Indoor Positioning Method Based on CGAN using modified Fingerprint DB with IEEE 802.11 RSSI Measurements

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Abstract

In the field of indoor positioning, the size of the fingerprint database directly affects the accuracy of positioning, and obtaining a large amount of fingerprint data is costly. This paper proposes a high-precision indoor wireless positioning method using Conditional Generative Adversarial Networks (CGAN). This method initially collects initial fingerprint data at fixed intervals indoors, then selects a portion of the original data, and uses Conditional Generative Adversarial Networks to generate more fingerprint data. This approach can economically and efficiently acquire a large amount of fingerprint data, thus expanding the original database and alleviating the drawbacks of offline fingerprint database construction.

Ⅰ. Introduction

With the development of wireless communication technology, location-based services have become a hot topic of interest. Consequently, pinpointing people's locations in indoor environments has become increasingly important. To address the issue of automatic positioning, the satellite-based Global Positioning System (GPS)[1] was developed. Its excellent transmission capabilities and location-based services (LBS) effectively solve many practical problems in civilian life. However, the effectiveness of GPS significantly decreases in indoor environments, where it experiences larger measurement errors. Therefore, precise indoor localization of targets has become a current focus of research.

In practical scenarios, when using traditional distance-based positioning technologies such as Received Signal Strength Indication (RSSI)[2], it is necessary to determine the signal propagation distance between the unknown target node and the adjacent reference nodes. However, in indoor environments with many obstructions, non-line-of-sight(NLOS) transmission and multipath signal transmission can occur, leading to signal loss and inaccurate distance estimates. Therefore, location-based fingerprinting technology has gradually become a hot topic of research.

When fingerprint data is limited, high positioning accuracy cannot be achieved. To reach higher accuracy, a substantial amount of fingerprint data is required to reduce the costs and time of data collection. This paper proposes an innovative indoor wireless positioning method based on Conditional Generative Adversarial Networks (CGAN)[3], applying CGAN innovatively in the field of indoor positioning. CGAN can generate a large volume of fingerprint data, thus reducing data collection costs. Based on these generated data, Deep Neural Network (DNN)[4]models are used for position prediction. We have validated the effectiveness of this method on a public dataset[5]. This approach can enhance the accuracy of wireless positioning based on a limited amount of fingerprint data.

We organize this paper as follows. Section I is the introduction. In Section II, we introduce the CGAN model. Section III describes the experimental evaluation on a public dataset. Section IV gives the experimental conclusions and future perspectives.

Ⅱ. Method

This section will introduce fingerprinting techniques, DNN ,CGAN, Environmental settings:

A: Fingerprinting technology

Fingerprint positioning is a type of non-distance-based positioning method, which differs from distance-based positioning. This method utilizes the variability of RSSI (Received Signal Strength Indication) at different locations. During the offline phase, an RSSI fingerprint database is constructed. Then, in the online phase, the RSS of the user is compared for similarity with the RSS in the fingerprint database, enabling rapid positioning.

B: Deep Neural Networks (DNN)

DNNs are used as classifiers, trained using a synthetic dataset. Due to their superior feature extraction capabilities and non-linear fitting advantages, they are particularly suited for classification problems. By properly configuring and fine-tuning the DNN, we train it until convergence and assess its performance on a validation set. Through multiple rounds of iteration and optimization, our model is able to predict locations based on the input RSSI data.

C: CGAN

In certain conditions, GANs [6] struggle to produce good results. The reasons include the difficulty of training GANs, their high sensitivity to hyperparameter settings, and the ongoing dynamic adversarial process between the generator and discriminator during training. However, one of the key factors that hinder GANs from producing high-quality fake data is the lack of effective information.

To alleviate this issue and enhance the performance of GANs, we can provide effective information (y) to both the generator and discriminator to aid in the model's adversarial performance. CGAN, or Conditional Generative Adversarial Network, involves adding an extra piece of auxiliary information (y) to the inputs of both the discriminator and generator in the existing network structure of GANs. In this paper, the auxiliary information (y) consists of coordinates (X, Y) from the public dataset. Based on this principle, we can derive the objective function of CGAN. Compared to GAN, there is no change in the overall function. The objective function of CGAN is as follows

$$\min_{G}\max_{D} V(D,G) = E_{x\sim p_{\text{data}}(x)}[\log D(x|y)] + E_{z\sim p_z(z)}\left[\log\left(1-D\left(G(z|y)\right)\right)\right] \tag{1}$$

In the generator, we take a random input z from a prior random distribution and concatenate it with the conditional input y to form a new hidden representation. In the discriminator, both real data x and generated data G(z) are input together with the conditional y for discrimination.

$p_{\text{data}}(x)$ is the distribution over data (x), specifically the distribution of the feature vectors of the RSSI fingerprints; $E_{x\sim p_{\text{data}}(x)}[\log D(x|y)]$ represents the true data drawn from the real data distribution. The discriminator D calculates the logarithmic probability to determine if these samples are real; the auxiliary information is y. $E_{z\sim p_z(z)}\left[\log\left(1-D\left(G(z|y)\right)\right)\right]$represents the noise z drawn from the noise distribution $p_z(z)$; the generator G creates samples based on the noise and auxiliary information y, while the discriminator D calculates the logarithmic probability that these generated samples are false.

D: Environmental settings:

The proposed CGAN and 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.

Ⅲ. Results

Using 50% real data for location prediction, the accuracy is only 0.32. With an additional 125 synthetic data added to the 50% real data, the accuracy improves to 0.59. The highest positioning accuracy is achieved using 100% real data combined with 125 synthetic data, resulting in the best accuracy of 0.69. Table 1 shows that by using data augmentation

Table 1: Accuracy Comparison

Data Type	Accuracy
50% actual	0.35
50% actual + 125 syn	0.59
100% actual	0.50
100% actual + 125 syn	0.69

IV. Conclusion

This paper addresses the issue of insufficient data volume in fingerprint positioning by proposing a wireless positioning method based on CGAN. When using fingerprint technology for indoor wireless localization, a deep learning model (DNN) is used to predict locations within the experimental setting. The paper applies the CGAN model to fingerprint indoor positioning, using CGAN to expand a small fingerprint dataset into a large one. The experimental results show that generating a synthetic database can mitigate the drawbacks of building offline fingerprint databases.

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