Breathing Rate Estimation Methods From PPG Signals, on CAPNOBASE Database

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Abstract

In the present work, a comparative study of different breathing rate estimation methods from PPG signal is proposed. The aim of this comparative study was to select the best algorithm, for respiratory rate estimation, among those already proposed in literature. The following methods were implemented and tested on the free access CAPNOBASE database, by segmenting the PPG signal in 32s and in 64s windows: empirical mode decomposition (EMD), EMD combined with principal component analysis, wavelets analysis, respiratory-induced intensity variation analysis (RIIV), respiratory-induced amplitude variation analysis (RIAV) and respiratory-induced frequency variation analysis (RIFV). Performances were then compared to six different methods already tested on CAPNOBASE. The best performances were reached by using respiratory induced signals over the IMFs and wavelets. The RIAV signal exceeded other methods in both 64s and 32s signal segments. Only the algorithm proposed by Khreis et al, using Kalman filtering and a data fusion approach outperformed the presented methods for breathing rate estimation from PPG.

1. Introduction

Breathing rate (BR) is defined as the number of breaths in a period of one minute and its estimation is important in predicting signs of pneumonia. When a person is at rest, it has an average rate between 12-20 breaths per minute. Respiratory measurement is usually performed by equipment as spirometers, pneumotachometers and capnographs. This equipment is not available in all situations, then arises the need to extract this information from other vital signs such as electrocardiogram (ECG) and photoplethysmogram (PPG). In mobile monitoring if an ECG signal is not available, at minimum, a PPG is available; the purpose of this work is to compare various methods proposed in literature, in order to select the best to integrate in a wearable device. From the PPG signal it is possible to extract the pulse rate (PR) and also information about the respiration rhythm. Recently, a study representing the state-of-the-art was reported by Khreis et al. [1] and tested on the public database CAPNOBASE [2]. The study implemented a Kalman smoother (KS) filter which respiratory induced time series with three respiratory quality indices. However in [1], other algorithms present in literature but not tested on the same database, were not taken into consideration. In order to explore different techniques, this article presents a performance comparison, on the CAPNOBASE database, of different breathing rate estimation methods, already proposed in literature. Four different algorithms have been implemented. These algorithms use respectively empirical mode decomposition (EMD) [3], EMD combined with principal component analysis (PCA) [4], wavelets decomposition [5] and three PPG derived time-series: respiratory-induced intensity variation (RIIV), respiratory-induced amplitude variation (RIAV) and respiratory-induced frequency variation (RIFV). Then a quadratic time-frequency function has been used for spectral analysis.

2. Materials and methods

2.1. Database

The algorithms were tested on the CAPNOBASE TBME RR benchmark dataset [2]. The database contains 42 eight-minutes recordings, sampled at 300 Hz, of patients under anesthesia in a clinical context. In addition to PPG signals, the dataset presents also ECG waveforms and respiratory signals annotated by experts, such as inhaled and exhaled carbon-dioxide (CO_2).

2.2. Methods

The BR estimation analysis has been carried out on segments of 32 and 64s without windows overlapping to conform to literature results. Moreover, only those signal segments whose respiration rate annotations were in the range 0-0.5 Hz, were considered to simulate a real-life scenario of adults at rest. The flowchart of the breathing rate estimation algorithms, is represented in Fig. 1 and each of these algorithms is fully explained in the following sections.

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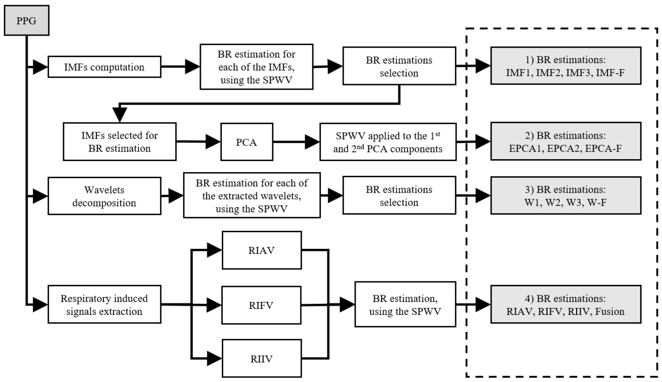

Figure 1: Breathing rate estimation algorithms flowchart

The PPG signal was windowed and an artifact detector based on Hjorth parameters [6] was implemented. Signal windows containing artifact segments were rejected as in [7]. Then, a time series carrying BR information was extracted from the PPG signal, using different approaches as described in the following.

2.2.1. Empirical mode decomposition

EMD is defined by a process called sifting, that decomposes the signal into a set of intrinsic mode functions (IMF)[8]. The IMFs were computed in the frequency bands 0-0.5 Hz and sifting stopped when the current sift relative tolerance (a Cauchy-type stop criterion) was less than 0.2. The EMD was applied to the PPG signal segments and for each of the segment the IMFs were extracted. Then, the respiration frequency was computed for each of the extracted IMFs, by using the SPWV distribution as previously described. Afterwards, these frequencies were sorted in descending order and the last two were discarded because they did not contain any respiration information. From the remaining, the last three BR estimations were retained, and called respectively *IMF1*, *IMF2* and *IMF3*. Finally, a new respiratory rate estimation, called IMF Fusion (*IMF-F*), was performed by averaging the two closest values among the three BR estimated.

2.2.2. Empirical mode decomposition with principal component analysis

Following the work in [4], the PCA was computed on the 3 IMFs, previously selected from the EMD algorithm. PCA converts the set of IMFs observations into a set of linearly uncorrelated variables, called principal components (PCs), ordered so that the first PC retains most of the variation present in the IMF signals, and so on. Once the PCs were obtained, the first and the second PCs were used to estimate the BR, by applying the SPWV: the resulting respiration rate estimations were named *EPCA1* and *EPCA2*. Finally, a new BR estimation, called PC Fusion (*EPCA-F*), was performed by averaging the two PC estimated BR.

2.2.3. Wavelet decomposition

To extract the respiration waveform, another solution consists in using the discrete wavelets transform (DWT). It is an iterative technique that decomposes the signal into different scales, originating the wavelets decomposition tree. In the present study, the discrete wavelets decomposition was performed on the PPG signal segments, with the Daubechies 1 wavelet as in [5]. All the details are extracted from the segments, up to level 12. The SPWV was then applied, as previously described, on each of the extracted details and afterwards, the BR was estimated. The three maximum respiration rates were called *W1*, *W2* and *W3*, and a new BR estimation, called wavelet fusion (*W-F*), was performed by averaging the two closest values of the three estimated BR.

2.2.4. Respiratory induced signals

PPG signal features, like peaks and troughs, may be used to derive time-series signals, carrying breathing information: the extracted time series are listed below:

- RIIV: the respiratory-induced intensity variation, corresponds to the time-series of amplitudes of the PPG peaks. This effect is due to variations in intrathoracic pressure, leading to a change in the baseline of perfusion, which is shown as a change in the absolute amplitude of the PPG peaks [9, 10].
- RIAV: the respiratory-induced amplitude variation is defined to be the difference in amplitude, between the corresponding peak and trough. The RIAV effect is caused by changes in cardiac output, which have a direct consequence in the quantity of refill in the vessels at the periphery [9, 10].
- RIFV: the respiratory-induced frequency variation is determined by the time between successive PPG pulses, and reflects the change in the value of the instantaneous PR during the respiratory cycle. It is known as respiratory-sinus arrhythmia (RSA), regulated by the vagal nerve [11].

These three time-series were computed from the PPG signal, detrended by removing its mean value. Then, the BR was estimated from each of the induced signals, by using the SPWV, as previously described. A new respiratory rate estimation, called Fusion (*Fusion*), was performed by averaging the two closest values of the three estimated BR.

2.2.5. Breathing rate estimation

To extract the BR information, a time-frequency analysis was performed using the Cohen's class quadratic time-frequency distribution, implementing the Smooth-Pseudo

Wigner Ville (SPVW). The parameters of the quadratic time-frequency distribution were the same used in [12]. For smoothing in time and in frequency, a Hamming window of 30s was used. Before applying the SPWV, signals were resampled at 2 Hz, by cubic spline interpolation, and detrended by subtracting the mean value. To get the signals analytic function, the Hilbert transform was computed. Then, for each frequency band of the signal, the total spectral power was estimated, and the frequency band carrying most of the power, was selected as the one corresponding to the BR.

3. Results

The methods validation was performed by computing for each signal segment, the absolute error between the estimated BR and the reference, as proposed in [1] for a direct comparison, in breath per minute (bpm), using the formula:

$$e_i = \left| BR_i^{ref} - BR_i^{est} \right| \quad [bpm] \tag{1}$$

The absolute errors box-plots are visualized in Fig. 2, whereas Table 1, for each box-plot, reports the statistical values of median, mean, interquartile range (IQR), 25th (Q1) and 75th (Q3) percentile. These values are obtained evaluating breathing segments in the range 0-0.5 Hz. For a literature comparison Table 2 records the results of other methods, tested on the same database and proposed by Khreis in [1], Pimentel in [11], Karlen [10], Flemming [13], Shelly [14] and Nilson [15].

4. Discussion

From the results it is possible to assess that the best performances were reached by using respiratory induced signals over the IMFs and wavelets. RIAV respiratory induced signal appears as a good compromise (in the 64s window, it has a similar behavior to the RIIV approach) and could be elected as the most performing, because it visibly is a good compromise with respect to other methods, in both 64s and 32s signal segments. In this case, the median of the absolute breathing rate error was of 0.57 (0.19-1.71 interquartile range 25th-75th) for the 32s window, and of 1.62 (0.09-1.71) for the 64s window in the 0-0.5Hz frequency range.

The presented methods outperformed the algorithms tested on the same database where the use of the SPWV distribution revealed to play a key role into algorithms performances as the comparison showed. The only study outperforming the present, is the work implemented in [1] using a KS filter on PPG respiratory induced time series. In the latter, the median of the absolute error was of 0.5 (0.2-1.1 interquartile range 25th-75th) for the 32s window, and of 0.2 (0.1-0.9) for the 64s window. The main difference between the proposed approach and the KS filter stands on the fact that the Kalman filter exploits previous BR estimations to make a new one, while this memory in the algorithm was not present in the proposed study.

5. Conclusion

After exploring the performances of ten approaches for PPG breathing rate estimation on the CAPNOBASE database, it can be concluded that the PPG respiratory-induced amplitude variation carries most of the respiration rate information. Additionally, the most suitable method for PPG breathing rate estimation revealed to be the one developed by Khreis et al. and the presented results encourage the implementation of the proposed methodologies in wearable devices.

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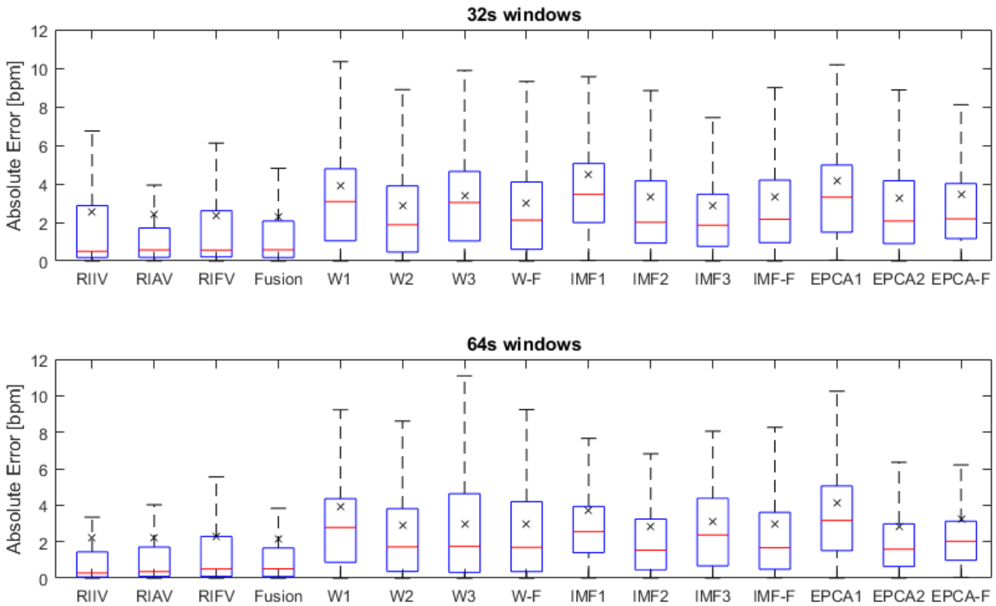

Figure 2: Absolute errors box-plots computed for the different algorithms used to estimate the breathing rate.

Table 1: Absolute errors statistics in [bpm], for boxplots in Fig. 2

	32s														
	RIIV	**RIAV**	RIFV	Fusion	W1	W2	W3	W-F	IMF1	IMF2	IMF3	IMF-F	EPCA1	EPCA2	EPCA-F
Median	0,50	**0,57**	0,56	0,58	3,08	1,88	3,04	2,12	3,46	2,01	1,86	2,16	3,30	2,08	2,18
IQR	2,69	**1,52**	2,40	1,89	3,73	3,44	3,61	3,49	3,07	3,22	2,71	3,24	3,48	3,25	2,86
Q1	0,18	**0,19**	0,21	0,18	1,05	0,46	1,04	0,60	1,99	0,93	0,75	0,95	1,49	0,91	1,16
Q3	2,87	**1,71**	2,61	2,07	4,78	3,90	4,65	4,10	5,05	4,15	3,46	4,19	4,97	4,16	4,02
Mean	2,57	**2,45**	2,35	2,30	3,94	2,89	3,37	3,02	4,49	3,29	2,85	3,30	4,15	3,27	3,42
	64s														
Median	0,28	**0,36**	0,50	0,51	2,78	1,71	1,75	1,69	2,55	1,53	2,37	1,67	3,17	1,58	2,02
IQR	1,38	**1,62**	2,19	1,56	3,48	3,45	4,31	3,84	2,53	2,78	3,70	3,12	3,54	2,33	2,14
Q1	0,06	**0,09**	0,10	0,09	0,87	0,36	0,31	0,36	1,40	0,46	0,68	0,48	1,51	0,64	0,98
Q3	1,44	**1,71**	2,29	1,65	4,36	3,81	4,63	4,20	3,93	3,24	4,38	3,60	5,05	2,98	3,12
Mean	2,24	**2,24**	2,26	2,18	3,94	2,87	3,00	2,96	3,70	2,80	3,11	2,95	4,14	2,86	3,26

Table 2: Results comparison in [bpm], of methods tested on the same CAPNOBASE database

	32s					
	Khreis (2019)	Pimentel (2016)	Karlen (2013)	Flemming (2007)	Shelly (2006)	Nilsson (2000)
Median	0,50	1,50	1,20	1,40	4,50	10,50
IQR	0,90	3,00	2,90	3,30	9,70	7,80
Q1	0,20	0,30	0,50	0,50	0,80	4,90
Q3	1,10	3,30	3,40	3,80	10,50	12,70
	64s					
Median	0,20	1,90	0,80	1,10	2,20	10,20
IQR	0,80	3,10	2,40	3,10	8,10	7,60
Q1	0,10	0,30	0,30	0,40	0,20	4,80
Q3	0,90	3,40	2,70	3,50	8,30	12,40

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