Accuracy of Kubios HRV software respiratory rate estimation algorithms

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Abstract

Respiratory rate (RESP) is one of the vital signs that is widely used in a range of clinical settings. Respiration can be directly measured using various techniques, but RESP can also be estimated from electrocardiogram (ECG) or RR interval recordings. The validation of two RESP algorithms, available in a commercial HRV analysis software (Kubios HRV Premium, ver. 3.5), is presented. Both resting HRV recordings ($N = 262$) and exercise recordings ($N = 123$) were used in validation. The observed correlation with true RESP was strong to moderate in resting HRV recordings ($R = 0.892$ vs. $R = 0.676$) and strong in exercise HRV recordings ($R = 0.922$ vs. $R = 0.881$), with higher correlations corresponding to the estimates that used both ECG and RR data in RESP estimation. Overall, the accuracy of the algorithm which utilized both ECG and RR data for RESP estimation was better with an average bias of 0.021 Hz and accuracy (error SD) of 0.062 Hz.

1. Introduction

Respiratory rate (RESP) is an important physiological parameter used in a range of clinical settings for the identification of abnormalities [1, 2]. It is also a key parameter in exercise physiology since it is a strong marker of physical effort, responding rapidly to variations in workload [3].

Additionally, RESP is an important parameter for heart rate variability (HRV) analysis. That is, respiration induces observable fluctuations in HRV time series. During inspiration, the chest cavity expands, lowering intrathoracic pressure and arterial blood pressure, which leads to a suppression of parasympathetic nervous activity and an increase in heart rate (HR). During expiration, the volume of the chest cavity decreases, increasing intrathoracic pressure and arterial blood pressure, which increases parasympathetic nervous activity and decreases HR. This breathing-induced component of HRV is also known as respiratory sinus arrhythmia (RSA), and it can be reliably assessed only if the RESP is simultaneously monitored with HRV [4, 5].

RESP can be estimated from electrocardiogram (ECG) or photoplethysmogram (PPG) recordings, since both are influenced by respiration. For example, when the volume of the chest cavity changes according to respiration, intrathoracic electrical conductivity also changes, which modulates ECG amplitude. The method of extracting the respiration component from the ECG signal is called ECG-derived respiration (EDR). Additionally, since respiration modulates HR, the RESP can also be estimated by analyzing these respiration-induced oscillations from beat-to-beat RR interval time series data. The first algorithms for the estimation of RESP from ECG or PPG recordings were proposed in [6] and [7]. Since then, several other algorithms for RESP estimation have been proposed. Overall, ECG-based algorithms have been observed to perform better than PPG-based algorithms, with the best algorithms reaching an accuracy (95% limits of agreement) of ±4.7 breaths/min, which corresponds to 0.08 Hz [8].

This paper provides validation of two RESP estimation algorithms which are available in a commercial software (Kubios HRV Premium, ver. 3.5, Kubios Oy, Kuopio, Finland). The algorithms are validated using resting and exercise recordings. The first algorithm estimates RESP by using both ECG waveform and RR interval time series data, whereas the second algorithm uses only RR data in RESP estimation.

2. Methods

2.1. Measurements

Two types of datasets were used for the current study: 1) HRV data measured at rest and 2) HRV data measured during a cardiopulmonary exercise test (CPET). Resting HRV data were available from 262 participants, and the length of the measurements was 5 minutes. CPET measurements were available from

123 participants, exercise tests were performed using a bicycle ergometer, and the length of the recordings varied from 20 to 47 minutes. Each CPET measurement consisted of a resting period, an exercise period with increasing load until volitional exhaustion, and a recovery period. The resting periods of the CPET data were used as part of the resting HRV data.

Respiration was measured using either an impedance-based measurement, a thoracic piezoresistive band, or a spirometer providing a continuous ventilatory flow signal. ECG data were recorded using different devices (including Biopac and Bittium Faros). Lead II ECG data were used for RESP estimation.

2.2. Respiratory rate estimation

The true RESP was extracted from the respiration measurement by counting the number of respiratory cycles within a time period. The 5-min resting HRV recordings were analyzed as one sample, thus providing an average RESP within the 5-min resting period. During the exercise test, however, RESP is expected to increase as a function of the exercise intensity. Therefore, the exercise data were processed at 30-sec intervals to yield fairly instantaneous RESP values throughout the exercise test. RESP values were presented in Hz, where 0.0167 Hz corresponds to 1 breath/min (see Table 1).

Table 1. Correspondence between RESP values in Hz and breaths/min.

Hz	0.1	0.15	0.2	0.25	0.3	0.35	0.4
breaths/min	6	9	12	15	18	21	24

To extract QRS complex times and RR interval time series data, the ECG data were processed using Kubios HRV Premium (ver. 3.4) software [9]. In the RESP estimation, we analyzed respiration-induced changes in the ECG amplitude as well as respiration-induced changes in RR interval time series. Two algorithm were developed:

Algorithm 1: Both ECG and RR data are used in RESP estimation. The algorithm can be utilized only when raw ECG data are available.

Algorithm 2: Only RR data are used in RESP estimation. The algorithm can be utilized for all HRV recordings with beat-to-beat time interval data (RR or IBI data).

2.3. Statistical analysis

The Pearson correlation coefficient was computed to study the correlation between the estimated and true RESP. The error in RESP estimation was computed as the difference between the estimated and true RESP (Estimated RESP − True RESP). Error statistics were presented using the mean, standard deviation (SD), and 95% confidence interval (CI) of the mean.

3. Results

The accuracy of the RESP estimates for resting HRV data are illustrated in Figure 1. The correlation coefficient between the true and estimated RESP was higher for algorithm 1, which used both ECG and RR data in RESP estimation when compared to algorithm 2, which used RR data only ($R = 89$ vs. $R = 0.68$). The average error between the estimated and true RESP values was approximately 0.01 Hz for both algorithms (which corresponds to less than 1 breath/min), but the error SD was lower for algorithm 1 (0.031 Hz vs. 0.050 Hz).

The accuracy of the RESP estimates for exercise HRV data are illustrated in Figure 2. The correlation coefficient was higher for algorithm 1 compared to algorithm 2 ($R = 92$ vs. $R = 0.88$). The average error (bias) was somewhat higher for algorithm 1 when compared to algorithm 2 (mean error 0.020 vs. 0.003 Hz). However, the standard deviation of the error between true and estimated RESP was lower for algorithm 1 (0.062 Hz vs. 0.074 Hz). Overall, the correlation coefficients were higher for exercise HRV data when compared to resting HRV data.

Finally, error statistics for RESP estimates were computed for different RESP bins in order to evaluate how the accuracy of the estimates is affected by different levels of RESP. Both resting and exercise HRV data were used for these analyses, and the results are summarized in Table 2 and Figure 3. On average, the mean absolute error of RESP estimation was 0.021 Hz for algorithm 1 and 0.029 Hz for algorithm 2. Considering the RR data-based algorithm (algorithm 2), the mean error was notably higher when the true RESP was above 0.7 Hz (above 42 breaths/min). Standard deviation of the error between true and estimated RESP was, on average, 0.062 Hz for algorithm 1 and 0.080 Hz for algorithm 2. The error SD was highest when RESP was between 0.8 and 0.9 Hz, which is at least partly explained by the low number ($N = 45$ or $N = 41$) of data segments available. In addition, both algorithms overestimate low (0.1-0.2 Hz) respiratory rates.

4. Discussion and conclusions

The accuracy of two RESP estimation algorithms were validated. Algorithm 1 estimated RESP by analyzing respiration-induced changes in ECG waveform

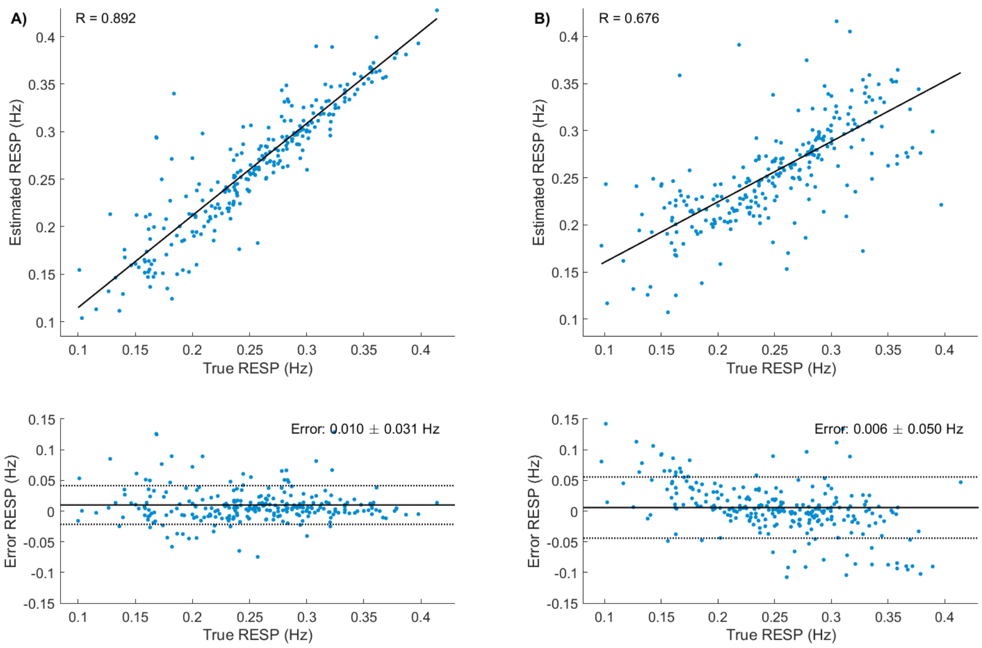

Figure 1. RESP estimates for resting HRV data when A) both ECG and RR data were used (algorithm 1) and B) only RR data were used (algorithm 2) in estimation.

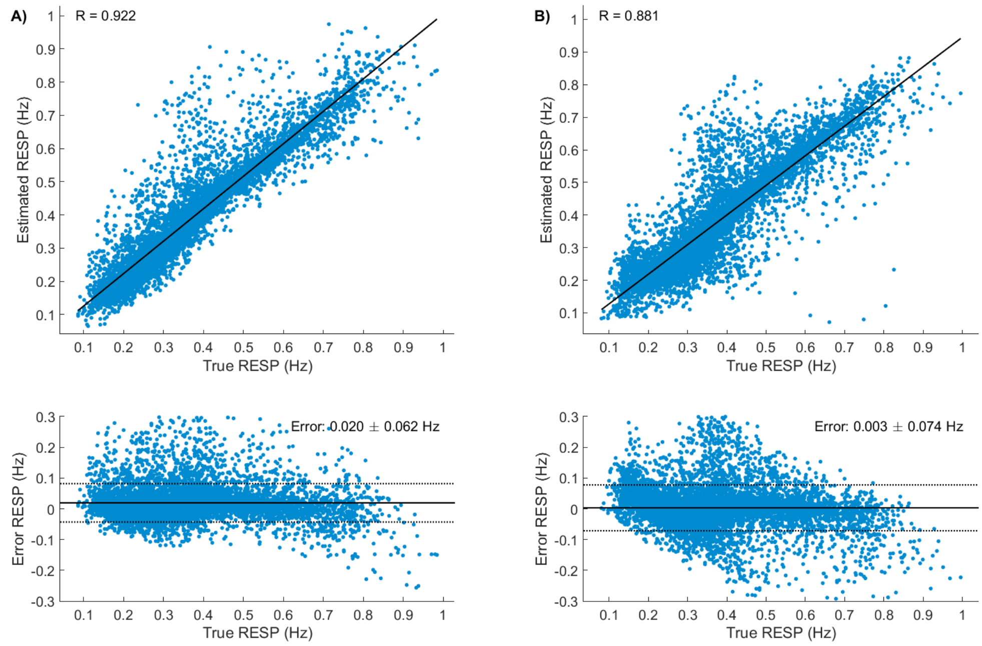

Figure 2. RESP estimates for exercise HRV data for A) algorithm 1 and B) algorithm 2.

and in RR interval time series data, whereas algorithm 2 utilizes RR interval time series data only in RESP estimation. Algorithms 1 and 2 showed a strong to moderate correlation with true RESP in resting HRV data ($R = 0.892$ vs. $R = 0.676$) and strong correlation in exercise HRV data ($R = 0.922$ vs. $R = 0.881$).

Table 2. Error statistics for RESP estimation algorithms. Estimates based on both ECG and RR data (algorithm 1) vs. estimates based on RR data only (algorithm 2). N is the number of data segments at each true respiratory rate bin (bins from 0.1 to 0.9 Hz). Error statistics are presented as mean, 95% CI of the mean and SD.

	Algorithm 1: RESP estimate (ECG+RR data) Error RESP (Estimated – True) [Hz]				Algorithm 2: RESP estimate (only RR data) Error RESP (Estimated – True) [Hz]			
True RESP	N	Mean	95% CI	SD	N	Mean	95% CI	SD
0.1-0.2 Hz	190	0.0341	[0.0269, 0.0412]	0.0502	183	0.0493	[0.0416, 0.0570]	0.0528
0.2-0.3 Hz	964	0.0150	[0.0115, 0.0185]	0.0553	940	0.0044	[0.0019, 0.0070]	0.0400
0.3-0.4 Hz	1366	0.0189	[0.0155, 0.0223]	0.0634	1376	-0.0010	[-0.0047, 0.0028]	0.0707
0.4-0.5 Hz	640	0.0383	[0.0328, 0.0437]	0.0697	630	0.0121	[0.0043, 0.0200]	0.1000
0.5-0.6 Hz	401	0.0255	[0.0195, 0.0314]	0.0604	369	0.0067	[-0.0005, 0.0139]	0.0701
0.6-0.7 Hz	245	0.0120	[0.0057, 0.0182]	0.0495	255	0.0098	[-0.0183, -0.0012]	0.0694
0.7-0.8 Hz	150	-0.0051	[-0.0158, 0.0057]	0.0666	158	-0.0463	[-0.0603, -0.0324]	0.0889
0.8-0.9 Hz	45	-0.0215	[-0.0467, 0.0037]	0.0839	41	-0.1032	[-0.1494, -0.0569]	0.1465

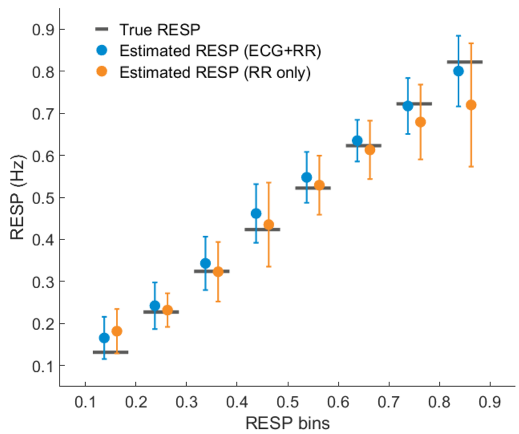

Figure 3. Accuracy of RESP estimates for exercise HRV data for A) algorithm 1 and B) algorithm 2.

Resting HRV data were available from 262 participants (one RESP value per participant), whereas exercise data were processed at 30-sec intervals, thus yielding on average 66 RESP values per participant (8063 RESP values in total from 123 participants). In addition, wider range of RESP values were naturally available from the exercise data.

In conclusion, the bias and accuracy of both RESP estimation algorithms was good. The average bias of algorithms 1 and 2 were both less than 0.03 Hz (0.021 Hz vs. 0.029 Hz), which corresponds to an average bias of less than 1.8 breaths/min. The accuracy of algorithm 1 was better on average compared to algorithm 2 (error SD: 0.062 Hz vs. 0.080 Hz). Algorithm 1, which used both ECG and RR interval data in RESP estimation, performed better at high RESP values which may be explained by the decreased or almost vanished HRV during high-intensity exercise.

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