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Extraction of Direct Respiratory Influences from the Tachogram using Multiscale Principal Component Analysis

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Abstract. Heart rate variability (HRV) studies are widely used to assess the functioning of the autonomic nervous system. Due to respiratory influences in the tachogram, the interpretation of HRV measures is questioned. This paper addresses this issue by estimating the respiratory component from the tachogram using multiscale principal component analysis (MSPCA), a technique that combines wavelet analysis with principal component analysis. Subsequently, the extracted respiratory component is subtracted from the tachogram in order to obtain a tachogram without respiratory influences. The results show that initial significant correlations and coherences between the tachogram and respiration are no longer present after the application of the proposed method, demonstrating that the direct, linear influence of respiration is reduced.

Keywords: Heart Rate Variability; Multiscale Principal Component Analysis; Respiratory Sinus Arrhythmia

1. Introduction

Heart rate variability (HRV) analysis is widely used to gain insights into the functioning of the autonomic nervous system (ANS). Starting from the tachogram, several HRV measures that quantify the ANS have been determined [Task Force of the ESC and NASPE, 1996]. In the power spectrum of the tachogram, a low-frequency (LF) band (0.04-0.15 Hz) and a high-frequency band (0.15-0.4 Hz) are defined. LF power is suggested to originate mainly from sympathetic outflow, although this is not generally accepted as it might contain parasympathetic influences as well. The HF power is often used as a measure of respiratory sinus arrhythmia (RSA), which is the phenomenon that the heart rate increases during inhalation and the heart rate decreases during exhalation [Hirsch and Bishop, 1981]. RSA normally operates in these frequencies and is generally considered an index of vagal control. Many papers however address the issue that the magnitude of RSA is influenced by the respiratory rate and the depth of breathing (tidal volume), independently of vagal activity [Grossman and Taylor, 2007; Ritz and Dahme, 2006]. Therefore, results from HRV analyses are often statistically corrected for these differing respiratory parameters. We believe that statistical correction of HRV studies might overcompensate for the effect of different respiratory parameters, and aim to remove the respiratory influence in the tachogram, prior to computation of HRV measures. Although HRV proved to be a useful tool when analyzing pathological conditions like myocardial infarction and diabetes [Task Force of the ESC and NASPE, 1996], the lack of consensus on the interpretation of HRV measures limits its use in practice.

This paper aims at extracting the component of the tachogram that is directly related to respiration, in order to reduce the respiratory influence and obtain a tachogram in which the ANS part of HRV that is not related to respiration is enhanced, an issue that is also addressed by Choi and Gutierrez-Osuna [Choi and Gutierrez-Osuna, 2011]. They use a linear system-identification model of the cardiorespiratory system to remove respiratory influences in the tachogram and show that this correction yields HRV measures with a higher discriminative power to classify mental stress. In this study, we will use multiscale principal component analysis (MSPCA) to extract the respiratory component from the tachogram. This procedure is hypothesized to help in the interpretation of HRV analyses where significant differences are found that are solely due to contributions from differences in respiratory parameters. Conversely, this research might unveil HRV analyses where differences are masked by dissimilar respiratory patterns.

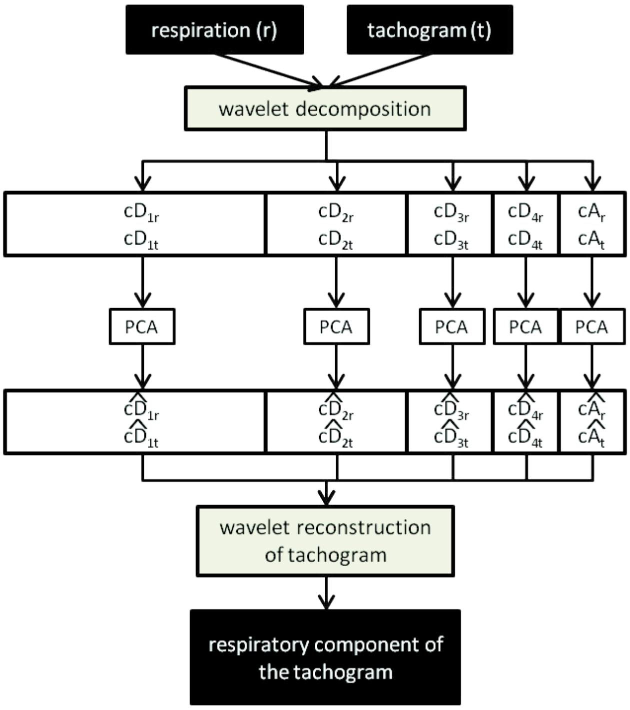

Figure 1. *Application of MSPCA to extract the respiratory component from the tachogram. First, the tachogram and respiratory signal are separately decomposed in 4 scales using wavelets. Next, PCA is performed on the coefficients of the corresponding scales of both signals. The new wavelet coefficients of the tachogram are then used to reconstruct the respiratory component of the tachogram.*

2. Methods

2.1. Data Acquisition and Preprocessing

The data for this research were measured at the Department of Psychology of the KU Leuven (Leuven, Belgium) in the context of a broader study which aims at investigating the effects of respiratory rate and inspiration/expiration ratio on subjective relaxation and heart rate variability during instructed breathing. The data consist of ECG (sampling frequency f_s = 200 Hz) and respiration f_s = 50 Hz) measurements of 30 undergraduate students using the LifeShirt System (Vivometrics Inc., Ventura, CA). Respiration was continuously recorded by means of respiratory inductive plethysmography (RIP) around the ribcage and the abdomen. Based on these two respiratory signals, the tidal volume is estimated. This volume will further be considered as the respiratory signal.

The data used in this study originate from a controlled environment where the subjects are instructed to breathe at a frequency of 0.2 Hz (12 breaths per minute), with a fixed inspiration and expiration time of 1.5 s and 3.5 s respectively, for a period of 5 minutes.

The tachogram is composed by detection of the R peaks in the ECG using the Pan-Tompkins algorithm. All detections are manually inspected and corrected where needed. Next, the respiratory signal and the tachogram are resampled at 4 Hz using cubic spline interpolation, and the phase shift between both signals is removed.

All processing steps of the data are performed in MATLAB R2010a (MathWorks, Natick, MA).

2.2. Multiscale Principal Component Analysis

Multiscale principal component analysis (MSPCA) was first introduced by B.R. Bakshi in [Bakshi, 1998]: "[MSPCA] *combines the ability of PCA to decorrelate variables by extracting a linear relationship with that of wavelet analysis to extract deterministic features and approximately decorrelate autocorrelated measurements*" (p.1597). This technique is suitable to compute the component of the tachogram that is directly related to respiration, as the application of PCA assumes a direct, linear relation. The respiratory component is then removed from the tachogram to obtain a respiratory-reduced tachogram (further termed the residual tachogram $RR_{residual}$).

Fig. 1 schematically shows how the MSPCA algorithm is applied to derive the respiratory component from the tachogram, using the following steps:

1. Decomposition of the respiratory signal and the tachogram using wavelets: the signals are decomposed using the Daubechies wavelet of order 4 (db4), up to level 4, yielding detail coefficients cD_{is} and approximation coefficients cA_s, with i the level and s the signal (respiration r or tachogram t).
2. Principal component analysis of the wavelet coefficients at each scale: if the first eigenvector explains over 90% of the variance in the data, the new wavelet coefficients are computed by projecting the coefficients on the first eigenvector. Otherwise, the wavelet

coefficients at that scale are set to 0. This way, only the wavelet coefficients of the tachogram that have an explicit linear relation with those of the respiration are used to construct the respiratory component of the tachogram. The new wavelet coefficients are $\hat{c}D_{is}$ and $\hat{c}A_s$.

3. Reconstruction of the tachogram using wavelets: the new wavelet coefficients $\hat{c}D_{it}$ and $\hat{c}A_t$ are used to reconstruct the tachogram. The result contains the component of the tachogram which is linearly related to the respiration, and is further referred to as the respiratory component of the tachogram (RR_{resp}).

Note that only the relevant steps of Bakshi's MSPCA are included here. A description of the full algorithm can be found in [Bakshi, 1998].

The residual tachogram is obtained by subtracting the derived respiratory component from the original tachogram.

2.3. Efficiency of MSPCA

The efficiency of MSPCA as a tool to construct the respiratory component of the tachogram is verified by assessing the correlations and coherences between the original tachogram and residual tachogram on the one hand, and the respiratory signal on the other hand. A high correlation and coherence is expected in the original tachogram. After removal of the computed respiratory component, a lack of correlation and coherence will demonstrate the efficiency of the proposed algorithm.

The correlation coefficient ρ is computed using Pearson's linear correlation and the magnitude squared coherence coefficient is defined here as the mean coherence in the interval 0.18-0.22 Hz.

3. Results

Fig. 2(a)-(b) show the tachogram (RR) and the original respiratory signal (vt) of subject 21. Fig. 2(c) displays the respiratory component from the tachogram which results from the application of MSPCA (RR_{resp}). Subtracting this component from the original tachogram yields the residual tachogram, as shown in Fig. 2(d). Note that the respiratory signal is in antiphase with the tachogram and the estimated respiratory component of the tachogram. This is due to the fact that inhalation is coupled with a decrease of the heart period, and vice versa. The figure shows that the original tachogram and respiration are highly correlated (ρ = -0.64). Likewise, the estimated respiratory component of the tachogram and respiration yield a high correlation coefficient of -0.76. The residual tachogram produces the insignificant correlation of ρ = 0.04 with respiration, demonstrating that MSPCA gives a good estimate of the direct respiratory component in the tachogram.

Fig. 3 shows the corresponding power spectra of subject 21. The spectra of the tachogram and respiration show a distinct peak at 0.2 Hz, yielding a coherence of 0.90. The peak at 0.2 Hz is also clearly visible in the spectrum of the respiratory component of the tachogram. The residual tachogram shows a strongly reduced coherence of 0.29 with respiration at 0.2 Hz. Note that all spectra are computed over the full 5-minute period.

The distribution of all correlation and coherence coefficients between the respiratory signal and both the original and residual tachogram is given in Fig. 4. Significant correlations between the respiratory signal and the original tachogram are present (mean ± std: -0.54 ± 0.16). The residual tachogram shows no longer significant correlations with the respiratory signal (-0.11 ± 0.09), demonstrating that the direct respiratory influence in the tachogram is strongly reduced. The magnitude squared coherence coefficients give similar results; the original tachogram has a high

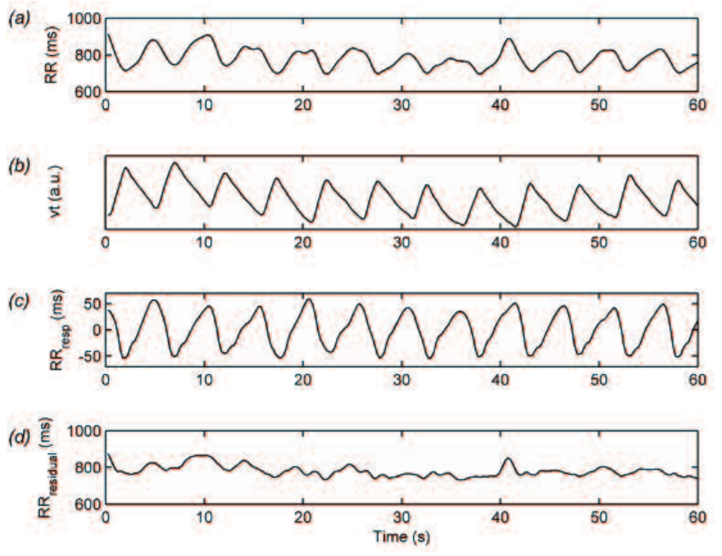

Figure 2. *Time signals of subject 21: (a) original tachogram (RR); (b) respiration (vt); (c) respiratory component of the tachogram (RR_{resp}); (d) residual tachogram ($RR_{residual}$).*

coherence around 0.2 Hz (0.86 ± 0.08), which is significantly reduced in the residual tachogram (0.34 ± 0.17).

4. Discussion

This paper presented some preliminary results of the objective to decouple the respiration and the tachogram. However, there is still a long way to go to achieve this goal, and it might even be impossible to completely decouple the cardiovascular and respiratory system as they interact closely. In this first effort, the direct, linear interaction between respiration and the tachogram has been reduced. This residual tachogram might be useful in the interpretation of RSA, especially since the respiratory signal is proportional to the tidal volume and it is claimed that the magnitude of RSA is inversely proportional to the respiratory frequency and proportional to the tidal volume. Using the tidal volume as respiratory signal in this study, thus, deals with both factors that are believed to modify RSA.

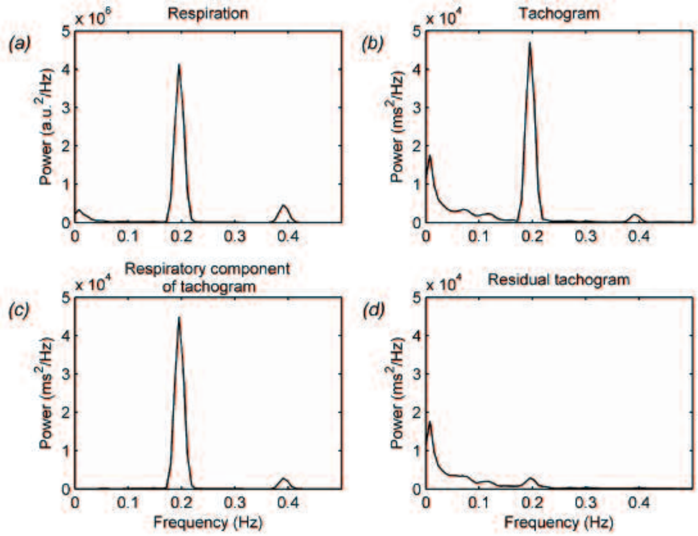

Figure 3. *Power spectra of the time signals of subject 21: (a) respiration; (b) original tachogram; (c) respiratory component of the tachogram; (d) residual tachogram.*

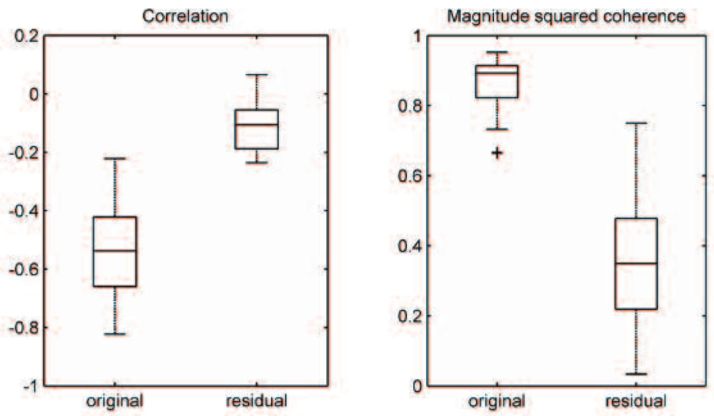

Figure 4. *Boxplots of the correlation and coherence coefficients between the respiratory signal and both the original and the residual tachogram.*

A limitation of this study includes the fact that PCA reduces only linear influences between respiration and the tachogram. Possible nonlinear interactions will not be detected in this algorithm and will still exist in the residual tachogram. This issue can be remedied by the use of a nonlinear variant of PCA, such as kernel PCA. Another limitation of this study originates from the instructed breathing pattern; the tachogram follows the pattern clearly, an effect that is not so prominently present during spontaneous respiration. Moreover, instructed breathing modifies the activity of the ANS [Stark et al., 2000], hence HRV studies during fixed patterns should be interpreted carefully. The last limitation that is addressed concerns wavelet analysis; a mother wavelet and order need to be chosen. More research on the effect of the wavelet is recommended. Yet, the obtained results using the Daubechies 4 wavelet seem promising.

The addressed limitations require further research of the proposed method. In addition, a validation study, assessing the impact of removing the respiratory component from the tachogram, is recommended, e.g. in HRV studies. ANS processes, masked by respiratory influences, might emerge.

Finally, the comparison with the paper of Choi and Gutierrez-Osuna [Choi and Gutierrez-Osuna, 2011], needs to be carried out. They addressed a similar issue and proved that removal of respiratory influences during stress testing, leads to HRV measures that have more discriminative power when mental stress is monitored. Additionally, the method proposed by Bailón *et al.* that uses respiratory information to quantify LF and HF power during stress testing will be evaluated for comparison with the MSPCA method as they suggest that their technique might clarify the relation between ANS control and stress testing [Bailón et al., 2010].

5. Conclusions

HRV studies are widely performed to assess the functioning of the ANS. However, due to respiratory influences in the tachogram, the interpretation of HRV measures is questioned, limiting its practical use. In this paper, we attempted to address this problem by estimating the respiratory component from the tachogram using multiscale principal component analysis, and subsequently subtracting this component to obtain a tachogram in which the direct, linear influence of respiration is reduced.

The efficiency of the method is assessed using the correlation and coherence coefficients between the original and residual tachogram on the one hand, and the respiratory signal on the other hand. Respiration showed significant correlations and coherences with the original tachogram, which are no longer present with the residual tachogram, demonstrating the use of the proposed method. Although further research on this method is needed, these promising results suggest that MSPCA might be a useful tool to clarify RSA and HRV studies which are strongly influenced by respiration.

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References

Bailón R, Mainardi L, Orini M, Sörnmo L, Laguna P. Analysis of heart rate variability during exercise stress testing using respiratory information. *Biomedical Signal Processing and Control*, 5(4): 299-310, 2010.

Bakshi BR. Multiscale PCA with application to multivariate statistical process monitoring. *AIChE Journal*, 44(7):1596-1610, 1998.

Choi J, Gutierrez-Osuna R. Removal of respiratory influences from heart rate variability in stress monitoring. *IEEE Sensors Journal*, 11(11):2649-2656, 2011.

Grossman P, Taylor EW. Toward understanding respiratory sinus arrhythmia: Relations to cardiac vagal tone, evolution and biobehavioral functions. *Biological Psychology*, 74(2):263-285, 2007.

Hirsch JA, Bishop B. Respiratory sinus arrhythmia in humans: how breathing pattern modulates heart rate. *American Journal of Physiology- Heart and Circulatory Physiology*, 241(4):H620-H629, 1981.

Ritz T, Dahme B. Implementation and interpretation of respiratory sinus arrhythmia measures in psychosomatic medicine: Practice against better evidence? *Psychosomatic Medicine*, 68(4):617-627, 2006.

Stark R, Schienle A, Walter B, Vaitl D. Effects of paced respiration on heart period and heart period variability. *Psychophysiology*, 37(3):302–309, 2000.

Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. Heart rate variability: standards of measurement, physiological interpretation and clinical use. *Circulation*, 93(5):1043-1065, 1996.