Kalman filter-based indoor localization method using improved fingerprint database and IEEE 802.11 RSSI measurements

Jin Long Li[1], Jun Gyu Hwang[1], Jimin Shin[1], Joon Goo Park[1] *

[1]Kyungpook National University, School of Electronic & Electrical Engineering

2023000464@knu.ac.kr; junkyu891015@gmail.com; *jgpark@knu.ac.kr

Abstract

To address the issue of low positioning accuracy in the Wi-Fi fingerprint indoor localization method based on Received Signal Strength Indicator (RSSI), this paper proposes a Wi-Fi fingerprint indoor localization method based on deep learning. A method based on Deep Neural Networks (DNN) and Kalman filtering is presented. First, an RSSI data fingerprint database is constructed by collecting RSSI data, and a DNN is trained on this database to learn the nonlinear mapping relationship between signal characteristics and positions. During the localization stage, real-time RSSI data is filtered using the Kalman filter to reduce the impact of signal noise and fluctuations on positioning accuracy. The filtered RSSI data is then fed into the pre-trained DNN model for position estimation. Experimental results show that this method achieves a low average positioning error in small and medium-sized indoor areas and improves both positioning accuracy and stability compared to existing methods.

Ⅰ. Introduction

Currently, outdoor positioning technology generally meets the needs for location-based services in outdoor scenarios. However, most of people's daily activities take place indoors, and outdoor positioning technology cannot meet indoor positioning needs due to limitations of satellite signals [1]. With the widespread use of wireless networks in indoor locations, effectively utilizing existing wireless network equipment for indoor localization to fulfill the demand for indoor location information has become a current research hotspot in positioning technology [2]. Wi-Fi technology, with advantages such as low cost, low power consumption, and wide signal propagation range, has been applied to indoor positioning.

When collecting RSSI data in indoor environments, various uncertain factors can affect Wi-Fi signal propagation, leading to signal instability, which severely impacts data collection and thereby localization performance. Therefore, this paper proposes a Wi-Fi fingerprint positioning algorithm based on deep learning to improve the stability and reliability of offline data collection. By utilizing the Kalman filter [3] algorithm, interference and errors in signal propagation are reduced, ensuring the efficiency and accuracy of Wi-Fi fingerprint positioning. The filtered RSSI data is then fed into a DNN [4] model to compute the location, resulting in a more accurate final position.

The structure of this paper is as follows. The Section I is the introduction. The Section II introduces the fingerprint positioning method, the Kalman filter, and the DNN model. The Section III presents the experimental evaluation conducted on a real dataset. The Section IV provides the conclusions of the experiment and future prospects.

Ⅱ. Method

A: Fingerprinting technology

The positioning process using fingerprint technology consists of two stages:

Offline Stage: First, the space is divided into a grid, with uniform sampling of the area. Feature parameters are collected for each virtual point to construct a fingerprint dataset, and the data in the fingerprint dataset is used to train a machine learning model.

Online Stage: When a node moves to a certain location, the fingerprint data collected at that location is used as input, and the trained model's output is calculated as the virtual coordinates of the unknown location. The workflow of the fingerprint positioning technology is shown in Figure 2.

B: Kalman Filter

Kalman filtering is an efficient algorithm for optimal filtering in Gaussian processes, capable of quickly eliminating random errors caused by sudden changes in certain factors in the signal propagation environment. It uses the minimum mean square error as the estimate and corrects the current predicted value with observed values to produce the best estimate, recursively generating an optimized result.

The filtering derivation process is as follows:

$$x_0 = y_1 \tag{1}$$

$$x_k^- = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{2}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{3}$$

$$K_k = \frac{P_k^- H}{HP_k^- H^T + R} \tag{4}$$

$$x_k = x_k^- + K_k(y_k - Hx_k^-) \tag{5}$$

$$P_k = (1 - K_k H)P_k^- \tag{6}$$

y_1 represents the first observation value of each data group, and x_k^- represents the one-step prediction result of the state. A and B are the state transition matrix and the state control matrix, respectively. u_{k-1} is the control variable, and w_{k-1} is Gaussian white noise. P_k^- represents the estimated covariance of x_k^- and P_k is the estimation coefficient. K_k is the Kalman filter gain, H is the observation matrix, Q is the system process covariance, and R is the measurement noise covariance, which is obtained through observation.

Equations (2) and (3) represent the prediction of the system. Equations (4) and (5) represent the estimation of the reference measurement value. The estimation coefficient is updated using Equation (6).

C: Deep Neural Networks (DNN)

Deep Neural Networks (DNN) are used for classification tasks and are trained using synthetic datasets. Thanks to DNN's powerful feature extraction capability and advantage in nonlinear fitting, it is particularly well-suited for handling classification problems. Through reasonable network configuration and parameter tuning, we train the model until it converges, and then evaluate its performance on the validation set. After multiple rounds of training and optimization, the model can predict the location based on the input RSSI data. As shown in Figure 4-1, we deployed 3 APs and 39 RPs in the lounge. Additionally, we collected data at 18 random points for random testing.

D: Environmental settings:

The proposed DNN models are implemented using Python 3.10.8 and the PyTorch 1.12.0 framework, and are trained and validated on a PC equipped with an NVIDIA GeForce GTX 1650. The dataset used in the experiments is a public dataset provided by scholar Dwi Joko Suroso, consisting of 1490 sets of RSSI data samples.

The experiment is take place on the 8th-floor lounge of the IT-1 building of Kyungpook National University. The lounge is approximately 63m^2.we deployed 3 APs and 39 RPs in the lounge. Additionally, we collected data at 18 random points for random testing.

Ⅲ. Results

To further demonstrate the effectiveness of our proposed method, we compared it with an existing method (XGBoost) [5]. Table 1 shows the comparison between our algorithm and the XGBoost method. The RMSE of the proposed method is 0.36m, indicating higher accuracy compared to the XGBoost method.

Table 1: Accuracy Comparison

	XGBoost	proposed
MAE	0.31	0.17
MSE	0.28	0.13
RMSE	0.42	0.28

IV. Conclusion

This paper addresses the issue of low accuracy in Wi-Fi fingerprint positioning and proposes an indoor localization method based on deep learning. By combining Kalman filtering with a DNN network, the initial estimated location of the target point is determined, and the final predicted position is calculated using the reference nodes in the RSSI fingerprint database. Experimental results show that, compared to existing methods, this approach effectively improves positioning accuracy and provides more reliable results, making it suitable for achieving relatively accurate positioning at a low cost in small to medium-sized indoor environments.

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