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Processing Technology of Multi-sensor Position Fingerprint Information

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***Abstract*—Aiming at the poor stability of the fingerprint library constructed using single sensor location fingerprint information and low positioning accuracy due to insufficient depth of fingerprint feature mining in traditional location fingerprint information processing technology, a new multi-sensor location fingerprint processing technology is proposed. First, the CSI phase and amplitude of the WiFi signal, the RSS of the 4G cellular network and the geomagnetic information are used as the joint location fingerprint information. Then, the convolutional neural network is used to further process the location fingerprint. Experiments show that the proposed method is superior to the commonly used neural network methods in terms of positioning accuracy and stability.**

Keywords-indoor positioning; multi-sensor; location fingerprint; convolutional neural network

I. Introduction

Location fingerprint technology [1] is very popular in the field of indoor positioning because of its low-cost and high-precision characteristics. This method uses a set of location fingerprint data collected in different environments to characterize the signal characteristics of the current location, and maps it to the actual environment, and then constructs a location fingerprint library corresponding to the actual environment. Finally, the current location is obtained by matching the collected location information to the fingerprint database. Therefore, how to deal with location fingerprint information is a problem that needs to be solved urgently.

The fingerprint information processing technology is also particularly important in the whole process of constructing the location fingerprint database. A good location fingerprint information processing technology can improve the stability of the location fingerprint database to a certain extent. Therefore, in order to solve the problems of insufficient depth of fingerprint feature mining and low positioning accuracy in the location fingerprint information processing technology, this paper aims at the limitations of the existing location fingerprint information processing technology solutions, and proposes a multi-sensor location fingerprint information processing technology based on convolutional neural network.

II. Related Work

Reference [2] uses RSS and Bluetooth as location fingerprint information, and uses the KL divergence kernel function to process RSS and Bluetooth information separately to generate their own location fingerprint database, and then uses the decision-level fusion processing technology to fuse the two sub-location fingerprint databases into a multi-sensor location fingerprint library.

Reference [3] uses the collected RSS information to establish a preliminary location fingerprint library, and corrects the RSS location fingerprint library with the position coordinates estimated by the inertial navigation data. Then, the K Nearest Neighbor(KNN) algorithm is applied to process the location fingerprint library, and generate the final location fingerprint library through the continuous feedback of the inertial navigation data. Although this solution can reduce the time complexity of the processing algorithm, it only roughly classifies the position reference point information, and does not learn the characteristics of the position fingerprint information, so the stability of the constructed position fingerprint database is not high.

Reference [4] uses WiFi, Bluetooth, and geomagnetism collected by smart phones as location fingerprint information, and a deep confidence network is used to process multi-sensor location fingerprint information. Although the deep belief network can effectively describe the signal characteristics of each location and perform pre-training to obtain a more accurate multi-sensor location fingerprint information processing model, this greedy layer-by-layer training method can only learn the local features of the location fingerprint information. It cannot reflect the characteristics of multi-sensor location fingerprint information globally, and the stability of the established location fingerprint database is naturally insufficient.

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Reference [5] uses geomagnetism and RSS information as location fingerprint information, and uses deep residual network in deep learning as a processing model for location fingerprint information, but the training time complexity is too high, and both geomagnetism and RSS data are low-dimensional data while the deep residual network is more suitable for processing high-dimensional data. Reference [6] only uses geomagnetism and CSI amplitude as location fingerprint data and proposes a CNN (Convolutional Neural Network) model, which will not make full use of the advantages of CNN in processing high-dimensional data and the rich characteristics of CSI signals.

This paper will make the best of the multi-sensor signal and propose a CNN-based comprehensive processing technology.

III. Collecting and Processing of Multi-Sensor Location Fingerprint Information based on Cnn

This section first collects the CSI phase and amplitude of the WiFi signal, the RSS and geomagnetism of the 4G cellular network as the joint location fingerprint information, and then proposes a multi-sensor location fingerprint information processing technology PTMLFI-CNN (Processing Technology of Multi-sensor Location Fingerprint Information-Convolutional Neural Network), to further process location fingerprint data.

A. *Steps of Multi-sensor Fingerprint Information Processing*

Step 1: Collect the CSI phase and amplitude from the WiFi signal at each reference point, 4G cellular communication network RSS and geomagnetic information, and then normalize these data, and format the fingerprint information of each reference point as the CNN network input;

Step 2: Divide the data and labels into training set and test set, and the ratio is 3:1;

Step 3: Import the training data into CNN for training, train the CNN model in a third-party library based on the TensorFlow framework, three convolutional layers are used to extract features from the input data, and two fully connected layers map the features to specific categories;

Step 4: After the training is completed, the CNN model is obtained, and the weight and bias of the CNN model and the coordinates of each reference point are used as the position fingerprint information, and the position fingerprint database is established. The fingerprint of the i-th reference point in the fingerprint library is expressed as FP(i)={(w_{1i}, b_{1i}), (w_{2i}, b_{2i}), (w_{3i}, b_{3i}), (w_{4i}, b_{4i}), (w_{5i}, b_{5i}), (x_i, y_i)};

Step 5: Import the test data into the CNN model to get the probability of its reference point at each position;

Step 6: Use radial basis function and Bayesian probability model to estimate the position of the point to be measured.

B. *Data normalization*

30 sub-carrier phases, 30 sub-carrier amplitudes, RSS data and the three-dimensional vectors (ma_x,ma_y,ma_z) of geomagnetic information, and the position coordinate $\mathrm{L} = (x_l, y_l)$ are collected from each reference point. For these data from different types of sensors, the min-max normalization method is used to transform it into the range of [0,1] to meet the input of the CNN model and accelerate the convergence. The calculation formula is as formula (1).

$$data_{nor} = \frac{data_{original} - \min(data_{original})}{\max(data_{original}) - \min(data_{original})} \tag{1}$$

Where $\mathrm{data}_{original}$ represents the original data, and data_{nor} represents the normalized data.

C. *CNN Parameter Training*

The structure of the CNN model is shown in Fig. 1. The numbers below the figure indicate the input size of each layer. First, the signal feature is converted into an image, as the input of CNN, and the stride is set to 1, so that the size of the input image will not be reduced by the convolutional layer, and there are enough images to be input to the fully connected layer. In addition, the pooling layer is not used because the multi-sensor signal feature image has a good description of location features, and pooling will reduce the size of the image.

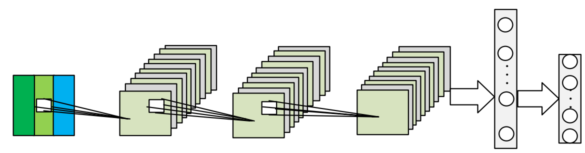

Fig. 1 CNN model structure diagram

For each position reference point, the number of geomagnetic data is 3, the number of RSS data is 1, the number of CSI amplitudes is 30, and the number of CSI phase is 30, so the total number of the joint fingerprint data is 64. To meet the input of CNN, when the fingerprint server processes the fingerprint information, the sampling interval is set to 64, and the 3 RGB channels of the image are simulated by 3 antennas, so the input of CNN is 3 pictures with a size of 64*64, and then use a convolution kernel with a size of 7*7*10. The number of the kernel is 10, and the stride is 1. The size of the second and third convolutional kernel is also 7*7*10.

After the processing of three convolutional layers, the data is output to the first fully connected layer. The number of neurons in this fully connected layer is 21160, and the number of neurons in the second fully connected layer is 2116, and finally, it is output to the decision-making layer. Among them, the activation function used in the three convolutional layers and one fully connected layer is a linear rectification function ReLU(Rectified Linear Unit). The neural network obtained by ReLU has good sparsity, which speeds up the calculation of the neural network. ReLU can be expressed as formula (2).

$$F_{ReLU}(x) = \max(0, x) \tag{2}$$

Where $F_{ReLU}(x)$represents the activation function ReLU. The method to avoid over-fitting in the first fully connected layer is to use a 30% pressure difference. The number of neurons in the output layer is equal to the number of location reference points, so each output neuron corresponds to a location reference point. Softmax is used in the output layer as the activation function [7], and the sum of the outputs of all neurons in the output layer is 1. The softmax function is shown in equation (3).

$$y(j) = \frac{e^{w_j{}^T x(i)}}{\sum_{j=1}^{K} e^{w_j{}^T x(i)}} \quad (3)$$

Where $y(j)$ represents the output of the j-th neuron in the output layer, K represents the total number of output neurons, which is equal to the number of position reference points, $x(i)$ is the output of the penultimate layer, w_j is the weight that connects the neurons in the penultimate layer to the output layer.

Cross entropy plus regular term is used as the loss function, as shown in formula (4).

$$LF_{cert}(w) = -\frac{1}{size_{ts}}\left[\sum_{i=1}^{size_{ts}} \sum_{j=1}^{K} \{lrp^{(i)} - j\} log \frac{e^{w_j{}^T x(i)}}{\sum_{l=1}^{K} e^{w_l{}^T x(i)}}\right] + \frac{w_{reg}}{2} \sum_{i=1}^{N_n} \sum_{j=1}^{K} w_{ij}^2 \quad (4)$$

Where $lrp^{(i)}$ is the i-th reference point, $size_{ts}$ is the size of the training set, N_n is the dimension of w_j, which corresponds to the number of neurons in the penultimate layer, w_{reg} (w_{reg}>0) is the weight of the regularization. The regular term can avoid overfitting. Stochastic gradient descent and backpropagation algorithms are used to train the network, and minimize equation (5) is used to optimize the model until the loss function drops below the threshold.

$$\frac{\partial LF_{cert}(w)}{\partial w_j} = -\frac{1}{M}\sum_{i=1}^{M}\left[x^{(i)}\left(\{z^{(i)} - j\} - \frac{e^{w_j{}^T x(i)}}{\sum_{l=1}^{k} e^{w_l{}^T x(i)}}\right)\right] + \lambda w_j \quad (5)$$

D. Position Estimation based on Data Fusion

In the online phase, test data is mainly used to test the location fingerprint database. Since the probabilistic location estimation method is better than the deterministic method in terms of performance, the Bayesian probability model is used, which is represented by equation (6).

$$\mathrm{P}(L_i|\mathrm{v}) = \frac{P(L_i)P(v|L_i)}{\sum_{i=1}^{N_{tlrp}} P(L_i)P(v|L_i)} \quad (6)$$

Where L_i is the position of reference point i, $P(L_i|v)$ is the posterior probability of the test point at the position reference point i, $P(L_i)$ is the prior probability of the mobile device at the position reference point i, and N_{tlrp} is the number of the reference point. Assume that $P(L_i)$ is uniformly distributed in the set. Therefore, $P(L_i)=1/N_{tlrp}$, based on the CNN model, $P(v|L_i)$ is defined as a radial basis function in the form of a Gaussian function, as shown in equation (7).

$$\mathrm{P}(\mathrm{v}|L_i) = \exp\left(-\frac{\|v-\hat{v}\|}{\sigma}\right) \quad (7)$$

Where v is the input raw data, $\hat{v}$ is the data processed by the CNN model, and σ is the standard deviation of the input raw data.

Finally, the weighted average of the coordinates of all reference points can be regarded as the estimated coordinates of the position to be measured, which is represented by equation (8).

$$L_{target} = \sum_{i=1}^{N_{tlrp}} \mathrm{P}(L_i|\mathrm{v})\, L_i \quad (8)$$

IV. Performance Evaluation

A. Average Positioning Error Evaluation

In two different environments, comparative experiments were carried out, and the performance of neural network schemes with different structures was evaluated through the average positioning error. In these two environments, 8 comparison experiments were carried out, and the number of samples at each reference point was 100. In each experiment, the positioning results were measured 10 times and the average value was taken as the positioning error.

As can be seen from Fig. 2 and Fig. 3, the office scenario with many desks and computers is more severely affected by multipath, while the empty lobby is relatively less affected, so the positioning accuracy in the lobby scenario is relatively high. The positioning error of PTMLFI-CNN in the lobby scenario is about 1.32m, and the positioning error in the office scenario is about 1.59m, obviously better than Deep Belief Network (DBN) and BP Neural Network (BPNN).

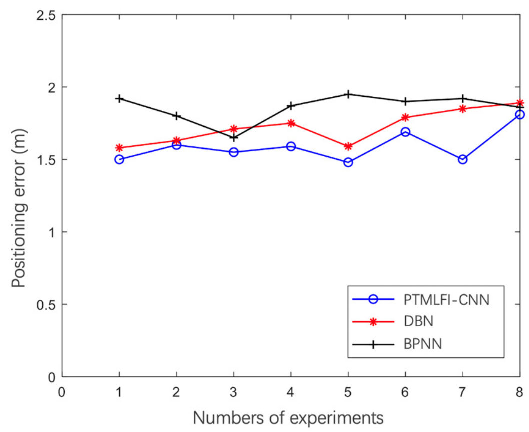

Fig. 2. Office scenario

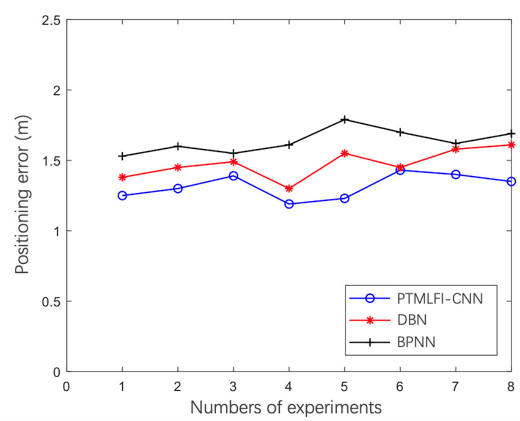

Fig. 3. Lobby scenario

B. Positioning Stability Evaluation

PTMLFI-CNN uses unique joint fingerprint data at different locations to locate targets. And complex and variable fingerprint data may interfere with positioning accuracy and cause positioning errors. It is not only necessary to evaluate the positioning accuracy of the training position, but also to calculate the positioning error of the untrained position, especially in a multipath environment such as an office with many desks and computers.

In the same office, 20 points were set as training points, and the other 20 points were set as test points. In the training phase and the test phase, 700 CSI images at 20 locations were selected to calculate the positioning error of PTMLFI-CNN and other neural network solutions. The stability evaluation was shown in Fig. 4.

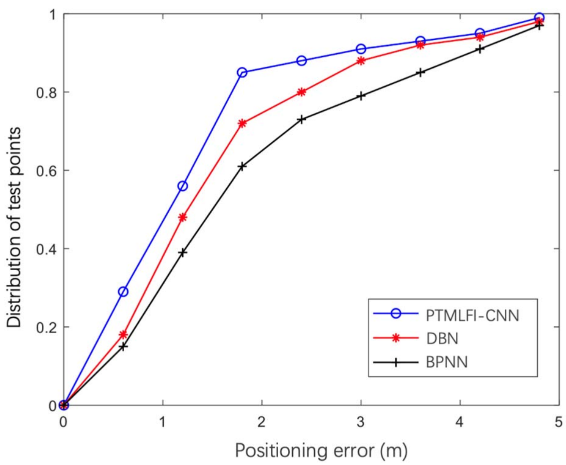

Fig. 4. Cumulative distribution error in an office scenario

For about 56% of the test points, PTMLFI-CNN can achieve a positioning error of less than 1.2 meters, while the number of test points for a stacked autoencoder and a BP neural network with a positioning error of less than 1.2 meters are 48% and 39%, respectively. For 85% of the test points, PTMLFI-CNN can achieve a positioning error of about 1.8 meters, which is 13% and 24% higher than Deep Belief Network and the BP Neural Network, respectively. Obviously, PTMLFI-CNN can fully learn the characteristics of complex indoor environments and deeply mine fingerprint features. Even in a complex indoor environment, it can also output high positioning accuracy.

V. CONCLUSIONS

This paper studies how to use machine learning methods to process multi-sensor location fingerprint data. Addressing the problems of insufficient depth of fingerprint data mining and low positioning accuracy in the location fingerprint processing technology, this method uses the CSI phase and amplitude of the WiFi signal, the RSS and geomagnetic information of the 4G cellular communication network as the joint location fingerprint information, and then proposes a multi-sensor location fingerprint information processing technology based on convolutional neural network. In the offline stage, different types of sensor data are normalized to meet the input of the convolutional neural network, and then the training data is imported into the proposed convolutional neural network model for training, and the trained weights are used as fingerprints to construct a location fingerprint library. In the online stage, the radial basis-based probability method is used to describe the similarity between the target position data and the data in the fingerprint library, and the probability of the target position at each reference point is calculated. Finally, the target position is estimated by the weighted average of each position probability. Experiments show that the proposed method is superior to the commonly used neural network methods in terms of positioning accuracy and positioning stability.

Future research can introduce landmark information to assist location marks, because landmark information can reflect some special locations such as inflection points, to further improve the accuracy and stability of positioning.

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