



Communication

A robust approach for ECG-based analysis of cardiopulmonary coupling



Jiewen Zheng^a, Weidong Wang^b, Zhengbo Zhang^{b,c,*}, Dalei Wu^d, Hao Wu^b,
Chung-kang Peng^{e,f}

^aThe Quartermaster Research Institute of the General Logistic Department, Beijing, PR China

^bDepartment of Biomedical Engineering, Chinese PLA (People's Liberation Army) General Hospital, Beijing, PR China

^cHarvard-MIT Division of Health Sciences and Technology, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

^dDepartment of Computer Science and Engineering, The University of Tennessee at Chattanooga, Chattanooga, TN 37403, USA

^eCenter for Dynamical Biomarkers and Translational Medicine, National Central University, Chungli, Taiwan

^fDivision of Interdisciplinary Medicine & Biotechnology and Margret & H.A. Rey Institute for Nonlinear Dynamics in Medicine, Beth Israel Deaconess Medical Center, Harvard Medical School, Boston, MA 02215, USA

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ABSTRACT

Deriving respiratory signal from a surface electrocardiogram (ECG) measurement has advantage of simultaneously monitoring of cardiac and respiratory activities. ECG-based cardiopulmonary coupling (CPC) analysis estimated by heart period variability and ECG-derived respiration (EDR) shows promising applications in medical field. The aim of this paper is to provide a quantitative analysis of the ECG-based CPC, and further improve its performance. Two conventional strategies were tested to obtain EDR signal: R-S wave amplitude and area of the QRS complex. An adaptive filter was utilized to extract the common component of inter-beat interval (RRI) and EDR, generating enhanced versions of EDR signal. CPC is assessed through probing the nonlinear phase interactions between RRI series and respiratory signal. Respiratory oscillations presented in both RRI series and respiratory signals were extracted by ensemble empirical mode decomposition for coupling analysis via phase synchronization index. The results demonstrated that CPC estimated from conventional EDR series exhibits constant and proportional biases, while that estimated from enhanced EDR series is more reliable. Adaptive filtering can improve the accuracy of the ECG-based CPC estimation significantly and achieve robust CPC analysis. The improved ECG-based CPC estimation may provide additional prognostic information for both sleep medicine and autonomic function analysis.

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1. Introduction

Human cardiovascular and respiratory systems interact with each other and present effects of modulation and synchronization [1,2]. The cardiovascular and cardiorespiratory systems are characterized by a complex interplay of several linear and nonlinear subsystems [3]. Analysis of cardiopulmonary coupling (CPC) provides information about the coupling dynamics between the cardiorespiratory systems at different time scales [4], leading to improved knowledge of the interacting regulatory mechanisms under different physiological and pathophysiological conditions [1]. Currently, cardiac inter-beat (R–R) interval (RRI) dynamics analysis has been widely investigated in the evaluation of autonomic nervous system

activities [5]. Compared with RRI dynamics analysis, CPC analysis utilizes information presented in both cardiovascular and respiratory variables. It has been demonstrated that CPC analysis during sleep can characterize different sleep stages and identify sleep apnea events, overcoming some potential limitations encountered in RRI dynamics analysis techniques [6,7]. A recent study shows the importance of monitoring CPC, proving that the strength of CPC progressively decreased as a function of sympathetic activation induced by head-up tilt test [8]. Therefore, CPC analysis might overcome or at least complement traditional univariate analysis techniques such as RRI dynamics analysis.

For the investigation of cardiorespiratory interaction, bivariate approaches are commonly applied [1]. For CPC analysis, both heart period variability and respiratory signal are required. Respiratory signal is usually measured by motion or volume change during respiration, or by airflow [9]. Compared with other techniques, ECG-derived respiration (EDR) is a more convenient and cost-effective

* Corresponding author. Department of Biomedical Engineering, Chinese PLA General Hospital, 28 Fuxing Rd., Beijing, PR China. Tel.: +86 10 66937921.

E-mail address: zhengbozhang@126.com (Z. Zhang).

alternative for respiration monitoring, which derives respiratory signal from ECG recording without using special-purpose hardware [10]. Hence, with solely ECG recording, information of heart period variability and respiratory signal can be derived and CPC analysis can be achieved. Recent studies have demonstrated the effectiveness of EDR and ECG-based CPC analysis as a screening or diagnostic tool for sleep disordered breathing [6,7,11,12].

EDR is a signal-processing technique deriving respiratory waveforms from ordinary ECG [10,13]. Recently, many algorithms have been developed such as amplitude modulation of ECG wave [14], autoregressive model-based method on heart rate series [15], band-pass filter on ECG waveform [16], and other methods combining both beat morphology and HR information [17,18]. For single ECG recording, amplitude-based EDR algorithms have been reported with satisfactory performance, especially in the context of sleep apnea monitoring [19,20]. Two forms of amplitude-based algorithms are commonly studied and implemented: R-S wave amplitude and area of the QRS complex [10,16,21]. As EDR is an indirect recovery of respiratory waveform from recorded ECG, it is relatively noisy. Many studies have been performed to evaluate and improve its performance [9,11,16–19,22–24]. However, most of these studies focused on the accuracy of breathing rate detection [9,16,18,22,24]. Little attention has been paid on the performance of EDR for CPC analysis [6,12].

The aim of our work is to provide a quantitatively evaluation on the ECG-based CPC analysis, compared to CPC values assessed from real respiratory signal such as respiratory inductive plethysmography (RIP). As EDR is a surrogate respiratory signal and relatively noisy, a recursive least squares (RLS) adaptive filter is employed to improve its performance for CPC analysis. In this study, CPC was assessed through probing the nonlinear phase interactions between the corresponding components extracted from RRI series and respiratory signals. The performance of the ECG-based CPC analysis was tested on paced breathing (PB) dataset and Fantasia Dataset [25]. In the PB dataset, a stepwise PB procedure was performed to generate different levels of cardiorespiratory interaction, testing the degree of agreement between the ECG-based CPC and the gold standard through the range of measurements. As elderly subjects usually exhibit attenuated amplitude of respiratory sinus arrhythmia (RSA) [26], we are curious to explore the effectiveness of the RLS adaptive filter in improving CPC estimation for elderly subjects based on the Fantasia dataset. Two datasets both have respiratory signals recorded by RIP. Compared with other respiration monitoring techniques, RIP has the advantages of greater accuracy and better sensitivity [27].

2. Materials and methods

2.1. Participants and protocol

2.1.1. PB dataset

We collected the PB dataset by a stepwise PB protocol, which was reviewed and approved by the Ethics Committee of Chinese PLA General Hospital. Twenty healthy volunteers (8 females and 12 males, with an average age of 30) participated in this experiment. Volunteers were excluded when they had a history of respiratory, cardiovascular or neurological diseases. During the experiment, each volunteer underwent a stepwise PB procedure in a sitting position at rest. The stepwise PB procedure consisted of one 3-min spontaneous breathing session and six PB sessions. Each PB session had a pre-defined breathing rate with a constant inspiration to expiration ratio (1:2), lasting 3 min. The six PB sessions were arranged in a stepwise order with guiding breathing rate changing from high to low in a protocol of [14, 12.5, 11, 9.5, 8 and 7] breath/min (BPM). During the stepwise PB procedure, participants were guided by six melodies to perform the six PB

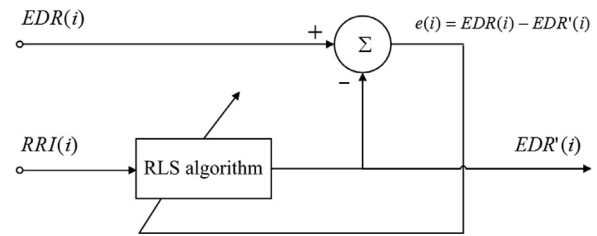


Fig. 1. Structure of adaptive estimation of respiratory signal by RLS algorithm, with EDR series as the primary input and RRI series as the reference input.

maneuvers. Each melody comprises two different tones, with a rising tone guiding inhalation while a lower tone accompanying exhalation. Physiological variables of ECG (lead II) and respiration were recorded during the experiment. All signals were sampled at 1000 Hz with amplifier bandwidths of 0.05–100 Hz for ECG and 0.05–20 Hz for respiration [28].

2.1.2. Fantasia dataset

The Fantasia dataset includes continuous recording of spontaneous respiration and ECG signals from twenty young (21–34 years old, mean age: 26) and twenty elderly (68–85 years old, mean age: 75) rigorously screened healthy subjects in supine resting position [25]. Each subgroup of subjects includes equal numbers of men and women. In this dataset, each record includes ECG and respiration sampled at 250 Hz, lasting 120 min. In our study, from each record, we randomly extracted 5-min stable signals to compare the performance of the ECG-based CPC analysis to the reference analysis from real respiratory signal. For the breath-by-breath phase coupling algorithm used in our study (see Section 2.3), 5 min data are enough to produce accurate CPC estimation.

2.2. Signal pre-processing

2.2.1. QRS complex detection

To achieve accurate QRS complex detection and EDR extraction, power line interference and baseline wander were first removed from raw ECG waveforms. ECG beat detection was performed using Hamilton & Tompin's QRS detector [29], and each beat annotation was verified by visual inspection. With this algorithm, we got each R wave location and RRI time series. Normal-to-normal sinus intervals, extracted from the R–R interval time series, were linearly interpolated at an even interval of 0.2 s (i.e., 5 Hz).

2.2.2. Deriving two basic types of EDR

The two commonly used EDR algorithms: R-S wave amplitude (with EDR series noted as EDR_RS) [16,21] and area of the QRS complex [10] (with EDR series noted as EDR_area) were tested to obtain EDR on a beat-to-beat basis. Both EDR_RS and EDR_area series were interpolated to 5 Hz. These two EDR series will further be processed by an adaptive filter to generate two enhanced types of EDR. RIP signals in both the PB and Fantasia datasets were also down-sampled to 5 Hz through a decimation method.

2.2.3. Enhanced types of EDR by adaptive filtering

The structure of the adaptive filter used in our study is shown in Fig. 1. In our study, we chose EDR series as the primary input and RRI series as the reference input to the adaptive filter. The output of the adaptive filter (EDR' in Fig. 1) is the common component of respiration-induced oscillations presented in both EDR and RRI time series. RLS algorithm was employed by taking into account the advantages of fast convergence speed and without eigenvalue spread problem [18]. Based on the two basic types of EDR (EDR_RS and EDR_area), two enhanced types of EDR (noted as EDR_RS_filt

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