IEEE Journal of Translational Engineering in Health and Medicine

MEDICAL IMAGING AND DIAGNOSTIC RADIOLOGY

Received 21 March 2019; revised 2 May 2019; accepted 21 May 2019. Date of publication 31 May 2019; date of current version 13 June 2019.

Digital Object Identifier 10.1109/JTEHM.2019.2919065

Non-Contact Early Warning of Shaking Palsy

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This work was supported in part by the National Natural Science Foundation of China under Grant 61671349, Grant 61301175, and Grant 61601338, in part by the China Postdoctoral Science Foundation Funded Project under Grant 2018T111023, in part by the Fundamental Research Funds for the Central Universities under Grant JB180205, and in part by the Natural Science Foundation of Shaanxi Province under Grant 2019JM-489.

ABSTRACT Parkinsonian gait is a defining feature of shaking palsy (SP) and it has one of the worse impacts on human healthy life than other SP symptoms. The objective of this work is to propose a Parkinsonian gait detection system based on an S-band perception technique to classify abnormal gait and normal walking. Due to the differences in the Gaits of Parkinson's patients compared with healthy persons, the wireless signals reflect and generates different variations at the receiver that could be used for SP diagnosis and classification. To detect a Parkinsonian gait, we first implement data preprocessing of the original data to obtain clear amplitude and phase information. Then, the feature extraction is carried out by principal component analysis (PCA). Finally, a support vector machine (SVM) classification algorithm is applied on collected data to classify the abnormal gait of SP patients compared with a normal gait. We evaluate the proposed system with different people, and the experimental outcomes show that the Parkinsonian gait detection of this training-based system achieves a high accuracy of above 90%. Moreover, the early warning of SP is achieved in a non-contact manner.

INDEX TERMS Parkinsonian gait detection, shaking palsy (SP), principal component analysis (PCA), SVM classification.

I. INTRODUCTION

Shaking palsy is a neurodegenerative disease that is commonly seen in middle and old age. It is mainly characterized by bradykinesia, tremor, gait disturbance and rigidity [1]. Gait disturbance is mostly considered to have worse or painful effect on human healthy life as compared to other symptoms because it may cause substantial discomfort and impairment in activities of daily living. Patients with SP often experience gait impairments, including small gait, festinating gait and gait hesitation.

- Small gait symptoms appears when the person is dragging his feet during walking. He is taking short and shuffling steps, moving more slowly than expected for his age and reducing arm movement during walking. In short, it means a decreased step length with decreased speed.
- Festinating gait is a quickening and shortening of normal strides. The characteristics are that the person walk increasingly quickly with the torso forward and cannot stop quickly [2].
- Gait hesitation is the symptom when a person feel hesitation before stepping forward or feeling difficulties in initiating walking. When a patient overcomes the block, he turns around in a small step, along with the head and torso. The most initial form of gait hesitation is 'start hesitation' followed in frequency by 'turning hesitation' [3], [4].

These gait impairments of SP are associated with and are largely as a result of a reduced amount of a neurotransmitter called dopamine because nerve cells begin to die inside the brain called the basal ganglia. The main treatments include physical therapy, corresponding other therapies medications and in worse case surgery (deep brain stimulation) is required. All these treatments and measurements taken to reduce independent functioning and reducing brain complications [5]. For example, most patients with SP use medications to help and manage their symptoms. Levodopa (L-dopa) and supplementary medications that support the brain produce dopamine or it is use more effectively to treat a Parkinsonian gait. Although medications use for SP are very effective, but determining the optimal dose is difficult. In addition, surgery and physical therapy shows improvements in gait function of patients with SP. In [6], Thevathasan *et al.* proposed the practice of pedunculopontine nucleus stimulation to improve gait freezing. In [7], the results showed that Parkinson patients recover from physical therapy in addition to their normal medication. The reactions to different treatments vary by person and the state of the disease, so the treatments for SP must be verified to the individual patient and their symptoms. Thus, regular monitoring is important for treatment.

While monitoring disease progression and assessing treatment with effectiveness and accurately, the gait of the SP patient must be monitored continuously. According to the gold standard of SP [8], the typical gait patterns include gait hesitation, festinating gait and small gait; each gait pattern has its own characteristics. All these patterns are included in the study of this paper. Considering these gold standard symptoms, the gait detection system is proposed for continuous ambulatory gait detection. This system uses the S-band sensing technique to capture the signals of different gaits. Several significant merits of this paper are summarized as follows.

- We design a non-contact and Parkinsonian gait detection system. It is sensuously comfortable compared to wearable devices.
- This system can detect the gait continuously and provide real-time signals. The gait information of the SP patient can be fed back to the doctor, family or caregiver in a timely fashion.
- Compared with other gait detection systems, our system is movable and flexible. We can move the system to the appropriate place, depending on the requirements for detection.

The structure of this paper is organize as follows. First, the works related to this paper are reviewed in Section II, and the system overview design of Parkinsonian gait detection is presented in Section III. Then, we elaborate on relevant data processing methods in Section IV, We describe the experimental contents and discuss results based on experiments in Section V. Finally, Section VI summarize finding and concludes this paper.

II. RELATED WORK

Based on measuring device used, the existing work on Parkinsonian gait detection can be divided into three categories: specialized hardware-based [9], sensor-based [10]–[13], and smartphone-based [14]–[16].

A. SPECIALIZED HARDWARE-BASED

Fine-grained informative signal measurements can be achieved by specially designed hardware. De. Venuto et al. proposed a real-time field-programmable gate array (FPGA)-based embedded cyber-physical for both gait analysis and postural instability detection [9]. This system is worn on the body.

B. SENSOR-BASED

Several studies have been conducted using tiny motion sensors to monitor gait such as accelerometers and pedometers [10]–[13]. The Dyna Port move monitor detected gait and different postures of patients with SP using a single and small wireless tri-axial accelerometer [10]. Han *et al.* used the W-AMS for measuring both the ankles acceleration and introduce a general algorithm of gait detection from the gait signals [11]. Pham *et al.* applied anomaly detection techniques to detect FoG events by using three tri-axial accelerometers [12]. Putri, Farika T., *et al.* proposed a low cost diagnostic tool for PD which use unidirectional microphone and Yamada multifunctional microphone DM-Q6000 to acquire voice data and use BITalino EMG sensor to acquire gait data [13]. These sensor-based methods require patients to wear sensors, which are intrusive.

C. SMARTPHONE-BASED

With the attractiveness of smartphones and the growth of internet technology, gait detection with smartphones has begun to appear [14], [15]. Mazilu *et al.* proposed a wearable assistant consisting of a smartphone and wearable accelerometers for online gait detection [14]. Pan *et al.* designed and developed a prototype mobile cloud-based mHealth app, ‘‘SP Dr’’, to collect SP-related motion data using a smartphone 3D accelerometer [15]. Wan *et al.* propose a deep multilayer perceptron (DMLP) classifier for behavior analysis to estimate the progression of PD using smartphones [16]. It is important to note that these methods require physical contact.

Compared to the aforementioned methods, our system extracts fine-grained information from the wireless channels. Accordingly, it is possible to achieve a high accuracy using this technique. In addition, our detection system is removable and requires no physical contact, and it is comfortable and convenient for patients. Additionally, the technique can continuously detect and report real-time signals.

III. SYSTEM OVERVIEW

In this section, we introduce some preliminaries related to the proposed Parkinsonian gait system. We also present the system design. This system uses S-band perception technique to detect gait in both patients with SP and ordinary persons.

A. PRELIMINARIES

The defined system uses an S-band spectrum sensing technique to obtain the wireless channel signal as the original data. In practical environments, signals are more likely to be affected by multiple paths, such as walls, floor, ceiling, desks and so on. As the physical space affects the radio propagation, the received signals contain information about the corresponding environments.

The wireless signals continuously record channel changes, which characterize the frequency response of the wireless channel [17]. Suppose that the transmitted and received responses of the signals in frequency domain are $X(f, t)$ and $Y(f, t)$ with carrier frequency f. Then, the relation formula of the two signals is as follows:

$$Y(f, t) = H(f, t) \times X(f, t) \tag{1}$$

where $H(f, t)$ is the complex valued signal having information of channel frequency response (CFR). According to the orthogonal frequency division multiplexing (OFDM) technology, $H(f, t)$ is modulated into 30 selected OFDM subcarriers:

$$H(f, t) = [H(f_1, t), H(f_2, t), \ldots, H(f_i, t), \ldots, H(f_N, \mathrm{t})]^T, \quad i \in [1, 30] \tag{2}$$

For each subcarrier, it contains the amplitude and phase information, which is expressed as

$$H(f_i, t) = \|H(f_i, t)\| \, e^{jsin\left|\angle H(f_i,t)\right|} \tag{3}$$

where $\|H(f_i, t)\|$ and $\angle H(f_i, t)$ are the amplitude and phase information of each subcarrier.

The signals are obtained by collecting the data in each packet, so there are different H values at different times. The wireless signals are expressed as a sequence over a period of time:

$$H = [H_1, H_2, H_3, \ldots, H_k] \tag{4}$$

where k is the total received number of data packets. We collected the wireless signals of normal walking for some time. Fig. 1. Shows the time history of the amplitude and phase information in the first subcarrier.

B. SYSTEM DESIGN

SP is one of the most common neurodegenerative disorders, and it occurs frequently in older people. However, many patients miss the best timing for treatment because of a lack of awareness about the early symptoms of SP. Gait change is an early symptom that is easily discovered and includes small gait, festinating gait and gait hesitation. By classifying these gaits and normal walking, we can detect SP early and provide better treatment. The variation of wireless signals caused by a Parkinsonian gait is entirely different from that caused by normal walking.

The system uses spectrum perception technique to obtain the gait detection information. Fig. 2 shows the structure of the Parkinsonian gait detection system. It consists of three main functional modules: (i) sensing, (ii) data processing and (iii) gait detection.

The sensing module is responsible for collecting the wireless signals. For collecting data, we build a microwave spectrum sensing platform (MSSP). Related equipment for the MSSP is listed in Table I, and this platform consist of a transmitter and a receiver. The transmitter drives on the S-band spectrum, and the receiver continuously records the wireless channel signals, where we analyze and obtained amplitude and phase information. Then, we pass these signals to the next module.

The data processing module is the most important part of this system, which works in three parts: information preprocessing, feature extraction and the classification

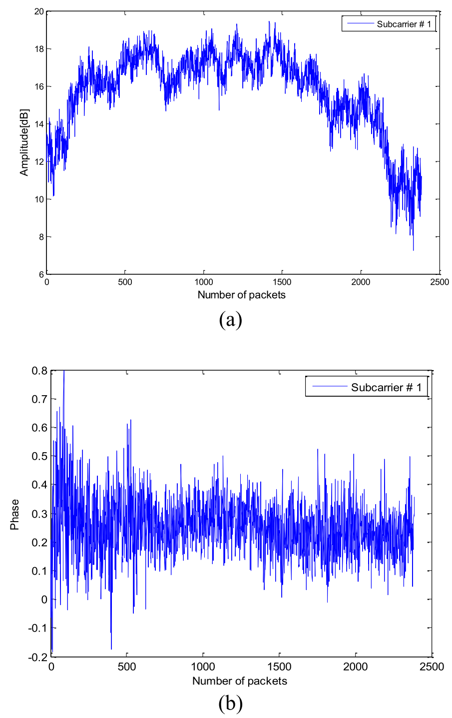

FIGURE 1. Time history of the amplitude and phase information in the first subcarrier.

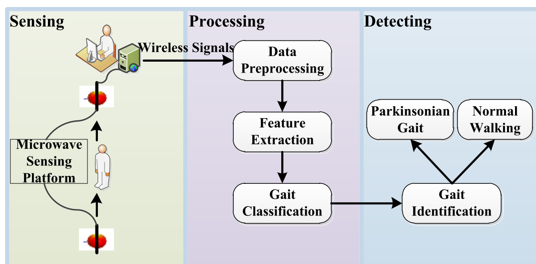

FIGURE 2. The structure of the Parkinsonian gait detection system.

TABLE 1. Related equipment for MSSP.

No.	Name
1	Spectrum analyzer
2	RF generator
3	Cables
4	Vector network analyzer (VNA)
5	Antennas
6	Industrial personal computer
7	Stopwatch

algorithm. In data preprocessing part, we follow an outlier substitution, normalization, and de-noising to extract the clear data sequences from wireless channel signals. In feature extraction approach, we choose Principal Component Analysis (PCA) to process data because it not only extracts the main information components but also compresses the raw data dimension. Subsequently, we adopt a machine learning algorithm (MLA) to classify data based on the mentioned features. The SVM classification algorithm is used to attain high classification accuracy in Parkinsonian gait detection.

IV. METHODOLOGY

Use either SI (MKS) or CGS as primary units. (SI units are strongly encouraged.) English units may be used as secondary units (in parentheses). This applies to papers in data storage. For example, write "15 Gb/cm^2 (100 Gb/in^2)." An exception is when English units are used as identifiers in trade, such as "31/2 -in disk drive." Avoid combining SI and CGS units, such as current in amperes and magnetic field in Oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity in an equation.

The SI unit for magnetic field strength H is A/m. However, if you wish to use units of T, either refer to magnetic flux density B or magnetic field strength symbolized as $\mu_0 H$. Use the center dot to separate compound units, e.g., "A·m^2."

In this methodology section, we elaborate on the approaches used in the data processing module, which include collected data preprocessing, desire feature extraction and a classification algorithm. It also important to mention that the human subjects gave informed consent for this research.

A. INFORMATION PREPROCESSING

Information preprocessing is an essential procedure in the data extracting technique that involves transforming raw data into a useful data. The wireless signals are influenced by environmental noise and human activities, so data preprocessing is essential. The data preprocessing includes noise filtering and data normalization.

1) DE-NOISING

The wireless channel signals describe how the amplitude and phase change when the signals travel from the transmitter to the receiver using subcarriers. When no moving object is present in the channel, the amplitude is fluctuant due to the influence of the surrounding environment but remains relatively constant. Fig. 3. Shows the time graph of the amplitude when there is no moving object in the experimental room. We can see that the amplitude change caused by noise is about 3 dB. It can be seen in fig. 4 that the signal change due to the Gait is greater than 10dB, indicating that the background noise will not affect the accuracy and reliability of the Gait perception. On the other hand, for most cases, the values are between -40dBm~-85dBm; through the measurement, it is

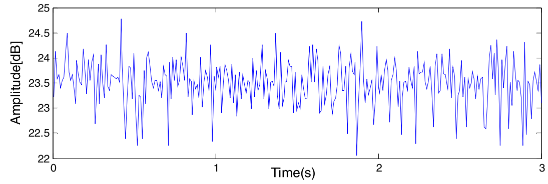

FIGURE 3. Time graph of the amplitude when there is no moving object in the experimental indoor environment.

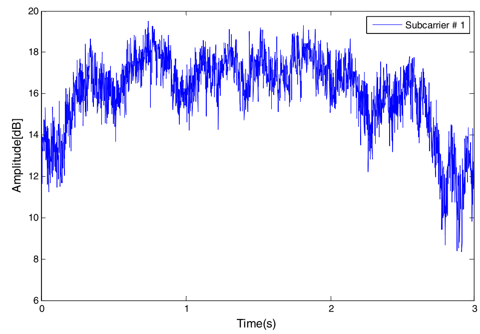

FIGURE 4. Time graph of the amplitude when a human walks normally in the experimental indoor environment.

found that the error margins is about -90dBm and for this value, it is almost impossible to establish channels.

Thus, we know that the wireless signals measurements obtained from the S-band sensing technique having noisy signal from various sources, including device interference devices, transmission power adaptation, and not proper clock synchronization [18]. Before we extract human gait features, we must filter out noises from the raw signals measurements. In received data the existence of high-level impulses and burst noises need de-noising approaches such as low-pass filters and median filters, the performance is not very good for this application. Theoretically, a low-pass filter or a median filter should be able to filter out these noises. However, after using these filters, still the residual noises are present and distorting the filtered signals. Fig. 5(a) shows a raw amplitude sequence with impulse noises. Fig. 5(b) shows the filtered result of the raw amplitude sequence after applying Butterworth filter, the filtering frequency is 100 Hz. Figure 5(c) shows the results of a 10-point median filter output. From Fig. 5(b) and 5(c), it is clear that the sequence is distorted after filtering. Therefore, directly using of these de-noising methods is not recommended.

We adopt a wavelet transform (WT)-based de-noising algorithm to filter noises in the wireless signals because it can perform better in collecting the amplitude of the signal. Specifically, when four level wavelet transform is utilized [19]. Fig. 5(d) demonstrates the WT filtered result derived from the raw amplitude sequence. The results shows that the original signal is noise free and provide clear information.

2) NORMALIZATION

To facilitate further data processing and improve the detection accuracy, we select data normalization to ensure the received

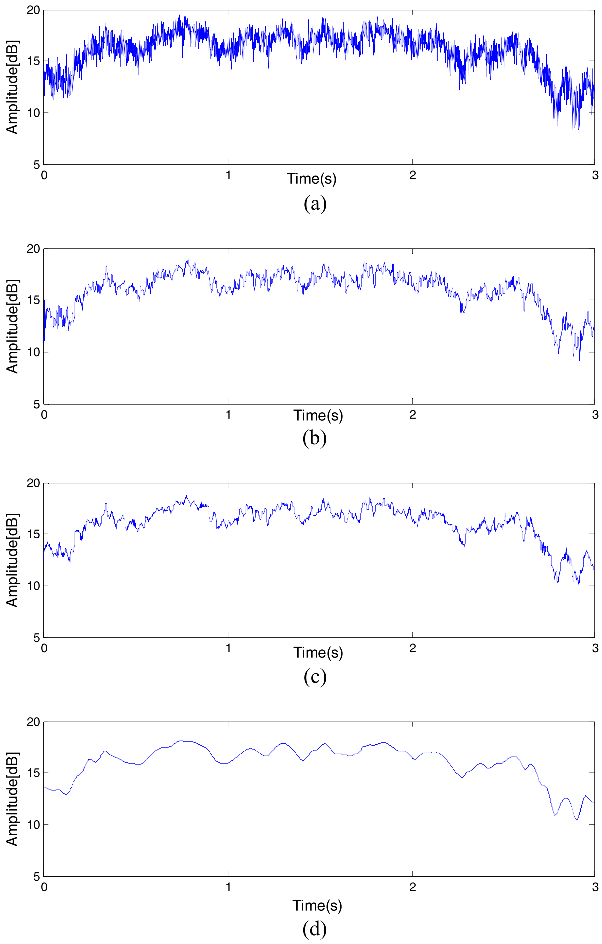

FIGURE 5. Time graph of the amplitude for a subject normally walking. (a) Raw amplitude sequence. (b) An amplitude sequence after low-pass filtering. (c) An amplitude sequence after median filtering. (d) An amplitude sequence after wavelet transform filtering.

values fall into the range [0, 1]. The formula is:

$$Y_i = \frac{X_i - X_{mean}}{X_{max} - X_{min}} \tag{5}$$

where X_i is the raw data, X_{mean} is the mean value, X_{max} and X_{min} represent the maximum and minimum value of the amplitude or phase after outlier removal, respectively.

B. FEATURE EXTRACTION

The principle component analysis (PCA) technique is applied to extract features for Parkinsonian gait detection, which can not only keep the characteristics of data intact but it is also causing decrease in data dimension [20]. It has an active effect in two aspects: it saves storage space and improves the calculation speed. For the collected amplitude and phase of the wireless channel signals, we can calculate the principal components for each data sequence through PCA. As a result, we obtain a matrix with dimension $p \times N$, where N defined the number of the collected data in unit time. We consider $p= 5$ for all of the experiments perform in this paper. The detailed process is presented as follows:

- Preprocessing: In the above–mentioned preprocessing procedure, the noise components have been removed. Therefore, we utilize the processed amplitude and phase of the wireless signals to create matrices as

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \cdots h_{1n} \\ h_{21} & h_{22} & h_{23} \cdots h_{2n} \\ \vdots & \vdots & \vdots \ddots \vdots \\ h_{m1} & h_{m2} & h_{m3} \cdots h_{mn} \end{bmatrix} \tag{6}$$

here m is the number of frequencies and h_{ij} represents the treated amplitude or phase of wireless signals that correspond to subcarrier i and packet j.

- Compute the correlation matrix: The following formula is use to find the correlation matrix R with size $n \times n$.

$$R = \frac{1}{n} H^T H \tag{7}$$

- Compute the eigenvectors: From the correlation matrix R, we use Eigen decomposition to calculate the Eigen vectors q_i, $i = 1, 2, \ldots$.
- Reconstruction of signal: a new matrix is construct via the correlation matrix and the eigenvectors as $h_i = q_i \times H$, where q_i is the ith Eigen vector and h_i is the ith principal component.

C. CLASSIFICATION

SVM is a one of the useful technique for classification. A classification methods usually works in two parts: training and testing of data, which consist of some data occurrences [21]. An SVM classifies data by judging the finest hyperplane that split up all data points of one class from those present in another classes. One realistic choice as the finest hyperplane is the one that signifies the prime separation or margin among the classes. Thus, we select the hyperplane so the distance on each side is maximized from it to the nearest data point.

Here, we employ SVM to classify the treated data for Parkinsonian gait detection. The treated data are randomly separated into two groups: one group is used for training and the other for testing. Then we construct a hyperplane in a high-dimensional space. The training process is given below.

Step 1: Let $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, $x_i \in R^n, y_i \in \{+1, -1\}, i = 1, 2, \ldots, n$ be a training data set of the extracted feature from the wireless signals amplitude or phase. Here, $+1$ and -1 represent two different categories. By maximizing the interval, the separation hyperplane is obtained, which is defined as:

$$y(x) = w^T x + b \tag{8}$$

The corresponding decision function is

$$f(x) = sign(w^T x + b) \tag{9}$$

where ω^T and b are the classification surface function parameter (ω^T is stated as normal vector, and b is the offset).

*Step 2:*Let the hyperplane add a certain constraint, as follows:

$$y_i(w^T x_i + b) \geq 1 \tag{10}$$

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The new objective function is expressed as

$$\min_{w,b} \frac{1}{2} \|w\|^2$$
$$s.t.\ \ y_i \left(w^T x_i + b\right) \geq 1, \quad i = 1, 2, \ldots, n \tag{11}$$

Step 3: With the Lagrangian multiplier α, the described function is formulated as

$$L\,(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum\nolimits_{i=1}^{n} \alpha_i (y_i \left(w^T x_i + b\right) - 1) \tag{12}$$

Step 4: We determine the maximum interval between the two boundary ends to determine w and b. Then, the final classification is transformed as

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \left\langle x_i, x_j \right\rangle$$
$$\text{s.t.}\ \ \alpha_i \geq 0, i = 1, 2, \ldots, n$$
$$\sum\nolimits_{i=1}^{n} \alpha_i y_i = 0 \tag{13}$$

where α_i and α_j are the Lagrangian multipliers.

Step 5: We seek the best w and b to achieve the maximum interval.

$$w^* = \sum\nolimits_{i=1}^{n} \alpha_i^* y_i x_i \tag{14}$$
$$b^* = y_j - \sum\nolimits_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x_j) \tag{15}$$

Step 6: According to formulas (14) and (15), we know that w and b are only related to α_i. We obtain the best value α_i using the sequential minimal optimization (SMO) algorithm. From this, we acquire the best w^* and b^*, and the SVM classifier is

$$\mathrm{f(x)} = \mathrm{sign} \left(\sum\nolimits_{i=1}^{n} y_i \alpha_i \left\langle x_i, x \right\rangle + \mathrm{b}\right) \tag{16}$$

However, the amplitude or phase data of the wireless channel signals are not linearly separable because of the complex indoor environments. Therefore, we use the Gaussian Radial Basis Function (RBF) work as a kernel function to solve this problem, which makes the processed data map into a high dimensional feature space. The new classifier is formulated as

$$\mathrm{f(x)} = \mathrm{sign} \left(\sum\nolimits_{i=1}^{n} y_i \alpha_i K \left\langle x_i, x \right\rangle + \mathrm{b}\right) \tag{17}$$

where $K \left\langle x_i, x \right\rangle$ represents the RBF kernel function, which is defined as

$$K \left\langle x_i, x \right\rangle = \exp \left\{ -\frac{1}{2\sigma^2} \|x - x_i\|^2 \right\} \tag{18}$$

where σ is the standard deviation.

V. RESULTS

In this part, the detail of experimental setups and implementation of our detection system is presented. We then discuss the experimental results and performance analysis of our system.

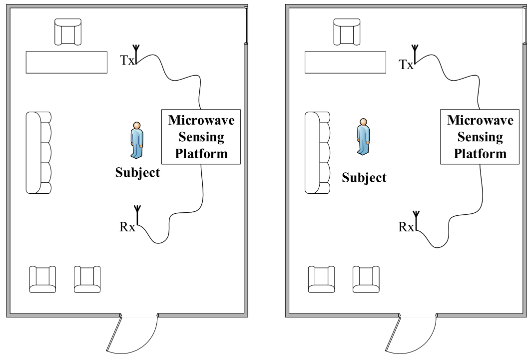

FIGURE 6. **Different experiment scenarios.**

A. EXPERIMENT SETUPS

We leverage MSSP to collect the wireless signals (MSSP is described in Section III). The MSSP works with the S-band. We can obtain the data of 30 subcarriers for each couple of a transmitting antenna and a receiving antenna. In our experiments, we used one transmitting antenna and three receiving antennas, so we obtain $1 \times 3 \times 30 = 90$ values at the same time. Since the sampling rate 800 packets/s is set in the system, we collected 800 values for the 90 streams per unit time. The transmitter power of this platform is set to -5 dBm, the antenna used in the experiment has a gain of 6 dBi and the received power is about -85dBm.

We conduct our experiments in our laboratory with an area of approximately 7×5 square meters. There is one sofa, one desk and some chairs in the space. The distance between Tx and Rx is 4m. Line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios are considered. In the LOS scenarios (shown in Fig. 6(a)), the subject stands in a line with the transmitter and the receiver.

In these experimental scenarios, we collect data of each participant for four different gaits (normal walking, small gait, festinating gait and gait hesitation of SP patients). Specifically, each participant is collected 30 samples for each gait in each scenario, so in each scenario we collect a total of 150 samples for each gait from the 5 subjects. The participants include 3 male and 2 female students and their ages in the range of 22-27. Before the experiment, these participants had practiced to imitate the Parkinsonian gait of SP patients according to medical videos.

B. RESULTS

We evaluate the performance of our Parkinsonian gait detection system from two aspects: (i) intuitionistic analysis and (ii) detection accuracy.

1) INTUITIONISTIC ANALYSIS

For each stream, the collected data are of size k $\times$ 30 matrix, where k is the number of packets. Fig. 7 gives the time graph of the amplitude for the person's four different gaits. From Fig. 7 we can observe that there are some differences between the amplitude of normal walking and the amplitudes of the three Parkinsonian gaits. However, detecting a specific gait

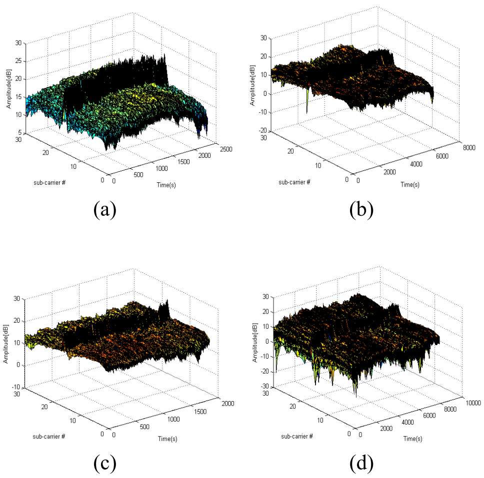

FIGURE 7. **The raw amplitude sequence of the person's four different gaits. (a). Normal walking. (b). Gait hesitation. (c). Festinating gait. (d). Small gait.**

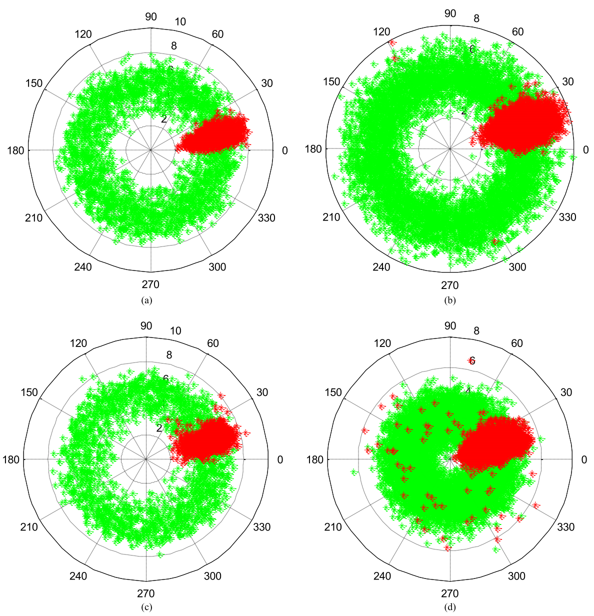

FIGURE 8. **The calibrated phase for four different gait.**

through the raw amplitude variation is limited and difficult. Thus, it is necessary for the raw data to be preprocessed and an SVM algorithm to be used.

The raw phase information is random (as shown in Fig. 1(b)) and cannot be used directly. Hence, we calibrate the raw phase information. Fig. 8 presents the calibrated phase for 4 different gaits. As we can see from this figure, the phase information of normal walking is similar to that of the three Parkinsonian gaits. Therefore, we consider the amplitude information to distinguish between normal walking and the Parkinsonian gait.

2) DETECTION ACCURACY

To evaluate detection accuracy, we use an SVM classifier to identify normal walking or Parkinson's gait. We apply RBF kernel function and implemented a one-versus-one (normal walking vs gait hesitation, normal walking vs festinating gait, normal walking vs small gait) method for the classification of the activity.

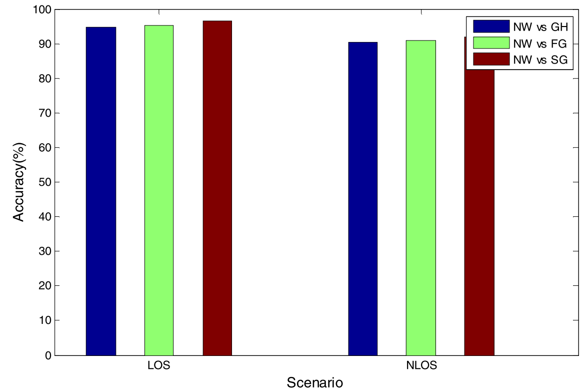

FIGURE 9. **Average Parkinsonian gait detection accuracy in different scenarios.**

- Accuracy of the LOS based experiments: In the LOS experiment scenario, our Parkinsonian gait detection system attains an average cross validation accuracy of 95.5% across three one-versus-one classification cases. Fig. 9 shows the accuracy of 10-fold cross validation.
- Accuracy of NLOS based experiments: Similarly, in the NLOS scenario, we select 10-fold cross validation to analyze the accuracy, and for this scenario, the average accuracy of classification is up to 91.1%.

We further compute the total accuracy of the abnormal gait and normal walking in both the LOS and NLOS scenarios. The three Parkinsonian gaits are considered of one class, and normal walking is of other class. We classify them by the above mentioned classification method. As a result, we achieve a 94% and 90% detection accuracy in the LOS and NLOS scenarios, respectively.

Consequently, the proposed Parkinsonian gait detection system carries a high classification accuracy up to 90%. The performance of this detection system can be improved by including more training sets. When we conduct real time experiments in lab environment, there are other students sitting in the same lab, and they do not move during the experiments. This illustrates that the proposed Parkinsonian gait detection system is robust to multiple students present at the same time. Applying this system to different environments is a future work, as it is collecting data from actual Parkinson's patients and evaluating the performance of this system with actual patients.

VI. CONCLUSIONS

In this paper, we introduce a Parkinsonian gait detection system by applying S-band spectrum sensing technique. Unlike the existing Parkinsonian gait detection methods, the proposed system involves non-contact and works in real time, and it is more flexibly. According to the mechanism of the system, we adopted MSSP operating in the S-band to collect the wireless signals of Parkinsonian gait and normal walking. Then, due to the influence of environment noises, we present several methods to preprocess the data. We next use the PCA technique for feature extraction from the preprocessed data. Finally, a SVM classifier is employed to classify the Parkinsonian gait and normal walking in both LOS and NLOS scenarios. The real time results show that the average accuracy of the Parkinsonian gait detection system can reach 95.5% and 91.1% for LOS and NLOS scenarios, respectively. In general, the proposed system provides high accuracy and good robustness and can be considered as a complement of the existing significant mechanism [22], [23] for Neuroscience sensing and judgement.

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