WiFi-based indoor personnel location monitoring method

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Abstract: With the development of wireless communication technology, WiFi-based indoor personnel positioning has received more and more attention. The channel state information (CSI) extracted from the commercial network card can be used to determine the position status of the indoor personnel. In this paper, we propose a method based on WiFi personnel to determine the presence and intrusion of indoor personnel by real-time positioning of personnel. The method uses principal component analysis to preprocess the data, extracts the main features in the amplitude information, and uses the support vector machine (SVM) to realize the training and classification of indoor position samples, and uses the obtained indoor position status information to determine the regional invasion situation and the specific location of the personnel. Experiments show that this method can effectively judge the intrusion of people in specific areas of the city and achieve precise positioning under the condition of low resource consumption.

1. Introduction

With the development of communication technology, location information services have attracted more and more attention in today's society. Conventional location acquisition methods such as GPS[1] have good performance in the application of outdoor coarse positioning, and with the progress of production and life, it is also important to realize the location information acquisition of indoor personnel. In real-life application scenarios such as bank vaults, art galleries, museums, computer rooms, it is often necessary to accurately obtain the location information of indoor personnel according to actual application requirements, to determine whether a person enters a special area and enter specific information after the area, according to get the location information to respond further. However, in practical applications, traditional positioning methods are affected by building obstruction, and it is difficult to achieve accurate indoor positioning. Common indoor location acquisition technologies such as UWB[2] and RFID[3] usually need to be carried by relevant personnel to achieve accurate positioning. In practical applications, for public environments such as galleries and exhibition halls, all personnel entering the designated area are required to wear relevant positioning. The lack of practical significance of the equipment, so the device-free indoor positioning technology based on WiFi technology came into being[4].

This paper aims to design a set of indoor key area monitoring methods that integrates intrusion detection and regional fine positioning into important indoor environments. The contribution of this method lies in the following points:
• We searched the relationship model between human location and CSI signal through a large number of experiments, extracted the main feature components according to different amplitude characteristics, and tested the accuracy and stability of the system under different experimental scenarios.

• This method is different from the traditional indoor personnel position detection system. It combines the personnel intrusion detection with the specific location identification of the personnel. Through the combination of SVC and SVR, the offline resources are rationally utilized, and the personnel pairs are respectively performed according to different practical application situations.

• The method does not require additional equipment, and can be directly deployed by the WiFi, and compensates for the shortcomings caused by the traditional wearable sensing device while realizing the location of the personnel.

2. Related work
In this section, we will introduce the existing indoor positioning methods. One is a tag-based indoor positioning system, which usually uses infrared, ultra-wideband and RFID technologies to obtain specific locations using TOA\[^5\] or AOA\[^6\] methods through devices or tags worn by personnel themselves. The other is the device-free passive indoor location sensing method, such as Bluetooth, WiFi and ZigBee. The biggest advantage of no device awareness is that you don't need people to wear tags or add specific devices, you can use existing wireless devices for widespread deployment. The current no-device awareness is mainly divided into two sub-categories based on RSSI and CSI-based\[^7\].

RSSI can reflect the change of signal reception intensity affected by the environment. By analyzing this change mode, a model of the position of the person and the RSSI signal can be constructed\[^8\]. In\[^9\], the author analyzes and discusses the influence of environmental noise on the RSSI signal, and tests the influence of different filtering noise reduction methods on indoor positioning accuracy. In\[^10\], the author proposes an enhanced indoor positioning scheme combined with machine learning. This scheme combines AP selection and signal strength reconstruction based on RSSI measurement. Experiments show that this method has higher positioning accuracy. Although the RSSI signal has a good performance in a non-line-of-sight indoor environment, it is itself coarse-grained information extracted by the MAC layer, which limits the improvement of recognition accuracy.

As the subcarrier information extracted by the physical layer of the device, CSI can provide fine-grained information of more paths of signals during transmission. In\[^11\], the author proposes the FIFS method to perform fine-grained indoor location acquisition based on CSI fingerprint information. In\[^12\], the author proposes the LiFS method, tries to find subcarriers that are not affected by multipath, and inputs the CSI data on the extracted subcarriers into the positioning model to improve indoor positioning accuracy. In\[^13\], the author proposes the deepfi algorithm in combination with the deep learning method, and obtains the estimated position by offline weight training and online radial basis function based probabilistic method. Inspired by the above method, we introduce support vector machine (SVM) in the traditional fingerprint library method to realize intrusion discrimination and intra-area personnel positioning.

3. System architecture
The method described in this paper also includes two phases, online and offline. The offline phase collects the state information in the sample points. Since the collected CSI information contains six links and multiple time packets, which belong to the high-dimensional matrix information, the information is utilized. The PCA processes the selected sample position information to obtain a valid main component, and provides the classifier for offline training, obtains the key values required for SVM discrimination, and obtains a discriminant function; in the online phase, the real-time obtaining personnel are effective indoors. The channel state information, after pre-processing the obtained information, provides the SVM classifier with a discriminant function to discriminate it, and judges whether the boundary is invaded according to the state, and if so, further iterates the fingerprints of
each offline position, thereby obtaining the accurate position of the indoor personnel. The method flow is shown in Figure 1.

![Image](image_url)

Figure 1 PCA + SVM algorithm flow chart.

4. Proposed algorithm

4.1. Data preprocessing

Real-time acquisition and matching of regional locations depends on the establishment of the classifier, where the number of data samples is positively correlated with the accuracy of the feature information. The original CSI data needs to extract the main feature information from a large number of high-dimensional samples of this data to ensure data accuracy. As an effective data dimension reduction and feature extraction method, PCA is suitable for extracting data with high contribution rate as the main feature when CSI data of different locations retain the original details.

According to the above steps, the PCA processing effect is shown in Figure 2:

![Image](image_url)

(a) Original CSI data       (b) PCA characteristic data

Figure 2 Image before and after processing by PCA algorithm

Fig. 2(a) shows that the data of CSI is processed by PCA, the waveform convergence is more compact than before. The new waveform extracted is more obvious when the original data features are retained, and the multiple amplitude data is more obvious. After weighted averaging, one sampling information of a single location point can be condensed into a set of effective feature wave forms to improve the efficiency and accuracy of subsequent sample training and classification.

4.2. Intrusion Detection and Regional Positioning

4.2.1. SVM Intrusion Classification Processing

After multiple sampling of the same location, sufficient feature fingerprints can be obtained, and an offline location fingerprint database is established, which describes the relationship between the CSI information and the sampling location in the specified environment. The SVM algorithm is used to train the samples to establish a mapping of feature position relationships. The SVM process is: Training the personnel position samples in the fingerprint database, setting q as the number of training samples, and constructing training samples \( (d_i, g_i) \), \( d_i = (d_{i1}, d_{i2}, \ldots, d_{in}) \) is the feature sample data set for each sample location point processed by PCA. To find the most categorical hyperplane, establish the SVC classification and solving the equations according to the constraints produces a classification function as follows:
\[ f(d) = \text{sign} \left( \sum_{i=1}^{n} \alpha_i K(d_i, d) + b \right) \]  

(1)

Where \(a\) and \(b\) are training sample data and test sample data, respectively, and when \(f(d) > 0\), there is a person invading in the area. When \(f(d) < 0\), the corresponding area is unoccupied.

4.2.2. SVM Intrusion Classification Processing. In the processing of the indoor area location problem, the position coordinate is the sought target value, and the input feature is processed by the PCA to process the position feature fingerprint information. The positioning model is mainly dependent on the mapping relationship between the location feature and the actual coordinates. In order to make positioning more efficient, SVR is chosen to estimate the position coordinates.

Here, the sample training model \(\{(d_i, (x_i, y_i))|i = 1, 2, \ldots, q\}\) is established, and \(d_i\) indicates that the fingerprint vectors \(x_i\) and \(y_i\) after processing by the PCA respectively represent the \(X\) and \(Y\) coordinates in the position model. The constructor relationship is as follows:

\[
\begin{align*}
\min & \left( \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{q} (\eta_i^+ + \eta_i^-) \right) \\
n s.t. & \quad (wd_i + b) - y_i \leq \varepsilon + \eta_i^+, 1 \leq i \leq q \\
& \quad y_i - (wd_i + b) \leq \varepsilon + \eta_i^-, 1 \leq i \leq q \\
& \quad \eta_i^+ \eta_i^- \geq 0, 1 \leq i \leq q
\end{align*}
\]  

(2)

By solving the above equations, the horizontal and vertical coordinate estimation values of the position information can be obtained, thereby obtaining the position of the personnel, thereby avoiding the redundancy of the classification of the position features in the conventional SVM classification problem, and greatly improving the efficiency of the algorithm.

5. Experimental verification

5.1. experimental design

The feasibility of the above proposed algorithm is verified, and the method is tested and compared with other methods for performance test. The experiment collects CSI data through two sets of equipment equipped with Atheros AR9380 type network card, one of which is set as transmitter MP and the other is set. Set to receiver AP. In the experimental test environment, the labs with more layouts and the empty conference rooms were selected. In the two experimental scenarios, the personnel intrusion detection experiment and the indoor area precise positioning experiment were carried out. Figure 3. (a) is a multi-path laboratory, (b) is a relatively empty meeting room.

![Figure 3 Experimental scene diagram](image)

5.2. algorithm performance analysis

On the basis of realizing indoor personnel positioning, the influence of relative position factors of key areas and overall indoor areas on regional monitoring and identification classification can be further considered. Control experiments were designed to conduct multiple sets of experiments on the presence of no one, the presence of personnel, and the situation of personnel at different specific
locations. Experiments were carried out in the laboratory and conference room for different experimental environments. The statistics were based on the specific conditions and real-time positioning results, and the influence of the location of the key areas on the experimental performance was analyzed.

Figure 4 Detection rate
Figure 4 reflects the relationship between the false negative rate and the detection rate of the matching results of different monitoring areas. In the case of the conference room, the comparison laboratory has higher recognition accuracy, and the accuracy of discrimination recognition is higher than the accuracy of positioning. When the area of the area is fixed, the closer the location of the key area is to the center of the total monitoring area, the smaller the multipath effect of the transmission path formed by the receiver and the transmitter, the higher the recognition accuracy of the overall system.

5.3. Positioning error analysis
The above three sets of contrast experiments can obtain the comprehensive experimental performance of the algorithm. In order to comprehensively evaluate the algorithm, in the experimental environment, the PCA+SVM algorithm, DeepFi algorithm, LiFS algorithm and FIFS algorithm are experimentally verified in the laboratory environment. The CDF map is constructed for comparative analysis, and the error cumulative distribution function of each algorithm is discussed.

It can be found from Fig. 5 that the positioning error is within 1 m, and the LiFS method is superior to other methods; the cumulative error distribution of the three methods is close to the range of 1-1.5 m, and the PCA+SVM method begins to surpass the LiFS method. In the other two methods; after more than 1.5 m of positioning error, the method has obvious advantages compared with the other two methods, showing a better positioning advantage.

6. Conclusion
This paper proposes a CSI-based indoor presence detection and indoor positioning method, which uses location information acquisition means to discriminate the activities of indoor area personnel. The CSI amplitude data is processed by the PCA, and the position estimation is implemented by using the SVM. In the experimental verification, the accuracy of the method in this experiment can reach 76.1% to 77.3%, and the recognition accuracy of personnel activities in and around the key areas with an area of about 1.28 square meters can reach 92% or more. One-step planning to study the acquisition and matching of personnel action information in key areas.

Acknowledgement
This work was funded by the National Natural Science Foundation of China 61616070, 61762079

References
[1] Paziewski, J., & Wielgosz, P. (2015). Accounting for galileo-gps inter-system biases in precise satellite positioning. Journal of Geodesy, 89(1), 81-93.
[2] Matteo, Ridolfi, et al. (2018) Analysis of the Scalability of UWB Indoor Localization Solutions for High User Densities. Sensors, 18(6):1875-1894.

[3] Seco, F., & Antonio R Jiménez. (2018). Smartphone-based cooperative indoor localization with rfid technology. Sensors, 18(1), 266-289.

[4] Yang, C., & Shao, H. R. (2015). Wifi-based indoor positioning. Communications Magazine IEEE, 53(3), 150-157.

[5] Khan, U. H., Rasheed, H., Aslam, B., Fatima, A., Shahid, L., & Amin, Y., et al. (2017). Localization of compact circularly polarized rfid tag using toa technique. Radioengineering, 26(1), 147-153.

[6] Cremer, M., Dettmar, U., Hudasz, C., Kronberger, R., Lerche, R., & Pervez, A. (2016). Localization of passive uhf rfid tags using the aoact transmitter beamforming technique. IEEE Sensors Journal, 16(6), 1762-1771.

[7] Zheng, Y., Zhou, Z., & Liu, Y. (2013). From rssi to csi: indoor localization via channel response. Acm Computing Surveys, 46(2), 1-32.

[8] Tateno, S., Li, T., Wu, Y., & Wang, Z. (2018). Improved Indoor Localization System Using Statistical AP Selection Method Based on RSSI. 2018 57th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE). IEEE. Nara, Japan:1652-1657.

[9] Nasrullah M., Yunus N. (2014). Filters for device-free indoor localization system based on RSSI measurement. International Conference on Computer and Information Sciences (ICCOINS). Kuala Lumpur, Malaysia:222-229.

[10] Cheng, Y.K.; Chou, H.J.; Chang, R.Y. Machine-Learning Indoor Localization with Access Point Selectionand Signal Strength Reconstruction. In Proceedings of the 2016 IEEE 83rd VehicularTechnology Conference(VTC Spring), Nanjing, China, 15–18 May 2016; pp. 1-5.

[11] XIAO J, WU K S, YI Y W, et al(2012). FIFS: Fine-grained indoor fingerprinting system, Proceedings of IEEE ICCCN. Piscataway, NJ: IEEE Press: 1-7.

[12] Wang, J., Jiang, H., Xiong, J., Jamieson, K., & Xie, B. (2016). LiFS: Low Human-Effort, Device-Free Localization with Fine-Grained Subcarrier Information. ACM MobiCom. New York:243-256.

[13] X. Wang, L. Gao, S. Mao, S. Pandey(2015). DeepFi: Deep learning for indoor fingerprinting using channel state information, Proc. IEEE WCNC, pp. 1666-1671

[14] X. Huang, M. Dai(2016), Indoor Device-Free Activity Recognition Based on Radio Signal, IEEE Transactions on Vehicular Technology, vol. PP, no. 99, pp. 1-1.

[15] T. Xin, B. Guo, Z. Wang, M. Li, Z. Yu, X. Zhou(2016). "FreeSense: Indoor Human Identification with Wi-Fi Signals", Book FreeSense: Indoor Human Identification with Wi-Fi Signals, pp. 1-7.