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Motion Detection with Local Linear Embedding and its Application to Indoor Device-Free Human Trajectory Tracking

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Device-free indoor human trajectory tracking is critical to support health care applications for elderly people. Many device-free localization algorithms depend on expensive hardware to achieve tracking accuracy. In contrast to such algorithms, this paper proposes a new device-free human trajectory tracking algorithm for indoor environments based on channel state information that is extracted from a Wi-Fi network interface card, which is a low-cost component. The proposed algorithm first uses the characteristics of locally linear embedding to detect whether a person is moving and applies quadratic discriminant analysis to determine the new location of the person. The determined locations of the person are connected to form a trajectory. Experimental results revealed that the proposed algorithm provides an effective solution for passive human trajectory tracking.

Keywords: device-free localization, trajectory tracking, channel state information, Wi-Fi, local linear embedding algorithm

1. INTRODUCTION

Most of people's daily activities, such as working, shopping, sleeping, and performing fitness exercises, occur in indoor environments. In recent years, the demand for location-based services and applications in indoor environments has increased rapidly. Indoor localization and tracking services have been widely used in smart home, property safety, asset management, health care, and other applications [1-5]. Many studies have been proposed to develop methods of human localization and trajectory tracking in indoor environments. Such methods can be categorized into two classes − active trajectory tracking [6-9] and passive trajectory tracking [10-16].

In active trajectory tracking, most of the proposed methods [6-9] require users to participate actively and carry smart devices. The position of a person can be identified by estimating the distance between the transmitter(s) and the receiver(s) according to changes in signals. A relatively high number of sensors must be deployed in the monitoring environment when methods based on wireless sensor networks are used, thus leading to high system costs. The primary challenge of active trajectory tracking methods is that users must wear the positioning device. Achieving this requirement in practice is

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not easy. This also makes the system unusable in many scenarios.

To solve this problem of active trajectory tracking, Wi-Fi signals are used for passive human tracking, which is an innovative application. Passive trajectory tracking neither requires the active participation of users nor requires users to wear any equipment. The location of a human can be identified by analyzing the influence of human body locations on the characteristics of a Wi-Fi channel. Subsequently, the trajectory, which is formed using the various locations when a human moves he will be tracked. Many passive trajectory tracking algorithms [15, 17, 19] have been proposed based on the passive tracking technology. The objectives of these methods include the human existence detection, activity classification, and gesture recognition. These methods capitalize on the effects of human motion on radio propagation by identifying changes in the channel state information (CSI) of a Wi-Fi signal to identify the location of a person. Passive human trajectory tracking enables omnidirectional coverage of people in a scene, and user privacy is protected. However, the complex multipath effects of indoor radio signals lead to unpredictable radio propagation behaviors. This remains a major challenge for passive trajectory tracking.

The purposes of all the aforementioned mechanisms are to solve the problems of indoor positioning and tracking. However, there is still a large gap in terms of positioning accuracy, real-time performance, and reliability, all of which require further improvement. The objective of this study was to propose a device-free human trajectory tracking mechanism that uses channel frequency response (CFR) information to identify the trajectory of a human in an indoor environment.

The contributions of this study are summarized as follows:

(1) First, in the mechanism, we integrate multiple differences of locally linear embedding (LLE) features to determine whether a signal detected in a time window belongs to a moving or stationary state.
(2) Second, we propose a device-free positioning system based on CSI to estimate the location of a target in the stationary state.
(3) Third, we integrate the motion detection mechanism and the device-free positioning system and propose a time-window-based human trajectory tracking system that is effective and accurate.

The remaining sections of this paper are organized as follows. Section 2 provides a brief review of related work. Section 3 briefly introduces the characteristics of the CSI in the physical layer of a Wi-Fi communication protocol. In Section 4, the proposed device-free human motion trajectory detection (HMTD) algorithm is introduced in detail. In Section 5, performance evaluation is introduced. Finally, Section 6 summarizes this study.

2. RELATED WORK

The methods of human trajectory tracking presented in the literature can be divided into two types – active and passive trajectory tracking methods. Because active trajectory tracking methods are limited by the requirement of active user participation, passive tracking methods, which do not require users to carry any equipment, have become the focus of recent studies.

The passive human trajectory tracking systems related to this study are mentioned as follows. Want *et al.* developed an infrared-based system, namely Active Badge [18], for indoor human tracking. The system deploys a wireless sensor network inside a building with at least one sensor node in each room. During the operation of the system, the person being tracked carries a tag. To allow the sensor to detect the tag information, each tag periodically transmits a signal to the sensor. Concurrently, the base station in the network periodically detects the sensor data, processes the data, and provides the result to the client in a visualized form. According to the signal received by the sensor from the tag, the room in which the person is present is determined, and the timing of the person's movement can be determined by combining the timings of the signals received by multiple sensors. Although the Active Badge system can track the trajectory of people in different rooms, the system cost is high due to the complex deployment of the system. Au *et al.* [19] proposed a stand-alone wearable system, namely 3D Action SLAM, that can track people in previously unknown multifloor environments. The system utilizes synchronous positioning and maps the relationships between actions and combines the dead reckoning data of the pedal-type inertial measurement unit. This system recognizes the action of a tester in different positions and updates the landmark map regularly to track the tester's movement trajectory. This system is ideal for patient tracking in e-health applications. Because the active tracking system requires a tester to carry a tracking device, this method is not feasible in some cases. For example, testers are reluctant to carry equipment all the time, and criminals deliberately do not carry equipment to prevent their movement trajectories from being tracked. Therefore, there is an urgent requirement for a passive indoor tracking system that obviates the necessity of carrying equipment.

To mitigate the inconvenience engendered by the necessity of carrying tracking equipment during active positioning, Mao *et al.* [20] proposed a passive tracking solution based on visible light. They proposed a passive human tracking system, iLight. The system consists of 40 sensor nodes, 10 normal light sources, and 1 base station. Their experimental results revealed that the iLight system has high positioning efficiency and accuracy. However, because the system contains multiple hardware devices, the cost of system deployment is increased. Mao *et al.* [21] proposed a high-precision acoustic tracker (CAT) that is used to replace the mouse with a smart device. Through the system, a user can perform clicking and sliding operations through voice control on the smart device. The system can interact with virtual reality or augmented reality headsets to control the smart device by moving the smartphone in the air. The core idea of the system is to continuously estimate the distance and speed of the mobile device relative to the speaker based on the received sound by using a distributed frequency-modulated continuous waveform to achieve continuous tracking of the mobile device trajectory. The designed system was tested on computers and smartphones. The test results revealed that the system has a high tracking accuracy. Wang *et al.* [22] proposed a device-free gesture tracking scheme, which can be deployed on mobile devices in the form of an application without modifying any hardware. The system employs the acoustic phase to obtain fine-grained motion and motion distance measurements. After removing the background sound signal that is relatively consistent over time, the system first extracts the sound signal that is reflected by hand or finger movements. The phase change of the sound signal is then measured and converted into the motion distance. Visible light solutions require strict line-of-sight conditions and do not work in dark environments. Sound-based solutions are susceptible to environmental noise and have a very small coverage. These methods have their own limitations when tracking a person in practical applications.

Due to the low cost and easy deployment of RF-based solutions, many RF-signal-based systems have been designed for indoor tracking. Li and Zhang [23] proposed a device-free indoor tracking system, namely Indo Track, based on commercial Wi-Fi. The system proposes Doppler-MUSIC and Doppler-AOA to jointly estimate the accurate trajectory of a target. Joshi *et al.* [24] proposed a passive tracking system, namely Wi Deo, based on a radio platform defined by WARP software to achieve fine-grained motion tracking. However, the system must modify the internal structure of the Wi-Fi hardware device, thus increasing the complexity of the system hardware design. The WiVi system proposed in [25] relies on special hardware to capture the reflection of its own transmitted signal. To track the signals on moving objects behind the wall, the system only tracks the relative motion but cannot obtain the absolute position. The Wi Dar [26] system tracks human motion by estimating the Doppler frequency. Wi Dar uses fast Fourier transform (FFT) to estimate Doppler shift by using CSI amplitude information, which is similar to the system proposed in [27]. Because the CSI amplitude does not provide direction information for the Doppler velocity, Wi Dar requires multiple Wi-Fi links with significantly different spatial characteristics to determine the direction of movement and the location of the person to be tracked. Therefore, to enable Wi Dar to work with only two receivers, the antennas of the Wi-Fi receiver must be separated from each other, which is difficult for commercial Wi-Fi equipment.

In [28], Teng *et al.* used a highly directional 60-GHz millimeter-wave radio to achieve passive target tracking. In this study, the passive tracking algorithm uses a discrete beam scanning mechanism to accurately locate the initial position of the object and acquire the target trajectory by using the signal phase information. The short wavelength of the 60-GHz signal can suppress the interference signal. Although the accuracy of tracking a person is improved, the complexity of the radio platform is relatively high.

In general, the aforementioned indoor passive trajectory tracking approaches can be categorized into non-Wi-Fi-based and Wi-Fi-based mechanisms. Although the non-Wi-Fi-based approaches can achieve good localization accuracy, their main drawback is that they have high hardware costs. The state-of-the-art component of Wi-Fi-based approaches is the Indo Track system [23]. The Indo Track system uses Doppler-MUSIC and Doppler-AOA to realize a tracking system with high accuracy. However, when the target stops moving, Indo Track cannot track the target. The proposed HMTD algorithm can distinguish between motion and stationary states of a target and determine the location when a target is stationary. A combination of the Indo Track system and HMTD algorithm can not only track a target in motion but also detect the location of a stationary target.

3. PRELIMINARY

3.1 Channel State Information

Due to complex radio propagation in indoor environments, the multipath effects in the subcarriers of a Wi-Fi signal are pronounced, a phenomenon that has a relatively high effect on reliable feature acquisition. In general, the characteristics of wireless signals can be analyzed from the time and frequency domains. In the time domain, the influence of the environment or human activities on the subcarrier channel can be described as disturbance to the channel impulse response (CIR) of the channel. In the frequency domain, the multipath propagation due to reflection results in a change in the CFR. Therefore, it is possible to reliably distinguish between various target locations through multiple omnidirectional subcarriers by analyzing the variations in CIR and CFR, even if there is interference of background noise.

A wireless communication system generally uses CIR to describe the multipath effect of a channel. Under the assumption of linear time invariance, the impulse response of a channel can be expressed as presented in Eq. (1):

$$H(k) = ||H(k)||e^{j\angle H(k)}, \tag{1}$$

where $H(k)$ denotes the CSI of the kth subcarrier, $||H(k)||$ denotes the amplitude of the kth subcarrier, and $\angle H(k)$ denotes the phase of the kth subcarrier.

The multipath propagation of a signal presents a time-delay distribution in the time domain and selective signal fading in the frequency domain. Therefore, the CFR of the wireless channel can also be used to describe the multipath propagation of signals based on the amplitude, frequency, and phase information. Under the conditions of an infinite bandwidth, CFR and CIR are Fourier transforms of each other. The frequency response of the channel can be expressed as presented in Eq. (2):

$$h(\tau) = \sum_{i=1}^{N} a_i e^{-j\theta_i} \delta(\tau - \tau_i), \tag{2}$$

where a_i represents the amplitude attenuation of the ith path, θ_i represents the phase offset of the ith path, τ_i represents the time delay of the ith path, N represents the total number of propagation paths, and $\delta(\tau)$ represents the Dirac pulse function.

Device-free human detection operates on the principle that part of the propagation paths are reflected by the presence or absence of a target. In the frequency domain, frequency changes are caused by CFR reflections. Human motion usually causes signal changes on only a few paths. Even when very few paths are changed, human motion can obviously change the CFR amplitude of all subcarriers. Moreover, in addition to the amplitude change in the CFR, human motion affects the phase of the CFR. However, the phase information has a uniform distribution and is related to the deployment location of the nodes. Therefore, we use the change in the amplitude characteristics of each subcarrier in the CFR to measure the sensitivity of the human body to determine the states of the body. The indoor trajectory tracking system based on the CFR amplitude is illustrated in Fig. 1.

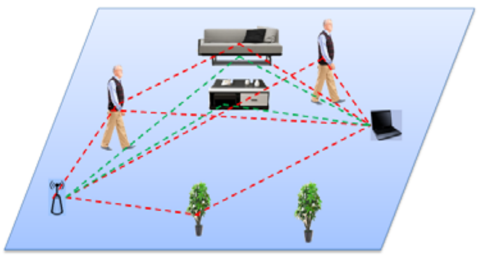

Fig. 1. Indoor device-free positioning scene.

3.2 Device-Free Stationary Human Location Detection Problem

The objective of this paper is to trace the moving route of a person in an indoor environment by analyzing the characteristics of the received signal without the necessity of the person carrying tracking equipment. In an indoor environment, let T denote the measurement time, and can be expressed as $T = \{t_1, t_2, \ldots, t_q\}$. Let the channel information be denoted as $C = \{c_1, c_2, \ldots, c_n\}$. Let L denote the measurement position and is expressed as $L = \{l_1, l_2, \ldots, l_m\}$, where $m = k^2$, $k \in N$, and N is a positive integer. Then, $x_{i,j,k}$ represents the CSI signal value measured at time t_i, position l_j, and channel c_k. Therefore, multiple sets of CSI signals can be expressed as $D_{T,L,C} = \{x_{i,j,k} \mid 1 \le i \le q, 1 \le j \le m, 1 \le k \le n\}$.

Let y_i denote the position of a person at time t_i and x_{ik} denote the CSI value measured by channel c_k at time t_i. Because each CSI packet includes channel information from 30 subcarriers, let X_i represent the extracted CSI at time t_i. The CSI values corresponding to n subcarriers can be expressed as $X_i = \{x_{i1}, x_{i2}, \ldots, x_{in}\}$.

To model the change in CSI when a person appears at various locations, a model ψ_D is established between the features obtained from the CSI channel and the target location. The indoor passive localization model ψ_D can be expressed as Eq. (3):

$$\psi_D = (X_i, y_i) = M_D, \tag{3}$$

where M_D represents the relationship function between X_i and y_i.

During CSI acquisition, let $\hat{x}_{ik}$ represent the CSI value measured at time $\hat{t}_i$ on channel c_k when a person is at position $\hat{y}_i$. Similarly, let $\hat{X}_i = (\hat{x}_{i1}, \hat{x}_{i2}, \ldots, \hat{x}_{in})$ represent the CSI value measured at time $\hat{t}_i$ on n channels at position $\hat{y}_i$. Therefore, according to the relational model ψ_D, $\hat{X}_i$, and $\hat{y}_i$, i must satisfy the following relationship (2) when the following measurement is performed:

$$M(\hat{X}_i) = \hat{y}_i \quad 1 \le i \le p. \tag{4}$$

Here, we assume that there are p groups of position data.

4. DEVICE-FREE HUMAN TRACKING ALGORITHM

The purpose of the proposed algorithm is to detect the trajectory of a person in an indoor environment without requiring the human to carry any tracking equipment. Fig. 2 shows an example scenario in which an indoor space is divided into 3×3 equal-sized subregions. As shown in Fig. 2, a Wi-Fi-based mobile access point (AP) and a laptop are deployed in the monitoring area. The AP plays the role of the sender and periodically sends signals to the laptop. The laptop receives the signal from the AP. The wireless connection between the AP and the laptop can be used to monitor *CSI* conditions in the indoor environment. The received CSI value changes when a human appears in the monitoring area. Therefore, we can determine the position of the human according to the change in the CSI value.

The proposed algorithm comprises a CSI acquisition phase, motion detection phase, and location discrimination phase. In the CSI acquisition phase, the mobile AP periodically sends broadcast information. The laptop computer continuously receives the signals from the AP and extracts valid CSI. In the motion detection phase, the motion state of a person is detected by applying the proposed LLE-Diff algorithm. Finally, the location discrimination phase identifies the location of the person at a particular time interval when the person is in a stationary state. Thus, the CSI is acquired continuously, and the extracted CSI can be sent to a remote server synchronously to detect the location of the person. Finally, the trajectory of a person can be obtained by repeating the aforementioned steps.

4.1 CSI Acquisition Phase

The aim of this phase is to acquire CSI at the receiver when people appear at some particular locations. Fig. 2 illustrates a scenario for the application of this phase. To effectively determine the location of a person, the indoor space is divided into $n \times n$ subregions. An AP and a laptop computer are deployed in the subregion and act as the sender and receiver, respectively. As illustrated in Fig. 2, the indoor space is divided into 3×3 subregions.

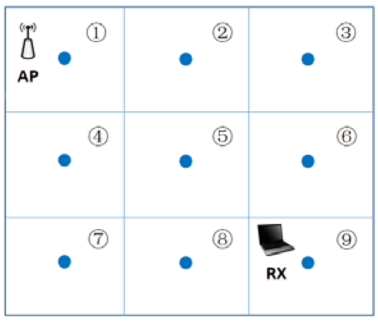

Fig. 2. Illustration of the HMTD scenario in which the indoor area is divided into 3×3 subregions.

4.2 Motion Detection Phase

In an indoor environment, the variation of the collected CSI sample is small when a person is in a stationary state. When a person is in a moving state, the collected CSI sample values vary greatly. The original dimension of the CSI sample is 30; this sample is too large to process. Moreover, the difference between various sets of the collected CSI samples in the moving state is large, thus causing the CSI-based tracking system to be highly complex. To accurately capture the trajectory of a person, it is necessary to reduce the dimension of the CSI sample and then use an effective algorithm to achieve the goal of trajectory tracking for a person.

LLE is a nonlinear dimensionality reduction algorithm that maintains the original manifold structure in a low-dimensional subspace. LLE is one of the classic algorithms of manifold learning. Many subsequent manifold learning and dimensionality reduction methods are closely related to LLE. The traditional dimensionality reduction algorithms, such as principal component analysis and linear discriminant analysis (LDA), focus on sample variance, whereas LLE focuses on maintaining the local linear structure of a sample during dimensionality reduction. Because LLE maintains the local structure of the sample during dimensionality reduction, it is widely used for image recognition, high-dimensional data visualization, and other applications.

In the proposed algorithm, LLE is used to reduce the dimension of the acquired CSI sample feature and to determine the degree of variation in samples. Assume that the CSI sample feature is linear in a short time interval; that is, a certain data can be linearly represented by several samples in its neighborhood. Let a CSI sample collected by the system be marked as x_1, and LLE uses the k nearest neighbors to find the three closest samples in its original high-dimensional neighborhood, x_2, x_3, and x_4.

The sample x_1 can be expressed using a linear combination of samples x_2, x_3, and x_4:

$$x_1 = w_{12}x_2 + w_{13}x_3 + w_{14}x_4,$$

where w_{12}, w_{13}, and w_{14} are the weight coefficients. After LLE dimension reduction, the corresponding projection x_1', x_2', x_3', and x_4' in the low-dimensional subspace maintains the same linear relationship:

$$x_1' = w_{12}x_2' + w_{13}x_3' + w_{14}x_4'.$$

Specifically, the weight coefficients w_{12}, w_{13}, and w_{14} of the linear relationship before and after the projection exhibit minimal changes. The linear relationship is only present in the vicinity of the sample. A sample that is far from the present sample has no influence on the local linear relationship. Therefore, the complexity of dimensionality reduction is reduced.

In this phase, we first select the neighborhood size, that is, the number of neighborhood samples required to linearly represent a sample. Here, we let the neighborhood size value $k = 6$. We then select the k nearest neighbors of the sample by using the Euclidean distance. After determining the k nearest neighbors of the sample x_1, we establish the linear relationship between x_1 and the k nearest neighbors; that is, we determine the weight coefficient of the linear relationship. This is obviously a regression problem. Suppose that there are m samples $\{x_1, x_2, \ldots, x_m\}$, each with n-dimensional features; the mean square error is considered the loss function of the regression problem, as presented in Eq. (5).

$$J(w) = \sum_{i=1}^{m} \| x_i - \sum_{j=Q(i)} w_{ij} x_j \|_2^2 \tag{5}$$

where $Q(i)$ represents the k neighbor sample sets of i. In general, the weight coefficient w_{ij} is normalized, that is, the weight coefficient must satisfy Eq. (6).

$$\sum_{j=Q(i)} w_{ij} = 1 \tag{6}$$

For the sample x_j that is not in the neighborhood of the sample x_i, we let the value of the corresponding $w_{ij} = 0$. Specifically, we find the weight coefficient by using the preceding two equations. The optimization problem can be solved using a matrix and Lagrange multiplier. Finally, a low-dimensional representation of the 30-dimensional sample feature can be obtained.

The detailed steps designed for the motion detection algorithm are shown in Table 1.

Table 1. Motion detection algorithm based on the LLE-Diff algorithm.

Motion detection Algorithm
Inputs: 1. A set of collected CSI data $\{\boldsymbol{x}\}$. 2. The nearest neighbor parameter, k. 3. The dimensionality d by which the dimension is reduced.
Output: Low-dimensional feature $\{\boldsymbol{y}\}$
1. For $i = 1$ to m, calculate x_i and the nearest k nearest neighbors by using the Euclidean distance $\{x_{i1}, x_{i2}, \ldots, x_{ik}\}$. 2. For $i = 1$ to m, calculate the local covariance matrix $Z_i = (x_i - x_j)^T(x_i - x_j)$ and calculate the corresponding weight coefficient vector. 3. The weight coefficient matrix W is composed of the weight coefficient vector W_i, and calculate the matrix $M = (I - W)^T(I - W)$. 4. Calculate the first $d + 1$ eigenvalues of the matrix M, and calculate the eigen vectors corresponding to the $d + 1$ eigenvalues $\{y_1, y_2, \ldots, y_{d+1}\}$. 5. The matrix formed by the second eigenvector to the $d + 1$th eigenvector is the output low-dimensional sample set matrix $D' = \{y_2, y_3, \ldots, y_{d+1}\}$.

The sample feature is reduced from 30 dimensions to 6 dimensions by using the LLE algorithm. Subsequently, the difference between the LLE values of adjacent sample features is calculated to determine the motion state of a person within a time slot. A large difference between the adjacent LLE results indicates that the person is in a moving state. However, a small difference between the adjacent LLE results indicates that the person is in a stationary state. Here, we calculate the difference between the LLE values of adjacent sample features, named as LLE-Diff.

4.3 Location Discrimination Stage

After phase 2, the motion state of the human (*i.e.*, stationary or moving) can be determined. When a person is in the moving state, the variation of the collected CSI is large, and it is difficult to calculate the exact location of the person. In the proposed algorithm, we only determine the location of a person in the stationary state. Let each location be denoted by a class; thus, the localization problem becomes a classification task. When a person is standing at a specific location, the collected CSIs are regarded as the training samples of the class that are associated with the corresponding location. Through the use of the CSI training samples of various locations, the classifier can be trained to solve localization tasks. We use discriminant analysis to solve classification tasks. LDA projects high-dimensional samples to the optimal discriminant subspace to extract low-dimensional features with the best discriminant capability. The extracted features maximize the ratio of interclass distance to intraclass distance in the new subspace. That is, the sample has the best class separation in the subspace. LDA assumes that all sample classes have the same covariance matrix. Because the collected CSI values have different covariance matrices, the collected samples cannot fulfill the requirements of the LDA algorithm. In this study, the quadratic discriminant analysis (QDA) that is conducted on samples with various covariance matrices is applied to solve CSI classification tasks.

The operations of the QDA algorithm are briefly described as follows. Let m denote the total number of different locations (classes). The first step of QDA is to calculate the mean vector μ_j and covariance matrix Σ_j of each class j ($j = 1, 2, \ldots, m$). Therefore, the quadratic discriminant function is defined as presented in Eq. (7):

$$\varphi_j(x) = -\tfrac{1}{2}\log|\Sigma_j| - \tfrac{1}{2}(x-\mu_j)^2 \sum\nolimits_j^{-1}(x-\mu_j) + \log \pi_j, \tag{7}$$

where π_j represents the prior probability of class j. According to the quadratic discriminant function in Eq. (7), the classification rule for an unknown sample x can be expressed as presented in Eq. (8).

$$\hat{G}(x) = \arg\max_j \varphi_j(x) \tag{8}$$

The unknown sample x is classified into class j if $\varphi_j(x)$ has a maximum value among all discriminant functions.

5. PERFORMANCE EVALUATION

5.1 Experimental Setting

To evaluate the performance of the proposed device-free HMTD algorithm, a laboratory experiment was conducted. As displayed in Fig. 3, the laboratory included computer tables, chairs, display, bookshelves, drinking fountains, and other furniture. Due to the existence of multiple indoor devices, various degrees of multipath effects would be generated for wireless communication links. We used a Wi-Fi-based mobile AP as the signal transmitter, and the laptop was used as the signal receiver. The mobile AP was placed above the bookshelf, the laptop with the CSI Tool software was placed on the computer desk, and the laptop regularly received signals from the AP. We divided the indoor space into 3×3 subregions and tested the performance of the algorithm in tracing the trajectory of a person in these subregions.

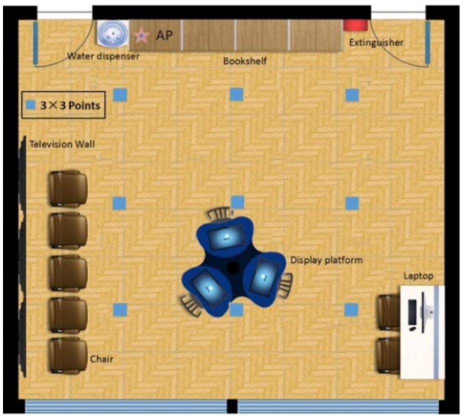

Fig. 3. Indoor experiment scene.

5.2 Performance Evaluation

We selected 5 people with heights of 165, 170, 175, 180, and 185 cm as our mobile testers. As mentioned, the laboratory was divided into 3×3 subregions, as shown in Fig. 4. The transmitter and receiver were deployed in subregions 4 and 3, respectively. The possible moving paths of a person are indicated by the red arrows in the figure. The system collected corresponding CSI when a tester moved between two adjacent subregions. According to the details presented in Table 2, 12 sets of CSI features were collected. Consider, for example, group 1 (1→2) presented in Table 2. The tester stayed in subregion 1 for 10 s and then walked from subregion 1 to subregion 2 at a normal speed. The tester finally stayed in subregion 2 for 10 s.

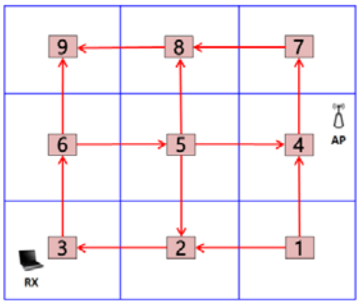

Fig. 4. Possible moving path for a person.

Table 2. Test path partition table.

Group	Moving trajectory	Moving speed
Group 1	①—>②	Constant speed
Group 2	①—>④	Constant speed
Group 3	②—>③	Constant speed
Group 4	③—>⑥	Constant speed
Group 5	④—>⑦	Constant speed
Group 6	⑤—>②	Constant speed
Group 7	⑤—>④	Constant speed
Group 8	⑤—>⑧	Constant speed
Group 9	⑥—>⑤	Constant speed
Group 10	⑥—>⑨	Constant speed
Group 11	⑦—>⑧	Constant speed
Group 12	⑧—>⑨	Constant speed

Consider, for example, the trajectory of group 1 presented in Table 2. The discriminant result of the motion state of a person determined by applying the LLE-Diff is displayed in Fig. 5. When a person is in the moving state, the value calculated by the LLE-Diff algorithm is high. By contrast, when a person is in the stationary state, the value obtained by the LLE-Diff algorithm is low. Therefore, in Fig. 5, the horizontal line indicates that the person is in the stationary state, whereas the peak value represents that the person is in the moving state on each LLE-Diff axis. To increase the confidence value

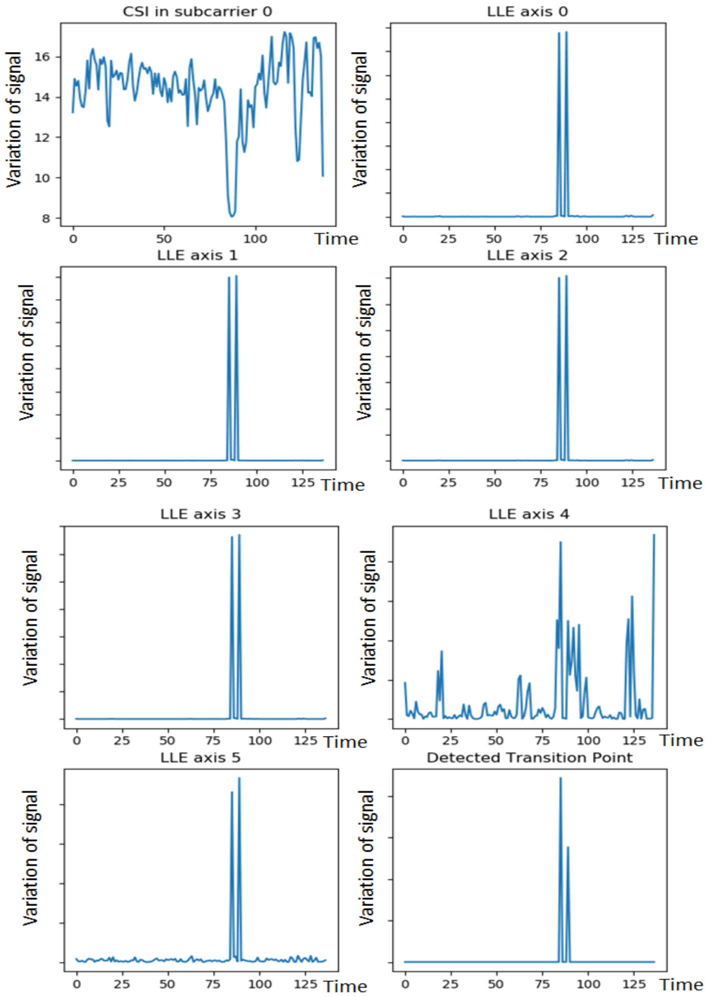

Fig. 5. Processing results of the subcarrier zero.

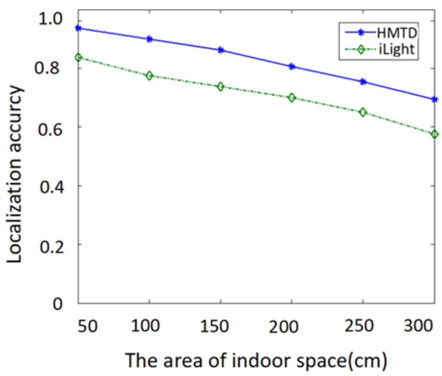

Fig. 6. Comparison between the tracking accuracies of the iLight and proposed HMTD algorithms.

of the calculated human states, the values from six LLE-Diff axes were multiplied. The final peaks were determined to correspond to the motion state of the person.

When the LLE-Diff algorithm finds that a person is in the stationary state, a reliable CSI feature extraction and location identification algorithm based on mean value calculation and QDA algorithm can be applied to determine the current position of the target. According to the location of the person in the previous and subsequent positions and the moving state of the person, the trajectory of the person can finally be determined.

Fig. 6 displays a comparison of the trajectory tracking accuracy of the iLight and the proposed HMTD algorithms. As illustrated in Fig. 6, the HMTD algorithm had a higher positioning accuracy level than did the iLight algorithm. Because the HMTD algorithm eliminates noise and interference information from a signal before executing location discrimination, a highly reliable signal can be obtained. The LLE-Diff algorithm can then be applied to recognize the motion state (*i.e.*, stationary or moving), and the location of the person can be determined using the QDA algorithm, which improves the recognition efficiency of the algorithm. By contrast, the iLight system requires 40 sensor nodes, 10 common light sources, and a base station. These results in a longer signal transmission and processing time, which reduces the position recognition efficiency.

6. CONCLUSIONS

This paper presents a device-free trajectory tracking algorithm based on CSI for identifying the trajectory of a person in indoor environments. The proposed HMTD algorithm is a trajectory tracking algorithm that does not require a person to carry any tracking device. Based on CSI, the proposed HMTD algorithm first uses LLE to reduce the dimension of CSI. Subsequently, the algorithm further recognizes the position of the person by using the QDA algorithm. Compared with existing algorithms, the proposed HMTD algorithm significantly improved the accuracy of device-free human trajectory tracking.

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