Multiscale Principal Component Analysis to Separate Respiratory Influences from the Tachogram: Application to Stress Monitoring

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Abstract

The effects of mental stress on heart rate variability (HRV) have been studied widely. However, the influence of respiration on short-term HRV is often ignored. Therefore, this study uses multiscale principal component analysis to separate the tachogram in 2 components: a component which is directly related to respiration, and a residual component which contains only changes in the heart rate that are unrelated to respiration. This approach is applied on data of 40 subjects during a baseline condition, a mental stress task and an attention task. The application of power spectral HRV analysis on the 2 components of the tachogram, reveals that stress influences the tachogram both via the respiration as well as directly via the functioning of the ANS. These results show that separation of the respiratory component of the tachogram can be a valuable tool to interpret HRV measures. Moreover, this approach might unveil changes in the functioning of the ANS that are otherwise masked by differing respiratory patterns.

1. Introduction

The effects of mental stress on heart rate variability (HRV) have been studied widely as stress is identified as an important risk factor for cardiovascular diseases [1]. HRV is a simple and noninvasive tool to assess the functioning of the autonomic nervous system (ANS). Starting from the tachogram, HRV measures that quantify sympathetic and parasympathetic activity are computed, such as low-frequency (LF: 0.04 - 0.15 Hz) and high-frequency (HF: 0.15 - 0.4 Hz) power [2]. HF power is an index of vagal control and is often used as a measure of respiratory sinus arrhythmia (RSA), which is the phenomenon where the heart rate changes in phase with the breathing pattern [3]. However, many papers question the accuracy of this measure as it is suggested that the magnitude of RSA changes with the respiratory rate and depth of breathing, independently of vagal activity [4, 5]. It is therefore important to take the influence of respiration on HRV into account, an issue which is often ignored, also when studying the effects of stress. Hence, this study aims at incorporating respiratory changes during HRV studies using multiscale principal component analysis (MSPCA).

In a previous study, we already proposed the use of MSPCA to decompose the original tachogram in two components, a component which can be directly related to respiration, and a component that contains the residual changes in the heart rate, unrelated to respiration [6]. This technique showed to significantly reduce the correlations and coherences between respiration and the tachogram. In a next step, we wish to evaluate this method during stress monitoring.

2. Methods

2.1. Data aquisition 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 assessing instantaneous changes in heart rate regulation, sigh rate and respiratory variability due to mental load in simulated office work [7, 8]. The electrocardiogram (ECG, sampling frequency $f_s = 200$ Hz) and respiration ($f_s = 50$ Hz) of 43 healthy students (age: 18-22 years) were recorded using the LifeShirt System (Vivometrics Inc., Ventura, CA). The participants were instructed to perform 3 tasks. During the first task, a baseline resting state was recorded. The second task was a nonstressful attention task where the participants had to indicate the largest number on a computer. During the third task, the students had to perform a mental arithmetic task which induces stress. The whole protocol consists of a baseline recording, an attention task (AT) and 2 mental stress tasks (MT1 and MT2), each followed by a recovery period. Each task had a duration of 6 minutes. For this study, only the baseline, AT and MT1 of 40 students were used. The experiment was approved by the

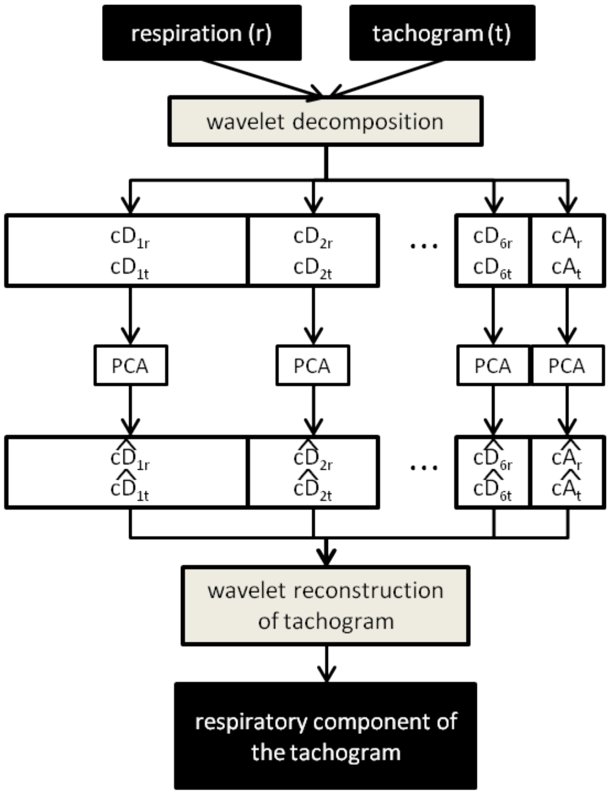

Figure 1. Application of MSPCA to extract the respiratory component from the tachogram. First, the tachogram and respiratory signal are separately decomposed in 6 scales using wavelets. Next, PCA is performed on the coefficients of the corresponding scales of both signals. The new wavelet coefficients of the tachogram are then used to reconstruct the respiratory component of the tachogram.

Ethics Committees of the Department of Psychology and of the Faculty of Medical Sciences.

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), a combination of PCA and wavelet analysis, is used to estimate the changes in the heart rate which can directly be related to respiration, further termed the respiratory component of the tachogram (RR$_{resp}$). This component is then removed from the original tachogram (RR) to obtain a respiratory-reduced tachogram (the residual tachogram RR$_{residual}$).

Fig. 1 schematically shows how the MSPCA algorithm is applied to derive the respiratory component from the tachogram. A short description of the MSPCA technique is given below. More details can be found in [6, 9].

1. Decomposition of the respiratory signal and the tachogram using wavelets, 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 normalized 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 onto the first eigenvector. Otherwise, the wavelet coefficients at that scale are set to 0. Next, the new wavelet coefficients are transformed back to non-normalized values, noted as $c\hat{D}_{is}$ and $c\hat{A}_s$.
3. Construction of the respiratory component of the tachogram using the new wavelet coefficients $c\hat{D}_{it}$ and $c\hat{A}_t$. The result contains the component of the tachogram which is linearly related to the respiration.

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

2.3. HRV analysis

To assess the value of the MSPCA approach, power spectral analysis of HRV is performed. The power spectrum of the tachogram is computed via Welch's method, using a 1024 point fast Fourier transform (FFT), a periodic Hamming window of a length such that eight equal sections of the tachogram are obtained, and an overlap of 50%. Low-frequency power (LF: 0.04-0.15 Hz) and high-frequency power (HF: 0.15-0.4 Hz), as well as the ratio of LF to HF power (LF/HF) are determined.

The HRV analysis was performed for RR, RR$_{resp}$ and RR$_{residual}$, and is further noted as LF, LF$_{resp}$, LF$_{residual}$, etc.

3. Results

Figure 2 shows an example of the time signals (RR, RR$_{resp}$ and RR$_{residual}$) and their corresponding power spectra during baseline recording after the application of MSPCA. In the original tachogram, clear influences from respiration can be observed. These influences are captured in the respiratory component of the tachogram. Both in time and frequency domain, the residual tachogram shows low similarity with the respiratory signal.

The differences in power spectral HRV measures between the 3 tasks (baseline, AT, MT) are assessed us-

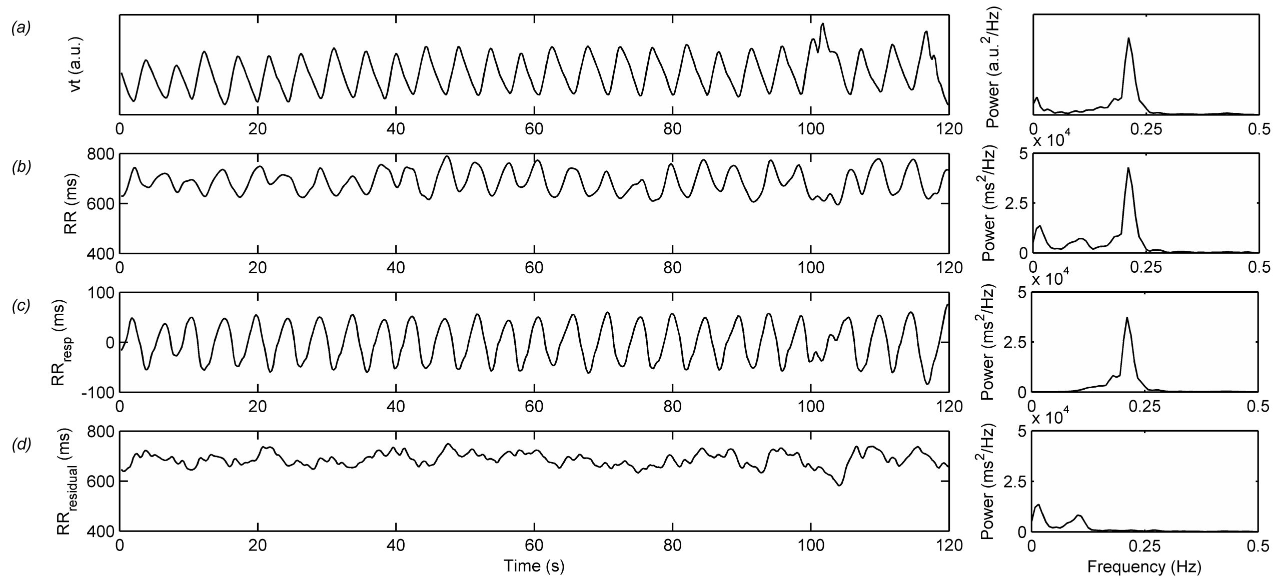

Figure 2. An example of the results after application of MSPCA. The tachograms originate from subject 3 during 2 minutes of baseline recording. The corresponding power spectra are visualized on the right. (a) respiration signal; (b) original tachogram (RR); (c) respiratory component of the tachogram (RR_{resp}); (d) residual tachogram ($RR_{residual}$)

ing the nonparametric Friedman test, for RR, RR_{resp} and $RR_{residual}$. Figure 3 shows the median and interquartile ranges of LF, $LF_{residual}$, HF, $HF_{residual}$ and HF_{resp} during the attention task and mental stress task with respect to the baseline condition. The results based on the original tachogram show that LF and HF are significantly higher during baseline than during MT and AT ($p < 0.001$). However, no significant differences are found between MT and AT. These findings are also observed in the residual tachogram ($LF_{residual}$ and $HF_{residual}$). In addition, the HF power of the respiratory component (HF_{resp}) is significantly lower during stress compared to baseline and AT ($p < 0.001$), indicating that stress also influences the breathing pattern, which in turn, affects the tachogram. The differences in HF power in the original tachogram can, thus, be attributed to stress factors that influence the tachogram via the respiration, and stress factors that directly influence the functioning of the autonomic nervous system. In all tachograms, LF/HF shows no discriminative power between the different conditions ($p > 0.05$).

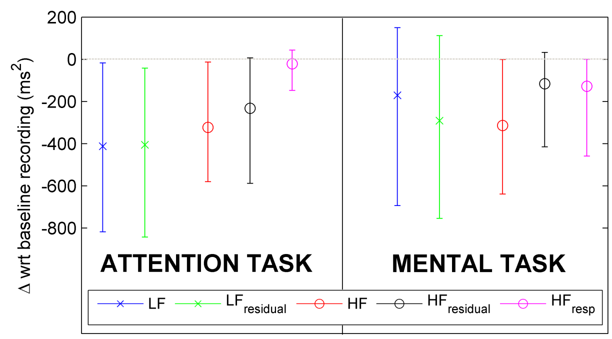

Figure 3. Median and interquartile ranges of LF, $LF_{residual}$, HF, $HF_{residual}$ and HF_{resp} during the attention task and mental stress with respect to the baseline condition.

4. Discussion and conclusion

Stress is a growing problem in today's society and its effect on the autonomic nervous system is studied widely via HRV analyses. However, due to the apparent influence of respiration on the tachogram, which is not taken into account, the accuracy of HRV measures is questioned, making the interpretation a source of discussion.

This issue was also addressed by Choi and Guttierez-Osuna by using a linear system-identification model to estimate the respiratory component of the tachogram [10]. They show that their approach yields power spectral HRV measures with a higher discriminative power when classifying rest and mental stress. Further research is needed to make a careful comparison with MSPCA, the technique which was proposed to take respiratory influences into account during stress monitoring by separating the tachogram in 2 components: a respiratory component (RR_{resp}), which was estimated using MSPCA, and a residual component ($RR_{residual}$). The use of MSPCA, however, has a few limitations, such as the fact that the mother wavelet and the order need to be specified, as well as the threshold for the explained variance by the first eigenvector. Additionally, only linear interactions are taken into account. Yet, in a previous study, it was shown that MSPCA was successful in estimating the respiratory component, as the residual part shows no correlations and coherences with the respiratory signal.

The results show that no differences between MT and AT could be found, except for HF_{resp}. However, it was also observed that stress influences the tachogram via the respiration as well as directly via the functioning of the ANS. Although stress also affects respiration, the breathing is under voluntary control and might not always be a good indicator of stress. The separation of the respiratory component of the tachogram can, thus, be a valuable tool to interpret the results as it might reveal changes in the functioning of the ANS that are otherwise masked by differing respiratory patterns.

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