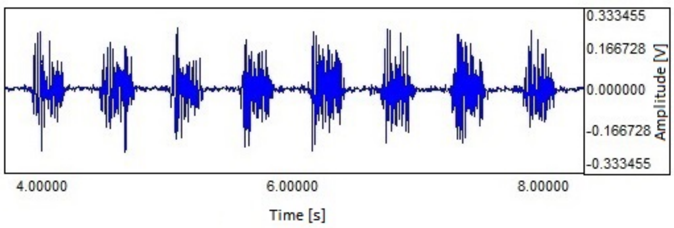


Figure 1: Part of EMG signal registered during dynamic activity.

However, there is no exact pattern of the occurrence of muscle inactivity. It depends on the moment of contraction and on the analyzed person. Thus, manually removing these moments can be a tedious, time-consuming, and not efficient task. A few studies presented EMG signal segmentation, such as [7], with similar goal, and [6], which decomposed signals to identify MUAPs.

As already mentioned, another application of EMG signals is muscle fatigue analysis, where this fatigue can be defined as the moment when the muscle starts to lose strength or tire. A traditional signal measurement for this purpose is median frequency (MDF), which quantifies spectral changes in the signal, estimating the frequency value that divides the power spectrum into two equal energy parts [1]. The MDF can be calculated according to equation (1) [4], where $P(f)$ is the signal power spectrum and f_S is half of the sampling frequency.

$$\int_0^{\mathrm{MDF}} P(f)df = \int_{\mathrm{MDF}}^{f_S} P(f)df \qquad (1)$$

MDF is traditionally applied to fatigue analysis of static muscle contractions because the spectral parameters are related to changes in muscle MUAPs requisitions. This change happens when the muscle starts to lose strength, indicating fatigue. As there are changes in the power spectrum, the median frequency changes accordingly [4]. This measure is also analyzed for dynamic contractions, as shown in [11, 13], where a decrease was observed as muscle fatigue occurs.

3 Materials and Methods

In this section, we present the EMG signals database and the methodology of semi-automatically removal of muscle inactivity parts of EMG signals recorded during a pedaling exercise.

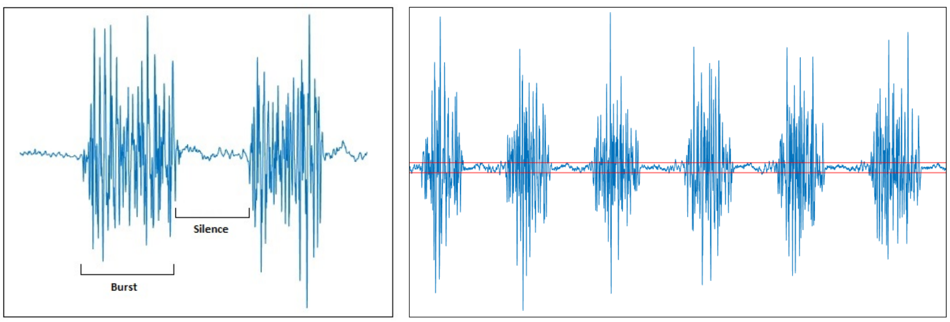
3.1 Database

The signals from the EMG database, already used in [10], were recorded and processed by the Study and Research Group on Neuromuscular System and Exercise (GEPESINE) at the State University of Londrina, where in this work were used signals from 17 participants of this database. They underwent the *Wingate* test, which is a 30-second high-intensity pedaling test. The subjects were 20 to 28 years old, weighting between 58.7 and 78.5 kg, and with stature of 170.5 to 178.5 cm. They were not professional athletes, but performed physical activities regularly, and in this exercise, they all reached exhaustion, which indicates they suffered muscle fatigue. Thus, the muscle behavior at the end of the EMG signal is considerably different from the initial behavior. This variability is important to validate the technique proposed in this work.

The signals acquisition followed the ISEK (*International Society of Electrophysiology and Kinesiology*) guidelines and the standardization proposed by SENIAM (*Surface EMG for a Non-Invasive Assessment of Muscle*). From each volunteer, the signals were collected from three muscles of the right leg: vastus lateralis (VL), vastus medialis (VM), and rectus femoris (RF), which are the extensor muscles of the knee and indicate muscle activity for the quadriceps.

3.2 Semi-Automatic Segmentation

Observing the behavior of a surface EMG signal of a dynamic contraction, such as in Figure 1, two behaviors are noticeable: areas of muscle activation, called *bursts*, and muscle inactivity, called *silence*, illustrated in Figure 2 (a). This happens because it is a dynamic activity, thus the muscle switches between contraction and relaxation.



(a) (b)

Figure 2: (a) EMG signal behaviors: muscle activity (*burst*) and relaxation (*silence*). (b) Amplitude range of the *silence* parts (in red).

As explained before, in studies related to muscle strength or MU activation, the *silence* parts may not be of interest as they are moments of muscle inactivity, that may interfere with the analysis. Therefore, removing the *silence* may improve the analysis as only the relevant information are considered. However, muscle behavior is not standardized, as the *silence* intervals and muscle activation are different throughout the exercise, mainly because the muscle strength changes as a result of fatigue. Additionally, *silence* and *bursts* are not the same in different muscles, even from the same person. So, the segmentation process are not synchronized in different muscles.

In this study, a method is proposed to perform semi-automatic segmentation of EMG signals, removing *silence* intervals irrespective of the muscle. The methodology is based on [9], which developed an automatic segmentation algorithm to identify stationary parts of a time series. Initially, we analyzed the signal's peaks and a *silence* amplitude range was manually determined as illustrated in Figure 2 (b). Then, for each signal, the *silence* range was chosen according to the highest and lowest peaks of the *silence* parts. It was observed that there was an approximate symmetry of the positive and negative values, which was considered in the algorithm for simplification. After this threshold definition, the samples with amplitudes in that range were removed. Also, in order to guarantee the effectiveness of the semi-automatic segmentation, the amplitude threshold was selected individually for each signal under analysis. For other types of exercises, this range may not be ideal and should be modified.

Analyzing the behavior of a single *burst*, Figure 2 (a), it observable that the signal's peaks in the *burst* part have different amplitudes, which may eventually be small enough to belong into the *silence* band. Therefore, a security step was implemented in the algorithm to avoid removing samples from the *bursts*. This consisted in verifying if the peak amplitude remained within the *silence* band for at least three samples, in which case, the peak was considered as *silence*, being removed, otherwise it was maintained as *burst*. This number of samples for the *silence* range was chosen by observing the signal behavior for this kind of exercise. Other values were also tested, like two and five, but with three, a better preservation of the *bursts* occurred.

In order to test the effectiveness of the semi-automatic segmentation, tests were performed comparing the proposed technique with totally manual segmentation of 25% of the database. This manual procedure consisted in observing the samples of the signal where the *burst* started and ended, then it was possible to selected only those parts of the EMG signal. So, just the parts that belong to the *bursts* were considered and the new EMG signal had the *silence* parts removed. Also, we observed if the samples belonging to *bursts* were removed or preserved in the resulting signal.

After the previous procedure, the MDF was estimated for the resulting signals using totally manual and semi-automatic segmentation. Then, each signal was divided in 41 time windows ordered according to the progress of the exercise in order to observe if the MDF values would decrease. Since the signals were collected from *Wingate* trials, the muscles were fatigued at the end (all subjects finished the activity exhausted). Therefore, the MDF values should decrease (in average) as the exercise progressed in time.

The MDF is obtained in the frequency domain using the power spectrum of each time window [1]. The objective of this analysis is to verify if the values and their linear regression slope are similar, what would mean the semi-automatic segmentation was effective. This is presented in the next section.

4 Results

As described previously, for the segmentation procedure, specific ranges of threshold values were considered for each muscle, chosen manually, consisting in the only manual part of the segmentation. Even though there is a security step, which prevents parts of the *bursts* from being removed, some errors still occurred. So, a comparison test was performed with 25% of the signals.

Comparing the number of samples for some randomly chosen *burst* parts from resulting EMG signals using both methods (manual and semi-automatic), we observed that more than 95% of the *bursts* were preserved. Furthermore, by visually analyzing the resulting signals, we confirmed that the muscle inactivity parts had been removed.

For illustration, Figure 3 presents the comparison of a time window of approximately four seconds of a VL muscle signal (top figure) and the resulting signal after semi-automatic segmentation (bottom figure). After the segmentation, the length of the signal is slightly more than two seconds. Thus, the *silence* removal was successful, maintaining only the relevant information for muscle fatigue analysis.

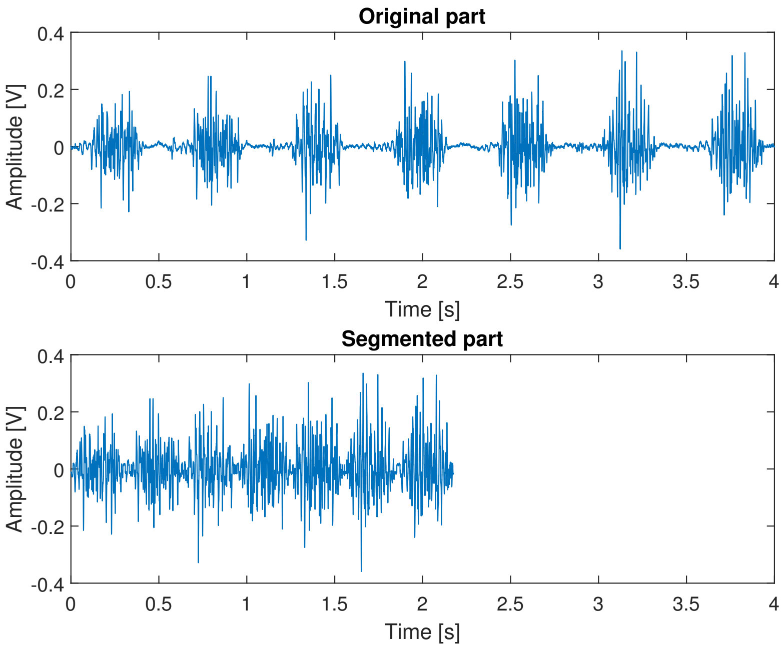


Figure 3: Comparison of a time window of approximately four seconds of a VL muscle signal (top figure) and the resulting signal after semi-automatic segmentation (bottom figure).

In addition, the shape of the *bursts* presented no visible alteration after the segmentation, it is still possible to identify all of them from the new signal. Thus, for the posterior MDF analysis, there is no difficulty in dividing the signal according to the number of *bursts*, since the segmentation process did not influence this.

Thus, after this procedure, the MDF values were estimated for each time window. As expected, the values decrease as the exercise progresses, what can be observed in Figure 4 for a VM muscle. In order to confirm that the semi-automatic segmentation is effective, a comparison was performed using MDF estimations for signals obtained with manual segmentation. The average results were similar for both methods and may be visualized in Figure 4, where (a) presents the MDF values using manual segmentation and (b) using the semi-automatic segmentation.

Comparing both results of the figure, the MDF values vary slightly from window to window, but the linear regression slopes are similar. The same behavior was observed for the rest of the analyzed EMG signals. This is an indication that the proposed semi-automatic segmentation method is equivalent (for the purpose of MDF estimations) to the manual approach; however, it is

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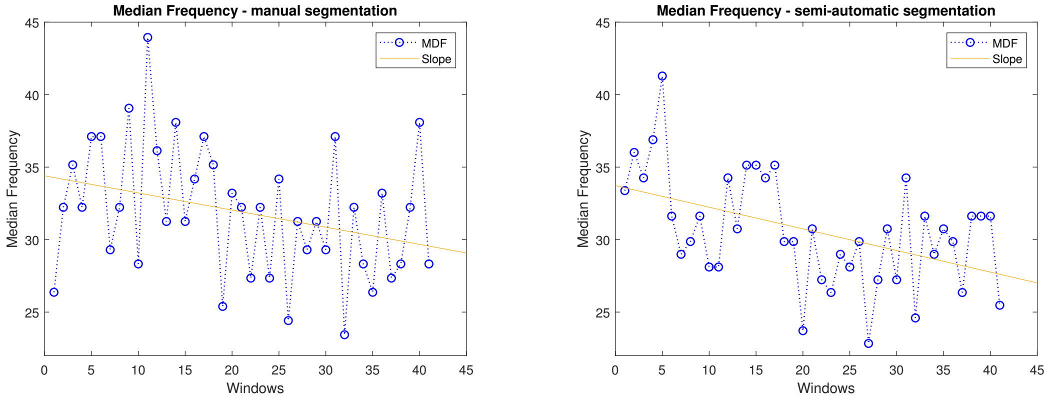
faster and less prone to human errors. Thus, the proposed method can be a good option in studies related to muscle intensity in dynamic contractions that do not need to consider the moments of muscle relaxation.



(a) Median frequency - manual segmentation.

(b) Median frequency - semi-automatic segmentation.

Figure 4: MDF values of an EMG signal of a VM muscle after segmentation using: (a) totally manual method and (b) proposed semi-automatic method.

5 Conclusions

This study presented a semi-automatic segmentation method of surface EMG signals recorded during a dynamic contraction aiming at removing muscle inactivity parts. The approach effectiveness was qualitatively assessed using visual comparison with totally manual segmentation and using MDF estimations, which is a common measurement for muscle fatigue analysis.

In studies related to muscle strength, moments of rest may not have relevant information, which could negatively interfere with the analysis. The removal of these moments can be interesting; however, the occurrence of *bursts* in the EMG signals depends on the moments of muscle activation and relaxation and there is no standardization of these moments. Therefore, we proposed a method that can automate the detection of *silence* parts but still permits manual adjustments according to each signal, speeding up the segmentation process.

The semi-automatic segmentation kept approximately 95% of the muscle contraction information and removed the information related to muscle relaxation. We tested the efficiency of the proposed method against a totally manual approach using the estimation of the EMG signals's MDF. For both methods, in average, the results were qualitatively similar, specifically the linear regression slopes of sequential time windows. Since the signals were collected during *Wingate* trials, the muscles must have fatigued; thus, as expected, the MDF slope would decrease with time.

The observed similarity of the results for both methods mean that the proposed approach performed satisfactorily and can improve fatigue analysis because a semi-automatic segmentation avoids human errors and saves time when compared to manual segmentation. Therefore, this method may be applied to muscle fatigue analysis using EMG signals recorded during dynamic contractions and other muscle strength applications.

Finally, with the semi-automatic method, it is still necessary to manually identify the threshold values of the *silence* band for each EMG signal. For future works, we intend to also automate this step and to estimate other signal measurements to identify muscle fatigue for dynamic contractions in conjunction with the segmentation.

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