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Cyclic spectral analysis of electrocardiogram signals based on GARCH model

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ABSTRACT

In this paper, the capability of Cyclic Spectral Density (CSD) is evaluated for ECG signal analyzing and a new feature generation method for them is presented. Although, the CSD presents a second-order statistical description in the frequency domain and reveals the hidden periodicity in EEG signals, it needs an efficient algorithm for calculating and also a suitable model for describing. By employing an efficient computational algorithm which is called the FFT accumulation method (FAM), the CSD of ECG signals can be computed. In this study, In order to choose an efficient statistical model for the Cyclic Spectral Analysis (CSA) coefficients of ECG signals, their statistical features are investigated at various regions of bi-frequency plane. It is revealed that the CSA coefficients are heteroscedastic and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is a suitable model for them. Hence, The GARCH parameters of CSA sub-bands are calculated and are employed to classify the ECG using a support vector machine (SVM) classifier. Evidently, the results reveal that the performance of the new method in ECG classification outperforms the former studies.

1. Introduction

Biomedical signal processing systems are designed to help physicians in order to diagnosis diseases more effectively. Several biomedical signals such as electrocardiogram (ECG) are extremely complex to decipher. The changes of the heart's electrical activity is recorded in the ECG waveform made by different electrical depolarization–repolarization patterns of the heart [1]. Any heart rate abnormality is appeared in the morphological pattern pathology that can be identified by the analysis of the recorded ECG signal [1–3]. Due to the fact that the ECG signals have long duration and their visual scanning is highly time consuming, their interpretations are highly subjective which cause disparity among cardiologist. Nowadays, to overcome this issue, automatic identification systems have been introduced in many literatures.

Generally, selection of a suitable representation method plays a major role in signal processing algorithms [4]. In fact, the quality of automatic identification systems performance is determined by signal representation algorithm and feature extraction schemes. Some type of representations includes using orthonormal basis functions, optimally time-warped polynomial functions and so on [5,6]. In Ref. [7], the fast Fourier transform (FFT) analysis has been employed which provides only frequency content and cannot be localized in time domain. To overcome this problem, the short time Fourier transform (STFT) has been used extensively in order to presents both time and frequency information using uniform window [8]. Also, both time and frequency components can be localized by the wavelet transform (WT), in this regard, the window size is adopted based on the signal's frequency content [9]. Although the algorithms based on the WT have successful performance in representation and description of the ECG signals, many surveys are continued concerning this issue.

Several recent studies on ECG modeling have fitted mathematical representations to ECG fiducially points. In Ref. [10], ECG beat shapes were modeled by employing Hermitic basis functions. In Ref. [11], ECG complexes were modeled utilizing lines or parabolas. The major of these methods require pre-processing to portray the ECG signals into meaningful components such as T-wave, P-wave, and QRS complex. In some studies, the Gaussian distribution has been employed to the heart rate estimation [12,13], denoise ECG signals [13,14], detect arrhythmias [15], and generate synthetic ECG signals for various types of arrhythmias [16]. This technique depends on a priori information and requires nonlinear equations

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in order to estimate it. Various studies are perused concerning this issue to determine a more efficient representation method; furthermore, a number of the researchers attempt to obtain an appropriate signal representation technique which can decipher ECG signals more effectively [2].

In this study, a novel technique for ECG representation based on Cyclic Spectral Analysis is recommended and the capability of this method for ECG classification is evaluated. The conducted experiments in this study on classification of ECG signals reveal that the extracted features from the cyclic spectral density coefficients are more potentially separable compared to the extracted features of other techniques. This function appears hidden periodicity of a signal using the second-order statistical explanation and grants more comprehensive information than the ordinary power spectral density [4,17]. The theory of cyclostationary signals and two equivalent methods for analyzing of cyclic spectral density, time and frequency-smoothing methods, have been introduced in Refs. [18–24]. One of the proposed methods is the FFT accumulation method (FAM). It is an algorithm belonging to time smoothing class and employs the computational efficiency of the FFT [24]. In the present study, the utilizing of cyclic spectral analysis for feature extraction is explained comprehensively. One ought to note that the CSD produces many features which contain redundant information and cause error in ECG classification. One can utilize a statistical model to describe the CSA coefficients and to diminish the number of these features as one of the successful schemes. The model parameters will be trustable if an appropriate model is chosen. In this research, the statistical characteristics of the CSA coefficients are investigated in order to choose the suitable statistical model. Next, the generalized autoregressive conditional heteroscedasticity (GARCH) model is used for theses coefficients since they are heteroscedastic and the GARCH model is matchable with properties of the CSA coefficients for instance heavy tail margin distribution [25,26]. As an application, the suggested procedure is employed to classify the ECG signals. To accomplish this goal, the GARCH parameters are extracted from Cyclic Spectral Analysis at various regions of bi-frequency plane. Due to the fact Markov random field (MRF) is an efficient approach to acquire more separable features; it is employed to provide the best features subset. On the other hand, since the support vector machine classifier offers best margin between different classes, it provides a considerable backing of the medical diagnosis [10,27–29]. Therefore, the SVM classifier is chosen amongst various classifiers for ECG classification. The obtained features are applied to the SVM classifier with five distinct outputs. The results of experiment reveal that the extracted features are appropriate for the ECG classification.

The remaining sections of this paper are organized as follows: In "Theoretical background" Section, cyclic spectral density, FAM algorithm and GARCH model are explained. The "Proposed Method" Section is allocated to illustrate the new proposed method and the experimental results are reported in "Experimental Results and Discussion" Section. Finally, last Section concludes the paper.

2. Theoretical background

In this section, we briefly explain Cyclic Spectral Density and GARCH model used in this work.

2.1. Cyclic spectral density

As a comparison to the other stationary based approaches, cyclostationary analysis is highly efficient to separate signals having distinct cycle frequencies and hidden periodicities [23]. This method has been utilized for digital modulation detection [30], texture classification [17,30], and EEG classification which their results indicated that the CSD based methods were robust to noise and other undesirable condition [31]. In this paper, a cyclostationary based method is suggested to analyze the ECG signals. These signals can be modeled as cyclostationary random processes that their statistical parameters are changing periodically. Cyclostationary analysis is based on the auto-correlation function of the signal [19,30]. Using auto-correlation, the hidden patterns in a time series such as the presence of sinusoids in a noisy signal can be detected. The cyclic autocorrelation function can be explained for a discrete time real value signal $x(n)$, is defined as [4]:

$$R_x^{\alpha}(k) = \lim_{N\to\infty} \frac{1}{(2N+1)} \sum_{n=-N}^{N} [x(n+k)e^{-j\pi\alpha(n+k)}][x(n)e^{j\pi\alpha n}]^{*} \tag{1}$$

where is the time lag between observations of the signal $x(n)$. The discrete-time Fourier transform of the $R_x^{\alpha}(k)$:

$$S_x^{\alpha}(f) = \sum\nolimits_k R_x^{\alpha}(k)e^{-j2\pi fk} \tag{2}$$

is called CSD. In this description, α presents cyclic frequency and depends on amount of frequency shift, and f shows spectral frequency variable [17]. The numerical value of α for which $S_x^{\alpha}(f) \neq 0$ is countable if the signal has finite average power [23]. In addition, if $\alpha = 0$, the ordinary power spectrum is obtained as follows:

$$S_x(f) = S_x^0(f) = \sum_{k=-\infty}^{\infty} R_x^0(k)e^{-j2\pi fk} \tag{3}$$

It is evident that the CSD can provide more extensive features with respect to the ordinary power spectral density [4]. Two inherent characteristics of the CSD are concluded easily from the definition expression of the CSD due to the fact that the ECG is a real value signal [31]. The first characteristic is periodicity corresponding with discrete time for each integer values of n and m, $S_x^{\alpha+n}(f+m+n/2) = S_x^{\alpha}(f)$, and the second is symmetrical relationships $S_x^{\alpha}(-f) = S_x^{\alpha}(f)$ and $S_x^{-\alpha}(-f) = S_x^{\alpha}(f)^{*}$. Hence, only a quarter of estimated points can describe entire CSD.

A number of computational techniques have been proposed which generally fall into frequency smoothing algorithms and time smoothing algorithms classes. In this research, the FAM algorithm is utilized as an efficient algorithm out of time class [22,23]. In this algorithm the cyclic cross periodgram is expressed as:

$$S_{xT}^{\alpha}(n,f)_{\Delta t} = \frac{1}{T}\langle X_T(n,f+\frac{\alpha}{2}) \times X_T^{*}(n,f-\frac{\alpha}{2})\rangle_{\Delta t} \tag{4}$$

where:

$$X_T(n,f) = \sum_{n=-N'/2}^{N'/2} a(r)x(n-r)e^{-j2\pi f(n-r)T_s} \tag{5}$$

The Eqs. (4) and (5) explain how frequency contents of a narrowband signal $x(n)$ are correlated over a specific Δt duration [4,24]. $X_T(n,f+\alpha/2)$ and $X_T^{*}(n,f-\alpha/2)$ are complex demodulates of the $x(n)$ and $a(r)$ presents a data capturing window with length $T = N'T_s$ which T_s is the period of data sampling and N' is the sliding window's length [24]. Subsequently, with correlation of complex demodulates on Δt seconds, the cyclic cross periodgram, for specific f_0 and α_0, can be calculated as follow:

$$S_{X_T}^{\alpha_0}(n,f_0)_{\Delta t} = \sum\nolimits_r X_T(r,f_1)X_T^{*}(r,f_2)g(n-r) \tag{6}$$

where $g(n)$ is a window with length $\Delta t = NT_s$; $f_1 = f_0 + \alpha_0/2$ and $f_2 = f_0 - \alpha_0/2$ [24]. In the FAM, Fourier transform is used to smooth out the time. When frequency changes from α_0 to $\alpha_0 + \varepsilon$, the output of the algorithm is expressed as [4,24]:

$$S_{X_T}^{\alpha_0+\varepsilon}(n,f_0)_{\Delta t} = \sum\nolimits_r X_T(r,f_1)X_T^{*}(r,f_2)g(n-r)e^{-j2\pi\varepsilon rT_s} \tag{7}$$