ECG-Derived Respiration for Ambulatory Monitoring

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Abstract

Respiration is an important physiological signal for the monitoring and diagnosis of different conditions. However, a respiratory sensor is rarely included in ambulatory systems. Hence, several studies have focused on the computation of the so-called ECG-derived respiration (EDR). This research evaluates four different EDR algorithms on ECG signals that contain non-stationarities and noise. Two of these algorithms are based on the amplitude of the R-peak, and two are based on principal component analysis. To evaluate how well each of these algorithms estimates the respiration, three physionet datasets were used, and correlation, coherence, and a measure of cardiorespiratory coupling were used as indices for this evaluation. It was found that the simplest algorithm, namely the R-peak amplitude, was less sensitive to noise. In addition, no significant differences were found between the cardiorespiratory coupling derived with this easy-to-compute EDR and the real respiratory signal. This is great news for ambulatory applications, since the simplest algorithm can accurately estimate respiratory information.

1. Introduction

Respiration plays an essential role in the diagnosis and monitoring of different conditions, such as stress and sleep disorders. However, its recording is often associated with invasive and intrusive sensors such as respiratory belts and thermistors. Despite the fact that these sensors are regularly used in a hospital setting and are unavoidable in different medical tests, it is very rare to find them in ambulatory systems. In fact, several monitoring systems avoid using these sensors, not only because of their interference with the natural breathing, but also because of the costs associated with their use. For these reasons, several studies have focused on the derivation of respiratory information from the single-lead ECG signal. Some algorithms have been proposed to derive respiratory rates from the tachogram [1], and others have shown that an approximation of the respiratory signal can be obtained from amplitude changes of the ECG [2,3]. This approximated signal is called the ECG-derived respiration (EDR), and its computation is possible due to the mechanical interaction between the respiratory movements and the morphology of the ECG. More specifically, during each breathing cycle, the electrical impedance of the thorax and the relative position of the electrodes with respect to the heart, change due to variations of the amount of air in the lungs. Consequently, these variations can be detected from the changes in the amplitude of the different waves of the ECG. In this context, this research aims to evaluate different existing EDR algorithms on ECG signals that contain noise and non-stationarities, which are typical in signals from ambulatory systems. The latter differentiates this study from others in the literature, for instance in [4] a respiratory pattern was imposed and patients were in a semi-supine position during the whole experiment, and in [5] only stationary segments were used. Here, all dynamics are taken into account, and an ambulatory dataset is included. This is important since many studies are currently focusing on maximizing the amount of information extracted from an ambulatory ECG, and these findings will help deciding which method to use to extract respiratory information.

2. Methodology

2.1. Data

In order to evaluate the different EDR algorithms three publicly available Physionet datasets were used. The first one corresponds to the Fantasia database [6], which consists of simultaneous recordings of ECG and respiration. Single-lead ECG (lead II) and respiratory signals were recorded from 20 young (age between 21 and 34 years), and 20 elderly (age between 68 and 85 years) healthy subjects. The respiratory signals were measured using a respiratory belt around the thorax. All subjects were in supine position while watching the movie Fantasia (Disney, 1940), and the signals were recorded for about 120 minutes with a sampling frequency of 250Hz.

The second dataset is the Apnea-ECG database [7] that contains 70 single-lead ECG signals (lead II), of which 8 are accompanied by three concomitant respiratory signals. Two of the latter correspond to the respiratory effort measured using respiratory belts around the abdomen and thorax, and one corresponds to the oronasal airflow recorded using a nasal thermistor. All the ECG and respiratory signals were sampled at 100Hz and their length range between 7h and 10h.

The last dataset used in this study is the “Stress Recognition in Automobile Drivers” database [8]. This set contains single-lead ECG (lead II) and respiratory signals amongst others, which were recorded from healthy volunteers while they were driving a car around Boston, Massachusetts. Respiratory signals were recorded using a respiratory belt around the thorax and were sampled at 31Hz, while the ECG was sampled at 496Hz.

2.2. ECG-processing

All ECG signals were segmented into epochs of 60s, and in total, 1210, 4772, and 3950 segments were collected for the drivers, fantasia and apnea datasets, respectively. Next, the segments were normalized to zero mean and unit variance, and the contamination level proposed in [9] was calculated for each ECG segment. After that, the R-peak positions were detected using the modified Pan-Tompkins algorithm proposed in [9], and baseline filtering was implemented using two median filters [3]. One filter of 200ms was first applied to remove the QRS complexes and P-waves. On this filtered signal the second median filter of 600ms was applied to remove the T-waves. The resultant *baseline* signal was then subtracted from the ECG. Finally, four different amplitude-based algorithms were used to derive the respiration from the ECG.

2.3. ECG-derived respiration

It is well-known that respiratory movements change the position of the electrodes with respect to the heart vector, and that changes in the thoracic electrical impedance are closely related with changes in the volume of air contained in the lungs [1]. These two effects clearly affect the morphology of the ECG, in the way that the amplitude of its characteristic waves changes with each breathing cycle. Moreover, these mechanical effects are more pronounced in the standard lead II, and this is why this and other studies in the literature focus on analyzing this single-lead ECG signal. Additionally, it is also well-known that lead II is one of the most informative leads for medical diagnosis [1], hence, it is widely used in ambulatory systems. Here, four different methodologies to derive the respiratory information from the morphology changes in the ECG were implemented, and they will be described below.

a) R-peak amplitude [2]: This methodology takes the amplitudes of the R-peaks on the baseline-corrected ECG segments. This EDR signal will be denoted by R_r.

b) R-peak amplitude w.r.t. the S-wave [4]: This EDR (R_{rs}) was calculated as $R_{rs}(i)=R_r(i)-S_{amp}(i)$, $i=1,\dots,N$, where N is the amount of heart beats per segment, and S_{amp} corresponds to the amplitude of the foot of the S-wave, which is computed as the minimum amplitude in a window of 80ms after the R-peak.

c) Principal component analysis [4]: This methodology takes into account not only the variations in the amplitude of the R-peak, but also the linear changes of the morphology of the QRS complex due to respiration. First, all QRSs are segmented using a symmetric window of 120ms around the R-peaks. Next, all windows are aligned with respect to the R-peaks and a matrix X is generated. Finally, a mean variation of all the points in X is obtained by means of principal component analysis (PCA). The first principal component is then used as the EDR signal, denoted by R_l.

d) Kernel principal component analysis [5]: Here, both linear and non-linear interactions between respiration and the morphology of the QRS complex are taken into account. The matrix X contained in the input space is first mapped to a higher dimensional space using a kernel function. Then, principal component analysis is applied to this new transformed dataset, and the first principal component is related to the EDR signal. However, this component needs to be mapped back to the input space before it can be used as the fourth EDR, denoted by R_k. Details on this computation can be found in [5].

2.4. Comparison

In order to evaluate the different EDR algorithms, the respiratory effort recorded using a respiratory belt around the thorax (R_{TH}) was used as a reference signal, and the following procedure was implemented:

1) All reference signals were segmented into epochs of 1 minute.

2) Both real and estimated respiratory signals were resampled at 5 Hz using cubic spline interpolation.

3) In order to evaluate the resemblance of the different EDRs to R_{TH}, the correlation coefficient and the mean magnitude squared coherence (MSC) were computed between each pair of signals. The correlation coefficient was determined as the maximum value of cross correlation over 10 lags [5], and the MSC was computed as

$$C_{xy} = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}, \qquad (1)$$

where $P_{xx}(f)$ and $P_{yy}(f)$ are the power spectral densities (PSD) of the signals x and y respectively, and $P_{xy}(f)$ is the cross-power spectral density of x and y. The PSD was computed using Welch's algorithm, with a 1024 point fast Fourier transform (FFT), and a Hamming window of 30s with an overlap of 50%.

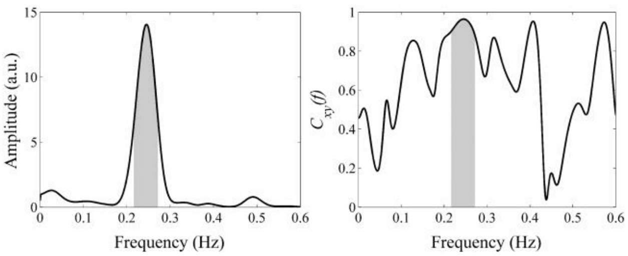

Figure 1. Computation of the mean magnitude squared coherence (MSC). (*left*) PSD of the real respiratory signal. The shaded area indicates the frequency range between the half-peak amplitude values of the fundamental respiratory frequency. (*right*) Coherence between the respiration and the EDR signal. The mean value of the coherence $C_{xy}(f)$ inside the shaded area is used for the comparison. a.u. stands for arbitrary units.

For the computation of the mean MSC it is important to consider only information about the respiration. Therefore, the frequency band is defined around the fundamental frequency of the real respiratory signal, and the cut-off frequencies correspond to the half-peak amplitude values. This is illustrated in Figure 1.

In addition to the correlation coefficient and the mean MSC, a measure of cardiorespiratory interactions was computed between the real respiration and the RR interval time series. This measure is calculated using bivariate phase rectified signal averaging (PRSA) proposed in [10]. At this point, the tachogram is computed and then resampled at 5 Hz. Then, the increasing points in the respiration (i.e. inspiration) are used as anchor points, and the quasi-periodicities of the heart rate preceding those anchor points are calculated, see [10] for details on the computation. For this example, the slope connecting the anchor point and the points immediately before and after in the average curve is measured. This slope indicates how fast the heart rate reacts to increasing points in the respiration. In other words, it can be used as an indication of cardiorespiratory coupling. The goal here is to determine whether the use of an EDR signal can result on different estimations of cardiorespiratory interactions.

3. Results and discussion

For the first part of the analysis, all segments of the datasets were used for the comparison between the different techniques. The results of this comparison are presented in Figure 2(top), where the correlation coefficients and mean MSC between each EDR signal and the real respiration R_{TH} are indicated. Note that the values of correlation and mean MSC are not different between the EDR signals, when all segments, (non-)stationary, clean and contaminated by artefacts, are taken into account. In the second part of the analysis, the contamination levels were computed for all segments, and a threshold of 0.9 was then applied to split the data into two groups, one with clean and one with "contaminated" segments. This was done in order to determine how the different algorithms performed in the presence of noise or transients in the signals. As can be seen in Figure 2(bottom), there are differences in the correlation and mean MSC between the EDR signals obtained with PCA and kPCA, and the real respiration. Moreover, it is clear that both methods based on the R-peak amplitude appear to be slightly less sensitive to noise when looking at the values of mean MSC. This is not a surprise, since it is well known that the performance of PCA is significantly compromised in the presence of noise. Therefore, these findings can be considered in real life applications, where transients, artifacts, changes in baseline, and noise contaminate the ECG signals.

For the last comparison, the measure of cardiorespiratory coupling obtained by means of PRSA was used. Figure 3 shows this measure calculated from different respiratory signals, real and estimated. Note that the values obtained using either signal are very similar, which indicates that it is enough to use the simplest EDR algorithm to get information about cardiorespiratory interactions. In addition, the strongest coupling can be observed in the Fantasia dataset, where the subjects were at rest and the strong effect of respiration is more pronounced in all segments of the dataset. In the drivers dataset on the other hand, patients were driving, and baseline and different dynamics typical of ambulatory systems, were observed. This can be seen in the lower values of this cardiorespiratory measure. Finally, the coupling between respiration and heart rate is affected during episodes of apnea, which is related to the lower values of BPRSA for the apnea dataset. With this, it is clear that this type of parameters can be easily computed using the simplest EDRs, namely R_r or R_{rs}.

4. Conclusion

The findings presented in this study can be considered in real life applications, where transients, artifacts, changes in baseline, and noise contaminate the ECG. In addition, the simplest method to extract respiratory information from the ECG offers reliable and robust performance, when compared to methods based on PCA. However, some complex interactions between respiratory movements and the morphology of the ECG might be missing with this simple algorithm.

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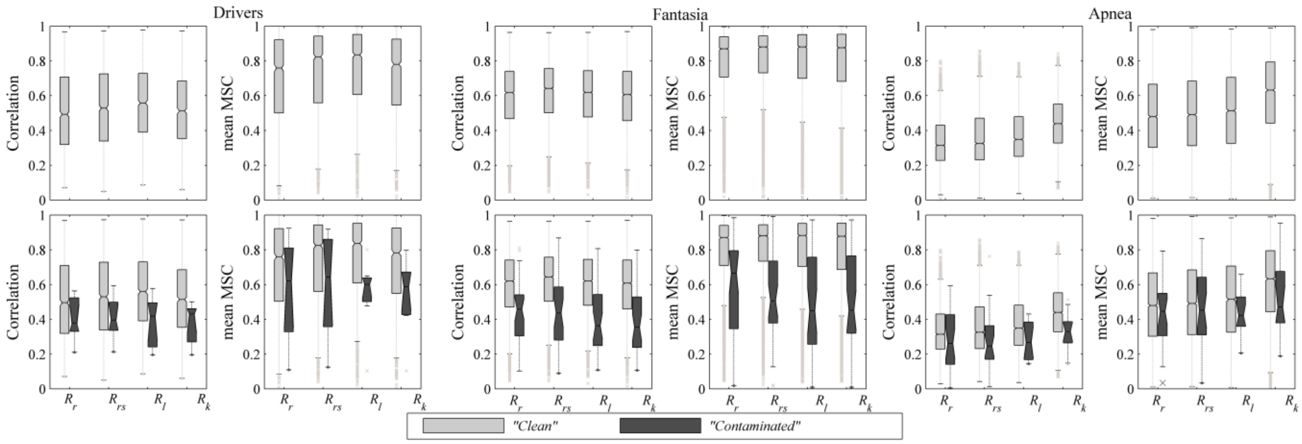

Figure 2. Correlation and mean magnitude squared coherence between the EDRs and the original respiratory signals. (*top*) values for all segments in the dataset. (*bottom*) Separation of the "contaminated" segments, (contaminated/all) 109/1210 in drivers, 73/4772 in fantasia, and 225/3950 in apnea dataset.

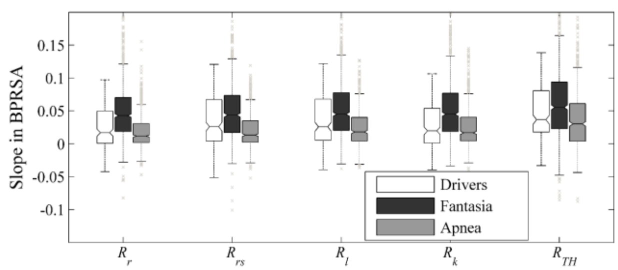

Figure 3. Measure of cardiorespiratory coupling using bivariate PRSA. The higher the slope, the stronger the coupling.

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