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Technical note

ECG-derived respiration methods: Adapted ICA and PCA

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ABSTRACT

Respiration is an important signal in early diagnostics, prediction, and treatment of several diseases. Moreover, a growing trend toward ambulatory measurements outside laboratory environments encourages developing indirect measurement methods such as ECG derived respiration (EDR). Recently, decomposition techniques like principal component analysis (PCA), and its nonlinear version, kernel PCA (KPCA), have been used to derive a surrogate respiration signal from single-channel ECG. In this paper, we propose an adapted independent component analysis (AICA) algorithm to obtain EDR signal, and extend the normal linear PCA technique based on the best principal component (PC) selection (APCA, adapted PCA) to improve its performance further. We also demonstrate that the usage of smoothing spline resampling and bandpass-filtering improve the performance of all EDR methods. Compared with other recent EDR methods using correlation coefficient and magnitude squared coherence, the proposed AICA and APCA yield a statistically significant improvement with correlations 0.84, 0.82, 0.76 and coherences 0.90, 0.91, 0.85 between reference respiration and AICA, APCA and KPCA, respectively.

1. Introduction

Respiration rate and volume are important measures in detection and treatment of many common diseases such as cardiac disorders, asthma, obstructive pulmonary diseases, and sleep apnea. Outside controlled laboratory environments, however, the usage of spirometers and respiratory effort belts is faced with challenges such as interfering with the subjects' natural respiration, limited measurement capacity, and motion artifacts. Respiration modulates several bioelectric and biomechanical signals such as electrocardiography (ECG) [1], impedance plethysmography [2] and thorax acceleration [3]. Thus, an indirect measurement of respiration is very attractive via ambulatory ECG being cost-effective and easy to measure.

ECG derived respiration (EDR) methods have been studied for some time already [4–6]. The traditional approach is based on the interaction of the electrical axis of the heart and mechanical thorax movements, along with the respiration that manifests as heart compression, thorax impedance alterations and relative electrode position changes [7]. In addition, the heart rate is varied by respiration [8,9].

EDR algorithms are based on measuring respiratory induced changes in the shape of the QRS-complexes or estimating the RSA component from heart rate variability [10–12]. Lately, more abstract methods, including principal component analysis (PCA), have been applied [13]. In the PCA method, the beat-to-beat morphological changes in ECG waveform segments are explained by a set of principal component (PC) signals, some of which are expected to capture respiratory information. In general, a major drawback of PCA is the fact that it operates on a linearity assumption. Recently, a kernel PCA (KPCA) based EDR method that can also take into account nonlinearities of the data [14] has been proposed outperforming previous methods.

We have noticed in our studies with linear PCA methods that the ordinal of a principal component offering the best surrogate respiration varies, also demonstrated by the original paper [13]. Thus, the fixed selection of the first PC does not produce optimal results [15].

We hypothesized that using a criterion to select the most respiration-like component would improve the performance. In this paper, we first develop a new independent component analysis (ICA) based EDR method called adapted ICA (AICA). Then, we describe our adapted PCA method (APCA), including a component selection algorithm similar to AICA. Finally, we provide an experimental comparison of the proposed methods with a selection of methods from the literature.

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2. Methods

2.1. Data

Fantasia database, freely available at Physionet [16] including 20 recordings from both young (21–34 years) and old (68–85) healthy subjects was used. During the measurements, the subjects were in a supine position, breathing spontaneously, and watching the Disney movie Fantasia made in 1940. Simultaneously, their respiration was measured with a belt attached around the thorax and the lead II ECG was captured (fs = 250 Hz). From each subject, a five-minute data sequence that contained no perceived movement artifacts in respiration channel was selected in order to obtain clean reference respiration signals (selected time indices can be requested from the corresponding author).

2.2. Preprocessing

For *R*-peak detection, we used the beat annotations supplied with the database. The following preprocessing steps were performed prior to decomposition-based EDR methods: AICA, APCA, and KPCA. First, Savitzky–Golay filter (polynomial order 3, frame size 7) was applied to remove the high frequency noise from the ECG with minimal distortion to morphology [17]. Then, the multivariate data matrix $\mathbf{x}$ is constructed from single-channel ECG by aligning consecutive segments of m length QRS-complexes x_n:

$$\mathbf{x} = [\, x_1 \; x_2 \; \cdots \; x_n \,] \tag{1}$$

n refers the ordinal of the *R*-peak getting values from 1 to the number of *R*-peaks in the signal. A fixed 120 ms window that corresponds to 30 samples (m = 1, .., 30) around *R*-peak was used. Data were centered by removing the baseline (mean) separately from every QRS segment [13].

2.3. Adapted independent component analysis

Independent component analysis (ICA) is a statistical method for decomposing signal datasets into their subcomponents. Subcomponents are assumed to be non-Gaussian signals and statistically independent. A generative model for ICA is

$$\mathbf{x} = A\mathbf{s}, \tag{2}$$

where $\mathbf{x} = [\, x_1 \; x_2 \; \cdots \; x_n \,]^T$ is comprised of observed measurements and $\mathbf{s} = [\, s_1 \; s_2 \; \cdots \; s_n \,]^T$ includes the unknown sources, i.e. independent components (ICs). The matrix A is m by n size mixing matrix, where n denotes the number of sensors/measurements and m the length of a measurement. Both A and $\mathbf{s}$ are estimated with ICA algorithm [18].

One of the ICA characteristics is that the numbers of ICs is the same as that of sensors/measurements. Because of that and the fact that QRS complexes are highly correlating due to the redundancy in the data, we first reduced the dimensionality of the original QRS data matrix $\mathbf{x}$ using PCA. In our approach, the size of $\mathbf{x}$ was finally 6 by n matrix, where n refers to number of QRS complexes. Then, the ICs are calculated using nonlinear ICA algorithm by FastICA toolbox [18].

2.3.1. Component selection

The ICA algorithm produces the ICs in random order. Thus, it is critical to select the best IC to represent the surrogate respiration signal. In the current 5 min data, we can assume that the subject's respiration frequency has limited variability and a peaked spectrum. Hence, for each component, we first estimated the power spectrum using Welch's method (Hamming 2^{13} samples window (32.8 s), a 2^{16} point FFT, 50% overlapping). Then, the global maximum of the spectrum is located and a fixed size (0.08 Hz) window is placed around it. Next, the spectral energy ratio between the spectrum outside the window and the spectrum within the window is calculated and the component that produces the lowest energy ratio is selected as the EDR.

This algorithm does not require complete stable respiration frequency but allow small variability of respiration frequency. In cases of more varying respiration and/or longer data, the EDR analysis and the proposed component selection algorithm can be applied in shorter segments (see, Section 4, for more info).

2.3.2. Resampling and filtering of independent components

The ICs yield information about the respiration only at sparsely occurring *R*-peak sites. Thus, we resampled the IC values to the original sampling rate. In order to reduce artifacts caused by irregular sampling sites, a smoothing spline with an appropriate tolerance parameter (cubic *B*-spline with tolerance parameter 0.0025) was used while resampling the EDR [19]. In addition, we noticed that using a bandpass filtering (Butterworth order 2, 0.08–0.5 Hz passband) reduced the baseline wander and high frequency noise that were often seen in the raw ICs (Fig. 1). These operations improved the performance of AICA; to make the EDR method comparison fair later on, we adopted these post-processing algorithms for all EDR methods.

2.4. Adapted principal component analysis

The method to obtain EDR using PCA [13] can be briefly described as follows: the covariance matrix Σ is computed for input matrix $\mathbf{x}$ (described in Section 2.2):

$$\Sigma = \mathrm{cov}(\mathbf{x}). \tag{3}$$

The eigenvectors $\alpha = [\, \alpha_1 \; \alpha_2 \; \cdots \; \alpha_n \,]$ and eigenvalues $\lambda = [\, \lambda_1 \; \lambda_2 \; \cdots \; \lambda_n \,]$ were computed as a solution to:

$$\Sigma\alpha = \lambda\alpha \tag{4}$$

PCs arranged in decreasing order of eigenvalue magnitudes were finally obtained using the observed measurements $\mathbf{x}$:

$$\mathrm{PC} = \alpha\mathbf{x}. \tag{5}$$

The EDR candidates are given by the eigenvectors (Fig. 2) and the same component selection algorithm as in the AICA method as described above is applied.

2.5. Reference EDR methods

An experimental comparison was made with the original PCA algorithm that utilizes the first PC, named PCA1 here [13], the traditional *R*-peak amplitude method (AMP) [20], and the Kernel PCA method (KPCA) [14], both of which are briefly described here. In the AMP method, the differences between *R*-peaks and *S*-amplitudes (minimum values 100 ms after the *R*-peaks) were calculated through the whole ECG [10,20], and the consecutive values generate the EDR.

In KPCA, the data are first mapped using nonlinear transformation Φ with a suitable kernel k into higher dimensional feature space [21]. Then, the PCA is applied in that new feature space and the first eigenvector is used to get an EDR. A Gaussian radial basis function kernel $k(x,\ y) = \exp(-\frac{\|x-y\|^2}{2\sigma^2})$ was used with the suggested rule-of-thumb parameter proposed in [14]: $\widehat{\sigma^2} = m * mean(var(\mathbf{x}))$. The data matrix $\mathbf{x}$ is described above in Section 2.2. Variable m determines the length of QRS segment.

2.6. Evaluation of performance

The comparison of EDR methods is achieved with a correlation and coherence study between obtained EDR signals and the