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Spectral fusion for estimating respiratory rate from the ECG

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Abstract— **A new method for extracting respiratory signals from the electrocardiogram (ECG) is proposed. The method performs AR spectral analysis on heart rate variability and beat morphology information extracted from the ECG and identifies the closest matched frequencies which then provide an estimate of the respiration frequency. Fusing frequency information from different sources reliably rejects noise and movement-induced artefact and is promising for application to ambulatory hospital data. The performance of the method was validated on two databases of simultaneously recorded ECG and reference respiration signals. The spectral fusion technique is found to correctly estimate respiratory rate 90% of the time in the case of non-ambulatory data and 86% of the time in the case of ambulatory data with a root mean square error of 0.92 and 1.40 breaths per minute, respectively.**

Index Terms— *ECG-derived respiration signal, respiration frequency, ambulatory ECG.*

I. INTRODUCTION

The current move towards continuous 24 h telemetry-based monitoring in acute care hospital wards requires the provision of accurate, robust data in a manner that remains largely unaffected by patient movement and is as unobtrusive as possible. Respiratory rate, an important indicator of a person's health, can be measured directly, by coupling a sensor to the airway, using techniques such as nasal thermistors or carbon dioxide sensors, or indirectly, by measuring changes in body volume: transthoracic inductance, impedance plethysmography, strain gauge measurements of thoracic circumferences, pneumatic respiration, as well as the whole body plethysmograph. While direct methods are more accurate, the placement of the measurement devices interferes with normal breathing, making the techniques unsuitable for continuous monitoring. Indirect methods are less intrusive but are very sensitive to body movement [10].

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It is a well known fact that respiration influences electrocardiographic measurements with respect to both the heart rate variability and the beat morphology [4, 7]. As a result, there has been a considerable amount of research effort directed towards obtaining a reliable respiratory rate measure from the ECG [1-11]. The physiological basis for most techniques is Respiratory Sinus Arrhythmia (RSA), the cyclic variation of heart rate which is associated with respiration [12]. Heart rate increases during inspiration and decreases during expiration [7, 12]. RSA is, thus, reflected in the variation in the time between successive R-wave peaks in the ECG, the R-R intervals. Plotting the value of the R-R interval against the time at which the interval ends produces a waveform which should be synchronous with respiration. The R-R interval time series (or heart rate variability (HRV) signal) commonly contains a low frequency (LF) component (0.04-0.1 Hz), related to short-term regulation of blood pressure, and a high frequency (HF) component (0.1-0.4 Hz) which is the RSA component. While RSA-based techniques yield good approximations of mean respiratory rates for young supine subjects, they have been found to underperform for elderly persons [4, 9], since RSA is often lost of embedded in other parasympathetic interactions [7] . Other studies [4] have found that beat morphology-based techniques were less reliable than RSA-based methods in young supine subjects or during sleep.

Most methods proposed in literature rely on obtaining an ECG-Derived Respiration (EDR) signal either from the R-R time series or by calculating R-amplitude or QRS-area estimates from the ECG and then interpolating in order to produce a smooth respiratory waveform. The EDR signal is then filtered to remove components unrelated to respiration, followed by a time- [3, 4, 6, 9, 11] or frequency-based [1, 2, 5, 7, 8] approach to estimate the respiration rate. While frequency-based approaches have been found to perform better than time/parametric ones, they rely on the assumption that the spectrum of the respiratory signal has a dominant peak. However, this is not always true during movement, when a more complex spectrum can make it more difficult to determine the dominant frequency.

A. Proposed technique

In the present paper, a new method is proposed which fuses spectral information from two different EDRs obtained from the ECG. The two EDRs are obtained by extracting and processing the R-R time series and the baseline wander of the ECG. Baseline wander is highly modulated by respiration, and is thus, a promising measure for extracting the respiratory frequency. The baseline wander is calculated by wavelet analysis rather than a more traditional polynomial fitting technique which could be easily corrupted by the presence of ectopic beats and noise in the ambulatory signal. The respiratory frequency is then estimated using autoregressive spectral analysis on the two different EDRs. Instead of searching for a main pole on the pole-zero plot (equivalent to locating the dominant frequency in the power spectrum), a frequency-correspondence criterion is used which measures how close poles are in the two pole-zero plots from each of the EDRs. "Pole pairs" are ranked according to the closeness of their matching for the two EDRs. The mean pole magnitude is also taken into account so that we can avoid selecting closely matched weak poles which are not characteristic of the respiratory frequency. The highest ranked pole-pair is then identified and the respiration frequency is determined by averaging the frequencies corresponding to the best matched pole-pair. Any frequencies which are unrelated to respiration (noise, movement artefact), that may be dominant in either the RSA or baseline EDR, are unlikely to be *"matched"* so the closest matched pole pair is most likely to be that due to respiration.

We tested the performance of the fusion algorithm on two databases of non-ambulatory and ambulatory data in terms of agreement between the respiratory rates estimated from the ECG and a reference Electrical Impedance Pneumography signal which was collected simultaneously.

In the following sections, an overview of the algorithm will be presented followed by its validation on the two databases.

II. MATERIALS AND METHODS

A. Databases

Two databases were used for validating the algorithm, one of non-ambulatory and one of ambulatory ECG so that the performance of the algorithm can be assessed firstly under laboratory conditions and secondly in the presence of noise/movement artefacts.

The non-ambulatory database was the PhysioNet Fantasia database [16] of 20 young (21-34 year old) and 20 elderly (68-85 years old) rigorously screened healthy adults who underwent 120 minutes of continuous supine rest while continuous ECG and respiration signals were recorded. 1-hour recordings from each subject were used for this work.

The second database includes data from 4 ambulatory patients from an ongoing clinical trial taking place at the John Radcliffe hospital in Oxford [6]. Two subjects from the Gerontology and two from the Surgical Emergency Unit were connected to a multi-parameter monitor and had a standard 3-lead ECG and Electrical Impedance Pneumography signals (via a chest band) collected using telemetry while they continued their daily routine on the hospital wards. A total of 6 hours of data was collected and processed.

B. Data preparation

EDR signals were extracted from the ECG using R-peak detection and wavelet decomposition. R-peak detection was performed using the Hamilton and Tompkins algorithm [15]. The R-R signal was obtained by calculating the R-R intervals and plotting them against the time at which the interval ends. The baseline wander signal was obtained by performing a 5-level wavelet decomposition of the ECG (using a biorthogonal 6.8 wavelet basis) and reconstructing the level-1 approximation coefficients [13]. Figure 1 shows an ECG-segment from the Fantasia Database and the corresponding wavelet-extracted baseline wander.

The unevenly sampled R-R signals were firstly cubic-spline interpolated at 4Hz while the smooth baseline wander signal was resampled also at 4Hz.

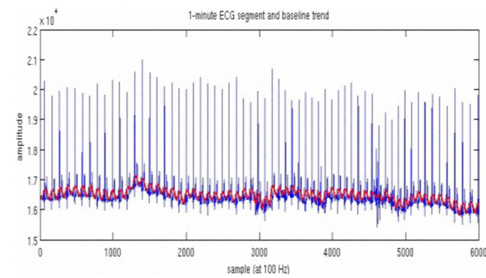

Figure 1. 1-minute ECG segment from the Fantasia database and baseline wander (in red) calculated from the wavelet approximation coefficients, following a 5-level wavelet decomposition of the ECG.

The signals were then band-pass filtered in the range 0.1-0.4 Hz (equivalent to the physiologically viable breathing rate range of 6-24 breaths per minute) using a zero-phase least-square FIR filter of order 50. Figure 2 shows the two EDRs obtained from the processed R-R and baseline wander time series and the corresponding reference signal. Peaks in the EDRs indicate breaths. The EDR obtained from the R-R time series is denoted by RSA-DR and the one obtained from the wavelet-based baseline wander by BASE-DR.

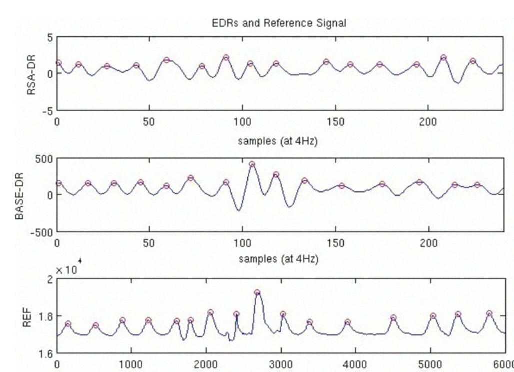

Fig. 2. EDRs and reference signal for 1-minute segment of data from the Fantasia database. The top plot shows the RSA-DR, the middle one the BASE-DR, and the bottom one the corresponding reference signal. Peaks in the EDRs and reference signal indicate breaths. We can see there is an approximate correspondence between the peaks of the EDRs and reference signal.

C. Spectral Analysis

The classic frequency-based approach to extracting the respiratory frequency from an EDR is to carry out spectral analysis [14] and look for the dominant spectral components.

Autoregressive (AR) spectral analysis has been chosen as an alternative to the more traditional discrete Fourier Transform (DFT) because there is no quantization of the angle on the pole-zero plot (and hence on the frequency estimates). The classic approach involves calculating the poles of each EDR and then identifying the one with the highest magnitude as the one representing the respiratory frequency. On an artefact-free zero-pole plot the main poles of the two different EDRs (i.e., the respiratory frequency) would be superimposed. However, the presence of noise and movement-artefact creates the appearance of additional poles and the most dominant one is not always the one linked to the respiratory frequency. Figure 3 shows the superimposed pole-zero plots for the same 1 minute segment from the RSA-DR and the BASE-DR. The data used here is from the ambulatory database.

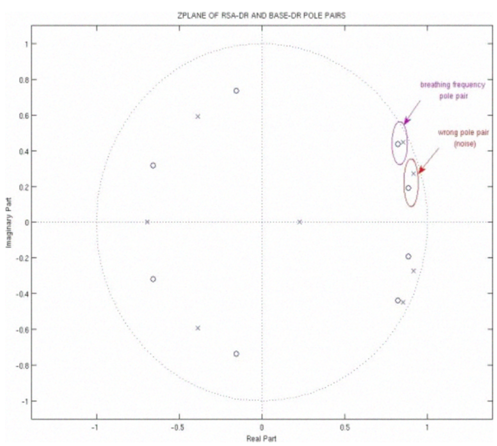

Figure 3. Pole-zero plots from 1-minute segments of RSA-DR (crosses) and BASE-DR (circles) signals. While individual EDRs might have dominant poles unrelated to breathing, the closest matched pole-pairs are most likely to be those linked to respiratory frequency.

For the work presented here we used a Yule-Walker AR model of order 8. (The order of the model was chosen as to optimize the performance of the algorithm with respect to the reference values.)

We can see that the main pole does not always coincide with the respiratory frequency due to the presence of other physiological factors (such as the blood-pressure modulation) or movement artefacts which introduce additional poles. In the current example the respiratory frequency (calculated from the reference signal) is 19 bpm and it is correctly estimated from the AR analysis of the BASE-DR. Although this frequency appears on the RSA-DR plot, it does not correspond to the greatest magnitude pole. The reverse case is also often observed where the RSA-DR correctly identifies the respiratory frequency but the BASE-DR does not. Our method relies on the assumption that the closest matched poles (of high enough magnitude) will be the respiration poles and applies a ranking criterion to all possible pole-pairs based on how closely they are in frequency and how large their magnitude is.

D. Spectral Fusion

The spectral fusion approach calculates a ranking criterion for pole pairs based on the frequency correspondence of the two poles and their average magnitude.

The pole ranking criterion (PRC) is calculated using

$$PRC = \frac{\overline{m}_{i,j}}{da_{i,j}^{\ 2}},$$

where

$$\overline{m}_{i,j} = \frac{m_i + m_j}{2},$$

And

$$da_{i,j} = |a_i - a_j|$$

for $i, j = 1,.....N$ where N is the number of poles calculated.

Here, a_i and a_j are the pole angles for the RSA-DR and BASE-DR, respectively, and m_i and m_j are the corresponding pole magnitudes.

For all possible RSA-DR and BASE-DR pole pairs, the PRC is calculated and the respiratory frequency is calculated by averaging the frequencies of the pole pair giving the highest PRC. The respiratory rate was calculated for 60-second windows, offset by 10 seconds. A 5-point median filter is applied to the estimated respiratory rate time series as a post-processing step in order to remove outlier estimates.

III. RESULTS

The algorithm was validated by calculating the Root Mean Square Error (RMSE) in breaths per minute (bpm) compared to the reference respiratory signal. The reference respiratory rate was calculated by wavelet de-noising the reference signal and then using peak-detection, followed by manual correction. The RMSE was also calculated when using single RSA-based and baseline-based techniques (using the highest-magnitude pole) in order to compare with the spectral fusion technique.

Table 1 summarises the results for the non-ambulatory and ambulatory databases.

	RSA	**Baseline**	**Spectral Fusion**
Fantasia	1.233	1.117	**0.9182**
JR Hospital	2.927	2.0511	**1.4028**

Table 1: Root Mean Square Errors (RMSE) for RSA-based, baseline-based and Spectral Fusion techniques(in breaths per minute (bpm)). The wavelet-based baseline method outperforms the RSA-based method and the spectral fusion approach is the best overall. The performance of all algorithms is better on the Fantasia database for which subjects lay supine.

Figure 4 shows a scatter plot of the respiratory rate estimates based on the spectral fusion technique evaluated on the Fantasia database. 90.14% of estimates are within 10% of the reference value. The equivalent plot for the JR ambulatory database is shown on Figure 5 where 86.25% of the estimates are within 10% of the reference value.

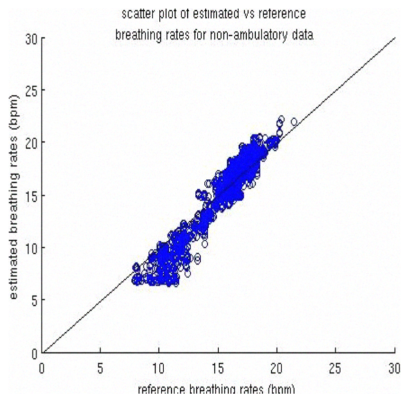

Figure 4: Scatter plot of breathing rates estimated from spectral fusion vs reference breathing rates for non-ambulatory data. 90.14% of estimates are within 10% of the reference value and the RMSE is 0.92 bpm.

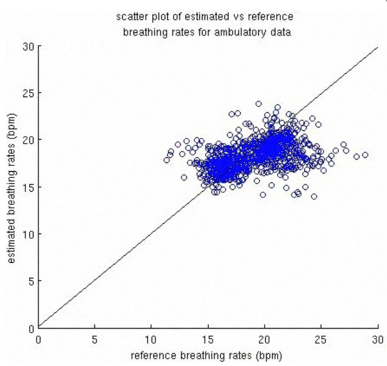

Figure 5: Scatter plot of breathing rates estimated from spectral fusion vs reference breathing rates for ambulatory data. 86.25% of estimates are within 10% of the reference value and the RMSE is 1.40 bpm.

IV SUMMARY AND CONCLUSIONS

We have presented a new algorithm for estimating respiratory rate from the ECG which fuses spectral information from the baseline wander and the R-R time series and identifies a respiratory frequency based on how closely matched poles from the two different sources are. The pole-matching approach ensures that dominant frequencies caused by artefact are not matched, by searching for the best matched poles between two different sources rather than identifying a dominant pole in each. We tested the performance of the algorithm on non-ambulatory and ambulatory databases and found an RMSE of 0.92 bpm for the non-ambulatory data and 1.40 bpm for the ambulatory data. A limitation to the study was that the ambulatory database consisted of only 4 subjects. While the performance of the algorithm in the presence of noise/artefacts for the limited database is satisfactory, further validation is required before a full assessment of the technique can be reported.

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