Respiratory rate estimation using a low-resolution infrared sensor array

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***Abstract*—Breathing rate together with heart rate, blood pressure, and body temperature, are considered as essential and vital signs of human body. In this demo, we present a novel system to estimate the respiratory rate using a low-cost, non-intrusive, and passive infrared thermopile sensor array. The thermopile sensor array can detect the thermal infrared energy and generate a low-resolution video from subjects within its viewing range. We collected low resolution 8×8-pixel thermal video clips from 40 subjects at resting position from a distance of one-meter between the thermopile sensor array and the subjects. We processed the image frames using Haar-like filters and generated a one-dimensional feature signal from each video. The signal exhibits an almost periodic behavior following the respiratory movements. A peak detection algorithm is used to detect each breath. The proposed method is computationally efficient because it is based on multiplierless Haar-type feature extraction and peak detection. We achieved a high positive correlation rate of 97.77% between the actual respiratory rate that was measured by monitoring the chest movements during inhalation and exhalation and the estimated rate in our dataset. We will demonstrate this IR array based respiration rate detection system during the demo session.**

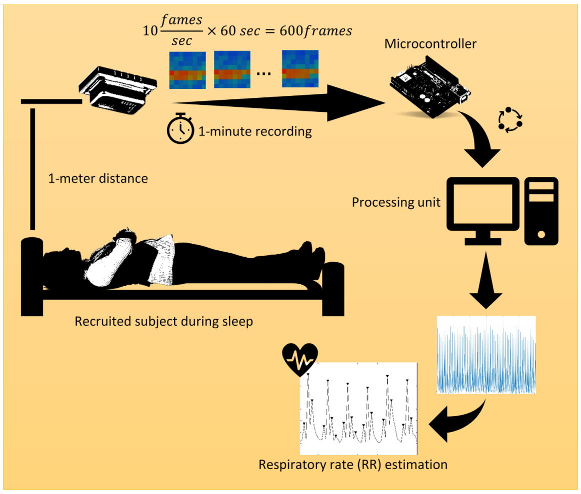

Fig. 1. Proposed system design to monitor and estimate the respiration rate using a low resolution, contact-free thermopile sensor array.

I. Introduction

The Respiratory Rate (RR) alongside the heart rate, blood pressure, and body temperature, is one of the four vital signs which are measurements of the human body's most basic functions [1]. The RR may provide an early warning of a disease or a health status deterioration [2]. The normal range of the resting RR for adults is between 12 to 20 breaths per minute [3], [4]. A large number of clinical situations can change the rate of respiration such as: heart failure, asthma, sleep apnea, diabetes, pain, and lately the COVID-19 disease [5], [6], [7]. Therefore, a continuous monitoring of respiration rate is a useful and important tool in hospitals, and home health care services [8]–[11], [13]. The RR monitoring systems are classified based on their operation and the way that they measure the respiratory rate into contact-based systems and contact-free systems [12], [14]. In contact-based systems all the measurement devices that are used to monitor the respiratory rate have a direct contact with the subject's body, while in the contact-free RR estimation systems, the devices have no contact of any type with the subject's body.

In this demo, we will present a novel system to estimate the respiratory rate using a passive infrared thermopile sensor array.

II. Haar-like Filter Based Feature Extraction

Our proposed RR estimation system contains a contact-free, low-resolution Panasonic Grid-Eye 8×8 Passive IR thermal sensors array. A microcontroller transfers the stream of 64-pixel thermal images that the thermal sensor array generates into a processing unit. Low-resolution IR images of a resting person is shown in Figure 2. The sensor generates 10 images per second. Haar-like filters are applied on the low-resolution thermal images to extract a feature vector (time-varying signal) from the video. The 1-D time series output of the Haar-like filter is low-pass filtered and downsampled because the respiration rate is between 12 to 20 breaths per minute. Finally, a peak detection algorithm is applied to estimate the respiratory rate as shown in Figure 1.

III. Results and Discussion

We collected IR data from forty healthy subjects (28 males, and 12 females). The subjects rested on a bed as shown in

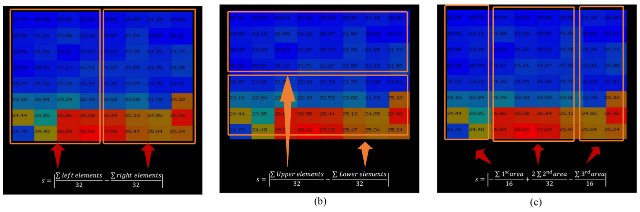

Fig. 2. Illustrated thermal images on which different Haar-like filters are applied.

Fig. 1 and the distance between the subjects and the sensor was about 1m.

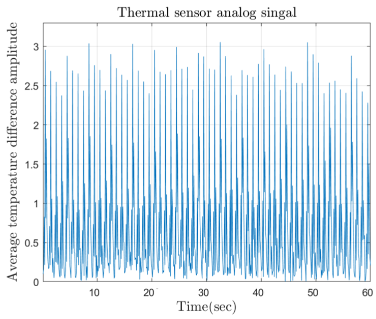

Fig. 3. A categorized output signal after applying the Haar-like filter on each captured frame.

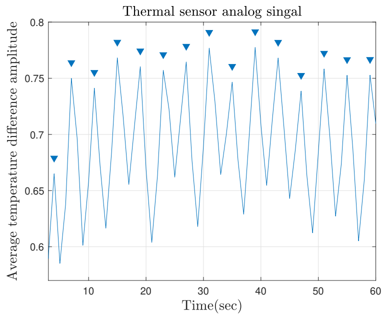

Fig. 4. The feature signal after applying the modified peak detection algorithm, the number of detected peaks represents the number of breaths per minute i.e respiration rate.

Haar-like filters	Left and right rectangular	Upper and Lower rectangular	Three regions rectangular
Average RMSE	**0.274**	0.591	0.387

TABLE I
AN AVERAGE RMSE OF THREE DIFFERENT HAAR-TYPE FILTERS THAT USED IN OUR WORK

We applied different types of Haar-like filters [16] on each frame to measure the absolute average temporal difference values as shown in Figure 2. Each filter generates a single value for each frame. As a result we obtain a time-varying feature signal $s(k)$ for each video as shown in Figure 3. The frame rate of the sensor is 10 Hz and it is too high for the purpose of respiration rate detection so we decimate the data by a factor of 10 to reduce the sampling rate to 1Hz. We apply the feature signal $s(k)$ to a Low-Pass Filter (LPF) with a cutoff normalized digital signal frequency equal to 0.1π and down-sample the output by a factor of 10 to obtain the signal shown in Figure 4. This signal is almost periodic because it follows the respiration pattern. We applied a modified peak detection algorithm to find the number of local maxima [15]. The number of maxima per minute determines the respiration rate or the number of chest movements within one minute as shown in Figure 4.

We measured the average Root Mean Squared Error (RMSE) for each Haar-like feature. We achieved an average RMSE equal to 0.387 breaths per minute when the Haar-like filter is applied to three different regions of each frame, while an average RMSE equal to 0.274 and 0.591 is achieved when the Haar-like filter is applied on the left and right side, and on the upper and lower side of each frame, respectively. The results are summarized in Table I.

We compared our system design with Lorato et al. [17] that used a thermopile sensor array to monitor the respiration rate in Table II.

	Our proposed system	**Lorato et al. [17]**
Sensor type	8×8 thermopile sensor array	8×8 thermopile sensor array
Approach	Haar like feature extraction and peak detection, count the number of peaks in the time domain	Hanning-windowed and 1DFFT, find the maximum peak in the frequency domain
Number of tested subjects	40 healthy subjects	6 healthy subjects
Average RMSE	0.274 breaths per minute (bpm)	1.59 bpm
Sensor distance	1m	0.2m
Ground truth obtained	by counting the chest movements over a 60sec period	by impedance pneumography
Correlation with the ground truth	97.77%	Was not specified

TABLE II
COMPARISON BETWEEN OUR APPROACH THAT USED A THERMOPILE SENSOR ARRAY TO MEASURE THE RESPIRATORY RATE WITH LORATO ET AL.

Our method is computationally more efficient than Lorato et al's [17] method as we do not use Fourier transform and do not search for a representative pixel representing the chest motion among the 64 pixels. It can be implemented using a low cost processor board such as an Arduino.

IV. CONCLUSION

In this demo we will present a novel algorithm to estimate the respiratory rate using a low-cost, contact-free, privacy preserving, low-resolution 8×8 passive IR thermopile sensor array. Our proposed algorithm is robust and computationally efficient. We will demonstrate the algorithm in the demo session.

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