Robust Electrocardiogram Derived Respiration from Stress Test Recordings: Validation with Respiration Recordings

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Abstract

In this work a method is presented for robust estimation of the respiratory frequency from exercise ECGs. The method is based on the rotation angles of the heart's electrical axis as induced by respiration, determined by aligning successive QRS loops to a reference loop using a least squares criterion. The respiratory frequency is estimated by power spectral analysis of the estimated rotation angle series. Special attention has been paid to handling highly non-stationary and noisy exercise ECGs. The ECG and respiratory signals of 14 volunteers and 20 patients were simultaneously recorded during stress testing to evaluate the method. The respiratory frequency was estimated from exercise ECGs and compared to the frequency obtained from respiratory signals. An error of 6.1%±3.7% (0.024±0.017 Hz, mean±sd) is achieved, suggesting that the method is useful for analysis of exercise ECGs.

1. Introduction

The joint study of the respiratory and cardiac systems is of great interest during stress testing. Conventional techniques for recording the respiratory signal, such as spirometry, pneumography or plethysmography, are unsuitable in this strenuous situation since they require the use of devices which may interfere with breathing, being uncomfortable for the patient. Therefore, methods for indirectly extracting respiratory information are particularly attractive in stress testing.

It is well-known that respiration influences electrocardiographic measurements. During the respiratory cycle, chest movements and alterations in impedance cause changes of the heart's electrical axis which influence QRS morphology. Several studies have developed signal processing techniques to derive the respiratory signal from the ECG, the so-called ECG-derived respiration (EDR) signal. Classical EDR methods fail, however, when applied during a stress test, since exercise ECGs are highly non-stationary and noisy, mainly due to muscular activity and motion artifacts. Moreover, the respiratory frequency is in itself highly dynamic during a stress test, changing with effort and work load.

The aim of this work is twofold: first, to develop a robust estimator of the respiratory frequency which handles noisy and non-stationary signals; second, to validate the results with those obtained from respiration signals recorded simultaneously by a thermistor, a sensor often used in spirometry. A method for estimating the respiratory frequency from the VCG was described in [1], which determines the rotation angles of the electrical axis by aligning successive QRS-VCG loops. The respiratory frequency is estimated by power spectral analysis of the rotation angle series. The present work extends this method to better account for the special characteristics of exercise ECGs.

2. Methods

Signal acquisition and study population: The standard 12-lead ECG and the thermistor-derived respiratory signal of 14 volunteers (10 males and 4 females, aged 28±4 years) and 20 patients (16 males and 4 females, aged 58±16 years) referred for stress testing were recorded simultaneously at the Department of Clinical Physiology, University Hospital of Lund, Sweden.

The stress test was performed on a bicycle ergometer (Ergoline 900C, Siemens-Elema) during which the ECG was recorded using the Siemens-Elema front-end. The leads were digitized at a sampling rate of 1 kHz and amplitude resolution of 0.6 μV. The respiratory signal was recorded using an airflow thermistor (Sleepmate), amplified (DA100C, Biopac), and digitized (MA100, Biopac) at a sampling rate of 50 Hz. The amplifier band-pass filter was used with lower and upper cut-off frequencies of 0.05 and 10 Hz, respectively.

The initial workload at 50 W for males, and 30 W for females, was increased by 15 W/min for males and 10 W/min for females. Blood pressure, heart rate and rate of perceived exertion (RPE, scored from 6 to 20 according to

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the Borg scale [2]) were monitored during the test. The stress test was ended when an RPE of 15 was reached for volunteers, and when prescribed by the clinical routine for patients. The ECG and respiratory signals were recorded from the beginning of exercise until at least four minutes of recovery when the subject was lying on a bed. In the present study, the signal analysis was terminated at the end of exercise.

A total of six recordings were excluded from the study. The underlying assumption in this work is that the spectrum of the respiratory signal has a dominant peak, whose position may vary with time during the stress test. Three of the recordings were discarded because they did not fulfil this assumption. Another one was excluded because of unattached electrodes, another one because of excessive amount of ectopic beats and the last one because the ratio between its heart rate and its respiratory frequency was too low to avoid aliasing.

Signal preprocessing: First, QRS complexes are detected and a VCG is synthesized by means of the inverse Dower transformation [3]. Baseline wander is attenuated using cubic spline interpolation in which isoelectric knots are estimated by averaging 20 ms of signal, starting 80 ms before the QRS detection mark.

EDR algorithm: The method performs minimization of the normalized distance ε between a reference loop ($N \times 3$ matrix $\mathbf{Y_R}$) and an observed loop ($(N+2\Delta) \times 3$ matrix $\mathbf{Y}$), with respect to rotation (3×3 matrix $\mathbf{Q}$), scaling (scalar γ), and time synchronization ($N \times (N+2\Delta)$ matrix $\mathbf{J}_\tau$) [4, 5]:

$$\varepsilon_{min} = \min_{\gamma,\tau,\mathbf{Q}} \frac{\|\mathbf{Y_R} - \gamma \mathbf{J}_\tau \mathbf{Y} \mathbf{Q}\|_F^2}{\|\gamma \mathbf{J}_\tau \mathbf{Y} \mathbf{Q}\|_F^2}, \ \mathbf{J}_\tau = \begin{bmatrix} \mathbf{0}_{\Delta-\tau} & \mathbf{I} & \mathbf{0}_{\Delta+\tau} \end{bmatrix} \quad (1)$$

where N is the number of samples of the QRS complex analysis window (120 ms centered around the QRS mark). The parameter Δ denotes the number of symmetrically augmented samples to allow time synchronization (30 ms) with $\tau = -\Delta, \ldots, \Delta$ incremented in steps of 1 ms. The dimensions of the $\mathbf{0}_{\Delta-\tau}$, $\mathbf{0}_{\Delta+\tau}$, and $\mathbf{I}$ (identity) matrices are $N \times (\Delta - \tau)$, $N \times (\Delta + \tau)$, and $N \times N$, respectively. The operator $\|\cdot\|_F^2$ stands for the Frobenius norm.

The rotation matrix $\mathbf{Q}$ can be viewed as three successive rotations around the leads, defined by the rotation angles ϕ_x, ϕ_y and ϕ_z,

$$\mathbf{Q} = \begin{bmatrix} * & \sin\phi_z \cos\phi_y & \sin\phi_y \\ * & * & \sin\phi_x \cos\phi_y \\ * & * & * \end{bmatrix} \quad (2)$$

The normalized distance ε is minimized by first finding the estimates of γ and $\mathbf{Q}$ for every value of τ, and then selecting that τ for which ε is minimum. For a fixed τ the optimal estimator of $\mathbf{Q}$ is given by $\hat{\mathbf{Q}}_\tau = \mathbf{V}_\tau \mathbf{U}_\tau^T$, where the matrices $\mathbf{U}_\tau$ and $\mathbf{V}_\tau$ contain the left and right singular vectors from the SVD of $\mathbf{Z}_\tau = \mathbf{Y_R}^T \mathbf{J}_\tau \mathbf{Y}$. The estimate of γ is then obtained by

$$\hat{\gamma}_\tau = \frac{tr(\mathbf{Y_R}^T \mathbf{Y_R})}{tr(\mathbf{Y_R}^T \mathbf{J}_\tau^T \mathbf{Y} \hat{\mathbf{Q}}_\tau)} \quad (3)$$

The estimation of $\hat{\mathbf{Q}}_\tau$ and $\hat{\gamma}_\tau$ is performed for all τ ($-\Delta \le \tau \le \Delta$). The set of values τ, $\hat{\mathbf{Q}}_\tau$, $\hat{\gamma}_\tau$ which minimizes ε, according to (1), defines the optimal estimate $\hat{\mathbf{Q}}$. Then, the rotation angles ϕ_x, ϕ_y and ϕ_z are estimated from $\hat{\mathbf{Q}}$.

At high noise levels, unreliable angle estimates occur. Outlier angle estimates are corrected/rejected based on a reference, computed from the standard deviation of the 100 previous estimates, which is recursively updated over time. The rotation angle set $\{\phi_x, \phi_y, \phi_z\}$ is computed from $\hat{\mathbf{Q}}_\tau$, obtained for different values of τ. Angle triplets are discarded if any of the angles is greater than 5 times their corresponding standard deviation (σ_x, σ_y, σ_z). The subset of rotation angles $\{\phi_x, \phi_y, \phi_z\}'$ is further required to satisfy that the correlation of the corresponding transformed loop and the reference loop is higher than 0.9 in leads X and Z (lead Y is usually the noisiest). Finally, the rotation angle triplet of the remaining which minimizes ε is selected. During exercise QRS morphology may change, specially the terminal part, affected by exercise-induced ST changes. To reduce the influence of exercise-induced QRS morphologic variations on angle estimates, an exponentially updated reference loop is considered, i.e., $\mathbf{Y_R}(k+1) = \alpha \mathbf{Y_R}(k) + (1-\alpha)\mathbf{Y}(k+1)$, where k represents beat index. The parameter α (0.8 [6]) should be chosen to follow exercise-induced QRS morphologic variations while avoiding adaptation to noise. The initial reference loop $\mathbf{Y_R}(1)$ is defined as the average of the first ten loops showing a correlation with the first loop higher than 0.9 in leads X and Z in order to have a more reliable initialization of the reference loop. Figure 1 displays $\mathbf{Y_R}$ (lead X) at the beginning and at peak exercise of a stress test. It can be appreciated how QRS morphology changes during exercise.

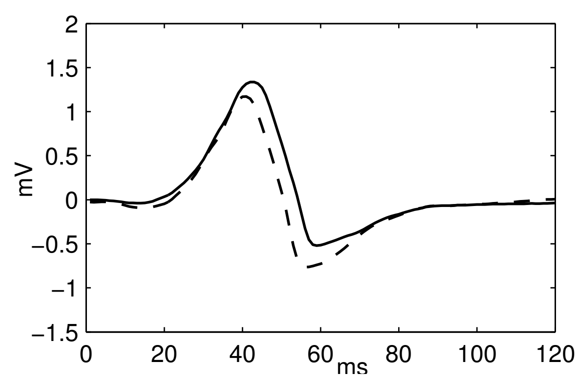

Figure 1. Reference loop (lead X) at the beginning (solid) and at peak exercise (dashed) of an exercise ECG.

Spectral analysis: The respiratory frequency is estimated as the peak frequency of the EDR signal. Spectral analysis is performed by means of Lomb's method [7] since the angle trends are unevenly spaced and contain gaps in noisy or ectopic periods.

The respiratory frequency is estimated from a running average of five spectra, each of which is estimated on a 40-second period, sliding 5 s each time. Spectral averaging is necessary to make the detection of the respiratory frequency more robust. Each 40-second spectrum is obtained, as well, as the average of m-second spectra ($m \leq 40$ s), delayed $\frac{m}{2}$ seconds each, in order to reduce the variance of the spectral estimation. Larger values of m produce spectra with better resolution and, therefore, more accurate estimation of the respiratory frequency. However, respiration spectra are not always unimodal (i.e. with a single frequency peak) but often bimodal, especially during exercise. In these situations, smaller values of m would be desirable to better estimate the gross dominant frequency, see Fig. 2.

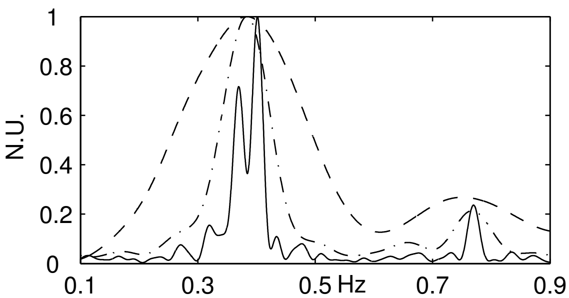

Figure 2. Spectral estimation for m=40s (solid), m=12s (dashdot) and m=4s (dashed).

The largest spectral peak (f_p) of each 40-second spectrum is searched and a parameter ζ is defined as the percentage of the total power enclosed in the bandwidth [$0.5f_p$,$1.5f_p$]. If ζ is below a threshold (35%), the spectrum is not used in the running average spectrum since it has no dominant respiratory frequency. The spectra of the estimated angle trends for each lead are summed to account for electrical axis rotation projections on any lead. Since respiration-induced rotation is often more pronounced around one of the leads, it would be enhanced in the summed spectra, especially when spurious peaks are also present. Only those lead spectra for which ζ is above the threshold are considered.

Furthermore, an interval-restricted search of the largest spectral peak is performed to reduce the risk of spurious peak selection. The largest spectral peak, $\hat{f}(k)$, is searched for in an interval of 0.4 Hz centered on a reference frequency, $f_W(k)$, which represents the smoothed running respiratory frequency, exponentially updated, according to $f_W(k{+}1) = \beta f_W(k){+}(1{-}\beta)\hat{f}(k{+}1)$, where k denotes the index of each averaged spectrum. The parameter β (0.7 [6]) should be chosen as a compromise between obtaining a stable estimate of the respiratory frequency and following its variations during the stress test. The initial reference frequency $f_W(1)$ is searched in the band 0.15-0.4 Hz.

An example of the interval-restricted peak search is presented in Fig. 3. A peak search in the whole spectrum would yield an erroneous estimate of the respiratory frequency since the largest peak would be selected. Since respiratory frequency is not expected to change abruptly, the respiratory frequency is identified with the largest peak in the interval.

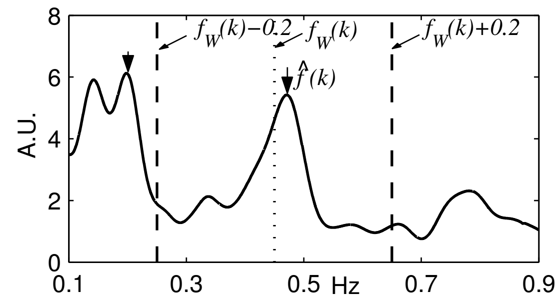

Figure 3. Interval-restricted peak search in the k-*th* averaged spectrum. Arrows show the selected peaks in the whole and restricted interval, respectively. Interval limits are marked with dashed lines and $f_W(k)$ with a dotted line.

Validation: To evaluate the method, frequency estimates are compared to those extracted from the respiratory signals. Spectral analysis, similar to the one described before, is applied to respiratory signals to obtain the frequencies used as reference, $\hat{f}_r(k)$. The ζ threshold used is 75 % since respiration spectra are, in general, more peaky than angle spectra.

An absolute error trend is defined as $\Delta f(k) = |\hat{f}(k) - \hat{f}_r(k)|$. The relative error trend is defined as $\Delta f_{\%}(k) = \frac{|\hat{f}(k)-\hat{f}_r(k)|}{\hat{f}_r(k)} \times 100(\%)$. For each record the mean and standard deviation (SD) of the error trends characterize the intra-subject error ($\mu_{\Delta f}$ and $\sigma_{\Delta f}$, respectively).

The intra-subject error is then compared to the intra-subject short term variability of the respiratory frequency (σ_{f_r}) during the stress test. The σ_{f_r} is defined as the mean of the SD of $\hat{f}_r$ estimated in 60-second windows, sliding 5 s each time.

3. Results

Figure 4 shows the respiratory frequency as estimated from the ECG and respiratory signals for a volunteer and a patient.

The mean and SD of the intra-subject error are shown in Table 1, as well as the percentage of the analyzed time (P_t) with respect to the total duration of exercise (i.e. the percentage of the time when respiratory frequency could be estimated both from the ECG and respiratory signals).

The value m=12 achieves the best mean intra-subject error for our study population. Lower values of m increase the mean error but decrease its SD due to the

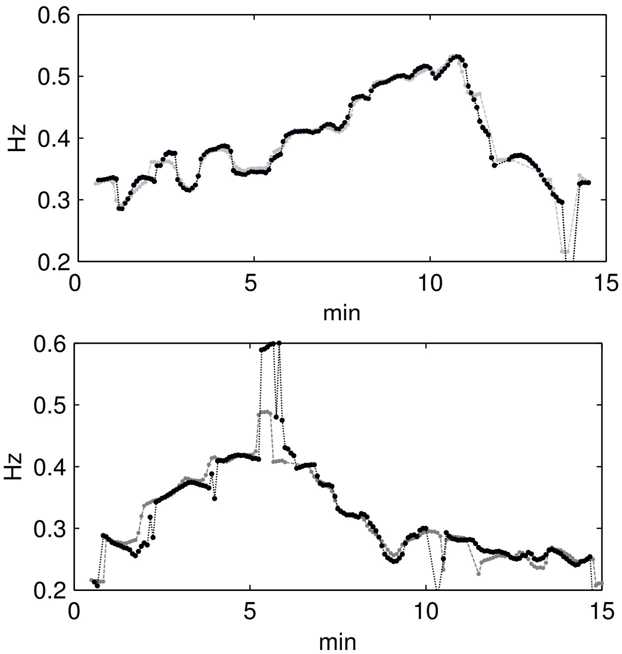

Figure 4. Respiratory frequency estimated from the ECG (dotted) and from the respiratory signal (dashed), m=12s, for a volunteer (top) and for a patient (bottom).

Table 1. Mean ± SD of the intra-subject error

m	12s	
	$\bar{\mu}_{\Delta f}$	$\bar{\sigma}_{\Delta f}$
Hz	0.024 ± 0.017	0.032 ± 0.020
%	6.1 ± 3.7	8.4 ± 4.4
$P_t(\%)$	83±13	

implicit spectral averaging. Higher values of m increase the SD of the error but also the percentage of analyzed time. The mean intra-subject short term variability $\bar{\sigma}_{f_r}$ is 0.020±0.007 Hz (5.2%±1.8%).

4. Discussion and conclusions

The proposed method retrieves the dominant respiratory frequency from most exercise ECGs with a mean error of 6.1% (0.024 Hz). This error is within the order of magnitude of the respiratory frequency short term variability itself, as estimated from the thermistor-derived respiratory signal.

The main limitation of the method is the underlying assumption that the spectrum of the respiratory signal has a dominant peak. Evidently, this is not always true during exercise, when a more complex spectrum sometimes makes it difficult to establish a dominant frequency. This is the motivation for using average spectral estimation of shorter windows. At the expense of loosing accuracy in the estimation of respiratory frequency, the overall tendency can still be obtained.

In this work, estimation errors are much larger than in the simulation study presented in [6] (6.1% ± 3.7% vs. 0.6% ± 0.3%), the reason being that, in the last one, respiration was modeled by a sigmoidal function with a well-defined dominant frequency.

Two sources of error are difficult to distinguish from each other: inaccurate estimates due to high levels of noise and non unimodal respiratory patterns. Nevertheless, the achieved error is small enough to obtain a reliable estimate of the dominant respiratory frequency without additional equipment.

As future work, the study of coupling between cardiac and respiratory systems can be approached using this method to get a more detailed HRV information, often obscured by this coupling.

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