Biomedical Signal Processing and Control 39 (2018) 312–326

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

Research paper

# ECG-derived respiration using Hermite expansion

Hemant Sharma*, K.K. Sharma

*Department of Electronics & Communication, Malaviya National Institute of Technology, Jaipur, 302017, India*

ARTICLE INFO

*Article history:*
Received 22 February 2017
Received in revised form 27 July 2017
Accepted 8 August 2017
Available online 30 August 2017

*Keywords:*
Respiratory rates
ECG-derived respiration
Hermite basis functions
Respiration

ABSTRACT

This paper presents a new ECG-derived respiration (EDR) technique from single-lead ECG based on the decomposition of each QRS complex of an ECG using the Hermite basis functions. We hypothesize that the respiration process, which is a quasi-periodic process, affects the energy in the QRS complexes of ECG signal and the distribution of energy along each component in the orthogonal signal expansion of QRS complex using the Hermite basis functions also. Respiratory-induced beat-to-beat variations in the QRS complexes of ECG signal are monitored by computing the energy and the standard deviation of the Hermite coefficients for deriving the respiratory signal. The performance of the proposed EDR technique is assessed over the *Fantasia* data by computing the correlation coefficient and respiratory rate errors between the EDR and the recorded respiration. The performance results of the proposed technique are compared with some of the well-known EDR techniques based on the principal component analysis (PCA), R-peak amplitudes (RPA), respiratory sinus arrhythmia (RSA), slopes of the QRS complex, and R-wave angle. Results demonstrate that the overall performance of the proposed EDR technique is better than the existing methods. Upon investigating the young and elderly subjects separately, the proposed method provided effective performance for the young subjects but outperformed the existing methods in the elderly subjects. The performance results confirm that the proposed EDR technique can be utilized for continuous monitoring of the respiration using single-lead ECG.



## 1. Introduction

Monitoring of the respiration is necessary to diagnose several respiratory as well as cardiovascular problems such as sleep apnea, stress examines and acute respiratory dysfunction [1], and it is also considered as a measure of severe illness [2]. Moreover, the respiratory rate is one of the other breathing-related parameters used in deciding the anaerobic point during sports training [3]. In clinical practice, the respiratory signal is acquired using some dedicated equipment such as the inductive plethysmograph (that measures muscles motions, thoracic volume, and tissue movements), thermistors for monitoring nasal airflow, and pulse oximetry that measures blood gas variations [4]. These techniques can be used for continuous monitoring of the respiration but may interfere with the natural breathing of the patient (particularly the direct methods which measure nasal airflow). Also, the indirect methods which are based on the observation of muscles movements and changes in the thoracic volume to track the respiration are less comfortable for the patients when long-time monitoring of the respiration is required such as sleep apnea monitoring, stress testing, etc. [5]. Due to these constraints, a considerable effort is directed to achieve a reliable estimation of the respiration signal using non-invasive techniques. Various approaches have been developed for acquiring the respiratory signal using some non-invasive instruments such as the electrocardiograph (ECG) [6] or pulse oximeters [7,8]. Recently, the quality the respiration signals derived from the ECG and photoplethysmograph (PPG) signals is investigated in [9,10], and it is claimed that the ECG signal provides a better quality of the respiratory signal as compared to the PPG.

The idea of deriving the respiration from ECG signal is mainly based on two known respiratory-induced effects: modulation of the heart rate and changes in the beat morphology of ECG [11]. In the modulation phenomenon, the heart rate increases during inspiration followed by a decline during expiration. This modulation of the heart rate due to the respiration is referred as the respiratory sinus arrhythmia (RSA). The event of RSA is associated with the respiration process due to the parasympathetic intervention, and it describes modulation of the heart rate during the respiration. On the other hand, variation in the thoracic impedance, as well as the change in the relative position of ECG electrodes with respect to the heart during the respiration, causes variation in the beat morphology of ECG signal [11]. These respiratory-induced variations in ECG

* Corresponding author.
*E-mail address:* hemantnitt@gmail.com (H. Sharma).

http://dx.doi.org/10.1016/j.bspc.2017.08.016

can be extracted non-invasively for deriving the respiration from ECG signal. The ECG derived waveform resembling the recorded respiration is called the ECG-derived respiration (EDR) signal.

In certain diagnosis processes such as the polysomnography, where simultaneous monitoring of the respiration and cardiac activities is required, the EDR approach can benefit in terms of reducing the cost and complexity of the home-based healthcare equipment by removing an additional sensor used for the respiration measurement. Also, the idea of reducing the number of sensors in the measurement of health parameters encourages the use of home-based healthcare instruments and online health monitoring applications. A variety of the EDR algorithms has been developed by the researchers to get a reliable estimation of the respiration from ECG signal [4,9–27]. Most of the EDR methods available in the literature can be classified into two categories: analysis of the beat morphology of ECG and RSA [4,11–20,24–27], and filtering of the ECG signal [21–23].

The filtering-based approaches to derive the respiration from ECG have also been investigated in [21,23]. In these approaches, the ECG signal is filtered using a band-pass filter in the pre-defined frequency band, and the output waveform is termed as the EDR signal. The filtering based approach provides low error at the lower respiratory rate but high error when the subject is breathing at a higher rate [21]. In [21], it is also concluded that any abrupt variations in the recorded respiration are not reflected in the derived respiratory signal. Application of the empirical mode decomposition (EMD) and wavelet decomposition techniques to derive the respiratory signal from ECG is presented in [22]. In [22], it is found that the EMD technique performs better than the wavelet decomposition based EDR technique [22]. Moreover, due to higher computational cost, the EMD approach is less suitable for the long segments of data.

In the category of beat morphology-based approaches, a simple technique based on tracking the amplitude of R-peaks for deriving the respiratory signal is widely used in [4,16,17]. O'Brien et al. presented three EDR techniques based on single-lead ECG as well as two-lead ECG, and compared their performances using the correlation coefficient computed between the EDR and the recorded respiration [4]. The mean value of the correlation coefficient is higher for the methods based on single-lead ECG as compared with two-lead ECG methods [4], and hence it is concluded that single-lead ECG-based EDR techniques outperform the two-lead ECG-based method. Other complex EDR methods based on the beat morphology of ECG extract changes in the QRS area or rotation in the electric axis caused by the respiration are described in [19,20]. In recent years, principal component analysis (PCA) technique has been employed to evaluate the respiratory-induced beat-to-beat fluctuations in the ECG signal [24,25]. To derive the respiratory signal from ECG, Langley et al. applied the PCA technique over different ECG signal portions such as the QRS complex, whole beat, P-wave, and T-wave. The approach in [24] is compared with the methods based on RSA and R-peak amplitudes (RPA) in terms of the correlation and coherence coefficients. Later, Widjaja et al. proposed an algorithm for deriving the respiratory signal using the Kernel PCA (KPCA) [25]. It is claimed that the KPCA technique provides better results than the PCA and RPA based methods, but less suitable for the long segments of data due to the higher computational cost [25].

A comparison between the RSA and RPA methods based on the respiratory rate error is presented in [12] which uses a threshold based heuristic approach to identify the valid breath cycles in the respiratory signal. Here, the EDR signals are first filtered using a band-pass filter in the frequency band of 0.1–0.45 Hz (6–27 breaths per minute) and then the respiratory rates are estimated. The authors in [12,14,26,27] concluded that both the RSA and RPA based EDR techniques perform satisfactory for the younger subjects, but for the elderly subjects, the RPA method is to be preferred. In the above cited works [4,12,14], the EDR has been derived based on the information/features extracted from R–R time series/R-peak amplitudes, but the morphological changes occurring in the QRS complex are not taken into account.

In [24], principal component analysis of the QRS complex is used for deriving the respiratory signal from single-lead ECG. The Hermite basis functions have also been applied to process the ECG signals for several types of applications including clustering of the QRS complexes of an ECG [28], detection of acute myocardial infarction [29], beat recognition [30], and sleep apnea detection [31]. The use of the Hermite functions to approximate the QRS complexes of any ECG is motivated by the shape similarity between the lower order Hermite basis functions and the QRS complex. As the shape of the lower order Hermite basis functions closely matches with the QRS complex, these functions can be employed to monitor variation in the ECG signal caused by the respiratory process. In this paper, our aim is to investigate respiratory-induced beat-to-beat variation in the QRS complex of ECG signal using the Hermite basis functions for deriving the respiratory signal. For this purpose, we hypothesize that the respiration process, which is a quasi-periodic process, affects the energy in the QRS complexes of ECG signal and the distribution of energy along each component in the orthogonal signal expansion of QRS complex using the Hermite basis functions also. This hypothesis is based on the fact that most of the variations in the morphology of ECG are induced by the respiratory process and skeleton muscle movements [32]. The proposed hypothesis is validated through experimental results, and therefore the beat-to-beat variation in the energy of QRS complex during inspiration and expiration can be monitored for a reliable estimation of the respiratory signal from single-lead ECG.

The rest of the paper is organized as follows. A brief review of the Hermite decomposition of a given signal is presented in Section 2. The data used for the experiment and data pre-processing steps are mentioned in Section 3. The proposed EDR methodology and performance measures are outlined in Section 3. Section 4 presents the experimental results. Outcomes of the work are discussed in Section 5. Finally, Section 6 concludes the paper.

## 2. Review of Hermite decomposition

A signal $x(t)$ can be represented in terms of $N$ orthogonal Hermite basis functions $\phi_{n,\sigma}(t)$ as given by [28]:

$$x(t) = \sum_{n=0}^{N-1} c_n(\sigma)\phi_{n,\sigma}(t) + e_\sigma(t) \tag{1}$$

where, $c_n(\sigma)$ are the coefficients of Hermite decomposition, and $\phi_{n,\sigma}(t)$ are the Hermite basis functions (see Fig. 1) defined as [28]

$$\phi_{n,\sigma}(t) = \frac{1}{\sqrt{\sigma 2^n n! \sqrt{\pi}}} e^{-t^2/2\sigma^2} H_n(t/\sigma) \tag{2}$$

where $\sigma$ is the scale parameter approximating the half power duration of the Hermite basis functions, and $H_n(t/\sigma)$ denotes the $n^{th}$ order Hermite polynomial. The Hermite polynomials satisfy the recursive relation as [28]

$$H_n(x) = 2xH_{n-1}(x) - 2(n-1)H_{n-2}(x) \tag{3}$$

With, $H_0(x) = 1$ and $H_1(x) = 2x$

In the Hermite decomposition, the approximation error $e_\sigma(t) \to 0$ as $N \to \infty$. Using the orthonormal property of the Hermite basis functions, the coefficients $c_n(\sigma)$ in (1) can be obtained as

$$c_n(\sigma) = \int_{t=-\infty}^{\infty} \phi_{n,\sigma}(t)x(t)dt \tag{4}$$