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Breathing Rhythm Analysis in Body Centric Networks

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ABSTRACT Respiratory rhythm is the marker of respiratory diseases. A compromised respiratory system can be life threatening and potentially cause damage to other organs and tissues. However, most people do not realize the importance of respiratory rhythm detection because of expensive and limited medical conditions. In this paper, we present a noncontact and economically viable respiratory rhythm-detection system using S-band sensing technique. The system leverages microwave sensing platform to capture the minute variations caused by breathing. Subsequently, we implement data preprocessing and respiratory rate estimation for acquired wireless data to achieve respiratory rhythm detection. The experimental results not only validate the feasibility of respiratory rhythm detection using S-band sensing technique but also demonstrate that the S-Breath system provides a good performance.

INDEX TERMS Respiratory rhythm detection, S-Band sensing technique, microwave sensing platform (MSP), respiratory rate estimation.

I. INTRODUCTION

Respiratory rhythm is a regular, oscillating cycle of inspiration and expiration, controlled by neuronal impulses transmitted between the respiratory centers in the brain and the muscles of inspiration in the chest and diaphragm [1]. Respiratory rhythm of normal breathing is even, steady, and regular. Bradypnea and tachypnea belong to the abnormal breathing [2]. Bradypnea is abnormally slow breathing. The criterion for this is when a person's breathing rate is less than 12 bpm. A number of underlying reasons or medical conditions can cause bradypnea, or it can even occur during a normal sleep. Tachypnea is a rapid shallow breathing or an abnormally rapid respiratory, which is because of an imbalance between carbon dioxide and oxygen in the body. Tachypnea is indicated by a breathing rate greater than 20 bpm [3]. It is a useful sign for the diagnosis of childhood pneumonia and is more specific and reproducible than auscultator signs. Therefore, detecting respiratory rhythm is of important significance to human health.

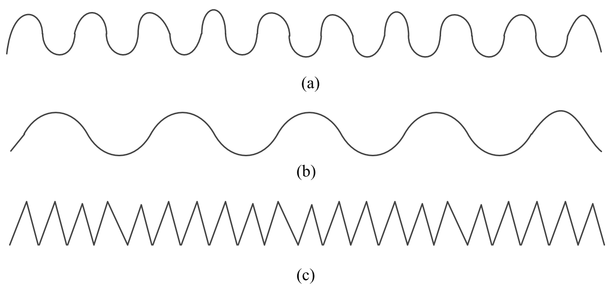

FIGURE 1. Respiration patterns of normal, bradypnea and tachypnea.

The typical respiratory rate for a healthy adult at rest is 12∼18 bpm [4]. A respiration rate below 12 bpm indicates bradypnea and the respiratory rate over 24 bpm is tachypnea, as shown in Fig. 1. These two cases may signal an underlying health problem. There are many causes of bradypnea, as anything that disrupts the brain's normal regulation of respiration can be a causative factor, such as certain brain disorders, hypothyroidism, kidney failure, overuse of narcotics, increased intracranial pressure, opioids, and so on. Similarly, tachypnea can be caused by a number of conditions, such as asthma, lung disease, pulmonary embolism, and so on. Abnormality of respiratory rhythm is a dangerous disorder that may be a secondary condition to a much more serious disease that affects the rest of the body involuntarily. Signs and symptoms that may be present in an individual suffering from bradypnea include abnormally low breathing rate, confusion, lightheadedness, fatigue, and so on.

A diagnosis of abnormal respiratory rhythm is often made in conjunction with an underlying cause or because of side effects of medication. Once the respiratory rate seems slower or faster than normal, the individual should be immediately taken to hospital for medical treatment. In emergency situations, some life support measures may be needed. Treatment depends on the type of underlying condition leading to the abnormal respiratory rate. Barschdorff *et al.* proposed a method of detecting respiratory rhythm using photoplethysmograph (PPG). However, it needs special medical devices to obtain the electrocardiogram (ECG), and then the respiratory waveform can be extracted from the ECG signal [5]. Most research is based on radio frequency (RF) signal monitoring mechanisms. For example, Droitcour *et al.* [6] used the Doppler radar and Salmi *et al*. [7] adopted the ultra-wideband radar; all these require special hardware with high frequency and incur high cost.

To overcome these disadvantages and promote the health of the human body, we need to design a system that can not only detect respiratory rhythm anomalies in time but also is economic and convenient for families. In this article, we propose a noncontact and economically viable respiratory rhythm detection system using S-Band sensing technique, namely S-Breath system. We present the detailed design of the proposed S-Breath system, which consists of data extraction and processing. When the transmitter sends a number of packets to the receiver, the amplitude and phase data of the wireless channel information are collected from the receiver. After the data is extracted, the data processing module of S-Breath system is applied. This module consists of data preprocessing and respiratory rate estimation. For data preprocessing, we employ outlier removal, data normalization, and noise filtering to obtain better respiration data. For respiratory rate estimation, we use breathing cycle calculation method based on peak detection to estimate the breathing rate to achieve high accuracy [8], [9]. Finally, depending on the respiratory rate, we can identify normal breathing, bradypnea, or tachypnea. We also validate the performance of the proposed system by extensive experimental results.

The main contributions of this article are summarized as follows.

- We validate the feasibility of respiratory rhythm detection using S-Band sensing technique. The amplitude and phase data of wireless channel information record the miniature variations in the chest caused by breathing.
- We design a noncontact and economically viable respiratory rhythm detection system, namely S-Breath system. It mainly consists of two modules: data extraction module and data processing module.
- Compared with other respiratory detection systems, our system focuses on respiratory rhythm detection and can provide real-time breath signal.

The rest of the article is organized as follows. The preliminaries are discussed in Section II. The overview of the system architecture is presented in Section III. In Section IV, we show the experimental results and evaluate its performance. Finally, Section V concludes the article.

II. PRELIMINARIES AND FEASIBILITY

A. PRELIMINARIES

The proposed method primarily uses the S-Band sensing technique to acquire wireless channel information as the initial indicator. The rationality of our detecting system is that some of the propagation paths can be disturbed by even very small movements. Orthogonal frequency division multiplexing (OFDM) is a modulation and multiplexing technology, which has been widely adopted in the physical layer or modern wireless communication systems, such as the Digital Audio Broadcasting (DAB) and wireless LAN networks [10], [11]. The principle of the OFDM technique is to divide the total spectrum into multiple orthogonal subcarriers [12]–[14]. Recently, OFDM has been used for wireless sensing. In OFDM, orthogonal subcarriers are used to transmit wireless signals in the frequency domain. The wireless signal transmitted on each subcarrier has different amplitudes and phases.

Using S-Band sensing technique, a group of 30 subcarriers can be obtained in the form of wireless channel information [15]:

$$H = \left[H\left(f_1\right), H\left(f_2\right), \ldots, H\left(f_i\right), \ldots, H(f_N)\right]^T, i \in [1, 30] \tag{1}$$

Here, H is known as the channel matrix various sensors.

Each wireless channel information depicts the amplitude and phase information of a subcarrier:

$$H\left(f_i\right) = \left\|H\left(f_i\right)\right\| e^{jsin\left|\angle H\left(f_i\right)\right|} \tag{2}$$

where $\|H\left(f_i\right)\|$ is the amplitude and $\angle H\left(f_i\right)$ is the phase of each subcarrier. The wireless channel information data is continuously recorded within a certain time window and is expressed as a sequence:

$$H = \left[H_1, H_2, H_3, \ldots, H_k\right] \tag{3}$$

Here, k represents the total number of data packets received and serves as the primary input for breathing detection motion.

B. FEASIBILITY ANALYSIS

In this section, some description and analysis are presented about why the wireless channel information data is the rationale of detecting breathing activity.

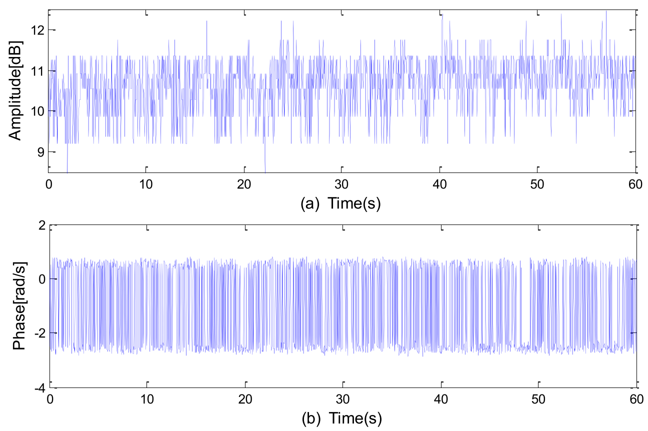

FIGURE 2. The raw amplitude and phase information of the collected wireless data.

On the one hand, we compare the amplitude information and the phase information of the obtained wireless data. Each wireless channel information records the amplitude and phase information of a subcarrier. Fig. 2 shows the raw amplitude and phase of the twenty-sixth subcarrier using data collected in one minute. From the amplitude information, it is clear that there are some wave-like patterns, which is caused by the breathing movement of the chest and abdomen. But from the phase information, we cannot see that it is related to breathing.

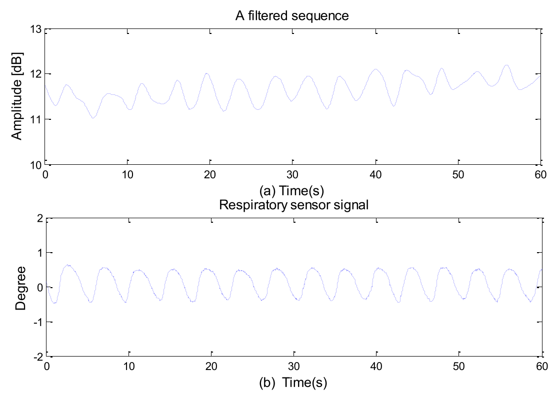

FIGURE 3. A comparison of (a) the amplitude information of a sequence after filtering and (b) the respiratory sensor data.

On the other hand, we compare the amplitude information of a subcarrier with the sensor data to see whether these waves are caused by the person's chest and abdomen movement. Fig. 3(a) shows the amplitude information of the twenty-sixth subcarrier and Fig. 3(b) shows the respiratory sensor data recorded in the meantime. By comparing the two, we can clearly see that they present high correlation between each other.

Based on the above two reasons, we select the amplitude information to identify bradypnea and normal breath.

III. SYSTEM DESIGN

In this section, we describe the design and architecture of our S-Breath system. The system principally uses S-Band sensing technique to detect bradypnea.

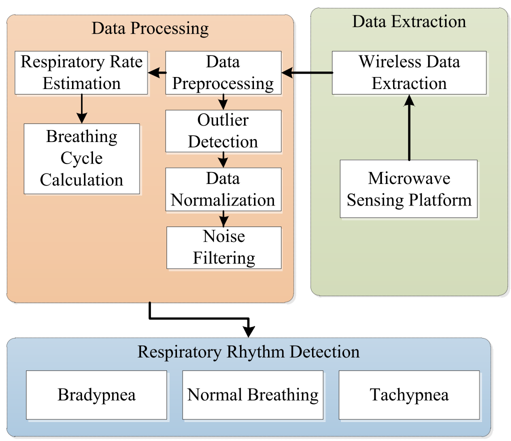

FIGURE 4. System architecture.

TABLE 1. Related experimental equipment of MSP.

No.	Name
1	Spectrum analyzer
2	RF generator
3	Cable
4	Respiratory sensor
5	Vector network analyzer(VNA)
6	Antenna
7	Absorbing material
8	Networked computer
9	Stopwatch

A. S-BREATH SYSTEM ARCHITECTURE

As shown in Fig. 4, our system mainly consists of two modules: (i) data extraction and (ii) data processing. For data extraction, we create a microwave sensing platform (MSP) to collect wireless data. Related experimental equipment of MSP is listed in Table 1, and this equipment constitutes a transmitter and a receiver. The transmitter operates on S-Band, and the wireless data with the same frequency can be extracted from the receiver, where the amplitude and phase information are thus obtained.

The data processing module comprises two parts: data preprocessing and respiratory rate estimation. For data preprocessing, we adopt outlier detection, data normalization, and noise filtering to calibrate the wireless data, and then obtain clear data sequences. With regard to the respiratory rate estimation, we choose breathing cycle calculation method based on peak detection, which aims to capture the periodic changes by measuring the number of peaks of the amplitude information in one minute. We then combine the number of peaks from multiple subcarriers to improve the robustness and the accuracy of the breathing cycle calculation. Finally, we obtain the respiratory rate. With this as distinguishing criteria, we identify normal breathing, bradypnea, and tachypnea.

B. DATA PROCESSING METHOD

The data processing module includes data preprocessing and respiratory rate estimation. We discuss each of these in the following sections.

1) DATA PREPROCESSING

The wireless channel information of all subcarriers is collected, and this information reflects the signal diversity in time and frequency domains. Because of the influence of environmental noise, the collected data must be processed by outlier detection, data normalization, and noise filtering.

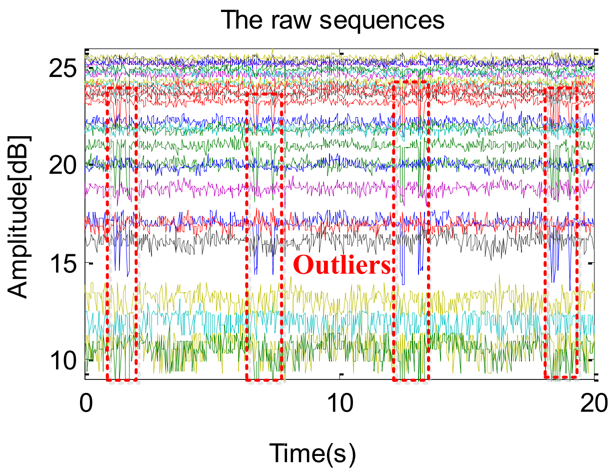

FIGURE 5. The raw sequences from all the 30 subcarriers.

Outlier detection: The first step to process data is to detect outliers and remove them. Based on the findings shown in Fig. 5, there are some outliers in the amplitude information, which are obviously not caused by breathing activity. These outliers must be eliminated. In this article, we adopt the 3σ criterion (also known as Pauta criterion) to exclude outliers [16]. First, we compute the mean value of the amplitude from a subcarrier.

$$\bar{X} = \frac{1}{n}\sum\nolimits_{i=1}^{n} X_i \tag{4}$$

here, $X_i (i = 1, 2, \ldots, n)$ is the i$^{\text{th}}$ sample of the amplitude information. Then we calculate the residual V_i and the standard deviation σ of the amplitude.

$$V_i = X_i - \bar{X} \tag{5}$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum\nolimits_{i=1}^{n} (X_i - \bar{X})^2} \tag{6}$$

Finally, for all $X_i (i = 1, 2, \ldots, n)$, if $|V_i| > 3\sigma$, we regard X_i as an outlier and replace it with the mean value $\bar{X}$. And the same procedure is repeated, until all samples are detected.

Data normalization: We select data normalization to improve the detection accuracy. The basic idea is to bring all values into the range [0, 1]. The formula is given as:

$$Y_i = \frac{X_i - X_{mean}}{X_{max} - X_{min}} \tag{7}$$

where X_i is the raw data, X_{mean} is the mean value of the amplitudes, X_{max} and X_{min} represent the maximum and minimum of the amplitudes in one minute after outlier removal, respectively.

Noise filtering: Before estimating the respiratory rate, the noise contained in the wireless data should be eliminated. Here, we apply the wavelet transform to filter noise because it can preserve better amplitude information of the signal. Specifically, we use four level 'db4' wavelet transform on the amplitude of each subcarrier [17]. Fig. 6 illustrates the amplitude of a subcarrier before and after using the wavelet transform. We can clearly see that the original data becomes cleaner.

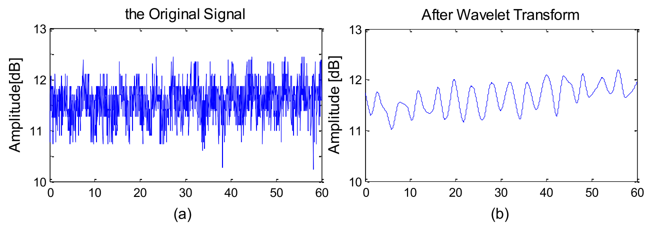

FIGURE 6. (a) The original signal of the amplitude before using the wavelet transform. (b) After using the wavelet transform.

2) RESPIRATORY RATE ESTIMATION

Respiratory rate is the number of movements indicative of inspiration and expiration per minute. Therefore, we use breathing cycle calculation method to estimate respiratory rate, which aims to capture the periodic changes caused by breathing during measurements. From Fig. 6(b), we observe that the amplitude of the subcarrier presents a sinusoidal-like periodic wave because of breathing. This observation suggests that we can compute the number of peaks in one minute to obtain the respiratory rate. We thus adopt the breathing cycle calculation method based on peak detection to estimate respiratory rate.

Peak Detection: Identifying and analyzing peaks is important in signal processing [18]. Peak detection is to identify the transition point at which the signal changes from an increasing to a decreasing trend. For respiratory rate estimation, there are three key improvements. The first improvement is to set a threshold on the minimum distance between two consecutive peaks based on human's maximum breathing period. The second improvement is to set a threshold on the minimum amplitude at which a peak is detected, and we compute the minimum amplitude threshold as $\mu_{peaks} - 2\sigma_{peaks}$, where μ_{peaks} and σ_{peaks} are the mean and standard deviation of the peak amplitudes. The third improvement is not only to identify the transition point from an increasing to a decreasing trend but also to detect the transition point from a decreasing to an increasing trend. At this point, the correct peaks can be identified, which are recorded as N. In addition, the estimated respiratory rate can be computed as $60/N$. Fig. 7(a) shows that the number of peaks is 8; therefore, the respiratory rate is an estimated 7.5 bpm. Similarly, from Fig. 7(b) and 7(c),

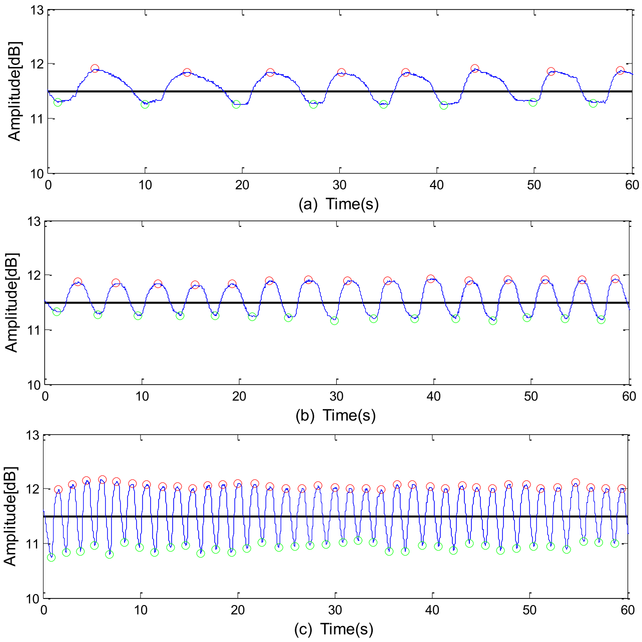

FIGURE 7. Respiratory rate estimation using breathing cycle calculation method based on peak detection. (a) In bradypnea. (b) In normal breathing. (c) In tachypnea.

the respiratory rate is estimated to be 4 bpm and 1.6 bpm, respectively.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, we present the details of experiment setups and extensive experimental study with S-Breath system working on S-band.

A. EXPERIMENT SETUPS

We build an S-band MSP to obtain experimental data (as descried earlier). In these experiments, we use a networked computer with an antenna as the transmitter and another networked computer connected with three antennas working as an access point (AP). The AP operates in the monitor mode, and the transmitter operates in the injection mode. They are placed on both sides of the human body's chest or abdomen, two to three meters apart, and visually in a straight line. To obtain wireless data, we set the transfer rate to 50 packets per second, which is consistent with the sample rate of the respiratory sensor. Then, our experiments were conducted and the receiver constantly recorded the wireless data to use for respiratory rhythm detection.

We conducted extensive experiments with S-Breath system with five participants. It is an office with dimensions 5m$\times$7m, and the room is surrounded by absorbing material. In the same scenario, we conducted three experiments, namely a bradypnea event, a normal breathing event, and a tachypnea event.

B. RESULTS AND DISCUSSIONS

We evaluated the performance of our S-Breath system on estimating respiratory rate in the three different breathing events. We collected wireless data from five participants for all three breathing events. Fig. 8(a) presents the mean estimation error of five participants in the bradypnea event. As can be seen from the figure, the mean estimation error of our respiratory rate estimation is lower than 1 bpm in the bradypnea event. Fig. 8(b) shows the cumulative distribution functions (CDF) of estimation error in respiratory rate estimation in the bradypnea event. It is corresponding to Fig. 8(a). We can see that over 80% estimation errors are under 0.5 bpm, and all the data have an estimated error under 1 bpm.

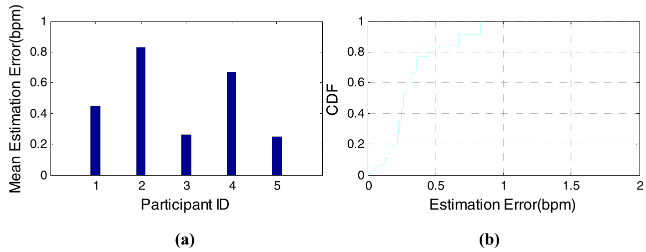

FIGURE 8. Performance in the bradypnea event. (a) Mean estimation error. (b) CDF of estimation error.

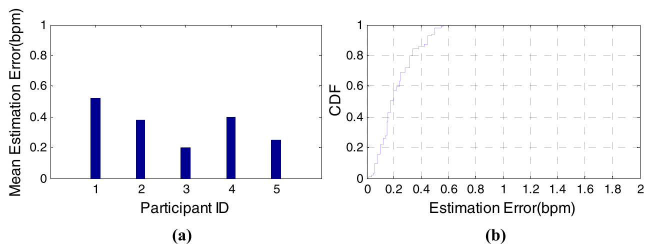

FIGURE 9. Performance in the normal breathing event. (a) Mean estimation error. (b) CDF of estimation error.

Figure 9 depicts the mean estimation error of five participants and the CDF of respiratory rate estimation in the normal breathing event. We find that the mean estimation error is lower than 0.6 bpm for all the participants in Fig. 9(a).

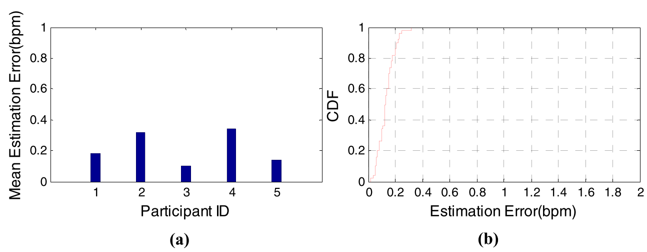

FIGURE 10. Performance in the tachypnea event. (a) Mean estimation error. (b) CDF of estimation error.

Moreover, Fig. 10(b) shows that over 80% estimation errors are less than 0.4 bpm. Comparing with Fig. 8, the accuracy of respiratory rate estimation is improving, which demonstrates that our S-Breath system is accurate for detecting different respiratory rate.

We next evaluated the performance of respiratory rate estimation in the tachypnea event. Fig. 10(a) presents the mean estimation error of five participants in the tachypnea event. We can see that it achieves the lowest estimation error of about 0.4 bpm because of the increase of breathing cycles. In addition, Fig. 10(b) shows that over 80% estimation errors are lesser than 0.2 bpm, which is better than the other two events.

Overall, the above results show that our S-breath system provides a high accuracy of respiratory rate estimation for different respiratory rhythms, with all mean estimation error under 1 bpm.

V. CONCLUSION

In this article, we proposed the S-Breath system to detect respiratory rhythm. The system adopts microwave sensing platform (MSP) to capture the minute variations caused by breathing. We first validated the feasibility of using S-Band sensing technique to detect respiratory motion on the MSP. By comparing with the contact respiratory sensor, our system can accurately capture the tiny movements of the chest and abdomen caused by breathing. We then introduced the S-Breath system in detail, which mainly includes two modules: data extraction and data processing. We applied the S-breath system to acquire wireless data in bradypnea event, normal breathing event, and tachypnea event for achieving respiratory rhythm detection. We also conducted extensive experiments with the three events. The experimental results showed that the S-Breath system provides excellent performance and robustness on respiratory rate estimation.

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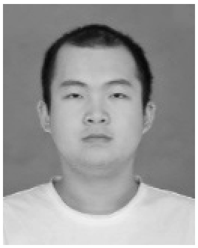

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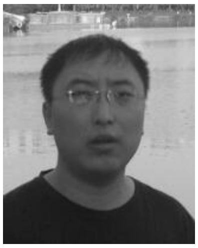

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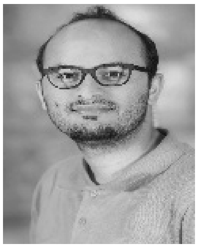

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