Deriving Respiration from the Electrocardiogram by Serial Comparison with Statistical Mean Shape

Kai Noponen[1], Suvi Tiinanen[1], Tapio Seppänen[1]

[1]University of Oulu, Oulu, Finland

Abstract

A new algorithm to derive a surrogate respiration signal from a single-channel electrocardiogram (ECG) was developed. The generalized mean shape of QRS-complexes was estimated and then used as a template to measure scale variation interpreted as the respiration. Compared to four other ECG-derived respiration (EDR) algorithms, median normalized cross-correlations and median magnitude squared coherences between the new EDR and actual spirometer or chest belt respiration signals showed consistent top-of-the-line performance across different breathing rates and postures. The relative performance of the new EDR algorithm was especially favourable in controlled breathing at the 0.33 Hz respiratory rate.

1. Introduction

Monitoring respiration is important in several diseases, including cardiac disorders, sleep apnea, asthma, and chronic obstructive pulmonary disease. Measurements with spirometers or respiratory effort belts are commonly used in laboratory environments. However, this approach faces challenges in ambulatory conditions as the sensor configuration may interfere with the subject's natural respiration, and lead to a poor user acceptance due to discomfort. Besides, the belt approach can be prone to motion artifacts common in uncontrolled measurements. Consequently, there is a need for methods measuring respiration transparently during mundane activities.

It is well known that respiration affects the ECG, and methods to derive respiration from it have been studied already several decades ago [1-3]. The effects occur due to a multitude of reasons: the mechanical action of respiration causes, e.g. movement in the thorax, displacement of the electrodes with respect to the heart, and changes in the thorax impedance [4]. Moreover, the heart rate is affected causing hastening with inhale, and slackening with exhale. This phenomenon is known as the respiratory sinus arrhythmia (RSA).

Many EDR methods in the literature are based either on measuring the morphological modulation of the QRS-complex [1-3,5-9], or on decoding of the RSA component of the heart rate variability [7,8,10,11]. Both approaches may use either single- or multi-channel ECG. Principal component analysis (PCA) has also been used to extract respiration [12], and recently, this approach has been generalized to non-linear effects using kernel-PCA (KPCA) [13]. Usage of other transforms such as the independent component analysis [11] or the empirical mode decomposition has also been proposed [14].

Major benefits of the ECG-derived respiration include low costs and unobtrusiveness, which is most prominent in the single-channel based methods. If the ECG is to be measured anyway, using it to obtain the respiration allows reducing the number of required sensors. Moreover, it allows for continuous measurements over long periods as the electrodes and wiring can be incorporated into a shirt [9], for instance.

In addition to EDR methods, other indirect means of respiratory monitoring have been suggested based, e.g. on acceleration [15], blood pressure, photopletysmography, or impedance plethysmography [16].

In this paper, we present a novel method to obtain ECG-derived respiration signal from single-channel measurements, and compare its performance to that of four other morphology based algorithms.

2. Materials and methods

2.1. Data

ECGs together with spirometer and chest belt based reference respiration signals were measured from twelve healthy volunteers, four of whom were female. All the volunteers gave their written informed consent, and the Ethics Committee of the Oulu University Hospital approved the measurement protocol that includes various controlled breathing rates at the frequencies of 0.10 Hz, 0.15 Hz, 0.25 Hz, and 0.33 Hz in a sitting posture, and free breathing rates in supine, sitting, and standing positions. Smokers and subjects with lung diseases, cardiovascular disorders, diabetes mellitus or any prescribed medication were excluded from the study.

During the controlled measurements, a metronome animated on a computer display was utilized to set the respiratory rate, and the subjects were allowed to familiarize themselves with using it a couple of days beforehand. All the measurements were performed between 8 a.m. and 10 a.m. Furthermore, the subjects were not allowed to use any caffeine products for 12 hours preceding the measurement, and heavy exercise was forbidden for 24 hours prior the test as well. The length of each recording with a given body position and respiration rate was one minute.

2.2. First phase

The proposed method works in two phases. First, there is a learning phase in which we estimate the mean shape of QRS-complexes. In batch processing, this can be done using all the data, whereas in online applications a separate data set can be gathered before the actual on-going measurements. As a pre-processing step, we reduce baseline wander by subtracting the output of a suitably long Savitzky-Golay smoothing filter from the signal.

Continuing with the learning phase, we define that the mean shape of QRS-complexes is the sampled signal that has the lowest Euclidean distance to the observed complexes when they all are aligned to each other in both time and scale as closely as possible. More precisely, the generalized mean shape estimate of *N* QRS-complexes collected into sample vectors $\mathbf{x}_i$ is defined to be

$$\hat{\mathbf{m}} = \arg\min_{\mathbf{m}} \frac{1}{N} \sum_{1}^{N} d_{\tau,s}^2(\mathbf{x}_i, \mathbf{m}), \tag{1}$$

where

$$d_{\tau,s}^2(\mathbf{x}_i, \mathbf{m}) = \min_{\tau,s} \|s(\tau \circ \mathbf{x}_i) - \mathbf{m}\| \tag{2}$$

denotes the minimum distance between the complex $\mathbf{x}_i$ and the mean shape candidate $\mathbf{m}$ when the former has been time-shifted and scaled to match the latter [17].

The mean shape can be estimated iteratively using the following algorithm. First, take the first QRS-complex $\mathbf{x}_1$ as the initial mean shape candidate $\mathbf{m}$. Second, align all the complexes $\mathbf{x}_i$ in time to the candidate $\mathbf{m}$ using FFT-based cyclic cross-correlation, and cubic spline interpolation. Third, project all the now shifted QRS-complexes $\mathbf{x}_i$ in the learning data set onto the mean shape candidate and normalize, i.e. calculate

$$s_i = \frac{\mathbf{x}_i \cdot \mathbf{m}}{\mathbf{m} \cdot \mathbf{m}} \tag{3}$$

to get the scale difference between the observed beats and the mean shape candidate. Fourth, normalize all the complexes via multiplication with the reciprocal s_i^{-1} of the scale. Fifth, calculate a new mean shape candidate by averaging the now time and scale aligned complexes. Finally, if the mean shape changed significantly, go back to the second step keeping the new mean shape candidate. Otherwise, quit as we have found a suitable estimate.

Instead of the mean, it is often beneficial to use the median for additional robustness in the iteration. In practise, the algorithm will converge in a few iterations.

2.3. Second phase

In the second phase, we first remove baseline wander. In the batch processing approach, this has already been done, but in on-line applications, the same pre-processing must be done before proceeding with the calculations.

Now, the estimated mean shape $\hat{\mathbf{m}}$ can be used to derive the surrogate respiration signal by comparing each of the observed QRS-complex $\mathbf{x}_i$ in series to the statistical mean shape estimate. This is accomplished in a similar fashion to the first phase, i.e. detecting a QRS-complex, collecting the corresponding samples in a vector, time aligning that vector with the mean shape, and then using the projection of (3) to measure the relative scale. To obtain a zero mean like signal, we subtract one from the scale values in the sequence because the unity represents the nominal reference for a relative difference.

The resulting scale value sequence is sparsely located at the R-peak instances, whereas the reference respiration signals have been measured with a fixed and significantly higher sampling frequency. Hence, in order to obtain a continuous signal that is sampled in the same timebase, and to reduce artifacts, we make a smoothing cubic spline fit to the scale values with a suitably tuned smoothness parameter to cover the range of respiratory frequencies. Finally, to remove any remaining baseline wander, the resulting spline signal is differentiated.

2.4. Reference methods

For comparison, we calculate EDRs using four other methods: the R-peak amplitude, as described in [13], the PCA in accordance with [12], the PCA with component selection dubbed as the advanced PCA (APCA), and the KPCA using a Gaussian radial basis function kernel with the suggested rule-of-thumb parameter of [13].

The R-peak amplitude method first reduces baseline wander using median filtering, and then takes the modulation of the detected R-peaks as the EDR-signal. The PCA and KPCA methods analyse the variation of a set of QRS-complexes, and for the purposes of this study, use the first principal component that explains the highest amount of the variation as the surrogate respiration signal.

The advanced PCA method works like the PCA method described above, but instead of the first PC, it selects the one that has the most clearly defined peak in

the power spectrum. More precisely, the selection procedure works as follows. First, for each PC we locate the global maximum of the power spectrum estimated with the Burg method. Second, we place a fixed size frequency window around it. Third, we calculate the ratio of the spectral energy outside the window to the energy within the window. Finally, we select the principal component that has the lowest ratio to represent the EDR.

3. Results

3.1. Correlation

To measure the amount of agreement between the EDR-signal and the reference respiration waveforms in the time domain, we calculate the normalized cross-correlation and report the maximum value within a fixed width window around the zeroth lag allowing for some phase difference between the signals.

Fig. 1 shows the medians of cross-correlations taken over all the test subjects. It can be seen that in most cases, the proposed method gives the highest median correlation to spirometer readings, but the APCA method comes close, and surpasses it in the controlled 0.25 Hz test and the supine free breathing test. Overall, it can be said that the R-peak method has the third best performance. What is more, the non-linear KPCA outperforms the traditional PCA that is consistently the worst performing one by a clear margin. Correspondingly, Fig. 2 shows the various EDR signals contrasted against the chest band measurements. In general, the correlations are higher, but the relative performances stay roughly the same. It should also be noted that during the free breathing tests, the respiratory rates were typically around 0.2 Hz.

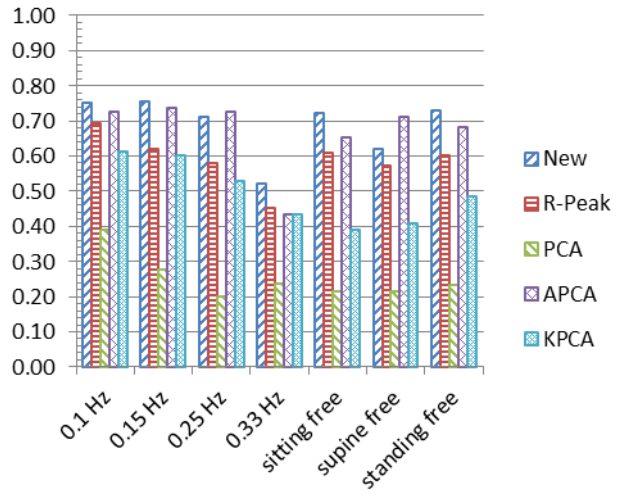

Figure 1. Medians of normalized correlations between the EDR-signals and the spirometer signal at the optimal lag in various postures and breathing rates.

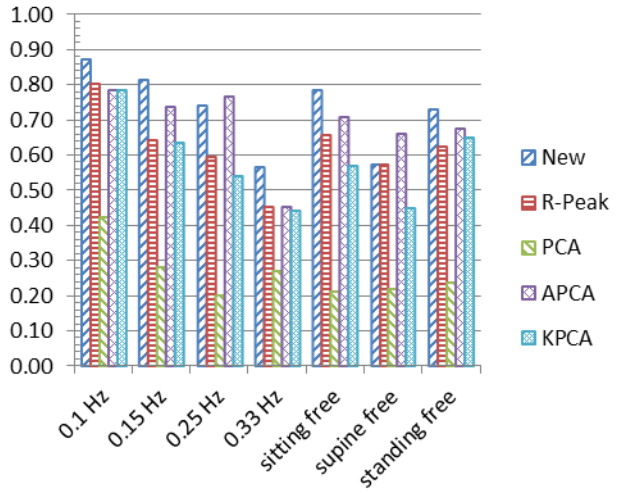

Figure 2. Medians of normalized correlations between the EDR-signals and the chest band signal at the optimal lag in various postures and breathing rates.

3.2. Coherence

We also compare the resemblance in the frequency domain with the magnitude squared coherence estimated using Welch's overlapped averaged periodogram method. Figures 3 and 4 show the medians of the coherence taken over all the test subjects using the spirometer and the chest band signal as a reference, respectively. Evidently, the outcomes are similar to the correlation results, but the KPCA shows better relative performance yielding, e.g. the highest coherence with the spirometer — but not the chest band — readings in the 0.15 Hz test.

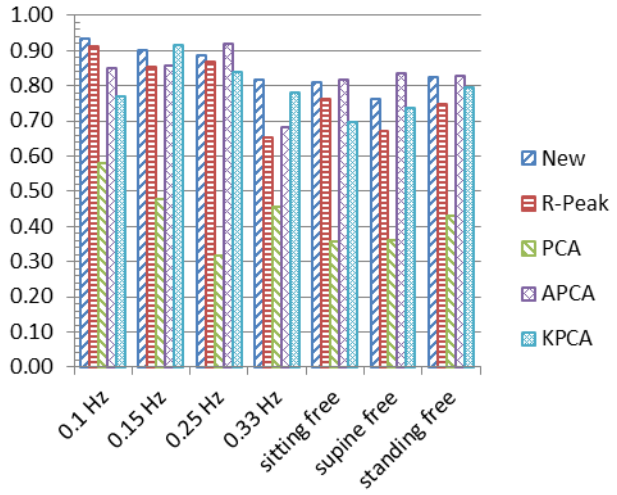

Figure 3. Medians of coherences between the EDR-signals and the spirometer signal at the respiration frequency in various postures and breathing rates.

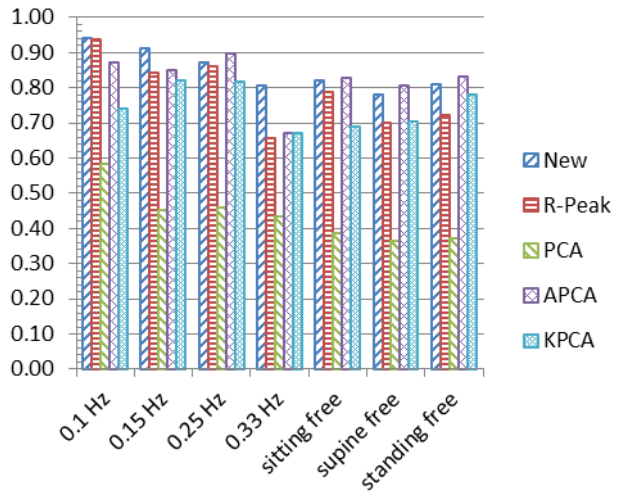

Figure 4. Medians of coherences between the EDR-signals and the chest band signal at the respiration frequency in various postures and breathing rates.

4. Conclusions

We have presented a novel EDR method that is based on a generalized mean shape used to measure the scale variation of the QRS-complexes. The variation is then taken as the surrogate respiration signal. In this regard, the method is similar to QRS-area or R-peak amplitude variation based methods [7,8,13]. However, a major advantage of the presented method is that the projection (3) discards signal components orthogonal to the mean shape, which can increase robustness.

The results show that the proposed method and the APCA method have a quite similar top-of-the-line performance across the various tests in the protocol. However, the most prominent advantage of the new and fast method is seen in the controlled breathing tests at the 0.33 Hz respiratory rate, which suggests better utility, e.g. in exercise tests. Overall, the results of the presented method are well comparable, and in many cases, able to surpass those presented in the literature [7,8,10,13].

Acknowledgements

M.Sc. Tiina Seppänen is gratefully acknowledged for her invaluable data collection work, and Walter Ahlström and Tauno Tönning Foundations for the financial support.

References

[1] Wang R, Calvert T. A model to estimate respiration from vectorcardiogram measurements. Ann. Biomed. Eng. 1974;2:47–57.

[2] Pinciroli F, Rossi R, Vergani L. Detection of electrical axis variation for extraction of respiration information. Comp Cardiol. 1985;2:499–502.

[3] Moody GB, Mark RG, Zoccola A, Mantero S. Derivation of Respiratory Signals from Multi-lead ECGs. Comp Cardiol 1985;12: 113-6.

[4] Malmivuo J, Plonsey R. Bioelectromagnetism — Principles and Applications of Bioelectric and Biomagnetic Fields. New York: Oxford University Press, 1995.

[5] Bailon R, Sornmo L, Laguna P. A robust method for ECG-based estimation of the respiratory frequency during stress testing. IEEE TBME 2006;53(7):1273-85.

[6] Arunachalam SP, Brown LF, Real-time estimation of the ECG-derived respiration (EDR) signal using a new algorithm for baseline wander noise removal. IEEE EMBC 2009:5681-84.

[7] Correa LS, Laciar E, Torres A, Jané R. Performance evaluation of three methods for respiratory signal estimation from the electrocardiogram. IEEE EMBS 2008:4760-63.

[8] Sobron A, Romero I, Lopetegi T. Evaluation of methods for estimation of respiratory frequency from the ECG. Comp Cardiol 2010;37:513-6.

[9] Park S-B, Noh Y-S, Park S-J, Yoon H-R. An improved algorithm for respiration signal extraction from electrocardiogram measured by conductive textile electrodes using instantaneous frequency estimation. Med. Biol. Eng. Comput. 2008;46(2):147–58.

[10] Schäfer A, Kratky K. Estimation of Breathing Rate from Respiratory Sinus Arrhythmia: Comparison of Various Methods. Ann. Biomed. Eng. 2008;36(3): 476-85.

[11] Tiinanen S, Tulppo M, Seppänen T. RSA component extraction from heart rate signal by independent component analysis. Comp Cardiol 2009;36:161-4.

[12] Langley P, Bowers EJ, Murray A. Principal Component Analysis as a Tool for Analyzing Beat-to-Beat Changes in ECG Features: Application to ECG-Derived Respiration. IEEE TBME 2010;57(4):821-9.

[13] Widjaja D, Varon C, Dorado A, Suykens JAK, Van Huffel S. Application of Kernel Principal Component Analysis for Single-Lead-ECG-Derived Respiration. IEEE TBME 2012;59(4):1169-76.

[14] Campolo M, Labate D, La Foresta F, Morabito FC, Lay-Ekuakille A, Vergallo P. ECG-derived respiratory signal using Empirical Mode Decomposition. Medical Measurements and Applications Proceedings (MeMeA), IEEE International Workshop, 2011:399-403.

[15] Drummond GB, Bates A, Mann J, Arvind DK. Validation of a new non-invasive automatic monitor of respiratory rate for postoperative subjects. Br. J. Anaesth. 2011;107:462-9.

[16] Mason L. Signal processing methods for non-invasive respiration monitoring (Ph.D. thesis). University of Oxford:2002.

[17] Noponen K, Kortelainen J, Seppänen T. Invariant trajectory classification of dynamical systems with a case study on ECG. Pattern Recog. 2009;42:1832–44.

Address for correspondence.

Kai Noponen
Department of Computer Science and Engineering,
P.O Box 4500,
FI-90014 University of Oulu,
Finland.