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A Computer Vision-Based Respiratory Rate Monitoring and Alarm System

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ABSTRACT

Breathing rate is one of the most important vital signals for monitoring health status and reflecting conditions of dangerous diseases. Previous contactless breath monitoring methods were more convenient than contact methods, but they were not suitable for the actual sleeping environment because of the narrow field of vision (FoV). This study proposed a breathing rate monitoring strategy using a mono camera to track and detect sleep apnea phenomena. Breathing rates were first tracked among consecutive image frames. The human body area was then isolated and magnified using a deep neural network (DNN) model before applying the optical flow algorithm to extract and monitor the up and down changes caused by respiration. The most variated directions of the body feature's motions were detected based on the Principal Component Analysis (PCA) method. Breathing rate was the number of times the signal amplitude peaks per minute. The comparison between predicted values and manually estimated was used for evaluating the accuracy of the method. The accuracy of our method in various light, position, and distance conditions is 2 breaths/minute (<10%) for children and less than 1 breath/minute (<5%) for adults. The study has two main contributions: (1) monitoring breathing rate at home gives comfortable feelings to patients and caregivers, expanding the potential of applying modern technology to clinics, (2) the study has solved the problem of tracking small movements in videos with relatively large FoV in real-time. Perspectively, we will be employed the method in a home-based respiratory rate monitoring system.

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1. Introduction

Breathing rate is an important vital sign and is one of the first considerations when people got health problems [1]. The respiratory rate value beyond a certain threshold is a sign of abnormality related to pathologies such as cardiopulmonary arrest [2], acute heart failure [3], and pneumonia [4], and can also be a sign of fatal apnea [5]. These signs require prompt medical intervention to prevent disease and save lives. This becomes more important in children and people at risk of stroke [6], [7]. About 6% of babies are at risk of sudden death during sleep [8]. The number of people at risk of new strokes identified each year is 795,000, of which 20-40% of strokes happen at night [7]. Vital signs can be measured by contact and non-contact methods [9]. The contact method uses small wireless devices by integrating breathing measurement function into them like smartwatches [10]. The SpO2 meter on the fingertip also measures health abnormalities by measuring blood oxygen saturation and measuring heart rate [11]. The mounting of measuring devices on the body creates uncomfortable feelings for users, especially for children [12]. Furthermore, the sleep analysis based on the deep learning model using the input of ECG signals was also investigated which gave good results [13]. However, these analyses are based on contact measurement device data [14]. The non-contact method can, therefore, eliminate those limitations.

There have been various ways of non-contact respiratory rate measurements. These methods measure changes in the nearby environment around the sleeping subject [9], [15]. In these studies, the sleeping environments were usually static, so small periodic changes caused by respiratory activity can be easily seen. Audio sensors and microwave Doppler radar were two types of sound wave sensors used to measure breathing [16], [17]. Breathing sound was measured by the periodic change in sound intensity during sleep [17], [18]. In the measurement process, non-breathing sounds such as fans and air conditioners were often non-cyclical and have different sound intensity thresholds that should be filtered to remove them [19]. While the audio sensor measures breathing based on breathing sounds through the microphones [16], the Doppler radar measures breathing by measuring microwaves based on the up-and-down movement of the chest-abdominal region [18].

Computer vision-based breathing rate measurement was a recent research direction due to the popularity of cameras and computers [20]. Breathing rate was measured by analyzing video sequences recorded from the camera, with the support of artificial intelligence or image processing algorithms [21]. Continuous motion tracking techniques such as optical flow and background subtraction were used to monitor respiratory activities that occur during sleep time [22], [23]. The optical flow algorithm tracks movement based on the movement of feature points in the frames while the background subtraction method compared the overall light intensity between two consecutive frames to see movements [21], [23]. Because the respiration signals were relatively small and concentrated in the chest-abdominal region, tracking points in the respiratory area had higher accuracy. The background subtraction algorithms were suitable for tracking large movements [24]. However, the input frames in some previous studies showed that they could not apply in a real sleeping environment because the frames had a narrow FoV, which leads to the result that the participant will be out of the camera view if they change their sleeping position [21], [25].

Consequently, this study proposed a breathing rate monitoring method using a mono camera to detect sleep apnea phenomena in children and adults at risk of stroke. The proposed method is implemented by tracking the movement caused by respiration at the chest-abdominal region. Firstly, the human body area is isolated by using an artificial neural network model [26]. Then, up and down fluctuations in the chest-abdominal area were extracted and monitored using an optical flow algorithm [27] with the support of the principal component analysis (PCA) technique [28]. Breathing rate is the number of times the signal amplitude peaks in one minute. The predicted breathing rate values will be compared with the real breathing values getting by counting manually the breathing rate called the visible measurement method. The measurement errors include absolute errors and relative errors. This study is the extension of the extended abstract that we presented in [29]. That extended abstract summarizes the first part of this study with results in only two individuals and limited in the sleeping environment including sleeping on the back and side without using any blanket [29]. This paper details the study after adjusting the algorithm for better performance, as well as testing on more subjects and sleeping environments.

In the following sections, we will describe in detail the video sequence processing for breathing measurement in Section 2. Then, the results of the measurement and analysis of the breathing rate are described in Section 3. Comparisons with other studies will be presented in which Section. Finally, conclusions and future developments will be stated in Section 4.

2. Materials and Methods

2.1. General modeling workflow

The general modeling workflow of different model generations is shown in Figure 1. The workflow includes (1) object detection, (2) motion tracking, and (3) measurement.

(1) The object is identified by an artificial neural network model [26], YOLOv4 [30], to limit the area where respiration occurs and warn in cases where the individual is covered with a blanket over the head.

(2) The respiratory movement is determined by tracking the characteristic points found by the Shi-Tomashi Corner detector algorithm [31], through the Lucas-Kanade algorithm [32], the respiratory movement direction is extracted by the principal component analysis technique [28].

(3) The respiratory rate is the number of times the breath signal amplitude peaks in 1 minute, this value will be compared with the normal breathing rate value to conclude.

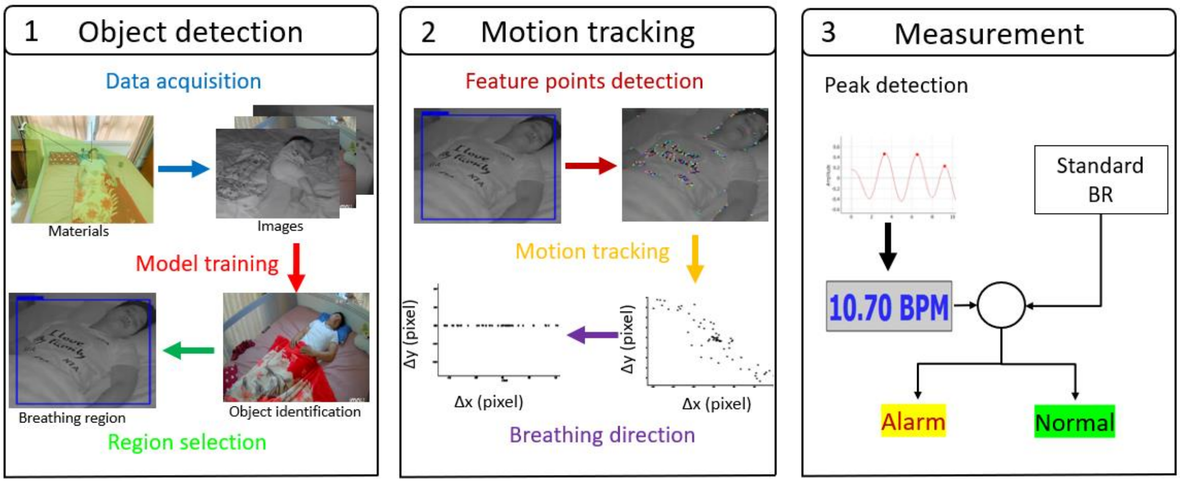


Figure 1. *The general workflow of model generations: (1) Object detection process, (2) Motion tracking process, and (3) Measurement process*

2.2. Data collections

The breathing monitoring system includes a camera to record videos of a sleeping subject and a computer to process the videos to give breathing results. Video data from the camera to the computer is transmitted over the local area network (LAN). The system uses an IPC-C22EP-A-IMOU camera, a resolution of 2 megapixels (1920×1080), speed of 20 frames per second. The size of the bed is 1.6m x 2 m or 1.8 m × 2 m. For installation, the camera is installed at an angle θ of from opposite the subject for seeing the rise and fall of the body when breathing occurs as shown in Figure 2. Our method detects breathing based on the movement of points on the subject's body which are determined based on the contrasting color of the clothes. For this reason, the participant is requested to wear the shirt and used the blankets with many contrasting color points. Videos are processed on the computer through the Python language platform, with the support of the OpenCV library, TensorFlow, and other support packages.

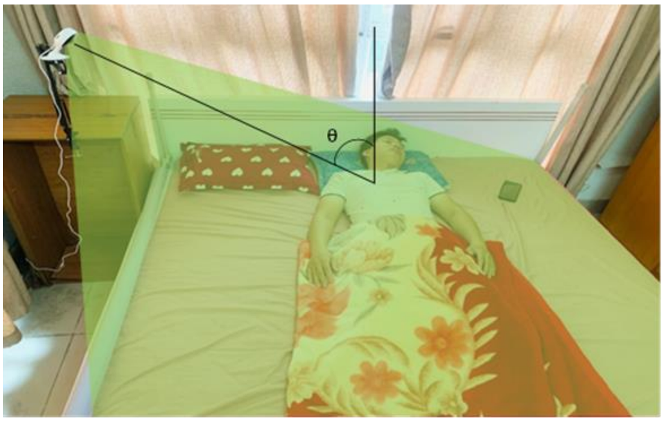
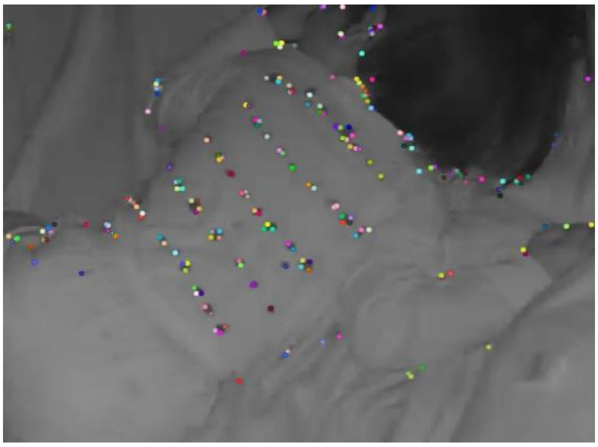


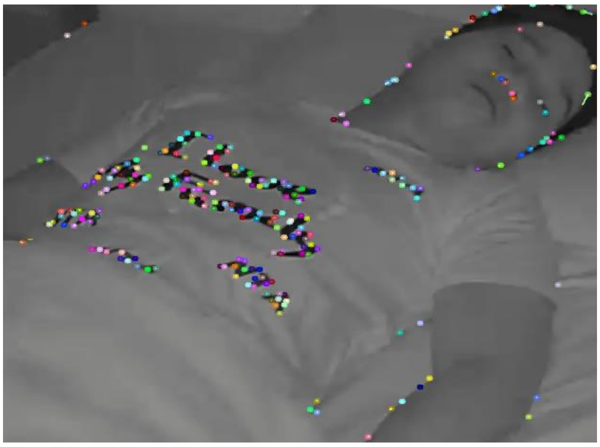
Figure 2. *Camera installation position*

2.3. Object detection

In our research, we use a camera with a large FoV to ensure that the sleeping individual is always within the input frame whatever where they are in the frames. This brings many parts of the frame that do not contain respiratory activity such as empty beds, unused pillows, and blankets. Limiting the motion tracking area eliminates unwanted movements during testing. Respiratory activity is visible in the upper body including the chest, abdomen, and even the shoulders. Our proposed method limits the respiratory monitoring area by predicting the human's position in the input frame using artificial neural network models [26]. The YOLOv4-tiny network is selected due to its fast processing speed, suitable for real-time processing [33]. We used 1000 images of sleeping individuals in different positions, lights, and distances to train the network. These images are obtained by collecting the subject's sleeping videos and extracting images from the videos. 90% of the images in the dataset are used to train the network. 10% of the images are used to validate the training results. Testing is done in real-time. The images are manually labeled, the labeled area is the upper body area from the abdomen to the head.



(a)



(b)

Figure 3. *Feature extraction in dark environments*

2.4. Motion tracking

Motion is tracked by tracking the change in the position of feature points across adjacent image frames. The feature points are defined as the corner points where there is a color contrast of clothes by the Harris method [34]. Breathing activity is most noticeable through the movement of fixed color points on clothes. Therefore, the application of corner feature detectors is more effective than other methods such as edge detectors or region detectors. The Harris method is based on the variation of brightness in a small area of the image. These regions will greatly change the luminous intensity when siding a small window across the image plane. The amount of change in intensity is the sum of the weights multiplied by the intensity difference for all pixels in the small sliding window [31], [34]. Because of this technique, participants were asked to wear clothes with lots of contrasting colors. However, the color difference between the bed sheet and the subject's clothes is enough to have color contrasts. In the case of dark environments, the grayscale image did not have many colors, but the contrast points were still clearly visible. Figure 3 shows the results of finding features based on the corner feature detection technique. The technique is still effective in dark environments.

Figure 4 shows the process of extracting and monitoring breathing rates, the general about how to transform the change in frames into breathing waves. In the first frame, the features are identified by the Shi-Tomasi algorithm [31]. This is an improved algorithm based on the Harris method with a better threshold for determining the angle [31], [35]. The technique returns the number and coordinates (in pixels) of corner features, called feature points. In each subsequent frame, the coordinates of the feature points are extracted through the Optical flow algorithm [27]. The Optical flow algorithm tracks the features over time through pixel difference, taking the displacement vectors of the feature points across the image frames. The position of the feature at time t is I(x,y,t) after time dt is I(x,y,t+dt) [32].

$$I(x, y, y) = I(x + dx, y + dy, t + dt) \tag{1}$$

Taylor expansion of equation 1, we get the displacement vector V(x,y) which is the velocity vector of the feature point in the x and y directions. This represents the change in the position of the pixel from the t frame to the t+1 frame [32]. From there, we determine the coordinates of the feature points in the adjacent image frames. The average value of the coordinate difference of all feature points in the current frame and the previous frame is the movement due to breathing. It means the breathing movement point in each frame is The respiratory movement point at each frame is determined by averaging the distance change of all moving points between two consecutive frames. The movement changes in both 2 dimensions x and y of the image plane, whose length depends on the size and resolution of the image. Figure 5a shows the correlation of the movement between the two frames. The points tend to move on both the x and y dimensions of the image coordinate plane, in which there is one dimension containing more movement, that is the respiratory dimension. The next step is to determine the direction of respiratory movement. The direction of respiratory movement is performed through PCA [28]. This technique reconstructs the original data by selecting the eigenvector with the highest eigenvalue after calculating the covariance matrix from the 2-D data. The pictures in Figures 5a and 5b present an example of the reconstruction results when scratching it in discrete time. Plotting the data in domain time, we get the respiratory signal (Figure 6). The Butterworth filter is used to filter the breathing signal.

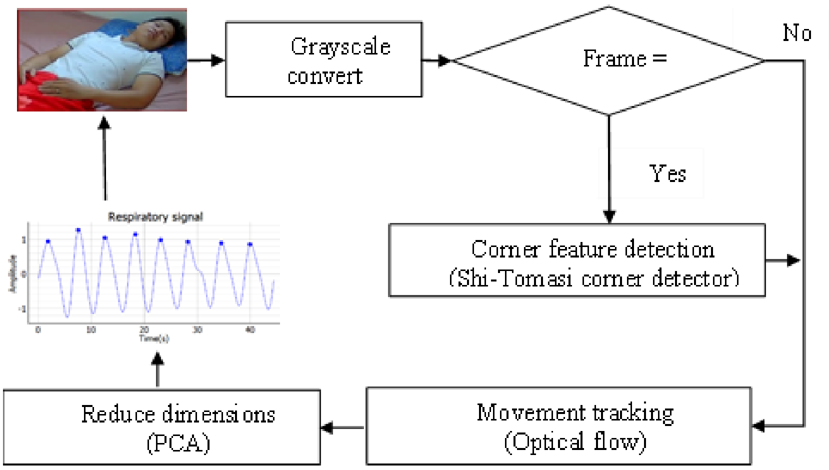


Figure 4. *The process of motion tracking*

2.5. Breathing rate measurement

By counting the number of times the signal amplitude peaks in one minute, we get the breathing rate or measure the time between two times the signal peaks continuously and then infer the breathing rate. The amplitude is peak when its value at time t is greater than the value at time t-1 and greater than the value at time t+1. That is, (t-1) value <(t) value>(t+1) value. Figure 6 shows the number of signal peaks in one minute. Finally, the respiratory rate results are displayed on the screen including a sine wave signal showing the ongoing respiratory activity and the number of breaths per minute of the subject. The results screen also shows whether the subject is an infant or an adult and also warns when breathing is out of normal limits.

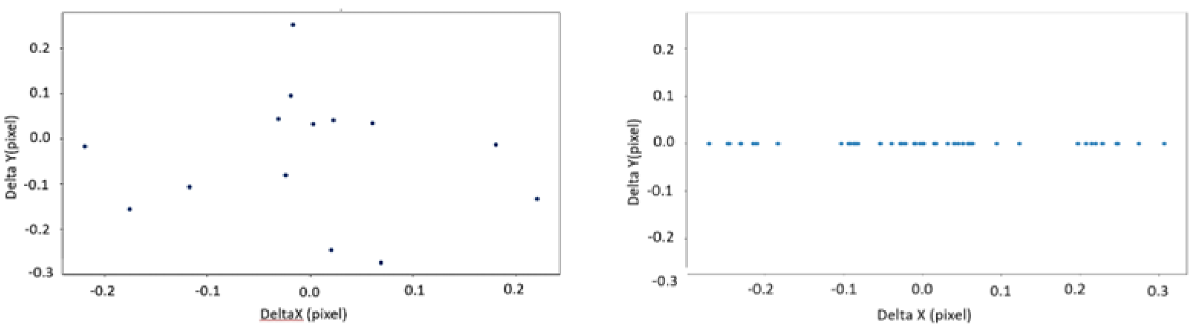


Figure 5. *The respiratory signal from motion data: movement points in 2 dimensions (left); respiratory movement data (right).*

All modeling and validating procedures were executed on a computer with the hardware configuration of 12th Gen Intel(R) Core(TM) i7-1255U 1.70 GHz, NVIDIA GeForce MX570, 2 GB GDDR6, 16GB (DDR4) RAM and developed in Python and related packages.

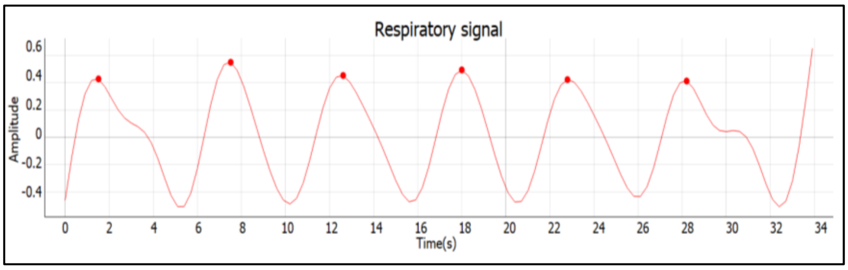


Figure 6. *Respiratory signal of our proposed method.*

2.6. Breathing rate validation method

The actual breathing rate is measured by the visual measurement method, which is considered ground-truth data to compare with the measurement results from the proposed method. This method has been applied in some previous studies [21], [23], [25]. Although the implementation is time-consuming, the measurement results are accurate for each specific breath and suitable for use in the research process. The visual breathing method is performed manually by counting the fluctuation of the points caused by the inhalation on the individual's upper body. The number of inhalations per minute is the breath rate.

3. Results and Discussion

3.1. Object detection

Figure 7 shows the result of the YOLO model after training 1000 images. The average accuracy of the model is 65.67%, recall is 0.77(thresh=0.25), crossover rate (IoU) is 44.00 %, precision is 0.55 (thresh=0.25), and loss is 0.4146. It can be seen that this result is not good because the average accuracy and precision are not high. The small number of images is the main reason leading to this limitation.

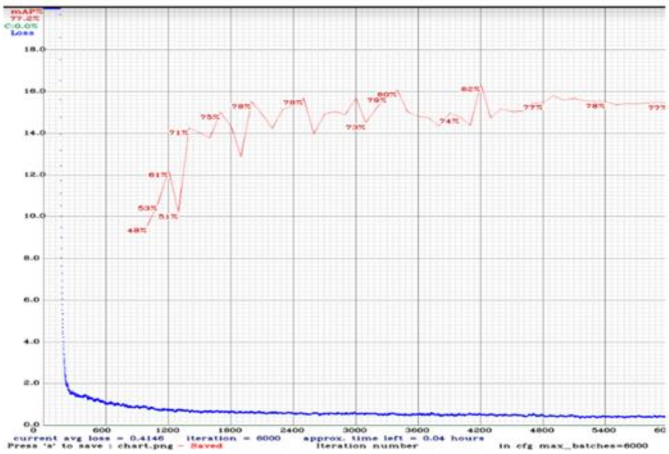


Figure 7. *YOLO training results*

The result of object detection was not good because of 2 main reasons. Firstly, the training data was small, 1000 images only. Secondly, confusion between 2 classes, adults and children. In fact, it is difficult to distinguish children and adults when sleeping, especially in the case of using blankets and lying on their side.

These limitations can be solved by increasing the training data. Instead of dividing into 2 classes (children and adults), just divide in 1 class (person). The reason is that the subject is a child or an adult is defined at the beginning, it can be set as an input selected by the users.

3.2. Breathing rate validation in Children and Adults

The study tested 3 subjects (1 child and 2 adults). Subjects slept in light (daytime) and dark (night) environments; distance from the camera to the subject from 1.2m to 2m; back, side, prone sleeping

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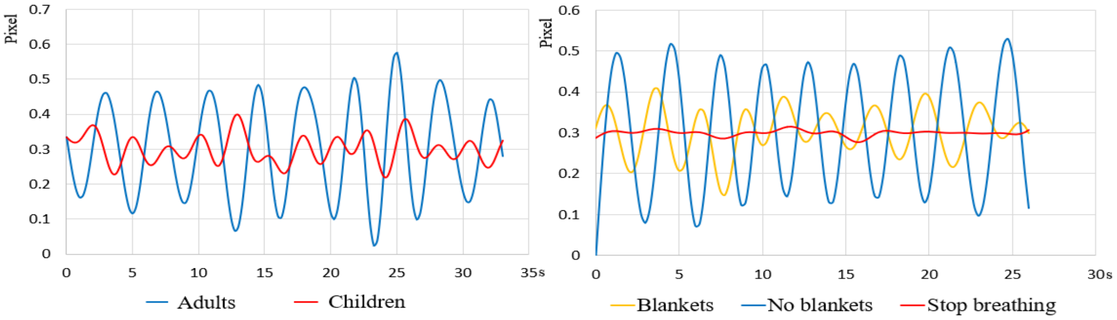
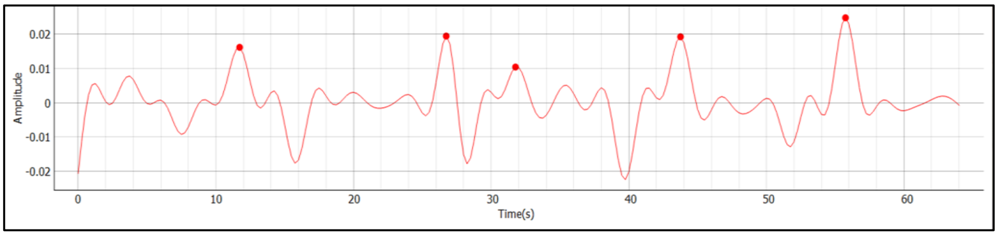
positions; with and without the use of blankets and fans. The total test duration was 130 min, randomly selected between subjects' sleep cycles.



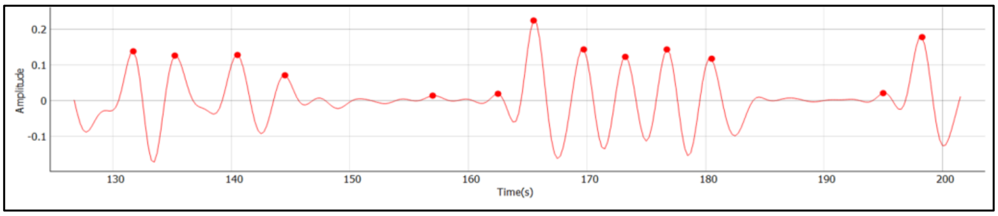
(a) (b)

Figure 8. *The respiratory signals: (a) amplitude difference between adults and children, (b) amplitude difference when using or not using blankets compared with stopping breathing*

The result shows that the amplitude of breathing signals in children and adults is different and affected by sleeping position and the usage of blankets. The adult amplitude signal is greater than in children (Figure 8a). The adult image part occupies a large area in the input frame, so the body movement caused by respiration is larger than that of the infant, so the breathing monitoring results are better. In addition to the effect of the subject's body size, breathing amplitude was also affected by the usage of blankets during sleep. Even so, the signal amplitude is still much larger than apnea (Figure 8b). Thus, the method has detected the sleep apnea phenomenon in children and adults.



(a)



(b)

Figure 9. *The respiratory signals in case of sleep apnea: (a) sleep apnea in children, (b) sleep apnea in adults*

The main purpose of the study was to identify sleep apnea, which is difficult to practice in reality. Therefore, we performed pseudo apnea in children and adults. It was not possible to fake apnea in children, so we performed respiratory rate measurement on a dummy subject, a teddy bear placed in a sleeping environment. The result in Figure 9a illustrates a really small signal found, the signal amplitude was almost 10 times smaller than when there is a real subject and only 5 peaks were found in 1 min period compared to 20-30 breaths/min in normal breathing rate. For adults, the signal amplitude was a small fluctuation during the time the subject intentionally stopped breathing. Figure 9b gives an example of stopping breathing in adults, the subject stopped breathing 2 times in 1 minute, and a really small fluctuation was found during this time compared with that of breathing. The good effect of tracking small movements is also challenging because it will involve noise from outside influences. Small oscillations that still occur without breathing are an example. However, the noise oscillation has a rather small amplitude compared to the respiratory oscillation. So, setting the limit range of the breath signal amplitude may give better results. It will be experimental at the advanced stage of this study.

Breathing rate measurement errors are different in different sleeping conditions. The given results in Table 1 show the absolute errors-AE and relative errors-RE between the predicted value and the ground-truth value. They were from 0.3 - 0.6 breaths/min (1.6% - 4.1%) in adults and from 0.2 - 1.8 breaths/min (0.9% - 8.1%) in children. The breathing rate is influenced by dynamic factors such as blankets, fans, distance, and sleeping position. When the subject lying on the stomach, the error was higher than in other cases because the vibrations of the thorax were obscured. However, the up and down of the thorax acts as a lever, causing the rise and fall of the upper body when breathing, thereby, the feature points on the back of the subject fluctuated. Although the fan generates noisy oscillations, these oscillation vectors are eliminated by the PCA technique, so the accuracy is maintained stable at about 97.5%. In the measurement respiratory rate of children, the accuracy is reduced when using blankets.

Table 1. *Measurement errors in cases of using blankets, fans, and normal sleep between adults and children*

Conditions		**AE**		**RE**	
		Adults	**Children**	**Adults**	**Children**
Day	Blankets	0.4	1.8	2.2	8.1
	Fan	0.4	1.0	2.3	4.8
	Normal	0.6	0.5	4.1	2.4
Night	Blankets	0.6	1	3.1	4.9
	Fan	0.3	0.4	1.6	1.9
	Normal	0.3	0.2	1.6	0.9

In addition, measurement errors are also affected by sleeping positions. Experimental results in 3 different cases including lying on your side with a blanket, lying on your side without a blanket and lying on your back without a blanket show that the error when lying on your side is 2 times higher than lying on your back in the case without a blanket (Table 2). Breathing accuracy in children is more unstable when subjects change sleeping positions than in adults. Even so, the system remained stable with an average accuracy of more than 95% in both adults and children.

Table 2. *Measurement errors in cases of sleeping on the side, and back between adults and children*

Conditions			**AE**		**RE**	
			Adults	**Children**	**Adults**	**Children**
Day	Side	Blankets	0.4	1.8	2.2	8.1
	Side	No blankets	0.4	0.5	2.3	2.4
	Back	No blankets	0.2	0.8	1.2	3.5
Night	Side	Blankets	0.6	1	3.1	4.8
	Side	No blankets	0.3	0.4	1.6	1.9
	Back	No blankets	0.3	0.2	1.6	0.9

This proposed method has detected sleep apnea in children and adults with higher practical implementation ability than in previous studies. The input image of the studies [21], [25] showed the limitation that the subject would be out of the camera frame if they changed their position, or moved to another position on the bed. We have overcome the above limitation by using a camera with a large FoV, then using the YOLO model to identify and process the algorithm on the subject area. Table 3 shows the detail in the comparison between our study and the previous study. It can be seen that the result of tracking respiratory using an optical flow technique is more efficient than the spatial difference. The average accuracy of our proposal is 4% higher than the previous study in the nearly same testing conditions [25]. Our method also gave good testing results in adults while the compared method tested on children only with a fixed sleeping position (Table 3).

Table 3. *The comparison between our study and the previous study* [25]

No	Content	Our method	Previous study
1	Technique	Optical flow + PCA	Spatial difference
2	Subject	Children and adults	Children
3	FoV	Large	Small
4	Conditions	Sleep on back and wind	Sleep on back and wind
5	Number of frames	18000	1940
6	Prediction (on children)	96.65%	92.32%

4. Conclusions

Detecting sleep apnea at home not only brings a safe feeling to patients and caregivers but also is a potential way to automate the health monitoring process. Our approach solved that problem by using a camera with a large view integrated with artificial intelligence and image processing algorithms. With an error of fewer than 2 breaths/minute, the method has the potential for practical implementation. This proposed method has 2 main contributions. First, regarding home-based applications, automated non-contact breathing monitoring reduces stress on caregivers, and gives a comfortable feeling to patients. Second, regarding academics, this research has solved the problem of tracking small movements in frames with a large FoV to respond in real time.

However, our proposed method also has limitations. The results of object detection by YOLO are limited due to confusion between two classifications (children and adults). In the next phase of the study, we will improve this result by using only 1 subclass for feature tracking because it is difficult to distinguish the object as a child or an adult while lying. The second limitation is that the number of tested samples is limited (3 people). The main reason is that setting up to monitor real sleep positions requires the consent of the participants because it is private and they do not really trust its effectiveness. However, on the tested samples, we tested their actual sleep patterns in different conditions and lighting environments. This initial result is really needed before expanding future deployments.

In perspective, we will develop the tracking algorithm to give better measurement results and the ability to monitor the breathing rate of many subjects at the same time.

Acknowledgments

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