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PAPER

Accelerometer-based estimation of respiratory rate using principal component analysis and autocorrelation

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Abstract

Objective. Respiratory rate (RR) is an important vital sign but is often neglected. Multiple technologies exist for RR monitoring but are either expensive or impractical. Tri-axial accelerometry represents a minimally intrusive solution for continuous RR monitoring, however, the method has not been validated in a wide RR range. Therefore, the aim of this study was to investigate the agreement between RR estimation from a tri-axial accelerometer and a reference method in a wide RR range. *Approach.* Twenty-five healthy participants were recruited. For accelerometer RR estimation, the accelerometer was placed on the abdomen for optimal breathing movement detection. The acquired accelerometry data were processed using a lowpass filter, principal component analysis (PCA), and autocorrelation. The subjects were instructed to breathe at slow, normal, and fast paces in segments of 60 s. A flow meter was used as reference. Furthermore, the PCA-autocorrelation method was compared with a similar single axis method. *Main results.* The PCA-autocorrelation method resulted in a bias of 0.0 breaths per minute (bpm) and limits of agreement (LOA) = [−1.9; 1.9 bpm] compared to the reference. Overall, 99% of the RRs estimated by the PCA-autocorrelation method were within ±2 bpm of the reference. A Pearson correlation indicated a very strong correlation with $r = 0.99$ ($p < 0.001$). The single axis method resulted in a bias of 3.7 bpm, LOA = [−14.9; 22.3 bpm], and $r = 0.44$ ($p < 0.001$). *Significance.* The results indicate a strong agreement between the PCA-autocorrelation method and the reference. Furthermore, the PCA-autocorrelation method outperformed the single axis method.

1. Introduction

Respiratory rate (RR), which is the number of breaths per minute (bpm), can be used as a predictor for serious clinical events such as cardiac arrest and admission to the intensive care unit, up to 24 h prior to the event (Liu *et al* 2019). Furthermore, relative variations in RR are larger than the variation in blood pressure and heart rate (HR), which makes RR a more sensitive marker of clinically relevant changes in a patient's condition (Subbe *et al* 2003, Elliott and Coventry 2012).

Subtle changes outside the normal RR range can indicate exacerbations in a patient's condition (Liu *et al* 2019), while the normal RR range varies with gender, weight, age, and overall health (Ambekar and Prabhu 2015). Clinical conditions can also cause an RR range outside the normal RR within the range of 12–20 bpm for adults (Fekr *et al* 2014, Doheny *et al* 2020). Therefore, it is important to be able to track subtle changes in RR across a wide range of RR.

To the best of the authors' knowledge, there are no official clinical guidelines for acceptable error margin for RR monitoring devices. However, Breteler *et al* (2020) concluded that ±3 bpm or within ±10% of the reference standard, is acceptable for clinical purposes.

In general wards, the measurement of RR is often neglected due to busy time schedules of nurses, lack of awareness regarding the importance of monitoring RR, and nurses subjectively assessing patients as stable (Elliott and Coventry 2012, Singh *et al* 2020). However, when RR is estimated it is usually performed by manual counting by nurses (Liu *et al* 2019), which provides only a momentary insight of the patient's condition. Thus, RR is not measured continuously, which may result in undetected deterioration of a patient's condition (Singh *et al* 2020). Furthermore, manual counting has shown to provide inaccurate estimates of RR (Liu *et al* 2019).

Several methods have been developed for continuous RR monitoring to improve patient outcomes (Elliott and Coventry 2012, Liu *et al* 2019). Current methods for RR monitoring are capnometry, modulation of photoplethysmography (PPG) signals, and respiratory belts (Liu *et al* 2019). Capnometry is often used as the gold standard, however, it requires expensive equipment, can be uncomfortable for the patient, and can interfere with the natural breathing of subjects (Liu *et al* 2019). Hence, it is impractical for continuous RR monitoring in general wards.

Since respiration induces changes in the peripheral circulation, it is possible to estimate RR from a PPG signal (Allen 2007, Liu *et al* 2019). This is a cost-effective method of RR estimation as it does not require any additional equipment (Liu *et al* 2019). However, Addison *et al* (2015) showed that the error of estimating RR from a PPG signal had a bias of −0.48 bpm and limits of agreement (LOA) = [−3.9; 3 bpm], calculated from the provided 1 standard deviation (SD) of 1.77 bpm, which exceeds the acceptable error margin proposed by Breteler *et al* (2020).

Respiratory belts can be used to measure RR by either strain gauge or impedance principles (Bates *et al* 2010). For short-term use, respiratory belts are popular, however, they are constrictive and uncomfortable, making them impractical for continuous RR monitoring (Bates *et al* 2010, Liu *et al* 2019).

A low-cost and minimally intrusive solution could leverage accelerometry and be applied across a broad range of settings, such as continuous monitoring in general wards (Doheny *et al* 2020). This method of RR estimation is performed by placing the accelerometer on the chest or abdomen to measure the accelerations affiliated with breathing, using data from either a single axis or multiple axes (Bates *et al* 2010, Fekr *et al* 2014, Hung 2017, Preejith *et al* 2017, Doheny *et al* 2020, Jacobs *et al* 2021, Schipper *et al* 2021, Romano *et al* 2022). Performance of RR estimation using accelerometers varies. Schipper *et al* (2021) reported an agreement interval, defined as the difference between the 97.5th and 2.5th percentiles of the distribution of differences in RR estimates between the accelerometer and respiratory impedance plethysmography. In a supine position, they reported an agreement interval of 0.67 bpm with 1 SD of 0.33 bpm across all subjects. Additionally, Schipper *et al* (2021) used a fusion of three axes with a novel form of principal component analysis (PCA). Romano *et al* (2022) reported LOA = [−4.7; 4.7 bpm] for participants in a standing position and using a single axis. However, participants in Schipper *et al* (2021) were instructed to breathe normally and in Romano *et al* (2022) the participants were instructed to breathe quietly. The RRs measured by Schipper *et al* (2021) and Romano *et al* (2022) were approximately 9–25 bpm derived by visual inspection of their Bland-Altman figures. Hereby, previous articles did not widely cover abnormal RR ranges, which are essential for detecting exacerbation in patient conditions.

Consequently, it is unknown whether the proposed algorithms are capable of estimating abnormal RRs outside the range 9–25 bpm. Fekr *et al* (2014) estimated RRs in a broad range of RRs (7–66 bpm) with an $r = 0.99$, however, no LOA or average error were reported. Thus, there is a potential in using an accelerometer in RR estimation, however, the use of the method in a broad range of RRs is still limited.

Additionally, breathing patterns (Benchetrit 2000) and breathing movements (Tobin *et al* 1983a, 1983b) vary between individuals, and hereby, the axis with the most prominent respiratory signal might also vary. Furthermore, changes in patient position might cause the axis of interest to change (Bates *et al* 2010). It has recently been shown that there is an interaction between posture and breathing pattern on abdominal muscle activation which may affect respiratory motion (Kawabata and Shima 2023). Consequently, a fusion of all three axes from the accelerometer may address the problem of the most prominent axis not being consistent.

Therefore, the aim of this study is to investigate the agreement between RR estimation, using a tri-axial accelerometer, and a reference method across a clinically relevant RR range.

2. Methods and materials

2.1. Criteria for participating in the study

Healthy participants above 18 years without any previous or currently known pulmonary or cardiac diseases were included. All participants were students recruited on campus, covered by an educational agreement with the scientific ethical committee of Northern Jutland. All participants gave written informed consent before participating. The research was conducted in accordance with the principles embodied in the

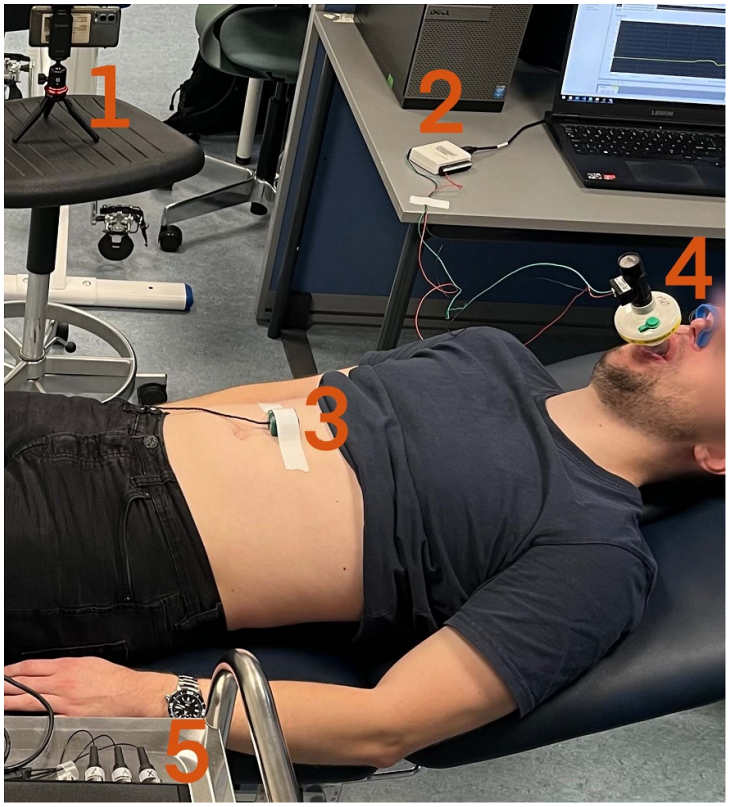

Figure 1. The experimental setup. 1: Camera. 2: NI-DAQ. 3: Accelerometer. 4: Flow meter. 5: iWorx Recorder. The participant was lying in a supine position on an examination couch with a 30° incline. A noseclip covered the participant's nose to ensure breathing occurred through the flow meter.

Declaration of Helsinki and in accordance with local statutory requirements. Pregnant women were excluded from the study.

2.2. Data collection

A tri-axial accelerometer (SDI 1521, Silicon Designs Inc. Kirkland, USA) was placed on the abdomen 3 cm above the umbilicus. The *x*-axis was in the superior–inferior (head-to-feet) direction, the *y*-axis was in the lateral-medial (left-to-right) direction, and the *z*-axis was in the dorsal–ventral (back-to-front) direction. The accelerometer was connected to an iWorx Recorder (IX-RA-834, iWorx Systems Inc. Dover, USA), which was connected to a PC with LabScribe (version 23.0901, iWorx System Inc. Dover, USA) installed. The sample frequency in LabScribe was configured to 5000 Hz. A one-directional flow meter (SFM3020, Sensirion, Stäfa, Switzerland) was used as the reference. The flow meter was connected to a mouthpiece with a breathing filter. The mouthpiece was sterilized for each participant, and the breathing filter was replaced for each participant. The flow meter was connected to a NI-DAQ ADC (USB-6009, Emerson, Missouri, USA) to sample the flow signal at 5000 Hz. A camera was used to record the experiment to verify any unexpected abnormalities in the collected data. The experimental setup is illustrated in figure 1.

During the recording session of 5 min, the participants were instructed to breathe in paces of slow, normal, and fast breathing in segments lasting 60 s each. The participants determined what they considered as slow, normal, and fast breathing paces. The participants were randomly and evenly divided into two groups with two different orders of breathing paces to reduce order bias. Group 1 had to breathe in the following order: normal, fast, normal, slow, normal. Group 2 had to breathe in the following order: normal, slow, normal, fast, normal.

2.3. Signal processing

The signal processing steps for the accelerometer data are illustrated in figure 2. The signal processing chain operates on a single 60 s data segment at a time. MATLAB (R2023a, Mathworks, Natick, USA) was used for all signal processing steps.

The signal processing algorithm was developed and tested using a random split of the recorded data, with 20% allocated for development and the remaining 80% used for testing the algorithm's performance.

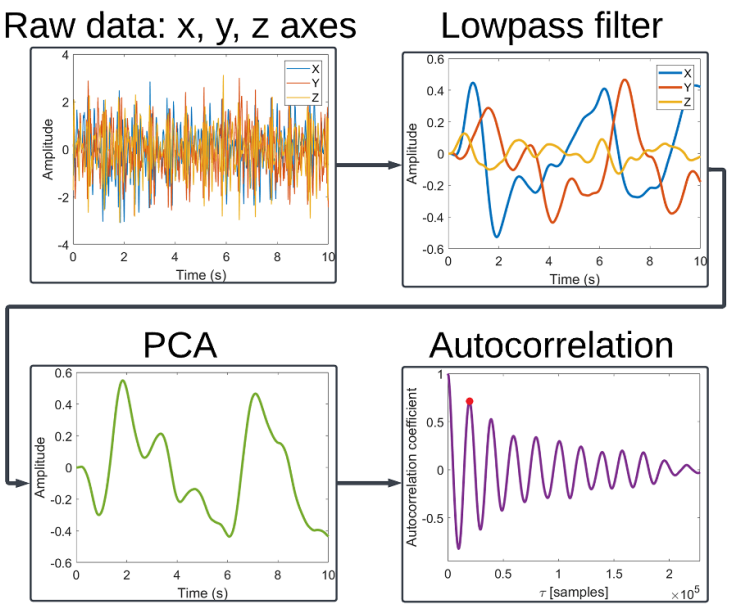

Figure 2. The signal processing steps for one participant. First, raw accelerometer data was recorded from the *x*, *y*, and *z* axes. Next, a lowpass filter was applied to all three axes. The filtered data was then fused using PCA by projecting it onto the first principal component. Finally, finding peaks within the autocorrelation was used to estimate the RR.

Lowpass filter: fourth-order Butterworth lowpass filters with cutoff frequencies ranging from 0.5–1.5 Hz with 0.1 Hz increments were evaluated on the development data. The evaluation resulted in a 0.8 Hz cutoff frequency as the optimal cutoff frequency. Consequently, all accelerometer data segments with RR measured from the flow meter above 48 bpm were excluded, since all RRs above 48 bpm would have been attenuated due to the filter's cutoff frequency. The lowpass filter was applied to all three axes of accelerometer data.

PCA: after lowpass filtering, a PCA was performed to fuse and make use of all three axes of the accelerometer data. As the accelerometer data was three-dimensional, the PCA returned three principal components where the first principal component was retained. The normalization step of the PCA was deliberately omitted. Afterward, the accelerometer data was projected onto the first principal component, and this projected signal served as the input for the RR estimation algorithm.

RR estimation algorithm: the autocorrelation of the projected signal was calculated. Autocorrelation identifies repeating patterns within a signal by measuring its similarity with lagged versions of itself, highlighting the primary periodic components (Shen *et al* 2018). For periodic signals, the autocorrelation function produces a series of decaying peaks corresponding to repeating patterns (Shen *et al* 2018). When multiple periodic components are present, such as respiratory- and heart-induced motion, two series of decaying peaks will be present, where the largest peak is assumed to represent the dominant respiratory motion. The lag of this peak can then be converted into an RR estimate. To detect peaks in the autocorrelation, the 'findpeaks()' function from MATLAB was used. The amplitudes of the first two detected peaks were compared, and the largest peak was selected, assuming that the respiratory-induced signal would be the most prominent after low-pass filtering. The autocorrelations appeared smooth with minimal noise, and manual visual inspection of the identified peaks confirmed that the 'findpeaks()' function reliably detected the correct peaks. The number of lags from lag zero to the largest detected peak was then converted to an RR estimate for each segment using the following equation:

$$\mathrm{RR} = \left(\frac{\mathrm{SamplingFrequency}}{\mathrm{LagsToLargestPeak}}\right) \cdot 60. \tag{1}$$

An upper limit on the maximum RR estimate was imposed by configuring the 'findpeaks()' function to ignore any peaks detected within the first 6250 lags. This corresponds to ignoring RR estimates above 48 bpm, as any peak earlier than the first 6250 lags would most likely be due to signal noise.

Single *z*-axis: to evaluate the effectiveness of combining all three axes of accelerometer data, a simplified signal processing method was also developed using only the *z*-axis from the accelerometer. This simplified method omitted the PCA step but still applied the exact same lowpass filter and autocorrelation peaks approach.

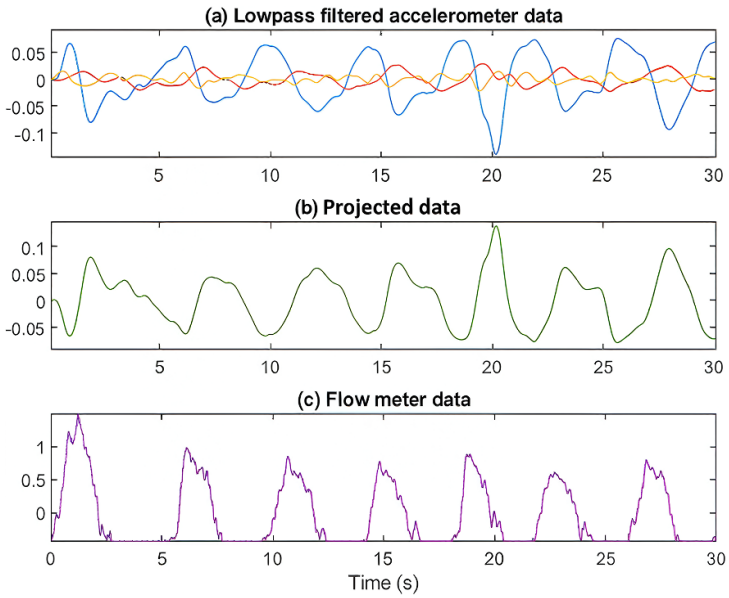

Figure 3. Data snippet from a single participant recorded simultaneously from the accelerometer and flow meter during a normal breathing pace segment. (a) Lowpass-filtered accelerometer data, with *x*-axis in blue, *y*-axis in red, and *z*-axis in yellow. (b) Accelerometer data after projection onto the first principal component. (c) Reference flow meter data.

2.4. RR measurements from the flow meter

The flow meter was used as a reference for measuring RR. Every breath recorded by the flow meter created a visible peak in the flow signal as seen in figure 3, which were marked by an algorithm, with following manual visual confirmation of registered breaths.

2.5. Statistical analysis

Statistical analysis was performed using IBM SPSS (v28.0.1.1, Armonk, USA). Estimated RRs from the accelerometer were compared to the RRs measured from the flow meter in the corresponding segment for all statistical analysis types. Q–Q plots were created to assess normality. Mean absolute error (MAE), Pearson correlation, a paired *t*-test, two-way repeated measures ANOVA, and Bland–Altman plots were conducted. The LOAs from the Bland–Altman plots were 95% LOA. If a bias was statistically significant, a 95% confidence interval (CI) was calculated. The LOAs were corrected for repeated measurements as described by Bland and Altman (2007), when including multiple segments from the same participant.

Additionally, to compare the overall performance of the PCA-autocorrelation method with the single *z*-axis method, the Wilcoxon signed-rank test was performed due to the non-normal distribution of the absolute differences. Descriptive statistics were reported as mean (SD). *P*-values <0.05 were considered statistically significant. To interpret the Pearson correlation coefficients, the naming convention described by Schober *et al* (2018) was used.

3. Results

3.1. Data obtained from the experiment

Twenty-five healthy participants, with an overall mean age of 24.2 (2.4) years and a mean BMI of 22.4 (3.1) kg m^{-2}, participated in the study. Eight participants (32%) were female. The mean age for female participants was 24.3 (0.9) years, with a mean BMI of 21.4 (1.6) kg m^{-2}. For male participants, the mean age was 24.1 (2.9) years, and the mean BMI was 22.9 (3.5) kg m^{-2}. An example of data recorded from the accelerometer and flow meter for one participant is illustrated in figure 3. As the data allocated for testing was 80% of the recorded data, the testing data set consisted of 100 segments, from 20/25 participants. Two of the 100 segments were discarded due to the RRs measured from the flow meter (91 bpm and 105 bpm) exceeding the exclusion criterion of RR $>$ 48 bpm. Hereby, 98/100 segments of the testing data were used for statistical analysis. The 98 segments of testing data consisted of 20 segments of slow breathing, 60 segments of normal breathing, and 18 segments of fast breathing. The included data had RRs ranging from 3–38 bpm, as illustrated on figure 4. Based on an analysis of Q–Q plots, the recorded data were considered normally distributed.

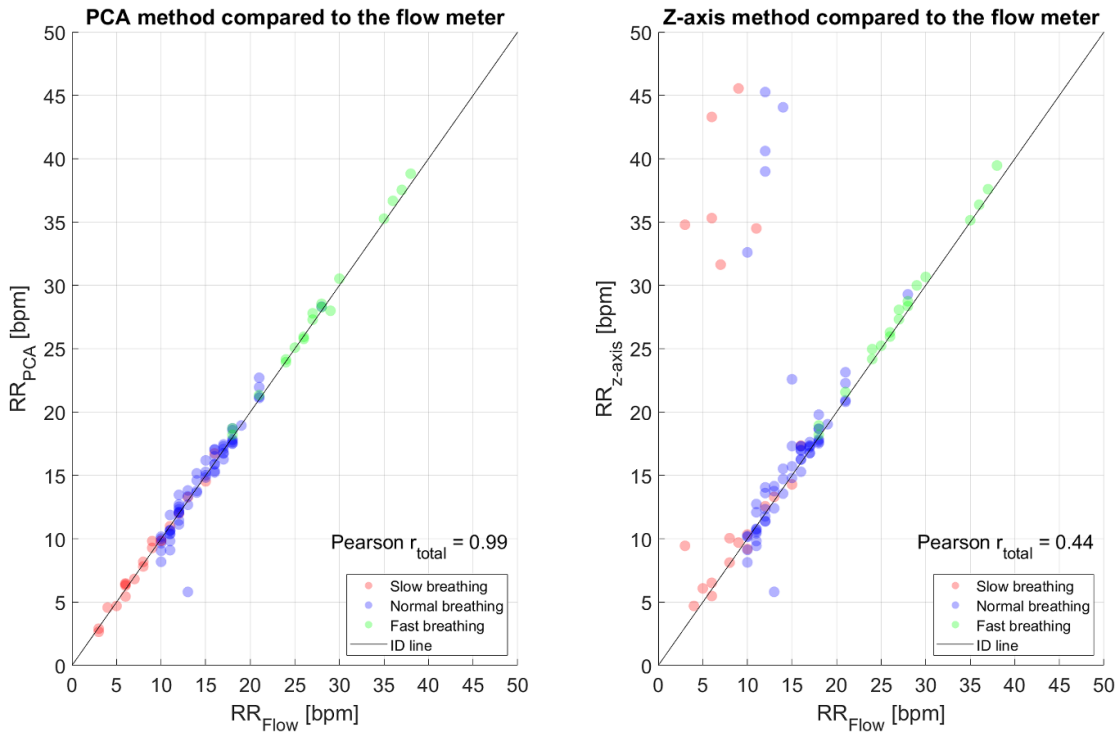

Figure 4. Left scatterplot: RR estimates from the PCA-autocorrelation method and flow meter. Right scatterplot: RR estimates from the *z*-axis method and flow meter. Each point represents the RR estimated in a single segment.

Table 1. Overview of results for $RR_{PCA} - RR_{flow}$ and $RR_{zaxis} - RR_{flow}$. Bias, CI, LOA, and MAE are in bpm. *: $p < 0.05$ **: $p < 0.001$.

	Parameter	Slow	Normal	Fast	Total
PCA	Bias	0.1	−0.1	0.3* (CI:0.1; 0.5)	0.0
	LOA	[−0.7; 0.9]	[−2.4; 2.2]	[−0.6; 1.1]	[−1.9; 1.9]
	r	0.99**	0.96**	0.99**	0.99**
	MAE	0.3	0.7	0.4	0.5
Z-axis	Bias	9.8* (CI:3.1; 16.5)	2.6* (CI:0.6; 4.7)	0.6** (CI:0.4; 0.8)	3.7** (CI:1.8; 5.6)
	LOA	[−18.3; 37.9]	[−13.8; 19.1]	[−0.2; 1.3]	[−14.9; 22.3]
	r	−0.05	0.27*	0.99**	0.44**
	MAE	10.0	3.3	0.6	4.2

The mean and SD of the RRs measured by the flow meter were 8.4 (3.7) bpm for slow breathing, 14.8 (3.6) bpm for normal breathing, and 27.6 (5.9) bpm for fast breathing.

3.2. Estimation of RR

An overview of the results from the statistical analysis can be seen in table 1. The Pearson correlation coefficient was $r = 0.99$ ($p < 0.001$) which indicated a very strong correlation between the PCA-autocorrelation method and the flow meter across all measured RRs as illustrated in figure 4.

As illustrated in figure 5, the results using the PCA-autocorrelation method for the segments for slow breathing had LOA = [−0.7; 0.9 bpm], the segments for normal breathing had LOA = [−2.4; 2.2 bpm], and the segments for fast breathing had LOA = [−0.6; 1.1 bpm]. Hereby, all segments were within the acceptable error margin of ±3 bpm.

The paired *t*-test showed a statistically significant but small systematic bias of 0.3 bpm ($p = 0.02$) for the PCA-autocorrelation method when evaluating the segments with fast breathing. No significant systematic bias was observed for the other breathing paces.

3.3. Comparison between the PCA-autocorrelation method and *z*-axis

When using the alternative *z*-axis algorithm, where the PCA step was omitted, the Pearson correlation coefficient was $r = 0.44$ ($p < 0.001$). This indicated a moderate correlation between the *z*-axis and flow meter across all breathing paces as seen in figure 4. Additionally, when using the *z*-axis, the best agreement was in the segments for fast breathing with LOA = [−0.2; 1.3 bpm] and the worst agreement was in the segments

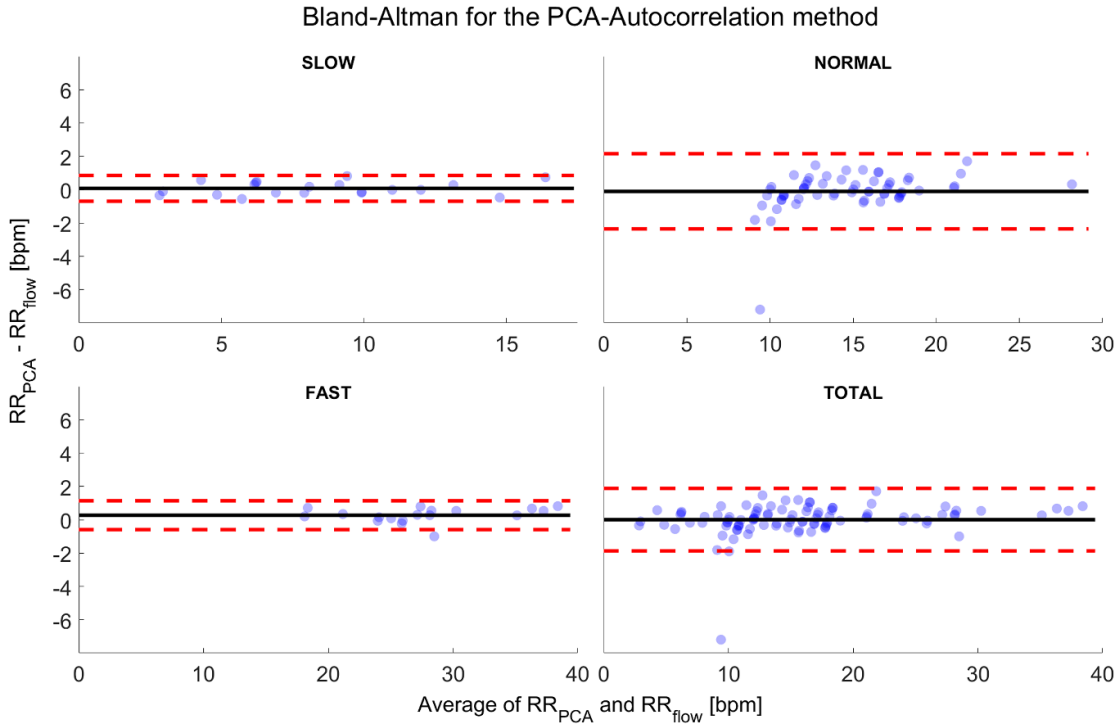

Figure 5. Bland–Altman plots of the difference between the RR estimates from the PCA-autocorrelation method and the flow meter. The red dashed lines represent the LOAs. The bias is represented by the black line. The blue points each represent compared RRs for one segment.

for slow breathing with LOA = [−18.3; 37.9 bpm]. The RRs estimated in the segments with fast breathing were within the acceptable error margin of ±3 bpm, however, RRs estimated in segments with other breathing paces were outside the error margin.

The Wilcoxon signed-rank test showed a statistically significant difference ($p < 0.001$) between absolute errors of the PCA-autocorrelation method compared to absolute errors of the z-axis when including all segments.

The two-way repeated measures ANOVA indicated that the z-axis method resulted in significantly different RR as compared to the PCA-autocorrelation method. A post-hoc test indicated that the z-axis on average estimated 4.0 bpm (CI: 1.4; 6.6 bpm) more than the PCA-autocorrelation method ($p = 0.005$). In the segments with fast breathing, the z-axis on average estimated 0.3 bpm more than the PCA-autocorrelation method, but the difference was significant ($p = 0.042$).

4. Discussion

In this study, we presented a novel PCA-autocorrelation method for RR estimation using a tri-axial accelerometer. The method was validated in 20 healthy participants with an accelerometer placed on the abdomen and using a flow meter as the reference. The study design focused on including a wide range of RRs to validate that the developed method was able to handle clinically relevant RRs. When using the developed method, 99% of the estimated RRs were within ±2 bpm compared to the flow meter. There was a very strong correlation between the PCA-autocorrelation method and the flow meter for all breathing paces.

4.1. Single-axis vs multi-axis

Fekr *et al* (2014) investigated a wide range of RRs (7–66 bpm) on 8 healthy participants and achieved a Pearson correlation coefficient $r = 0.99$ compared to spirometry, using a peak and valley detection on the single z-axis. Thus the current PCA-autocorrelation method achieving $r = 0.99$, is similar in estimating RR compared to the results achieved by Fekr *et al* (2014) and is superior compared to using our z-axis achieving only $r = 0.44$. Consequently, we demonstrated that the PCA-autocorrelation method proved to be superior to using a single axis.

Furthermore, when using a single axis, the positioning of the accelerometer is crucial, since the orientation of the axis must align with the respiratory movements. PCA reduces this requirement of precise positioning of the accelerometer, thus healthcare professionals can be less attentive when positioning the

accelerometer. Additionally, changes in patient position, and thereby a change in the axis of interest as described by Bates *et al* (2010), will also be addressed by using PCA, as demonstrated by Schipper *et al* (2021) in their study on the robustness of PCA in different positions.

Schipper *et al* (2021) proposed a novel form of PCA combined with a frequency domain method for RR estimation. In 20 healthy participants who were lying in a supine position and measuring an RR range of approximately 9–23 bpm, they reported an agreement interval of 0.67 (0.33) bpm across all participants. While this metric is not directly comparable to our 95% LOA, our study obtained a total LOA = [−1.9; 1.9 bpm] but included a larger range of RRs (3–38 bpm).

The larger LOA was primarily located in the segments with normal breathing. This might be due to two-thirds of the normal segments following either a fast or slow segment, causing a transitional period where breathing rates did not immediately stabilize to a normal pace. This transitional adjustment may have introduced additional variance in the normal segments, potentially affecting the algorithm's performance in accurately estimating RRs.

Previous studies have predominantly applied a single accelerometer for the measurement of RR (Bates *et al* 2010, Fekr *et al* 2014, Hung 2017, Preejith *et al* 2017, Doheny *et al* 2020, Jacobs *et al* 2021, Schipper *et al* 2021, Romano *et al* 2022). However, Ashe *et al* (2024) recently reported results using six accelerometers, yielding accuracy estimates as high as LOA = [−0.9; 0.9 bpm] in exercising healthy adults during controlled laboratory conditions, with flow signals as the reference. While this multi-sensor approach demonstrated excellent agreement, it relies on placement at multiple key anatomical landmarks, which may introduce practical challenges, including increased complexity, cost, and considerations for ease of setup and patient comfort. Our findings indicate that clinically acceptable performance can be achieved with a simpler single-accelerometer setup. Specifically, we introduced a novel yet simple combination of PCA and autocorrelation, tested on a clinically relevant range of RRs. This method achieved results within the acceptable error margin of ±3 bpm for clinical use proposed by Breteler *et al* (2020).

4.2. Advantages and limitations of autocorrelation

Respiratory signals are generally regarded as periodic sinusoidal signals, simplifying the task of analyzing their periodic components (Shen *et al* 2018). Autocorrelation was chosen for RR estimation because it identifies repeating patterns within a signal by measuring its similarity with lagged versions of itself. This makes it highly adaptive to variations in breathing patterns and differences between patients, as it only requires consistent periodicity within the same breathing segment rather than strict uniformity across signals. An additional advantage of autocorrelation is its independence from signal amplitude, eliminating the need for predefined thresholds. This makes it a robust choice for RR estimation. Autocorrelation has also been successfully applied in other domains, such as HR estimation and radar-based RR estimation (Shen *et al* 2018, Laurino *et al* 2020). However, an important limitation is its reliance on periodicity within the analyzed segment. Irregularities, such as those caused by apnea, is expected to reduce its accuracy in estimating RR.

4.3. Effective range for RR estimation

Due to the implemented lowpass filter, the developed PCA-autocorrelation method was limited in the maximal measurable RR. Therefore, the trade-off between the maximal measurable RR and the amount of noise reduction by the filter was an important consideration. Even though the accelerometer was placed on the abdomen, and not on the chest, as done in most articles (Fekr *et al* 2014, Hung 2017, Preejith *et al* 2017, Schipper *et al* 2021, Romano *et al* 2022), the noise from the heart was still contaminating the respiratory signals. Increasing the cutoff frequency, and thereby the maximal measurable RR, the noise from the heart would not be attenuated sufficiently, and the PCA-autocorrelation method would likely register the HR instead of the RR.

A solution to extending the maximal measurable RR, while avoiding the HR, would have to involve a different type of filtering. However, similar articles (Bates *et al* 2010, Fekr *et al* 2014, Preejith *et al* 2017, Doheny *et al* 2020, Schipper *et al* 2021) all used lowpass filters. In our study, the design of the filter combined with the PCA-autocorrelation method was able to accurately estimate RR in a range of 3–38 bpm and theoretically would be able to estimate up to 48 bpm, before being attenuated by the corresponding cutoff frequency of 0.8 Hz. However, it can be argued that in a general ward setting, a respiratory monitoring system should issue a warning well before reaching 48 bpm, as such a high RR is unusual for a resting adult patient and could indicate a critical situation requiring clinical intervention. That said, the upper limit of 48 bpm poses a limitation for pediatric applications, where higher RRs are common. For example, in infants (1–12 months), normal RRs can reach up to 60 bpm (Ambekar and Prabhu 2015).

Nevertheless, despite the limitations imposed by the lowpass filter, the developed method can still estimate RRs outside the normal RR range of 12–20 bpm for adults.

4.4. Study limitations

Our study included 25 healthy participants with an overall mean age of 24 (2) years and a mean BMI of 22.4 (3.1) kg m^{-2}. Of these, 8 participants (32%) were female. This gender imbalance in the composition of our participant group is similar to those reported for similar studies (Preejith *et al* 2017, Breteler *et al* 2020, Doheny *et al* 2020). The accelerometer was placed consistently at 3 cm above the umbilicus for all participants, minimizing the potential impact of anatomical differences between genders on the recorded respiratory-induced accelerations. Comparable BMI and age between genders further reduce the likelihood of this imbalance affecting the findings.

Only one position was investigated in our study, with participants lying still in a supine position in a controlled laboratory setting. Conducting a study with multiple positions, as done in other articles (Hung 2017, Doheny *et al* 2020, Schipper *et al* 2021, Romano *et al* 2022), would be beneficial. Nevertheless, it is expected that the PCA handles the problem of patients changing their position, as shown by Schipper *et al* (2021).

To ensure accurate reference RR measurements, a flow meter with a mouthpiece and nose clip was used. While this setup enables precise validation, it is known to slightly lower RR and increase tidal volume (Tobin *et al* 1983a). Additionally, participants were instructed to voluntarily alter their breathing to achieve a wide range of RRs, a necessary approach to validate the method across clinically relevant ranges. Whilst expectedly more natural than metronome-paced breathing, voluntarily controlled slow or fast pace might not fully replicate natural breathing.

Our method has not yet been evaluated in a clinical setting, where irregular breathing patterns, such as apnea, can occur. This could potentially be a challenge for the PCA-autocorrelation method, as the autocorrelation algorithm operates under the assumption of regular breathing within a given time segment.

5. Conclusion

Our study advances the field of accelerometer-based RR estimation by presenting a novel, simple PCA-autocorrelation method which proved to be superior to using a single axis. RR was measured on healthy participants in a clinically relevant range of RRs. The results indicate a very strong correlation, with clinically acceptable agreement between the developed PCA-autocorrelation method and a flow meter used as the reference. A clinical study should be conducted to explore performance in a clinical setting.

Data availability statement

The data that support the findings of this study cannot be made publicly available upon publication. However, in accordance with the Danish Data Protection Act, § 10, these data can be shared upon reasonable request for research purposes, provided that such processing is solely for statistical or scientific studies of significant societal importance.

The data that support the findings of this study are available upon reasonable request from the authors.

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The author's have confirmed that any identifiable participants in this study have given their consent for publication.

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