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Indoor Localization Algorithm Based on Artificial Neural Network

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Abstract: Indoor environment is complex and changeable, and the application scenario of indoor positioning(IP) requires higher accuracy, while the technology of outdoor positioning cannot meet people's requirements for IP, so IP technology is born. Since artificial neural network(ANN) are highly adaptive, fault-tolerant and suitable for complex indoor environment analysis, this paper introduces neural networks to solve the indoor localization problem. After the simulation study of ANN localization algorithm(LA) in this paper, the localization error accumulation probability and root mean square error of localization are compared between ANN localization model and other classical LAs, and it is found that compared with several LAs such as KNN, MLP and SVR, ANN LA has better performance and higher localization accuracy under low signal-to-noise ratio.

1. Introduction

Indoor localization methods are a popular research direction in LAs, and as the Internet of Everything gradually enters people's daily life, the implementation of location-based services has become one of the most urgent needs today. Due to the complexity of indoor environment, ANN localization methods have superior performance in indoor localization, but there are still many problems and challenges to be solved in the current ANN localization technology.

Currently, many studies have proposed a series of indoor LAs. For example, it has been pointed out that Bayesian filtering algorithms can effectively reduce the measurement uncertainty and apply them to real environment localization applications, thus improving the robustness of localization. However, filtering algorithms have limitations on the tracking capability of localization systems, and it is difficult to achieve a balance between robustness and tracking capability [1]. Some scholars have proposed -a competing topological back-propagation neural network based on shallow neural networks and applied it to indoor localization, achieving better results in terms of speed and accuracy, however, the shallow architecture limits the fitting ability , leading to predictions that are vulnerable to signal fluctuations [2]. Because of the nonlinear fitting capability of neural networks, research scholars have also applied ANN to the optimization process of LAs. For example, some scholars have proposed positioning algorithms using ANN to optimize the Wi-Fi received signal strength (RSSI), or some have proposed using fingerprint recognition methods and neural networks in UWB systems to optimize the positioning results [3-4]. From the above research results, it seems that all IP algorithms have achieved good positioning results.

In this paper, we first introduce several IP techniques and positioning systems, and then propose an IP algorithm based on ANN, as well as metrics to evaluate the performance of the positioning algorithms, and finally conduct split-pin experiments to compare the error accumulation probability (CDF) and positioning RMSE of ANN positioning algorithms with KNN, MLP, and SVR using the evaluation metrics.

2. IP Technology and Positioning System

2.1. Basic IP Techniques

Positioning techniques are based on the location estimation based on the distance between the target to be located and the nodes at a known location or the measurement between the nodes. Collaboration between nodes can improve the performance of indoor localization, and collaborative localization between nodes is very beneficial for performance improvement when traditional localization techniques cannot achieve accurate positioning, especially in the case of complex indoor scenarios [5].

(1) Time Difference of Arrival (TDoA)

TDoA performs position estimation by calculating the time difference between signals sent from a target with localization to arrive at many known location nodes. For each TDoA measurement, the difference in distance between two measurement units is constant, so that the unknown node must lie on a hyperbola [6]. This measurement is performed between nodes with known locations and, instead of absolute time measurements, relative time measurements are used at each receiver node.In the TDoA localization method, no synchronized time is required for localization, only time synchronization at the receiver is required [7].

(2) WIFI IP

WIFI IP is a method to finally predict the indoor location of the user of the mobile terminal through various mobile network devices with the help of the currently feasible WIFI network communication technology and using relevant IP algorithms. This method has many features, such as strong adaptability, high real-time, low cost and easy portability of the device [8]. WIFI-based IP technology has played a great role in advancing the development of IP services.

(3) Fingerprint positioning

All APs (routed access points) around the world have world unique MAC addresses and regardless of their encryption, any device with a wifi module can obtain the names, MAC addresses and their signal strengths of all AP nodes around [9]. In an indoor network environment, mobile terminal devices can obtain the WIFI signal strength values from different AP nodes by establishing connections with them. The signal strength values from different APs can be used as a form of identifiable (i.e., fingerprint) that is applied to differentiate with different locations. It is possible that the receiving device will not receive the signal of a particular AP node due to the failure of the AP node or the AP node is blocked by an obstacle, or the WIFI signal is so weakened during indoor propagation that the receiving device cannot detect this signal [10-11]. This method does not need to know the location information of the anchor node in advance compared to other methods, but it requires the localization area to be divided and sampled [12].

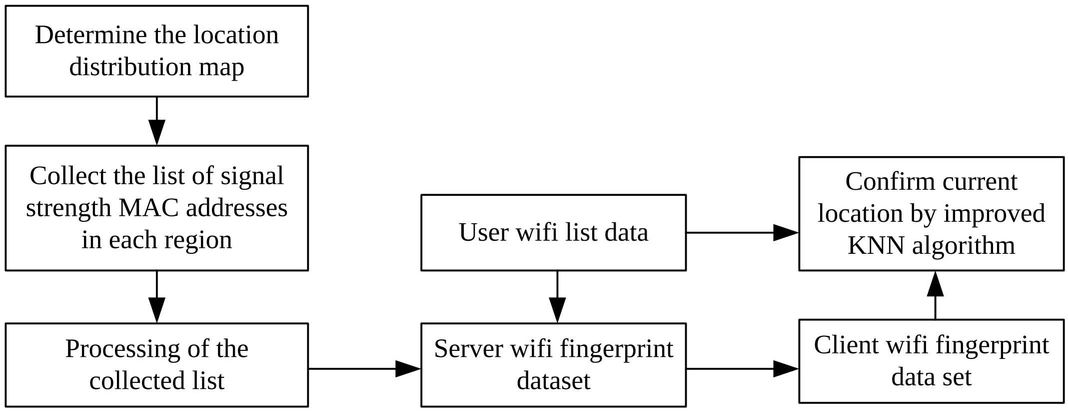

Figure 1. Wifi fingerprint localization process

Figure 1 shows the flowchart of Wifi fingerprint localization. The classical method is to deposit the data into the server after collection, and use the K-nearest neighbor algorithm to compare the real-time collected Wifi signals with the sampled signals saved in the server when performing localization. The center vector of the Wifi fingerprint dataset is taken as the Wifi fingerprint without saving the whole dataset, and it is experimentally proven that this method can achieve a correct rate of more than 90% when the acquisition points are separated by a distance of 2 meters [13]. The advantage of using this method is that a large number of Wifi fingerprint datasets can be reduced and the datasets can be saved to mobile terminals, thus enabling offline localization; after the user Wifi list data is sent to the server, the server makes the Wifi fingerprints of the user's location and its vicinity into the client Wifi fingerprint dataset, and the ware requests the fingerprints near the next location to continue offline localization, and Wifi fingerprint localization can be applied to a large number of users positioning methods [14-15].

2.2. Common IP Systems

(1) UWB-based positioning system

UWB technology (UWBT) is based on sending ultra-short pulses of less than 1ns with signal from 1 to 1000. The transmitted signal in UWB is sent through multiple frequency bands. Signals in UWB can be sent in multiple ways in indoor scenarios.

Position estimation in UWB-based applications is estimated based on radio signals propagating between the target node and a reference node at a known location. This process can be accomplished using ToA, AoA, TDoA, and fusion techniques. Positioning systems based on UWBT achieve centimeter accuracy [16]. With ToA or TDoA based 3D positioning, an accuracy of 15 cm can be achieved in indoor scenes. In fact, multipath signal components can be separated at UWB receivers because of their high bandwidth characteristics. In scenes satisfying the LOS condition, the signal component of LOS is the path with robustness, so researchers commonly use it as information for localization [17].

(2) WLAN-based localization system

Typically, WLAN to find networks that are available for connectivity. When need to be repeated in order to minimize the localization error. Periodic updates are required as the positioning device moves along the trajectory. Therefore, each device performs a scan of all available APs on the relevant channel at a rate equal to the update rate (UR). Averaging a set of RSS measurements reduces the effect of noise, and devices concerned with positioning accuracy perform scans at a rate higher than the UR [18].

3. Indoor LA Based on ANN

3.1. ANN Localization Idea

The neural network localization idea is to use the ANN structure diagram shown in Figure 2, using a three-layer structure, the number of nodes uses the number of anchor nodes in the localization area, the number of anchor nodes is 4, so there are 4 nodes in the input layer, 2 nodes in the hidden layer, using the sigmoid function, and only one node in the output layer, using a linear function, using a separate neural network for each dimension. The experiments in this paper used two dimensions and therefore two separate neural networks were used. Some studies used radial-based neural networks at the beginning because of their local variation characteristics, making them more suitable for features that vary in parts of the data at different localization locations, but in actual use it was found that radial-based neural networks produced results with high standard deviation, while ANN were able to obtain better localization results, so the ANN was finally used as the neural network structure for localization.

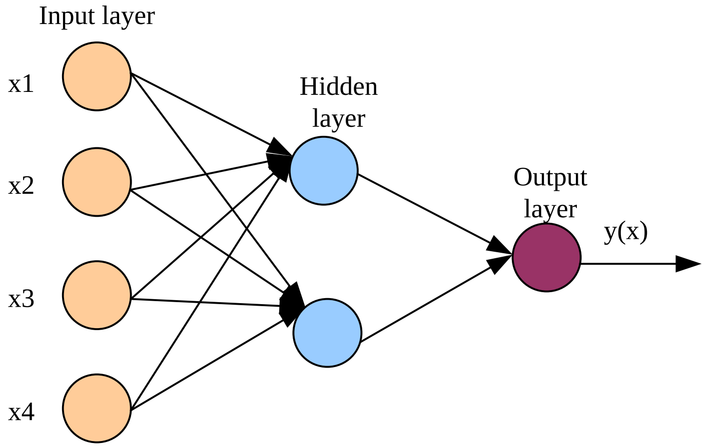

Figure 2. ANN model

The expression of the sigmoid function f(x) is shown in equation (1).

$$f(x) = \frac{1}{1+\exp(-x)} \tag{1}$$

3.2. LA Evaluation Indexes

(1) Localization Accuracy

Accuracy is used by most researchers as one of the metrics for evaluating the performance of localization methods. Accuracy is generally measured using RMSE or the ME of the estimated position and the true position given by the LA.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left\| \hat{y}_i - y_i \right\|^2}{n}} \tag{2}$$

$$ME = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left\|\hat{y}_i - y_i\right\|^2} \tag{3}$$

where $\hat{y}_i$ denotes the position estimated by the LA at the ith sample point, y_i denotes the true position at the ith sample point, n is the total number of samples tested, and $\|\cdot\|$ denotes the Euclidean distance.

(2) Cumulative probability distribution function

Since the positioning accuracy can only measure the magnitude of the error value of the positioning algorithm, it cannot reflect the probability distribution of the positioning error. Therefore, the CDF can be used to measure the positioning performance. The CDF is also called the distribution function, and the CDF curve is obtained by integrating the probability density function. The cumulative distribution function represents the probability that the positioning error is distributed over a certain interval. The distribution function curve is a monotonically increasing curve, and in general, a steep CDF curve represents that the positioning error is concentrated in a smaller interval, indicating that the positioning accuracy of the positioning algorithm is higher. When comparing the performance of different IP algorithms, the performance of each algorithm can be compared and analyzed by comparing the shape of CDF curves of positioning errors of different positioning algorithms.

(3) Positioning delay

Positioning delay time is the time interval between the sending time of positioning request and the result return time. The positioning system aims to provide real-time positioning feedback to users and the shorter the positioning delay time, the better the user experience. Therefore, positioning delay time is one of the important indicators for evaluating the performance of IP algorithms.

4. Indoor Localization Simulation Based on ANN

4.1. Simulation Environment

In this paper, we use a 40-meter-long, 40-meter-wide, and 3-meter-high indoor environment as the simulation environment, and install the WLAN localization system indoors. In this indoor environment, three AP nodes at different locations are set up, and the terminal device is visible with the AP nodes, and RSSI signal data are collected along a straight line path, with the sampling interval set to 0.6m and frequency 1Hz.

4.2. Influence of Personnel Obstruction on Signal Strength

Users are an important part of the IP system, but user movement indoors is a common phenomenon in IP, and user occlusion of the signal propagation path can directly affect the received signal strength. This experiment uses measured signal strength data to analyze the effect of user occlusion on signal strength. The experimental personnel carry the receiving device with their backs to the AP node at a uniform speed and then face the AP node to return to the starting position, and the signal strength collected from the experiment is shown in Table 1. the results show that the occlusion of the personnel significantly reduces the received signal strength value.

Table 1. Received signal strength (RSSI/dBm) for human occlusion

Reference point location	0	5	10	15	20	25	30
Facing AP	-45	-41	-48	-52	-57	-59	-50
Unobstructed mean	-42	-42	-42	-42	-42	-42	-42
Back to AP	-23	-44	-36	-38	-34	-42	-53
Obstructed mean	-47	-47	-47	-47	-47	-47	-47

4.3. ANN LA Testing

(1) Performance testing of LAs

In order to test the performance of ANN LAs, this paper compares with classical localization methods such as KNN, MLP, and SVR. It is worth noting that for SVR and MLP, their training sets use the points on the path as the training set in order to make the comparison more reasonable. For KNN, the training set of SVR is used as the database of KNN since there is no training set only offline database. For the KNN algorithm, the optimal KNN parameters are selected. the MLP algorithm selects the neural network with the number of neurons in the hidden layer as 100, 150. 100 for nonlinear learning respectively. the SVR algorithm selects the RBF function as the kernel function and the parameters are selected based on the grid-seeking optimization algorithm. Figure 3 gives the error accumulation probability distribution curves of different algorithms under the condition that the noise level is 15 dB. From Fig. 3, it can be seen that the ANN LA outperforms the other algorithms.

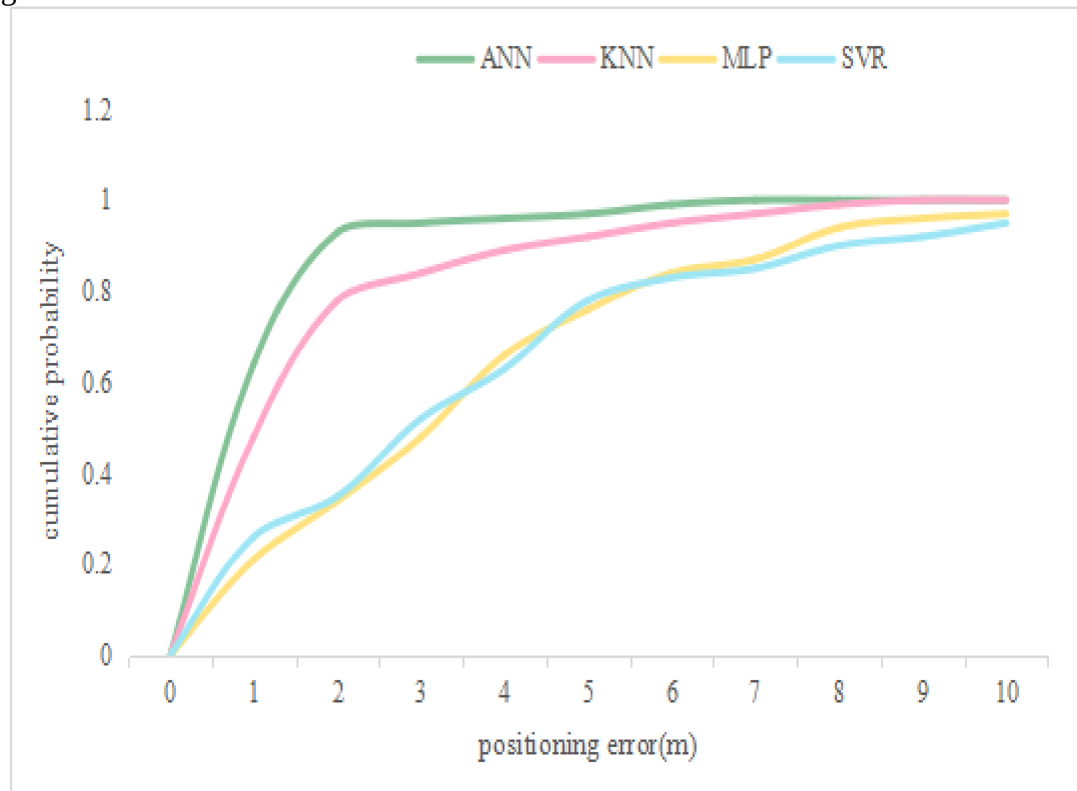

Fig. 3. Cumulative probability distribution curves of errors of different positioning algorithms

(2) Noise resistance analysis

Table 2. RMSE of different positioning algorithms

Signal to noise ratio(STNR)(dB)	10	15	20	25	30	35	40
ANN	0.96	0.91	0.87	0.86	0.84	0.81	0.77
KNN	1.05	0.98	0.94	0.92	0.89	0.83	0.78
MLP	1.08	1.04	1.01	0.95	0.90	0.85	0.79
SVR	1.17	1.11	1.08	0.99	0.91	0.82	0.77

Also, in order to compare the robustness of various LAs to noise, the localization accuracy of ANN, KNN, MLP, and SVR under different STNR conditions is compared. The root mean square error of localization of several algorithms under different STNR conditions is compared. From Table 2, it can be seen that the root mean square error of these LAs are getting smaller as the STNR becomes larger. The localization accuracy of the ANN LA under low SNR conditions is significantly higher than that of several other model algorithms, while the localization accuracy of several models under high SNR conditions is relatively close.

5. Conclusion

Many of the recent indoor localizations are based on ANN. The classical algorithm before is based on comparing data sets in a database, which is slower compared to the ANN approach because of the higher number of comparisons. In practice, many problems to be solved are very complex behavior patterns, due to the consideration of more factors, classical algorithms need to manually build models, often not comprehensive enough, the model is not complete to solve the real problem or can only solve the problem in a small area, the introduction of neural networks can make these problems can be better solved. The performance simulation experiments of the ANN LA in this paper also verify the superiority of the LA.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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