RSA Component Extraction from Cardiovascular Signals by Combining Adaptive Filtering and PCA Derived Respiration

Suvi Tiinanen[1], Antti Kiviniemi[2], Mikko Tulppo[2], Tapio Seppänen[1]

[1]University of Oulu, Oulu, Finland
[2]Verve, Oulu, Finland

Abstract

Respiratory sinus arrhythmia (RSA) means heart rate changing synchronously with respiration and is usually in high frequency range (HF, 0.15-0.4Hz). Depending on measurement protocol, respiration rates may alter in both low frequency (LF, 0.04-0.15Hz) and HF range distorting frequency domain indices of heart rate interval (RRi) series and systolic blood pressures (SBP) series. Adaptive filtering can be used to extract the RSA component from cardiovascular signals. However, this method requires a reference respiration signal. We demonstrate how ECG derived surrogate respiration by principal component analysis (PCA) can be used as a reference signal in Least Mean Square (LMS) adaptive filter. Data set consist of 23 healthy males performing spontaneous breathing at rest. RRi and SBP series were adaptively filtered using measured respiration and ECG derived respiration. We conclude that the ECG-based respiration surrogate is adequate to extract the RSA component.

1. Introduction

Heart rate accelerates during inspiration and decelerates during expiration. This commonly known heart rate variation that is synchronous with respiration is called as respiratory sinus arrhythmia (RSA) (1). The RSA arises mainly via two different mechanisms: 1) mechanical effects of respiration (mainly changes in venous return which directly modulates sinus node) (1), and 2) through autonomic nervous system (2). Periodical respiration component is also seen in blood pressure mainly due to mechanical intrathoracic pressure changes. Respiration component can easily been seen in frequency domain analysis of heart rate interval (RRi) series and systolic blood pressure (SBP) values as a power peak at respiration frequency. Usually respiration peak occurs at high frequency range (HF, 0.15-0.4Hz).

Depending on the respiration frequency of the subject, the RSA may overlap the low frequency range (LF power, 0.04-0.15Hz) and thus distort the frequency domain indices, e.g. the LF power or LF peak frequency. Also baroreflex analysis in frequency domain can be easily biased when respiration rate is within the LF band. Therefore, it is useful to extract the RSA component to have “respiration-free” HRV indices. The extracted RSA component itself may also be a useful index of cardiovascular system.

We have previously proposed an adaptive least mean square (LMS) filtering method for reducing bias in BRS estimation with spontaneous respiration protocol (3). The LMS filter was selected because of its good stability, efficiency and simple structure. The LMS filter requires a reference signal from interfering source, i.e. respiration. An ideal arrangement in practical applications would be that no separately measured reference of respiration is needed since the number of sensors would be reduced in the measurement setups. An additional benefit would be, e.g., that previously recorded data with no respiration signals could be analyzed for respiration effects.

Methods to derive a surrogate respiration signal from electrocardiogram (ECG) have been introduced in the literature. A surrogate respiration signal is a signal with varying amplitude corresponding to temporal pattern of respiration. Principal component analysis (PCA) was recently used to derive a surrogate respiration signal from single-lead ECG (4). In this paper, we utilize this PCA derived respiration as a reference signal in our LMS-based adaptive filter to extract the RSA component from RRi and SBP series and thus obtain more accurate HRV analysis.

2. Methods

2.1. Data

ECG was measured from twenty (N = 23) healthy men in a resting position (Cardiopac 3M33, Nec-Scan –ei instruments, Japan). A noninvasive blood pressure signal was acquired from a finger by Finapres (Ohmeda, USA). Subjects breathed spontaneously and respiration was acquired using a temperature sensor (thermistor) and a monitor (Hewlett Packard GMBH, USA). Sampling frequency was 1000Hz. Measurements were performed in Verve, Oulu, Finland. The RRi series, i.e. tachogram was obtained by means of detecting automatically R-peaks with a method that uses a threshold for amplitude and a first derivative. The series of SBP values, i.e. systogram was derived from the continuous blood pressure signal by detecting the maximum value of blood pressure between the corresponding adjacent R-peaks. Detections were verified visually. Tachogram and systogram were interpolated at 2Hz and respiration was downsampled regularly at 2Hz, respectively, in order to get time-synchronous signals. Very low-frequency components (<0.04 Hz) of the RRi and SBP oscillations were removed using the Savitzky-Golay method (polynomial order 3. frame size 51). Eleven subjects had a mean respiration rate < 0.15Hz, while the rest of them had a respiration rate > 0.15Hz. It is important to note that these groups are defined by the peak frequency of respiration. In practice, the frequency range of the subjects of Group 1 often overlaps partly the HF band.

2.2. Adaptive filtering

The respiratory component was extracted using LMS adaptive filter described previously (Figure 1) (3). Used technique is presented here briefly. Note that equations are written for RRi series but applied similarly also for SBP series. First, the resampled respiration denotes as RESP, and either RRi series or SBP series are applied sample by sample to Finite Impulse Response (FIR) -filter according to equation (1):

$$\hat{RRi}_{RESP}(k) = \sum_{i=0}^{N-1} w_k(i) RESP(k-i) , \qquad (1)$$

where the filter output $\hat{RRi}_{RESP}(k)$ is an estimate of respiratory component in the RRi series and N is the number of adjustable filter coefficients $w_k(i)$. An estimate of respiration-free RRi series, $\hat{RRi}_{real}$, is then calculated by subtracting the estimate of respiratory component $\hat{RRi}_{RESP}$ from the RRi series denoted as RRi:

$$\hat{RRi}_{real} = RRi - \hat{RRi}_{RESP} \qquad (2)$$

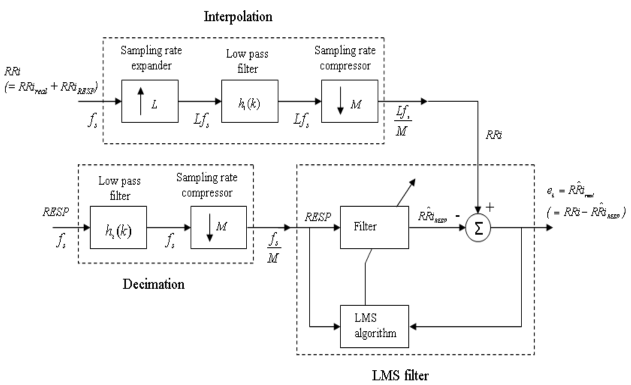

Figure 1. Block diagram of signal preprocessing and LMS adaptive filter.

The LMS adaptive algorithm adjusts the filter coefficients by minimizing the mean squared error between the RRi series and the estimate of respiration component. A new set of weights is obtained iteratively with equation:

$$w(k+1) = w(k) + 2\mu e_k RESP(k) , \qquad (3)$$

where parameter μ controls stability and the rate of convergence. The following constraint ensures the convergence of the filter coefficients:

$$0 < \mu < \frac{2}{\text{tap input power}} = \mu_{\max} , \qquad (4)$$

where the *tap input power* refers to a sum of mean-squared values of the filter inputs *RRi(k), RRi(k-1),...,RRi(k-N+1)*. For the sample-by-sample based adaptation, a safety factor of 10 in convergence parameter μ ($\mu \le 0.1\mu_{\max}$) is commonly applied and used also in this study.

2.3. Principal component analysis

PCA can be used to reduce the dimensionality of multivariate data. By PCA the underlying hidden and more simplified structure of complex data set can be found. We adopted the method to apply PCA for ECG from previously published and added a part which aims to select the correct PC to act as respiration reference in LMS filter.

First the multivariate data set **X**(t) is constructed from single-channel ECG by aligning consecutive segments of QRS-complexes $x_n(t)$:

$$\boldsymbol{X}(t) = [x_1(t), x_2(t), ..., x_n(t)] \qquad (5)$$

Each segment $x_n(t)$ is obtained as a fixed 200ms window around R-peak from which the mean is removed (Figure 2). The covariance matrix **Σ** is then defined:

$$\boldsymbol{\Sigma} = \operatorname{cov}(\boldsymbol{X}) \qquad (6)$$

Next the eigenvectors ($\boldsymbol{\alpha}_j$) and eigenvalues (λ_j) are computed as a solution to

$$\boldsymbol{\Sigma}\boldsymbol{\alpha}_j = \lambda_j \boldsymbol{\alpha}_j \quad j = 1,2,...,n \qquad (7)$$

and PCs are obtained as:

$$PC_j = \boldsymbol{\alpha}_j \boldsymbol{X} \quad j = 1,2,...,n \qquad (8)$$

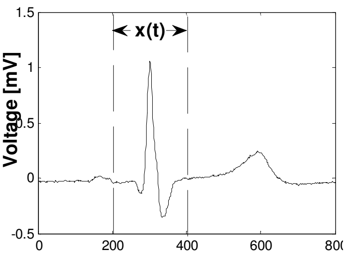

Figure 2. QRS-segment selection

PCs are arranged in order of magnitude of eigenvalues. The surrogate respiration signals are given by corresponding eigenvectors. The PCs explain most of the variability in the QRS complexes. This variability is mostly respiratory-origin but non-respiratory variability may also occur. Thus a critical point is to select the correct surrogate respiration signal that is suitable for adaptive filtering as well. We developed a simple algorithm to select the correct eigenvector as surrogate respiration. The algorithm does the LMS filtering using four first eigenvectors and current tachogram signal. The eigenvector which minimizes the residual tachogram power is selected to act as a surrogate respiration signal. PCA and selection of eigenvector using this algorithm was done separately for each subject and received surrogate signals were verified to correlate with measured respiration signals. The PCs which produce the correct surrogate respiration signal varied subject-wise such that proportions in whole study group were: 22%, 30% and 48% had PC2, PC3 and PC4 as surrogate, respectively. In Figure 3 is plotted one case of PCs and their eigenvectors.

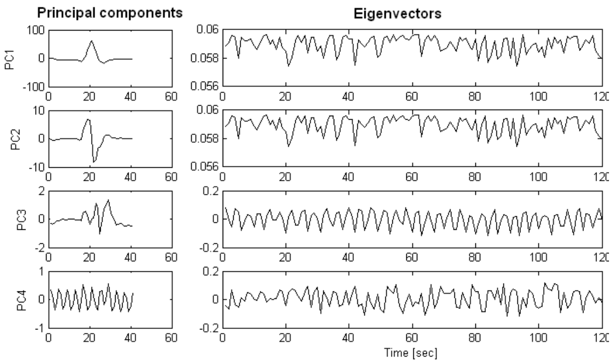

Figure 3. First four PCs and their eigenvectors. PC3 presents here the selected surrogate respiration signal.

2.4. Spectral indices and statistics

Power spectral densities (PSD) were calculated for both RRi and SBP series by Welch's method (64s window, 1024 point FFT and 50% overlapping windows). Powers were integrated in LF and HF range and center frequencies were defined as maximal peak frequencies. Statistical differences between adjacent spectral domain indices were calculated from three cases: baseline, LMS filtering, LMS filtering with PCA derived respiration. We used Wilcoxon Signed Ranks Test with values *p <0.05* considered statistically significant. All the statistics were calculated using SPSS® software (SPSS Inc, USA).

3. Results and discussion

Data was divided in two groups according to subject respiration frequency: Group 1 consisted of subjects whose respiration rate had a mean respiration rate < 0.15Hz and Group 2 had respiration rate had a mean respiration rate > 0.15Hz. In Figure 4 is presented a typical example of PSD of original RRi series and RRi estimate and extracted RSA estimate obtained by adaptive filtering when subject is breathing at lower frequency rate (<0.15Hz). Upper figure A) is obtained using LMS adaptive filter with the measured respiration as a reference while B) is obtained using PC derived surrogate respiration signal. It can be seen that both respiration references produce similar results.

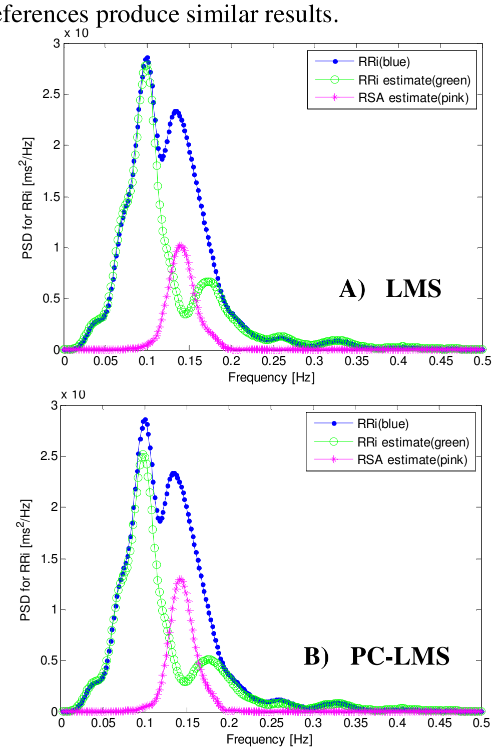

Figure 4. PSD of original RRi, residual RRi estimate, and substracted RSA estimate. Subject's respiration rate < 0.15 (Group 1). A) LMS with real respiration reference and B) LMS with PCA derived respiration reference.

LF energy is clearly reduced at respiration frequency when RSA component is extracted. From Figure 4 it can also been seen that spontaneous respiration rate may not be totally in either LF or HF band but it can partly overlap both bands. Thus when respiration component is extracted it reduces both LF and HF powers.

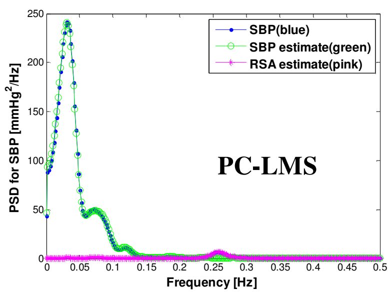

Figure 5. PSD of original SBP, SBP estimate, and substracted RSA estimate.

Figure 5 illustrates a case were respiration frequency is within the HF band. The adaptive filter removes the RSA component completely. As a result, frequency domain indices will not be biased.

Figure 6 illustrates how the RSA overlapping LF band distorts the peak frequency estimation. Clearly the most dominant LF peak in the PSD of SBP originates from respiration. Removing the RSA peak reveals that dominant LF peak is within the lower frequencies.

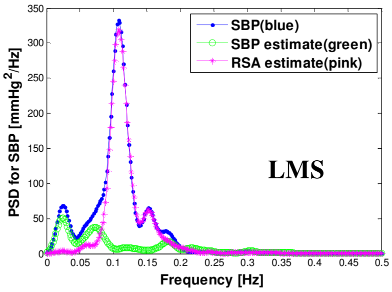

Figure 6. PSD of original SBP, SBP estimate, and substracted RSA estimate.

LF and HF powers were integrated and center frequencies for RRi and SBP were defined without the RSA component extraction (=Baseline) and with RSA component extraction by adaptive filtering. Adaptive filtering was performed using both measured respiration signal (=LMS) and PC derived surrogate signal (=PC-LMS) and results are presented in Table 1 and Table 2 for RRi and SBP series, respectively.

When RSA is extracted the power of original RRi or SBP is reduced at respiration range. With Group 2 subjects the power in LF band did not change implying that the adaptive filter reduces the respiration effect only. With Group 1 subjects there is a decrease in HF band power because the respiration frequency range overlaps partly the HF band, as explained in Section 2.1. The peak frequencies of the bands were only slightly changed by adaptive filtering in that band from which respiratory component was extracted. The filtering did not change the peak characteristics of respiratory-free band. Results reveal clearly that both respiration signals (real or surrogate) are able to extract the RSA component from RRi and SBP series with similar performances without significantly distorting other spectral characteristics.

Table 1. Spectral indices for RRi series (* indicates $p<0.05$ when compared with baseline)

HRV parameters	Group 1 (resp < 0.15Hz) Baseline	LMS	PC-LMS	Group 2 (resp >0.15Hz) Baseline	LMS	PC-LMS
LF [ms^2]	2412 ± 1446	858 ± 461*	996 ± 434* †	1151 ± 964	1137 ± 945	953 ± 718*
HF [ms^2]	894 ± 734	410 ± 294 *	380 ± 292 *	702 ± 712	291± 228 *	275± 208 *
Cent_f_LF [Hz]	0.11 ± 0.17	0.089 ± 0.022*	0.099 ± 0.024*	0.92 ± 0.014	0.92 ± 0.015	0.92 ± 0.014
Cent_f_HF [Hz]	0.21 ± 0.060	0.20 ± 0.039	0.21 ± 0.061	0.24 ± 0.037	0.20 ± 0.037*	0.21 ± 0.042*

Table 2. Spectral indices for SBP series (* indicates $p<0.05$ when compared with baseline)

HRV parameters	Group 1 (resp < 0.15Hz) Baseline	LMS	PC-LMS	Group 2 (resp >0.15Hz) Baseline	LMS	PC-LMS
LF [mmHg^2]	6.6 ± 2.8	2.8 ± 1.5*	3.1 ± 1.6*	5.5 ± 5.3	5.6 ± 5.3	5.1 ± 3.9
HF [mmHg^2]	1.1 ± 0.86	0.36 ± 0.20*	0.39 ± 0.29*	1.1 ± 0.86	0.55 ± 0.78*	0.79 ± 1.0*
Cent_f_LF [Hz]	0.093 ± 0.021	0.069± 0.021*	0.083 ± 0.017*	0.068.± 0.022	0.071 ± 0.021	0.078 ± 0.019
Cent_f_HF [Hz]	0.20 ± 0.046	0.19 ± 0.029	0.18 ± 0.23	0.23 ± 0.042	0.22 ± 0.055	0.22± 0.47

4. Conclusions

The ECG-based PCA derived surrogate respiration signal was used as reference signal in LMS adaptive filtering to extract the RSA component from RRi and SBP series. The results show that the method reached similar results as when measured respiration was used as a reference in adaptive filter. The filtering distorted spectral properties o the signals only slightly.

References

[1] Hirsch JA, Bishop B. Respiratory sinus arrhythmia in humans: how breathing pattern modulates heart rate. Am.J.Physiol. 1981 Oct;241(4):H620-9.

[2] Eckberg DL. The human respiratory gate. J.Physiol. 2003 Apr 15;548(Pt 2):339-352.

[3] Tiinanen S, Tulppo M, Seppanen T. Reducing the effect of respiration in baroreflex sensitivity estimation with adaptive filtering. IEEE Trans.Biomed.Eng. 2008 Jan;55(1):51-59.

[4] 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 Trans.Biomed.Eng. 2010 Apr;57(4):821-829.

Address for correspondence.

Suvi Tiinanen
email: suvi.tiinanen@ee.oulu.fi,
Department of Electrical and Information Engineering,
Linnanmaa PO BOX 4500,
FIN-90014 UNIVERSITY OF OULU, FINLAND