Computer Methods and Programs in Biomedicine 154 (2018) 45–56

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms

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ARTICLE INFO

Article history:
Received 16 April 2017
Revised 22 September 2017
Accepted 29 October 2017

Keywords:
Muscle fatigue analysis
Surface electromyography
S-transform
EMBD
Time-frequency features
SVM

ABSTRACT

Background and objective: Surface electromyography (sEMG) based muscle fatigue research is widely preferred in sports science and occupational/rehabilitation studies due to its noninvasiveness. However, these signals are complex, multicomponent and highly nonstationary with large inter-subject variations, particularly during dynamic contractions. Hence, time-frequency based machine learning methodologies can improve the design of automated system for these signals.
Methods: In this work, the analysis based on high-resolution time-frequency methods, namely, Stockwell transform (S-transform), B-distribution (BD) and extended modified B-distribution (EMBD) are proposed to differentiate the dynamic muscle nonfatigue and fatigue conditions. The nonfatigue and fatigue segments of sEMG signals recorded from the biceps brachii of 52 healthy volunteers are preprocessed and subjected to S-transform, BD and EMBD. Twelve features are extracted from each method and prominent features are selected using genetic algorithm (GA) and binary particle swarm optimization (BPSO). Five machine learning algorithms, namely, naïve Bayes, support vector machine (SVM) of polynomial and radial basis kernel, random forest and rotation forests are used for the classification.
Results: The results show that all the proposed time-frequency distributions (TFDs) are able to show the nonstationary variations of sEMG signals. Most of the features exhibit statistically significant difference in the muscle fatigue and nonfatigue conditions. The maximum number of features (66%) is reduced by GA and BPSO for EMBD and BD-TFD respectively. The combination of EMBD- polynomial kernel based SVM is found to be most accurate (91% accuracy) in classifying the conditions with the features selected using GA.
Conclusions: The proposed methods are found to be capable of handling the nonstationary and multicomponent variations of sEMG signals recorded in dynamic fatiguing contractions. Particularly, the combination of EMBD- polynomial kernel based SVM could be used to detect the dynamic muscle fatigue conditions.

1. Introduction

Bioelectric signals represent physiological functions of various tissues/organs associated with the human body. Research on these signals aims at extracting useful biomarkers that reflect the functional state of the human system. In the recent years, several advanced signal processing algorithms and machine learning methods have been reported in the literature. However, the analyses of these biosignals are still complex due to its inherent random and nonstationary variations. The surface electromyography (sEMG) signals are the electrical activities recorded over the surface of the skin during muscle contractions. The analysis of these signals finds application in various areas such as clinical diagnosis, prosthetic myoelectric control, ergonomics and sports biomechanics [1]. Recently, this non-invasive sEMG technique is widely used to analyze the muscle fatigue [2].

Muscle fatigue is a neuromuscular condition in which muscles fail to generate the required force. It occurs in both normal and abnormal subjects [1,2]. Neuromuscular fatigue is a most common symptom in neurological disorders such as multiple sclerosis, Parkinson disease and stroke. It is reported that around 60% of neuromuscular patients suffers from severe fatigue [3]. The detection and prevention of fatigue help to improve the performance in

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https://doi.org/10.1016/j.cmpb.2017.10.024
0169-2607/

sports related scenarios and aids in the financial growth of industries [4,5]. The characteristics of sEMG signals are found to largely vary with fatigue conditions due to metabolic, structural and energetic changes in muscle [6].

The frequency and amplitude characteristics of sEMG signals are random, multicomponent and nonstationary due to the physiological parameters such as motor unit recruitment patterns, firing rate and anisotropic nature of volume conductors. However, these signals are considered as stationary in isometric contractions. Several measures such as root mean square value, zero crossing and median frequency have also been employed for these sEMG analysis [1,7]. However, these measures do not account for the time-varying frequency characteristics of sEMG signals [8].

Several researches have been carried out on the sEMG signals detected under isometric contractions. However, dynamic muscle contractions better represent the real life activities [8]. The stationarity assumption does not hold for the signals recorded under dynamic contractions because the frequency components vary continuously with time. Changes in muscle force, muscle shape, elbow-joint angle, and movement of the innervation zone with respect to the recording electrodes results in the high degree of nonstationarity [8,9]. Short time Fourier transform (STFT) has been widely used to characterize the time varying frequency components of sEMG signals. However, this method suffers from limitations such as stationarity requirement and the uncertainty principle [2]. These nonstationary signals are typically analyzed using time-scale representation and/or time-frequency distribution techniques.

Continuous wavelet transform (CWT) represents the signal in the time-scale space and it has a wide range of application in the analysis of biomedical signals. It can also be seen as an extension of STFT. A recently developed time-frequency method called Stockwell transform (S-transform) is actually a combination of CWT and STFT. S-transform is an effective time-frequency technique, which preserves phase information and provides good time-frequency resolution using movable and scalable Gaussian window [10,11]. Recently, this technique has been utilized for the analysis of electroencephalography and electrocardiography signals in order to track changes in signal amplitude, frequency and phase [12,13]. However, the applicability of S-transform has not been explored for the sEMG based muscle fatigue analysis.

All time-frequency techniques that belong to Cohen class represent the signals in time-frequency axis. Choi–Williams and Born–Jordan distributions are smoothed version of Wigner-Ville distribution (WVD) which are widely used to analyze the nonstationary property of the sEMG signals [14–16]. B-distribution (BD), Modified B-distribution (MBD) and extended modified B-distribution (EMBD) belongs to reduced interference Cohen class TFDs [17]. Recently, BD and MBD based techniques have been used for the sEMG analysis [18]. EMBD based TFD has been reported to perform better than MBD in the representation of slow and fast variations of frequency contents associated with heart sound signals [19]. Further, this technique has been extensively used to study the multicomponent nonstationary nature of new born seizure EEG and fetal movement signals [20]. The focus of this work is to introduce these high-resolution time-frequency methods such as EMBD and S-transform for the muscle fatigue analysis and to compare the classification performances using machine learning techniques.

In addition to conventionally used time-frequency features such as instantaneous mean and median frequency, other attributes such as time-frequency based statistical and complexity features are also used to provide deeper insight about the muscle mechanisms in fatigue condition. Several classification algorithms have been reported for the differentiation of muscle nonfatigue and fatigue conditions. The K-nearest neighbor, naïve Bayes and genetic algorithm based support vector machine have been used for the classification of sEMG signals under various neuromuscular conditions [21].

In this work, sEMG signals are recorded from the biceps brachii muscle during dynamic fatiguing contractions. The nonfatigue and fatigue segments are subjected to S-transform, BD and EMBD techniques and then twelve time-frequency features are extracted from each TFD. Then the feature selection and machine learning algorithms are applied to differentiate muscle nonfatigue and fatigue conditions. The performance of these TFDs is compared using classifier performance.

2. Material and methods

2.1. Material (Experimental protocol and signal acquisition)

The sEMG signals are recorded using Biopac MP36 data acquisition system. The signal to noise ratio and common mode rejection ratio of this system are 89 dB and 110 dB respectively. The signals are acquired at the sampling rate of 10,000 Hz with the gain of 1000 [22,23].

Fifty two untrained healthy subjects with no history of neurological and neuromuscular disorders participated in this study. The participants are instructed to take 12 h of complete rest before the start of experiment. The nature of the study is well explained to the subjects and informed consent is obtained. This experiment adhere the tenet of Declaration of Helsinki. Two Ag–AgCl disc type disposable electrodes are placed with an inter electrode distance of 3 cm over the muscle belly after the skin preparation. The differential configuration set-up has been used for this study. The reference electrode is placed at the elbow joint [18].

The subjects are instructed to stand erect on the wooden platform to prevent electric shocks. Then, the subjects are asked to perform continuous biceps curl exercise with 6 kg dumbbell load using their dominant hand until they experiences fatigue or unable to continue the exercise. The subjects are asked to maintain the curl speed at their comfortable pace. sEMG signals are acquired from the dominant hand for the entire duration of exercise [18,21].

The sEMG signals associated with the muscle nonfatigue and fatigue conditions are extracted from the first and last curl of the exercise. The peak of first and last curl is identified using the moving average root mean square value and a segment of 250 ms is extracted before and after the peak for the analysis [24]. The motion artifacts, power line interference and high frequency noises are removed using band pass filter (10–400 Hz) and notch filter (50 Hz) [18].

2.2. Methods

This study consists of computation of time-frequency spectrum, feature extraction, feature selection and classification of muscle fatigue and nonfatigue conditions.

2.2.1. Time-frequency representation of sEMG signals

Fourier spectrum represents the frequency components present in the signals. However, it does not provide information about how the frequency component varies with time. The time-frequency methods show the nonstationary nature of biomedical signals and it has become an ideal tool for this analysis [14].

2.2.1.1. Stockwell transform. The Stockwell transform (S-transform) addresses the issue of fixed window of STFT. It uses scalable localized Gaussian window. The dilation process associated with this transform aids in providing good resolution. The mathematical expression of S-transform for a signal $x(t)$ is defined as [11]

$$S(t,f) = \int_{-\infty}^{\infty} x(\tau) g(t-\tau,\sigma) e^{-j2\pi f\tau} d\tau \tag{1}$$