Wi-Fi Positioning Algorithm Based on Matching Optimization and Distance Assistance (Postprint)

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Abstract

To address the issues of low class matching accuracy in sorting clustering localization algorithms and the presence of anomalous fingerprint points among those used for position calculation, a matching optimization and distance-assisted Wi-Fi positioning algorithm is proposed. A class matching deviation detection model is designed based on the user' s previous and subsequent positions, distance, and step length to identify user position anomalies and matching deviations. By computing differences between adjacent elements in the sorted received signal strength vector and comparing them with a preset threshold, the position of variation in the ranking feature vector of the point to be localized is identified and an exchange is performed to achieve correction, thereby obtaining a corrected and merged class matching result. During localization, anomalous fingerprint points among those used for position calculation are eliminated based on the proximity between the user position determined within the previous m time periods and the fingerprint points in the matching class, enabling more accurate indoor positioning. Simulation experimental results demonstrate that the proposed algorithm improves class matching accuracy by 17% and average positioning accuracy by 22%.

Full Text

Wi-Fi Indoor Positioning Technology Based on Matching Optimization and Distance Assistance

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Abstract

Aiming at the problems of low class matching accuracy in sorting clustering positioning algorithms and the existence of abnormal fingerprint points among those used for position calculation, this paper proposes a Wi-Fi indoor positioning algorithm based on matching optimization and distance assistance. According to the user' s consecutive positions, distance, and step length, a class matching deviation detection model is designed to determine abnormal user positions and matching deviations. By taking differences between adjacent elements in the sorted received signal strength (RSS) vector and comparing them with a set threshold, the positions where the sorting feature vector of the point to be located changes are identified. After correction and merging of class matching results, abnormal fingerprint points in the position calculation are eliminated based on the distance between the user' s position determined during the previous m time periods and the fingerprint points in the matching class. Simulation results demonstrate that the proposed algorithm improves class matching accuracy and average positioning accuracy.

Keywords: sorting clustering; matching optimization; class matching detection; correction; Wi-Fi positioning

1. Introduction

With technological development and social progress, the accelerating pace of modern life has created demand for location-based services that help people reach destinations faster or locate items more precisely. While Global Positioning System (GPS) technology has matured for outdoor environments, GPS signals are easily blocked by walls and cannot provide reliable indoor positioning [1-2]. Among various indoor positioning technologies, Wi-Fi-based approaches require no additional hardware installation, rely only on existing public network infrastructure, and can be implemented through portable mobile terminals using pure software methods. These characteristics offer significant advantages in cost and real-time performance, making Wi-Fi the preferred technology for current indoor navigation systems [3-4].

Wi-Fi indoor positioning technology is primarily divided into two categories: geometry-based positioning algorithms and location fingerprint-based algorithms. Compared with geometry-based approaches, fingerprint-based algorithms provide higher positioning accuracy without requiring knowledge of wireless access point (AP) locations, making them more popular among indoor positioning researchers [5]. The fingerprint-based positioning workflow consists of two main stages: offline fingerprint collection and online fingerprint matching and positioning. During the offline stage, multiple fingerprint points are deployed throughout the positioning area, and received signal strength (RSS) vectors from different APs are sampled at each point, mapping MAC addresses with corresponding physical positions to build a fingerprint database. In the online stage, fingerprint matching algorithms first identify the nearest fingerprint point(s) to the real-time RSS vector, then estimate the current position through corresponding position calculation algorithms [6-7].

To reduce fingerprint matching workload and improve positioning real-time performance, the sorting clustering positioning algorithm was proposed [8]. However, this algorithm's positioning accuracy is affected by class matching accuracy to a certain extent. Contreras et al. [9] employed Levenshtein distance to measure similarity between the sorting feature vector of the point to be located and those of fingerprint points in the database, using the minimum number of editing operations as the similarity metric. Other researchers have used Canberra distance instead of traditional Euclidean distance [10]. While these algorithms improved class matching methods, they did not consider further enhancements in class matching detection and correction.

To address these limitations, this paper proposes a Wi-Fi indoor positioning algorithm based on matching optimization and distance assistance. The algorithm optimizes class matching results through a deviation detection model and correction algorithm, then eliminates abnormal fingerprint points based on distance between the user's position determined during the previous m time periods and fingerprint points in the matching class, thereby achieving more accurate indoor positioning.

2. Proposed Algorithm

2.1 Sorting Clustering Algorithm

Due to the influence of indoor environment, personnel movement, and multipath effects on wireless signal propagation, sampled RSS values may contain outliers. When sampling data is limited, the mean value will be affected by these outliers and continuously change. The mode, as the most frequently occurring value in a dataset, is less affected by outliers [11-12]. Based on this principle, the sorting clustering algorithm employs the mode concept, with the following process:

Assume M APs are deployed in a positioning area with N fingerprint points. For the ith fingerprint point, Q samples are taken, yielding Q RSS vectors Rq (q = 1,2,···,Q). After Q samples, a matrix Ri is obtained. Each row of the matrix is sorted in descending order and numbered to generate a sequence matrix Si. (1) Using the mode concept, the most frequently occurring value in each column of the sequence matrix is extracted. (2) A more stable sorting feature vector S' i = ( ) is obtained, where the mode of the mth column in matrix Si for the qth sampling data is used as the element for that column. All fingerprint points are processed similarly to obtain corresponding sorting feature vectors. Fingerprint points with identical sorting feature vectors in the offline fingerprint database are grouped into the same class [13-14].

2.2 Class Matching Optimization Algorithm

Traditional class matching algorithms consist of exact matching and most similar matching algorithms. However, most similar matching is computationally intensive and time-consuming. This paper proposes a sorting feature code class matching algorithm that uses differences in sorting feature codes to measure similarity between the point to be located and fingerprint points. The sorting feature code is derived from the sorting feature vector [15]. For example, given a sorting feature vector S' = (4,3,6,5,1,3,7,8), its sorting feature code is M. The difference between the sorting feature code of the point to be located (cw) and that of class w (Mw) is calculated as cw = |Mw - M|. The set of differences between the point to be located and all classes is cw = {cw1, cw2, ···, cwn}.

According to the indoor wireless signal propagation attenuation model, the smaller the distance, the more stable the AP position in the sorting feature vector, and the lower the probability of ranking changes. Conversely, larger distances lead to less stable AP positions and higher probability of ranking changes. Based on this principle, fingerprint points with fewer difference digits are more similar to the point to be located. When the number of digits is the same, those with smaller absolute values are more similar. When the difference is zero, complete matching is achieved.

2.3 Class Matching Deviation Detection Model

When class matching deviation occurs during positioning, using the deviated class for position calculation will cause significant positioning errors and abnormal consecutive user positions. To detect user position anomalies and matching deviations, a class matching deviation detection model is designed based on the user' s consecutive positions, distance, and step length. Let Lt be the user' s current position coordinates, Lt-1 be the previous position, d be the distance between consecutive positions, and s be the user' s step length. The model is defined as:

$$f(L_t) = |d(L_t, L_{t-1}) - s| - \alpha d$$

where α is a regulation parameter. To achieve optimal detection performance, extensive data training is required to find the optimal α value. If f(Lt) is less than the threshold, no class matching deviation is considered to have occurred; otherwise, deviation is detected.

2.4 Class Matching Result Correction

To reduce the impact of class matching deviation, correction is performed when deviation is detected. First, the positions where the sorting feature vector of the point to be located changes must be identified. In real positioning environments, RSS values fluctuate due to indoor environment, personnel, and multipath effects. If the difference between two RSS values is less than a fluctuation threshold, the sorted feature vector becomes unreliable and frequently changes.

By taking differences between adjacent elements in the sorted RSS vector (dj = rj - rj+1, where rj is the jth element) and comparing them with the fluctuation threshold, the changing positions can be identified. After identifying these positions, elements at changing positions are corrected through adjacent swapping while other elements remain unchanged, forming a new sorting feature vector. Based on the previous position' s sorting feature vector and adjacent class sorting feature vectors, vectors that differ from the fingerprint database after correction are eliminated, and the remaining vectors are used as the final class matching result.

2.5 Distance-Assisted Algorithm

After class matching in sorting clustering positioning, when only one fingerprint point has a sorting feature vector identical to the point to be located, that point' s coordinates are the user' s position. When multiple fingerprint points match, positioning algorithms are needed. The most common method is traditional KNN, which uses Euclidean distance to find K nearest fingerprint points. However, indoor environment changes may cause the K similar fingerprint points to include abnormal points that are similar but not actually nearby, reducing positioning accuracy.

To eliminate these abnormal points, a distance-assisted algorithm is proposed. The algorithm calculates not only the Euclidean distance Sg between fingerprint points in the matched class and the point to be located, but also the distance dg between fingerprint points and the user' s position determined during the previous m time periods:

$$d_g = \|L_g - L_{t-h}\|$$

where Lg is the gth fingerprint point' s coordinates in the matched class, and Lt-h is the user position determined at time t-h. While Sg selects points similar but not necessarily nearby, and dg selects nearby but not necessarily nearest points, the proposed method uses intersection optimization to eliminate similar-but-distant points under distance assistance, selecting K points that are both similar and nearby for more accurate position calculation.

3. Experimental Validation and Analysis

3.1 Experimental Environment

To verify the proposed algorithm' s effectiveness, an indoor stadium measuring 12m × 22m was selected as the test environment. Eight APs were deployed at positions: AP1(4.6,26), AP2(11.4,26), AP3(8,21), AP4(4.4,15), AP5(11.6,15), AP6(8,9), AP7(4.6,4), AP8(11.4,4). In the offline fingerprint collection stage, fingerprint points were placed at 1m intervals, shown as white circles in [FIGURE].

3.2 Stability Analysis of Sorting Feature Vectors

The sorting feature vectors obtained using mode are more stable than those using mean. To verify this, one AP was fixed on the ceiling and sampled continuously for 12 hours at 1Hz sampling frequency. The data was divided into 10-minute intervals, and mean and mode were calculated for each interval. The results show that while mean values change continuously over time, mode values remain more stable in short periods, making mode-based sorting feature vectors more reliable.

3.3 Selection of Regulation Parameter α

Through experimental testing with user step length set to 0.7m, different α values were evaluated. The results show that when $\alpha = 0.3$, the algorithm achieves optimal class matching performance. Under this optimal value, the class matching accuracy of the proposed algorithm reaches [VALUE], representing a [VALUE]% improvement over traditional class matching algorithms. The correct rates in exact matching and most similar matching are improved by 14% and 17% respectively.

3.4 Analysis of Nearest Neighbor Fingerprint Points

To verify the distance-assisted algorithm, actual walking trajectories were compared with positioning results. The user walked eastward, then southward, then westward, and finally northward. The proposed algorithm shows smaller position fluctuations and more stable, reliable trajectories closer to actual walking paths compared with traditional KNN. The positioning error comparison is shown in [FIGURE].

3.5 Positioning Results Analysis

The positioning error probability distribution for three algorithms is shown in [FIGURE]. Compared with traditional KNN and optimal KNN algorithms, the proposed algorithm improves positioning accuracy probability within 2m by 9% and 25% respectively, and within 3m by 28% and 48% respectively. The average positioning error of the proposed algorithm is [VALUE] with maximum error [VALUE], representing improvements of 22% and 44% respectively over traditional KNN and optimal KNN. The maximum positioning error is reduced by [VALUE]%.

4. Conclusion

Aiming at the problems of low class matching accuracy in sorting clustering positioning algorithms and similar-but-not-near fingerprint points in KNN positioning, this paper proposes a matching optimization and distance-assisted Wi-Fi indoor positioning algorithm. The algorithm improves class matching accuracy through deviation detection and correction, and eliminates abnormal fingerprint points through distance assistance. Experimental results demonstrate that the proposed algorithm achieves class matching accuracy of [VALUE], average positioning accuracy of [VALUE], and reduces maximum error to [VALUE], enabling more precise indoor positioning. Future work will focus on adaptive real-time fitting of user step lengths, as different users and movement patterns result in non-constant step lengths that require dynamic estimation for optimal positioning accuracy.

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