Respiratory Rate Estimation Using the Photoplethysmogram: Towards the Implementation in Wearables

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Abstract

Respiratory rate (RR) is one of the most important physiological parameters. In recent years, the RR estimation from PPGs widely used in smart devices has been promoted. The effect of respiration on PPGs manifests in three ways: BW (intensity variation), AM (amplitude variation), FM (frequency variation). In addition to sophisticated RR estimation methods, reliable results can be achieved with simple and efficient methods implementable in wearables. The BW signal (respiratory signal estimation, RS) can be obtained by linear filtering of the PPG. The RR estimation is based on BW extremes (sBW), BW autocorrelation extremes (aBW) and their spectra (SBW, ABW). Estimation of the AM RS requires PPG extremes detection and interpolation. The RR estimation is based on extremes of the AM signal (sAM), its autocorrelation (aAM) and their spectra (SAM, AAM). The fusion of RR estimates leads to more robust results. To test the algorithms, the annotated BIDMC and CapnoBase Datasets were used. RR estimates were made for 60 s sections. The simplest and the most accurate method for both datasets is the RR estimation based on sBW (RsBW). The median absolute error was 0.40 (0.16-1.09 interquartile range 25-75th) bpm for the 60s window, mean absolute error was 1.42 bpm.

1. Introduction

Respiratory rate (RR) is one of the key physiological features. Resting RR ranges from 12 to 24 breaths per minute (bpm), i.e. 0.2-0.4 Hz. The whole range of RR is much greater. In spite of the modern technologies, the RR is often monitored manually [1]. Alternatively, uncomfortable methods such as impedance pneumography or inductance plethysmography can be used. In recent years, the trend is to estimate RR from electrocardiograms (ECG) and/or photoplethysmograms (PPG). PPG-based methods are of high potential thanks to the mass use of wearables with integrated PPG sensors. The effect of respiration on PPGs manifests in three ways: BW (respiratory-induced intensity variation), AM (respiratory-induced amplitude variation) and FM (respiratory-induced frequency variation).

In general, extraction of respiratory signal (RS) is based on two principles: filtration and features extraction. RS extraction using filtration can be performed by e.g. linear filters [2], decomposition using Wavelet Transform (WT) [3], decomposition using Empirical Mode Decomposition (EMD) [3], [4] or homomorphic filtration [5]. Some methods are based on extraction of features such as width, height and amplitude of PPG pulses [6], [7], [8]. These and other methods are reviewed in [1].

In this work, the algorithms for RR estimation based on drift, drift autocorrelation and amplitude variation derived from PPG signals are described. Proposed algorithms were tested on BIDMC [8] and CapnoBase [9] datasets in order to develop universal algorithm for both datasets. According to Charlton et al. [1], only these two publicly available datasets contain breath annotations. We focused on simple and efficient methods, which often lead to better results than sophisticated algorithms. For example, in the work of Lazazzera et al. [10] simple algorithms (BW, AM, FM) are more accurate than methods based on EMD or WT. Moreover, simple methods can be effectively integrated into wearables.

There are only a few works in which the described algorithms are tested on both datasets used in this work. Pimentel et al. [8] use autoregressive models. Sharma et al. [11] combine Ensemble EMD (EEMD) and Kalman filtration. Bian et al. [12] introduced two methods. The first one is referred to as Smart Quality Fusion and it is a combination of smart fusion [7] and quality fusion [13]. The second method is based on deep learning.

2. Methods

2.1. Data

Algorithms for PPG-based RR estimation were tested on two datasets – the BIDMC and the CapnoBase. RRs were estimated in one-minute segments of PPG signals. In both datasets, reference RR (annotations) provided by experts using impedance RSs are included. CapnoBase dataset includes 42 8-minute signals (sampling frequency f_s=300 Hz). Seven 1-minute segments were excluded from analysis due to missing annotations. BIDMC dataset includes 53 8-minute signals (sampling frequency f_s=125 Hz) and reference RR provided by two experts. From BIDMC dataset, 25 1-minute segments were excluded because the expert annotations of RR differ by more than 2 breaths per minute. As a reference RR, we used the mean of both experts' annotations.

2.2. Extraction of respiratory signals

Pilot experiments on both datasets showed that the best RR estimations were based on RS derived from drift (BW methods). FM based methods showed the lowest accuracy. For RS extraction, we used three methods (Figure 1):

a) PPG signal drift (sBW) – sBW signal is the simplest method of RS extraction. It is based on filtration using reasonable low-pass filter. Generally recommended cut-off frequency is 0.5 Hz. Nevertheless, final RR estimation is very sensitive to setting of the cut-off frequency and steepness of the filter. As a compromise for both datasets, low-pass FIR filter with $5f_s$ impulse response length was used. Filter was applied in forward and reverse directions. Resulting cut-off frequency f_c is 0.46 Hz (-3 dB).
b) PPG signal drift autocorrelation (aBW) – in some cases aBW is better than sBW for RR estimation.
c) PPG systolic peak amplitude variation (sAM) – this method is based on systolic peaks detection and spline interpolation. Drift was not filtered in this method, thus the extracted RS is a fusion (addition) of drift and interpolated systolic peaks.

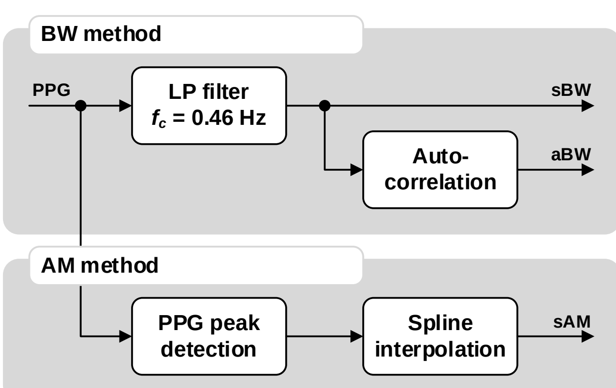

Figure 1. Designed RS extraction methods.

All RSs were downsampled at 25 Hz. Downsampling reduces the computational demand of the algorithm which is beneficial for the future usage in wearables.

2.3. Estimation of respiratory rate

In the **time domain**, RR estimation is based on the peak-to-peak distance of RS (Figure 2, upper part). The quality of the RS may vary depending on the quality of initial PPG signal. We found it depends on whether the RR will be estimated from positive or negative peaks of RS. For RR estimation we used extremes with higher absolute median value. Then we considered only extremes of selected polarity which were higher than the threshold. The setting of the threshold was based on the mentioned median value (50 % of median peaks).

For RR estimation, we used median of the detected peaks differences (instead of mean) to prevent influence of possible false negative and false positive detections of RS extremes. RR derived from RS sBW, aBW and sAM are denoted as RsBW, RaBW and RsAM, respectively. Fusions of RR estimations: median(RsBW, RaBW, RsAM), median(RsBW, RsBW, RaBW, RsAM) and mean of the two closest values from (RsBW, RaBW, RsAM) proved reasonable.

In **frequency domain**, we calculated spectra of extracted RS sBW, aBW and sAM (Figure 2, lower part). Spectra were calculated with frequency step of 0.3 bpm. As a RR we considered maximum of the spectra from 8.5 bpm. The reason is elimination of false extremes in lower frequencies. Estimated RRs are further denoted as RSBW, RABW and RSAM.

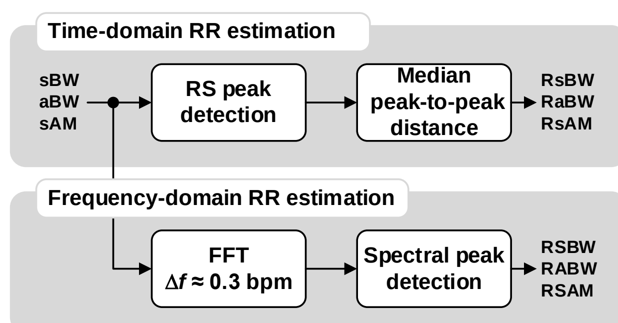

Figure 2. Designed RR estimation methods.

2.4. Evaluation of methods performance

For evaluation of RR estimation algorithms performance, we used Mean Absolute Error (MAE):

$$MAE = \frac{1}{MN-X}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|R(m,\,n) - R_{ref}(m,\,n)\right| ,$$

where R is estimated RR, R_{Ref} is reference RR, M is number of signals in dataset (M = 53 or 42), N is number of one-minute segments (N = 8). For X excluded segments, it was set: $\left|R(m,\,n) - R_{ref}(m,\,n)\right|$= 0.

In addition to MAE we calculated Median Absolute Error (MedAE) and inter-quartile range (25-75th percentiles) from all one-minute segments.

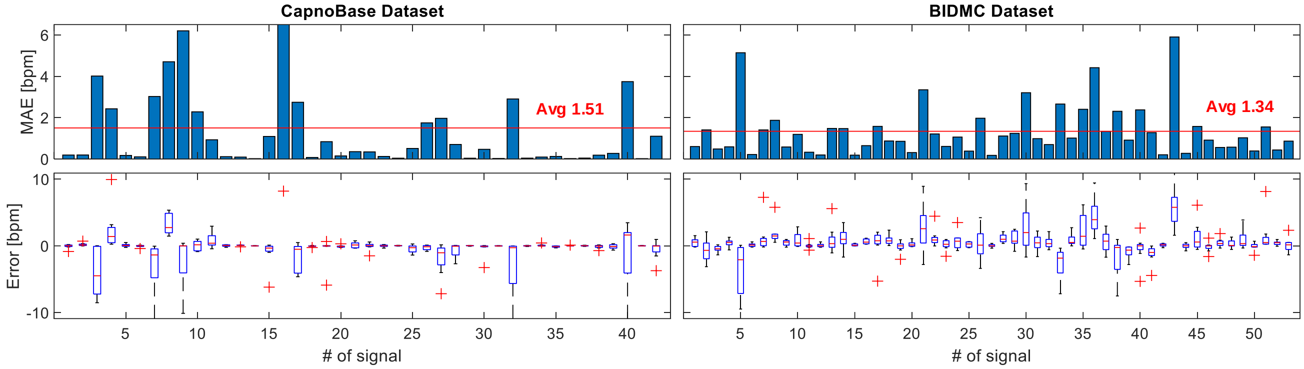

Figure 3. MAEs (upper) and boxplots (lower) of RR estimations using RsBW tested on each signal of both datasets – CapnoBase (left, 42 signals) and BIDMC (right, 53 signals). (Note: MAE for signal no. 16 from CapnoBase is 21.7 bpm).

3. Results

In Table 1, MAE values for each method of RR estimation and their fusions tested on CapnoBase (3rd column) and BIDMC (4th column) datasets are shown. Both datasets contain a total of 728 one-minute segments with reference RR values (399 segments in BIDMC and 329 segments in CapnoBase). Results for both datasets together are shown in the 2nd column of Table 1. The overall result was calculated as a weighted mean of results from each dataset. Weights were set according to the number of segments in each dataset: 0.55 for BIDMC dataset and 0.45 for CapnoBase.

Table 1. Results of RR estimation algorithms tested on CapnoBase and BIDMC. Window of 60 s length is used.

Methods	MAE, MedAE (25-75th percentiles) [bpm]		
	All	**CapnoBase**	**BIDMC**
(1) RsBW	1.42, 0.40 (0.16-1.09)	1.51, 0.13 (0.04-0.59)	1.34, 0.62 (0.25-1.50)
(2) RaBW	2.16, 0.27 (0.09-2.15)	2.90, 0.16 (0.05-3.05)	1.56, 0.36 (0.12-1.42)
(3) RsAM	2.05, 0.64 (0.23-2.43)	2.47, 0.30 (0.08-2.94)	1.70, 0.91 (0.35-2.01)
(4) RSBW	2.30, 0.35 (0.17-1.03)	2.98, 0.38 (0.20-0.80)	1.75, 0.32 (0.14-1.22)
(5) RABW	2.38, 0.33 (0.15-1.17)	3.13, 0.38 (0.20-1.00)	1.77, 0.28 (0.11-1.30)
(6) RSAM	2.47, 0.41 (0.22-1.88)	2.76, 0.37 (0.20-1.04)	2.24, 0.44 (0.24-2.56)
median (1,2,3)	1.51, 0.35 (0.12-1.08)	1.88, 0.13 (0.04-1.78)	1.20, 0.53 (0.19-1.32)
av2nearest (1,2,3)	1.50, 0.34 (0.13-0.98)	1.84, 0.13 (0,05-0.69)	1.22, 0,51 (0,20-1.22)
median (1,1,2,3)	1.44, 0.39 (0.15-1.13)	1.68, 0.13 (0.04-0.78)	1.24, 0.60 (0.24-1.41)
median (1,2,4)	1.82, 0.25 (0.07-1.19)	2.44, 0.16 (0.04-1.31)	1.31, 0.32 (0.10-1.10)

From Table 1 follows, that one of the best methods applied on both datasets is the RsBW (based on the PPG signal drift). Similar results have the fusion methods, but their computational demand is much higher.

Upper pictures in Figure 3 show MAEs of RR estimations using RsBW method tested on both datasets (CapnoBase on the left, BIDMC on the right). Lower pictures show boxplots of errors from 8 one-minute segments of each signal from both datasets (CapnoBase on the left, BIDMC on the right). The highest MAE of 21.7 bpm occurred in signal no. 16 from CapnoBase. It is probably caused by the high reference value (around 40 bpm, i.e. 0.67 Hz) which cannot be detected by our algorithm because it uses low-pass filter with cut-off frequency of 0.46 Hz. Omitting this signal would significantly decrease the MAE of RsBW, RaBW and fusions (tested on CapnoBase).

4. Discussion

The aim of the work was to develop simple, efficient and accurate RR estimation algorithm which has potential to be implemented in wearables. Such algorithm should be as much universal as possible to work on both datasets.

In Table 2, the results of other authors are shown. We selected only those authors, who tested their algorithms on both datasets (CapnoBase and BIDMC). In comparison with Pimentel et al. [8], our results are always better (for all algorithms and both datasets). In comparison with Sharma et al. [11], our results are better for all algorithms tested on BIDMC and for RsBW and the first three fusions tested on CapnoBase. Our results surpass the results of both algorithms of Bian et al. [12]. Very encouraging is the fact that our simple algorithms are more accurate than deep-learning based algorithm [12] which is much more computationally demanding.

Table 2: Results of other authors' RR estimation algorithms tested on CapnoBase and BIDMC datasets. In methods [8] and [11], window of 64s length is used.

Methods	CapnoBase	BIDMC
	MedAE (25-75th percentiles) [bpm]	
Autoregressive models [8]	1.9 (0.3-3.4)	2.7 (1.5-5.3)
EEMD+Kalman filter [11]	0.1 (0-3.4)	1.1 (0.2-2.9)
	MAE ± std, (25-75th percentiles) [bpm]	
Smart quality fusion [12]	2.6 ± 0.4, (2.3-2.8)	
Deep learning [12]	3.8 ± 0.5, (3.3-4.2)	

The MAE also varies depending on the subject's RR. In the normal range of RR, the MAE is around 1 bpm, while outside this range the MAE rises as can be seen in Figure 4.

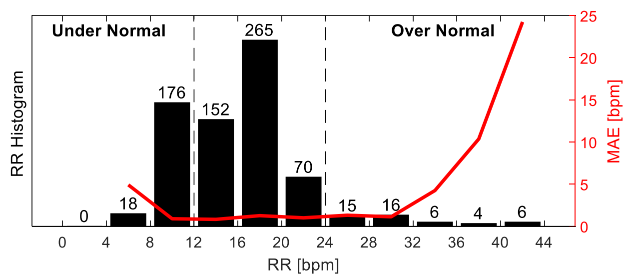

Figure 4. Red: Dependence of MAE on RR for RsBW. Black: RR histogram of subjects (includes both datasets). Dashed lines indicate RR range considered normal.

5. Conclusion

We proposed six algorithms and four fusions for RR estimation from PPG signal. All the algorithms were tested on two datasets – CapnoBase and BIDMC including altogether 728 one-minute segments of PPG signal. The performance of majority of proposed algorithms is better than the results of other authors. The simplest and the most accurate method is the RR estimation based on sBW (RsBW). The MedAE was 0.40 (0.16-1.09 interquartile range 25-75th) bpm for the 60 s window, MAE was 1.42 bpm. Proposed algorithms are simple, fast, efficient and accurate. They can work real time (with buffer) and they use only PPG signal which is nowadays sensed by majority of wearables. Due to these advantages, proposed algorithms are suitable for implementation in wearables.

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