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EMG based muscle fatigue detection using autocorrelation and k-means clustering

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Abstract: The electromyogram (EMG) can be commonly used to detect muscle fatigue during exercise to prevent injury or muscle disorder. A traditional way to indicate fatigue is based on extracting features from EMG segments in time-domain or frequency-domain. In this work, muscle fatigue detection is developed by extracting three features from the autocorrelation function of EMG segments. The classification is done using a k-means clustering approach. The proposed method has also successfully classified unknown EMG segments into non-fatigue and fatigue state. The accuracy of the proposed method is evaluated in detecting the signal of transition-to-fatigue stage.

I. Introduction

Muscle fatigue is defined as a decrease in the muscle's ability to evoke a force. Intensive exercise and vigorous physical activities can cause muscle fatigue which may lead to injury in some cases. Usually, the muscle fatigue is detected through analysing time-domain features [1], e.g., RMS, or using frequency-domain features [2], e.g., mean frequency, or time-frequency domain [3] of the recorded electromyogram (EMG) signal. The structure in these characteristics can be classified as follows: The RMS value increases and the mean frequency value decreases, according to muscle fatigue [1–3]. However, the uncertainty in the measurement of EMG signals, e.g., due to noise, artifacts, and outliers, makes these features not always reliable in the time and/or frequency domain for fatigue detection. This issue could be solved by considering autocorrelation function (ACF) as a feature, since the ACF is associated with the oscillatory structure of EMG during muscle activity [4]. Therefore, in this work, ACF is considered to extract features from the recorded EMG signals. Then, k-means clustering approach is considered to categorize the segmented EMG signal from one subject into non-fatigue and fatigue state.

II. Methodology

II.I. Data collection

The largest muscle on the ventral portion of the arm, known as biceps brachii, is considered in this work. The EMG signals were recorded using Ag/AgCl electrodes and Biopac MP36R ($f_{\text{sampling}} = 1\,\text{kHz}$) from six healthy participants (3 females and 3 males). These EMG signals are filtered with 3$^{\text{rd}}$ order Butterworth bandpass filter with passband frequencies ($f_{c1} = 35$ Hz, $f_{c2} = 350$ Hz). The protocol of recording is as follows, each subject was asked to choose a dumbbell with suitable weight either 5 kg or 7.5 kg. Then, the subjects were informed to lift the dumbbell at the beginning of each signal tone and to bring the dumbbell down before the next signal tone. The tone signal is generated using MATLAB with random time intervals varying between 4-6 seconds and it is recorded simultaneously with EMG signal using mic to indicate the start/end of the task. The segmentation of EMG signal is done by using the recorded signal tone. The subjects were asked to repeat the task until exhaustion, and to report the first repetition associated with localized mild pain in the biceps muscle or symptoms of fatigue. The first fatigue state is denoted as the transition-to-fatigue stage (TTF).

II.II. Features extraction

The ACF can be used to detect the oscillatory structure of a signal [4]. It means that the ACF is directly related to the characteristics/oscillations in the EMG signal. Fig. 1A shows a change in the amplitudes of ACF with respect to the fatigue. The ACF is calculated with maximum lag equal to 40 ms. Since it is symmetric, only positive lags are used. In this work, three features, denoted as F1 (peak), F2 (valley) and F3 (peak), are selected from ACF to present each EMG segment (see Fig. 1A).

II.III. Fatigue/non-fatigue classification

The *k*-means clustering is commonly used to partition data into *k* clusters. Since the EMG segments can be either in non-fatigue or fatigue state, two clusters are needed to classify EMG segments. The effect of fatigue is noted as increase/decrease/increase in the selected features F1, F2 and F3 in the one-sided ACF, respectively (see Fig. 1B). The classification of non-fatigue and fatigue state of EMG segments of each subject individually is based on clustering the proposed features into two clusters (see Fig. 2).

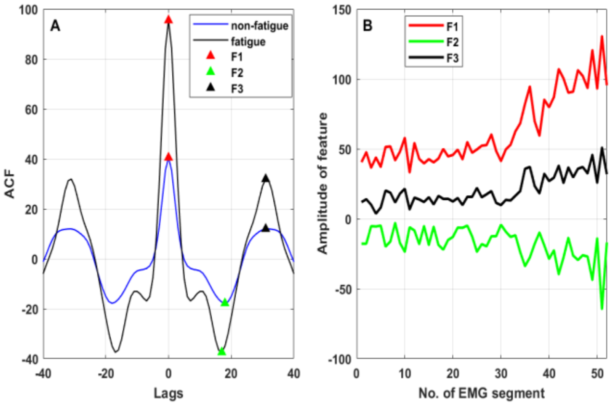

Figure 1: A. The autocorrelation function (ACF) of a non-fatigue/fatigue EMG segment of a subject, and the location of the selected features F1, F2 and F3, B. The amplitude of these features for successive EMG segments of a subject.

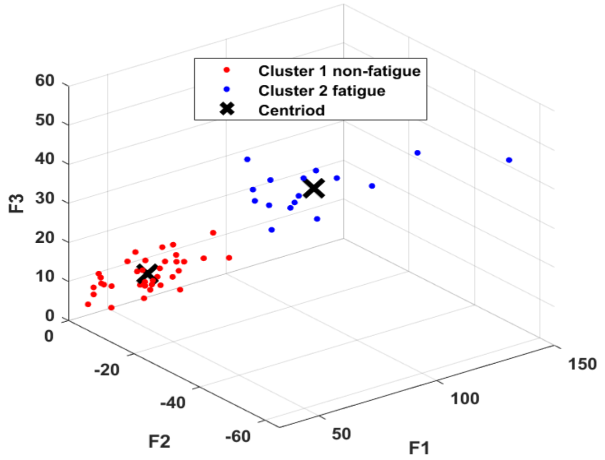

Figure 2: Clustering the selected features F1, F2 and F3 of successive EMG segments from the first subject into two clusters, cluster 1 (non-fatigue) and cluster 2 (fatigue).

III. Results and discussions

Fig. 3 shows the detected TTF stage, however, there is changing between non-fatigue and fatigue state, then stalled to fatigue state (it is noted for all subjects).

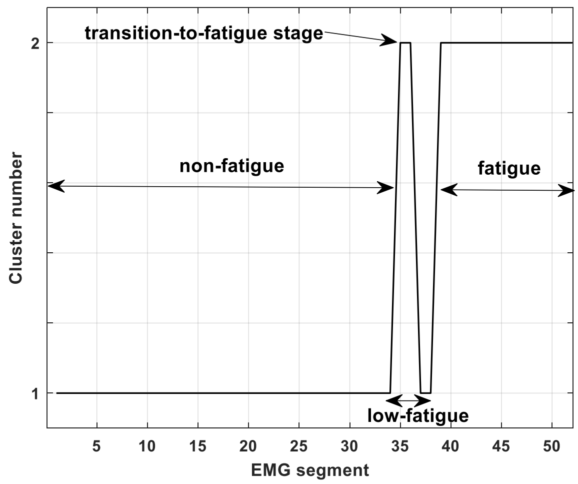

Figure 3: Plot of the cluster number of consecutive EMG segments in the case of the first subject.

We defined this region as a low-fatigue state. This can be very useful information to avoid injuries due to excessive training or workouts. The proposed method is evaluated using the difference between the reported and the estimated segment of transition-to-fatigue stage (see Table 1).

The average and standard deviation of error of TTF is about 2±3 segments (approximately 10±15 seconds). The developed fatigue detection method based on autocorrelation and *k*-means clustering can be considered as a successful extension of the detection of the transition-to-fatigue stage method proposed by [5].

Table 1: The result of six subjects in terms of total number of EMG segments and the reported/estimated segment of transition-to-fatigue (TTF).

	Total No. of EMG segments	Reported segment TTF	Estimated segment TTF
Subject 1 (m)	52	36	35
Subject 2 (m)	80	43	46
Subject 3 (m)	130	56	61
Subject 4 (f)	34	12	18
Subject 5 (f)	18	17	17
Subject 6 (f)	41	28	26

IV. Conclusions

The proposed features F1, F2, and F3 obtained from the autocorrelation function of an EMG segment can lead to a good estimation of not only the transition-to-fatigue, but also the low-fatigue state (multiple switching between non-fatigue state and fatigue state). This can be used to prevent injury due to excessive muscle fatigue.

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Author's statement

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