# A Non-Contact Vision-Based System for Respiratory Rate Estimation

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***Abstract*— A non-contact vision-based system is presented for continuous respiratory rate monitoring. The system identifies feature points in a video feed and tracks them over time. Two methods are presented for comparison - a method which uses principal component analysis (PCA) and a simple averaging approach. These methods condense the feature point trajectories into a compact set of representative signals. The signal which most closely resembles an expected respiratory trace is selected based on spectral analysis. System performance is assessed by comparing the estimated respiratory rate to the rate determined via inductance plethysmogram. The system was evaluated on 5 participants in 4 simulated sleep scenarios. Accuracies of within 1 breath/minute were achieved for more than 97% of the recorded time in all scenarios. The proposed system is accurate, cost-effective, and simple, making it a suitable candidate for at-home installation.**

## I. INTRODUCTION

The monitoring of respiratory activity is of great importance as changes can signal the deterioration of an individual's health. For continuous monitoring, commonly used methods rely on measuring airflow (via nasal cannula or face mask) or chest motion (inductance plethysmograph) [1]. While these methods are convenient for usage in a clinical setting, they introduce discomfort and limit mobility, making them suboptimal solutions for at-home monitoring. Non-contact solutions are more suitable as they do not impose physical constraints on the user. Continuous home monitoring is particularly important for more vulnerable populations such as neonates or the elderly, as respiratory failure during sleep often precedes sudden infant death syndrome (SIDS) or cardiac arrest [2, 3].

Previously investigated non-contact methods for measuring respiratory rate include thermal imaging [4, 5], microwaves [6, 7], and ultra wideband radar [8, 9]. Unfortunately, these methods require specialized equipment which can be expensive and impractical for home usage. Computer vision approaches have also been explored recently. Using a video or camera feed, these methods are able to estimate respiratory rate based on changes in colour or light intensity [10, 11] or by tracking the motion of the chest cavity [12].

The objective of this study is to validate algorithms for estimating respiratory rate based on motion data analysis. This work adapts and modifies the method proposed by Balakrishnan et al. for pulse detection based on head motions [13]. Since future applications of this system could involve respiratory rate monitoring during sleep, various scenarios that occur during sleep are simulated. The successful implementation of a non-contact system for respiratory rate estimation would significantly decrease discomfort for individuals requiring continuous monitoring of vital signs while providing valuable information for diagnosis of sleep disorders.

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(a) (b) (c) (d)

Fig. 1. Sleep scenarios tested. (a) Supine, (b) left side, (c) right side, (d) supine, torso obscured.

## II. METHOD

### A. Experimental Setup

Five participants were recruited for this feasibility study (3 women, 2 men, age = 31.2 ± 11.5 years, BMI = 23.0 ± 1.8 kg/m$^2$). Participants were asked to lie down on a bed in the sleep laboratory which was kept dark to simulate overnight sleep and was illuminated with infrared (IR) light. Video data was recorded with a Point Grey 0.3 MP Firefly MV camera (model number FMVU-03MTM) with an IR-sensitive Micron M9V022199ATM image sensor. Videos were recorded at a resolution of 640x480 pixels at 30 fps. The camera was mounted on a tripod positioned 1.4 m above the head of the bed, such that the head and torso of the participant were in the view of the camera. Simultaneously, respiratory inductance plethysmography was used to measure chest and abdominal movements. These movements were used to determine the respiratory rate which was used as the gold standard for validation. The data was recorded with the sleep laboratory's polysomnogram system and Embla Sandman software at a sampling rate of 85.3 Hz.

The experimental protocol included four different scenarios, each lasting for five minutes. The scenarios were: lying in the supine position, lying on the left side, lying on the right side, and lying supine while the torso was obscured with a white sheet (Fig. 1). Due to technical difficulties during one of the recording sessions, only the five minute session of lying supine was recorded for one participant. A total of 21 trials were analyzed.

### B. Data Analysis

A computer vision based method is used to estimate the respiratory rate via the processing of an IR video stream. Several feature points are identified in the first video frame and tracked over time. The processing of these motion

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trajectories reveals the chest motion induced by respiration. The processing represents feature point trajectories in terms of multiple motion signals and the signal which most closely resembles a respiratory signal is chosen. The respiratory rate is extracted as the peak of the frequency spectrum of that component.

Video analysis is implemented in Python 2.7 and using OpenCV 2.4.6. To avoid image segmentation and localization of body parts, the frame is divided into a grid (10×13 cells) and feature points are extracted in each grid section. A feature point detector is applied in each cell to identify the $P$ most distinguishable points for feature tracking. By running feature point selection separately for each grid section, the set of feature points extracted is spread over the entire video frame, ensuring that the chest motion will be captured in various sleeping positions.

Features are tracked over time using optical flow. A sliding window of length $\tau$ is processed to estimate the respiratory signal. Within each window, feature trajectories are split into their horizontal and vertical components and treated separately. Points with erratic trajectories are discarded as they may have been impacted by tracking errors. Similarly, points with very little variation are excluded as these are assumed to not be on the individual and therefore do not provide any useful information. As a simple method of discarding such points, the maximum frame to frame displacement for each point is found and the top $M$-th and bottom $N$-th percentile are discarded. To further filter out feature trajectories, those with a range of motion less than the mean are also discarded. As the window slides forwards, a new respiratory rate estimate is computed every second.

Specific implementation details are selected empirically for a combination of performance and efficient processing. A Harris corner detector is used for feature point detection while the Lucas-Kanade algorithm is used for point tracking [14, 15]. Ten feature points are selected in each grid cell ($P$ = 10). Discarded percentiles $M$ and $N$ are both set at 25% and the sliding window is set to be half a minute long ($\tau = 30\ s$).

Two different methods of identifying respiratory related motion from feature point trajectories were used, including a simple averaging approach and principal component analysis (PCA). Each method condenses the feature point trajectories into a compact set of signals. The expectation is that the signal with the highest periodicity is most representative of the respiratory rate.

The averaging method generates three signals based on the feature point trajectories by computing the average horizontal trajectory, the average vertical trajectory, and the average displacement trajectory. These signals are passed through a $5^{th}$ order Butterworth filter chosen for its flat passband. The passband used was [0.1, 1.0] Hz, equivalent to 6-60 breaths/minute. Signals are convolved with a Hamming window to reduce edge effects before performing a fast Fourier transform (FFT) for spectral estimation. The most periodic of the three signals is selected as the one with the highest ratio of spectral power in its peak relative to the rest of the spectrum. The frequency at which maximal power occurs is taken as the respiratory rate.

Alternatively, PCA decomposes the feature point trajectories into a set of linearly uncorrelated signals. Before applying PCA, the horizontal and vertical trajectories are pooled together and passed through a $5^{th}$ order bandpass Butterworth filter with a passband of [0.1, 1.0] Hz. An expectation-maximization (EM) implementation of PCA is used as it circumvents computation and diagonalization of the sample covariance matrix as required in traditional PCA [16]. These operations can become prohibitively expensive when the number of features is large. To avoid this computational bottleneck, the $C$ principal components which explain the most variance in the original dataset were iteratively computed using the EM implementation. For all reported results, $C$ = 10.

Similarly to the averaging method, principal components are convolved with a Hamming window and spectral estimation is performed using FFT. In the absence of motion artifacts, it was empirically determined that the component with the highest variance generally provides better estimates than the most periodic component, so it is chosen for the initial estimate. Therefore, for the initial respiratory rate, the component with the highest variance is used and the frequency value of its peak in the spectrum is taken as the initial respiratory rate.

For subsequent estimates, the predicted respiratory rates from the component with the highest ratio of peak to total power (i.e. the most periodic component) and the component which explains the highest variance are both calculated. These two values are compared to the previous estimate and the prediction which is closest to the previous estimate is chosen. The reasoning for this approach is two-fold. PCA can often extract highly periodic components which explain very little variance in the original data. However, the component which explains the most variance will be most affected by participant voluntary motion (e.g. tossing and turning at night) which can lead to an inaccurate estimate. Estimation accuracy is therefore improved by the combination of these two methods. This approach relies on the assumption that changes in the respiration rate are generally slow in comparison with the update rate of 1 Hz. It is also assumed that no motion artifacts affect the first 30 seconds of video.

Estimates from the vision-based system were compared to estimates generated from the plethysmograph data. Since the plethysmograph data was in the form of a respiratory trace and not respiratory rate, the respiratory rate was extracted by applying the same Butterworth filter and FFT used for the vision-based system. The frequency corresponding to the maximal power in the frequency spectrum was taken as the ground truth respiratory rate.

## III. Results

Fig. 2 provides an example of the predicted respiratory rate versus the ground truth respiratory rate. While there were sharp transitions that existed in the respiratory rate as a result of the FFT, the predicted rate was still accurate compared to the true rate.

TABLE I

RESPIRATORY RATE ESTIMATION RESULTS USING AVERAGING AND PCA METHODS

| | | Supine | Left | Right | Obscured | **Average** |
|---|---|---|---|---|---|---|
| RMS Error (breaths/minute) | Averaging | 0.84 ± 0.30 | 0.79 ± 0.48 | 0.94 ± 0.84 | 1.50 ± 1.24 | **1.02 ± 0.85** |
| | PCA | 0.67 ± 0.34 | 0.66 ± 0.32 | 0.81 ± 0.81 | 0.81 ± 0.64 | **0.74 ± 0.57** |
| % prediction within ± 1.0 breaths/minute | Averaging | 96.5% ± 2.3% | 96.8% ± 3.1% | 97.8% ± 1.8% | 86.1% ± 15.7% | **94.3% ± 9.4%** |
| | PCA | 97.2% ± 1.3% | 98.1% ± 0.9% | 98.4% ± 2.0% | 97.0% ± 3.6% | **97.7% ± 2.3%** |
| % prediction within ± 0.5 breaths/minute | Averaging | 90.8% ± 5.0% | 92.8% ± 4.0% | 93.2% ± 4.6% | 80.7% ± 19.4% | **89.4% ± 11.7%** |
| | PCA | 92.3% ± 3.8% | 95.2% ± 1.1% | 94.9% ± 3.7% | 95.3% ± 4.1% | **94.7% ± 3.6%** |
| % prediction within ± 0.25 breaths/minute | Averaging | 76.2% ± 7.5% | 79.8% ± 5.9% | 77.1% ± 11.2% | 66.8% ± 18.1% | **75.0% ± 12.7%** |
| | PCA | 81.2% ± 5.5% | 83.9% ± 2.1% | 80.4% ± 10.2% | 86.4% ± 5.4% | **83.0% ± 6.9%** |

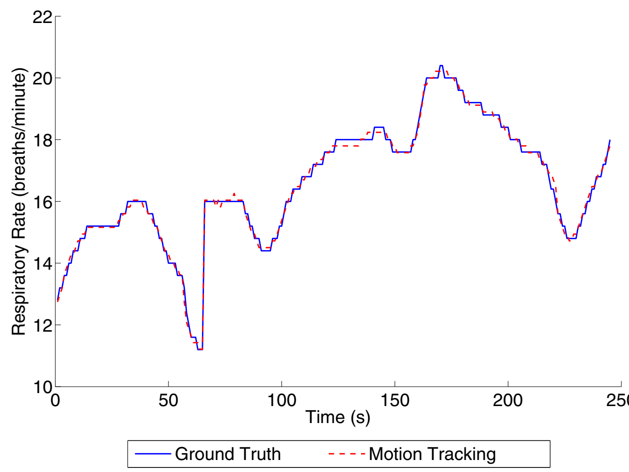


Fig. 2. Example of motion tracking based respiratory rate estimation compared to ground truth for a 5 minute video.

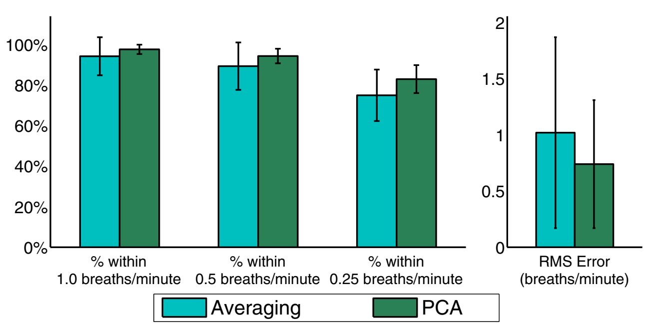


Fig. 3. Comparison of respiratory rate estimation results from averaging and PCA methods. Error bars are standard error.

A summary of results (± standard error) is provided in Table I. The RMS error between the vision-based system and the ground truth was computed, as well as the percentage of estimates which were within 1.0, 0.5 and 0.25 breaths/minute of the true respiratory rate. Comparing the two methods (Fig. 3), the PCA-based approach was more accurate than the averaging approach and had reduced average RMS error and standard error.

For both methods, estimates were better for left and right lateral positions versus supine which lends some credence to the notion that estimation will be worse if motion is primarily in the axis of the camera lens. In the obscured scenario, the sheet may make motion tracking more difficult as it distributes the motion in different directions, i.e. motions in opposite directions will cancel each other when averaged.

## IV. DISCUSSION

In this study, a highly accurate system was developed for detecting respiratory rate with no contact to the patient. The results indicate that for supine, lateral and obscured supine positions, the PCA-based method can detect respiratory rate with less than 1.0 breaths/minute error in more than 97% of cases. These results provide strong evidence that this system can be applied for detecting respiratory rate with minimal interference to the subject's normal lifestyle.

In order for a system to be attractive for implementation in a domestic environment, it must fit certain criteria. The American Academy of Sleep Medicine identified six key considerations for portable monitoring systems: safety, ease of use, reliability, durability, economy and diagnostic accuracy [17]. Our system is safe and easy to use as it requires minimal setup and the non-contact nature eliminates any hazards associated with wires or probes connected to the user. Durability of system components would be high since there is no need to reposition the system regularly and no moving parts that would result in cable tugging. Our results demonstrate that the system has high accuracy when compared to the true respiratory rate and is reliable for multiple participants in different scenarios. The cost of the system is low as the required camera specifications could be easily reached with a standard webcam or mobile device provided they can capture IR light.

Optical flow methods are criticized as being poor in areas of high homogeneity, making them unsuitable for sleep monitoring [18]. However, the results show that there is no need for textured surfaces for an optical flow based respiratory monitoring system to achieve high accuracy. While the tested detection distance is only 1.4 m, it is expected that increasing the resolution of the camera would allow for better discernibility of small motions, improving the range of operation.

The choice of FFT for spectral estimation provides a crude way of predicting the respiratory rate. FFT assumes that data is stationary, which may not be true for physiological signals. However, it is useful for providing a numerical value of respiratory rate for comparison. A correlational analysis of true and predicted respiratory traces would be a stricter measure of prediction accuracy and would validate FFT results.

An inherent limitation of the current setup is that the camera is placed above the person, meaning that motions of the chest cavity in supine position may be significantly decreased when projected into the plane of the camera's view. Placing the camera at an angle or using a depth camera would alleviate this issue.

The results of our experiments may have been influenced by multiple factors. The respiratory trace was recorded at 85.3 Hz and had to be downsampled to 30 Hz to match the video frame rate. This downsampling may have introduced errors into the respiratory signal. In addition, the camera used includes software which automatically adjusts gain and contrast during recording, sometimes resulting in flashing. Since the flashing generally occurred at a rate much higher than the band pass filter that was applied, it is not expected to have significantly influenced results. However, the magnitude of its impact is unknown. Disabling of the auto gain and auto contrast functions is recommended for future recordings. Lastly, the experiment represents only a simulated sleep recording. Sleeping individuals will breathe less deeply and have more variable respiration depth than when they are awake, which could present a more difficult signal processing challenge [19]. Individuals who are awake are also voluntarily controlling their respiratory rate, meaning that it is more likely that sudden spikes can occur. This breaks the assumption of our algorithm that respiratory changes will be slow, and may have led to inaccurate estimation.

While the results of the system are promising, it is not possible to draw any strong conclusions regarding which method or which positions have higher accuracy. Due to the small sample size available, any statistical significance testing will have very little strength. This will be addressed in the future as data is collected for more participants. Although the more accurate method cannot be identified based on current information, there are additional factors to account for besides accuracy. PCA has been successfully used for extraction of physiological signals and is adept at identifying underlying signals from noisy data [12, 13]. The averaging approach has a much lighter computational load than PCA, but it also has a decreased ability to handle signal noise caused by extraneous motion such as sudden deep inhales or exhales.

## V. Future Work

For future work, experiments will involve multiple cameras to provide more consistent motion information regardless of the person's orientation. The ability of the system to measure respiration depth will also be investigated. Additional trials will be performed with thicker blankets as these may impact system performance. Trials will also be performed on sleeping subjects to determine how the system performs when respiratory depth is decreased. One of the most important future applications of this system is continuous monitoring of sleep breathing disorders such as sleep apnea.

## Acknowledgements

This work was funded by the Toronto Rehabilitation Institute and by ApneaDx$^{TM}$. The authors also wish to acknowledge the study participants and technicians who graciously volunteered their time for this feasibility study.

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