Research on Wi-Fi Indoor Positioning Technology based on Deep Neural Network

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Abstract: Various research works have been proposed for Wi-Fi based indoor positioning, such as K-Nearest Neighbor Algorithm (KNN), Weighted K-nearest Neighbor Algorithm (WKNN), and Bayesian Algorithm, but these algorithms have different complexity due to indoor environment. In order to make the indoor positioning more precise, this paper designs a Wi-Fi indoor positioning technology based on deep neural network. The value of RSSI obtained is preprocessed to adapt to the neural network, and then the system further trains the value of RSSI according to the actual position to obtain a more accurate indoor positioning model. Through the test, the positioning algorithm in the paper has higher positioning accuracy and better stability.

1. Introduction

Because the Global Positioning System (GPS) does not meet the user's requirements for accurate positioning of the indoor environment, researchers have begun to explore other technologies to achieve accurate indoor positioning [1]. In recent years, with the widespread deployment of Wi-Fi in indoor environments, and the popularity of terminal devices with Wi-Fi communication capabilities, especially smart phones, coupled with the superior performance of Wi-Fi fingerprint location technology based on RSSI in indoor environments, making fingerprint positioning has become an important solution to today's indoor positioning problems. This article will introduce the Wi-Fi localization technology based on deep neural network. This method has relatively strong nonlinear mapping ability and self-organizing training ability. Because it is based on the obtained mapping relationship between the location point RSSI and the location coordinates, on the one hand, it helps to reduce the time cost of the positioning system layout and save the storage space of the fingerprint library; on the other hand, it shortens the online phase in real time. Therefore, this is a more efficient fingerprint localization algorithm.

2. Deep Neural Network Theory

In recent years, Hinton et al. proposed a machine learning method for deep neural networks based on the idea of human brain learning. DNN is also called Deep Learning [2]. This method is a multi-layer unsupervised neural network, and features the output characteristics of the upper layer as the input of the next layer, mapping features of existing spatial samples to another feature space by mapping layer-by-layer features, to learn to have better feature representation of existing inputs. The main difference between deep neural network and traditional neural network is the training mechanism, which overcomes the shortcomings of traditional neural network which is easy to over-fitting and slow in training. The core ideas of deep neural networks can be described as follows.

1)Unsupervised learning is used for pre-training of each layer of network.

2)Unsupervised learning layer by layer, that is, the output of the previous layer is used as the input of the next layer.

3)Supervised learning to fine tune all layers (plus a classifier for classification).

3. Indoor Positioning Algorithm Design

The main task of the deep neural network indoor positioning algorithm is to construct a neural network model suitable for the environment of the area to be located. The work is also divided into two steps. First, in the offline training stage, the main task is to train the best neural network positioning model. In the online positioning stage, the received signal strength obtained in real time by the point to be measured is input to the trained neural network, thereby outputting the position coordinates of the point to be measured. Figure 1 below is a specific operation flow chart based on deep neural network Wi-Fi positioning.

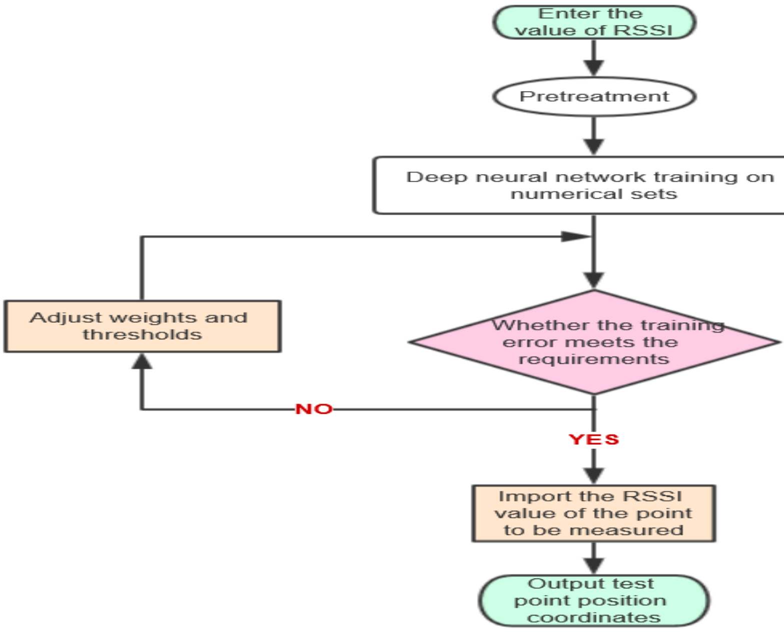

Fig 1. Wi-Fi positioning flow chart based on DNN

3.1 Input Data Preprocessing

The main distribution range of the Wi-Fi signal strength RSSI is between -120dBm and -50dBm, and the position point coordinates X, Y are irregularly distributed. The WIFI signal strength and the range of coordinate data are large, which is not conducive to the training of the neural network, and it is easy to cause the network to not converge. Therefore, the input data needs to be preprocessed to accelerate the convergence speed of neural network training [3]. The input data preprocessing method is shown in formula (1). In the formula, $RSSI_c$ is the original signal strength value of Wi-Fi, $RSSI_c$ is the signal strength value after preprocessing, X_i and Y_i is the original position coordinate, and X_c and Y_c is the position coordinate after preprocessing.

$$\begin{cases} RSSI_c = 0.01 * RSSI_i \\ X_c = \dfrac{(X_i - X_{min})}{(X_{max} - X_{min})} \\ Y_c = \dfrac{(Y_i - Y_{min})}{(Y_{max} - Y_{min})} \end{cases} \quad (1)$$

As a basic form of deep learning, DNN improves the feature representation ability formed from input data by stacking hidden layers. After a lot of time-intensive training, DNN can convert data into high-dimensional nonlinear data. The feedforward network structure of DNN has an input layer, multiple hidden layers and an output layer, in which data is input from the input layer, and high-dimensional nonlinear transformation is performed through the hidden layer, and finally the output layer is classified and predicted [4]. Figure 2 shows the WIFI location structure based on DNN.

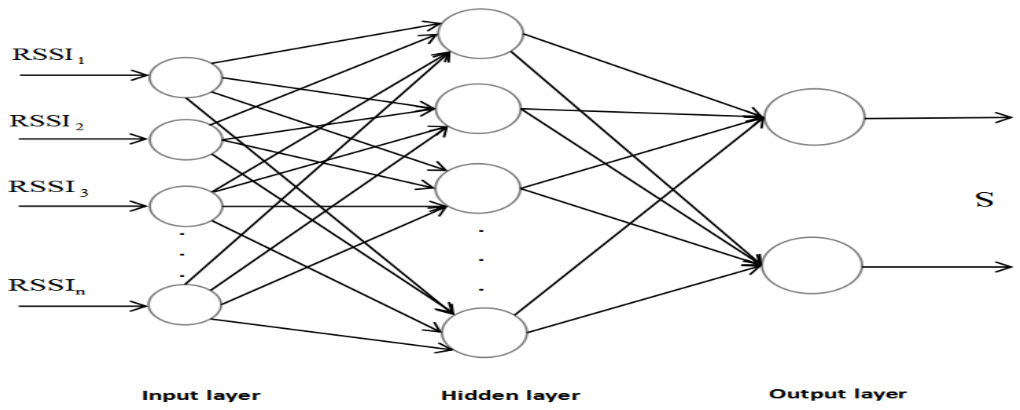

Fig 2. WIFI positioning structure based on DNN

The training data X= {$RSSI_1$, $RSSI_2$, $RSSI_3$, …$RSSI_N$} represents N m-dimensional input vectors. For a deep neural network with L hidden layers, W^l and b^l represents the weight and deviation of layer l (l=1,2, …, L) [4]. Assuming that the output of the layer l is h^l, h^0 is the input x of the network. If a training sample x is input from the input layer, the feedforward operation of the network can be written as follows.

$$h^l = \sigma(h^{l-1}) = \sigma(w^l h^{l-1} + b^l) \tag{2}$$

Where б () represents the activation function Sigmod of the neuron. Therefore, after the input data RSSI passes through multiple hidden layers to the output layer, the output of the network is as follows.

$$\mathrm{S} = W^{L+1} h^L + b^{L+1} \tag{3}$$

The original input data is abstracted into high-level features by multiple layers of hidden layers. The next step is to use the BP algorithm to supervise the network in a supervised manner. The process is equivalent to the training process of other feedforward neural networks. Using cross entropy as an error function.

$$L(x, y) = -\frac{1}{n}\sum_x (y \ln a + (1-y)\ln(1-a)) \tag{4}$$

Where a=SoftMax (S), y is the data label. Then, the training sample X is studied so that DNN can find parameter Ө= {W^l, b^l} that makes the loss function as small as possible.

$$\{W^l, b^l\} = \arg\min_\theta \sum_{n=1}^{N} L(x_n, y_n), \quad (n = 1,2,\cdots N) \tag{5}$$

4. System Test Results and Analysis

4.1 Experimental Environment and Methods

The experimental environment in this paper is a typical conference room. The plan view of the experimental site is shown in Figure 3. A long table is placed in the middle, and chairs are placed around. The conference room is a rectangle 12 meters long and 8 meters wide. We set 32 reference points in the experiment, such as the small triangle in the picture, the distance between each two reference points is 1 meter. In order to make the data more adequate during the experimental processing and avoid repeating the experiment in the future, we performed multiple data acquisitions at each reference point, collecting an average of 500 data packets per point. We put the wireless router and notebook on the table, and then the experimenter stands at different reference points. For a period of time, the data at different locations is obtained. The signal is more stable when the router is operating in the 5GHz band, and the experimental results are better [5]. Therefore, all the data used in this paper are obtained in the 5GHZ operating band.

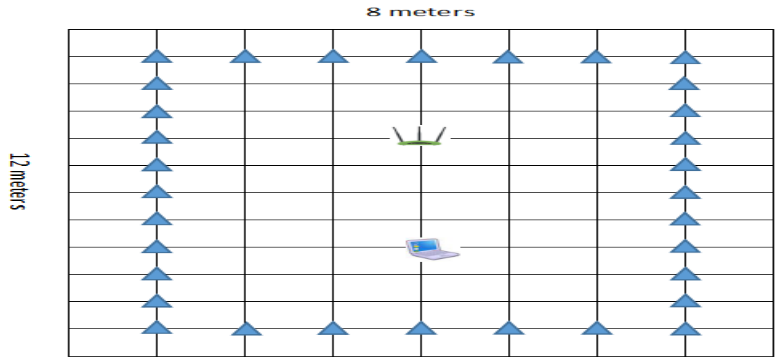

Fig 3. Plan of the experimental scene

4.2 Comparison of Different Positioning Algorithms

In order to avoid generality, we used multiple sets of different algorithms for localization in the experiment, which can better compare the performance of DNN and other indoor positioning algorithms (KNN and WKNN). The experimental results are shown in Figure 4 below.

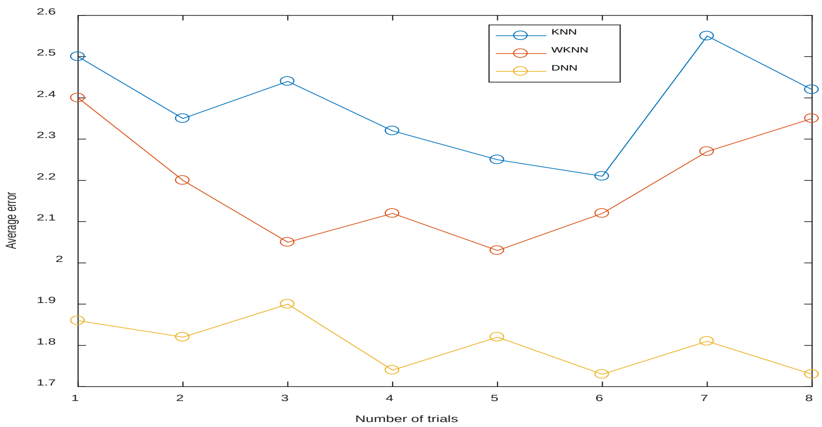

Fig 4. Comparison of positioning results of different algorithms

4.3 Result Analysis

From Figure 4 we can see that under 8 experiments, using KNN algorithm for positioning, the best average error is about 2.3 meters; using WKNN algorithm for positioning, the best average error is about 2.1 meters, and the best error of the DNN algorithm in this study is about 1.8 meters. In addition, we can also see that when using KNN and WKNN algorithm for positioning, the average error has large fluctuations and instability, while the DNN algorithm has less fluctuation and is more stable.

5. Conclusion and Prospects

5.1 Conclusion

In order to solve this limitation of GPS, this paper proposes a WIFI indoor positioning technology based on DNN. The experimental results show that compared with other localization algorithms, the DNN algorithm has the advantages of high stability and high positioning accuracy.

5.2 Prospects

Although the RSSI is analyzed and processed in the process of experimental positioning, and three WIFI-based positioning methods are compared, there are still defects, and the basis of this research can be further optimized and expanded.

1). The method of using RSSI for positioning is limited in its own positioning accuracy. If CSI (Channel State Information) information is used, the positioning result will be more accurate, because it is based on the status information [5].

2). The test is only carried out in a simple indoor environment. If you can test in a more complex and practical environment, you may get more useful information.

3). The experimental environment of this paper is a fixed area selected in advance and the positioning result can only represent the two-dimensional space coordinates. In practical applications, the location change speed is fast and the moving target may move from the two-dimensional space to the three-dimensional space. How to make the positioning system adapt to the complex and changing place is also the focus of research in the future.

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