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The Influence of Subcutaneous Fat Layer on sEMG Signals During Fatiguing Isometric Contractions in Young Males

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Abstract **–** The purpose of this study is to investigate how the sEMG signal is affected by the subcutaneous fat layer of the biceps brachii during isometric contractions. Surface Electromyography (sEMG) was recorded from 14 male subjects performing isometric contraction of the biceps brachii until fatigue occurred. The subjects were divided into two groups; one group of 7 males participated that were obese and the other group also had 7 participants that were classified as non-obese. Two feature extraction methods (Total Band Power and Dominant Frequency) were used and the sEMG signal parameters were compared to determine how the sEMG classification performance is affected by obesity. The results show that classification accuracy decreased in the obese group of participants, suggesting that the subcutaneous fat layer affects the sEMG signal, while the classification accuracy was high for both sEMG parameters in the non-obese group.

Keywords**:** sEMG, muscle fatigue, isometric contractions, classification, obesity.

1. Introduction

Physiological studies have highlighted the importance of detecting muscle fatigue in various aspects of our lives, including sports, rehabilitation and ergonomics. Nevertheless, the threshold for muscle fatigue is individual due to the variability of the muscle characteristics of each person, hence there is no set threshold for determining fatigue. Several factors might influence the onset of muscle fatigue, such as the subject's fitness level, age and sex [1]. Additionally, the subcutaneous fat layer in the studied muscle will influence the recording of the sEMG signal.

Electrical signal detected during muscle contraction is called the myoelectric signal and for the last decades, has been well established as a reliable method in muscle fatigue research. Surface electromyography (sEMG) signals give useful information about transformations in the muscle, which is used for localised muscle fatigue analysis [2- 4].

Manifestation of muscle fatigue is usually investigated in terms of signal amplitude, muscle fibre conduction velocity (MFCV) and the frequency content of the signal. Previous research on muscle fatigue during static contractions has demonstrated that an increase in the EMG signal amplitude, as well as a change in the spectrogram are clear indicators of fatigue occurrence [5-10]. Various feature extraction methods have been applied in sEMG signal analysis. Most of these parameters are investigated in either time or time-frequency domains, both focusing on the frequency at a set time in the signal [5-10].

In the frequency domain, the RMS (Root mean squared) is a well-established feature that easily detects the changes in the signal during muscle fatigue [11-12]; however, other common parameters include MNF (Mean Frequency) [13], and the IMF (instantaneous mean frequency) [14], which redefined the MNF to represents the stochastic nature of the sEMG signal. Some studies have established new parameters that combine both the time and frequency domains of the signal, such as the STFT (Short-Time Fourier Transform) [15]; however, Karlsson et al. [16] acknowledge that other combined techniques, such as the CWT (Continuous Wavelet Transform) could more precisely analyse the signal. The signal is decomposed into a numerous multi-resolution component with a wavelet transform [17,18]. Several studies have adapted wavelets in muscle fatigue research, such as Kumar et al. [19], Walker et al [20] and more recently a pseudo-wavelet established by Al-Mulla et al. [21].

Other feature extraction methods utilised by A-Mulla et al., is the Total Band Power (TBP) and the Dominant Frequency (DF) [22]. Estimated using Welch's method, the TBP is proven a useful and reliable parameter in muscle fatigue research. Furthermore, the Dominant Frequency is the most repeated frequencies in the band power, which was between 19 hz to 46 hz.

Previous studies have determined that the sEMG signals are affected by fat layers in various muscle groups. As the fat layer thickness increased, the sEMG crosstalk simultaneously increased above the region of the muscle [23]. Furthermore, it was discovered that the RMS value in the sEMG signal amplitude decreased substantially with a greater thickness of fat tissue of the studied muscle. It has been found that the RMS (Root Mean Square) and MPF (Mean Power Frequency) of the sEMG signal in women is highly sensitive to the fat layer thickness, albeit this varies greatly between different muscle groups [24]. Research on the rectus abdominal muscle established that the RMS of the sEMG signal decreases in subjects with greater BMI and increased fat layer tissue.

This research is investigating the influence of fat layer on the sEMG signal in fatiguing isometric contractions in male subjects. Two groups will be performing isometric contractions in the biceps brachii; one group of healthy male subjects with a BMI index between 18 and 25 and the second group will have a high BMI index of 30 or more. The sEMG signals will be analysed using two different feature extraction methods: the Total Band Power and the Dominant Frequency. By comparing the findings of the two groups as well as the various sEMG parameters, this study will determine how the classification performance is affected by obesity.

2. Methodolgy

The data were collected from two groups. The first is a control group of seven healthy, male subjects that are non-obese (BMI 18-25). In the second group, the 7 male participants had a BMI index of 30 or more, which would categorise them into the obese group of subjects. All the participants have a mean age 28 +/- 2.5 yr) and were non-smokers with no other common illnesses. With their informed consent, the subjects were willing to reach a physical fatigue state but not a psychological one.

The participants were seated on a preacher biceps curl machine to ensure stability and biceps isolation while performing a static biceps curl activity. Once the participants reached total biceps fatigue (not able to exert force) they stopped. The experiment team encouraged the subjects to continue exerting force for as long as possible. For each of the five participants, three trials in total were carried out (two trials for training and one for testing). In all the trials we used 30% Maximum Voluntary Contraction (MVC) for each subject. There was a resting period of five days for each of the three trials ensuring full recovery of the biceps brachii.

In this study two types of sensors are used for signal acquisition: goniometer and sEMG electrodes. The goniometer measured the angle between the elbow joints, where the subjects should maintain an angle of 90 degrees. A flexible electro-goniometer (Biometrics Ltd.) was placed on the lateral surface of the dominant arm's elbow to measure the elbow angle, with adhesion on the areas distal and proximal to the joint. An important consideration in selecting the most appropriate goniometer sensor is that it must be capable of reaching across the joint, so that the two end blocks can be mounted where least movement occurs between the skin and underlying skeletal structure.

Once the signal has been acquired, two different feature extraction methods were used to compare the classification accuracy of the signal between the obese and the non-obese group. The Total Band Power and the Dominant Frequency were selected as suitable parameters for the comparison. A Linear Discriminant Analysis (LDA) method is used to compare and validate the performance of the two features. LDA is a well-established classifier, which has been previously utilised in muscle fatigue research to classify the sEMG signal.

3. Findings

Figure 1 shows the classification accuracy in both non-obese and obese participants. For the classification of the non-obese group, both parameters show persistently high classification accuracy; however, the DF has an even higher classification percentage for each participant. Although the TBP has a classification accuracy of 78.4 % and above, the results fluctuate more when using this feature extraction method. This shows that the DF is a more reliable feature extraction method for determining the classification accuracy of fatigue occurrence in the sEMG signal.

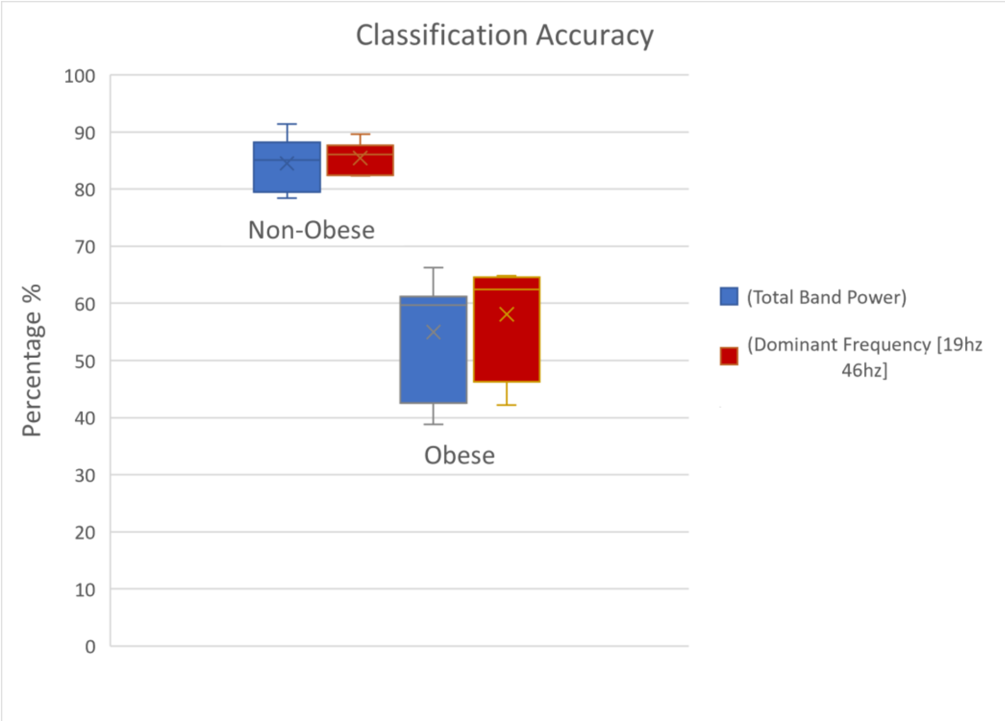

Figure 1: Comparison of the classification accuracy between the Total Band Power and the Dominant Frequency for non-obese and obese participants.

For the second group with the obese subjects, the classification accuracy is significantly lower for both parameters, as shown in Fig. 1. In this group, both feature extraction methods have a great variety of classification accuracy, varying from 48.8-66.3 for the DF and 42.2-64.6 for the TBP respectively. Although both parameters can successfully classify the signal, the greater fluctuation in the classification performance suggests that it is more difficult to classify the sEMG signal in obese subjects.

Moreover, Fig. 1 clearly displays the high classification accuracy for non-obese subjects, which is over 75% for both parameters for all the subjects. This indicates that both TBP and the DF are reliable methods used for sEMG signal classification for muscle fatigue research. However, when comparing these results, it is evident that the classification accuracy for the obese group is significantly lower for both signal feature extraction methods, with a classification accuracy of 40 percent and above. The different parameters also vary, with the classification accuracy in the obese group is 42-62%, for the TBP, while for the DF the classification accuracy is between 47-67%. This suggests that both parameters have fairly similar classification accuracy for all the participants in the obese groups although the DF appears to have a slightly higher classification performance across subjects.

4. Discussion and Conclusion

This study is comparing the classification accuracy of sEMG signal from fatiguing isometric contractions of the biceps brachii in obese and non-obese participants. Results clearly show that the sEMG classification performance decreases in signals acquired from the obese group of participants. By using the sEMG signal extraction methods TBP and the DF, classification of the fatigue content of the signal was successful. The findings also suggest that the DF is a slightly more reliable parameter for sEMG signal classification, which falls in line with previous findings [22]. Nevertheless, TBP is also a reliable parameter for signal classification as the results are consistent across subjects.

By comparing the non-obese and the obese group, the results indicate that the classification accuracy drops significantly in the subjects of the obese group. This may be due to the subcutaneous fat layer that is covering the biceps brachii and which again may affect the quality of the signal. One explanation of the decrease in signal classification may be due to crosstalk, which has been previously established in other studies [23,24]. A few of the participants had a much lower classification accuracy for both feature extraction methods, which may indicate that the subjects had a higher BMI index than the rest of the subjects. Further studies are needed to determine the correlation between high BMI values and a decrease in classification accuracy.

In conclusion, the subcutaneous fat layer affects the sEMG signal classification performance with a significant decrease in classification accuracy. Hence, in future research it is important to acknowledge this factor when studying muscle fatigue in obese participants. Moreover, new methods should be established to overcome this issue to obtain more reliable and sEMG signals classification from obese subjects.

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