Respiratory Rate Simultaneous Estimation from Two ECG-derived Respiratory Waveforms Using an Adaptive Frequency Tracking Algorithm

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Abstract. *Monitoring the respiratory rate (RR) in a fast, inexpensive and continuous manner is of great interest as its direct measurement requires bulky, expensive and inconvenient equipment. In this study, the RR is estimated in an instantaneous manner from the electrocardiogram (ECG) using two ECG-derived respiratory waveforms: the respiratory sinus arrhythmia (RSA) and the modulation of R-peak amplitudes (RPA). An adaptive weighted oscillator-based (W-OSC) frequency tracking algorithm is used to estimate their common frequency. The algorithm is evaluated on a public data set and it is shown that combining RSA and RPA is beneficial to using either alone.*

Keywords: Respiratory rate, adaptive frequency tracking, respiratory sinus arrhythmia.

1. Introduction

Respiration influences cardiac activity and thus the electrocardiogram (ECG) in several ways. The heart rate increases during inspiration due to physiological processes and the autonomic control of the cardiorespiratory system [1]. On the ECG, this modulation of the R-peak intervals by respiration is referred to as respiratory sinus arrhythmia (RSA). Furthermore, the mechanical aspects of respiration alter the electric dipole of the heart and the impedance of the thorax, which yield a respiratory modulation of the R-peak amplitudes in the ECG, referred to as the R-peak amplitudes (RPA) waveform [1].

Several methods exist to estimate the respiratory rate (RR) from either the RSA or the RPA waveforms [1]. In a pioneering work, Orphanidou *et al.* fused spectral information from both the RSA and RPA waveforms in order to derive the RR [2]. The most dominant peak from the autoregressive estimated spectra of the RSA and RPA was taken as representing the RR. However, this method does not provide a robust, real-time and automatic estimate of the RR in a continuous manner. Motivated by this concept of information fusion, the purpose of the present study was to estimate the instantaneous real-time RR by using the weighted multi-signal oscillator based band-pass filtering (W-OSC) algorithm [3] to track the common frequency component present in the RSA and RPA waveforms. This multi-signal frequency tracking method operates recursively on several signals simultaneously to track a common frequency component. It is instantaneous and provides an automatic approach to RR estimation from the RSA and RPA, in contrast to the ad hoc processing proposed in [2].

2. Materials and Methods

Data Set

The publicly available Physionet Fantasia data set [4][5] was used to evaluate the proposed algorithm. This data set contains 2-hour long records of simultaneously acquired ECG and respiratory (pneumography) waveforms from 20 young (21-34 years) and 20 elderly (68-85 years) subjects. The recordings were digitized at 250 Hz.

Extracting the Respiratory Waveforms from the ECG

The RSA is the modulation of the interbeat interval time series by the respiratory activity. The ECG R-peaks were extracted using a classic maxima detection algorithm. The time differences between consecutive peaks were computed and resampled uniformly using cubic splines at 2 Hz. This waveform was then band-pass filtered at respiratory frequencies, i.e., 0.1-0.5 Hz. The R-peak amplitudes were also resampled and filtered similarly to the RSA [1, 2].

Estimating the RR from the RSA and RPA waveforms

The W-OSC frequency tracking algorithm is based on a band-pass filter (BPF), the central frequency of which is adaptively updated to correspond to the common frequency of the inputs [3]. The inputs, i.e., the RSA and RPA waveforms, were filtered with the same BPF. At each new sample, the central frequency of the BPF was updated using a linear combination of the optimal updates for each input based on the difference between each output and a discrete oscillator model. The weights were computed in a recursive manner and were proportional to the inverse of the variance of the estimates of each input, in order to maximize the effect of inputs with high signal-to-noise ratio outcomes.

At each new sample, the overall central frequency coefficient $\propto$ was a weighted sum of coefficients obtained for each of the m = 1,…M inputs, i.e.,

$$\propto [n] = \sum_{m=1}^{M} W_m[n] \propto_m [n] \qquad (1)$$

where W_m is the weight of the mth input and $\propto_m$ is the central frequency coefficient corresponding to the input. The instantaneous frequency f was computed as

$$f[n] = \arccos(\propto [\mathrm{n}]) / 2\pi. \qquad (2)$$

In order to assess the benefit of using RSA and RPA simultaneously, as opposed to either separately, the RR is also estimated by using the OSC algorithm, which is the single-signal version of the W-OSC algorithm, on the RSA and RPA waveforms separately.

This tracking algorithm is adaptive and has an inherent adaptation delay, which should be taken into account. This delay is estimated by using the cross-correlation between the estimate RR and the reference RR. An average delay is computed and used in all evaluations. The average delay was 25 ± 12 samples (which corresponds to 12.5 ± 6 s) over the data set.

Reference RR

The reference RRs were estimated from the data set respiratory waveform, which were resampled at 2 Hz. A combination of eight different estimates was used: a short time Fourier transform maximum frequency estimate, an estimate using the empirical mode decomposition followed by the Hilbert transform [6], an estimate based on respiration peak intervals, an estimate based on the number of peaks per window, an estimate based on the Teager-Kaiser energy tracking operator [7], an estimate based on the modified covariance method [8], an estimate based on autoregressive modelling [2] and an estimate based on Prony's method [9]. At each sample, the median of the eight estimates was computed, and the three closest estimates to it were averaged to produce a robust RR reference. The reference RR was filtered using a low-pass filter with a normalized cut-off frequency of 0.2 to smooth sudden changes due to the imperfect fulfilment of the assumptions regarding the different methods.

Experimental Setup

The W-OSC and OSC tracking algorithms were applied to RSA and RPA waveforms. Errors with respect to the reference RR were computed in 60 s sliding windows. The mean absolute error (MAE) was computed in breaths-per-minute (bpm) as

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|bpm_{estim} - bpm_{ref}\right| \quad (3)$$

And the error percentage (EP) was computed as

$$EP = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|bpm_{estim} - bpm_{ref}\right|}{bpm_{ref}} \quad (4)$$

where N is the length of the window, bpm_{estim} is the estimate RR and bpm_{ref} is the reference RR.

3. Results

An example RR estimate from the W-OSC is presented in Figure 1. The reference RR and the respiratory signal are shown as well. The estimate is truthful to the real RR in this example.

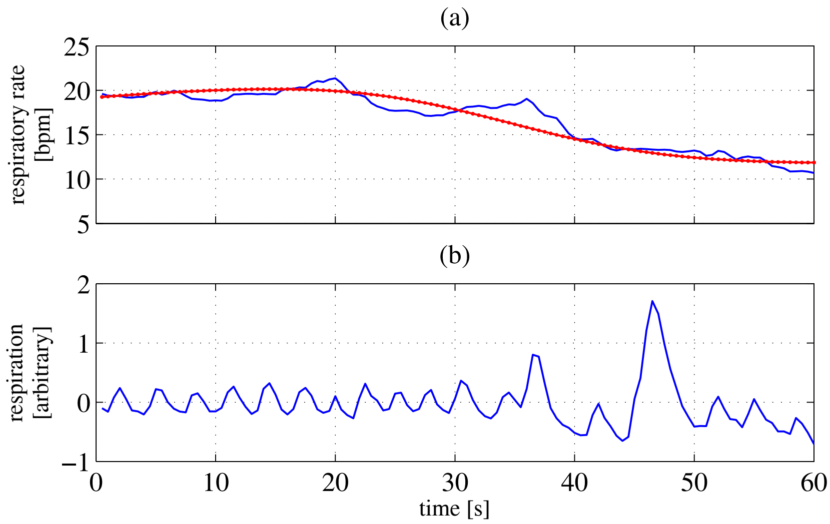

Fig. 1. RR estimate from the W-OSC method. (a) W-OSC RR estimate (solid blue) and the reference RR (dotted red); (b) respiratory waveform. Signals from minutes 33 to 34 of the Fantasia f1y08 record.

The estimates from the W-OSC tracking method with the RSA and RPA simultaneously and the estimates from the OSC tracking method with the RSA and RPA separately are compared to the reference RR in terms of MAE and EP in Table 1. It can be seen that the W-OSC estimate using both RSA and RPA results in higher accuracy than the OSC estimates using either the RSA or the RPA. Furthermore, the errors are smaller for the young population than for the elderly population using either both, or the RSA alone. However, the RPA yields more accurate estimates for the elderly population than for the young population.

Table 1. Errors of the W-OSC and the OSC tracking estimates over the Fantasia data set.

	young		elderly	
	MAE [bpm]	EP	MAE [bpm]	EP
W-OSC(RSA, RPA)	1.1	8.70%	1.39	9.25%
OSC(RSA)	1.72	12.12%	2.06	13.16%
OSC(RPA)	2.63	22.14%	2.01	14.49%

4. Discussion

Tracking the common respiratory frequency component of the RSA and RPA simultaneously yields a better RR estimate than tracking the respiratory frequency in either alone. Even though estimation errors regarding the elderly population are slightly higher than those of the young population, the difference is smaller than those of either the RSA or the RPA alone. Thus, this scheme compensates for the decreasing RSA in the elderly.

The W-OSC tracking algorithm yields estimates comparable to the state of the art [2]. However, direct comparison is impossible, as the W-OSC is an instantaneous method in contrast to [2]. Also, in this reference, the ground-truth RRs were computed differently and parts of the records were discarded.

The W-OSC tracking is an adaptive method, however, it has an inherent adaptation delay of around 12 s. This is better than the state-of-the-art, where at best, estimates are produced for 60 s windows [2].

The W-OSC tracking is an automatic method and does not require any identification of abnormal beats, as it can rectify their effect within a few iterations.

5. Conclusions

This paper presented the instantaneous RR estimation from the RSA and the RPA using the W-OSC frequency tracking method. This RR estimate is comparable in accuracy to the state-of-the-art and is computed with a smaller delay. The method is automatic and does not require special subject-dependent adjustments. It has the potential to be used in real applications, where an RR estimate is needed and a single-lead ECG is available.

Acknowledgements

This work was funded thanks to the NanoTera ObeSense initiative.

References

[1] Bailon R, Sornmo L, Laguna P. Ch 8: ECG- Derived Respiratory Frequency Estimation. Advanced Methods and Tools for ECG Data Analysis. Artech House, Norwood, MA, USA, 1 edition, 2006.

[2] Orphanidou C, Fleming S, Shah SA, Tarassenko L. Data fusion for estimating respiratory rate from a single-lead ECG. *Biomed. Sig. Process. Control*, 8(1):98–105, 2013.

[3] Prudat Y, Vesin JM. Multi-signal extension of adaptive frequency tracking algorithms. *Sig. Process.*, 89(6):963–973, 2009.

[4] Iyengar N, Peng CK, Morin R, Goldberger A, Lipsitz LA. Age-related alterations in the fractal scaling of cardiac interbeat interval dynamics. *Am. J. Physiol.*, 271(4):1078–1084, 1996.

[5] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circ.*, 101(23):215–220, 2000.

[6] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen NC, Tung CC, Liu HH. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. Roy. Soc. London.*, 454(1971):903–995, 1998.

[7] Potamianos A, Maragos P. A comparison of the energy operator and the hilbert transform approach to signal and speech demodulation. *Sig. Process.*, 37(1):95–120, 1994.

[8] So HC. A comparative study of three recursive least-squares algorithms for single-tone frequency tracking. *Sig. Process.*, 83(9):2059–2062, 2003.

[9] Fertig LB, McClellan JH. Instantaneous frequency estimation using linear prediction with comparisons to the DESAs. *IEEE Sig. Process. Let.*, 3:54–56, Feb. 1996.