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An Indoor Positioning Method Based on RSSI Probability Distribution

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An Indoor Positioning Method Based on RSSI Probability Distribution

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Abstract. In view of the influence of the time-variation of RSSI on the positioning accuracy in Wi-Fi indoor positioning, this paper proposes to use the probability distribution of RSSI value as a fingerprint feature over a period of time, and combines the dimension reduction algorithm and the weighted K nearest neighbor algorithm to achieve positioning. The method firstly calculates the probability distribution of the received RSSI value, uses the dimensionality reduction algorithm to reduce the dimension of the statistical probability distribution.The K-reference points with the smallest Euclidean distance were combined with the weighted nearest neighbor algorithm to obtain the positioning results. Through simulation experiments, it is shown that the positioning accuracy is higher than the traditional method, and the positioning time is significantly reduced.

1. Introduction

With the development and popularity of wireless sensor network technology [1], location-based services are widely used in military[2], intelligent transportation[3], environmental monitoring[1], agricultural production[4], emergency communications[5], Medical and health[6] and other fields. Indoor positioning technology mainly includes Wi-Fi[7], Bluetooth[8], ZigBee[9], RFID[10], ultrasonic[11], infrared [12], ultra wideband [13] and so on. Commonly used localization methods are TDOA[14], approximate triangulation (APIT)[15], DV-Hop[16], centroid method [17], etc.

The fingerprint matching and positioning technology based on Wi-Fi signal strength directly uses the existing wireless network, and does not need to add other equipment. Wi-Fi based indoor positioning technology mainly includes three-side positioning and fingerprint positioning. For the effect of signal fluctuation on positioning accuracy, a fingerprint matching positioning model based on signal strength probability distribution is proposed. The probability distribution is better to describe the time-varying and random characteristics of the signal intensity. Moustafa[18] formally proves that the location technology based on probability distribution provides higher accuracy. Suk et al.[19] proposed a new model of signal fluctuation matrix (SFM) to create a fingerprint, ignoring the light distributed difference between the Wi-Fi access point and the reference point. The model uses a small amount of signal strength to show the fluctuation of signal strength in the form of a two-dimensional matrix. Because the radio signals are easily affected by diffraction, reflection, refraction and other noise during the propagation process, a WKNN location method based on RSSI probability distribution received in short time is proposed in order to reduce the influence of signal fluctuation. First, the probability distribution statistics of RSSI values collected from multiple AP points in a short time are collected, and then the probability distribution corresponding to all AP points are merged.The fusion probability distribution is reduced, and the dimensionality reduction results are stored as fingerprint features in the fingerprint database. In the online phase, according to the similarity between the fingerprint features and the fingerprint features in the fingerprint database, select the K reference points with the highest similarity. K the highest similarity reference points assign different weights to get the location result.

2. Indoor positioning method based on RSSI probability distribution

In order to solve the problem of time-varying in environment-influenced signals in indoor positioning, a fingerprint localization algorithm based on signal strength probability distribution is proposed in this paper. This method fully uses the RSSI data received by the reference point to reduce the influence of time-varying on the positioning result. Fingerprint localization algorithm based on probability distribution of signal strength is also divided into two phases: offline training and online positioning.

2.1. RSSI probability distribution model

Assume that the number of Wi-Fi access points is n, and the number of RSSI of the i access point AP_i received by the reference point A in time Δt is m_i .The RSSI value of the I access point received by the reference point A during Δt is expressed as:

$$R_i = \left(RSSI_{i1}, RSSI_{i2}, \cdots, RSSI_{im_i}\right) \quad (1)$$

$RSSI_{ij}$ indicates that the reference point receives the j RSSI of the i access point AP_i. Calculate the probability distribution of RSSI, calculate the probability of -1 to -100 appearing in R_i , the probability P_{ir} of signal strength r is expressed as:

$$P_{ir} = \frac{S_{ir}}{m_i}(-100 \le r \le -1, i \le n) \quad (2)$$

S_{ir} indicates the number of r. The probability distribution of the RSSI of the i access point collected by reference point A during Δt is expressed as:

$$P_i = \begin{pmatrix} P_{i-1} \\ P_{i-2} \\ \vdots \\ P_{i\mathrm{num}} \\ \vdots \\ P_{i-100} \end{pmatrix} (-100 \le num \le -1) \quad (3)$$

The RSSI probability distribution of all access points received by reference point A is expressed as:

$$P_A = (P_1, P_2, \cdots, P_q) = \begin{pmatrix} P_{1-1} & P_{1-2} & \cdots & P_{q-1} \\ P_{1-2} & P_{2-2} & \cdots & P_{q-2} \\ \vdots & \vdots & \vdots & \vdots \\ P_{1num} & P_{2num} & \cdots & P_{qnum} \\ \vdots & \vdots & \vdots & \vdots \\ P_{1-100} & P_{2-100} & \cdots & P_{q-100} \end{pmatrix} (q \le n) \quad (4)$$

The probability distribution of RSSI received at each reference point is merged to obtain a probability distribution vector as a location fingerprint feature. The feature vector may be a high-dimensional vector. In order to eliminate redundancy, reduce the amount of fingerprint matching data processing, and improve the positioning efficiency, this paper reduces the dimension of the fused feature vector.

2.2. Indoor positioning method based on RSSI probability distribution

The main work of the off-line phase is to build a fingerprint database. First select a reference point in the location area, collect RSSI values of multiple access points at a reference point, then use formula (2) to statistically calculate the probability distribution of RSSI values, and use formula (4) to merge the probability distributions obtained by formula (2)(3). Then, the probability distribution statistics of the signal strength of multiple access points are reduced in dimension. Finally, add the reference point position coordinates and the reduced-size RSSI probability distribution statistical vector to the fingerprint database.

In the online phase, the RSSI values of the test points in a short period of time are collected, statistical probability distribution, merge, and dimensionality reduction operations are performed, and finally the vector after dimensionality reduction is performed. The similarity between the vector of the test point and the reference point feature vector of the fingerprint database is calculated. The K reference points with the largest similarity are selected, and the weight is assigned to the reference point according to the similarity.

Calculate the similarity $d_i (i \le N)$ between the probability distribution vector of test point S and the probability distribution vector of the reference point in fingerprint database. The similarity is sorted from largest to smallest, K (k ≤ N) reference points with the highest similarity are selected, and the selected reference point is assigned a weight d_i according to the size of the similarity.

Suppose that the K similarity selected are $(d_1, d_2, \cdots, d_k; i \le k)$, the coordinates of the corresponding reference point are $(X_1, X_2, \cdots, X_k; X \le k)$,the weight of the i reference point is expressed as:

$$W_i = \frac{1}{d_i} \times W \tag{5}$$

Where W is given by formula (6):

$$W = \frac{1}{\sum_{i=1}^{k} \frac{1}{d_i}} \tag{6}$$

The coordinate X_i of the i reference point is represented as (x_i, y_i) .

The positioning coordinates $X_s(x_s, y_s)$ is represented by the formulae as:

$$x_s = \sum_{i=1}^{k} (W_i \times x_i) \tag{7}$$

$$y_s = \sum_{i=1}^{k} (W_i \times y_i) \tag{8}$$

3. Simulation experimental

In the simulation experiment, the influence of the sampling times, the number of AP,and the K value on the positioning error is compared. At the same time, the positioning accuracy and location time of different dimensionality reduction methods are compared.

The simulation experiment area is 22m x 22m, which sets at least 6 AP access points, 100 reference points, each reference point is 2 meters apart, and 40 test points are randomly generated in the experimental area (no overlap with the reference point). As shown in Figure 1：

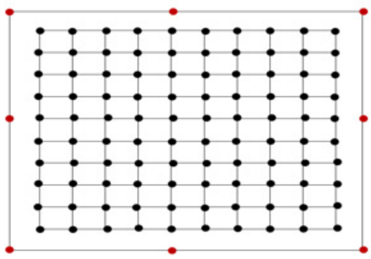

Figure 1. Simulation experiment environment

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Calculate the distance between reference point or test point to AP point d. The corresponding RSSI value is calculated according to the distance loss model. In order to make the simulated data conform to the real environment, Gauss noise is added to the calculated RSSI value.

3.1. The effect of different sampling numbers on positioning error
Figure 2 shows the effect of different sampling times on the positioning error of various positioning methods. As can be seen from the figure, the PCA-WKNN positioning effect is better with the number of sampling times, and the PCA-WKNN has the best positioning effect when the number of samples is 60, 160. When the sampling times are 60 and 160, the positioning error is 2.0m and 1.6m. In order to shorten the sampling time of the test point, the sampling times can be set to 60.

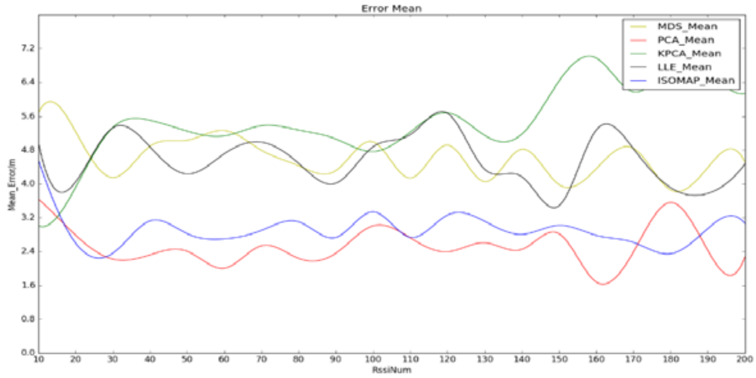

Figure 2. The positioning error with different RSSI sampling times

3.2. The effect of different AP numbers on positioning error
Figure 3 shows the effect of different AP numbers on the positioning error of various positioning methods. When the number of APs increases from 6 to 12, the corresponding positioning error gradually becomes smaller. Changes in the number of APs have less impact on PCA, KPCA, and ISOMAP dimensionality reduction methods.

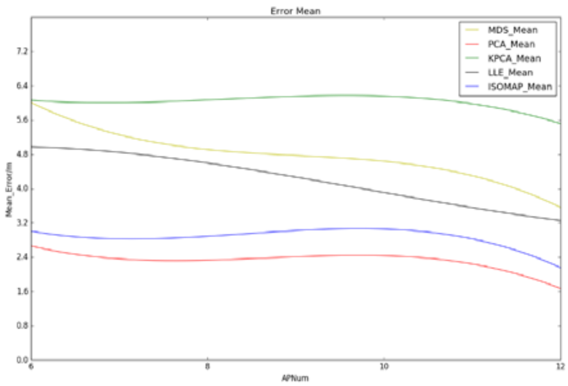

Figure 3. The positioning error of different AP numbers

3.3. Influence of Different K Values on Positioning Error
Figure 4 shows the effect of different K values on the positioning error of various positioning methods. For PCA and ISOMAP dimension reduction methods with smaller positioning error, the positioning error is the minimum when K is equal to 2, and the K value is increased when K is greater than 2, and the positioning error is also slowly increased.

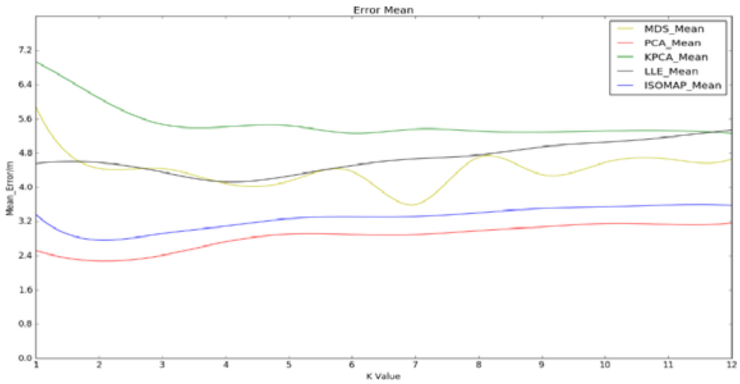

Figure 4. The positioning error of different K value

3.4. Comparison of the location effect of different dimensionality reduction methods

Figure. 5 shows the cumulative error probability of positioning errors corresponding to different dimensionality reduction methods when K is set to 2 and the dimension is reduced to 2. It can be seen from the figure that as the cumulative error increases, the cumulative error probability of using the PCA as the dimension reduction method is always the largest, and the cumulative error probability when the positioning error is less than 1 meter, 2 meters, and 3 meters is 37.5 %, 77.5%, 92.5%. When the positioning error reaches 5 meters, the cumulative error probability reaches 97.5%. When the positioning error is 3 meters, the cumulative error probability of different dimensionality reduction methods is 37.5%, 92.5%, 25%, 72.5%, and 77.5%.

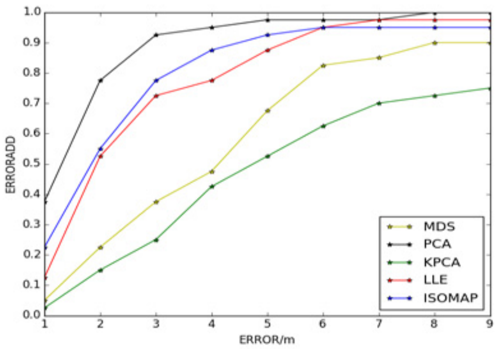

Figure 5. Cumulative probability of location error corresponding to different dimensionality reduction methods

3.5. Comparing calculation time of online positioning in different positioning methods

Table 1 shows the average positioning time using different positioning methods during the online phase of all test points.

Table 1. Average time-consuming time for different positioning methods

Method	KNN	WKNN	PCA_WKNN	ISOMAP_WKNN
Time/s	3.67	3.68	0.78	0.82

It can be clearly seen from Table 1 that compared with the general KNN and WKNN algorithms, the dimensionality reduction algorithm combined with the K nearest neighbor algorithm significantly reduces the time required for positioning in the online phase.

4. Conclusions

This paper proposes using the probability distribution of RSSI in a short time as a fingerprint feature to solve the problem of time-varying RSSI signal in Wi-Fi indoor positioning. This method counts the probability distribution of RSSI over a period of time, and retains more RSSI information at the reference point location. Using the dimensionality reduction algorithm to reduce the dimensionality of the RSSI probability matrix, eliminating redundant information greatly reduces the time required for the online positioning stage. In the simulation environment, the number of test points is 60, the down dimension is 2, and when K is 2, the PCA dimension reduction method is used, and the average positioning error is 1.6 meters.

References

[1] Potdar V, Sharif A, Chang E. Wireless Sensor Networks: A Survey[J]. Computer Networks, 2002, 38(4):393-422.
[2] Chong CY.,Kumar SP..Sensor networks: Evolution, opportunities, and challenges[J].Proceedings of the IEEE,2003,(8):1247-1256.
[3] Du X D, Ji J T, Yan D P. Application Research of Wireless Sensor Network in Intelligent Transportation System[J]. Advanced Materials Research, 2010, 108-111:1170-1175.
[4] Zheng B G, Wang H. Application Research of Wireless Sensor Network in the Fine Production of Agriculture[J]. Applied Mechanics & Materials, 2014, 513-517(7):3695-3698.e
[5] Chen J H, Chen X Z. Study on Coal Mine Safety Monitoring System with Emergency Voice Communication Based on Wireless Sensor Network[J]. Applied Mechanics & Materials, 2012, 195-196:956-961.
[6] Gao T, Greenspan D, Welsh M, et al. Vital Signs Monitoring and Patient Tracking Over a Wireless Network[C]// International Conference of the Engineering in Medicine & Biology Society. Conf Proc IEEE Eng Med Biol Soc, 2005:102.
[7] Yang Qiang，Pan Jialin，Zheng Wenchen.Estimating location using Wi-Fi[J].IEEE Intelligent Systems，2008，23（1）：8-13.
[8] Zhou Sheng，Pollard J K.Position measurement using bluetooth[J].IEEE Transactions on Consumer Electronics，2006，52（2）：555-558.
[9] Luoh L.ZigBee-based intelligent indoor positioning system soft computing[J].Soft Computing，2014，18（3）：443-456.
[10] Saab S S，Nakad Z S.A standalone RFID indoor positioning system using passive tags[J].IEEE Transactions on Industrial Electronics，2011，58（5）：1961-1970.
[11] Enrique González,Laura Prados,Antonio J. Rubio,José C. Segura,Ángel Torre,José M. Moya,Pablo Rodríguez,José L. Martín. ATLINTIDA: A Robust Indoor Ultrasound Location System: Design and Evaluation[M].Springer Berlin Heidelberg:2009-06-15.
[12] Yi Zhang,Hong Song Chen,Yuan Luo. A Novel Infrared Landmark Indoor Positioning Method Based on Improved IMM-UKF[J]. Applied Mechanics and Materials,2014,3006(511).
[13] Xu Y, Shmaliy Y S, Li Y, et al. UWB-Based Indoor Human Localization With Time-Delayed Data Using EFIR Filtering[J]. IEEE Access, 2017, 5:16676-16683.
[14] Luo X, Li W, Lin J. Geometric Location Based on TDOA for Wireless Sensor Networks[J]. Isrn Applied Mathematics, 2014, 2012(2012):1240-1249.
[15] He T, Huang C, Blum B M, et al. Range-free localization and its impact on large scale sensor networks[J]. Acm Transactions on Embedded Computing Systems, 2005, 4(4):877-906.
[16] Wang H B. Research of Node Localization Algorithm Based on DV-HOP in Wireless Sensor Networks[J]. Advanced Materials Research, 2012, 403-408:1442-1446.
[17] Bulusu N, Heidemann J, Estrin D. GPS-less low-cost outdoor localization for very small devices[J]. IEEE personal communications, 2000, 7(5): 28-34.
[18] Youssef M A, Agrawala A. On the Optimality of WLAN Location Determination Systems[C]// Communication Networks & Distributed Systems Modeling & Simulation Conference. 2003:205--218.
[19] Jung S H, Moon B C, Han D. Performance Evaluation of Radio Map Construction Methods for Wi-Fi Positioning Systems[J]. IEEE Transactions on Intelligent Transportation Systems, 2017, PP(99):1-10.