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Electrocardiogram Derived Respiration from QRS Slopes

Jesús Lázaro, Alejandro Alcaine, Eduardo Gil, Pablo Laguna and Raquel Bailón

***Abstract*— A method for estimation of respiratory rate from electrocardiogram (ECG) signals, based on variations in slopes of QRS complexes, is presented. 12 standard leads, 3 leads from vectorcardiogram (VCG), and 2 additional non-standard leads derived from VCG loops were analysed. A total of 34 slope series were studied, 2 for each analysed lead: slopes between the peak of Q and R waves, and between the peak of R and S waves. Information of QRS slopes series was combined in order to increase the robustness of estimation.**

Evaluation is performed over a database containing ECG and respiratory signals simultaneously recorded in 17 subjects spontaneously breathing during a tilt table 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 $0.72 \pm 4.34\%$ (0.46 ± 7.59 mHz). These results outperform those obtained with other known methods, motivating the use of QRS slopes to obtain reliable respiratory rate estimates.

I. INTRODUCTION

Monitoring respiration is important in many situations, e. g., an abnormal respiratory rate is a sensitive early indicator of critical illness [1].

The respiratory signal is usually recorded with techniques like spirometry, pneumography, or plethysmography. These techniques require the use of cumbersome devices that may interfere with natural breathing, and which are unmanageable in certain applications such as ambulatory monitoring, stress testing, and sleep studies [2]. Consequently, obtaining respiratory information from non–invasive devices is useful in several applications.

Many algorithms for deriving respiration from electrocardiogram (ECG) have been developed, some of them are collected in [3]. These algorithms can be classified by the type of information they explode: beat occurrence time instants and/or beat morphology.

On one hand, it is well known that respiration influences heart rate, making it higher during inspiration than during expiration. On the other hand respiration also affects the ECG measurements through electrode movements with respect to the heart and changes in the thorax impedance distribution due to filling and emptying of the lungs, which causes a rotation of the electrical axis of the heart having effect on beat morphology [3].

Several methods were studied in [2] and [4], based on heart rate, QRS complexes amplitude, QRS complexes area, and electrical axis rotation angles, being this last method the one which offered the best results in respiratory rate estimation (from ECG) error terms. Recently, a respiratory modulation in QRS complexes slopes was observed and mentioned in [5], although it was not studied. In this work, QRS slopes are proposed to estimate respiratory rate from the ECG. A total of 34 ECG derived respiration (EDR) signals based on QRS slopes are studied.

Respiratory rate is estimated by a time–frequency technique presented in [4], which can combine information from several EDR signals offering robust estimates. For comparison purposes, electrical axis rotation angles EDR signals are analysed in the same way than QRS slopes based ones.

II. METHODS

A. Signal acquisition and preprocessing

The database used for evaluation is the same used in [4]. It contains 17 (11 men) registers from volunteers, aged 28.5 ± 2.5 years, during a tilt table test according to the following protocol: 4 minutes in early supine position, 5 minutes tilted head-up to an angle of 70°, and 4 minutes to later supine position. Table takes 18 s to tilt during transitions.

The standard 12 lead ECG was recorded with a sampling rate of $F_s = 1000$ Hz, and the respiratory signal was recorded by a plethysmography-based technique with a sampling rate of 125 Hz. Vectorcardiogram (VCG) was synthesized using the inverse Dower matrix obtaining its 3 orthogonal leads denoted $l_{\text{X}}(n)$, $l_{\text{Y}}(n)$, and $l_{\text{Z}}(n)$ in this paper.

QRS complexes in all ECG leads were detected using the ECG analysis software Aristotle [6], normal sinus beat locations $n_{\text{N}_{l,i}}$ were determined according to [7], and baseline wander was removed by cubic-spline interpolation. Then, wave delineation was performed using a wavelet-based technique [8] determining among other points, $n_{\text{Q}_{l,i}}$, $n_{\text{R}_{l,i}}$, $n_{\text{S}_{l,i}}$, and $n_{\text{ON}_{l,i}}$, which denote Q peak, R peak, S peak (or QRS end when no S wave is present), and QRS onset, of the i^{th} QRS complex in lead l, respectively. Fig. 1 illustrates these points.

B. Non-standard leads

In addition to the 12 standard leads and the 3 orthogonal leads of the VCG, 2 other non-standard leads were derived in order to study their QRS slopes: the loop derived lead (LDL), and the N loops derived lead (NLDL).

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J. Lázaro, A. Alcaine, E. Gil, P. Laguna and R. Bailón are with the Communications Technology Group, I3A, University of Zaragoza and CIBER de Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN), Spain, {jlazarop, aalcaineo, edugilh, laguna, rbailon}@unizar.es

The first one, LDL, was presented in [5] and represents the projection of VCG loop onto dominant direction $\boldsymbol{u}_i$ of the i^{th} QRS loop, obtained by maximizing the following equation:

$$\boldsymbol{u}_i = [u_{\mathrm{X}_i}, u_{\mathrm{Y}_i}, u_{\mathrm{Z}_i}]^T = [l_{\mathrm{X}}(n_{0_i}), l_{\mathrm{Y}}(n_{0_i}), l_{\mathrm{Z}}(n_{0_i})]^T \tag{1}$$

being

$$n_{0_i} = \underset{n\in\Omega_{\mathrm{QRS}_i}}{\operatorname{argmax}} \left[l_{\mathrm{X}}^2(n) + l_{\mathrm{Y}}^2(n) + l_{\mathrm{Z}}^2(n)\right] \tag{2}$$

where Ω_{QRS_i} is a 140 ms interval starting 10 ms before the earliest QRS onset in the 3 VCG leads n_{ON_i}:

$$n_{\mathrm{ON}_i} = \min\left\{n_{\mathrm{ON}X,i}, n_{\mathrm{ON}Y,i}, n_{\mathrm{ON}Z,i}\right\} \tag{3}$$

$$\Omega_{\mathrm{QRS}_i} = [n_{\mathrm{ON}_i} - 0.01F_s, \quad n_{\mathrm{ON}_i} + 0.13F_s]\,. \tag{4}$$

Then, the LDL $l_{\mathrm{LDL}}(n)$ is computed at each beat and then concatenating as:

$$l_{\mathrm{LDL}}(n) = \frac{[l_{\mathrm{X}}(n), l_{\mathrm{Y}}(n), l_{\mathrm{Z}}(n)]\,\boldsymbol{u}_i}{||\boldsymbol{u}_i||}, \quad \forall n \in \Omega_{\mathrm{QRS}_i} \tag{5}$$

Note that $l_{\mathrm{LDL}}(n)$ follows the beat-to-beat variations of the dominant direction of QRS loop, and these variations are in part, due to respiration [2] so cancelling them may result counter-productive in this application. For this reason, a new QRS loop derived lead, NLDL, is proposed in this paper. NLDL is similar to LDL with only one difference: the direction which the VCG is projected onto is estimated with the first N beats and it is not updated, as define:

$$\bar{\boldsymbol{u}} = \sum_{i=1}^{N}\left\{\frac{\boldsymbol{u}_i}{||\boldsymbol{u}_i||}\right\} \tag{6}$$

$$l_{\mathrm{NLDL}}(n) = \frac{[l_{\mathrm{X}}(n), l_{\mathrm{Y}}(n), l_{\mathrm{Z}}(n)]\,\bar{\boldsymbol{u}}}{||\bar{\boldsymbol{u}}||} \tag{7}$$

being N set to 5 beats in this work.

C. QRS slopes measurement algorithm

QRS slopes measurement algorithm was presented in [9]. Two slopes are measured: upward slope of the R wave ($\mathcal{I}_{\mathrm{US}_{l,i}}$) and downward slope of the R wave ($\mathcal{I}_{\mathrm{DS}_{l,i}}$).

Once $n_{\mathrm{Q}_{l,i}}$, $n_{\mathrm{R}_{l,i}}$, and $n_{\mathrm{S}_{l,i}}$ are determined as described in Section II-A, the time instants associated with the maximum slopes of the ECG signal between $n_{\mathrm{Q}_{l,i}}$ and $n_{\mathrm{R}_{l,i}}$, and between $n_{\mathrm{R}_{l,i}}$ and $n_{\mathrm{S}_{l,i}}$ are computed as:

$$n_{\mathrm{U}_{l,i}} \;=\; \max_{n\in\left[n_{\mathrm{Q}_{l,i}}, n_{\mathrm{R}_{l,i}}\right]} \{|l_l'(n)|\} \tag{8}$$

$$n_{\mathrm{D}_{l,i}} \;=\; \max_{n\in\left[n_{\mathrm{R}_{l,i}}, n_{\mathrm{S}_{l,i}}\right]} \{|l_l'(n)|\} \tag{9}$$

where $l_l'(n)$ is the first derivative of lead l:

$$l_l'n) = l_l(n) - l_l(n-1). \tag{10}$$

Finally, a straight line is fitted in the least squares sense to the ECG signal in two 8 ms-length intervals, one of them centred at $n_{\mathrm{U}_{l,i}}$ and the other one at $n_{\mathrm{D}_{l,i}}$. The slopes of this lines are denoted $\mathcal{I}_{\mathrm{US}_{l,i}}$ and $\mathcal{I}_{\mathrm{DS}_{l,i}}$, respectively. Fig. 1 illustrates relevant points in this algorithm. The length of interval in which the least squares adjustment is performed, represents a trade-off between the robustness of estimation and the possibility of taking samples which not correspond to the estimating slope. The 8 ms value has shown to deal successfully with this trade-off situation.

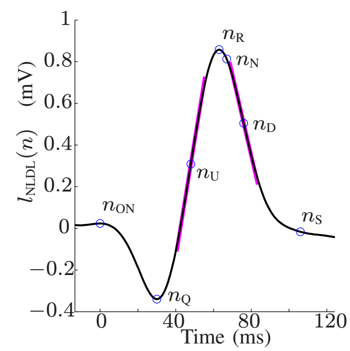

Fig. 1. Relevant points in the slope measurement algorithm, over a QRS from $l_{\mathrm{NLDL}}(n)$.

D. Electrocardiogram derived respiration signals

1) From QRS slopes: Each QRS slope series leaded to an EDR signal generated by assigning to each normal sinus beat occurrence $n_{\mathrm{N}_{l,i}}$, an amplitude value proportional to its associated QRS slope:

$$d^u_{\{\mathrm{US,\,DS}\}_l}(n) = \sum_i \mathcal{I}_{\{\mathrm{US,\,DS}\}_{l,i}}\delta\left(n - n_{\mathrm{N}_{l,i}}\right) \tag{11}$$

where the superindex "u" denotes the signal is unevenly sampled. These signals were processed as in [4]: first, a median absolute deviation (MAD)-based outlier rejection rule was applied, then, a 4 Hz evenly sampled version of each EDR signal was obtained by cubic splines interpolation and, finally, a band-pass filter (0.075–1) Hz was applied. These filtered signals are denoted with the same nomenclature than the unevenly sampled versions, but without the superindex "u", e. g., $d_{\mathrm{US_{NLDL}}}(n)$ is the 4-Hz, outlier-rejected, evenly sampled, band-pass filtered version of $d^u_{\mathrm{US_{NLDL}}}(n)$.

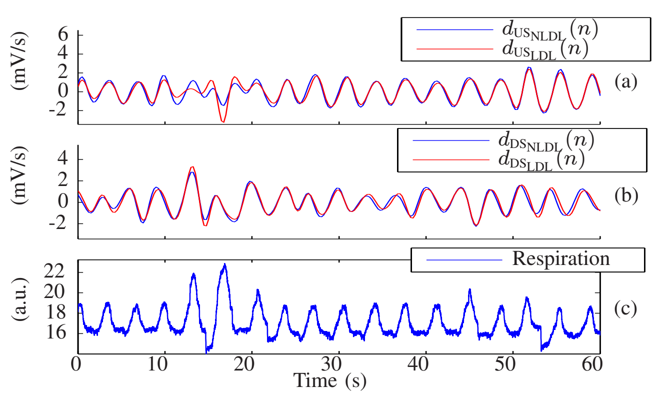

Fig. 2. Example of some EDR signals: a) $d_{\mathrm{US_{NLDL}}}(n)$ and $d_{\mathrm{US_{LDL}}}(n)$, b) $d_{\mathrm{DS_{NLDL}}}(n)$ and $d_{\mathrm{DS_{LDL}}}(n)$, and c) respiratory signal for visual comparison.

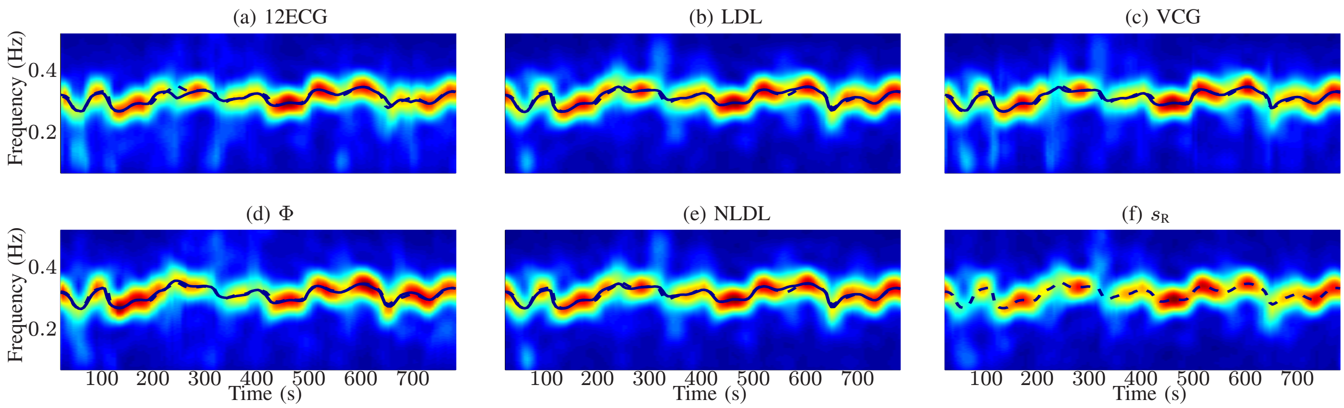

Fig. 3. Example of peak-conditioned averaged running spectra obtained from the studied combinations: a) 12ECG, b) LDL, c) VCG, d) Φ, e) NLDL, and f) from the reference respiratory signal $s_{\mathrm{R}}(n)$. Estimated respiratory rate from each combination is plotted with continuous black line over its associated time–frequency map, and reference respiratory rate obtained from $s_{\mathrm{R}}(n)$ is plotted with slashed black line over all time–frequency maps.

A total of 34 EDR signals were studied corresponding to $\mathcal{I}_{\mathrm{US}_{l,i}}$ and $\mathcal{I}_{\mathrm{DS}_{l,i}}$ in the 17 leads. Fig 2 shows an example of some of these EDR signals.

2) From electrical axis rotation angles: For comparison purposes, three additional EDR signals based on the electrical axis rotation angles were obtained by the algorithm presented in [2] based on spatio-temporal alignment of successive QRS–VCG loops with respect to a reference loop. These three EDR signals were processed in a similar way to the QRS slopes EDR ones. Resulting signals are denoted $d_{\Phi_X}(n)$, $d_{\Phi_Y}(n)$, and $d_{\Phi_Z}(n)$ in this paper.

E. Reference and delay correction

The reference respiratory signal was also resampled to 4 Hz and (0.075–1) band-pass filtered, leading to a signal denoted $s_{\mathrm{R}}(n)$ in this paper. Then, the delay of each EDR signal with respect to the reference signal is estimated as the point in which the absolute value of cross-correlation $r(\tau)$ reaches its maximum value. This delay is constrained to 1 s as defines:

$$\tau_{\{\mathrm{US,\,DS}\}_j} = \underset{\tau\in[0,1]}{\operatorname{argmax}} \left\{ \left| r_{s_{\mathrm{R}},d_{\{\mathrm{US,\,DS}\}_j}}(\tau) \right| \right\}. \tag{12}$$

The series alignment is performed to avoid mismatches in the time allocation of the respiratory frequency estimation from the different EDR signals.

F. Respiratory rate estimation algorithm

Respiratory rate estimation algorithm was presented in [4] and it is applied in this work using the same values for all parameters. This algorithm allow to combine information of several respiratory signals, increasing the robustness of the estimation. It consists of two different phases: power spectrum estimation, and "peak-conditioned" averaging.

For power spectrum estimation of j^{th} EDR signal and k^{th} running interval $S_{j,k}(f)$, the algorithm uses the Welch periodogram. Every 5 s, a 42 s spectrum is estimated by averaging spectra obtained from subintervals of 12 s using an overlap of 6 s.

Once all the $S_{j,k}(f)$ are computed, for each one of them, a peak $f_p^{\mathrm{II}}(j,k)$ is chosen as respiration peak based on its amplitude and its proximity to a respiratory frequency reference $f_{\mathrm{R}}(k-1)$ obtained from previous $(k-1)$ steps. This peak must be inside a reference interval $\Omega_{\mathrm{R}}(k)$ that represents the band in which respiration is estimated to be.

Subsequently, the peakness of $S_{j,k}(f)$ is computed as the percentage of power around $f_p^{\mathrm{II}}(j,k)$ with respect to the total power in $\Omega_{\mathrm{R}}(k)$. Then, the $S_{j,k}(f)$ are peak-conditioned averaged leading to $\bar{S}_{\mathrm{k}}(f)$, which means that only those $S_{j,k}(f)$ whose peakness fulfil 2 criteria take part in the average. The 2 peakness criteria are threshold-based, being one of them a fixed threshold (only peaked spectra take part in the average), and the other one a time-varying threshold which depends on the maximum peakness reached by all spectra at each time instant (only the most peaked spectra at each time instant take part in the average). Subsequently, the respiratory rate $\hat{f}(k)$ is estimated from a peak of $\bar{S}_{\mathrm{k}}(f)$ whose choice is also based on its amplitude and its proximity to $f_{\mathrm{R}}(k-1)$. Further details are given in [4].

Respiratory rate was estimated 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 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). Fig. 3 shows an example of respiratory rate estimation from these combinations.

G. Performance measurements

This work uses the same performance measurements than [4]. They are based on absolute ($e_{\mathrm{A}}(k)$) and relative ($e_{\mathrm{R}}(k)$) error signals:

$$e_{\mathrm{A}}(k) = \hat{f}_d - \hat{f}_{\mathrm{RES}}(k) \tag{13}$$

$$e_{\mathrm{R}}(k) = \frac{e_{\mathrm{A}}(k)}{\hat{f}_{\mathrm{RES}}(k)} \times 100 \tag{14}$$

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.

III. 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 as in [4].

Table I shows the results obtained from each one of the combinations described in Section II-F, and the best and worst results obtained estimating respiratory rate individually from each one of EDR signals which take part of them. The criterion used for choosing best and worst results was the minimum (best) and maximum (worst) of the sum of intersubject means of means plus STDs of $e_{\text{R}}(k)$. Note that for the combinations LDL and NLDL, results obtained with all individual estimations are shown, since only 2 EDR signals take part on these combinations.

TABLE I

INTER–SUBJECT MEAN OF MEANS AND STDS OF $e_{\text{A}}(k)$ AND $e_{\text{R}}(k)$.

		$e_{\text{R}}(k)$ [%]		$e_{\text{A}}(k)$ [mHz]	
		Mean	**STD**	**Mean**	**STD**
12ECG	**Combination**	0.66%	5.07%	0.50	9.27
	Best ($d_{\text{DSV2}}(n)$)	0.19%	5.75%	−1.42	11.37
	Worst ($d_{\text{DSaVL}}(n)$)	5.19%	24.45%	−1.66	44.74
VCG	**Combination**	0.70%	5.55%	0.32	9.81
	Best ($d_{\text{USX}}(n)$)	0.12%	8.55%	0.31	16.33
	Worst ($d_{\text{USY}}(n)$)	10.61%	19.59%	9.61	33.53
LDL	**Combination**	0.78%	4.46%	0.63	8.17
	$d_{\text{USLDL}}(n)$	0.37%	6.41%	−0.63	11.61
	$d_{\text{DSLDL}}(n)$	5.28%	13.56%	6.45	23.78
NLDL	**Combination**	0.72%	4.34%	0.47	7.59
	$d_{\text{DSNLDL}}(n)$	2.53%	8.21%	2.42	12.75
	$d_{\text{USNLDL}}(n)$	8.66%	8.22%	9.26	15.09
Φ	**Combination**	1.82%	6.84%	2.17	11.87
	Best ($d_{\Phi\text{X}}(n)$)	4.28%	10.95%	5.07	17.27
	Worst ($d_{\Phi\text{Y}}(n)$)	24.37%	31.28%	30.32	48.99

IV. DISCUSSION AND CONCLUSIONS

In this paper, several methods for the estimation of respiratory rate from the ECG signal have been presented. They explode the changes that respiration causes in morphology of the QRS complexes, particularly the variations in their slopes.

Combinations obtained results that outperform those obtained individually for EDR signals, demonstrating the advantage of performing the combination.

Results obtained for combinations 12ECG ($0.66 \pm 5.07\%; 0.50 \pm 9.27$ mHz) and VCG ($0.70 \pm 5.55\%; 0.32 \pm 9.81$ mHz) are similar, and they are outperformed by those obtained with combinations LDL ($0.78 \pm 4.46\%; 0.63 \pm 8.17$ mHz) and NLDL ($0.72 \pm 4.34\%; 0.46 \pm 7.59$ mHz). Results obtained with NLDL are slightly better than those obtained with LDL, probably because NLDL does not follow the variations of electrical axis as LDL does, and these variations are, in part, due to respiration [2].

Any of these results obtained with the methods based on QRS slopes outperform those obtained for the method based on electrical axis rotation angles Φ, which was chosen as reference method for comparison because in [4], it obtained better results than any other ECG-based method ($2.05 \pm 6.92\%; 2.63 \pm 11.50$ mHz). In this work, results obtained for this method Φ are slightly different ($1.82 \pm 6.84\%; 2.17 \pm 11.87$ mHz) even though the same database is used for evaluation. This slight difference could be explained by the delay correction, which was not performed in [4]. Nevertheless, in [2], it was demonstrated that electrical axis rotation angles used in Φ are highly suitable for analysis of ECG signals as noisy as those acquired during stress test (results obtained were $5.9 \pm 4\%; 22 \pm 16$ mHz).

The combinations of QRS slopes studied in this paper require a high number of electrodes (10 for the 12ECG, and at least 7 for the VCG, LDL or NLDL). However, the respiratory rate estimation algorithm could combine a smaller number of series which would require a smaller number of electrodes. Note that results obtained from $d_{\text{DSV2}}(n)$ which requires only 2 electrodes ($0.19 \pm 5.75\%; -1.42 \pm 11.37$ mHz) have also outperformed those obtained from the reference for comparison method.

These results suggest that proposed methods based on QRS slopes are highly suitable for respiratory rate estimation from ECG signals even in non-stationary situations such as tilt testing, but further studies must be elaborated in order to test the behaviour of proposed methods with noisy signals.

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