Denoising Cyclostationary Framework for Enhanced Electrocardiogram Analysis

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Abstract

We present a novel two module scheme for efficient analysis of noisy Electrocardiogram (ECG) signals. The first module consists of a segmentation algorithm which uses cyclostationary analysis for the detection of a single heart beat or cycle (P wave-QRS complex-T wave). The time domain cyclostationary (CS) algorithm exploits the statistical properties of the recorded periodic ECG signal and does not use any prior knowledge about signal morphology. Using the obtained cycle length the next module uses repeated applications of Principal Component Analysis (PCA) to reduce multiple additive noises from the multi trial and multi channel recorded ECG signals. PCA has been used for noise reduction in ECG but the method of repeated applications of PCA is novel. In this study, PCA was applied in 2 stages. In the first stage, PCA was applied to multi-channel ECG signals from one trial. The output ECG signals from the first stage were used in the second stage, where PCA was applied to multi-trial ECG signals from a single channel. The proposed scheme was tested with the 12-lead ECG signals from PTB Diagnostic database (National Metrology Institute of Germany) provided on physionet website which showed significant improvement in Signal to Noise ratio. We suggest that this simple scheme can be used for automatic analysis of noisy ECG signals where the extraction and denoising of single heart beat provide enhanced physiological features which enables better clinical interpretation of cardiovascular functionalities.

1. Introduction

The Electrocardiogram (ECG) is the most commonly used biomedical signal [1]. A normal ECG waveform illustrates the electrical activity in the heart, and can be decomposed into characteristic components, such as the P, Q, R, S, and T waves. Each component has its own typical form and behavior. The important fact is that cardiovascular diseases and abnormalities such as myocardial ischemia and infarcts cause a change in ECG wave shape. Hence it can be used for detection, diagnosis and treatment of cardiac diseases. For instance, the S-T segment in the ECG signal indicates an imbalance of myocardial oxygen and is used for early diagnosis of ischemia and myocardial infarction, the Q-T interval is a good indicator of long QT syndrome (LQTS) and is also currently the gold standard for evaluating effects of drugs on ventricular repolarisation[2]. Similarly in our previous work [3] we intelligently detected ectopic beats by using information from ECG and blood pressure waveforms. However in many cases the activities relating to given disease are embedded in a single cycle of heart beat. Therefore the analysis depends directly on efficient ECG beat segmentation results. Many proposed works use heuristic rules to segment heartbeat automatically from the ECG signal after preprocessing [4, 5]. It is also made difficult because the shape of ECG is quite variable both within and across patients which is due to variety of factors like location of electrode, position of subject's body and poor electrode contact. There is also considerable variability in periodicity of a single heart beat between healthy and unhealthy subjects. Thus a segmentation scheme robust to these inherent variability's and relying on minimal heuristics is desired.

Also another motivation for this work stems from the fact that when an electrocardiogram is recorded, it is usually contaminated with many kinds of noise , such as the baseline wander, EEG noise, 50 or 60 Hz power-line interference, EMG noise and motion artifacts [1]. Removal of noise has been one of the major concerns of biomedical signal processing which needs reliable signal processing techniques to preserve the diagnostic information of the recorded signal. Numerous techniques have been proposed to extract ECG components contaminated with noise. Filter based techniques are only partially successful and often lead to a reduction in the amplitudes of the component waves (e.g. the Q or R wave). Also noise and background artifacts are random in nature with wide frequency range and simple filters fail to remove in-band noise (i.e. noise in same frequency as the cardiac signal). Also adaptive filters architecture [6], independent component analysis (ICA) [7], genetic algorithm (GA) and independent component analysis [8] have been used to extract noise free signal from the noisy ECG. Over the past few years wavelet transform methods have also been used significantly [9, 10] in bio-signal processing, however they are limited by the fact that no entropy criterion is known to be appropriate for biomedical applications. In our previous study [8] we proposed a GA and ICA based approach to reduce additive noise. GA with ICA might however be a time consuming technique and also the framework did not include any segmentation module to enable clinical diagnosis.

To solve the above discussed problems we present a compact automated two module scheme for enhanced cardiac signal analysis. In this paper we propose a novel segmentation approach using the time domain cyclostationarity algorithm which exploits the cyclic nature of the recorded ECG signal to obtain the periodicity in the first module. Using the obtained periodicity we then propose the use of 2-stage PCA as the second module of the scheme to reduce background noise and artifacts for enhanced cardiac signal analysis.

2. Methods

The scheme to reduce background noise and artifacts from 12-lead ECG signals for enhanced cardiac analysis is shown in Figure 1 below. Cardiac systems normally perform rhythmic operations and hence the resulting ECG signal is almost periodic and maybe referred to as cyclostationary signal [1]. The statistics of the ECG signal vary within the duration of the cardiac cycle but repeat at regular intervals. The time domain cyclostationary (CS) algorithm exploits this statistical property (i.e. cyclic nature) of the recorded periodic ECG signal for segmentation of a single heart beat (i.e. to obtain the periodicity) which enables PCA analysis.

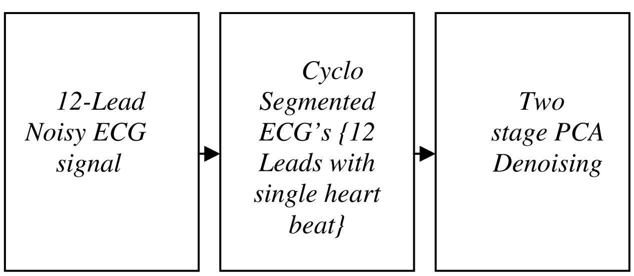

Figure 1: Scheme for ECG signal analysis.

2.1 Cardiac Segmentation using Cyclostationary Analysis

The theory of cyclostationary signals is briefly discussed below. A discrete-time signal which has periodic mean and correlation is said to be cyclostationary [11]. In particular a signal $s(t)$ is called first-order cyclostationary [12] if its time-varying mean $m_x(t) = E[s(t)]$ is periodic.

$$m_s(t + lp_1) = m_s(t), \qquad \forall t, l \varepsilon Z. \tag{1}$$

Similarly, x is second-order cyclostationary [12] if it's time-varying correlation.

$$R_{ss}(t;\tau) = E[s(t)s(t+\tau)]. \tag{2}$$

is periodic in t for any fixed τ.

$$R_{ss}(t + lp_2;\tau) = R_{ss}(t;\tau), \quad \forall t, l \varepsilon Z. \tag{3}$$

Here p_1 and p_2 are the smallest positive integers such that (1) and (3) are true. If p_1 and p_2 = 1, we observe from Eqns. (1) and (3) that mean is time invariant and the correlation depends on the time difference only. Then $s(t)$ is considered as a stationary signal or in the given discussion context a cyclostationary signal with period 1.

In the time domain cyclostationary (CS) analysis considering $s(t)$ we can define the autocorrelation function for various lags (in this study it is lagged twice the length of the signal) which is then averaged as below in Eqn. (4). The lagged sum is then squared to obtain the periodicity as illustrated in Figure 2 in the experimental study (Section 3).

$$R_{ss}(t;\tau) = E[\overline{s(t)s(t+\tau)}]. \tag{4}$$

2.2 Noise reduction using PCA

PCA is a statistical technique commonly employed to reduce the dimension of the feature set [13, 14]. It has also been used to reduce noise from biomedical signals like Visual Evoked Potential (VEP) signals [15] for analysis of alcoholics and for noise reduction in ECG signals [16] where PCA was applied only once. The method proposed here for ECG signals works by applying PCA twice like in [15]; firstly with multi-channel ECG signals from one trial and secondly with multi-trial ECG signals from one channel. The novelty of the method lies in the 2-stage application of PCA for ECG signal enhancement. The method does not assume any property of ECG signals but it requires that ECG signals be recorded from many channels and across many trials. This requirement of multi-channel and multi-trial recordings is not a drawback for ECG signal analysis because most ECG recordings are obtained from many channels and across many trials which are generally used to remove background noise and artifacts through averaging.

The ECG signals consist of two parts: noise and ECG. Therefore, using PCA, it is possible to separate ECG part (i.e. signal part) from noise and background artifacts using the fact that the noise subspace will consist of principal components (PCs) with eigenvalues chosen below a certain threshold and eigenvalues with PCs above this threshold represent the ECG signal subspace. Assuming matrix **x** to represent the extracted ECG signal from noise, the covariance of matrix x was computed using (7):

$$R = E[xx^T]\,. \tag{5}$$

Next, matrices *Ei* and D were computed where *Ei* is the orthogonal matrix of eigenvectors of R and D is the diagonal matrix of its eigenvalues, D = *diag* (*d*1... *dn*). The PCs were computed using:

$$y = Ei^T x^T\,. \tag{6}$$

In this work, percentage of total power (variance) retained
is used to give the number of required PCs [13]. Using this method, PCs that account for 95% of the total power was assumed part of the signal in the first-stage PCA, while PCs that account for 98 % of the total power was assumed part of the signal in the second-stage PCA. The PCs that account for the 5% and 2%, respectively account for noise. These values were obtained heuristically after some preliminary experimentation for the tested dataset. The higher value of power retained in the second-stage PCA is to reflect that noise decreases after the first stage. The signal part of the ECG was reconstructed from the selected PCs using

$$y = \hat{Ei}\,\hat{y}\,, \tag{7}$$

where $\hat{Ei}$ and $\hat{y}$ are eigenvectors and PCs respectively.

Two-stages of PCA were applied to the segmented single cycle ECG signal contaminated with noise and background artifacts like in [15]. First, PCA was applied to each of the single cycles of the 12 channel ECG signal (we may say channel down PCA). PCA was applied again to the output signals using 25 segmented single cycle ECG signals from the same channel (we may say channel across PCA). Percentage of total power retained was used to determine the number of PCs to reconstruct the data which is suited to automated procedures as compared to other methods like scree graph test since it does not involve manual inspection. These PCs, which account for most of the variance in the data, can be assumed to represent the signal part of the VEP. The rest of the PCs can be considered to account for noise in the data. With multi-channel real ECG signals few PCs may be enough to represent all the ECG signals and the correct number of PC selection is crucial to preserve only the signal part of the noisy ECG signal. Figure 3 in the experimental study section shows diagrammatically the enhancement of ECG signals contaminated with noise and background artifacts.

3. Experimental study and results

To test our proposed scheme we used Normal ECG signals (N). These datasets were obtained from PTB Diagnostic database (National Metrology Institute of Germany). To show the effectiveness of the proposed method, different types of noises [random, Electroencephalogram (EEG) and Electromyogram (EMG)] were added to the ECG signal. Figure 2 shows clean , noisy and cyclostationary analyzed ECG signals.

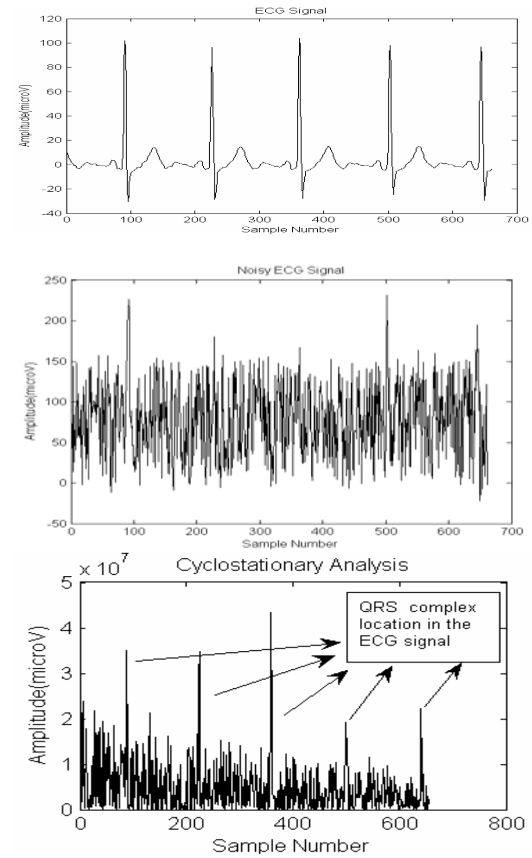

Figure 2: ECG signal, ECG signal with noise added and Cyclostationary analyzed ECG signal.

The peaks in the cyclostationary analyzed signal indicate the position of the QRS complex. Cyclostationary analysis also helps minimize the added noise and artifacts (It is especially effective with the random noise which decreases with increasing lag). The distance between the QRS complex location indicates the periodicity of ECG signal (or single heart beat) which is used for 2-stage PCA denoising [15] as in Figure 3. The SNR improvement is highlighted diagrammatically for only channel one due to space constraints.

4. Discussion and conclusions

This work addresses the problem of beat segmentation and artifacts removal for noisy ECG signals. There has been considerable interest in signal processing frameworks for segmentation and noise removal because it helps in patient monitoring. We propose a new two module scheme using CS and PCA analysis for ECG denoising task. The motivation for this work is the fact that cyclostationary (CS) algorithm is able to exploit the cyclic nature of the recorded ECG signals while PCA does not assume any property of ECG signals. The results obtained with this novel approach is encouraging which maybe used for wide range of purposes like detection of the presence of heart beat, initiation of an alarm signal in holter devices and calculation of instantaneous or average heart rate.

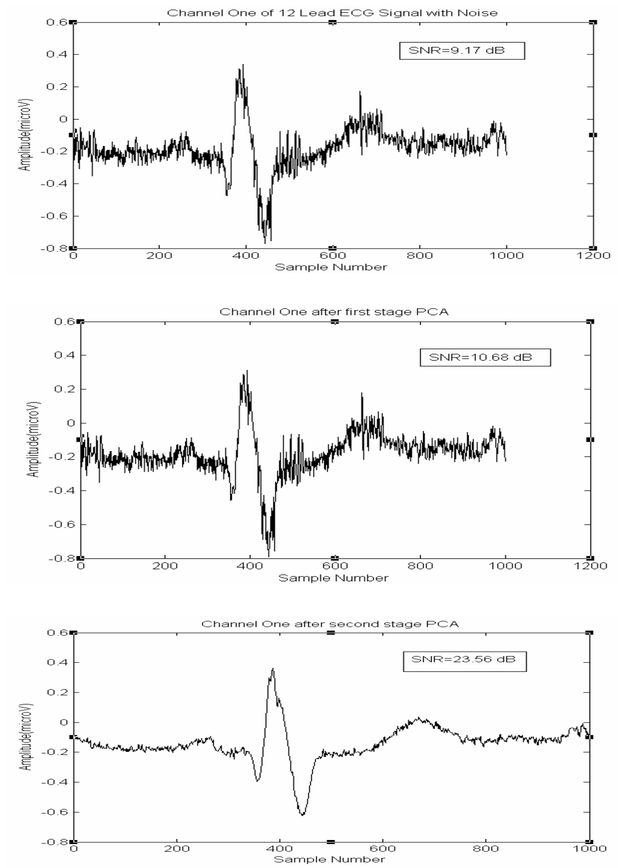

Figure 3: Two level PCA denoising with SNR calculations for first channel of 12-Lead ECG

Acknowledgements

The first author acknowledges the support from Overseas Research Students Award Scheme (ORSAS), United Kingdom and the University of Essex Doctoral fellowship for this research work. The authors also thank National Metrology Institute of Germany for providing the datasets to test the methodologies on the www.physionet.org website.

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