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Research Article

Fingerprint localization method based on multi-source processing fusion

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Abstract
With the widespread popularity of mobile devices and the extensive coverage of corresponding infrastructure, wireless signal based fingerprint positioning has become the most attractive location calculation method in indoor location-based services. However, traditional WiFi RSSI fingerprint positioning is susceptible to multipath effects and signal noise in complex and changing indoor environments, making it difficult to meet high-precision positioning requirements. This article focuses on the key issues of indoor positioning technology in complex and changing environments, and designs a high-precision indoor positioning system based on Kalman filtering, particle swarm optimization (PSO) algorithm, and bidirectional long short-term memory network (Bi LSTM). The system first uses Kalman filtering to preprocess the RSSI signal, effectively reducing the impact of noise interference and outliers, and improving data stability. Secondly, the PSO algorithm is used to optimize the partitioning of the fingerprint database, improve the location update strategy and fitness function, and enhance the efficiency and accuracy of fingerprint matching. In addition, the system uses Bi LSTM network to mine the temporal characteristics of RSSI data, further improving the positioning accuracy. In order to enhance the processing capability of multi-source signals, this paper introduces variational autoencoder (VAE) technology to achieve deep fusion of WiFi and Bluetooth signals, complete feature extraction and data dimensionality reduction, and verify its applicability in large-scale and multi terminal scenarios. The experimental results show that the system proposed in this study has significantly improved signal stability, positioning accuracy, and computational efficiency, providing new ideas and technical support for the research and application of indoor positioning technology.

Keywords: *Indoor Localization, BiLSTM, Convolution Network, Deep Learning, Kalman filtering.*

1. Introduction
With the widespread application of Location Based Services (LBS), indoor positioning technology has become a hot research topic, especially in the urgent need to achieve high-precision positioning in large and complex indoor environments. Due to the easy signal shielding of Global Navigation Satellite Systems (GNSS) in indoor environments, which cannot meet the precise positioning requirements, wireless signal based indoor positioning technology has emerged, among which WiFi fingerprint positioning and multi-source information fusion technology have gradually become the mainstream research directions.

The WiFi fingerprint positioning method collects wireless received signal strength indicator (RSSI) data, constructs an offline fingerprint library, and performs real-time matching during the online phase to estimate the location. Its advantage lies in the easy deployment and low cost of hardware devices, but WiFi signals are easily affected by multipath effects, noise interference, and other factors in practical applications, leading to a decrease in positioning accuracy. To address this issue, researchers have proposed various optimization strategies, such as RSSI filtering algorithm, including mean filtering, Kalman filtering, and hybrid filtering methods, to improve data stability and reliability. In addition, in terms of positioning algorithms, the introduction of different distance measurement methods has significantly improved the positioning accuracy. In addition, regional partitioning and dynamic fingerprint selection methods further optimize the positioning process and reduce the error of fingerprint matching.

In order to overcome the limitations of single signal source localization, multi-source information fusion technology has become the current research trend. The fusion of WiFi and Bluetooth signals has been widely applied in both the data layer and decision layer. Data layer fusion achieves feature fusion of WiFi and Bluetooth signals through deep learning models, fully exploring the feature correlation of different signals. Decision level fusion utilizes Bayesian estimation and other methods to weight and fuse the positioning results of WiFi and Bluetooth, improving the positioning accuracy and stability of the system. In addition, the introduction of deep learning technology provides a new research path for indoor positioning, especially for optimizing RSSI feature extraction and pattern matching in complex indoor environments. Researchers have effectively modeled the temporal characteristics of RSSI data and improved localization accuracy by combining long short-term memory networks (LSTM) with self attention mechanisms. Meanwhile, feature dimensionality reduction and fusion are achieved through models such as Multi Layer Perceptron (MLP) and Variational Autoencoder (VAE) to reduce data complexity and further improve localization performance.

On the basis of summarizing existing research, this article proposes a high-precision indoor positioning system (KPBL) that integrates Kalman filtering, particle swarm optimization (PSO) algorithm, and bidirectional long short-term memory network (Bi LSTM) to address issues such as unstable signals, low fingerprint matching efficiency, and insufficient algorithm robustness in indoor positioning. The performance advantages of KPBL are verified through experiments.

2. System

2.1 System Framework

This article focuses on the key issues of insufficient fingerprint library accuracy, poor online stage matching accuracy, and the impact of sudden noise in the current RSS fingerprint positioning technology based on WIFI signals. The main research contents are as follows:

(1) In indoor environments, various interference factors can cause fluctuations and anomalies in the received RSSI data. In order to improve signal stability, this article uses Kalman filtering to process these data, reducing fluctuations and improving positioning accuracy.

(2) Traditional fingerprint localization algorithms have high computational complexity when dealing with large-scale fingerprint databases, as they need to traverse the entire database to find the best match. This problem is particularly prominent when the fingerprint database is large in scale. To address this challenge, this paper adopts a strategy based on particle swarm optimization (PSO) algorithm, which successfully improves the accuracy of clustering evaluation and solves the accuracy problem that existed in the previous evaluation process.

(3) In the localization stage, this article uses a bidirectional long short-term memory network (Bi LSTM) to process the merged signals and extract temporal features from them, based on which preliminary localization results are obtained.

2.2 Data preprocessing

In the field of indoor positioning, complex environmental conditions often lead to outliers and fluctuations in received signal strength indicator (RSSI) data, which affects the accuracy of positioning. To solve this problem, this article adopts an advanced filtering technique - Kalman filter, to process RSSI data. The core advantage of the Kalman filter lies in its ability to dynamically estimate and correct the system state through state equations and observation equations, thereby reducing the impact of noise on the signal.

Specifically, the Kalman filter consists of two key steps: prediction and correction. In the prediction stage, the filter predicts the current state and its uncertainty (i.e., error covariance) based on the state estimation from the previous moment and the known state transition model. Subsequently, in the correction phase, the filter uses the current observed data to correct the prediction, balancing the difference between the predicted and observed values by calculating the Kalman gain to obtain more accurate state estimation and update the error covariance.

The application of Kalman filter in indoor positioning can significantly smooth the fluctuations of RSSI signals, improve the stability and reliability of data. This is crucial for subsequent positioning algorithms, as high-quality input data is a prerequisite for achieving high-precision positioning. Through this filtering process, we can effectively extract real signal features from noise, providing a solid data foundation for experiments. Overall, the Kalman filter not only improves the quality of RSSI data, but also enhances the performance and robustness of the entire positioning system.

2.3 Bluetooth WiFi Fusion Space Division

2.3.1 Integration of Bluetooth and WiFi

In our research, we employed Variational Autoencoder (VAE) technology to achieve deep fusion of WiFi and Bluetooth signals. This process not only extracts key features, but also reduces the dimensionality of the data. VAE is a deep learning model that converts high-dimensional input data into low dimensional latent spatial representations through an encoder, and then restores these latent representations to the original data form through a decoder. In this way, VAE can learn the most informative features in the data and use them for subsequent processing.

Specifically, we first take the RSSI fingerprint data of WiFi and Bluetooth as input, and through the VAE encoding process, convert these data into low dimensional latent representations. This step aims to preserve the most important features related to distance while reducing the dimensionality of the input data. Then, we take the output of the encoder as the input of the Bi LSTM network for further training and extracting the fused features.

In this way, we can effectively combine the advantages of WiFi and Bluetooth signals, utilizing their complementarity to improve the accuracy of positioning. The introduction of VAE enables us to achieve more accurate and efficient indoor positioning in large-scale, multi terminal scenarios. In addition, VAE, as a probabilistic generative model, can handle uncertainty and noise in data, which is important for improving system robustness in complex indoor positioning environments.

2.3.2 PSO partition subspace

We adopted the Particle Swarm Optimization (PSO) algorithm to optimize the partitioning of the fingerprint database, in order to improve the efficiency and accuracy of localization. PSO is an intelligent algorithm that simulates bird flocks foraging, exploring and locating the optimal solution to a problem by simulating the flight movements of particles in the solution space.

(1) Location update

In the PSO algorithm, each particle represents a potential solution, and the position and velocity of each particle are adjusted based on its own and the best position previously discovered by the entire population. The formula for updating the position of particles is as follows:

$$p_i^{t+1} = p_i^t + v_i^{t+1}$$

In the given context, p_i^{t+1} represents the new position of particle i at time $t+1$, p_i^t is the current position of particle i at time t, and v_i^{t+1} is the new velocity of particle i at time $t+1$.

The velocity update equation is as follows:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot \left(p_{best,i} - p_i^t\right) + c_2 \cdot r_2 \cdot (g_{best} - p_i^t)$$

In the given context, w represents the inertia weight, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are random numbers, $p_{best,i}$ is the personal best position of particle i, and g_{best} is the global best position of the swarm.

(2) Fitness function

The fitness function is the key to population evolution, and the higher the fitness function value, the more complete the evolution of the population. In this article, PSO algorithm is used to optimize K-means clustering algorithm. Based on the iterative characteristics of PSO algorithm and the basic idea of K-means algorithm, a new fitness function is adopted. The fitness function is as follows:

$$fitness = \frac{1}{\sum_{i=1}^{n} \|p_i - c_i\|^2}$$

In the given context, p_i represents a data point, c_i represents the cluster center, and n is the number of data points. The fitness function aims to minimize the average distance between the data points and the cluster centers, thereby enhancing the cohesion and separation of the clusters.

2.3.3 Optimization during the positioning phase

In the positioning stage of indoor positioning systems, we face the challenge of accurately predicting location coordinates. Although traditional recurrent neural networks (RNNs) are capable of handling sequential data, their performance often declines when faced with long-term dependency problems, as they struggle to remember relevant information from early inputs. To overcome these limitations, we introduced a bidirectional long short-term memory network (Bi LSTM). Unlike unidirectional LSTM, Bi LSTM consists of two LSTM networks that handle forward and backward input sequences, respectively. This structure enables Bi LSTM to simultaneously consider past and future information in time series, providing us with a more comprehensive perspective to understand and predict positional changes. In the positioning stage, Bi LSTM can utilize this bidirectional information to optimize the prediction of position coordinates, resulting in significant improvements in accuracy and stability.

By applying Bi LSTM to optimize the positioning stage, the positioning accuracy has been effectively improved, and more stable and reliable positioning has also been achieved in complex indoor environments.

3. Experimental results and analysis

This article conducts comparative experiments on multi terminal positioning in large-scale scenarios. The experimental scenario is a 1200 square meter office building with 1200 sampling points. 100 iBeacons were placed as APs in the entire area. To verify the stability of our system's performance on different devices, this experiment used a smartphone for sampling.

In order to evaluate the positioning accuracy of the system, this article compared the positioning effect of the KPBL system with CNN on changes in the number of APs and changes in the site area.

3.1 Changes in the number of APs

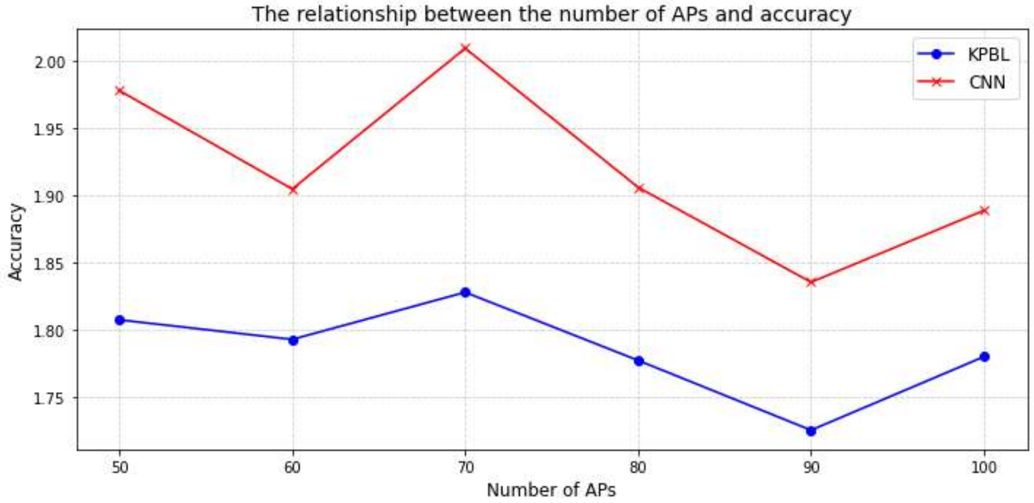

Fig. 1. Localization accuracy map of changes in the number of APs

From Figure 1, it can be seen that as the number of APs increases from 50 to 100, the positioning accuracy shows a gradually increasing trend. This indicates that increasing the number of APs can effectively improve the accuracy of the positioning system. This phenomenon is mainly due to the fact that more APs can provide richer signal information, thereby helping the system to determine the location more accurately. However, the number of APs is not necessarily better, indicating that when the number of APs reaches a certain level, their effect on improving accuracy tends to saturate.

3.2 Changes in site area

Figure 2 shows the change in positioning accuracy when the coverage area increases from 100 square meters to 500 square meters. Indeed, it can be clearly seen that as the area of the region increases, the positioning accuracy also improves. In addition, in larger coverage areas, the density of existing APs may not be sufficient to provide sufficient signal support, which may affect the positioning effect.

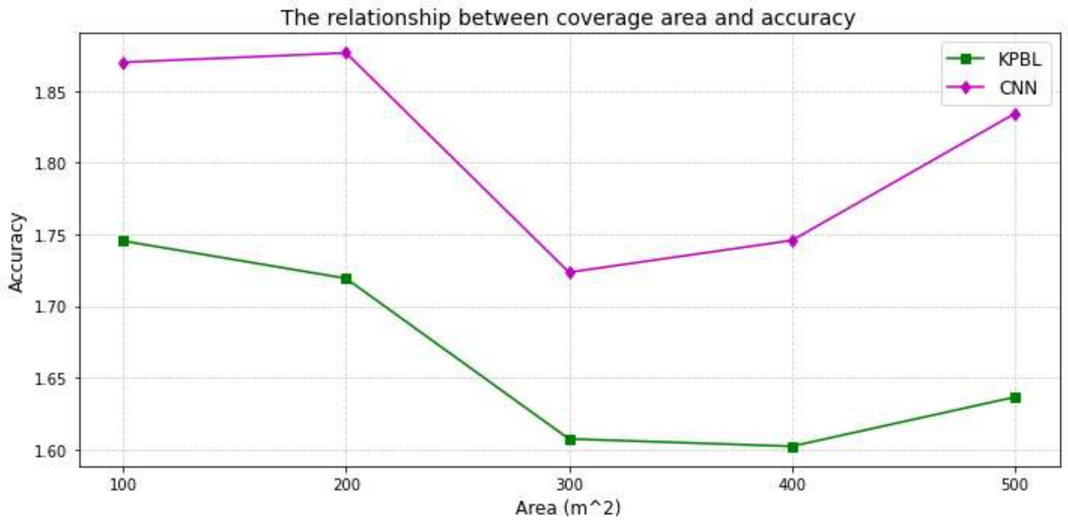

Fig. 2. Accuracy Map of Site Area Change Localization

4. Conclusion

This article designs and implements a fusion of Kalman filtering, particle swarm optimization (PSO) algorithm, and bidirectional long short-term memory network (Bi LSTM). The system first uses Kalman filtering to preprocess the RSSI signal to reduce the impact of signal fluctuations and outliers, thereby enhancing the stability and reliability of the data. Subsequently, the PSO algorithm was used to optimize the partitioning of the fingerprint database, improve the location update strategy and fitness function, significantly enhancing the efficiency of fingerprint matching and the accuracy of localization. In addition, the system uses a Bi LSTM network to extract temporal features from RSSI data, further improving the system's predictive performance in dynamic environments. At the same time, the introduction of Variational Autoencoder (VAE) technology has achieved deep fusion of WiFi and Bluetooth multi-source signals, fully leveraging the complementary advantages between different signals, and realizing feature extraction and data dimensionality reduction.

The experimental results confirm that our system exhibits excellent robustness and accuracy in multi terminal and large-scale scenarios, significantly improving performance compared to traditional methods.

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