RSA Component Extraction from Heart Rate Signal by Independent Component Analysis

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Abstract

Respiratory sinus arrhythmia (RSA) is a phenomenon where heart rate changes synchronously with respiration. It can be measured by high frequency power (HF power, 0.15-0,4Hz) of heart rate interval (RRi) series, which is an important and widely used parameter in cardiovascular research. Due to the altering respiration rates, it is important to have methods to separate the RSA from the RRi. We applied Independent Component Analysis (ICA) to extract the RSA from the RRi series. The performance of ICA was evaluated with a simulation study where real 5min RRi (n=20) and respiration data (n=2) of spontaneously breathing males were superimposed. According to residual analysis in time and frequency domain, the extracted RSA follows the shape of simulated RSA (3.3 – 5.4 % RMS error of total variability), and ICA is able to remove RSA without changing the power content of RRi (p <0.05). Thus, ICA is a capable method to extract RSA from RRi series.

1. Introduction

Spectrally calculated high frequency power (HF power, 0.15-0,4Hz) component of heart rate interval (RRi) series is a widely used parameter both in clinical settings and physiopathological investigations (1). HF power is obtained from the power spectrum of the RRi series by integrating the power in HF area. The HF power is mainly originated from respiration, and the mechanism that affects the HF power peak is called respiratory sinus arrhythmia (RSA). Thus, the peak originated from respiration can be named as RSA component. Heart rate changes synchronously with respiration via two different mechanisms: 1) mechanical effects of respiration (mainly changes in venous return which directly modulates sinus node) (2), and 2) trough autonomic nervous system (3). The delay between the mechanical and neural effect is so small that we have assumed the RSA component to be just one component.

Depending on the respiration rate of the subject, the RSA may overlap the low frequency (LF power, 0.04-0.15Hz) range and thus distort the frequency domain indices, e.g. the LF power or LF peak frequency. Also baroreflex estimators can be easily biased when respiration rate is within the baroreflex 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.

Several algorithms and methods to remove the respiration effects from ECG and RRi series are introduced in the literature. Many of these methods use respiration signal as a reference. The ideal situation regarding, for example a real-time application, would be that no reference of respiration is needed. Thus far, effective algorithms for this purpose have not been developed. Adaptive filtering has been proposed to be an effective method to extract RSA by researchers in [4] who used lattice filter structure in their study. Least mean square (LMS) filter has also been proposed to extract effectively RSA component from RRi series (4). Adaptive filters uses respiration as a reference.

In this paper, we demonstrate how independent component analysis (ICA) can be applied to extract the RSA component from the RRi series, which is a quite new algorithm for separating components from mixed observation signals (5). We performed a simulation study to evaluate the obtained components that are the RSA component and remaining “respiration-free” tachogram caused by neuronal regulation.

2. Methods

2.1. Data

ECG was measured from twenty (N = 20) healthy men in a resting position (Cardiopac 3M33, Nec-Scan –ei instruments, Japan). 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. Detection was verified visually. Tachogram was interpolated at 2Hz and respiration was downsampled regularly at 2Hz, respectively, in order to get time-synchronous signals. Tachograms were detrended using Savitzki-Golay filter (polynomial order 3. frame size 51). Ten (N = 10) testees had a mean respiration rate < 0.15Hz, while the rest of them had a respiration rate > 0.15Hz. Systogram (series of beat-to-beat systolic blood pressure values) is a very similar to tachogram signal, and it is also periodically affected by respiration. According to similarity of these signals and our previous work, the methods presented in this paper can be applied to the systogram signal as well. This was also preliminary tested.

2.2. Simulation study

In order to reliably evaluate the extent to which the RSA component can be removed from the tachogram, we performed a simulation study. The main idea was to add a known RSA component to the *original* tachogram signal and then apply ICA method to extract the RSA component from the tachogram. The obtained respiration-free tachogram signal is called as *filtered* signal. After these operations, we performed a residual analysis to evaluate how well the RSA component is extracted.

Simulation was performed such that we first picked arbitrarily two of the testees, one having a respiration rate <0.15Hz and the other >0.15Hz. Then, we applied an adaptive Least Mean Square (LMS) filter that we have previously successfully used in our studies [5] to extract their RSA components. These two extracted RSA components and their corresponding respiration signals where then used in simulations by adding the extracted RSA components to the tachograms (n=20) and applying then the ICA. We decided to use this protocol instead of using, e.g. an artificial signal, such as sine waves to mimic as much as possible real signals in order to be closer to a practical application. Before adding the extracted RSA components, we had to handle the data by removing a person's own RSA components with a LMS filter [5]. This was done to reduce the confusing effect which a second RSA component in a signal may affect.

Simulation was performed in two study groups. In *Simulation 1*, we used the extracted RSA component from a person whose respiration rate is < 0.15Hz, and in *Simulation 2*, the respiration rate was > 0.15Hz. Simulation was done this way because we wanted to study if the RSA could be extracted successfully from the same frequency band than the remaining filtered tachogram signal (i.e. in *Simulation 1*).

2.3. Independent component analysis

Independent component analysis (ICA) is a statistical and computational method for decomposing datasets of measurements, signals, or random variables into their subcomponents (5). A generative model for ICA is constructed by observation vectors x(t) = [xi], i = 1..N, N =amount of sensors and sources s = [s1, s2,..., sN]^T with the equation:

$$x(t) = As(t), \tag{1}$$

where M * N mixing matrix A and a source vectors s(i) are unknown. The sources that are assumed to be nongaussian and mutually independent and are called independent components which can be found by ICA. We applied FastICA software package in our ICA studies [7].

The **ideal** situation would be that the tachogram signal and pure RSA signal represent the observation signals. In **practice,** we do not know the absolute RSA signal, and thus instead we use the respiration signal as the observation signal. These two cases are demonstrated in flow charts in Figure 1. T denotes original tachogram signal, RESP the measured respiration signal. T^N_{REM} denotes reminder normalized respiration-free tachogram and RSA^N the normalised RSA signal. T, RSA, and RESP are observation signals in ICA, while RSA^N and T^N_{REM} are unknown sources, i.e. independent components.

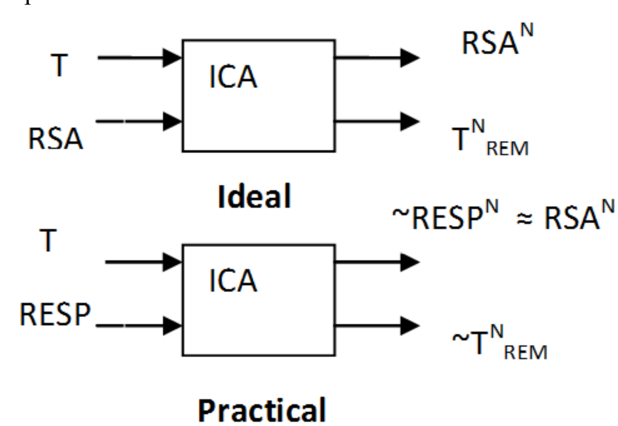

Figure 1. Extraction of RSA component from tachogram.

Since the variance of each independent component is unit variance, the components must be scaled in order to calculate e.g. absolute power spectrum estimates. We applied linear regression model (2) to reconstruct original tachogram *T* from the independent normalized components by defining scaling factors α and β:

$$T = \alpha T_{RSA}^{N} + \beta T_{REM}^{N} \quad (2)$$

$$T = [T_{RSA}^{N} T_{REM}^{N}]\theta = \bar{T}\theta, \quad (3)$$

$$\text{where } \theta = \begin{bmatrix}\alpha \\ \beta\end{bmatrix}$$

$$\text{From (2):} \quad \hat{\theta} = \bar{T}^{+}T, \quad (4)$$

where $\bar{T}^{+}$ is a pseudoinverse.

Scaling factors α and β are then used to scale the extracted components to the original magnitude.

3. Results and discussion

An example of the power spectrums of the original tachogram signal, simulated tachogram signal, and filtered tachogram is presented in Figure. 2. In this example, the RSA component which is within the HF range is first added to the original tachogram (namely simulated tachogram). By the ICA procedure, the RSA is then extracted, and the power spectrum of the remaining filtered tachogram is plotted. Figure 2 demonstrates that after the ICA the RSA component has been removed and it will not substantially change the spectral characteristics.

In Table 1, there are listed absolute powers as means ± standard deviations from the original signals and the both simulation groups. In Simulation 1, the added RSA is within the LF range, while in Simulation 2 the RSA is within the HF range. In addition, the absolute powers of added (A) and extracted (E) RSA components are listed in Table 1.

The characteristics of extracted RSA components in time and frequency domain (power spectra) are examined case by case in Figure 3 where every RSA component from Simulation 1 and Simulation 2 are plotted in the same figures.

According the mean spectrum results in Table 1, the both simulations have succeeded to keep the power components numerically the same as the prior simulation ($p < 0.05$). The absolute powers of extracted RSA components do not differ from the original ones, either. In addition, the shape among extracted RSA components in time and frequency domain are almost the same and do not differ from simulated ones (Fig 3.). RMS error of total variability was 5.4 % in Simulation 1 and 3.4 % in Simulation 2.

It was expected that ICA would work sufficiently at least with Simulation 2. ICA worked well also in Simulation 1, where added RSA component was within the same frequency band than the remaining respiration-free component. Thus, ICA is a very promising method in cardiovascular signal processing. In future studies, we would like to study if ICA could also be applied without respiration as a reference. That kind of "self-referencing" application would be very useful in practical applications.

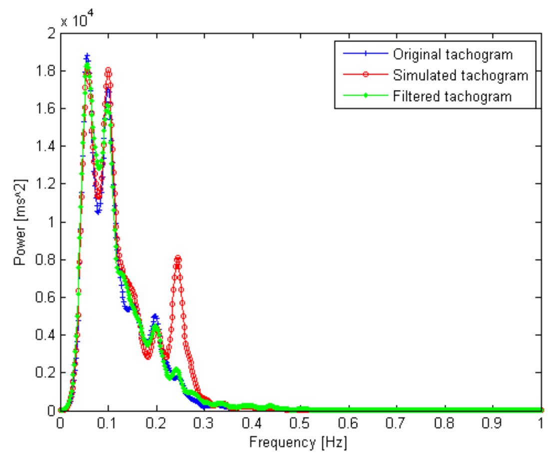

Figure 2. Illustration of data and simulation: power spectrums of original, simulated, and filtered tachograms.

Table 1. Absolute power spectrum components from original and simulation protocols and added/extracted RSA power spectrum components

Protocol	LF power [ms^2]	HF power [ms^2]	TOT power [ms^2]	
Original	690 ± 350	289 ± 228	978 ± 525	
Simulation 1*	721 ± 389	388 ± 215	1109 ± 558	
Simulation 2¤	654 ± 369	370 ± 220	1024 ± 542	
RSA	Original 1 (A)	Simulation 1 (E)	Original 2 (A)	Simulation 2 (E)
component [ms^2]	399	356 ± 132	1001	804 ± 200

*(RSA in LF range)
¤ (RSA in HF range)

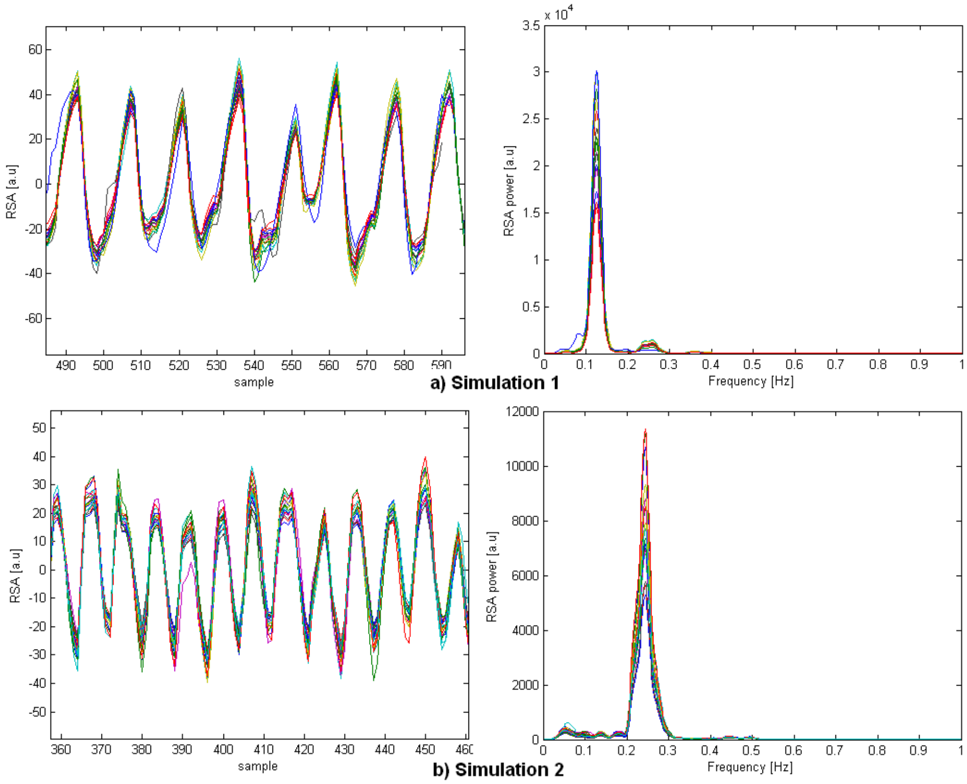

Figure 3. Extracted RSA components in time (left) and frequency (right) domains: from a) Simulation 1 (respiration <0.15Hz) and b) Simulation 2 (respiration <0.15Hz).

4. Conclusions

The Independent Component Analysis was applied in this paper to remove the distorting effect of respiration, i.e. also known as RSA, from the series of RRi. According to simulation results, the ICA removed successfully RSA-component from the tachogram signal without changing the spectral or time domain characteristics of the remaining "respiration-free" components. The proposed method can also be applied with a series of beat-to-beat blood pressure values. As a conclusion, ICA can be applied to remove the RSA component from ECG and blood pressure signals, and thus is a promising tool in cardiovascular signal processing.

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