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Indoor Mobile Robot Positioning Based on Wireless Fingerprint Matching

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***Abstract*—**This paper discusses the design of an indoor mobile robot positioning system. The problem of indoor positioning is solved through Wi-Fi fingerprint positioning to implement a low cost deployment. A wireless fingerprint matching algorithm based on the similarity of unequal length sequences is presented. Candidate sequences selection is defined as a set of mappings, and detection errors caused by wireless hotspot stability and the change of interior pattern can be corrected by transforming the unequal length sequences into equal length sequences. The presented scheme was verified experimentally to achieve the accuracy requirements for an indoor positioning system with low deployment cost.

***Keywords*—**Fingerprint match, indoor positioning, mobile robot positioning system, Wi-Fi, wireless fingerprint.

I. Introduction

INDOOR wireless mobile robot localization is difficult problem and has attracted much research attention. It is a typical application of location based service (LBS) [1], which focuses on accurate positioning and tracking. Demand for indoor location services in the indoor environment has strongly increased, such as crowd monitoring, large venue management, disaster relief [2], mine management, mobile marketing [3], etc. In the outdoor environment, satellite navigation technology has been widely used, but this is not applicable to indoor applications as the satellite signals are usually lost, and the positioning technology is faced with many problems [4]. Current common indoor positioning technology can be categorized as satellite navigation and positioning, such as pseudo satellite technology, etc.; wireless location, such as wireless communication signals, radio frequency wireless tags, ultrasound, light tracking, wireless sensor positioning, etc.; and other technologies, such as computer vision, dead reckoning etc. Fingerprint matching technology has the advantages of simple deployment and low cost, which makes it suitable for many indoor location requirements [5].

Several indoor positioning technologies based on wireless signals have been developed, such as RFID, Wi-Fi, ZigBee, iBeacon, etc. Wi-Fi hotspot is a low cost wireless base station that is widely used within buildings [6], [7], and Wi-Fi based indoor positioning has attracted a great deal of research interest.

Wireless fingerprint matching receives wireless signals containing scene information in real time, and matches the current scene to information recorded in the fingerprint database to judge the position of the measuring point. In the indoor environment, particularly large buildings or underground constructions, radio waves contacting various obstacles lose energy due to propagation loss, reflection, refraction, diffraction, and multipath propagation [8]. This forms specific wireless signal features at the measurement point, including the number of signals, intensity, phase, etc., and the measurement position can be derived from the specific signal characteristics. Wireless fingerprint matching is generally divided into two processes [5], discrete regional signals feature acquisition, associated with the location information; and characteristic analysis of the signals to be measured. Thus, identifying and comparing wireless signals characteristics are key steps. For the indoor environment, changes in the pattern of interior architecture, moving of facilities and persons, and changes of wireless signal sources all produce changes in the wireless signals, and lead to positioning error. Common positioning evaluation criteria are position accuracy, complexity, scalability, and robustness [9]. However, this type of localization is more concerned with robustness of the algorithm, i.e., how is location accuracy affected when the signal changes. In contrast, Wi-Fi fingerprinting [10], [11] does not need to establish a complex propagation model. Its accuracy is generally higher than propagation model approaches, and it also has open access and relatively low cost [12]. Therefore, much research has focused on fingerprint location methods. However, there is the problem of poor positioning accuracy for Wi-Fi fingerprint recognition, caused by RSS time characteristics. Transforming the time series RSS signal into a sliding window can significantly improve location accuracy and robustness [13].

Wi-Fi signal stability, building structure [14], and facility location have great influence on signal propagation. This increases the difficulty of matching fingerprint recognition and prior information. This is especially the case when representing a same point using unequal sequences [15] in the absence of hot spot signals. There are two approaches to matching unequal length sequences, based on segment matching, such as the sliding window; or sequence extension after matching. Sequence expansion requires increased dimension calculations, so attribute reduction [16] and performance evaluation [17] of characteristics matching is often employed to help solve unequal length sequences matching.

II. System structure

To realize localization of an indoor robot, much preparatory

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work has already been undertaken:

1. Wi-Fi environment layout. In principle, at least three hot spots are required to achieve positioning, and the number of hotspots influences positioning accuracy. We consider a rectangular indoor area of 15×9 m, with four Wi-Fi hotspots. To improve effectiveness, the four devices were located at the four corners of the area.

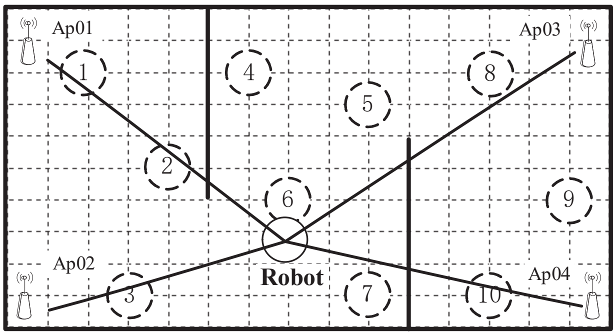

Fig. 1 Wi-Fi environment layout

In practice, a device can receive many Wi-Fi signals in an indoor environment, e.g. Wi-Fi signals from nearby rooms, from base stations of telecom operators, etc. Compared with outdoor positioning, indoor positioning covers a relatively narrow range, where the base station signal for each positioning point does not change, so this need not be considered. However, signals from nearby rooms will have a positive impact on robot indoor positioning, and reasonable use of these environmental signals can help obtain higher positioning accuracy.

2. Construction of Wi-Fi fingerprint database. The Wi-Fi fingerprint database is the basic information source for indoor positioning. As the limited by the positioning accuracy of Wi-Fi, partition the coordinates with larger grain size (m) to determine the indoor position symbol system within the range of positioning. Then the fingerprint information is collected and stored in the database. This process does not depend on the number or position of specific hot spots, and can be achieved through two means. The first is manual acquisition. Since the indoor range is small, artificial acquisition will not greatly increase the workload. Second is autonomous collection by the robot. Under program control, the robot passes through each symbol site, and obtains the corresponding fingerprint sequence information.

Since the data acquisition process does not rely on the number and position of the Wi-Fi hot spot, and hot spots are becoming more common in social environments, adaptability of the robot facilitates defining the new environment. That is, when the robot arrives at an unfamiliar environment, provided the environment has more than three hot spots coverage, the robot can automatically develop an indoor map and create a Wi-Fi fingerprint database.

3. For practical realization, the fingerprint information of each collecting point is stored in the database, with the location tag of the indoor geographical symbol system as the database index. The Wi-Fi fingerprint of the measured position is compared with the fingerprint database records, and the position with the minimum value is the reference value of the location of the position to be measured. The process of fingerprint acquisition and matching is shown in Fig. 2.

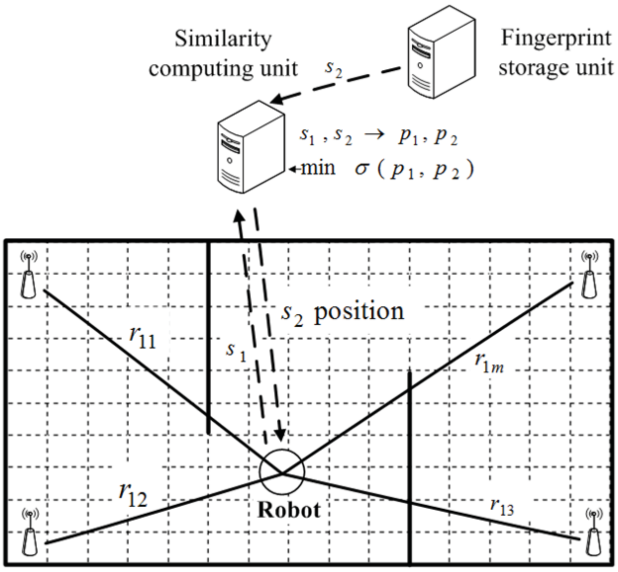

Fig. 2 Fingerprint acquisition and matching process

The fingerprint storage unit records the positioning point ID, physical location, and Wi-Fi sequence strength details. Merging and similarity calculation of unequal length sequences is implemented in the similarity computing unit. The robot accesses the nearby Wi-Fi hotspots, packs the signals into s_1 and sends it to the similarity computing unit. It then obtains Wi-Fi sequence, s_2, of the reference point from the known fingerprint database, and converts it to equal length sequences, p_1 and p_2, and calculates the similarity. Finally, the position information corresponding to sequence s_2, which has minimum similarity, is returned.

III. Technical Scheme

A technical scheme for indoor wireless location and navigation was developed, incorporating an efficient implementation of the algorithm, data mining, and the late application are plotted.

This paper discusses wireless location, indoor navigation and other aspects. In addition, building Wi-Fi deployment, billing and payment, license plate recognition, APP development and other aspects need to do an auxiliary research and development.

A. Wireless Fingerprint Matching Algorithm

The Wi-Fi sequence is greatly influenced by the environment, and the stability of individual nodes is poor, which leads to difficulties computing sequence identification and similarity. The problems are mainly related to signal interference in sequence identification, object indexing [18], Wi-Fi identification of the same position, similarity calculation [15], [19], eliminating errors due to missing nodes, etc.

The core process is the similarity calculation for Wi-Fi fingerprint sequences. The presented method involves two stages: determining candidate sequences, and calculating the similarity between unequal length sequences.

- Candidate Sequence Determination

With increasing numbers of hotspots deployed, the number to search for matching can be very large. In real applications, location recognition is a local property, i.e., confined to a relatively small range. Within this range, there are a certain number of hotspots to be recognized and candidate sequences. Therefore, it is not necessary to match all sequences in the sequence database. This can greatly reduce the computation of the next step. Identification of candidate sequences is carried out in two steps.

1. The number of signals received is likely to change from location to location due to the stability of the Wi-Fi base station and the change of the state of the propagation channel. Therefore, signals in the sequence to be recognized are sorted according to intensity, and the N strongest intensity signals are selected, $AP_1, AP_2, ..., AP_N$.
2. A fingerprint sequence including AP_i is selected from the fingerprint database based on the index of each of the N signals. The signal indexing is done offline, so that the candidate sequence containing these signals can be obtained quickly. The signal indexing process is shown in Fig. 3.

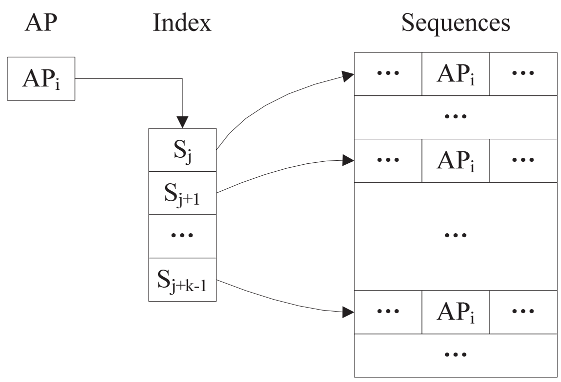

Fig. 3 Signal indexing process

Algorithm 1. Get Candidate Sequence
Input: Signals (from Sensors), FingerPrintDataBase
Output: Sequences

```
Vector Sequences = NULL
Vector Signals = GetSignals()    //from Sensors
Signals = SortByStrength(Signals)
Signals = GetTheFirstNSignals(Signals, N)
For Each APi ∈ Signals Do
    Sequences = Index(APi, FingerPrintDataBase)
End For
```

In principle, the number of indexes is the same as the number of wireless hotspots. However, due to the local nature of Wi-Fi, signals contained in the fingerprint sequence are generally from the nearby hotspots, so the index length can be set shorter (generally 10–20 signals is desirable). Assuming the index length is k, the indexing process is equivalent to a mapping, and its time consumption can be regarded as constant. The process is shown in Algorithm 1.

The objective of Algorithm 1 is to obtain a set of candidate sequences related to the sequence to be identified. These are then used to calculate similarity and determine the position to be measured in the next step.

- Unequal Length Sequence Similarity Calculation

Calculating the Wi-Fi fingerprint similarity may be considered as the calculation of the similarity of unequal length sequences. Let $s_1 = (r_{11}, r_{12}, ..., r_{1m})$ and $s_2 = (r_{21}, r_{22}, ..., r_{2n})$ represent the hotspots in two Wi-Fi sequences, where m and n represent the number of hotspots in each sequence. The similarity between the two Wi-Fi fingerprints can be expressed as the similarity between s_1 and s_2. Since m and n are not necessarily the same, the method to calculate which using the sequence similar attribute ratio and attribute value mean variance weighted fusion is used in this paper.

The key of this algorithm is to transform the unequal length sequences to equal length sequences, and then calculate the mean square deviation of the equal length sequences. This is achieved through the following steps.

(1) First construct the union, U, of hotspots that are included in sequences s_1 and s_2. Then sort U according to the name or ID of the hotspots into new sequence p, with size t.

(2) The intensity values of hotspots come from s_1 or s_2 were respectively labeled to sequence p, then two new sequences $p_1 = (r'_{11}, r'_{12}, ..., r'_{1t})$ and $p_2 = (r'_{21}, r'_{22}, ..., r'_{2t})$ were formed. r'_{1i} and r'_{2i} are respectively represent the intensity values of hotspot i in the two sequences. The intensity values of absent hotspots in the original sequence are marked by zero. Thus, the unequal length sequences are transformed into equal length sequences, and similarity between s_1 and s_2 is transformed into similarity between p_1 and p_2.

The sequences transformation process is shown in Fig. 4.

(3) The mean square deviation of p1 and p2 is

$$\sigma = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(r'_{2i} - r'_{1i})^2} \,. \quad (1)$$

This is a simple and fast calculation method. It reflects the intensity differences of the original sequences, as well as the influence of hotspots on the sequence similarity. Of course, the mean square deviation is only an alternative.

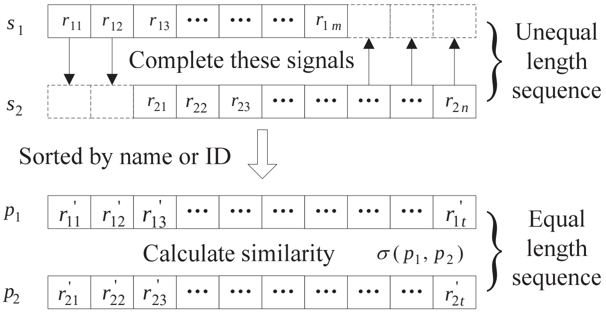

Fig. 4 Sequence transformation process

Next, we will do a comparative study of other methods for calculating sequence similarity.

The process is as shown in Algorithm 2.

Algorithm 2. Unequal Length Sequence Similarity Calculation

```
Input: Vector V, Sequences
Output: Result //The most similar sequence with V in Sequences
Double Min = 0
Vector Result = NULL
For Each Si ∈ Sequences Do
    Vector Temp = V-Si  // Extend V
    Set Temp.signals = 0
    V = V ∪ Temp
    Temp = Si – V      // Extend Si
    Set Temp.signals = 0
    Si = Si ∪ Temp
    Double Sim = Simlarity(V,Si)
    If Sim<Min Then
        Min = Sim
        Result = Si
    End If
End For
```

The algorithm identified the most similar candidate sequence to that detected, and the result is used to search the location from the background database.

B. System Optimization

System optimization involves two aspects: First is optimization of the system efficiency. The robot positioning system is highly dependent on real time processing, and the optimization scheme will be considered in the design process. Algorithm execution efficiency directly affects system performance. The implementation mechanism of the optimization algorithm includes fingerprint extraction for the indoor space, path traffic update, handheld terminal algorithm optimization, background of large-scale data accurate and efficient calculation method, and high performance calculation platform and data processing platform application etc. In addition, handheld terminal computing power is limited, so a more practical solution is to use a background server. The proposed scheme requires a dedicated computing server to enable real time computing and large data processing.

The presented scheme implements a dynamic update strategy for the Wi-Fi fingerprinting. Due to the stability of low grade Wi-Fi hotspots and other factors, the Wi-Fi sequence strengths will drift. Where a user directly confirms a location, the confirmation can be used to update the fingerprint database.

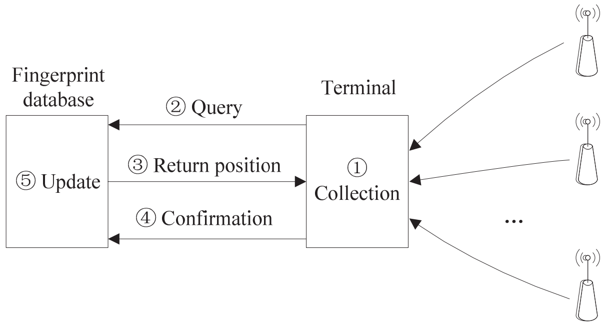

Fig. 5 Update process of the fingerprint database

The update process is shown in Fig. 5. The process is divided into five steps, with the first three steps similar to the process shown in Fig. 4. When user confirmation is required, the user sends a confirmation message and s_2 is replaced with s_1 in the fingerprint database. Alarm information is given by the system for a reference point if it does not update in a certain period of time. It will be collected and updated by the management staff.

IV. Experiments

An experiment was performed in an indoor space of 15×9 m, as discussed in Section II, and shown in Fig. 1. Four Wi-Fi hotspots were installed in the corners, 10 reference points were selected. And the Wi-Fi fingerprints for each determined, as shown in Table I.

TABLE I
POSITIONING DATA FOR THE REFERENCE POINTS

Location ID	Signal strength from Wi-Fi (dBm)			
	AP01	AP02	AP03	AP04
1	-36	-47	-72	-87
2	-42	-45	-70	-81
3	-48	-39	-63	-79
4	-62	-53	-50	-64
5	-60	-55	-45	-53
6	-51	-46	-53	-67
7	-53	-48	-59	-75
8	-65	-60	-36	-48
9	-70	-68	-45	-40
10	-78	-73	-51	-37

The 10 Wi-Fi fingerprint sequences were measured for each point, and the results were verified. Example data for location ID 6 are shown in Table II. Columns two to five are the measured fingerprint sequences, column six ("To 4") is the distance between the test sequence and the sequence of location ID 4. Other three columns are similar to this. From the table, it can be seen that the value of the eighth column is the smallest among the last four columns. So the positioning result is determined to be location ID 6. The same process was

performed for the other nine points.

TABLE II
TEST DATA FOR LOCATION ID 6

	Signal strength from Wi-Fi (dBm)				Distance to Location ID (m)			
	AP01	AP02	AP03	AP04	4	5	6	7
1	-51	-46	-55	-68	14.53	22.07	2.24	8.54
2	-50	-43	-55	-67	16.67	23.24	3.74	10.68
3	-48	-45	-52	-64	16.25	20.35	4.47	14.28
4	-53	-46	-53	-65	11.83	18.38	2.83	11.83
5	-54	-48	-54	-70	11.87	21.33	4.80	7.14
6	-49	-46	-56	-67	16.22	22.78	3.61	9.64
7	-50	-47	-52	-69	14.46	21.66	2.65	9.75
8	-51	-43	-53	-66	15.30	21.40	3.16	12.08
9	-49	-43	-53	-68	17.15	23.54	3.74	11.22
10	-55	-49	-54	-69	10.30	19.95	5.48	8.12

To verify the location effect of a missing node, we closed AP01. The algorithm automatically excluded the dimension data in the calculation range, and the final result was not affected.

To further test the interference of other Wi-Fi hotspots, an interference node was added in the region. The addition of this node had no influence on the accuracy of positioning.

V. CONCLUSION

A system for indoor robot positioning based on Wi-Fi fingerprinting was proposed. The scheme uses Wi-Fi hotspots in the environment to realize indoor positioning without the need for additional base stations. Thus, the proposed system has very low deployment cost, while enhancing user experience and may be applied to shopping malls, supermarkets, office buildings, and other places with high positioning demands.

A wireless fingerprint matching algorithm based on the similarity of unequal length sequences was proposed. This algorithm solves the problem of determining similarity between candidate sequences of unequal length. Thus, it overcomes adverse effects of Wi-Fi multipath effects and instability in positioning accuracy.

Wi-Fi hotspots as low cost wireless base station, in the parking lot, shopping malls and other scenes with significant value. However, stability, failure rate, and other factors can have significant impact on positioning accuracy. The terminal location intelligence of robot is weak, which is highly dependent on the system. So it is difficult to achieve high precision positioning in the Wi-Fi environment.

In future work, we will focus on improving positioning requirements, eliminate the impact of hotspots on positioning, and investigate increasing positioning accuracy for application to applications with higher requirements. We will also investigate further optimization of sequence matching and indoor navigation algorithms to further enhance system performance.

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