A Personnel Trajectory Tracking Method Based on Channel State Information Postprint

Authors: Hao Zhanjun, Li Beibei, Dang Xiaochao

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Abstract

To address the problems of high communication overhead and high algorithmic complexity in indoor trajectory tracking processes, a personnel trajectory tracking method based on CSI (channel state information) signals is investigated. First, the AOA (angle-of-arrival) spectrum representing the probability of the target position (angle) is extracted from CSI, and the Doppler frequency shift obtained through the MUSIC algorithm is combined with the AOA spectrum to determine the moving speed and position of the personnel; finally, an improved trilateration centroid algorithm is utilized to determine the personnel position, simulate the movement trajectory, and achieve accurate tracking and localization of indoor personnel. Through comparison with other algorithms and different personnel moving speeds, simulation experiments demonstrate that the personnel tracking method proposed in this paper can significantly improve the accuracy and stability of localization.

Full Text

Preamble

Title: A Method for Personnel Trajectory Tracking Based on Channel State Information

Authors: Hao Zhanjun[1,2], Li Beibei[1], Dang Xiaochao[1,2]
[1]College of Computer Science & Engineering, Northwest Normal University, Lanzhou 730070, China;
[2]Gansu Province Internet of Things Engineering Research Center, Lanzhou 730070, China

Abstract: This paper investigates a personnel trajectory tracking method based on CSI (channel state information) signals to address the problems of high communication overhead and algorithmic complexity in indoor trajectory tracking processes. First, the AOA (angle-of-arrival) spectrum, which represents the probability of target position (angle), is extracted from CSI. The Doppler shift obtained through the MUSIC algorithm is then combined with the AOA spectrum to determine personnel movement speed and position. Finally, an improved trilateration centroid algorithm is employed to pinpoint personnel locations and simulate movement trajectories, achieving precise indoor personnel tracking and localization. Through comparisons with other algorithms and across different movement speeds, simulation experiments demonstrate that the proposed tracking method significantly improves localization accuracy and stability.

Keywords: CSI signal; trajectory tracking; trilateration; centroid algorithm; tracking localization

0 Introduction

Localization technology, as a crucial component of ubiquitous computing and the Internet of Things, has attracted increasing attention. While Global Navigation Satellite Systems (GNSS) play a key role in outdoor precision positioning, they fail to deliver high-accuracy localization indoors due to multipath effects, scattering, and diffraction characteristics exhibited by signals during propagation. Current CSI-based localization research has achieved promising results, even reaching meter-level or sub-meter-level precision.

In recent years, institutions including MIT, Stanford University, University of Washington, Hong Kong University of Science and Technology, and Tsinghua University have conducted extensive research on CSI-aware application systems. Reference [1] utilized commercial Wi-Fi to achieve device-free indoor personnel tracking with high localization accuracy even under packet loss and latency conditions, but did not consider multi-person tracking, real-time tracking, or multipath effects. Reference [2] employed software-defined radio (USRP) to implement gesture recognition across an entire experimental area and used FFT to detect Doppler shifts. Reference [3] constructed a virtual touchscreen using RFID and leveraged AoA information for fine-grained tracking. WiDraw utilized AoA information to provide a viable approach for position determination using phase information, but required Wi-Fi transmitters to cover all directions in the environment [4], which proves difficult to implement in practice due to multipath effects. Reference [5] developed LIFS, a low-cost, high-precision passive target localization method based on a CSI model that effectively combined CSI characteristics for target localization, but did not consider the relationship between detection area and detection rate. Reference [6] applied phase information from CSI to mouth movements during speech to achieve finer-grained localization, though phase information is difficult to obtain and requires specialized USRP equipment, resulting in low stability and practicality. The FIMD system in Reference [7] achieved finer-grained personnel detection in static environments by leveraging CSI stability, but did not achieve high detection rates and its overall performance was affected by environmental changes. The BFP system in Reference [8] utilized CSI for behavior-agnostic movement detection with good overall performance, but suffered from low algorithmic efficiency.

Existing trajectory tracking methods generally sacrifice high communication overhead and algorithmic complexity to improve accuracy. In contrast, the CSI-based personnel trajectory tracking method proposed in this paper effectively avoids these issues. First, extracted CSI signals are processed using a smoothing algorithm to form an enhanced CSI algorithm that compares previous CSI values with current ones, reducing kinetic fluctuations of moving personnel targets. Finally, an improved trilateration centroid algorithm is used to determine each activity point, with all activity points plotted to form trajectory images for visual display, enabling more precise indoor personnel tracking and localization.

1.2 CSI Signal Doppler Shift Extraction

Multipath propagation occurs in indoor environments with a pair of transmitters and receivers, where signals travel not only along direct paths but also reflect off objects (such as people) and walls. The signal received at the receiver is therefore a superposition of signals from all paths. When a person moves in the environment, the lengths of reflected paths change accordingly, causing Doppler shifts in the carrier frequency of reflected signals. The carrier frequency is given by:

$$f = f_c + \frac{v_{path}}{c} f_c$$

where f_c is the original carrier frequency, v_{path} is the rate of path length change, and c is the propagation speed of Wi-Fi signals in air. When people move, the introduced frequency shift for Wi-Fi signals is only a few tens of hertz for 5 GHz channels. Clearly, detecting such fine-grained Doppler carrier frequency shifts is extremely difficult.

1.1 Channel State Information

CSI is channel state information that measures channel conditions, belonging to the PHY layer and derived from decoded subcarriers in OFDM systems [9-10]. CSI is fine-grained physical information that is more sensitive to environmental changes and has been applied in activity recognition, gesture recognition, keystroke recognition, and tracking. To determine the received power of a measured node, the transmit power of the transmitting node is used as a reference and then converted to the distance between nodes using a signal propagation attenuation model. Finally, the position of an unknown node can be simply determined using an improved trilateration algorithm.

The relationship between transmit power and receive power of wireless signals can be expressed as:

$$P_R = \frac{P_T}{d^n}$$

where P_R is the received power, P_T is the transmit power, d is the distance between transceiver units, and n is the propagation factor whose value depends on the wireless signal propagation environment.

Taking the logarithm of both sides of the equation yields:

$$10 \log P_R = 10 \log P_T - 10n \log d$$

The left half of equation (3), $10 \log P_R$, represents the received signal power converted to dBm. Substituting the known transmit power into equation (2) gives:

$$10 \log P_R(\mathrm{dBm}) = A - 10n \log d$$

where $A = 10 \log P_T(\mathrm{dBm})$ is the received signal power when the signal travels 1 meter. From equation (4), A is a CSI constant, and the values of n and A determine the relationship between received signal strength and signal transmission distance.

Since the signal attenuation differs at each reference point, a single value of n lacks generality and is difficult to validate for accuracy. From equation (4), we derive equation (5) to obtain a set of n_i values:

$$n_i = \frac{A - 10 \log P_{R_i}}{10 \log d_i}$$

The average of this set of values, $\bar{n}$, is the propagation factor we seek.

2.1 MUSIC-Based Doppler Estimation

During CSI acquisition, packet loss/delay caused by environmental noise and interference can prevent normal transmission and reception of sample data packets. To address these issues and obtain accurate Doppler shift estimates using Wi-Fi devices, this paper proposes a MUSIC-based algorithm for precise Doppler frequency shift estimation.

Assume the first CSI sample is collected at time t_0, with each subsequent sample having a sampling interval of Δt. Within a short sampling window, the path change rate is treated as constant because attenuation differences across CSI samples vary. The phase difference between the i-th CSI sample and the first sample can be expressed as:

$$\Delta\phi_i = 2\pi f_c \frac{v_{path} \cdot i\Delta t}{c}$$

The Doppler vector and CSI sample matrix with M samples can be directly written as equation (4), where v_{path} is the rate of path length change.

When only one path signal exists, the Doppler shift can be easily calculated from phase measurements of CSI samples. In practical multipath scenarios, L path signals arrive at the receiver. The CSI sample matrix can be expressed as:

$$\mathbf{X}(f,t) = \sum_{i=1}^{L} \mathbf{a}(v_i) s_i(f,t) + \mathbf{N}(f)$$

where $\mathbf{a}(v_i)$ is the steering vector for the i-th path signal, $s_i(f,t)$ is the i-th path signal' s CSI measured at the first sampling time, and $\mathbf{N}(f)$ is the noise matrix.

To obtain the Doppler shift for each path signal, this paper adopts multiple snapshots in the frequency domain from CSI samples. As shown in Figure 1 [Figure 1: see original paper], devices provide CSI across multiple subcarriers. Let K be the number of CSI subcarriers with M snapshots. For the i-th CSI sample:

$$\mathbf{x}_i(f_0 + \Delta f_k, t_0 + i\Delta t) = [x_i(f_1, t_0 + i\Delta t), \dots, x_i(f_K, t_0 + i\Delta t)]^T$$

The correlation matrix $\mathbf{R}$ with M eigenvalues can be expressed as:

$$\mathbf{R} = E[\mathbf{X}\mathbf{X}^H] = \mathbf{A}E[\mathbf{S}\mathbf{S}^H]\mathbf{A}^H + E[\mathbf{N}\mathbf{N}^H] = \mathbf{A}\mathbf{R}_s\mathbf{A}^H + \sigma^2\mathbf{I}$$

where $\mathbf{R}_s$ is the signal matrix correlation matrix, $\mathbf{I}$ is the identity matrix, and σ^2 is the noise variance. The correlation matrix $\mathbf{R}$ has M eigenvalues, with the smallest $M-L$ eigenvalues corresponding to noise and the remaining L eigenvalues corresponding to path signals.

The eigenvectors corresponding to the smallest eigenvalues construct a noise subspace $\mathbf{E}_N = [\mathbf{e}_{L+1}, \dots, \mathbf{e}_M]$. Since signal and noise subspaces are orthogonal, the Doppler velocity spectrum function can be expressed as:

$$P_{\text{MUSIC}}(v) = \frac{1}{\mathbf{a}^H(v)\mathbf{E}_N\mathbf{E}_N^H\mathbf{a}(v)}$$

where peaks correspond to maxima in the spectrum function. With known original carrier frequency and propagation speed, the Doppler velocity can be obtained.

2.2 Improved Trilateration Centroid Algorithm

In complex indoor localization, detected personnel movement trajectories change constantly [14-16], and external uncertainties cause significant fluctuations in CSI signal values, leading to large localization errors that fail to meet expected performance. This paper introduces a smoothing algorithm that compares adjacent CSI signal values, removes those with excessive fluctuations, and achieves precise localization. The improved smoothing algorithm implementation consists of two phases: distance estimation and position estimation.

2.2.1 Distance Estimation

The CSI localization mechanism consists of reference nodes and unknown nodes. In a two-dimensional coordinate system, the standardized Euclidean distance between fixed reference node coordinates and CSI values received by unknown nodes is calculated. Taking the reference point' s x-coordinate value as x_i and each collected unknown node' s CSI value as y_i, their standardized Euclidean distance is given by equation (15):

$$d(x_i, y_i) = \sqrt{\frac{(x_1 - y_1)^2}{s_1^2} + \frac{(x_2 - y_2)^2}{s_2^2} + \cdots + \frac{(x_n - y_n)^2}{s_n^2}}$$

To avoid accidental errors, we derive equation (16) from equation (15). The data smoothing process is defined as:

$$R_{est}(n) = \lambda R_{pre}(n) + (1 - \lambda)[R_{mean}(n) + V_{pre}(n)T_s]$$

where $R_{est}(n)$ is the n-th smoothed CSI range estimate, $R_{pre}(n)$ is the n-th predicted CSI range, $R_{mean}(n)$ is the n-th measured CSI range, $R_{rat}(n)$ is the n-th smoothed range ratio, $R_{pre\_rat}(n)$ is the n-th predicted range ratio, λ and ξ represent gain constants, and T_s is the variation time period.

The processing steps are as follows: a) Calculate $R_{est}(n)$ and $R_{rat}(n)$ using equations (17) and (18). b) Compare the n-th CSI value' s range with the ratio estimate and prediction. c) Obtain the n-th reference point value from equation (20), then calculate the CSI value using equation (5). Since the propagation factor' s effect on signal attenuation is included in the calculation, the CSI value contains some error. The obtained CSI values are averaged to produce a more accurate value sent to unknown nodes.

2.2.2 Position Estimation

Traditional trilateration determines the intersection point of three circles with known radii and centers. As shown in Figure 2 [Figure 2: see original paper], the connections between three circle centers cannot accurately converge to a single point during ranging.

To reduce errors between estimated and actual coordinates, this paper proposes an improved trilateration method using weighted least squares to estimate unknown node coordinates. The method proceeds as follows: a) For n points in the two-dimensional coordinate system, fit a curve at the center of the sample data. b) Introduce a squared loss function. Let Q be the residual sum of squares, with the sample regression model given by equation (21):

$$\hat{y}_i = \beta_0 + \beta_1 x_i + e_i$$

where e_i is the error for sample i. The squared loss function is:

$$Q = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i)^2$$

Treating β_0 and β_1 as variables, this becomes an extremum problem solvable through differentiation. Taking partial derivatives of Q with respect to the two parameters:

$$\frac{\partial Q}{\partial \beta_0} = -2 \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i) = 0$$
$$\frac{\partial Q}{\partial \beta_1} = -2 \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i) x_i = 0$$

The extremum points where partial derivatives equal zero yield the activity point location. Solving gives:

$$\beta_1 = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{n \sum x_i^2 - (\sum x_i)^2}$$
$$\beta_0 = \frac{\sum y_i - \beta_1 \sum x_i}{n}$$

The resulting (x, y) represents the coordinates of the sought activity point.

2.3 CSI-Based Personnel Trajectory Tracking Method

Based on the theoretical analysis above, this paper proposes a CSI signal-based personnel trajectory tracking method. The algorithm implementation process is shown in Figure 3 [Figure 3: see original paper].

a) Extract CSI signal values from the deployed experimental environment.
b) First, use the MUSIC algorithm to estimate Doppler shift (the proposed Doppler-Music algorithm), then estimate the AOA spectrum to determine whether personnel are within the preset range. If yes, proceed to step c); otherwise, return to step a).

c) Apply the smoothing algorithm to remove redundant points from the activity points obtained in step b), then use the improved trilateration algorithm to determine activity point positions. Check if results are within the reference range. If yes, proceed to step d); otherwise, return.
d) Process the points within the activity range, collect sufficient points to simulate the trajectory image, and terminate the program.

2.4 Communication Overhead and Algorithm Complexity Analysis

To calculate communication overhead E, we introduce several parameters: N represents the number of nodes in the network; A represents the number of anchor nodes; G represents the average network connectivity; C represents the average number of neighbor nodes; and K represents the number of anchor nodes participating in multilateration localization.

The overhead of this algorithm primarily manifests in inter-node communication and packet transmission processes, making node distance a critical factor affecting communication overhead. When an unknown node obtains distances to three or more anchor nodes, trilateration localization is performed. Let the unknown node coordinates be (x, y) and anchor node coordinates be (x_i, y_i). The distances from the unknown node to anchor nodes are r_i. Establishing a linear system yields equation (26):

$$\begin{bmatrix} 2(x_1 - x_k) & 2(y_1 - y_k) \\ 2(x_2 - x_k) & 2(y_2 - y_k) \\ \vdots & \vdots \\ 2(x_{k-1} - x_k) & 2(y_{k-1} - y_k) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x_1^2 - x_k^2 + y_1^2 - y_k^2 + r_k^2 - r_1^2 \\ x_2^2 - x_k^2 + y_2^2 - y_k^2 + r_k^2 - r_2^2 \\ \vdots \\ x_{k-1}^2 - x_k^2 + y_{k-1}^2 - y_k^2 + r_k^2 - r_{k-1}^2 \end{bmatrix}$$

After solving for the unknown node position using least squares, the distance between adjacent nodes is calculated as X. The average distance for C neighbor nodes is CX, where $X = \frac{1}{n} \sum_{i=1}^{n} |x_i - \hat{x}|$. Additionally, packet transmission incurs communication overhead. Using controlled flooding to transmit messages in the network, each anchor node broadcasts packets while intermediate nodes only forward unsent packets. Each node sends an average of A packets, and since the flooding process occurs twice, each node sends an average of $2A$ packets. The communication overhead for N network nodes is $2AN$. Thus, total communication overhead is $E = CX + 2AN$.

After obtaining unknown node positions through trilateration, matrix multiplication using least squares requires calculations involving the number of anchor nodes K and the number of anchor nodes participating in multilateration A. Therefore, the time complexity of this algorithm is $T(AK)$, approximately $T(n^2)$, and the space complexity is $O(n)$.

3.1 Experimental Environment

CSI signals can be obtained through Intel 5300 and Atheros 9380 wireless network cards. This paper adopts the Atheros 9380 solution. The localization algorithm requires: two desktop computers equipped with Atheros 9380 network cards (Intel Core i3-4150 CPU, Ubuntu 10.04 LTS operating system, with customized kernel and wireless card drivers), one serving as a signal transmitter and the other as a receiver. The experimental site is a 9 m $\times$ 6 m office area divided into 25 square zones (0.8 m $\times$ 0.8 m each), with transmitter-receiver separation of 4.5 m and antenna height of 1.2 m. The floor plan and detailed zone layout are shown in Figure 4 [Figure 4: see original paper], with on-site testing shown in Figure 5 [Figure 5: see original paper].

The office environment floor plan is illustrated in Figure 6 [Figure 6: see original paper]. The tracking area measures 9 meters $\times$ 6 meters. Markers were placed on the floor and a camera recorded when subjects passed them. In the experiment, five students walked along different paths (lines, rectangles, circles) at the same time each day for two weeks. One hundred trajectories were collected per person to report tracking errors and demonstrate performance.

3.2 Tracking Performance Analysis

To verify the impact of packet loss/delay on tracking performance, controlled experiments were conducted with varying loss and delay magnitudes, with results shown in Figure 10 [Figure 10: see original paper].

Figure 10 indicates that without packet loss/delay, the algorithm' s tracking error is approximately 8%. In real environments, packet loss/delay occurs due to environmental noise and interference. Therefore, randomly dropping some CSI packets simulated packet loss/delay scenarios. Even with 50% packet loss, the method maintains high tracking accuracy similar to the no-loss case. Figure 10 also shows the CDF of tracking errors in the laboratory environment, where multipath effects are more pronounced due to numerous obstructions. The method still achieves excellent tracking performance, demonstrating that static environment tracking performance is significantly higher than in dynamic environments.

To further investigate speed's impact on tracking performance, targets walked at three speeds: slow (<1 m/s), normal (1-1.5 m/s), and fast (1.5-3 m/s). Speed effects are shown in Figures 11 [Figure 11: see original paper] and 12 [Figure 12: see original paper].

Figure 11 shows that speed affects tracking performance, with the slowest speed producing about 8% less error than the fastest speed, indicating better tracking performance at lower speeds. Figure 12 demonstrates that velocity direction error increases with movement speed.

The Doppler-Music method was compared with the partition-based K-means algorithm. Since K-means estimates Doppler velocity based on CSI amplitude, it cannot provide direction information. Therefore, K-means was used only for Doppler velocity magnitude estimation while Doppler-Music provided direction information. As shown in Figure 9 [Figure 9: see original paper], even with direction information improving performance, K-means still exhibits 44% error at normal speed and 17° direction error—far exceeding Doppler-Music' s performance. This is because Doppler-Music estimates Doppler velocity using CSI phase, which is more stable than the CSI amplitude used by K-means. Moreover, unlike other methods, Doppler-Music can simultaneously estimate both magnitude and direction of Doppler velocity.

The effects of antenna power (PA) and static component (RS) on trajectory tracking accuracy are shown in Figure 9. Without adjusting antenna power or removing static components, velocity error is 37% and direction error is 26°. Adjusting only antenna power yields 19% relative velocity error and 17° direction error. Removing only static components produces 17% relative velocity error and 8° median direction error. Adjusting both antenna power and removing static components achieves 11% relative velocity error and 7° median direction error. Removing strong interference static components significantly improves tracking performance, while adjusting both antennas'power yields more accurate Doppler velocity direction information.

Figure 7 [Figure 7: see original paper] shows tracking results using the proposed algorithm in a real environment, while Figure 8 [Figure 8: see original paper] depicts human velocity direction accuracy. Figure 7 demonstrates that tracking performance is closest to expected results when the subject' s trajectory is circular, indicating optimal tracking for this pattern. Figure 8 shows that normal-speed movement amplitude error is as low as 14% while direction error is only 7°.

Tracking five targets simultaneously, error analysis is shown in Figure 13 [Figure 13: see original paper]. The results demonstrate consistent performance across different targets.

3.3 Performance Comparison

To further demonstrate the proposed algorithm' s tracking performance advantages, comparisons were made with traditional K-means and PCA algorithms. Communication overhead performance is compared in Figure 14 [Figure 14: see original paper], and algorithmic complexity in Figure 15 [Figure 15: see original paper].

Figure 14 shows that the proposed algorithm exhibits stable communication overhead earlier over time and significantly outperforms PCA. More stable performance indicates lower communication overhead, more accurate node positions, and better trajectory tracking performance. Figure 15 reveals that Doppler-Music' s time complexity remains constant after a period and significantly outperforms the other two algorithms, indicating lower time complexity than PCA and K-means, saving time and reducing energy consumption while enabling more precise trajectory tracking.

In summary, the CSI trajectory tracking algorithm based on Doppler-Music demonstrates clear superiority in both communication overhead and time complexity, offering a new solution for achieving precise trajectory tracking.

4 Conclusion

This paper designs a method for indoor personnel trajectory tracking using CSI signals, achieving precise tracking of an individual' s trajectory. Future work must address multi-person tracking, real-time tracking, and other challenges. Indoor personnel tracking methods have broad application prospects. Another important challenge is that the current experimental environment operates at 2.4 GHz; the next step is to migrate the development environment to 5 GHz to achieve more precise localization performance.

References

[1] Xu Yuan, Xu Xiaoliang, Li Cainian, et al. Pedestrian detection based on SVM classifier and HOG feature extraction [J]. Computer Engineering, 2016, 42(1): 56-60.

[2] Xie Juanying, Wang Yanqi. K-means algorithm for minimum clustering optimization of initial cluster center [J]. Computer Engineering, 2014, 40(8): 205-211.

[3] Li Chuanpeng, Qin Pinle, Zhang Jinjing. Image denoising based on deep convolutional neural network [J]. Computer Engineering, 2017, 43(3): 253-260.

[4] Wang Jue, Vasisht D, Katabi D. RF-IDraw: virtual touch screen in the air using RF signals [J]. ACM SIGCOMM Computer Communication Review, 2014, 44(4): 235-246.

[5] Sun Li, Sen S, Koutsonikolas D, et al. Widraw: enabling hands-free drawing in the air on commodity wifi devices [C]//Proc of the 21st Annual International Conference on Mobile Computing and Networking. New York: ACM Press, 2015: 77-89.

[6] Wang Wei, Liu A X, Sun Ke. Device-free gesture tracking using acoustic signals [C]//Proc of the 22nd Annual International Conference on Mobile Computing and Networking. New York: ACM Press, 2016: 82-94.

[7] Yun Sangki, Chen Yichao, Qiu Lili. Turning a mobile device into a mouse in the air [C]//Proc of the 13th Annual International Conference on Mobile Systems, Applications, and Services. New York: ACM Press, 2015: 15–29.

[8] Sen S, Choudhury R R, Radunovic B, et al. Precise indoor localization using PHY information [C]//Proc of the 10th ACM Workshop on Hot Topics in Networks. New York: ACM Press, 2011: 413-414.

[9] Qian Kun, Wu Chenshu, Yang Zheng, et al. Decimeter level passive tracking with Wi-Fi [C]//Proc of the 3rd Workshop on Hot Topics in Wireless. New York: ACM Press, 2016: 44-48.

[10] Yang Wei, Wu Chenxi, Liu Yunhao. Location Computing: Wireless Network Positioning and Positionability [M]. Beijing: Tsinghua University Press, 2014.

[11] Peng Yuxu, Yang Yanhong. A Bayesian indoor location algorithm based on RSSI [J]. Computer Engineering, 2012, 38(10): 237-240.

[12] Wang Qi. Indoor positioning technology based on RSSI ranging [J]. Electronic Science & Technology, 2012, 25(6): 64-66.

[13] Shi Xin, Yin Aimin, Chen Wei. Multi-dimensional scale indoor positioning algorithm based on RSSI [J]. Journal of Scientific Instrument, 2014, 35(2): 261-268.

[14] Zhang Yong, Huang Jie, Xu Keyu. WLAN indoor positioning method based on PCA-LSSVR algorithm [J]. Journal of Scientific Instrument, 2015, 36(2): 408-414.

[15] Wang Xuyu, Gao Lingjun, Mao Shiwei, et al. CSI-based fingerprinting for indoor localization: a deep learning approach [J]. IEEE Trans on Vehicular Technology. IEEE, 2017, 66(1): 763-776.

[16] Xiao Jiang, Wu Kaishun, Yi Youwen, et al. FIFS: fine-grained indoor fingerprinting system [C]//Proc of International Conference on Computer Communications and Networks. Piscataway, NJ: IEEE Press, 2012: 1-7.

[17] Wu Zhefu, Xu Qiang, Li Jianan, et al. Passive indoor localization based on CSI and naive Bayes classification [J]. IEEE Trans on Systems Man & Cybernetics Systems, 2017, PP(99): 1-12.

[18] Wu Zhefu, Zhou Yan. Passive positioning based on channel state information [J]. Journal of Transduction Technology, 2015, 28(5): 677-683.

[19] Li Shengjie, Li Xiang, Niu Kai, et al. AR-alarm: an adaptive and robust intrusion detection system leveraging CSI from commodity Wi-Fi [C]//Proc of International Conference on Smart Homes and Health Telematics. Cham: Springer, 2017: 211-223.

[20] Pu Qifan, Gupta S, Gollakota S, et al. Whole-home gesture recognition using wireless signals [C]//Proc of International Conference on Mobile Computing & Networking. New York: ACM, 2013: 27-38.

Note: Figure translations are in progress. See original paper for figures.