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ECG-derived respiration estimation from single-lead ECG using gaussian process and phase space reconstruction methods

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ABSTRACT

Respiratory activity influences electrocardiographic measurements (ECG) in various ways. Therefore, extraction of respiratory information from ECG, namely ECG-derived respiratory (EDR), can be used as a promising noninvasive method to monitor respiration activity. In this paper, an automatic EDR extraction system using single-lead ECG is proposed. Respiration effects on ECG are categorized into two different models: additive and multiplicative based models. After selection of a proper model for each subject using a proposed criterion, gaussian process (*GP*) and phase space reconstruction area (PSR_{Area}) are introduced as new methods of EDR extraction for additive and multiplicative models, respectively. We applied our algorithms on Fantasia database from Physionet, and the performance of our algorithms is assessed by comparing the EDR signals to the reference respiratory signal, using the normalized cross-correlation coefficient. The proposed method is also compared with other EDR techniques in the literature. The extracted EDRs using *GP* and PSR_{Area} methods, considering their selected appropriate models, show mean correlations of 0.706 and 0.727 with reference respiration which is significantly better than most of the state-of-the-art methods. It can be seen that after selecting the model of each subject and using either PSR_{Area} or *GP* (*combined* method), the correlation result, 0.717, is improved. Statistical significant differences ($p < 0.05$) are found in the correlation coefficients of our algorithms and most of the state-of-the-art methods, showing that our combined methods outperforms them and is comparable to the well-known EDR technique, principal component analysis (PCA) based EDR extraction. A model selection criterion and two EDR extraction methods, *GP* and PSR_{Area}, have been proposed. The combined method using *GP* and PSR_{Area} following model selection for each subject yields EDR estimation system which results better than most of the state-of-the-art single-lead EDR extraction in terms of correlation coefficient and can be used as a promising algorithm to obtain ECG-derived respiratory signals.

1. Introduction

Respiration signal is usually recorded with techniques like spirometry, pneumography, or plethysmography. These techniques require the use of devices that may interfere with natural breathing and be hard to use in certain conditions such as ambulatory monitoring, stress testing, and sleep studies. Thus, methods developed for indirect extraction of respiratory information are useful to pursue [1].

One of these techniques is continuous noninvasive respiratory monitoring using a surface electrocardiogram (ECG) measurement. Potential advantages of such a method are its low cost, high convenience, and the ability to simultaneously monitor cardiac and respiratory activity [2]. During the respiration process, some morphological changes in the ECG signal arise due to some mechanisms such as: I) changes in volume of lung during inspiration and expiration cycles which in turn cause change in electric impedance of thorax, and II) changes in the heart vector position with respect to ECG electrodes [3]. Furthermore, it is well known that respiration modulates heart rate such that it increases during inspiration and decreases during expiration [1]. According to these effects of respiration on recorded ECG signal, many signal processing techniques which are aimed at extracting respiratory information, so-called ECG-derived respiration (EDR), have been developed.

We try to group previously developed and published EDR methods into different categories based on similar principles:

1) Methods based on tracking oscillatory pattern of rotation angle of mean electrical axis (AMEA) of the heart induced by respiration cycles: These multi-lead algorithms have utilized

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vectorcardiogram (VCG) signals, or synthesized VCG from ECG leads [4–6], or have estimated the direction of the AMEA projection on the plane defined by two orthogonal leads [7–9]. Using multi-lead ECG may result in a more adequate EDR at the cost of patient's convenience in multi-lead ECG monitoring systems.

2) Single-lead methods based on ECG morphologic variations which in turn divide into two different approaches: 2-1) EDR time series which are generated by sampling respiration-related features hidden in recorded ECG. Respiration features induce respiration effects on recorded ECG and are extracted beat by beat. Many respiration features have been proposed such as R amplitude [10,11,2,12,13], RS amplitude [14,11]. Robustness of respiration features in noisy ECG signal has made main motivation for introducing other features like QRS area [15,16,13,17], QRS slopes [18,19], ECG statistics such as 4th order cumulant [20], area under major portrait radius (MPR) curve derived from phase-space loop [21]. The drawback of these methods is aliasing which may arise when the ratio of heart and respiration frequency is lower than 2. Furthermore, these methods need precise QRS and R peak detection, and possible errors in R detection can degrade their performances. EDR time series could also be created by applying transformations like PCA (principal component analysis) [22], KPCA (kernel PCA) [23,17], and ICA (independent component analysis) [24] to data matrix constructed by aligning consecutive QRS waves. PCA method only takes into account linear relation between respiration and ECG, so in order to overcome the drawback of linear PCA, KPCA was introduced. ICA method decomposes ECG into statistically independent subcomponents, one of which hopefully could be correlated to respiration. The main assumption in ICA method is that recorded ECG has been superposed by respiration activity, so ICA method performance degradation depends on whether it is built upon a realistic assumption or not. 2-2) ECG transformation and decomposition to find respiration component hidden in recorded ECG. Filtering methods such as single bandpass filter [25], discrete wavelet transform (DWT) [25], empirical mode decomposition (EMD) [26,27], and homomorphic filter [3] have been used for EDR extraction. The main drawback of these techniques is that subjects' frequency information such as respiratory bandwidth is needed prior to EDR extraction filtering.

3) Methods based on the heart rate variation. When respiration-induced heart variations have naturally changed with age or illness, this method often breaks down.

Before EDR extraction, it is necessary to consider recorded ECG signal as a combination of original heart electrical activity (clean ECG) and respiration activity and noise signals. There are different assumptions about *ECG-respiration* model which justify the use of various EDR methods. In [12,20,2] it is taken for granted that respiratory activity acts as an amplitude modulation of the clean ECG; hence a nonlinear *ECG-respiration* model is used. Respiration, also, has been considered as an additive signal to the clean ECG source, so linear filtering and ECG decomposition are applicable. Since these two distinct models are originated from differences between individuals' breathing process, in this study we hypothesized that considering the well-fitted *ECG-respiration* model for each subject and applying an EDR extraction method based on each model would improve the performance of overall EDR extraction.

This work concentrates on single-lead EDR extraction which is of benefit when one lead is available. After model selection using a proposed criterion, two new EDR estimation techniques are proposed: *Gaussian process or GP-based source separation* and *phase space reconstruction (PSR)* methods which are appropriate for linear and non-linear model, respectively. Then we provide an experimental comparison of the proposed methods with the ones from the literature.

2. Method

We take two different *respiration-ECG* models into consideration: Amplitude additive (superposition) $u(t)=s(t)+r(t)+a(t)$ and multiplicative (modulation) $u(t)=s(t)\times(1+r(t))+a(t)$; models, where the recorded ECG or observation signal, $u(t)$, is composed of clean ECG source, $s(t)$; noise sources, $a(t)$; and EDR signal, $r(t)$. In multiplicative model, $r(t)$ is assumed to modulate the amplitude of clean ECG signal. Our aim is to extract the variations of respiration activity (inspiration and expiration cycles) which affect ECG recording in two different ways depending on difference in individual's respiration activity (belly or chest breathing), so EDR signal can be reflected as a zero mean signal in both models, and what is important is variation of extracted EDR signal showing respiration cycles. GP approach is suggested for additive model and phase PSR feature-based algorithm is proposed for multiplicative model and that is why we consider using *GP* and PSR_{Area} following model selection as the combined method.

In the following subsections, GP to model quasi-periodic signals for EDR extraction and PSR methods are briefly discussed. Afterwards, the model selection criterion is described. The proposed methods are tested on real data, which are presented in the next subsections.

2.1. Gaussian process EDR extraction

Gaussian process is a learning method designed to solve regression and probabilistic classification problems. Gaussian process regression approach is concerned with supervised learning, which is the problem of learning input-output mapping using empirical data (the training dataset) and making inferences about the relationship between inputs and targets [28]. In our case, we are involved in modeling signals by GP regression in which inputs and targets (outputs) are times and amplitudes of signals, respectively. GP regression has been used for modeling signals which have the quasi-periodicity characteristic such as ECG in order to extract fetal ECG from maternal ECG [29–31]. In this work, GP regression as a probabilistic source separation approach is used for extraction of ECG components such as EDR. The details of ECG components modeling using gaussian process are described in Appendix A in which GP models with appropriate covariance functions (Eq. (A.4)) are fitted to different components of ECG including our objective component, EDR signal; $r(t)$. After estimating the hyperparameters of covariance function of GPs, EDR signal can be extracted using GP source separation (Eq. (A.5)).

The covariance functions and their hyperparameters used for modeling each ECG components are given in:

$$\begin{aligned}
&k_s(t,t';\{l_s,\sigma_s\})=\sigma_s^2\exp\left(-\frac{\sin^2(\Phi(t;\{\tau_k\})-\Phi(t';\{\tau_k\}))}{2l_s^2}\right)\\
&k_n(t,t';\{\sigma_n\})=\sigma_n^2\delta(t-t')\\
&k_b(t,t';\{l_b,\sigma_b\})=\sigma_b^2\exp\left(-\frac{(t-t')^2}{2l_b^2}\right)\\
&k_r(t,t';\{\sigma_r,\{\tau_{k'}\}\})=\sigma_r^2(\cos^2(\Phi(t;\{\tau_{k'}\})-\Phi(t';\{\tau_{k'}\}))
\end{aligned} \quad (1)$$

Fig. 1 shows functions drawn at random from a zero-mean GP prior with covariance function $k_b(t,t')$ and $k_s(t,t')$. Because $\{\tau_k\}$ for k_s are not uniformly spaced, time-varying periodicity in random function drawn from GP described by k_s is obvious (Fig. 1b).