Separating respiratory influences from the tachogram: methods and their sensitivity to the type of respiratory signal

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Abstract

Respiration is one of the main modulators causing heart rate variability (HRV). However, when interpreting studies of HRV, the effect of respiration is largely ignored. We, therefore, previously proposed to take respiratory influences into account by separating the tachogram in a component that is related to respiration and one that contains all residual variations. In this study, we aim to investigate the sensitivity of two of such separation methods, i.e. one based on an ARMAX model and another one based on orthogonal subspace projection (OSP), towards different respiratory signal types, such as nasal airflow (the reference), thoracic and abdominal efforts, and three ECG-derived respiratory (EDR) signals. The sensitivity of both separation methods to the type of respiratory signal is evaluated by assessing the information transfer from the reference respiratory signal to the residual tachogram, where the latter is obtained using each time a different type of respiratory signal. The results show that OSP is the least sensitive to the different types of respiratory signals. Even when an EDR signal obtained using kernel principal component analysis is used, OSP yields a correct separation in 13 out of 18 recordings, demonstrating that in many cases, the separation of the tachogram can successfully be conducted even if only the ECG is available.

1. Introduction

Our heart is beating at a rate such that it can properly respond to the needs of our body. This creates continuous variations over time in our heart rate, termed heart rate variability (HRV). One of the main modulators of our heart rate is linked to our breathing; this is called respiratory sinus arrhythmia (RSA) and represents the fluctuation of the heart rate with respiration. These respiratory-related heart rate variations have been associated with vagal activation. However, this has been highly debated as several publications reported that measures of RSA are dependent of tidal volume and respiratory rate, independent of cardiac vagal tone [1]. The lack of consensus on this interpretation, and consequently on certain HRV features, motivated the use of a different approach: the separation of the tachogram in a part related to respiration and a part unrelated to respiration, the so-called residual tachogram. Recent research showed that inclusion of respiratory information using this approach yields almost perfect classification in periods of rest and stress when spectral HRV features from the residual tachogram are used [2]. This study showed that it is interesting to investigate these residual heart rate variations as they might be masked by the dominant influence of respiration onto the tachogram.

Two separation methods, one based on an ARMAX model [3] and one based on orthogonal subspace projection (OSP) [4], have been used to conduct this separation of the tachogram. However, these methods require the recording of a respiratory signal. It is well-known that different modalities to record the breathing also yield respiratory signals with diverse morphologies. In this paper, we aim to investigate how sensitive these separation methods are towards different types of respiratory signals, by comparison of their performance when nasal airflow, and thoracic and abdominal displacements are used. Additionally, we aim to investigate whether the separate recording of respiration is really necessary by evaluating the performance when several ECG-derived respiratory (EDR) signals are used as surrogate respiration.

2. Methodology

2.1. Data acquisition and preprocessing

The first dataset used in this study originates from the PhysioNet database [5] for the Computing in Cardiology

Challenge 2000 for ECG-based apnea detection (Apnea-ECG). Eight records (age: 43.3 yr $\pm$ 8.3) contain single-lead ECG recordings and multiple respiratory recordings: nasal airflow recorded with a thermistor (RSP$_{ref}$), thoracic (RSP$_{TH}$) and abdominal effort (RSP$_{AB}$). All signals are sampled at 100 Hz.

The second dataset is recorded in the University Hospital Leuven (UZ Leuven, Belgium), and consists of polysomnography data of 10 patients (age 48.8 yr $\pm$ 11.8) with habitual snoring, witnessed apneas and hypersomnolence. Different signals are extracted from this dataset, namely, single-lead ECG (Lead II), respiratory effort measured around the thorax (RSP$_{TH}$) and the abdomen (RSP$_{AB}$), and nasal airflow (RSP$_{ref}$) recorded with an oronasal thermistor (Braebon, NY, USA). The sampling frequency is 200 Hz.

From all 18 recordings, 5 minutes without apneic events are selected. All ECGs are upsampled to 500 Hz using cubic spline interpolation to obtain tachograms with an accuracy of 2 ms. The nasal airflow signals are always used as the reference respiratory signal (RSP$_{ref}$). All respiratory signals, including the EDR signals as computed below, and tachogram are resampled at 4 Hz, and high pass filtered at 0.05 Hz to remove baseline wander.

2.2. ECG-derived respiration

Apart from the separately recorded respiratory signals, the performance of the separation methods will also be evaluated when several ECG-derived respiratory signals are used. The goal is to test whether the recording of only ECG is sufficient to reliably separate the tachogram. We will consider three EDR methods:

- *EDR$_{RA}$*: This EDR signal is determined by the amplitude of the R peaks in the baseline-corrected ECG, where the baseline wander is removed using 2 median filters of 200 ms and 600 ms.
- *EDR$_{PCA}$*: The EDR signal based on principal component analysis (PCA) relies on the changing correlation between the QRS complexes over several heart beats, where it is assumed that the largest variations between the QRS complexes are caused by respiration [6].
- *EDR$_{kPCA}$*: This EDR signal is based on the approach using PCA, but exploits non-linear interactions between the ECG and respiration by the use of the nonlinear kernel PCA (kPCA) instead of the linear PCA [7].

2.3. Separation of the tachogram

Several methods have been proposed in the literature to separate respiratory variations from the tachogram such that we have two components: one that is strictly related to respiration (RR$_{RSP}$), and one that contains all heart rate variations that are unrelated to respiration, i.e. the so-called residual tachogram (RR$_{res}$). We will evaluate the sensitivity to the type of respiratory signal of two methods that proved to be successful in conducting this separation. Both methods are based on the estimation of the respiratory component of the tachogram (RR$_{RSP}$) when the original tachogram (RR$_{orig}$) and a recorded respiratory signal (RSP) are given:

- *ARMAX*: This separation approach was proposed by Choi *et al.* and estimates RR$_{RSP}$ as a linear combination of past respiratory inputs [3]. Delays up to 3 s are taken into account.
- *OSP*: In this approach, the tachogram is projected onto a respiratory subspace to obtain RR$_{RSP}$. The respiratory subspace is constructed from delayed detail signals from the wavelet decomposition of the respiratory signal using a Daubechies 4 wavelet, up to level 5. Also here, delays up to 3 s are included [4].

After computation of the respiratory component of the tachogram, the residual component RR$_{res}$ can simply be found by RR$_{res}$ = RR$_{orig}$ $-$ RR$_{RSP}$.

2.4. Sensitivity to the type of respiratory signal

In the first stage, the similarity between all 'indirect' respiratory recordings, including the thoracic and abdominal efforts as well as the three computed EDR signals, and the nasal airflow RSP$_{ref}$ is assessed via their coherence. As similarity measure, the mean magnitude squared coherence between the respiratory signals in a range of the full width at half maximum of the fundamental respiratory frequency is computed [7].

Secondly, the sensitivities of ARMAX and OSP to the type of respiratory signal are evaluated by testing whether they succeed in separating the respiratory-related heart rate variations from residual variations when respiratory signals other than RSP$_{ref}$ are used to conduct the separation:

1. Computation of RR$_{res}$ using all six types of respiratory signals and both separation methods, resulting in 12 residual tachograms RR$^{type}_{res,OSP/ARMAX}$.
2. Assessment of the cross entropy from the reference respiratory signal RSP$_{ref}$ to all residual tachograms RR$_{res}$.

For the computation of the cross entropy, consider the bivariate process $\{X, Y\}$, where X_n and Y_n are the processes sampled at the present time n. Then the cross entropy, which is defined as the information transfer that quantifies how much of the information carried by Y_n can be predicted by the past of X, can be computed as CE$_{X\to Y}$ $= H(Y_n) - H(Y_n|\mathbf{X_n^-})$, with $\mathbf{X_n^-} = [\ X_{n-1} \quad X_{n-2} \quad \cdots\ ]$ and $H(.)$ the Shannon entropy. The (conditional) entropies are then estimated via a model-based approach, where the processes are represented by a vector autoregressive model with order p, as optimized by

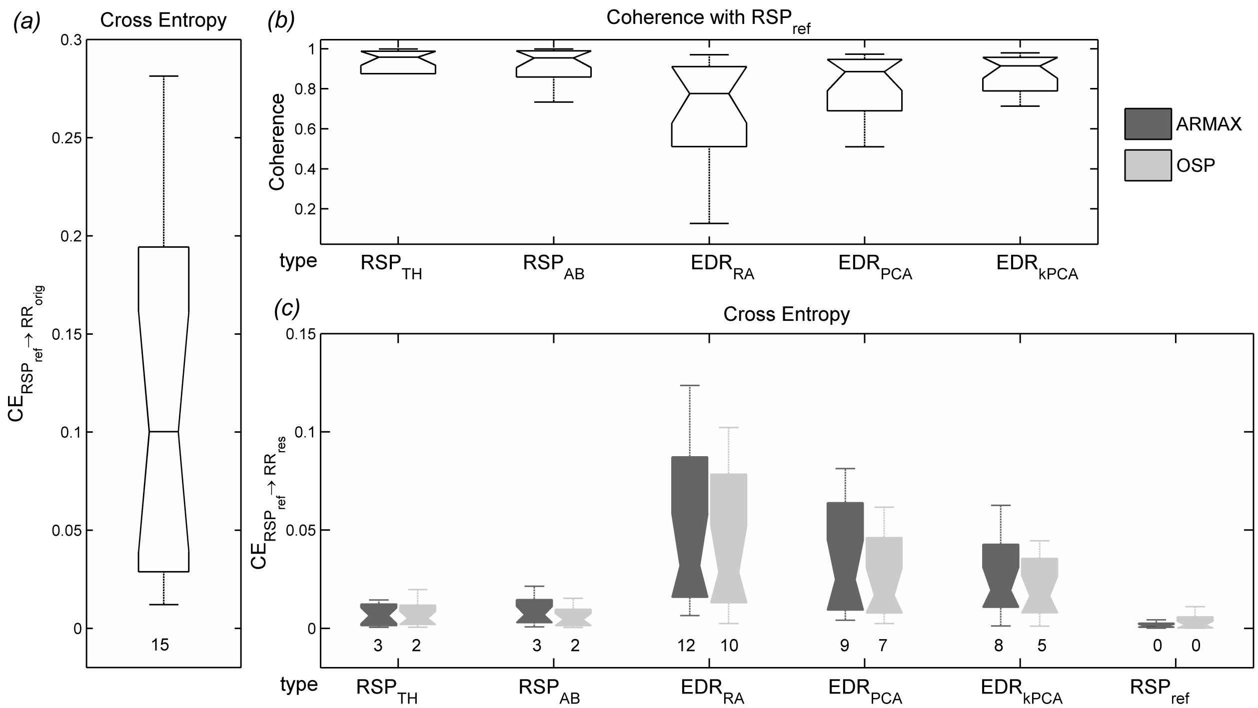

Figure 1. Boxplots of the results; (a) cross entropy from RSP$_{ref}$ to RR$_{orig}$; (b) mean magnitude squared coherence between RSP$_{ref}$ and the other types of respiratory signals; and (c) cross entropy from RSP$_{ref}$ to RR$_{res}^{type}$ obtained using ARMAX and OSP. The number below each boxplot indicates the number of significant cross entropies.

the Akaike information criterion, and delays up to 3 s [8]. Based on this parametric representation, the statistical significance of the cross entropy from X to Y can be assessed by an F-test checking whether the past of X explains a significant portion of the variance of Y. For a correct separation of respiratory-related and residual variations, the cross entropy from the reference respiratory signal $X = \text{RSP}_{ref}$ to the residual tachograms $Y = \text{RR}_{res}$ should be quasi-zero, or non-significant.

3. Results and discussion

Figure 1 shows the results of the above described analyses. In Figure 1(a) the cross entropy from the reference respiratory signal to the original tachogram is given. We can observe that 15 out of 18 recordings have a significant information transfer.

Next, a comparison between the different types of respiratory signals is conducted via the mean magnitude squared coherence with the reference nasal airflow. These results are displayed in Figure 1(b), where we can see that, as one could expect, both recorded respiratory efforts RSP$_{TH}$ and RSP$_{AB}$ yield high coherences. From the three EDR signals, the algorithm based on the R peak amplitude performs the worst. As described in [7], EDR$_{PCA}$ yields better EDR signals, but the best resemblance to the nasal airflow is for EDR$_{kPCA}$ with coherences around 90%, which are similar as the recorded RSP$_{AB}$.

In Figure 1(c), the cross entropies from RSP$_{ref}$ to residual tachograms obtained with the other types of respiratory signals are displayed. When looking at CE$_{RSP_{ref}\rightarrow RR_{res}^{RSP_{ref}}}$ obtained both using ARMAX and OSP, we can observe that the cross entropies are very small and none of them even exhibit a significant information transfer. This indicates that both separation methods successfully separate the respiratory influences from the tachogram. Also, the cross entropies from RSP$_{ref}$ to the residual tachograms obtained using RSP$_{TH}$ and RSP$_{AB}$ are quasi-zero. However, both signals yield respectively 3 and 2 significant cross entropies when ARMAX and OSP are used, indicating that in some cases, the separation methods do not fully succeed to separate respiratory-related heart rate variations and residual variations when 'indirect' recordings of respiration are used. When EDR$_{RA}$ is used to compute the residual tachogram, either using ARMAX or OSP, there are still many significant cross entropies, showing that the R peak amplitude method can not be used as surrogate respiratory signal to conduct the separation. The results improve, but are still not perfect, when PCA and kPCA are used to compute the EDR signals. Note here that the mechanical interaction between respiration and ECG is used to compose the three EDR signals, causing that the information contained in these signals might be different than in the recorded respiratory signals. The best results with surrogate respiratory signals are obtained when EDR_{kPCA} is combined with OSP. Although there are still 5 out of 18 significant cross entropies, the cross entropies are significantly reduced when we compare this with $\text{CE}_{RSP_{ref} \rightarrow RR_{orig}}$. These results suggest that OSP is a solid technique, that might also be useful in several home monitoring applications, such as sleep apnea detection or epilepsy monitoring, where it is desired to use only few sensors. We have shown here that in most cases, enough respiratory-related information can be extracted from the ECG to reliably conduct the separation, and that it might not be needed to separately record the respiration. However, it should be investigated whether e.g. the results for stress classification can be reproduced when EDR_{kPCA} is used [2].

From all these results, we can observe that OSP has always fewer significant cross entropies than ARMAX, indicating that OSP is less sensitive to the type of respiratory signal. We hypothesize that this is due to the inclusion of the wavelet transform in OSP that reduces the impact of artifacts and different signal morphologies.

4. Conclusion

The two methods that we evaluated to separate respiratory influences from the tachogram perform well as demonstrated by the lack of information transfer from the reference respiratory signal to the residual tachogram obtained using that reference signal. When other recorded respiratory signals are used, such as abdominal or thoracic displacements, the separation is also good. The ECG-derived respiratory signals on the other hand, do not manage to completely separate the respiratory influences from the tachogram. However, the separation method based on OSP successfully separates 13 out of 18 recordings when the EDR method based on kPCA is used. We can conclude that OSP is less sensitive than ARMAX to the different morphologies of several respiratory signal types. Additionally, the reported preliminary results suggest that the separation of the tachogram could be feasible even if only the ECG signal is available.

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References

[1] Ritz T, Dahme B. Implementation and interpretation of respiratory sinus arrhythmia measures in psychosomatic medicine: Practice against better evidence? Psychosomatic medicine 2006;68(4):617–627.

[2] Widjaja D, Vlemincx E, Van Huffel S. Stress classification by separation of respiratory modulations in heart rate variability using orthogonal subspace projection. In Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2013. 2013; 6123–6126.

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

[4] Caicedo A, Tachtsidis I, Papademetriou M, Van Huffel S. Decoupling the influence of systemic variables in the peripheral and cerebral haemodynamics during ecmo procedure by means of oblique and orthogonal subspace projections. In Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2012. 2012; 6153–6156.

[5] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals. Circulation 2000;101(23):e215–e220.

[6] 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 Transactions on Biomedical Engineering 2010;57(4):821–829.

[7] Widjaja D, Varon C, Dorado AC, Suykens JA, Van Huffel S. Application of kernel principal component analysis for single-lead-ecg-derived respiration. IEEE Transactions on Biomedical Engineering 2012;59(4):1169–1176.

[8] Faes L, Montalto A, Nollo G, Marinazzo D. Information decomposition of short-term cardiovascular and cardiorespiratory variability. In Computing in Cardiology Conference (CinC), 2013. IEEE, 2013; 113–116.

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