Real-Time Respiratory Rate Estimation using Imaging Photoplethysmography Inter-Beat Intervals

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Abstract

Imaging photoplethysmography (iPPG) has emerged as a contactless heart-rate monitoring technique. As the respiratory activity modulates the heart rate, we investigate the accuracy of iPPG in conveying the inter-beat variation due to the respiratory modulation of the heart rate. The instantaneous respiratory rate was estimated in real-time from the iPPG inter-beat variations with an algorithm based on a bank of short FIR notch filters. The comparison of the iPPG-based respiratory rate estimates to ECG-based estimates showed that the iPPG ones were only slightly less accurate in spite of the challenging conditions related to this contacless technique.

1. Introduction

Photoplethysmography (PPG) is a non-invasive technique to measure the blood volume changes due to heart beats by placing a small illumination and detection probe on the surface of the skin [1]. PPG systems produce a waveform representing blood volume changes caused by heart beats by measuring reflectance or transmittance of the light source on skin. This method has been shown to have many medical uses in the measuring of cardiovascular features such as heart rate, blood volume, oxygen saturation and even the respiration rate [1, 2].

Recently, it has been shown that PPG signals can be acquired in an entirely contactless manner, bringing forth the imaging photoplethysmography (iPPG) [3,4]. In iPPG systems, a visible-light or infrared video camera is placed in front of the subject at a distance of about $1\ m$ and captures skin tone changes (often in the face) in visible red, green, blue or infrared channels [5]. The variation of skin tone in time is then extracted from the pixels of each frame to produce the iPPG waveform.

The iPPG waveforms are often used for measuring cardiac features such as the heart rate [6]. However, they have also been used to estimate respiratory information directly [5, 7] or indirectly through the respiratory modulation of the inter-beat intervals. The latter is usually measured as the high frequency (HF) component of the heart rate variability (HRV) [8]. These studies employ spectral estimation or empirical mode decomposition, which require analyzing fixed bandwidths and/or fixed-length segments of the iPPG waveforms. Fixed bandwidths, namely the HF $0.15 - 0.4\ Hz$ band [9] are restrictive and result in erroneous estimations when respiratory rates are lower than $0.15\ Hz$ (9 breaths-per-minute) and fixed-length segments analysis is detrimental when considering real-time applications.

In the present study, we aim to estimate the respiratory rate from the iPPG signal (acquired in a contactless manner) by using the HRV, and a real-time-capable algorithm, without restrictive bandwidths. We used the instantaneous and real-time notch filter bank (NFB) algorithm [10, 11] to track the main frequency component of the HRV, which is the respiration. We compared our estimates to an estimate computed from the simultaneously recorded electrocardiogram (ECG), which is an accepted method of estimating the respiratory rate from cardiac activity [2, 12].

2. Methods

2.1. Data

Data were acquired from 12 subjects with two different protocols: respiratory and isometric hand-grip exercise. The subjects were supine, facing a RGB camera (20 frames-per-second, with artificial light) at a distance of $1\ m$ and wore ECG and respiration impedance belt Biopac® sensors. The respiratory protocol included a short apnea and an increase in the respiration rate from 5 to 15 bpm. The handgrip protocol alternated between rest and contraction periods of 15 to 30 seconds. All the subjects gave oral informed consent. In total, 96 minutes of data were acquired. All procedures were in accordance with the Declaration of Helsinki.

2.2. Processing

The iPPG waveform was obtained from the consecutive frames of the video by averaging pixels, in a region-of-interest extracted from the forehead of the subjects. The waveforms corresponding to the reflectance of each of the three RGB channels of red, green and blue were extracted separately [13]. Figure 1 shows an example of the ECG, iPPG (green channel only) and the reference respiration signals for a duration of 50 seconds during the hand-grip protocol.

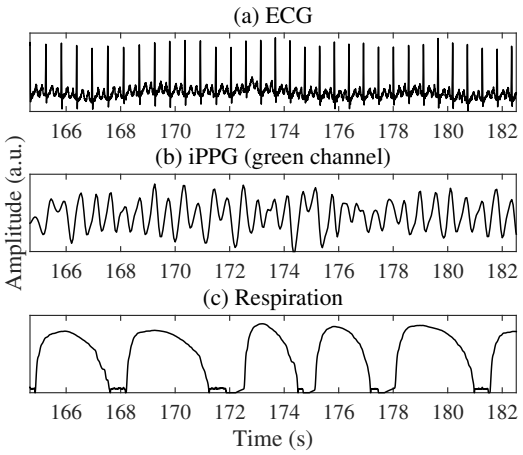

Figure 1. The (a) ECG, (b) iPPG and (c) reference respiration signals for one subject.

The instantaneous heart rate was computed by using the NFB algorithm [10, 11] with the three channels as simultaneous inputs. The mean heart rate was used to compute an appropriate inter-beat estimate for an extrema detection method to identify the heart beats in each channel. The inter-beat interval time series were created for each channel and all three series were re-sampled uniformly at a sampling rate of $4\ Hz$ using linear interpolation to avoid delays [14]. The re-sampled series were then band-pass filtered between 0.09 and $1\ Hz$, considered to be a large respiratory band comprising rates from 5.4 to 60 bpm. The respiratory rate was estimated using a modified version of the NFB algorithm with each of the three filtered iPPG inter-beat intervals as input. This modified version (compared to [10, 11]) comprises an extra pre-processing step in which a sliding window singular value decomposition algorithm [15] was applied to extract the principal component of the inter-beat interval series. This step was added as the wide-band filtering does not produce an oscillatory signal and thus might result in erroneous estimation through the classic NFB. For comparison, the respiratory rate was similarly estimated from the inter-beat intervals of the ECG.

The reference respiratory rate was computed from the reference respiratory signal acquired with the impedance belt. This signal was re-sampled uniformly at $4\ Hz$ and filtered similarly to the iPPG and ECG inter-beat intervals. Its instantaneous frequency was then estimated in three ways: (1) by identifying the largest peak of the Welch spectrum in sliding windows, (2) using the NFB, and (3) the average of (1) and (2).

The correlations between the iPPG and ECG inter-beat intervals were computed with Pearson's correlation coefficient. The errors of their smoothed ($4\ s$ windows) estimates were computed as the mean absolute difference, in bpm, between the estimates and the smoothed ($4\ s$ windows) reference rate. However, due to large artifacts in the iPPG, it was necessary to develop a quality index to identify portions of sufficient quality and to consider errors only in good quality segments. Indeed, in practice, one would prefer to know that the signals are of poor quality rather than being presented with a bad estimate. Therefore, an empirical quality index based on the amplitude of the iPPG signals was developed. To compute this quality index, an amplitude index was computed as the squared amplitude of the signal, divided by its variance (computed in a sliding window). The quality index was set to 1 where the amplitude index was smaller than ten times its interquartile range (computed in a sliding window) and 0 elsewhere. Portions with a quality index of 1 were retained when computing the correlations and the errors.

3. Results

The evaluation was performed on the entire length of the recordings over all parts of the protocols where the quality index was equal to 1. Among the three iPPG channels, the green channel yielded the inter-beat intervals most similar to the ECG ones with an average correlation of 0.65 ± 0.27 (all per-record correlations were significant with $p < 0.001$). The red and blue channels intervals yielded correlations with the ECG intervals below 0.5 as reported in Table 1. Therefore the green channel was retained for respiratory rate estimation.

Table 1. The mean correlations between the inter-beat intervals of the three iPPG channels and the ECG inter-beat intervals over all subjects.

	iPPG red	iPPG green	iPPG blue
ECG	0.04 ± 0.11	0.65 ± 0.27	0.38 ± 0.24

Figures 2 and 3 illustrate the iPPG and ECG respiratory rate estimates and the reference for two subjects. The iPPG quality index is shown as well. It can be seen that both estimates follow the steep increase in the reference for both subjects.

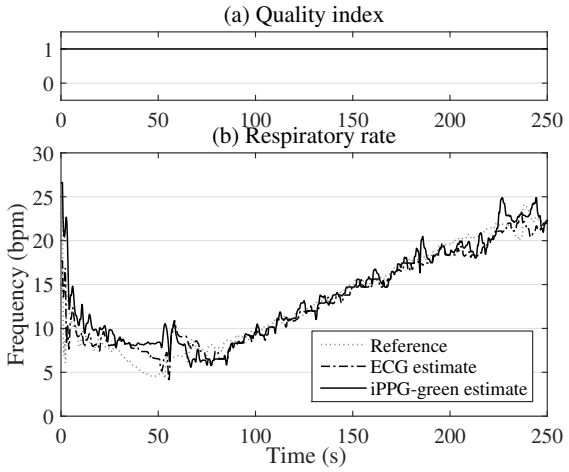

Figure 2. The iPPG-green (a) quality index and (b) respiratory rate, ECG-derived respiratory rate and reference for subject 1.

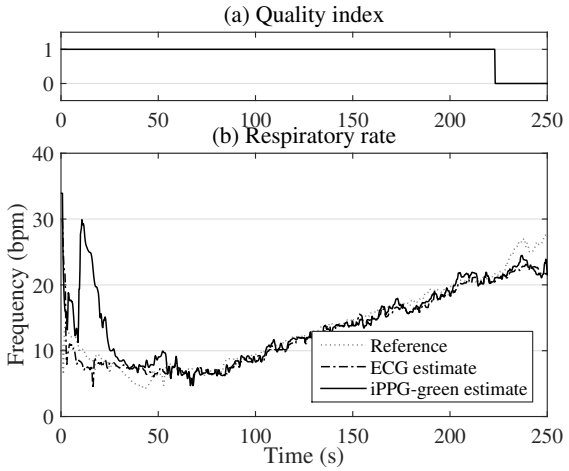

Figure 3. The iPPG-green (a) quality index and (b) respiratory rate, ECG-derived respiratory rate and reference for subject 2.

The errors between the estimates and the reference are reported in Table 2 for both the ECG and the iPPG. The difference between the ECG and iPPG estimates was 3.05 ± 1.69. The results were obtained on 88% of the data selected as having sufficient iPPG quality.

4. Discussion

Accuracy: The iPPG green channel yielded the inter-beat intervals most similar to the ECG ones, which corroborates earlier findings on the green wavelength being more suitable than red and blue to capture skin tone differences due to blood circulation because of its better absorption by hemoglobin [4]. The accuracy of the iPPG estimates was slightly less than that of ECG estimates. However, considering the challenging conditions of the iPPG acquisition and processing, the errors are still comparable to errors reported in the literature for estimating the respiratory rate from the ECG or the PPG [2, 12].

Table 2. The mean ($\pm$ standard deviation) error in breaths-per-minute of the ECG and iPPG green estimates compared to the reference over all subjects.

	Welch ref. (1)	NFB ref. (2)	mean ref. (3)
ECG	3.18 ± 2.94	2.86 ± 3.67	2.74 ± 3.25
iPPG	4.06 ± 1.88	3.49 ± 2.32	3.52 ± 1.99

Apnea detection: It has been shown that the respiratory influence on the inter-beat intervals subsists in a weaker form even without respiration [16], which means that apneas cannot be detected reliably via the inter-beat intervals. Therefore the subject of apnea detection with iPPG-derived inter-beat intervals was not addressed in the present study.

Limitations: In the present study, the subjects were in a supine position. In this position, most often the respiratory influence on the HRV is much stronger than the baroreflex activity, occurring at $0.1\ Hz$. Therefore, the main component of the HRV in all but one subject was the respiration. However, in an orthostatic position, the baroreflex activity would be larger than that of the respiration and the previous assumption would not hold.

Despite our best care and intentions, the reference respiratory rates were prone to errors and artifacts and do not represent a ground-truth.

5. Conclusion

In this study, the real-time respiration rate was estimated from the inter-beat variations of the contactless iPPG, acquired in visible light with a commercial video camera. The estimation errors are comparable to commonly reported errors for respiratory rate estimation from the ECG and the conventional contact-based PPG. Moreover, the data were recorded with varying respiration rates, which is challenging. These findings are encouraging in the use of iPPG for real-time contactless respiration rate monitoring.

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