Electrocardiogram Derived Respiration from QRS Slopes: Evaluation with Stress Testing Recordings

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Abstract

A method for respiratory rate estimation from electrocardiogram (ECG), based on variations in QRS complexes slopes, is evaluated over stress testing recordings. Besides the 12 standard, and the 3 vectorcardiogram (VCG), 2 additional leads derived from the VCG are analyzed. A total of 34 slope series were studied, 2 for each lead: slopes between the peaks of the Q and R waves, and between the peaks of the R and S waves. Respiratory rate is estimated by using a time-frequency based algorithm which can combine information from several derived respiration signals.

Evaluation was performed over a database containing ECG and respiratory signals simultaneously recorded from 30 subjects spontaneously breathing during a stress test. Respiratory rate estimation is performed with information of 4 different combinations of QRS slope series. The best results in respiratory rate estimation error terms are $-1.07 \pm 8.86\%$ *(*-11.47 ± 37.97 *mHz). These results suggest that proposed methods based on QRS slopes are highly suitable for respiratory rate estimation from ECG signal, specially at very non-stationary and noise scenarios as stress test.*

1. Introduction

Respiration is usually recorded by techniques that require cumbersome devices which may interfere with natural breathing, and which are inconvenient in certain applications such as ambulatory monitoring, stress testing, and sleep studies [1]. Thus, deriving respiratory information from non-invasive devices is appropriate in many situations.

In [2], some algorithms for deriving respiration from electrocardiogram (ECG) are collected. These algorithms are based either on beat occurrence time or on beat morphology, as it is well known that respiration influences them both. The first one, beat occurrence, is affected by respiration since it modulates the heart rate, making it higher during inspiration. The second one, beat morphology, is also affected by respiration because it produces electrode movements with respect to the heart, and variations in the thorax impedance distribution due to the filling and emptying of the lungs. Different methods were studied in [1] and [3], including some based on heart rate, QRS complexes amplitude and area, and electrical axis rotation angles, being this last one the method which offered the best results in respiratory rate estimation (from ECG).

A method based on QRS slopes was recently presented in [4]. It was evaluated over tilt test recordings, offering results that outperform those obtained for electrical axis rotation angles. However, the QRS-slopes-based method has not been studied over noisy environments such as stress testing, while the high suitability over this environment was demonstrated in [1] for electrical axis rotation angles. In this work the performance of the QRS-slopes method to estimate respiratory frequency [4] is evaluated over ECG signals recoded during stress testing, which are characterized for being extremely non-stationary and noisy.

2. Methods

2.1. Data and signal preprocessing

The database used for evaluation contains registers of 12-lead ECG and airflow-based respiratory signal simultaneously recorded from 14 volunteers (10 males) aged 28 ± 4 years and 15 patients (16 males) aged 58 ± 14 years, referred to the Department of Clinical Physiology at the University Hospital of Lund, Sweden, for stress testing.

The standard 12-lead ECG was digitalized using a samplig rate of 1000 Hz, and the respiratory signal $s_{\mathrm{r}}(n)$ was recorded by an airflow-thermistor-based technique using a sampling rate of 50 Hz. Vectorcardiogram (VCG) was synthesized using the inverse Dower matrix obtaining its three orthogonal leads $l_{\mathrm{X}}(n)$, $l_{\mathrm{Y}}(n)$ and $l_{\mathrm{Z}}(n)$.

QRS complexes were detected, and normal sinus beat locations $n_{\mathrm{N}_{l,i}}$ were determined by applying the technique presented in [5]. Baseline wander was attenuated by cubic-spline interpolation, and subsequently, a wavelet-based technique [6] was applied for wave delineation, obtaining among other points, $n_{\mathrm{Q}_{l,i}}$, $n_{\mathrm{R}_{l,i}}$, $n_{\mathrm{S}_{l,i}}$, and $n_{\mathrm{ON}_{l,i}}$, which denote Q, R and S wave peaks (or QRS offset when no S wave is present), and QRS onset, of the i^{th} QRS complex in lead l, respectively. An example of these points is shown in Fig. 1.

2.2. Non-standard leads

The QRS slopes were studied in the 12 standard leads, the 3 VCG leads, and 2 non-standard leads: the loop derived lead (LDL) and the N loops derived lead (NLDL).

The LDL, denoted $l_{\mathrm{LDL}}(n)$ in this paper, was presented in [7] and it is the projection of VCG onto dominant direction of the i^{th} QRS loop. This dominant direction is updated beat-to-beat following variations, and these beat-to-beat variations of the dominant direction are in part due to respiration [1], so cancelling them may be inconvenient in this application. For this reason, the NLDL was proposed in [4]. The NLDL, denoted $l_{\mathrm{NLDL}}(n)$ in this paper, is a modification of the LDL which consists of estimating the dominant direction (in which VCG is projected onto) only once. This direction is estimated as an average of the first N dominant directions obtained from the first N beats. Further details are given in [4].

2.3. QRS slopes measurement algorithm

In order to measure the QRS slopes, the technique presented in [8] was applied. For each studied lead, two slopes are measured: maximum slopes between $n_{\mathrm{Q}_{l,i}}$ and $n_{\mathrm{R}_{l,i}}$ ($\mathcal{I}_{\mathrm{US}_{l,i}}$), and between $n_{\mathrm{R}_{l,i}}$ and $n_{\mathrm{S}_{l,i}}$ ($\mathcal{I}_{\mathrm{DS}_{l,i}}$). First, the algorithm searches for the maximum variation points $n_{\mathrm{U}_{l,i}}$ and $n_{\mathrm{D}_{l,i}}$, by using the first derivative.

Subsequently, a straight line is fitted in the least squares sense to the ECG signal in two 8 ms-length intervals centred at $n_{\mathrm{U}_{l,i}}$ and $n_{\mathrm{D}_{l,i}}$. The slopes of these lines are denoted $\mathcal{I}_{\mathrm{US}_{l,i}}$ and $\mathcal{I}_{\mathrm{DS}_{l,i}}$, respectively.

2.4. Electrocardiogram derived respiration signals

For each one of the QRS slopes series, an EDR signal was generated by assigning to each normal sinus beat instant $n_{\mathrm{N}_{l,i}}$ an amplitude value proportional to its QRS slope:

$$d^u_{\{\mathrm{US,DS}\}_l}(n) = \sum_i \mathcal{I}_{\{\mathrm{US,DS}\}_{l,i}} \delta\left(n - n_{\mathrm{N}_{l,i}}\right) \qquad (1)$$

where the superindex "u" denotes the signal is unevenly sampled, as the beats occur uneven in time. A median-

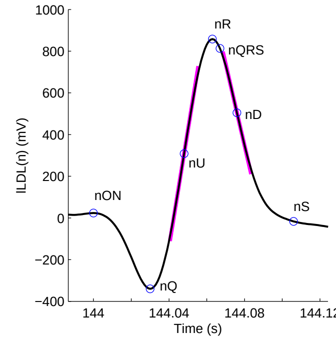

Figure 1. Relevant points in the slope measurement algorithm, over a QRS from $l_{\mathrm{NLDL}}(n)$.

absolute-deviation-based outlier rejection rule was applied as in [1] and then, a 4 Hz evenly sampled version of each EDR signal was generated by cubic splines interpolation. Finally, a band-pass filter (0.075-1) Hz was applied. Nomenclature of these signals is the same than their unevenly sampled versions, but with no superindex "u", e. g., $d_{\mathrm{US_{NLDL}}}(n)$ is the outlier-rejected, 4 Hz evenly sampled, band-pass filtered version of $d^u_{\mathrm{US_{NLDL}}}(n)$.

2.4.1. Respiratory rate estimation algorithm

Respiratory rate was estimated by using a method based in [3]. It allows estimating the frequency rate from up to M EDR signals, combining them in order to increase robustness.

First, the power spectrum $S_{j,k}(f)$ of the j^{th} EDR signal is estimated by Welch periodogram in each k^{th} running interval of 42 second-duration, averaging spectra obtained from 12 second-subintervals overlapped 6 s. A $S_{j,k}(f)$ spectrum is generated every 5 s.

A reference interval $\Omega_{\mathrm{R}}(k)$ is established around a reference frequency $f_{\mathrm{R}}(k-1)$:

$$\Omega_{\mathrm{R}}(k) = [f_{\mathrm{R}}(k-1) - \delta, f_{\mathrm{R}}(k-1) + \delta]. \qquad (2)$$

For each $S_{j,k}(f)$, the location of largest peak $f^{\mathrm{I}}_p(j,k)$ is detected. All peaks at least larger than 85% of $f^{\mathrm{I}}_p(j,k)$ inside $\Omega_{\mathrm{R}}(k)$ are detected, and $f^{\mathrm{II}}_p(j,k)$ is chosen as the nearest to $f_{\mathrm{R}}(k-1)$.

Then, L_s spectra $S_{j,k}(f)$ are "peak-conditioned" averaged; only those $S_{j,k}(f)$ which are sufficiently peaked take part in the averaging, understanding "peaked" as a certain percentage (ξ) of the spectral power must be contained in an interval centered around $f^{\mathrm{II}}_p(j,k)$. In mathematical terms "peak-conditioned" average is defined as:

$$\bar{S}_k(f) = \sum_{l=0}^{L_s-1} \sum_j \chi^{\mathrm{A}}_{j,k-l} \chi^{\mathrm{B}}_{j,k-l} S_{j,k-l}(f) \qquad (3)$$

where $\chi^{\mathrm{A}}_{j,k-l}$ and $\chi^{\mathrm{B}}_{j,k-l}$ represent two criteria referred to decide whether $S_{j,k-l}(f)$ is peaked enough or not:

$$\chi^{\text{A}}_{j,k} = \begin{cases} 1, & P_{j,k} \geq \xi \\ 0, & otherwise \end{cases} \quad (4)$$

$$\chi^{\text{B}}_{j,k} = \begin{cases} 1, & P_{j,k} \geq \lambda \max_{i \neq j} \{P_{i,k}\} \\ 0, & otherwise \end{cases} \quad (5)$$

where $P_{j,k}$ denotes the "peakness":

$$P_{j,k} = \frac{\int_{f_p^{\text{II}}(j,k)-0.4\delta}^{f_p^{\text{II}}(j,k)+0.4\delta} S_{j,k}(f)df}{\int_{f_{\text{R}}(k-1)-\delta}^{f_{\text{R}}(k-1)+\delta} S_{j,k}(f)df} \quad (6)$$

In the averaged spectrum $\bar{S}_k(f)$ the algorithm also searches the largest peak (denoted $f_p^{\text{I}_a}(k)$) and $f_p^{\text{II}_a}(k)$ as the nearest to $f_{\text{R}}(k-1)$ inside the interval $\Omega_{\text{R}}(k)$ which is at least larger than 75% of $f_p^{\text{I}_a}(k)$. At this time the reference frequency $f_{\text{R}}(k)$ can be updated as:

$$f_{\text{R}}(k) = \beta f_{\text{R}}(k-1) + (1-\beta)\, f_p(k) \quad (7)$$

where β denotes the forgetting factor and $f_p(k)$ is defined by:

$$f_p(k) = \begin{cases} f_p^{\text{II}_a}(k), & \exists f_p^{\text{II}_a}(k) \\ f_p^{\text{I}_a}(k), & otherwise \end{cases} \quad (8)$$

Finally, estimated respiration rate $\hat{f}(k)$ is defined as:

$$\hat{f}(k) = \alpha \hat{f}(k-1) + (1-\alpha)\, f_p(k) \quad (9)$$

$$\alpha = \begin{cases} \alpha_2, & \exists f_p^{\text{II}_a}(j,k) \\ \alpha_1, & otherwise \end{cases} \quad (10)$$

where $\alpha_2 \leq \alpha_1$, providing more memory when $f_p^{\text{II}_a}(k)$ could not be set.

Note that it is possible that no spectrum is peaked enough at a concrete k. In that case, there is no respiratory rate estimation at that time instant.

For comparison purposes, respiratory rate was also estimated with the algorithm used in [4] which was presented in [3], denoting this estimation $\hat{f}^*(k)$. This algorithm have two main differences with respect to the one described above:

1. The reference interval was asymmetric: $\Omega^*_{\text{R}}(k) = [f_{\text{R}}(k-1)-\delta, f_{\text{R}}(k-1)+2\delta]$.
2. Offering a respiratory rate estimation even when no spectrum is peaked enough. This estimation consists of giving the same value than the previous estimate.

Respiratory rate was estimated by the two methods from each one of the 34 QRS slopes-based EDR signals, from each one of the 3 electrical axis rotation angle series, and from 5 different combinations: QRS slopes of the 12 standard leads (24 EDR signals) (12ECG), QRS slopes of the 3 leads from the VCG (6 EDR signals), QRS slopes of the LDL (2 EDR signals), QRS slopes of the NLDL (2 EDR signals), and electrical axis rotation angle series (3 EDR signals) (Φ).

2.5. Performance measurements

The used performance measurements are based on absolute ($e_{\text{A}}(k)$) and relative ($e_{\text{R}}(k)$) error signals:

$$e_{\text{A}}(k) = \hat{f}_d - \hat{f}_{\text{RES}}(k) \quad (11)$$

$$e_{\text{R}}(k) = \frac{e_{\text{A}}(k)}{\hat{f}_{\text{RES}}(k)} \times 100 \quad (12)$$

where $\hat{f}_d(k)$ and $\hat{f}_{\text{RES}}(k)$ are the respiratory rates estimated from the evaluated EDR signals or combination of them, and $s_{\text{r}}(n)$, respectively. Note that the same absolute differences can correspond to very different relative error due to the $\hat{f}_{\text{RES}}(k)$ normalization.

3. Results

In order to evaluate the EDR signals, the mean and standard deviation (STD) of both $e_{\text{A}}(k)$ and $e_{\text{R}}(k)$ signals were computed for each subject and, subsequently, the intersubject mean of both means and STDs.

Results obtained from each one of the combinations described in Section 2.4.1 are shown in Table 1. In addition, the best and worst results obtained estimating respiratory rate individually from each one of the EDR signals which take part in each combination, are also shown in Table 1. The criterion used for choosing best and worst results was the minimum (best) and maximum (worst) of the sum of the intersubject mean of means plus intersubject mean of STDs of $e_{\text{R}}(k)$.

4. Discussion and conclusions

This paper analyzes the performance, over an environment as noisy and non-stationary as stress testing, of a recently developed method [4] for deriving respiration from ECG signals based on QRS slopes. The respiratory rate estimation algorithm used in [4] has been adapted for stress test signals in this paper. Stress test represents a highly noisy environment under which taking care of quality of the signals is particularly relevant. For this reason, the algorithm has been modified for not giving an estimate when no spectrum is peaked enough. Furthermore, in [4] the reference interval $\Omega_{\text{R}}(k)$ is asymmetric with respect to $f_{\text{R}}(k-1)$. The reason of this asymmetry is that the most important contamination observed in power spectra of EDR signals studied in [3] (where method used in [4] was presented), was in LF band due to the sympathetic nervous system activity. In contrast, EDR signals based on QRS slopes or rotation angle series shows no particular contamination in LF band, so algorithm has been modified for using a symmetric $\Omega_{\text{R}}(k)$.

In relative error terms, results obtained with the method presented in this work outperform those obtained with the

Table 1. Inter–subject mean of means and STDs of $e_{\text{A}}(k)$ and $e_{\text{R}}(k)$ obtained from the two methods.

		Proposed method					**Method used in [4]**			
		$e_{\text{R}}(k)$ [%]		$e_{\text{A}}(k)$ [mHz]		Time measuring [%]	$e_{\text{R}}(k)$ [%]		$e_{\text{A}}(k)$ [mHz]	
		Mean	STD	Mean	STD	Mean	Mean	STD	Mean	STD
12ECG	Combination	1.25	12.80	-4.64	40.95	99.78	3.39	13.55	2.37	43.95
	Best ($d_{\text{US}_{\text{aVF}}}(n)$)	-1.50	10.07	-18.96	36.13	53.22	0.11	15.69	-11.85	59.95
	Worst ($d_{\text{US}_{\text{V6}}}(n)$)	10.22	12.52	21.08	34.24	58.00	18.53	22.57	50.43	67.18
VCG	Combination	-1.07	8.86	-11.47	37.97	90.78	0.11	11.06	-8.73	44.99
	Best ($d_{\text{DS}_{\text{Z}}}(n)$)	0.90	$6,02$	1.36	19.66	63.65	2.32	14.31	-0.50	50.24
	Worst ($d_{\text{US}_{\text{Z}}}(n)$)	1.19	6.87	4.05	24.12	67.76	8.84	20.74	22.77	58.65
LDL	Combination	-0.60	10.69	-8.76	37.91	82.43	-0.01	13.58	-10.67	49.06
	$d_{\text{US}_{\text{LDL}}}(n)$	-0.6	9.72	-22.74	30.27	67.44	-1.74	13.67	-15.91	57.38
	$d_{\text{DS}_{\text{LDL}}}(n)$	-3.06	8.03	-5.27	27.22	68.55	10.43	17.00	23.42	54.58
NLDL	Combination	-0.94	10.74	-12.28	40.15	82.88	-1.74	10.86	-9.52	42.70
	$d_{\text{US}_{\text{NLDL}}}(n)$	-1.63	9.67	-15.49	30.36	68.69	-1.88	11.62	-14.72	49.90
	$d_{\text{DS}_{\text{NLDL}}}(n)$	-1.96	9.07	-19.95	27.43	72.23	2.37	14.48	-0.49	48.29
Φ	Combination	-0.08	10.59	-6.42	38.40	82.37	4.51	18.53	10.80	52.16
	Best ($d_{\Phi_{\text{Z}}}(n)$)	-2.53	9.96	-18.85	35.25	59.48	3.07	19.12	5.12	58.52
	Worst ($d_{\Phi_{\text{Y}}}(n)$)	8.58	13.33	17.68	42.99	62.11	6.94	23.72	17.63	71.52

method used in [4], increasing the accuracy at the expense of not offering an estimate every time. In general, results obtained for individual EDR signals are not worse than those obtained for combinations, but combinations provide respiratory rate estimation during more time. The percentage of time providing an estimate and the accuracy of that estimate represent a trade-off situation. VCG combination obtained results that are comparable in accuracy ($-1.07 \pm 8.86\%$) to those obtained by rotation angle series (-0.08 ± 10.59), but VCG combination provided estimates during more time (90.78% instead of 82.37%).

Regarding to the method used in [4], results obtained for the 5 different combinations outperform those obtained for individual EDR signals, demonstrating the advantage of combining information. Best results in terms of relative error were obtained by the VCG combination ($0.11 \pm 11.06\%$). The rest of combinations of QRS-slope-based EDR signals 12ECG, LDL and NLDL, obtained comparable results to each other. These results also outperform those obtained for the rotation-angle-series-based methods ($4.51 \pm 18.53\%$), which are the reference for comparison methods because they obtained the best results among the ECG-based methods in [3].

Note that the combinations 12ECG and VCG make no use of the QRS loop, and this represents a computational advantage over LDL, NLDL, and Φ.

These results suggest that studied methods based on QRS slopes are highly suitable for respiratory rate estimation from ECG signals even in noisy situations such as stress testing.

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