Respiratory rate estimation from the ECG using an instantaneous frequency tracking algorithm

Leila Mirmohamadsadeghi*, Jean-Marc Vesin
Swiss Federal Institute of Technology Lausanne, Lausanne, Switzerland

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ABSTRACT
Monitoring the respiratory rate (RR) is important in many clinical and non-clinical situations but it is difficult in practice, for existing devices are intrusive, bulky and expensive. The extraction of the RR from the routinely acquired electrocardiogram (ECG) has been proposed lately. Two approaches exist, one exploiting the modulation of the heart rate by the respiration, known as the respiratory sinus arrhythmia (RSA) and the other using the modulation by the respiration of the R-peak amplitudes (RPA). In this study, the weighted multi-signal oscillator based band pass filtering (W-OSC) algorithm is applied to track the common frequency in the RSA and RPA waveforms simultaneously, as an estimate of the instantaneous RR. On the public PhysioNet Fantasia data set, it is shown that the presented method is automatic, instantaneous and comparable in accuracy to the state-of-the-art.

1. Introduction
The respiratory rate (RR) is one of the human vital signs that need to be monitored in clinical and non-clinical applications for diagnosis and control purposes [1]. It is currently difficult to accurately and continuously monitor the RR, for the apparatus and devices are intrusive, expensive and uncomfortable for the patient [2]. It is therefore of great interest to provide easy and inexpensive means for the accurate, continuous and convenient monitoring of the RR. The respiratory and heart activities are linked through physiological processes. The respiration modulates the heart rate such that it increases during inspiration and decreases during expiration [3]. A waveform can be extracted from the heart rate time series representing this modulation, which is referred to as respiratory sinus arrhythmia (RSA). Furthermore, the filling and emptying of the lungs during respiration causes a rotation of the electrical axis of the heart and a change in the impedance of the thorax, which yields changes in the electrocardiogram (ECG) beat morphology. As a result, the R-peak amplitudes are modulated by the respiratory activity. A waveform can be extracted from the ECG representing this modulation, which is referred to as the R-peak amplitude (RPA). In the last twenty years, many researchers have investigated the possibility of deriving the RR by exploiting the influence of respiration on the heart rate or ECG beat morphology by using the RSA or RPA waveforms. A summary of studies prior to 2007 can be found in [3].

In a more recent work, a windowed spectral analysis was applied to extract the RR from the RSA waveform [4]. A windowed temporal analysis using peak count was also applied to estimate the RR from the RSA waveform [4,5] as well as from the RPA waveform [5]. Furthermore, correlation analysis was used to compute the RR from the RSA waveform [4]. Past studies have highlighted the difficulty of deriving, for comparison purposes, a reference RR from a respiratory signal recorded by nasal thermistry or pneumography, as the latter is neither band-pass, nor stationary [4]. Proposed solutions consisted in applying the same frequency estimation methods as for the RSA or RPA waveforms to the respiratory signal to estimate the reference RR.

In a pioneering work, Orphanidou et al. fused spectral information form ECG-derived RSA and RPA waveforms in order to derive the RR [6]. The most dominant peak from the autoregressive (AR)-estimated spectra of the RSA and RPA waveforms was selected according to several criteria as representing the RR. Vehkaa et al. also used RSA and RPA signals simultaneously and combined their temporal maxima and minima counts after ad hoc filtering to estimate the RR [7]. However, none of these two methods provides a robust, real-time and automatic means to estimate the RR continuously. Both discarded parts of records and required special subject-dependent treatment.

Motivated by the recent contribution of Orphanidou et al. to fuse respiratory information from the RSA and RPA waveforms
extracted from the ECG [6], 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 [8] 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. This method has been shown to successfully track a common frequency component in biomedical signals such as electroencephalogram signals [9]. Furthermore, 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 [6]. Therefore it can be implemented in a real-time setting to estimate the RR continuously without the need for subject-dependent adjustment. The performance of this tracking method was assessed on the single-lead ECG recordings of the PhysioNet Fantasia data set, using a reference RR computed from the combination of eight different frequency estimates of the simultaneously recorded respiratory signal.

2. Materials and methods

2.1. Data set

The PhysioNet Fantasia data set [10,11] is used to evaluate algorithms in this study. This data set provides 120 min long records of simultaneously acquired single-lead ECG and spontaneous respiration signals (acquired through inductance plethysmography [12]) from 20 young (21–34 years of age) and 20 elderly (68–85 years of age) subjects. The subjects were healthy and laid supine watching the movie “Fantasia.” Both sets of signals were digitized with a sampling rate of 250 Hz.

2.2. Extraction of the respiratory waveforms from the ECG

In order to extract the RSA and RPA waveforms, the ECG baseline wander was first removed using a double median filter [13]. The local maxima of the corrected ECG were then extracted as the R-wave peaks $R[n]$ using a classic extrema detection method [14]. No special processing was performed to identify irregular beats. The time differences $t_n[n] - t_{n-1}[n]$ between all pairs of consecutive peaks were computed in order to create the R-peak to R-peak time series. The time abscissa associated to each difference was the midpoint between the two peaks. This series was re-sampled at 2 Hz using cubic spline interpolation in order to ensure regular sampling. The resulting signal is the interbeat interval waveform, from which, the RSA waveform was extracted by band-pass filtering (between 0.1 Hz and 0.5 Hz to isolate components relevant to respiration [3]). The R-wave peaks $R[n]$ were also re-sampled at 2 Hz and band-pass filtered in the same manner as the inter-beat interval waveform to produce the RPA waveform. Forward-backward filtering using a Chebyshev type I filter is used in the demonstrations presented in this article.

2.3. Estimation of the RR from the RSA and RPA waveforms

An adaptive band-pass filter (BPF) with an oscillator-based mean-square error update algorithm [15] was used to estimate the common frequency present in the RSA and RPA waveforms. The algorithm is referred to as OSC. It was later extended to be applied to several signals simultaneously in order to track a common frequency component in them [8]. This multi-signal extension is referred to as W-OSC. This algorithm can track a common frequency present in $M$ signals $(x_m, m = 1, \ldots, M$ of the form:

$$x_m[n] = s_m[n] + b_m[n]$$

where the $s_m[n]$ are oscillations at time-varying frequency $\omega_m[n]$ and the $b_m[n]$ are additive white noises. All $M$ signals are filtered with the same BPF and the tracking quality of the outcome is used to weigh the contribution of each signal to the filter update in order to track a common oscillation $\omega_m[n]$ in the signals. The transfer function of the BPF is:

$$H(z; n) = \frac{1 - \beta}{z - \alpha} = \frac{1 - \beta z^{-2}}{1 - \alpha[n](1 + \beta)z^{-1} + \beta z^{-2}}$$

(2)

where $0 < \beta < 1$ defines the bandwidth of the BPF and $\alpha[n] = \cos(\omega_m[n])$ is the central frequency coefficient of the filter. The output of the filter for signal $m$ is:

$$y_m[n] = (1 + \beta)\alpha[n]y_m[n - 1] - \beta y_m[n - 2] + \frac{1 - \beta}{2}(x_m[n] - x_m[n - 2]).$$

(3)

It is desired that the filter output follows the oscillator model:

$$y_m[n] = 2 \cos(\omega_m[n])y_m[n - 1] - y_m[n - 2].$$

(4)

In order to update the filter such that the output follows (4), the following cost function is minimized:

$$J_m[n] = E[(y_m[n] - 2\alpha[n + 1]y_m[n - 1] + y_m[n - 2])^2]$$

(5)

with $E(\cdot)$ denoting the expectation. The minimization of $J_m$ yields the optimal $\alpha[n + 1]$ as:

$$\alpha[n + 1] = \frac{E[y_m[n - 1][y_m[n] + y_m[n - 2]])}{2E[y_m[n - 1]]}.$$  

(6)

In practice, the expectations in the expression of $\alpha[n + 1]$ cannot be computed and are replaced by time recursive estimates such that:

$$\alpha[n + 1] = \frac{Q_m[n]}{2P_m[n]}$$

(7)

with

$$Q_m[n] = \delta Q_m[n - 1] + (1 - \delta)[y_m[n - 1][y_m[n] + y_m[n - 2])$$

(8)

$$P_m[n] = \delta P_m[n - 1] + (1 - \delta)[y_m[n - 1]$$

(8)

where $0 < \delta < 1$ is the update coefficient. If the frequency of one signal is estimated, (7) describes the update of the filter. If the common frequency of $M$ signals is estimated, it is natural to weigh the contribution of each signal to the update of the BPF central frequency. For each signal, (7) yields $\alpha_m[n]$, which gives a frequency estimate $\omega_m[n] = \arccos(\alpha_m[n])$. This estimate can be written as $\omega_m[n] = \omega_0 + \Delta_m[n]$, where $\Delta_m[n]$ is the deviation of the estimate.

Nomenclature

| AR       | autoregressive                   |
| BPF      | band-pass filter                 |
| bpm      | breaths per minute               |
| ECG      | electrocardiogram                |
| EMD      | empirical mode decomposition     |
| EP       | error percentage                 |
| IMF      | intrinsic mode function          |
| MAE      | mean absolute error              |
| OSC      | oscillator based band-pass filtering |
| RPA      | R-peak amplitude                 |
| RR       | respiratory rate                 |
| RSA      | respiratory sinus arrhythmia     |
| STFT     | short time Fourier transform     |
| W-OSC    | weighted multi-signal oscillator based band-pass filtering |
from the true frequency $\omega_0$. A set of weights $\{W_m \mid \sum_{m=1}^{M} W_m = 1\}$ are sought based on the variances of the $\Delta_m[n]$ to minimize deviations [8]:

$$W_m = \frac{1/\sigma_m^2}{\sum_{i=1}^{M} 1/\sigma_i^2}. \quad (9)$$

These weights maximize the effect of signals with low-variance estimates and minimize the effect of signals with high-variance estimates. As the variances in (9) cannot be computed, it is assumed that they are proportional to:

$$\sigma_m^2 \propto \frac{J_m}{S_{xx}} \quad (10)$$

where $J_m$ is defined in a recursive manner as:

$$J_m[n] = \lambda J_m[n-1] + (1-\lambda)y_m[n] - 2\omega[n+1]y_m[n-1]$$

$$+ y_m[n-2]$$

and $S_{xx}$ is the variance of the input $x$, which in its recursive estimate form is:

$$S_{xx}[n] = \lambda S_{xx}[n-1] + (1-\lambda)x[n]x[n]$$

with $0 < \lambda < 1$. The weights in (9) are therefore obtained as:

$$W_m[n] = \frac{S_{xx}[n] J_m[n]}{\sum_{i=1}^{M} S_{xx}[n] J_i[n]}. \quad (13)$$

The inclusion of the weighting process yields:

$$\sigma[n+1] = \sum_{m=1}^{M} W_m[n] \frac{Q_m[n]}{2P_m[n]} \quad (14)$$

The instantaneous frequency is computed as:

$$f[n+1] = \arccos(\sigma[n+1]) \quad (15).$$

The RR is estimated using the W-OSC algorithm with the RSA and RPA as inputs to track common frequency component. In order to assess the benefit of using both RSA and RPA simultaneously, as opposed to either separately, the RR is also estimated by using the OSC algorithm on each one separately.

2.4. Estimation of the reference RR

To evaluate the RR estimated from the RSA and RPA waveforms, one needs to compare the estimate with the true RR. However, deriving the RR from a real respiratory signal is a challenging problem as the respiratory signal derived from thoracic volume changes (measured with impedance pneumography) or nasal/oral airflow is neither stationary nor band limited. It also contains many artifacts and noise due to the acquisition process. Many methods have been proposed, but no single automated technique exists to reliably compute the RR in a window or instantaneously.

A common practice to estimate the RR is to compute the power spectrum in a sliding window over the signal and to consider the dominant peak frequency as the RR [3]. The power spectrum can be computed using either a non-parametric or a parametric estimator. AR modeling has been used for the respiratory signals of the PhysioNet Fantasia data set [6], which are thought to be impedance pneumography ones. Extrema detection to compute the RR [16] has also been applied to the PhysioNet MIMIC data set respiratory signals [17,11], which are thought to be obtained by nasal thermistry.

In this study, eight frequency estimation algorithms were used to estimate the RR from the PhysioNet Fantasia respiratory signals. Various frequency-domain and time-domain estimates were combined to provide a robust estimate, which is used as ground truth RR. The majority of the chosen methods are instantaneous, however several are window-based. The optimal length of the windows are chosen based on the properties of each method in an empirical manner.

Prior to the reference RR estimation process, the respiratory signal was re-sampled at 2 Hz using cubic spline interpolation. In addition, a high pass filter with a normalized cutoff frequency of 0.025 was applied to the re-sampled respiratory signal in order to remove its baseline wander.

2.4.1. Short time Fourier transform maximum frequency estimate

In order to determine the frequency content of a non-stationary signal by using its spectrum, the short time Fourier transform (STFT) is used. The instantaneous RR was computed as the normalized frequency corresponding to the local maximum in the magnitude of the STFT in 75 s long windows. The window length was found to allow for necessary frequency resolution based on several trials. This window length is applicable to other data sets and moreover, the outcome is moderately sensitive to the exact length.

2.4.2. Frequency estimate using the empirical mode decomposition followed by the Hilbert transform

The Hilbert transform allows to generate, from a real signal, a complex signal, termed the analytic signal with separable amplitude and phase components [18]. However, for the Hilbert transform to be meaningful, the input signal must be narrow band [19]. Empirical mode decomposition (EMD) is a data analysis method that decomposes the signal into a set of intrinsic mode functions (IMFs) based on the extraction of energy from different intrinsic time scales [20]. EMD is used to extract a component of the respiratory signal, which contains the RR and is narrow band such that the Hilbert transform outcome is meaningful. When the EMD is applied to the respiratory signal, the first IMF is observed to contain oscillations within the range of the RR. The instantaneous frequency was obtained by differentiating the phase of the analytic representation of the first IMF.

2.4.3. Frequency estimate based on respiration peak intervals

The time difference between two respiratory peaks $p[n-1]$ and $p[n]$, denoted as $t_{p}[n] = t_{p}[n] - t_{p}[n-1]$, is interpreted as a respiratory cycle. The respiratory peaks were extracted by local maxima detection. The time series of their differences, attributed to the time index of the second peak, was created and inverted in order to estimate the instantaneous respiratory frequency. The resulting RR was re-sampled at 2 Hz using cubic spline interpolation in order to ensure equal spacing of points such that comparison and combination with other RR is possible.

2.4.4. Frequency estimate based on the number of peaks per windows

The number of local maxima in a window determines the number of respiratory cycles in that window. The RR in a window was estimated as the ratio of the number of respiratory cycles in the window by the length of the window. 20 s windows, centered on each sample were chosen based on several trials. This window length is applicable to other data sets and moreover, the outcome is moderately sensitive to the exact length. Respiratory peaks were extracted by local maxima detection.

2.4.5. Frequency estimate based on the Teager–Kaiser energy tracking operator

The RR was estimated using the Teager–Kaiser operator. This energy tracking operator estimates the energy required to generate a given amplitude and frequency modulated signal, which is then used to separate the amplitude and frequency components [21].
2.4.6. Frequency estimate based on the modified covariance method

A recursive modified covariance method was used to estimate the RR. The modified covariance method is a recursive frequency tracking algorithm derived from the linear prediction property of sinusoids [22]. The minimization of the squared error between the linear prediction estimate and a sinusoidal model in a recursive manner yields an estimate of the signal frequency.

2.4.7. Frequency estimate based on AR modeling

The RR was extracted as the largest peak, within 20 s windows centered on each sample, of the spectrum estimated using an AR model fit to the data [3]. The window length was empirically found to be optimal based on several trials. It is applicable to other data sets and moreover, the outcome is moderately sensitive to the exact length. A Yule-Walker 10th order AR model was used. In [6], an AR model of order 8 was used to estimate the spectrum of the respiration signal. However, several trials showed that increasing the order to 10 yielded more detailed RR estimates.

2.4.8. Frequency estimate based on Prony’s method

Prony’s method is a technique for modeling a discrete-time signal as a linear combination of exponentials. It extends Fourier analysis by directly estimating frequency, damping, strength and relative phase of modal components present in a signal [23]. In the original approach, a model is fit to the data and then the frequency and other signal attributes are computed from the model parameters. Later, a modified instantaneous linear-prediction-based version of Prony’s frequency estimator was proposed [24], which uses five data points to directly estimate the instantaneous frequency of a sinusoidal signal. The latter version was implemented for use in this study.

At each time index, the three closest estimates to the median of the eight estimates were chosen as the three most accurate RRs. The reference RR was computed as the mean of the three retained estimates and expressed as the number of breaths per minute (bpm) as \( \text{bpm} = 60 \times f \), where \( f \) was the RR in hertz. This combination method is robust to outliers and allows to take into account different estimates, some of which are spectral and some other temporal. Estimates 1, 4 and 7 are computed in windows and estimates 2, 3, 5, 6 and 8 are instantaneous.

A low-pass Butterworth filter with a normalized cutoff frequency of 0.2 was used to filter the estimates 2, 5, 6, 7 and 8 in order to smooth sudden changes due to the imperfection of the respiratory signal with respect to the assumptions of each algorithm. The final reference RR was filtered as well. The re-sampling rate as well as the filter cutoff frequencies were heuristically chosen based on several trials.

In the filtering operations mentioned, forward-backward filtering was used in order to avoid phase shifts.

2.5. Experimental setup

The W-OSC tracking algorithm was applied to the RSA and RPA waveforms extracted according to Section 2.2 with parameters \( \beta = 0.8, \delta = 0.9 \) and \( \lambda = 0.9 \), which were found to allow for a good compromise between filter bandwidth and tracking adaptation. A larger \( \beta \) entails a narrower filter, however, a narrower filter has a longer adaptation delay. Mirroring was applied at the beginning of the signals in order to avoid border effects.

For comparison purposes, and in order to assess the benefits of using both RSA and RPA waveforms, the OSC tracking algorithm was used to estimate the RR from the RSA and RPA separately with the same parameters as the W-OSC algorithm as they function in a similar manner.

Fig. 1. RSA, RPA and the respiratory waveforms. Minutes 33–34 of the PhysioNet Fantasia fly08 record: (a) RSA waveform; (b) RPA waveform; (c) respiratory signal.

Errors were computed in two ways: (1) instantaneous; (2) window-based, where both the estimated RR and the reference RR were averaged in 60 s windows.

The mean absolute error (MAE) was computed as:

\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |\text{bpm}_{\text{estim}} - \text{bpm}_{\text{ref}}|
\]

and the error percentage (EP) was computed as:

\[
\text{EP} = \frac{100}{N} \sum_{i=1}^{N} \frac{|\text{bpm}_{\text{estim}} - \text{bpm}_{\text{ref}}|}{\text{bpm}_{\text{ref}}}
\]

where \( N \) is the length of the signals in the instantaneous error computation and the number of windows in which the window-based error is computed. \( \text{bpm}_{\text{estim}} \) is the estimate RR and \( \text{bpm}_{\text{ref}} \) is the reference RR.

3. Results

3.1. RR tracking on the RSA and RPA

An example of the RSA and RPA waveforms are illustrated in Fig. 1 along with the simultaneously recorded respiratory waveform. An oscillatory component corresponding to the respiration can be observed in both the RSA and RPA waveforms. However, this component is more regular in the RSA waveform than in the RPA waveform.

An example of the resulting instantaneous frequency estimate from the RSA and RPA, as well as the time evolution of the weights of the RSA and RPA waveforms are displayed in Fig. 2. The reference respiratory signal is shown as well. By visual inspection and by counting breaths, the estimate instantaneous RR meets the real respiratory activity. Furthermore, it is observed that in this example, the RSA weights are mostly dominant with respect to the RPA weights.

Over the data set, the average RSA weight was 0.57 ± 0.14 for the young subjects and 0.43 ± 0.15 for the elderly subjects and the average RPA weight was 0.4 ± 0.14 for the young subjects and 0.46 ± 0.16 for the elderly subjects.

3.2. Evaluation

Two examples of RR estimation using the W-OSC tracking algorithm on the RSA and RPA waveforms is illustrated in Fig. 3 for the two age groups. The RR estimates from the OSC tracking on the RSA and RPA waveforms separately and the reference RR are shown as
Fig. 2. Instantaneous frequency. Estimate of the W-OSC tracking on the RSA and RPA waveforms on the minutes 33–34 of the ECG recording from the PhysioNet Fantasia ffly08 record: (a) RR estimate (solid blue) and reference RR (dotted red) [bpm]; (b) weights of RSA (dashed green) and RPA (dot-dashed magenta) signals in the frequency update process; (c) reference respiratory signal. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Comparison of RR estimates. W-OSC tracking on the RSA and RPA waveforms (solid blue), OSC tracking on RSA separately (dashed green), OSC tracking on RPA separately (dot-dashed magenta) and reference RR (dotted red) [bpm] (a) on minutes 33–34 of the PhysioNet Fantasia ffly08 record; (b) on minutes 30–31 of the PhysioNet Fantasia ffly10 record. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

well. It is observed that the RR estimate using both the RSA and RPA waveforms (solid blue) follows the reference RR (dotted red) better than the estimates using the RSA or RPA waveforms separately (dashed green and dot-dashed magenta).

The W-OSC frequency tracking is a recursive method, therefore it presents an inherent adaptation delay. For each signal, this delay was estimated in a range of 1–50 samples in 10 min segments using the cross-correlation of the W-OSC RR and the reference RR. The average delay was 25 ± 12 samples (which corresponds to 12.5 ± 6 s) over the data set. Of course, in a real application, a pre-computed average delay must be introduced. Table 1 shows the error rates when the optimal delays for each computation window are compensated, both for instantaneous and window-based comparisons and Table 2 shows error rates when the average delay is compensated, also for instantaneous and window-based comparisons.

Table 1 shows that using both the RSA and RPA waveforms yield more accurate RR estimates than using either of the waveforms separately.

The errors of the W-OSC method were found to be statistically smaller (p-value < 0.001) than both the errors of the OSC method, for both age groups, using the Wilcoxon signed-rank test [25], with $H_0: \text{error}_{W-OSC} = \text{error}_{OSC}$ and $H_1: \text{error}_{W-OSC} < \text{error}_{OSC}$.

Table 2 shows that using the average delay instead of the optimal delays slightly decreases accuracy, as expected.

Histograms of instantaneous errors and window-based errors are presented in Figs. 4 and 5 respectively. In the case of instantaneous errors, 75% of the errors are below 2.5 bpm and in the case of window-based errors 85% of the errors are below 2.5 bpm. It can also be seen that naturally, the window-based errors are in general smaller than instantaneous values, as extreme cases are compensated in the process.

Table 1

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<td>11.88%</td>
<td>1.78</td>
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<td>W-OSC (RSA, RPA)</td>
<td>2.13</td>
<td>15.51%</td>
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<td>OSC (RSA)</td>
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<td>26.44%</td>
<td>2.67</td>
<td>19.55%</td>
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<tr>
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<td>8.44%</td>
<td>1.33</td>
<td>8.81%</td>
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<tr>
<td>Window-based</td>
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<td>12.01%</td>
<td>2.27</td>
<td>14.55%</td>
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<tr>
<td>W-OSC (RSA, RPA)</td>
<td>2.69</td>
<td>22.19%</td>
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<td>15.13%</td>
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Table 2

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<td>1.10</td>
<td>8.70%</td>
<td>1.39</td>
<td>9.25%</td>
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4. Discussion and benchmarking

The W-OSC tracking algorithm can follow the RR present in the RSA and RPA waveforms extracted from the ECG. It yields an instantaneous RR estimate in a continuous and automatic manner, without requiring special adjustments based on subject characteristics. Furthermore, sudden changes in the RR estimate because of abnormal beats or bad quality segments in the recordings are rectified within a limited number of iterations due to the adaptive nature of the algorithm, thus no special data-dependent pre-processing is needed, especially for irregular beats due to arrhythmias.

Through the weight distribution of the frequency component between the RSA and RPA waveforms, the W-OSC algorithm shows that the RR is better observed in the RSA waveform than in the RPA waveform for both age groups. The lower error rates of the tracking estimate from the RSA waveform with respect to the RPA estimate (Table 1) are coherent with this observation. While confirming similar conclusions drawn in [6], it is deduced that the RSA waveform better represents the respiration both for young and elderly subjects. However, the contrast between the RSA and RPA performance is lower for elderly subjects. The combination of the RSA and RPA using the W-OSC method yields better estimates than the OSC method with either one, in both age groups. It can be concluded that even though in general the RSA waveform is less informative with respect to the RR, it helps to refine the estimate with respect to an estimate only based on the RSA waveforms. Altogether, the algorithm performed similarly for both age groups.

Since the number of input signals in the W-OSC algorithm is not limited, the RPA waveforms extracted from more than one lead can be used to estimate the RR if multiple ECG leads are available. Using RPA waveforms from several leads theoretically will improve the estimate, as the RPA is often dependent on subject position and electrode movement.

This method is instantaneous by definition. However, due to the recursiveness of computations, a tracking delay inherent to the algorithm exists. This tracking delay is of the order of 25 samples. In a real application, an average delay over the data set can be used, which slightly decreases the accuracy of the estimate as seen in Tables 1 and 2. Furthermore, the forward-backward filtering of the RSA and RPA must be replaced by forward filtering. Experimentally, using forward filtering, the average error rate of the W-OSC estimate increases by only 1% and the estimated delay increases in average by 5 samples (2.5 s).

It must be noted that despite the effort to obtain an accurate reference RR from the respiratory signal, it was visually observed that this reference was not always coherent with the actual RR, which accounts for a portion of the errors.

**Benchmarking:** Results obtained in the present study can be compared to those of Orphanidou et al. [6], which were also presented on the PhysioNet Fantasia data set. The results of Vehkaoja et al. [7] relate to ECG recordings acquired with in-house electrodes placed in bed sheets and are not comparable. Furthermore the time-based methods in the latter study are not relevant to the present study.

It must be noted that Orphanidou et al. used the same AR-based frequency estimation method on both the ECG respiratory waveforms and the respiratory signal to derive estimated RRs and reference RRs. A degree of correlation may therefore exist between the derived RRs. Furthermore, a validity criterion was used to exclude up to 35% of the data.

In the present study, the OSC tracking method is excluded for reference estimation in order to avoid bias in the results. Due to the unavoidable differences in methodology and the different reference RR, the W-OSC estimate is not directly comparable to Orphanidou et al.’s. However, the order of magnitude of the presented error rates are similar, considering errors were computed over the entire data set in the present study.

Unlike the AR-based method of Orphanidou et al., the W-OSC method is an automatic and instantaneous tracking method, which is robust to abnormal beats and segments of bad quality data. The delay in the estimates of Orphanidou et al. is half the window length, which is 30 s. In the W-OSC tracking, the delay is estimated about 12.5 s. Furthermore, the W-OSC parameters are not based on the age group and the method can be used in real-time clinical situations.

5. Conclusions

This article presents an RR estimation technique using a multi-signal frequency tracking algorithm W-OSC on the respiratory RSA and RPA waveforms extracted from the ECG.

The tracking algorithm successfully estimated the RR from the two respiratory waveforms simultaneously. Furthermore, it was shown that using the two together is advantageous with respect to using either one separately. In addition, the algorithm performance was similar for young and elderly subjects.

In sum, the W-OSC method yields estimates which are comparable to the state-of-the-art in terms of accuracy. Furthermore, this tracking algorithm is recursive and instantaneous and introduces a smaller delay in computations compared to existing methods. It is automatic and does not require special adjustments based on subject characteristics. In addition, due to being recursive, the method is robust to abnormalities in the input signals. In conclusion, in contrast to current similar methods, it has the potential to be used in real-life situations, in which a single-lead ECG is available and an accurate, convenient, and inexpensive RR estimate is required in a continuous and automatic manner.

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References


