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Real-Time Estimation of the ECG-Derived Respiration (EDR) Signal using a New Algorithm for Baseline Wander Noise Removal

Shivaram P. Arunachalam, *Student Member, IEEE* and Lewis F. Brown, *Senior Member, IEEE*

***Abstract*—Numerous methods have been reported for deriving respiratory information such as respiratory rate from the electrocardiogram (ECG). In this paper the authors present a real-time algorithm for estimation and removal of baseline wander (BW) noise and obtaining the ECG-derived respiration (EDR) signal for estimation of a patient's respiratory rate. This algorithm utilizes a real-time "T-P knot" baseline wander removal technique which is based on the repetitive backward subtraction of the estimated baseline from the ECG signal. The estimated baseline is interpolated from the ECG signal at midpoints between each detected R-wave. As each segment of the estimated baseline signal is subtracted from the ECG, a "flattened" ECG signal is produced for which the amplitude of each R-wave is analyzed. The respiration signal is estimated from the amplitude modulation of R-waves caused by breathing. Testing of the algorithm was conducted in a pseudo real-time environment using MATLAB™, and test results are presented for simultaneously recorded ECG and respiration recordings from the PhysioNet/PhysioBank Fantasia database. Test data from patients were chosen with particularly large baseline wander components to ensure the reliability of the algorithm under adverse ECG recording conditions. The algorithm yielded EDR signals with a respiration rate of 4.4 breaths/min. for Fantasia patient record f2y10 and 10.1 breaths/min. for Fantasia patient record f2y06. These were in good agreement with the simultaneously recorded respiration data provided in the Fantasia database thus confirming the efficacy of the algorithm.**

I. Introduction

MANY investigators have pursued the derivation of a patient's respiratory signal by digital signal processing of the electrocardiogram (ECG). Such a respiration signal obtained from the ECG is called the ECG-derived respiration (EDR) signal and several clinical significances of the EDR signal have been reported [1]. Several methods have been reported for deriving the EDR signal. Respirations induce apparent modulation in the direction of the mean cardiac electrical axis (MEA) and investigators have reported algorithms for producing the EDR signal from approximations of this modulation [2]. Other reported methods derive the EDR from very complex algorithms requiring ECG signals simultaneously recorded from multiple lead connections [3-5]. Still other reported approaches are based on complex mathematical transforms and non-real-time ECG data to derive the EDR signal [6-8].

These previously reported methods for EDR derivation are typically very computationally intensive, performed off-line (non-real-time environment) and some require simultaneous recording of multi-lead ECG signals. Moreover, the accuracy and reliability of these techniques has been somewhat limited as reported. Highly desirable is a reliable technique for deriving the EDR signal from a single conventional lead recording in real-time. The authors recently presented a real-time algorithm for deriving the EDR signal from analysis of real-time detected ECG R-wave amplitude analysis [9-10]. In this paper the authors describe the algorithm and its testing in a pseudo real-time environment using Matlab™ (Mathworks, Inc., Natick, MA). New results are reported from testing with simultaneously recorded ECG and respiratory records of publicly available patient data from the PhysioNet/ PhysioBank Fantasia database.

II. Methods

The focus of this work was on deriving the EDR signal from an accurate estimation of the amplitude modulation of ECG R-waves caused by respiratory movement of the thorax. Success requires accurate beat-to-beat estimation of ECG R-wave amplitudes. Since ECG signals frequently contain noise, careful consideration must be given to noise removal, especially baseline wander, in order to extract accurate R-wave amplitude measurements.

Assume that R(t) is the composite amplitude of a detected ECG R-wave, which can be described in terms of its signal components as:

$$R(t) = a(t) \cdot r + n_1(t) + n_H(t) + n_G(t) + b(t) \qquad (1)$$

where R(t) is the composite ECG R-wave amplitude; a(t) is the amplitude modulation due to respiratory movement of the thorax; r is the true R-wave amplitude at the middle of a resting tidal volume breath (r = constant); $n_1(t)$ is narrow band noise due to 60 Hz, etc.; $n_H(t)$ is other high frequency noise due to EMI, EMG, noise artifacts, etc.; $n_G(t)$ is zero-mean Gaussian white noise; and b(t) is the baseline offset and wander noise.

The desire is to find an estimate of a(t) to approximate the respiratory waveform. After conventional lowpass filtering to remove $n_H(t)$, notch filtering to remove $n_1(t)$, and baseline removal to remove b(t), then for the i^{th} detected R-wave, equation (1) can be simplified to:

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Shivaram P. Arunachalam is with the Electrical & Computer Science Department at South Dakota State University, Brookings, SD 57007 USA (phone: 605-695-9489; fax: 605-688-5878; e-mail: shivaram.poigai@sdstate.edu).
Lewis F. Brown is Professor and Dean of Engineering at South Dakota State University, Brookings, SD 57007 USA (e-mail: Lewis.Brown@sdstate.edu).

$$R_i(t) = a_i(t) \cdot r + n_{G_i}(t) \quad (2)$$

Further assume that a(t) has unity mean value, which is equivalent to saying that at the middle of a resting tidal volume breath, there is no respiratory influence on the R-wave amplitude (i.e., $a(t) \equiv 1$); and during normal respirations, the amplitude modulation factor has a value that is symmetric about this unity value. Following the capture of every detected R-wave from the filtered ECG waveform, the desire is to compute the running average of the R-wave amplitude in equation (2). Then, it can be shown that the average detected R-wave amplitude for large n (i.e., large number of detected R-wave amplitudes) can be approximated by:

$$a_n(t) \approx \frac{R_n(t)}{\overline{R_n(t)}} \quad (3)$$

where $\overline{R_n(t)}$ is the running average R-wave amplitude [9]. Therefore, an algorithm for approximating the respiratory waveform, a(t), is:

1. lowpass and notch filter the ECG waveform to remove the 60 Hz and other high frequency noises
2. remove the baseline offset and wander, b(t)
3. as each i^{th} R-wave is detected,
   a. compute the amplitude, $R_i(t)$
   b. compute a running average of the current and all previous R-wave amplitudes, $\overline{R_n(t)}$
   c. estimate most recent $a_n(t)$ value from equation (6)
   d. compute the running interpolation of $a_n(t)$, which is the desired EDR signal. The accuracy of $a_n(t)$ improves with increasing i.

Step 2 of the algorithm requires removal of the baseline wander (BW) noise. The authors used the real-time T-P knot algorithm for estimation and removal of the BW noise as reported in [10]. Removal of baseline wander is necessary for accurate estimation of R-wave amplitudes (i.e., the baseline must be "flat"). The baseline wander estimation from the T-P algorithm is based on a moving cubic spline interpolation of the four most recently determined R-R midpoints (i.e., the ECG signal amplitude at the location midway between successive R-waves, or "T-P knots"). As each new R-wave is detected, a cubic spline interpolation of the four most recent T-P knots is performed to estimate a new segment of the BW noise, which is then backward subtracted from the ECG signal. Fig. 1 shows a segment of ECG signal with the T-P knots identified as filled circles.

Fig. 2 illustrates the signal processing steps used to implement the EDR algorithm. The upper portion of the diagram is for producing a cleaned and flattened (i.e., baseline removed) ECG signal by pre-filtering which includes a 60 Hz 2^{nd}-order IIR notch filter (Q=14) and a 2^{nd}-order Butterworth lowpass filter to substantially reduce 60 Hz noise, motion artifacts, EMG noise etc. The lower portion is used to analyze this cleaned ECG signal and detect each R-wave location and amplitude for estimating $a_n(t)$ from equation (3). The Pan & Tompkins R-wave detection algorithm is employed to obtain the proximity of each QRS complex [11]. This information is used for approximating the baseline signal, b(t), using the T-P knot interpolation technique. The approximated baseline signal is then subtracted from the clean ECG signal still containing baseline wander, resulting in a clean and flattened ECG signal that is next ready for R-wave analysis as required in equations (1)-(3).

Fig. 1. ECG segment showing T-P knots as filled circles.

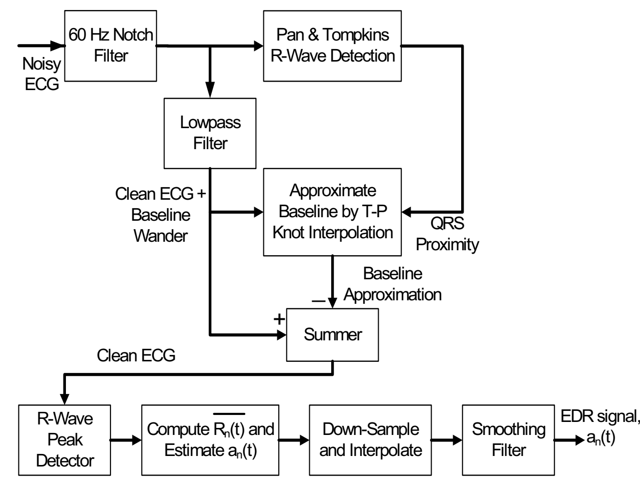

Fig. 2: Block diagram of the EDR algorithm.

The peak amplitude and location of each R-wave of the clean ECG signal are next detected. A running average of these R-wave amplitudes is computed and the ratio of the current R-wave peak value to the current running average value yields the desired estimation of the respiratory amplitude modulation factor, a(t), from equation (3). A final cubic spline interpolation of preceding respiratory modulation factor amplitudes (at their corresponding R-wave peak locations) yields a continuous approximation for the EDR signal. Since a 3^{rd}-order interpolation polynomial is used for this purpose, four values of the modulation factor must be produced before the estimated EDR signal can be produced. A final 3^{rd}-order elliptic smoothing filter is used to reduce high frequency noise in the EDR. As the respiration signal has a very low frequency (less than 0.5 Hz), the smoothing filter and final interpolation of the EDR signal are performed at a 1:100 down-sampled sampling rate (i.e., 2.5 Hz for an ECG sampling rate of 250 Hz).

MATLAB™ was used for simulating a real-time DSP environment using pseudo real-time code within a single virtual A/D sampling loop to process the digitized signal at a sampling rate of 250 Hz. Portions of the T-P knot algorithm were written to emulate serial shift registers performing block operations with data from four R-R intervals.

III. RESULTS

Testing of the EDR algorithm was accomplished using simultaneously recorded patient ECG and respiration data from PhysioNet/PhysioBank [12]. Actual recordings were downloaded from the Fantasia data set. Each set includes simultaneously sampled (250 Hz) and recorded ECG and respiration belt data from 20 young and 20 elderly subjects [13]. The authors selected challenging excerpts from data files f2y10 (Start time = 20 s; End time = 80 s) and f2o06 (Start time = 60 s; End time = 120 s) for testing the algorithm. Fig. 3 shows the noisy ECG signal (upper) and simultaneously recorded respiratory belt signal (lower) from the f2o06 data file. The ECG data show significant baseline wander and rapid motion artifact noise. The authors selected the f2o06 and f2y10 data records to provide a good test for the efficacy of the EDR algorithm.

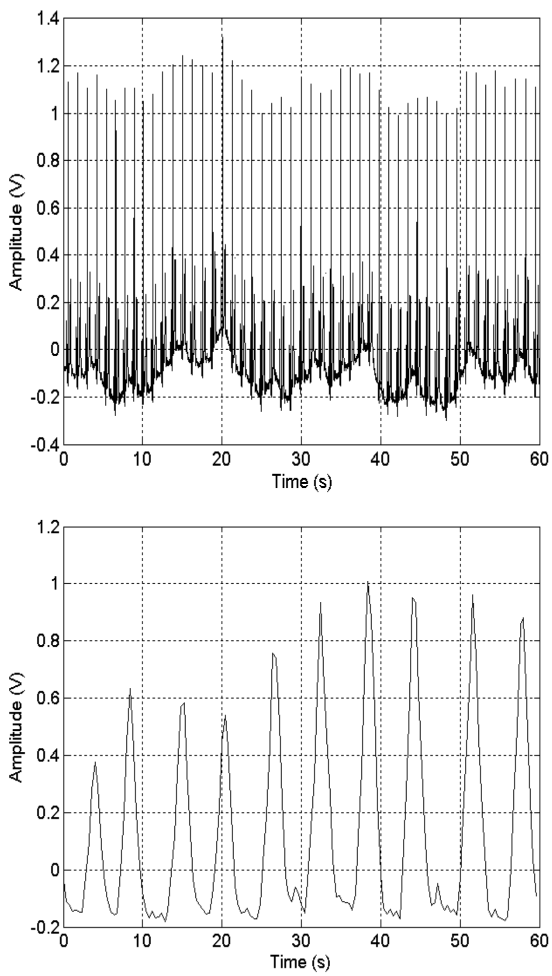

Fig. 3. Original noisy f2o06 ECG data (upper) and respiratory belt signal (lower).

Fig. 4 shows the "flattened" f2o06 ECG data after filtering and removal of the BW noise with the authors' algorithm and Fig. 5 shows the resulting EDR signal.

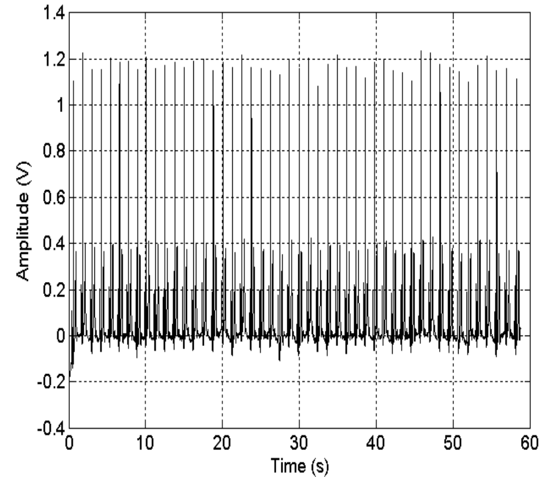

Fig. 4. F2o06 ECG data after filtering and BW noise removal.

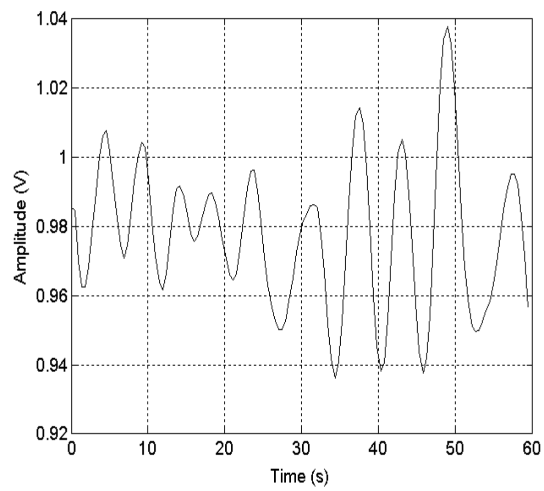

Fig. 5. EDR signal for the f2o06 data.

Figures 6 and 7 show the original respiratory belt and resulting EDR signals respectively for the f2y10 excerpt.

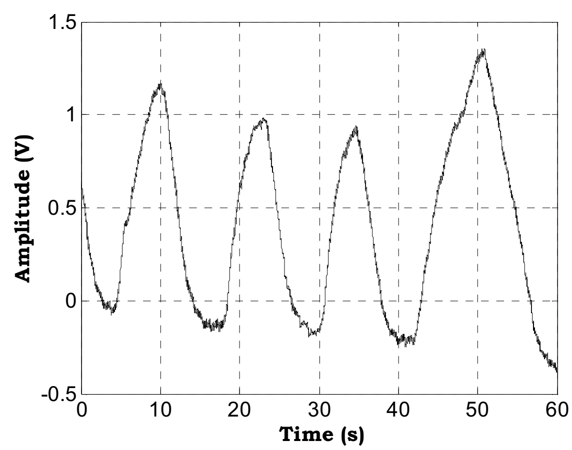

Fig. 6. Original respiratory belt data for the f2y10 data excerpt.

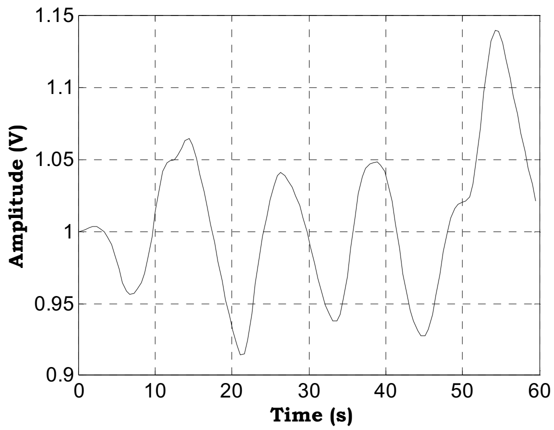

Fig 7. EDR signal for the f2y10 data.

IV. Discussion

The respiratory belt waveform of Fig. 6 and the resulting EDR signal in Fig. 7 show similar respiration rates. The figures show a phase lag of approximately 4 seconds for the EDR signal as compared to the original respiratory belt waveform. This can be attributed to the phase lag introduced by the 3rd-order elliptic smoothing filter. Both figures show four prominent peaks and valleys with respiration rates of slightly more than four per minute. The authors did not consider this phase lag of great significance for purposes of monitoring respiratory rate.

The respiratory belt waveform of Fig. 3 (lower) and the resulting EDR signal in Fig. 5 both show the same number of positive peaks in respiration for the f2o06 data excerpt. The f2o06 data segment was recorded from a subject with a higher respiration rate of approximately 10.0 Breaths/min (i.e., closer to normal adult resting respiration rate). The authors' algorithm produced an EDR signal with a respiration rate of 10.1 Breaths/min, agreeing well with the actual recorded respiration signal. The results of testing with the two data sets are summarized in Table I.

TABLE I. Comparison of Respiration Rates Between the EDR Signal and Actual Respiration Recordings.

Data File	Actual Recording (B/min)	EDR Estimate (B/min)
f2o06	10.0	10.1
f2y10	4.4	4.5

IV. Conclusions

In this paper the authors presented a real-time algorithm for estimating and removing BW noise and obtaining the ECG-derived respiration (EDR) signal. This algorithm utilizes a real-time filtering and baseline wander removal technique which produces a cleaned "flattened" ECG signal for which the amplitude of each R-wave is analyzed. The respiration signal is then estimated from the amplitude modulation of each detected R-wave caused by breathing. Testing of the algorithm was conducted in a pseudo real-time environment using MATLAB™, and the test results were presented for simultaneously recorded ECG and respiration recordings from the PhysioNet/PhysioBank Fantasia data-base. The test results proved to be good tests of the algorithm under extreme conditions of baseline wander noise and broad ranges of respiration rate. The algorithm provided reasonably accurate estimates of respiration rate for both sets of data as illustrated in Table I and proved robust for all data sets tested including those with extreme baseline excursions and PVCs. Of key importance for accuracy is the need for removal of baseline wander and other noise signals that impact R-Wave amplitude. Since the algorithm depends on detection of respiratory induced R-wave amplitude modulation, shallow respirations (i.e., low amplitude modulation of the ECG signal) prove more challenging than deep respirations for reliable derivation of the EDR signal. Another challenge noted by the authors was the need to vary the cutoff frequency of the final EDR smoothing filter depending on the respiratory rate. An adaptive filter approach might prove to be more robust than the fixed parameter lowpass filter used by the authors. More investigation is also required for comparing the results of this algorithm with other approaches. However, a challenge is the lack of published results using publically available simultaneously recorded ECG and respiration data.

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