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Detection and Diagnosis of Paralysis Agitans

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ABSTRACT Humans' daily behavior can reflect the main physiological characteristics of neurological diseases. Human gait is a complex behavior produced by the coordination of multiple physiological systems, such as the nervous system and the muscular system. It can reflect the physiological state of human health, and its abnormality is an important basis for diagnosing some nervous system diseases. However, many early gait anomalies have not been effectively discovered because of medical costs and people's living customs. This paper proposes an effective, economical, and accurate non-contact cognitive diagnosis system to help early detection and diagnosis of paralysis agitans under daily life conditions. The proposed system extract data from wireless state information obtained from antenna-based data gathering module. Further, we implement data processing and gait classification systems to detect abnormal gait based on the acquired wireless data. In the experiment, the proposed system can detect the state of human gait and carries high classification accuracy up to 96.7%. The experimental results demonstrate that the proposed technique is feasible and cost-effective for healthcare applications.

INDEX TERMS Neurologic disease, abnormal gait, wireless state information, automatic detection system, paralysis agitans.

I. INTRODUCTION

Increasing prevalence of neurological diseases has posed several challenges for early diagnosis on it. Most neurological diseases have significant features such posture gait disorders. Human gait is a complex motion produced by the coordination of multiple physiological systems. Mesopontine Tegmentum Locomotor Region(MLR), Spinal cord Locomotor Region(SLR), and Cerebellar Locomotor Region(CLR) are three centers that are specifically described to regulate locomotion through muscles [1]. Gaits can reflect the physiological health of a person because it depends not only on the strength of the muscles involved, but also on the complex psychological coordination process. Contrarily, each person's gait has certain differences because of those factors. Based on these differences, there has been a lot of research about identifiability through gait in recent years [2].

Gait abnormalities are caused by neurodegeneration in one or more of the above tracts [1]. Many common neurological diseases or injuries such as Polio, Alzheimer's disease, and paralysis agitans can cause obvious abnormalities in the gait. There are some phenomenon in the medical field that are used to describe different abnormal gait: fontal gait, spastic gait, progressive supranuclear palsy (PSP) gait, parkinsonian gait, ataxic gait, waddling gait, stoppage gait, antalgic gait, psychogenic gait, multifactorial gait disorder [3]. Where description of normal gait is relatively subjective, and its analysis belongs to biomechanics and neurophysiology. Clinically, the following seven criteria: posture, base, initiation, stride length, stride appearance, stability, and turns are used to measure normal gait [3]. The commonalities of human gait can be used to detect abnormal gait, which helps the detection and diagnosis of these neurologic disease.

Paralysis agitans is a long-term degenerative disorder of the central nervous system that mainly affects the motor system. The symptoms generally come on slowly over time. Early in the disease, the most obvious are shaking, rigidity, slowness of movement, and difficulty with walking. In this paper we emphasize on three abnormal gait in paralysis agitans:

(1) Festination: starts with tiny steps which progressively increase in velocity before the destination, where the patient appears to be running and seems lose control of speed.

(2) Turn: subtype of freezing [3], which usually appears to be suddenly and temporarily unable to move. It means that patient move at a very small angle and speed to complete a 180° turn, which demands more steps.

(3) Small stride: Similar to normal gait, but the stride is short, the movement speed is very low and uncoordinated.

Detection of abnormal gait could be divided into two major categories: contact and non-contact. Contact detection contains special device such as sensor, accelerometer, which extract the required parameters or features from people. In [4] Chen *et al.* have developed a cost-effective shoe-integrated gait analysis system based on a suite of sensors for acquiring force, flexion, three dimensional angular rate and acceleration parameters of foot. Nyan [5] discussed a body area network (BAN) composed by torso and thigh wearable inertial sensors, which were used to distinguish between normal gait and abnormal gait. It requires both experimental object and the environment. The experimental subject needs to wear a huge number of specific equipment. Moreover it has high-cost, difficult to maintain, and complicated deployment. Furthermore, it is inconvenient for the patient to wear these devices all day. The non-contact detection is based on photoelectric and electromagnetic techniques, such as infrared, ultrasonic, video frames, radar, and wireless signal. It can acquire state information and required parameters of the subject without any contact with the person to be detected. Sekine *et al.* [6] proposed a method of detecting gait abnormality using Root mean square ratio(RMSR) based on wireless sensors, which encompass 3-axial accelerometer. Chaaraouiin [7] utilizes a novel joint motion history (JMH), which encode spatial-temporal feature based on low-cost RGB-D devices for abnormal gait detection. Seifert *et al.* [8] explored a method of classifying gait by extracting gait features form radar signatures of different human waling styles. In [9] Ye *et al.* a presented gait monitoring system based on tri-axis acceleration wireless sensor to measure patient activities acceleration. All these required special devices such as tri-axis acceleration sensor, depth cameras like Microsoft Kinect or ultra-wideband radar. These hardware is relatively high cost and less versatile.

To overcome these disadvantage and automatic detect neurological disease through human gait, we need to design a system that can not only detect abnormal gaits, but also economic and convenient for families. In this article, a non-contact cognitive diagnosis system using wireless devices is presented which consist of antenna-based data gathering system, data processing and classification module. The antenna-based data gathering system extract data that receiver obtains from the transmitter and send it to the data processing module which consists of outlier detection, noise filtering and data image processing. Finally, we apply it to the data classification module to classify data and detect abnormal gaits.

The rest of this article is organized as follows. Section II introduces the preliminaries of the proposed wireless detection system. The proposed system and experimental design is described in Section III. In Section IV, we explains the experimental results and relative discussion are listed about performance. The article is finally concluded in Section V.

II. RELATED WORK

A. THEORY OF WIRELESS STATE INFORMATION

The proposed method using S-Band sensing technique comes from physical layer of wireless signal. The wireless link use Orthogonal frequency-division multiplexing (OFDM) technique, which is a frequency-division multiplexing (FDM) scheme used as a digital multi-carrier modulation method, first introduced by Chang of Bell Labs in 1966 [10]. The principal of OFDM technique is to divided the channel into a set of orthogonal sub-channels and convert the high speed data signals into parallel low speed sub-data streams then modulated it to each sub-carrier. Through OFDM technique, 30 orthogonal sub-carriers can be extracted from the physical layer in the form of channel state information, which includes amplitude and phase information according to IEEE802.11n standard [11].

The channel frequency response (CFR) of each antenna, for 30 sub-carriers using S-Band can be presented as follow

$$H(f_k) = \left\| H(f_k) \right\| e^{j\angle H(f_k)} \tag{1}$$

Where $\left\| H(f_k) \right\|$ denotes the amplitude information of k-th sub-carrier whose central frequency is f_k, $\angle H(f_k)$ is the corresponding phase information.

A group of 30-subcarries response information can be presented as follows:

$$H(f) = \left[H(f_1), H(f_2), H(f_3), H(f_j) \ldots, H(f_n) \right]^T \quad j \in [1, 30] \tag{2}$$

In OFDM mechanism, CFR describes the channel performance for each subcarrier with following signal transmission model:

$$Y(f) = H(f)X(f) \tag{3}$$

Here $X(f)$ represents the transmitted signal, where $Y(f)$ denotes the received signal.

To obtain continuous gait data from CFR of sub-carriers, the record of the data lasted for certain period of time:

$$H = \left[H(f)_1, H(f)_2, H(f)_3, H(f)_k, H(f)_N \right] \quad k \in [1, N] \tag{4}$$

Where N is the number of data package received, which serves as the primary input for abnormal gait detecting.

Under optimal conditions, wireless signal travel in a direct path from the transmitter to the receiver, known as line-of-sight (LOS). In fact the path is often partially obstructed, usually by a physical object in the innermost Fresnel zone. So the wireless signal reaches to the receiver through reflection, scattering and diffraction, and the receiver receive wireless signals from multiple sources called non-line-of-sight (NLOS). The wireless signal under NLOS contains information relative to the physical environment characteristics of the signal propagation, therefore it can be used to detect human gait.

B. SUPPORT VECTOR MACHINE FOR PATTERN CLASSIFICATION

Support vector machine (SVM) is among the best supervised learning model used for pattern classification and regression estimation, which have gained huge success in the last decade. It was first introduced by Vladimir N. Vapnik in 1963 [12]. SVM constructs a separating hyperplane or set of hyperplanes in a high or infinite-dimensional space described as:

$$y_i\left(w^T x_i + b\right) > 0 \tag{5}$$

Where given training data $\left\{x_i, y_i\right\}$, i=1,2,3,..,N, $x_i \in R^m, y_i \in [-1, 1]^i$.

Distance to the separate hyperlane can be described as:

$$d\left(x_i, \text{w}, \text{b}\right) = \frac{y_i\left(w^T x_i + b\right)}{\|w\|} \tag{6}$$

After scaling we make $y_i\left(w^T x_i + b\right) = 1$, changing $\max_{w,b} \frac{1}{\|w\|}$ to $\min_{w,b} \frac{1}{2} w^T w$ shows:

$$\min_{w,b} \frac{1}{2} w^T w$$
$$\text{s.t. } \min y_i\left(w^T x_i + b\right) \geq 1, \quad \text{i} = 1, 2, \ldots, \text{N} \tag{7}$$

It is a convex quadratic programming problem, introduce Lagrangian multipliers:

$$\min_{w,b}\left(\max_{all\ \alpha_i \geq 0} \mathcal{L}\left(\text{w}, \text{b}, \alpha\right)\right)$$
$$= \min_{w,b}(\max_{all\ \alpha_i \geq 0}(\frac{1}{2} w^T w + \sum_{i=1}^{N} \alpha_i (1 - y_i\left(w^T x_i + b\right))) \tag{8}$$

Here α_i denotes the Lagrangian multipliers, with the Lagrangian dual problem:

$$\min_{w,b}(\max_{all\ \alpha_i \geq 0} \mathcal{L}\left(\text{w}, \text{b}, \alpha\right))$$
$$\geq \max_{w,b}(\min_{all\ \alpha_i \geq 0} \mathcal{L}\left(\text{w}, \text{b}, \alpha\right)) \tag{9}$$

After Karush-Kuhn-Tucker (KKT) conditions :

$$\alpha_i \geq 0 \tag{10}$$
$$y_i\left(w^T x_i + b\right) \geq 1 \tag{11}$$
$$\sum y_i \alpha_i = 0, \quad \text{w} = \sum y_i \alpha_i x_i \tag{12}$$
$$\alpha_i\left(1 - y_i\left(w^T x_i + b\right)\right) = 0 \tag{13}$$

Further described as:

$$\max_{w,b} \mathcal{L}\left(\text{w}, \text{b}, \alpha\right) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K\left(x_i, x_j\right)$$
$$\text{s.t. } \sum_{i=1}^{n} \alpha_i y_i = 0, 0 \leq \alpha_i, \quad i = 1, 2, 3 \ldots N \tag{14}$$

In order to work with non-linearly separable datasets a functional margin ξ_i stands for margin violation, a control parameter C trade between large margin and margin violation was introduced :

$$\max_{\alpha_i \geq 0, \beta_i \geq 0}\left(\min_{w,b,\xi} \mathcal{L}\left(\text{w}, \text{b}, \alpha\right)\right) = \frac{1}{2} w^T w$$
$$+ C \cdot \sum_{i=1}^{N} \xi_i + \sum_{i=1}^{N} \alpha_i \left(1 - \xi_i - y_i\left(w^T x_i + b\right)\right) - \sum_{i=1}^{N} \beta_i \xi_i \tag{15}$$

The equation then can be substituted into:

$$\max_{w,b} \mathcal{L}\left(\text{w}, \text{b}, \alpha\right) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$
$$\text{s.t. } \sum_{i=1}^{n} \alpha_i y_i = 0 \quad 0 \leq \alpha_i \leq C, \quad i = 1, 2, 3 \ldots N \tag{16}$$

When the Karush-Kuhn-Tucker (KKT) conditions are modified as follows:

$$0 \leq \alpha_i \leq C \tag{17}$$
$$y_i(w^T x_i + b) \geq 1 \tag{18}$$
$$\sum y_i \alpha_i = 0, \quad \text{w} = \sum y_i \alpha_i x_i \tag{19}$$
$$\alpha_i(1 - y_i(w^T x_i + b)) = 0 \tag{20}$$
$$\beta_i = C - \alpha_i \tag{21}$$

The training data whose Lagrangian multiplier $\alpha_i \neq 0$ are called the support vectors (SVs). K $(\cdot)$ is the kernel function that can transform the non-linear non-separable training data into high-dimension feature space where the transformed data can be separated. There are three kernel functions used for detecting abnormal gait :

Linear kernel:

$$K\left(x_i, x_j\right) = x_i^T x_j \tag{22}$$

Polynomial kernel:

$$-K\left(x_i, x_j\right) = (\varphi + \gamma x_i^T x_j)^n \quad with\ \varphi > 0, \ \gamma > 0 \tag{23}$$

Gaussian kernel which also called Radial Basis Function:

$$K\left(x_i, x_j\right) = e^{(-\gamma \|x_i - x_j\|)^2} \quad with\ \gamma > 0 \tag{24}$$

III. SYSTEM AND EXPERIMENT DESIGN

Fig. 1 shows the system architecture of S-Band wireless abnormal gait detection system, including three major components: antenna -based data gathering module, data preprocessing module, and classification module.

Antenna-based data gathering subsystem was used to gather information from wireless state information. To be more specific, the access point works as a transmitter in S-Band, and three antennas connected to the computer as the receiver, that extract the amplitude and phase information from 30 sub-carriers data in different position.

The module of data preprocessing is composed of three parts: outlier removal using improved Hampel identifier, noise filtering with a soft-hard threshold wavelet filter and image processing.

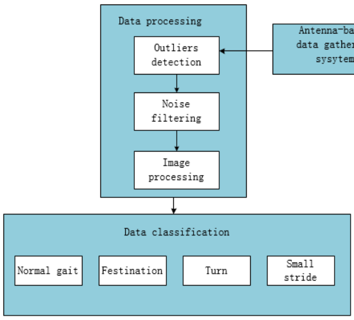

FIGURE 1. System architecture.

The Hampel filter is a member of the class of the decision filter, where the central value in the data window with the median lies far enough from the median to be deemed an outlier [13]. An outlier point is that falls out of the closed interval $\left[\left(median_{i,k} - \gamma * MAD\right), \left(median_{i,k} + \gamma * MAD\right)\right]$ where $\mathrm{MAD} = \mathrm{abs}(x_i - \mathrm{median}_{i,k})$. Here i is the position of the data point, k is the size of window,γ denotes the factor of violation and $\mathrm{median}_{i,k}$ is the median of the window. Because of $\mathrm{median}_{i,k}$ the MAD is less sensitive to the presence of the outliers in the data. We choose them instead of mean and standard deviation. Fig. 2 shows the amplitude of a subcarrier before and after using the hampel identifier. As shown clearly that the outliers are replaced by the median values.

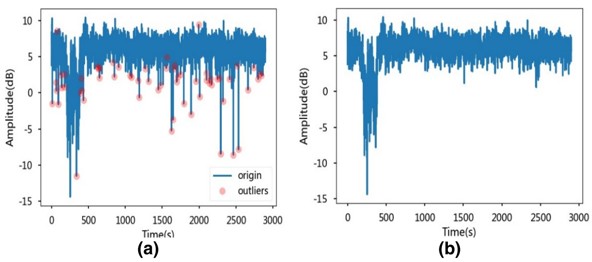

FIGURE 2. (a) The origin data of the amplitude with outliers denote. (b) Signal with outliers removed after using the Hampel filter.

In noise filtering, after outlier detection, the noise contained in the wireless data must be eliminated. Here we apply the wavelet filter instead of traditional filters (e.g, Chebyshev and Butterworth filters) because it can preserve better local information. To be more specific, we used four level 'db4' wavelet transform on each subcarrier of wireless data [14].Then we refactor it with a soft-hard compromise threshold [15]. Fig. 3 and Fig. 4 illustrates the amplitude of all 30 subcarriers before and after using the wavelet filtering respectively. We can see that original data becomes much cleaner.

The module of image converter first converts the raw numerical time sequence data that obtain from data gathering module to image. Single frequency are selected according to their variance. Secondly thresholding the image that make the image pixel gray, value to 0 or 255. After binarization the entire image only consists black and white and we then resize

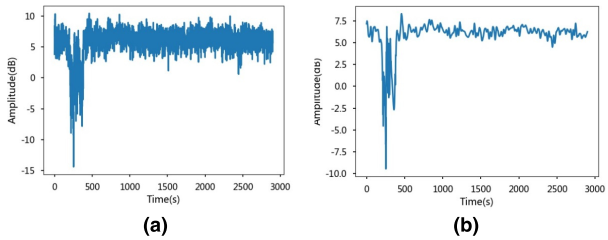

FIGURE 3. (a) The origin data of the amplitude with outliers removed from a subcarrier. (b) After using wavelet filter.

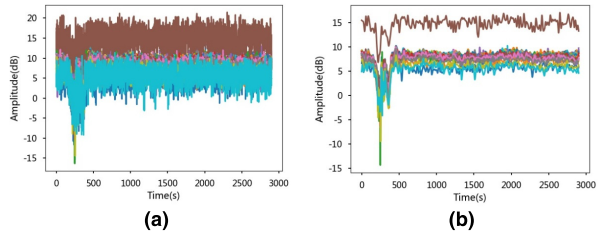

FIGURE 4. (a) The origin data of the amplitude with outliers removed from all 30 subcarriers. (b) After using wavelet filter.

the image to reduce the size of data. Finally we normalize the value of these pixels and chop it to a proper size. It improved the accuracy of gait classification.

To evaluate the effectiveness of our proposed system, we performed the following experiment. We used S-Band antenna, working in injection mode as the transmitter and a Lenovo PC, operating on Ubuntu with three antennas operating in monitor mode as receiver. They were placed on both sides of the aisle, where a participant passes. The distance between transmitter and receiver was hold at 1.5m, and the distance between each receiver was kept at 0.15m.The transfer rate was set at 1000 packets per second.

The experiment was conducted in a 12 × 13 m room as shown in Fig. 5.Two 25 years old subjects were asked to imitate normal gait and abnormal gait including small stride, festination and turn. The subjects were required to perform each gait posture five times. The wireless signal was interfered by the human motion which caused corresponding wireless frequency response through LOS and NLOS.

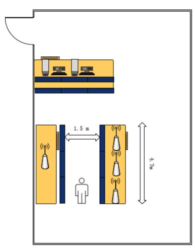

FIGURE 5. Experiment design for abnormal gait detection.

IV. EXPERIMENT RESULTS AND DISCUSSION

We carried out four experiments by processing wireless data to evaluate the performance of our abnormal gait detection

TABLE 1. The Confusion Matrix for the four gait types with different kernel (without image processing module).

Kernel Function	Actual Types	Estimated Types (%) Normal	Festination	Small stride	Turn
Linear	Normal	90.1	0	2.3	7.6
	Festination	0.1	94.3	0.2	5.4
	Small stride	0	5.5	91.2	3.3
	Turn	0.7	0.1	4.7	94.5
Polynomial	Normal	94.1	0.1	0.1	5.7
	Festination	0	90.2	2.2	7.6
	Small stride	0	5.5	91.2	3.3
	Turn	0.7	0.1	4.7	94.5
RBF	Normal	0	100	0	0
	Festination	0	100	0	0
	Small stride	0	30	70	0
	Turn	0	13	0	87

TABLE 2. The Confusion Matrix for the four gait types with different kernel (with image processing module).

Kernel Function	Actual Types	Estimated Types(%) Normal	Festination	Small stride	Turn
Linear	Normal	99.5	0.2	0	0.3
	Festination	0	99.5	0	0.5
	Small stride	0.3	0.7	97.7	1.3
	Turn	0.1	0.5	2.7	96.7
Polynomial	Normal	99.5	0.2	0	0.3
	Festination	0.2	96.1	2.7	1
	Small stride	0.3	0.7	97.7	1.3
	Turn	0.1	0.5	2.8	96.6
RBF	Normal	0	100	0	0
	Festination	0	100	0	0
	Small stride	0	55	45	0
	Turn	0	55	0	45

system. Table 1 and 2 show multi-classification comparisons with and without using image processing module under different kernel function of SVM. For example, in the case of the normal gait under linear kernel, the True Positive(TP) rate of Normal in table 1 is 94.3%. Where is 99.5% in table 2 and 5.2% higher than table 1. Among all the data belonging to Festination in linear kernel, 99.5 percent are correctly classified as Festination, while 0.5% is incorrectly identified as Turn in table 2. The results obtained using the RBF kernel function shows that it does not work for all four situations. RBF kernel cannot distinguish between Normal and Festination. Table 2 illustrates that both linear and polynomial kernel archived highest score in both four gait patterns. Table 3 and 4 show the binary classification for all four human gaits using linear kernel. It is shown in table 4 that classification between normal gait and festination has the highest accuracy rate (99.9%) among the all binary classification. While the binary classification between small stride and turn archived the worst accuracy rate of 95.7%. However, without using image process module the accuracy rate is 90.2% which is 5.5% smaller than using image process module. Based on the comparison above, we conclude that the image process module improves the accuracy of the system at least 5%.

TABLE 3. The accuracy rate (%) of binary classification using SVM with linear kernel (without image processing module).

Gait types	Normal	Festination	Small stride	Turn
Normal	-	91.7	91.1	93.2
Festination	91.7	-	91.3	90.2
Small stride	91.1	91.3	-	90.2
Turn	3.2	90.2	90.2	-

The results of binary classification in same human gait type performed by different subjects are shown in Fig. 6. We found that all the binary classification accuracy rate in same gait patterns expect normal gait is not less than 95%. The accuracy of normal gait is 90%, which is the lowest accuracy in binary classification.

To summarize, the results above illustrate that through our wireless gait detection system the accuracy rate of

TABLE 4. The accuracy rate (%) of binary classification using SVM with linear kernel (with image processing module).

Gait types	Normal	Festination	Small stride	Turn
Normal	-	99.9	97.7	97.8
Festination	99.9	-	99.8	97.5
Small stride	91.1	91.3	-	90.2
Turn	3.2	90.2	90.2	-

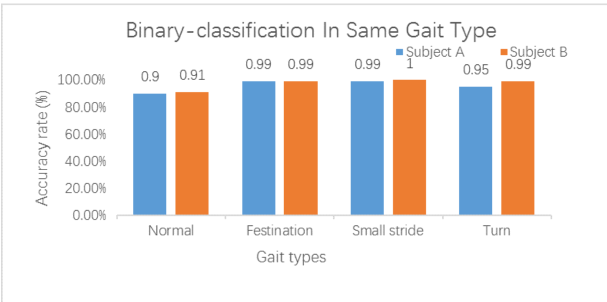

FIGURE 6. Binary-classification results for the 2 subjects in same gait type.

multi-classification for all four human patterns is around 96.7%. The accuracy rate of binary classification in same gait patterns performed by different subjects including festination, small stride, and turn is not less than 95%, while the result of normal is around 90%.

V. CONCLUSION

In this paper, we presented a complete diagnosis system for non-contact human abnormal gaits detection based on S-band wireless state information. The proposed system can help early detection of gait abnormalities, which is essential in clinical diagnosis. We mainly focused on four human gait patterns including normal, festination, small stride and turn. Hamper filter are utilized to detect outliers and wavelet transform are applied to filter the noise in wireless data. After obtaining the image of data, we then linearize the image, resize and chop it to a proper size. SVM was selected because its high precision and robustness in many traditional machine learning problems. It was applied to both binary classification and multi-class classification. Comparisons between using and not using image processing module illustrate that it can improve the performance of the system at least 5%. The multi-class accuracy rate of our method is 96.7% which demonstrate that our system is an efficient, low-cost and reliable solution for automatic detection and diagnosis paralysis agitans based on their abnormal gaits. The future task work on improve the speed on detection is warranted.

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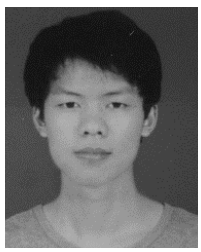

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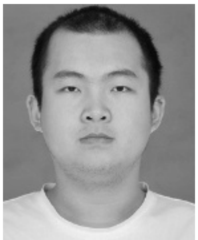

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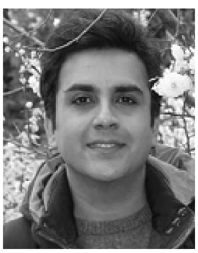

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