RGB-thermal Imaging System Collaborated with Marker Tracking for Remote Breathing Rate Measurement

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***Abstract*—The pixel variation signal extracted from the nasal region of RGB-thermal images can be used to achieve breathing rate (BR) measurement. However, this method fails when the nasal region is not detected in complicated motion scenarios. In this paper, we develop an RGB-thermal imaging system collaborated with marker sticker to achieve unobtrusive and accurate BR measurement. Pixel variation signal of Regions of interest (ROI) is extracted from the thermal video and chest movement signal is extracted from the RGB video with the assistance of marker stickers. Subsequently, a custom-made time-domain signal processing approach is developed for determining BR. We further propose a method of splicing computation to measure the BR after separate processing of signal segments. We construct an RGB-thermal video dataset with different head and body movements to evaluate the effectiveness of the proposed algorithm. After linear regression analysis, the determination coefficient (R^2) of 0.905 has been observed for the estimated and reference BRs, indicating the feasibility of our proposed method in complex motion scenarios.**

***Index Terms*—Respiration measurement; RGB-thermal imaging; Motion-based breathing detection; Splicing calculation process.**

I. INTRODUCTION

Breathing rate (BR) is one of four main vital physiological signals as an important predictor of serious illnesses. The abnormal respiratory rate is always associated with many potential diseases such as hypoxemia, hypercapnia, etc[1]. There are numerous existing non-invasive measurement techniques such as electrical impedance tomography [2] to estimate BR. However, the contact measurement approaches always require many sensors to be attached to the body and bring physical burdens to users. Luckily, non-contact techniques can offer a way to measure BR without pressure.

For contactless BR measurements, the viability of movement variation analysis using video data has been investigated by many researchers[3]. Shao et al., extracted the breathing signal from small movements of shoulders [4]. However, the video-based methods are sensitive to significant movements of the subject and illumination changes. To solve this shortcoming, Anushree et al., used the thermal imaging technique to record temperature variations in nostrils and mouth regions, which accompany the inhalation and exhalation, and the breathing signal can be extracted for determining BR irrespective of changes in position, body movement or illumination intensity[5,6]. Pereira et al., acquired a great agreement between the estimated BR and ground truth with the 95% limits of agreement [7]. Similar results were also obtained by other groups of investigators [8,9,10,11].

Nevertheless, the above methods only work when recognizing the face region precisely in the RGB images. When the testers turn their heads to the side or back (over 90 angles), the system is invalid to estimate BRs. Considering the high sensitivity to significant movements of the motion detection method and limitations of thermal imaging method that faces must be detected in the RGB videos, we establish a collaborative respiratory detection system which is more suitable for the practical application scenarios. If faces are detected in the RGB videos, we use the thermal imaging method to extract the breathing signal by temperature variations of ROI. When faces are undetected in the RGB videos, we turn to apply the motion detection method to extract the breathing signal by changes of coordinates of detected marker points.

The paper is organized as follows: Section II describes the principle of thermal imaging system and motion detection system for BR measurement; Section III describes our collaborative method; In section IV, we compare our collaborative method with the thermal imaging method and marker point motion detection method; Section V concludes this paper.

II. PRINCIPLE OF THERMAL IMAGING METHOD AND MOTION DETECTION METHOD

Due to the lack of geometric and textural facial details of thermal images[12], RGB images are used to assist in automatically recognizing the facial region and its tissue in thermal images based on reliable face detection algorithms. After locating the corresponding ROI in thermal images, we can gain the pixel changes to measure BRs.

As for the motion-based BR detection method, the principle is based on the movement of the subject's chest obtained by the motion of marker stickers on the thoracic surface of the subject in RGB videos. After recognizing marker stickers based on the color and shape features[13], we can obtain the motion trajectories and estimate BRs from the subtle changes of longitudinal coordinates relative to the camera.

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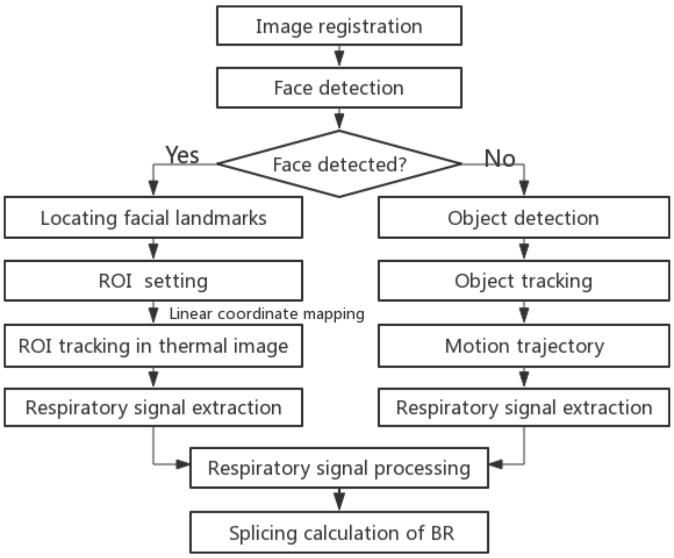

Fig. 1. The workflow of the proposed collaborative BR measurement method.

III. PROPOSED COLLABORATIVE METHOD

The principle of our system is to use the motion-based breathing detection method for assisting the thermal imaging method when faces are undetected in RGB images and to extract the respiratory signal fragments from two different acquisition systems separately. Subsequently, the time-domain method is used to process these signal segments and the BRs can be derived by the splicing calculation of respiratory signal segments. The workflow of our collaborative BR measurement method is demonstrated in Fig 1.

A. Hardware and Software of Imaging System

A thermal imager (MAG62, Magnity Electronics Co.Ltd., Shanghai, PR China) and an RGB camera with a resolution of 640480 are used in this experiment. These two cameras are parallel to each other in such a way that the field of view is almost the same. A custom-built image acquisition software is developed for generating two trigger signals which is utilized to capture frames at the rate of 10 frames per second, thereby allowing the simultaneous acquisition of thermal and RGB videos. At the same time of video collection, the reference BR is recorded by Sleep Respiratory Monitor (GY-6620, South China Medical and Electrical Technology Co., Ltd., Henan, China).

B. RGB and Thermal Video Dataset for BR Measurement

In our experiments, a total of 20 volunteers including sixteen males and four females with the ages from 20 to 38 years old consented to be the subjects and were instructed to sit on the testing chair with red discs four centimeters in diameter as marker stickers on the thoracic surface for one minute. Volunteers were asked to sit with some body and head movement including turning head to the side and back sometimes to simulate more complex experimental scenarios thus forming 20 pairs of RGB and thermal videos.

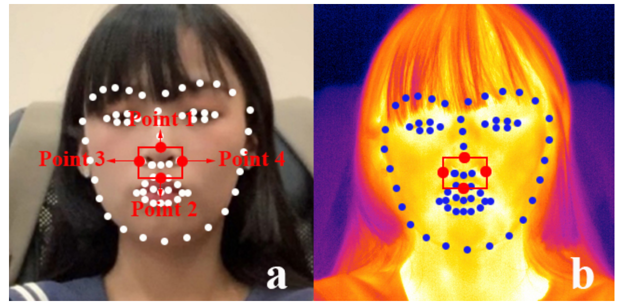

Fig. 2. Illustration of the facial landmarks for the determination of the ROI:(a) ROI determined by four facial landmarks. (b) ROI setting in thermal image after linear coordinate mapping.

C. Respiratory Signal Extraction

Due to the spatial deviations of these two cameras, the affine transformation [14] is applied to register the RGB image using the thermal image as a reference. After the affine transformation, we use the face-recognition open source project built with deep learning to detect facial regions [15]. A total of 66 landmark points in face are located (Fig 2). After selecting the specific landmark points, we can get the ROI which cover nostrils regions, thereby allowing us to obtain the temperature fluctuations throughout the inspiration and expiration cycle. In this study, ROI is set to a rectangular area determined by four points, the fourth point from top to bottom of the nose bridge (Point 1), the middle point of the upper lip (Point 2) and the two corner points of the nose tip (Point 3 and 4) shown in the Fig 2. The ROI is calculated according to

$$\overrightarrow{ROI} = \begin{pmatrix} X & Y & H & W & \theta \end{pmatrix}^T \tag{1}$$

$$= \begin{pmatrix} x_1 + H\sin\theta/2 \\ y_1 - H\cos\theta/2 \\ \cos\theta[y_1 + y_4 - y_2 - y_3 - \tan\theta(x_1 + x_4 - x_2 - x_3)] \\ (x_4 - x_3)/\cos\theta \\ \tan^{-}1(y_4 - y_3)/(x_4 - x_3) \end{pmatrix} \tag{2}$$

where $\overrightarrow{ROI}$ is the ROI formation vector containing the horizontal ordinate (X), vertical coordinate (Y), height (H), width (W) and inclination angle (θ). The (x_1, y_1), (x_2, y_2), (x_3, y_3) and (x_4, y_4) are the coordinates for point 1, 2, 3 and 4, respectively.

Once the ROI have been confirmed, the linear coordinate mapping is used to determine the corresponding regions in thermal videos and we can track the ROI in the thermal videos using the tracking algorithm in the face recognition library [15]. Subsequently, the respiratory signal is extracted from the thermal videos by computing the average pixel intensity of ROI.

However, there is a possible experimental phenomenon when testers sit with big head movements and body twists leading faces undetected in RGB images. In this situation, the motion detection technique is used to acquire the breathing signal instead of the thermal imaging method. The object detection and tracking algorithm [13] based on color and shape features are employed to recognize the marker sticker

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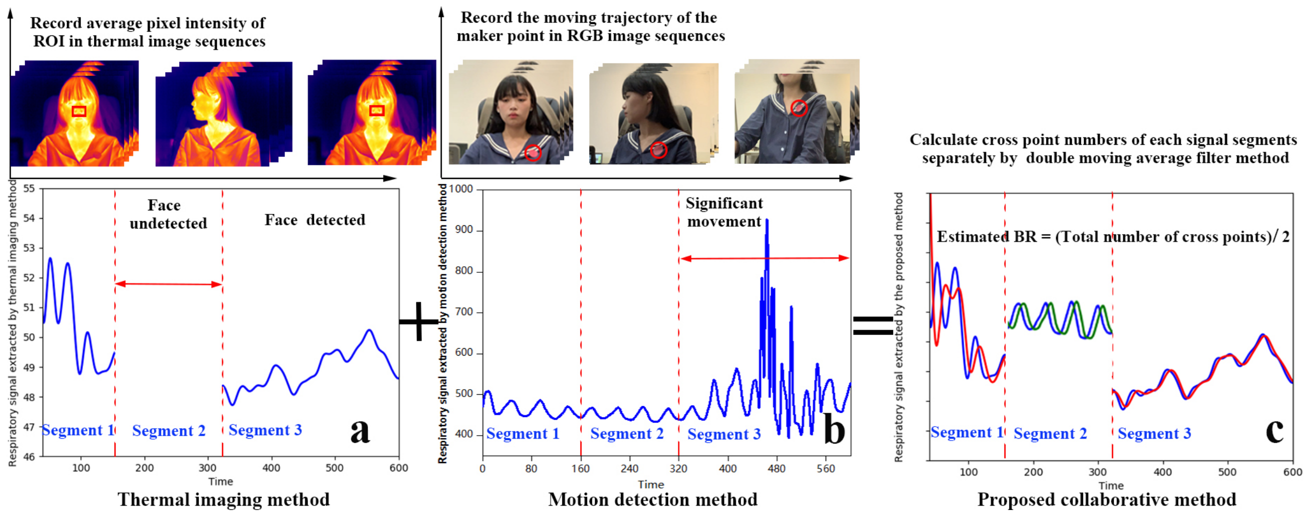

Fig. 3. The process of BR splicing calculation of respiratory signal segments: (a) the respiratory signal extracted by thermal imaging method; (b) the respiratory signal extracted by motion detection method; (c) segmented signals by two methods and estimated BR can be calculated. (The red line and green line stand for the processed signals after the moving average filter.)

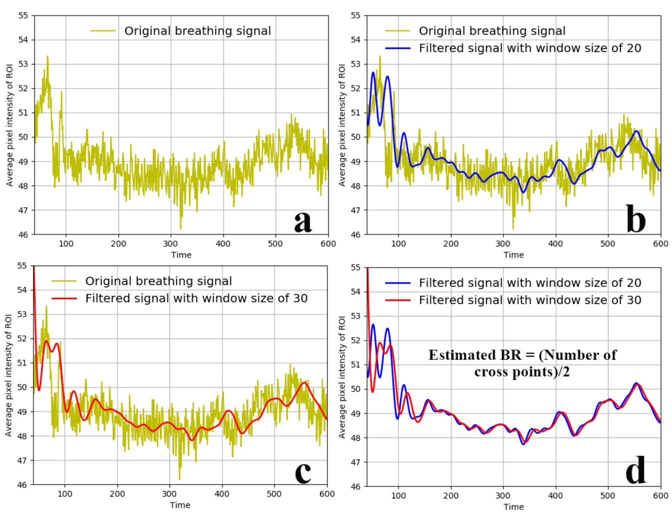

Fig. 4. The procedure of signal processing for BR measurements: (a) the original breathing signal; (b) the processed signal after the moving average filter with the window size of 20 ; (c) the processed signal after the moving average filter with the window size of 30; and (d) the two filtered signal and the BR can be calculated by the cross point numbers of two curves.

of the red disc and track the motion trajectory for the pixel of the center of the disc. Then the BR is determined by the variation frequency of longitudinal coordinate of the marker point relative to the camera.

Consequently, in the proposed collaborative method, all respiratory signal segments extracted from the thermal imaging system and the motion detection system will be processed by time-domain methods, and the numbers of breaths in each period will be calculated separately.

D. Respiratory Signal Processing

For the non-contact measurement approaches, there exists a lot of noise from the factors such as the slight movement and illumination variation in the original extracted respiratory signals. Based on the related literature [16], the range of BR related frequency is between 0.167-0.667Hz in the Fourier power spectrum which means that we can obtain the breathing signal from the raw signal by eliminating the signals of high frequencies. So the moving average filter is used to wipe off high-frequency signals to derive the clearer breathing signal (Fig 4(b)). Owing to a phase hysteresis in the obtained signals when changing the window size of the sliding average window, we apply a time-domain method called double moving average filter method [11] to filter the original signal with two different window sizes and the BR can be calculated by the cross point numbers of two curves (Fig 4(d)).

To demonstrate the overall BR splicing calculation method intuitively, one sample is chosen from our dataset to clearly describe the whole procedure (Fig 3). As shown in Fig 3(a), the respiratory signal extracted from the thermal imaging system is truncated since there is no face detected for a period of time when the subject carries out significant head motion in our experiment. So the measured BR is lower than the reference value on account of the loss of signal. However, from Fig 3(b), we can observe that the signal segment 3 extracted from the motion detection system fluctuates rapidly and tremendously which is not related to respiratory changes. This phenomenon occurs because the subject has tremendous body movements during the time leading to the inaccuracy of measured BR. Our proposed method shown in Fig 3(c) avoids these shortcomings, each signal segment is processed by double moving average filter method, and the intersection points of all signals can be spliced to calculate the total number of breaths.

IV. RESULTS AND DISCUSSION

To test the performance of bimodal imaging system in tandem with proposed algorithms in an unobtrusive and contactless manner, a statistical analysis method namely linear correlation analysis is applied for validating the data from the small-scale pilot experiment. We empirically compare our collaborative BR measurement method with the thermal

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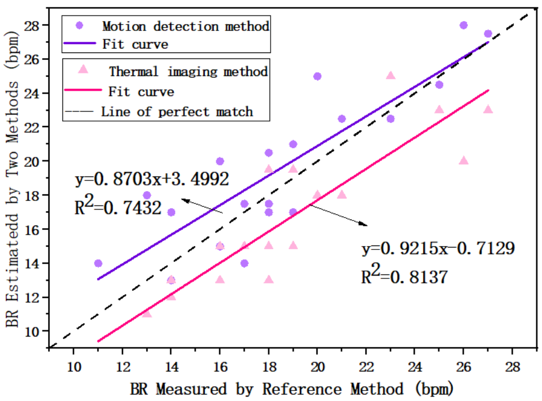
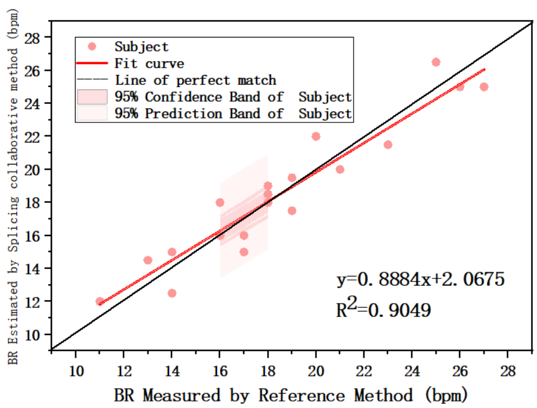


(a)



(b)

Fig. 5. Statistical analysis of BR measurement using different BR measurement methods: (a)The result of BR measurement by thermal imaging method and motion detection method; and (b)The result of BR measurement by our collaborative method.

imaging method and motion detection method, respectively. The results of linear correlation analysis for the reference BR and the BR measured by different methods are demonstrated in Fig 5.

As shown in Fig 5(a), the most scatter points are distributed around the line of perfect match. However, there is the measured deviation that the most pink data points which represent the measured data from thermal imaging method are distributed below the line, and the purple data points measured by motion detection method tend to be distributed above the line. For the pink data points, the reason for the deviation may be that there is no face detected for a period of time resulting in the lack of breathing signal. For the purple data points, the poor performance may be attributed to the high sensitivity to body movements of testing subjects during the experiment.

Moreover, we can observe that all scatter points derived from the proposed method are located between the 95% upper and lower confidence intervals(Fig 5(b)), and most of them are close to the line of perfect match which reveals the capability of RGB-thermal imaging system coupled with proposed algorithms for BR estimation in a more complex experimental scene. From the linear correlation analysis, the determination coefficient (R^2) is found to be 0.905 which is higher than 0.743 and 0.814 of two methods above. Additionally, the fitting curves further illustrate the superiority of our collaborative BR measurement method.

V. CONCLUSION

The RGB-thermal imaging system collaborated with marker tracking can measure BR unobtrusively and accurately in complicated motion scenarios. Based on the small pilot study, the estimated BR is found to be strongly correlative with the reference BR with R^2 of 0.905. By comparative analysis, the superiority of our collaborative method is further verified.

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