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A fingerprint-based localization algorithm based on LSTM and data expansion method for sparse samples

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ABSTRACT

The accuracy of WiFi fingerprint-based localization is related to the number of reference points, generally, to obtain better positioning accuracy, enough samples must be collected, which will inevitably lead to a huge sampling workload. Thus, it will be of great significance to design an algorithm using sparse samples to achieve positioning accuracy like that of dense samples. This paper proposes a WiFi fingerprint-based localization algorithm using Long Short-Term Memory Network (LSTM) with explainable feature and a sparse sample expansion algorithm (PGSE) based on Principal component analysis and Gaussian process regression for sparse samples. Specifically, in the case of limited number of collected reference points, principal component analysis is used to select the access point, and Gaussian process regression is used to model the reference point coordinates and the corresponding received signal strength values in the training sample set, to expand the signal data and construct a new fingerprint database. The effectiveness of the PGSE algorithm is verified by using the public dataset 'UJIIndoorLoc'. At the same time, the applicability of PGSE expansion algorithm to data with temporal information is verified in the fingerprint-based localization method. In addition, this paper also proposes a WiFi-RSSI indoor localization method based on Long Short-Term Memory Network. Lots of experiments are conducted in the actual scenes and the results are compared with several existing methods. The results indicate that the proposed method improves the precision of indoor localization on an average level compared to state-of-the-art methods.

1. Introduction

Recently, with the development of Internet of Things technique, people have a demand more and more for location information. Different localization methods are usually used in different localization environments. For outdoor environment, global positioning system (GPS) [1] has been widely applied. Compared with the outdoor environment, the indoor environment is more complex. Existing typical indoor localization technology mainly includes infrared positioning [2], ultrasonic positioning [3], Bluetooth positioning [4], RFID positioning [5], UWB positioning [6] and WiFi positioning [7]. Building a perfect indoor localization system has become a research hotspot in the field of location-aware services. Due to the popularity of WiFi equipment, WiFi signal has basically covered all indoor places. Compared with other positioning methods, WiFi does not require additional equipment, and the Internet of Things(IoT) has the potential to involve citizens with smart phones directly, which makes WiFi fingerprint-based positioning technology widely studied and adopted [8]. The overall positioning process based on WiFi fingerprint positioning is shown in Fig. 1. It can be seen that the positioning process is divided into two stages : offline data acquisition and online position matching. In the offline data acquisition phase, a large amount of data need to be collected to construct the location fingerprint database. The online location

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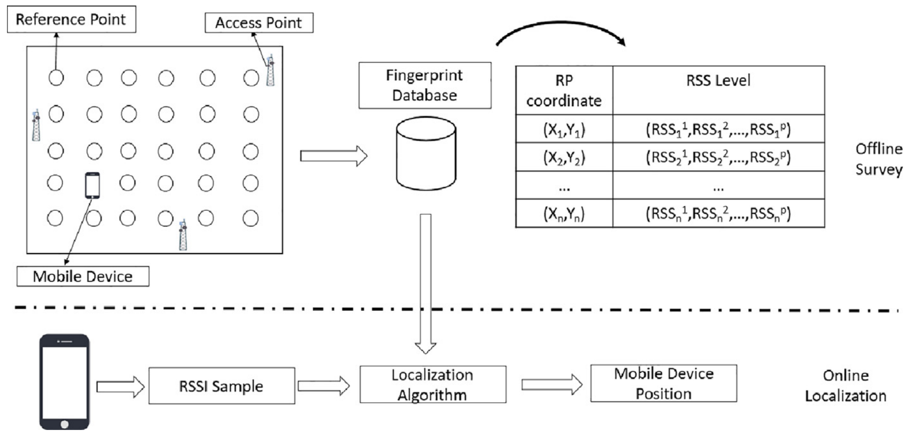

Fig. 1. Structure diagram based on location fingerprint-based localization.

matching phase will locate the user in real time by fingerprint matching algorithm.

The efficient construction of fingerprint database is the basis of WiFi fingerprint-based localization. In general, the quality of a fingerprint database will affect the positioning accuracy, which is mostly positively correlated with the number of reference points(samples). However, the more intensive the sample collection, the greater the labor cost, so how to use limited samples to achieve positioning accuracy close to dense samples has become a very meaningful research topic. Now most studies expand WiFi fingerprint samples by interpolation [9,10] and propagation model [11,12]. For the interpolation method, the representative methods are the spline function method [9] and the nearest neighboring point method [10]. Specifically, the former uses polynomial to fit the sampled reference points, and obtains a smooth curve to realize the prediction of RSSI value. It is only suitable for fitting the signal value with change, but not suitable for predicting the signal value with drastic change. The latter needs to divide the positioning area into sub-regions, and assign values to other reference points in the region by using the sampled reference point signal value in the sub-region. The disadvantage of which is that only the distance between the reference points is considered, ignoring the spatial distribution of the signal. For the propagation model, the representative methods are the one-slope model [11] and the multi-wall multi-floor (MWMF) [12] propagation model. Specifically, the former only considers the attenuation of signal strength with distance, which is simple to implement, but ignores the influence of obstacles, multipath effects and other factors, which is not suitable for predicting signal values in complex environments. The latter considers the influence of different obstacles in space on wireless signals, but due to the fluctuation of wireless signals and environmental factors, the predicted signal value is somewhat different from the real signal value. Some people also try to use Transfer Learning(TL) technology [13] to achieve data expansion. For example, [14] uses TL to transfer part of the information in the network trained by a large dataset to another network that only has a small training dataset to achieve data expansion. But TL is computationally intensive and influenced by trained networks. We carried out the research on the indoor localization algorithm for sparse samples, and proposed a fingerprint expansion method for sparse samples. This method fully considered the spatial distribution of signal propagation and environmental factors. Gaussian process regression was used to model the relationship between the reference point coordinates and the corresponding signal RSSI values, which effectively avoided the above problems, realized the low-cost sample expansion, and the expanded samples had strong adaptability.

The selection of localization algorithm is very important in the positioning process. With the development of artificial intelligence, the use of artificial intelligence to achieve localization has become a trend. Most of the current artificial intelligence-based localization algorithms are based on machine learning [15,16] and deep learning [17,18]. The commonly used machine learning based localization methods are K nearest neighbor algorithm (KNN) [15], random forest [16], etc. KNN [15] selected the average of the reference points with the minimum Euclidean distance as the coordinates of the target to be located. In [16], the grid position is used for secondary filtering and put into the random forest model to obtain the ultimate indoor position value. The mainstream methods based on deep learning include deep learning network [17], deep learning classifier [18], etc. In [17], integrating a recurrent neural network (RNN) and a stacked improved sparse autoencoder (SISAE), SISAE is constructed by adding logic regression layer as output layer in stacked encoder. In [18], The data preprocessing algorithm of deep learning classifier effectively fills the missing RSSI in the database, and the post-processing algorithm uses deep learning classifier to locate. Although the method mentioned above can realize position estimation, it does not consider that our positioning data has timing information, which will affect the accuracy of positioning in varying degrees. Here, we propose a WiFi fingerprint-based localization method based on Long Short-Term Memory networks, which can effectively improves the positioning precision of data with temporal information and has good applicability. At the same time, our location model based on LSTM is explainability.

This paper mainly studies the WiFi fingerprint-based localization algorithm based on PGSE (PCA-GPR sparse sample expansion algorithm) and LSTM (Long Short-Term Memory network) for sparse samples. The main contributions are as follows :

- A sparse sample expansion algorithm PGSE is proposed. PCA is used to select access points (APs). The coordinates of reference points in the training samples set and the corresponding RSSI values are modeled by GPR. Based on the RSSI value of the sampling reference point, the RSSI value of the unsampled reference point is generated.

- A localization algorithm based on LSTM is proposed. Considering the RSSI signal has timing information, the localization accuracy of the current position is improved by learning the historical signal data. Several sampling algorithms are designed to simulate different scenes of actual life and verify the adaptability of the algorithmic.

- The proposed PGSE algorithm can use a small number of samples to expand the data, while ensuring the localization effect, greatly reducing the workload of data collection. Compared with other localization algorithms, the LSTM localization algorithm not only improves the positioning accuracy, but also applies to various localization scenarios.

The other parts of this paper are divided as follows. The second part introduces the related work involved in the study. The third section gives the principle and implementation of PGSE extension algorithm. Section 4 introduces WiFi-RSSI localization model based on LSTM. Section 5 verifies the effectiveness of PGSE expansion algorithm, and describes WiFi-RSSI database and experimental results. The sixth part summarizes the full text. Finally, we look forward to the future work.

2. Related work

In the fingerprint database establishment phase need to collect a mass of data samples, will consume huge manpower. It is a trend to collect only a small part of the reference point data and generate unsampled point data based on the existing data.

Huang et al. [19] established a probabilistic framework on how to sample enough RSS measurements in off-line site surveys. Performance analysis was carried out based on limited sampling, and the sampling-related problems were solved theoretically, which provided meaningful guidance for efficient fingerprint database construction. In an effort to achieve the expansion of limited fingerprint database samples, Li et al. [20] added new sampling points on the third-order polynomial fitting curve to achieve the expansion of data. To reduce the influence of extended fingerprint database on localization precision. TAN et al. [21] transformed the high spatial correlation of RSS into a weighted kernel norm to accurately recover the unknown data, and then combined with KNN method to solve some problems that matrix completion cannot deal with. Recently, LI and WANG [22] trained the Gaussian process regression (GPR) model using the preprocessed fingerprint data, and optimized the hyperparameters of the model through the symbiotic biological search (SOS) algorithm to generate the fingerprint prediction model based on SOS-GPR to predict the RSS of non-reference nodes.

In summary, although many studies have been done on the expansion of fingerprint database, there is still a significant gap in the positioning performance between the application in the actual positioning scene and the use of dense samples. Specifically, in the existing research, when designing the fingerprint database expansion algorithm, the influence factors of RSS are not fully considered, and the data positioning accuracy after prediction expansion is not good enough. The paper proposes a sparse samples expansion algorithm PGSE based on PCA-GPR. The algorithm first uses Principal Component Analysis (PCA) to select the access points (APs), and then models the reference point coordinates and corresponding RSSI values in the training sample set through Gaussian Process Regression (GPR), The RSSI value on each non sampled reference point is generated according to the RSSI value of the sampled reference point, so as to expand the signal data under the WiFi signal with limited samples.

At present, many people are committed to the research of fingerprint-based localization method, aiming to construct an indoor positioning system (IPS) with low cost, high precision and strong adaptability.

To improve the robustness of the localization system, Paramvir Bahl et al. [23] used KNN method to find the closest position matching based on the original WiFi fingerprint-based localization system. Then, [24–26] proposes a Bayesian-based filtering method. Subsequently, [27] uses support vector machine (SVM) and [28,29] uses compressed sensing (CS) to associate RSSI samples with fingerprint database. In terms of reducing the collection burden of fingerprint database, Sinno Jialin Pan et al. [30] put forward a transfer learning. Newly, Yangming Li et al. [31] put forward a method of shunting short-term memory to solve the localization problem in dynamic condition. Zhang and Liu et al. [32] proposed to use a Deep Neural Networks to extract the characteristics of the wireless signal, perform coarse localization, and finally pass the coarse localization results into the Hidden Markov Model to obtain the final location. Jang et al. [33] first converted one-dimensional wireless signal data into two-dimensional data, and then used a Convolutional Neural Networks to extract features.

However, in the actual environment, due to target occlusion, etc., wireless signals will fluctuate, which is the main factor affecting fingerprint-based localization accuracy. RSSI is different at different times, even at the same location. To improve positioning accuracy, we need to collect a large number of access point (AP) information. Therefore, the fingerprint database data will continue to grow. How to pick-up effective features from a mass of data and find optimal location matching is a challenge for WiFi-based IPS. In this study, considering the data is time series, a localization model based on LSTM is proposed to solve the indoor localization problem. LSTM framework is divided into offline training stage and online positioning stage. Offline training stage, by learning the historical signal value to predict the current location; in the online localization stage, the test data is used to verify the localization performance of the regression model.

3. Sparse samples expansion based on PGSE

PGSE algorithm realizes the expansion and improvement of the fingerprint database with limited sampling, and improves the coverage and availability of the fingerprint database. The fingerprint database with limited sampling means that in the case of limited manpower and time, only a small amount of reference points are collected in the localization area, and the RSSI data on the corresponding reference point is less.

3.1. Principle of PGSE algorithm

3.1.1. Positioning area division and selection of reference points

Let the length and width of the positioning area be l and W, and take the direction of the length as the $x-axis$ and the direction of the width as the $y-axis$. The localization area is divided according to the interval size. Each small area represents a reference point. The coordinates of the center point of the region is used as the coordinates of the corresponding reference point, and the corresponding coordinates is recorded according to their positions in the coordinate system. In order to reduce the workload of data collection, it is necessary to determine the reference point for data collection in advance. When meshing has been performed, select some reference points according to the interval in the $x-axis$ direction and the interval in the $y-axis$ direction. The specific interval size determined by the size of the location area, environment and other factors.

3.1.2. Construct training samples

The collected data is preprocessed to remove the incorrect data, and the missing RSSI value is compensated by -100 dBm. Then, the coordinate position of the reference point and the corresponding RSSI values vector group are spliced to form a fingerprint data. Finally, all the collected data are combined to construct training samples. The implementation of the specific PGSE algorithm is shown in Fig. 2.

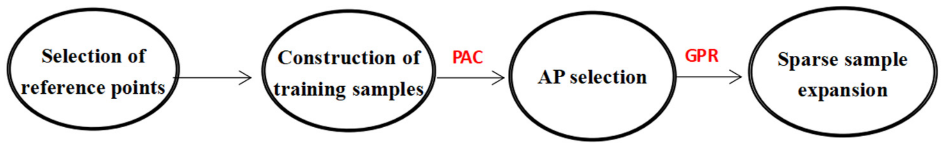

Fig. 2. Overall flow chart of PGSE algorithm.

3.1.3. AP selection algorithm based on PCA

In the process of location, increasing the number of APs in the fingerprint database can improve the location positioning in some degree, but the number of APs is not the more the better. Some AP points only have RSSI values at individual reference points, which are missing in most reference points. Such AP points like this will not help indoor location, but will waste the storage capacity of fingerprint database and consume unnecessary computing resources. To solve this problem, we used Principal Component Analysis (PCA) [34] to select AP. In the AP selection algorithm based on PCA, we assume that there is m n-dimensional RSSI data, and the original RSSI data is recomposed into a row and column matrix X according to the column. For each row of matrix X minus the mean of the row; the covariance matrix of X is solved, and the corresponding eigenvalues and eigenvectors are solved according to the covariance matrix; the feature vector is composed of $n \times n$ dimension feature matrix P by column, the maximum of each column is regarded as the evaluation index of the i column, and the $n \times 1$ evaluation vector S is formed, and the S is normalized. Finally, the first k of S is selected according to the numerical size, which is the corresponding effective AP is obtained.

3.1.4. Sparse sample expansion process based on GPR

In many location scenarios based on fingerprint database, there will be insufficient RSSI data collected in the localization area. We can use GPR [34] to model the relationship between the coordinates of the reference point and the corresponding RSSI signals value, and predict and generate the corresponding signal value on the unsampled reference points through the existing signal value, Then realize the expansion of fingerprint database.

Gaussian Process Regression [35] is defined as:

$$f(x) \sim GP(m(x), k(x, x')) \tag{1}$$

where, $x, x' \in R'$ represents any random variable, $m(x)$ and $k(x, x')$ are mean function and covariance function respectively.

We can assume that $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ is a set of training samples [36,37]. Considering the interference of noise in the real positioning environment, we can define this random process as a random process with noise term, as shown in formula (2):

$$y_i = f(x_i) + \varepsilon \tag{2}$$

where x_i represents a reference point coordinate defined on R, and y_i represents an output value defined on R, and the RSSI signals value corresponding to x_i; f represents the function value; ε is a Gaussian noise term satisfying $\varepsilon \sim N(0, \sigma_n^2)$ [38]. The matrix composed of n reference points is represented by X, and the vector composed of the corresponding signal values of n reference points is represented by Y. According to the training sample set, the posterior probability distribution of function f can be obtained by GPR.

The key of GPR is that for any two reference points x_p and x_q, the covariance of the corresponding function values $f(x_p)$ and $f(x_q)$ is not equal to 0. The specific value depends on the correlation between the two reference points. The signal distribution in indoor localization conforms to this law. For any AP, the signal values collected at different reference points are related. This property can be described by kernel function $k(x_p, x_q)$ [39]. Gaussian kernel is the most widely used at present, as shown in formula (3):

$$k(x_p, x_q) = \sigma_f^2 e^{-\frac{(x_p - x_q)^2}{2l^2}} \tag{3}$$

where σ_f^2 is the variance of the signal and l represents the length of the feature, which is used to describe the strength of the correlation between two reference points. The two parameters jointly determine the smoothness of the function cluster estimated by GPR [40]. The correlation between the values of any two reference point functions can be inverted by the formula (3). Due to the interference of many factors in the real environment, the random noise brought by the environment will be introduced more or less in the process of collecting data. To better express the signal distribution in the real environment, it is necessary to add the noise factor to the covariance function, so the covariance of the signal value with noise is obtained, as shown in formula (4).

$$Cov(y_p, y_q) = k(x_p, x_q) + \sigma_n^2 \delta_{pq} \tag{4}$$

where σ_n^2 denotes the Gaussian observation noise, and δ_{pq} denotes the strength relationship between p and q at the sample point. When $p = q$, $\delta_{pq} = 1$ otherwise $\delta_{pq} = 0$. For any set of reference points X, the covariance of the corresponding signal value Y is

$$Cov(Y) = K + \sigma_n^2 I \tag{5}$$

where K represents a $n \times n$ dimensional covariance matrix, $K[p, q] = k(x_p, x_q)$ and I represents an n-order unit matrix. Formula (5) denotes the prior probability in the function space. For any set of reference points X and signal value Y, a covariance matrix K can be calculated by Gaussian kernel function, and the signal value obeys the joint Gaussian distribution, $Y \sim N(0, K + \sigma_n^2 I)$. Therefore, under the premise of known training samples X, Y, it is necessary to confirm the function value of the unsampled reference point x_*.

Formula (3) can be obtained that the posterior function value obeys $N(u_*, \sigma_{x_*}^2)$, and then according to the Bayesian formula to get

$$p(f(x_*)|x_*, X, Y) = N(f(x_*); u_{x_*}, \sigma_{x_*}^2) \tag{6}$$

where,

$$u_{x_*} = k_*^T (K + \sigma_n^2 I)^{-1} Y \tag{7}$$

$$\sigma_{x_*}^2 = k(x_*, x_*) - k_*^T (K + \sigma_n^2 I)^{-1} k_* \tag{8}$$

where k_* represents the $n \times 1$ dimensional covariance vector between x_* and n reference points, K represents the n-order covariance matrix between training samples X. It can be concluded from formula (7) that the mean value is a linear combination of signal values of training samples, and the weight of each signal value is determined by k_*. $(K + \sigma_n^2 I)^{-1}$ is the inverse matrix of formula (5), and $\sigma_{x_*}^2$ is not related to the signal value Y.

For a specific AP point, the RSSI value is correlated at different reference points. The training sample consists of input vector X and observation value Y. X represents the coordinate of the reference point. Without considering the floor, it is a two-dimensional plane coordinate, and Y represents the RSSI value

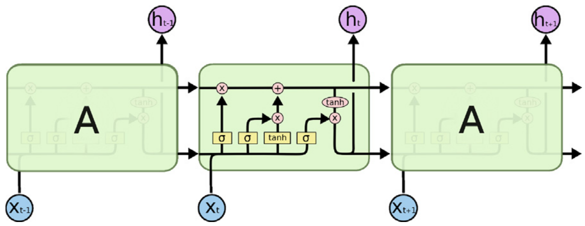

Fig. 3. The structure of LSTM.

collected at the corresponding reference point. Assuming that each AP is independent of each other, the relationship between the reference point coordinates and the corresponding RSSI value in training sample set is modeled by GPR, and the RSSI value on each unsampled reference point is generated according to the RSSI value of the sampled reference point. According to formula (7) and formula (8), the corresponding signal value $RSSI_* = \mu_*$ for any reference point loc_* can be obtained, and the uncertainty of the estimation result is σ_*^2. Through further calculation, the mean and variance of RSSI value of AP corresponding to each reference point can be obtained.

In the process of calculation, parameters σ_n^2, l and σ_f^2 are important for results, which are collectively called hyperparameters. Let the hyperparameters be $\theta = \{\sigma_n^2, l, \sigma_f^2\}$[31], and we use the logarithmic likelihood function of the maximum signal value vector Y to calculate. Since the signal value vector follows the joint Gaussian distribution, the log-likelihood function can be obtained as shown in formula (9), and then the optimal solution can be obtained by Newton iteration method or conjugate gradient descent method.

$$logp(Y|X,\theta) = -\frac{1}{2}(Y^T(K+\sigma_n^2 I)^{-1}Y + log|K+\sigma_n^2 I| + nlog2\pi) \quad (9)$$

For the partial derivative of formula (9), as shown in formula (10):

$$\frac{\partial}{\partial\theta_j} logp(Y|X,\theta) = \frac{1}{2} tr((K^{-1}Y)(K^{-1}Y)^T \frac{\partial K}{\partial\theta_j}) \quad (10)$$

If Eq. (10) is equal to 0, the hyperparameters θ can be solved. Taking Gaussian kernel function as an example, for each covariance $K[p,q]$ in K, the corresponding partial derivative is:

$$\frac{\partial K}{\partial\sigma_f^2} = 2\sigma_f e^{-\frac{1}{2}(\frac{x_p - x_q}{l})^2} \quad (11)$$

$$\frac{\partial K}{\partial l} = \sigma_f^2 e^{-\frac{1}{2}(\frac{x_p - x_q}{l})^2} \frac{(x_p - x_q)^2}{l^3} \quad (12)$$

$$\frac{\partial K}{\partial\sigma_n^2} = 2\sigma_n \delta_{pq} \quad (13)$$

3.2. PGSE algorithm implementation

The sparse sample expansion algorithm PGSE is mainly written and implemented in Python based on numpy, pandas, skleran and other deep learning frameworks.

The implementation process of PGSE algorithm such as Algorithm 1.

Algorithm 1 The sparse sample expansion algorithm.

INPUT:
The set of the AP' information,denoted $\{R_{n,m}, L_{n,2}\}$;
OUTPUT:
The fingerprint database, denoted $\{R'_{N,M}, L'_{N,2}\}$;
Read R_{nm}, L_{n2};
Matrix X that restores the original data to m rows and n columns by column;
Each row of X minus the mean of this row;
Calculating the covariance matrix $C = \frac{1}{m}XX^T$;
Calculating the eigenvalues and eigenvectors of C;
The feature vector forms a $n \times n$-dimensional feature matrix P in columns and the maximum of each column is used as the evaluation index of the $i-th$ column to form an evaluation vector S of $n \times 1$,and S is normalized.
Selecting the first k according to the numerical value of S to obtain the corresponding AP.
Construct a training sample set based on matrices S and L, denoted $T_{n,k+2}$;
Initialize the AP's number and the coordinates that need to be predicted denoted by AP Num and $pred_{coor}$;
for each AP Num **do**
  Choose gaussian kernel;
  Use GPR to model the reference point coordinates and corresponding RSSI values;
  Generate RSSI value at each prediction point;
  for each RSSI **do**
    Use the normal distribution to expand the data.
  end for
end for
Dimension transformation of the expanded data, joint coordinates $pred_{coor}$, and build a fingerprint database;
Output the fingerprint database $\{R'_{N,M}, L'_{N,2}\}$.

4. WiFi-RSSI location model based on LSTM

4.1. Location principle based on LSTM

RNN [41] has a Long-Term dependency problem. As the gap between relevant information and points increases, RNN becomes unable to learn connection information. LSTM can solve this problem well. In this paper, we propose a location method based on LSTM to predict location. LSTM [42] is a special RNN that can learn Long-Term dependencies. Its structure is shown in Fig. 3.

LSTM controls the state of neural units mainly through the forgetting gate, input gate and output gate. Each layer of neural network will splice the current input X_t and the output h_{t-1} of the previous layer to get the vector $[X_t, h_t]$, and the vector will be four different operations. Through the control structure, LSTM avoids the problems of gradient explosion and gradient disappearance. Practice shows that LSTM is superior to RNN in time series prediction [42].

4.2. Location model based on LSTM

The localization model is shown in Fig. 4, which consists of offline training and online localization. In the offline training phase, put fingerprint data into LSTM for training. First, the data are preprocessed, and the data are reconstructed according to the specific length. Then initialize the network parameters and train them. After a series of fine-tuning, the regression model is finally obtained. LSTM training is to determine the structure of the neural network and the weights of each neuron. In the online localization stage, the performance of the regression model is evaluated by using the test database.

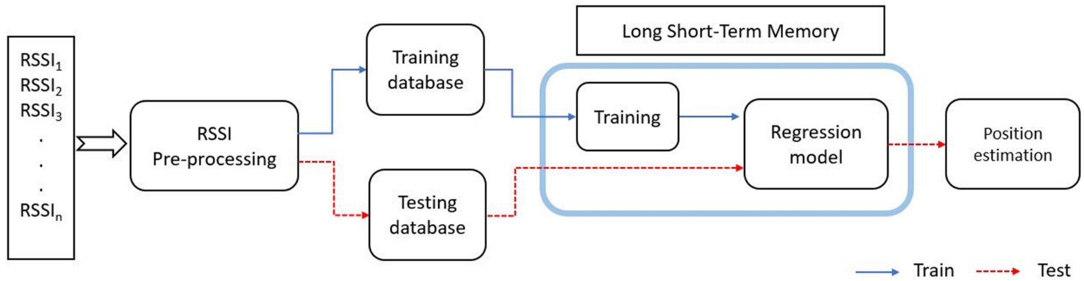

Fig. 4. The structure of WiFi localization model based on LSTM.

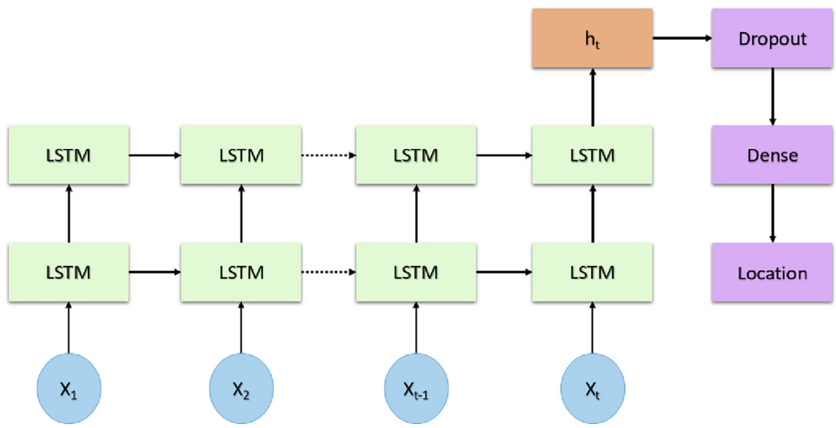

Fig. 5. The structure of double layer LSTM.

In this study, a double-layer LSTM is used, which mainly includes feature extraction network and output network. The network structure is shown in Fig. 5. X_i is the RSSI signal value received at the i time, and h_t is the output value at the t time.

Feature extraction network, we set the input signal sequence to $M = [x_1, x_2, \ldots, x_n]$, which represents the signal strength of a continuous n time to be located. $X_i = [r_1, r_2, \ldots, r_k]$ is a one-dimensional vector, which represents the signal strength received at the i time, where r_k represents the RSSI signal value received at the k AP. After calculation of forgetting gate, input gate and output gate, the output result h_t of the network is finally obtained.

Output network, add Dropout layer and Dense layer after feature extraction network. Dropout is a regularization technique commonly used in neural networks. By setting the dropout_rate value($dropout\_rate \in [0, 1]$), the partial connection in the network is broken randomly, which can effectively avoid the problem of overfitting. The Dense layer is a fully connected layer, which is used to set the dimension of output. In this paper, LSTM is mainly used for positioning, so the output dimension here is 2. In addition, the activation function will be set in different ways to calculate the final results.

Our localization process uses a deep learning model, and the explainability of deep learning is very important in the field of artificial intelligence. The strength of explainability will affect the trust of the model. In the process of establishing the model, we have reliable theoretical support from data collection and data preprocessing, data feature extraction, model parameter setting, and model output verification. It can be seen from Figs. 4 and 5 that the WiFi fingerprint-based localization model based on LSTM constructed by us can easily follow the decision of LSTM model, so the positioning process based on LSTM is explainability and satisfies X-AI(explainable artificial intelligence). In the localization model, Pandas is used to read the data, Scikitlearning and Numpy are used to normalize and format the data, and Keras calculates and updates the parameters.

Table 1
The reconstructed sequence data.

Signal value sequence	Location
$[R_0, R_1, R_2]$	$[x_2, y_2]$
$[R_1, R_2, R_3]$	$[x_3, y_3]$
…	…
$[R_{n-3}, R_{n-2}, R_{n-1}]$	$[x_{n-1}, y_{n-1}]$
$[R_{n-2}, R_{n-1}, R_n]$	$[x_n, y_n]$

4.3. Data pre-processing

In order to eliminate the adverse effects of abnormal data and improve the calculation speed, the data are regularized between [0, 1] through the maximum and minimum normalization. Because LSTM is suitable for processing sequence data, and the original data does not have this feature, it is necessary to reconstruct the original data to make it have timing information. First, select k consecutive data over time to construct the sequence, use the location of the last time point as the label, and then construct in turn by sliding a window each time, repeat this process until all data are processed. The reconstructed sequence data are shown in Table 1. For the convenience of drawing tables, the construction process of $k = 3$ is shown.

4.4. Basic parameter settings and optimizer selection

According to Kingma et al. [43], the Adam method is a stochastic gradient descent method based on first and second moment adaptive estimation, which has high computational efficiency, small memory requirement, and constant diagonal rescale of gradient, and is very suitable for the problem of large data/parameters. Therefore, Adam is selected as the optimizer in this study.

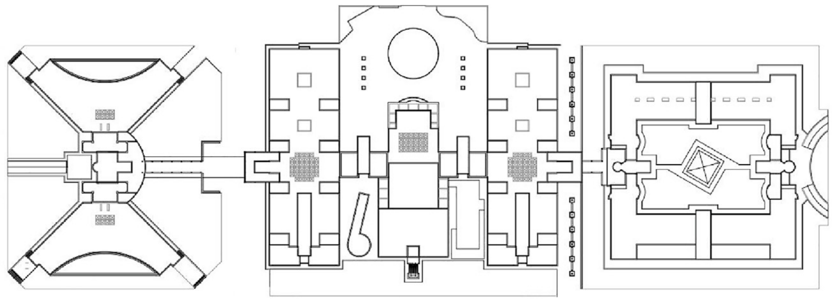

Fig. 6. UJI Riu Sec campus map.

The dimension of input layer data is 24, which is the coordinates x, y of 22 RSSIs (22 APs) obtained at the reference point and the reference point. The output layer output is the coordinates, so the output dimension is 2, the dimension of the hidden layer is 256, the training cycle is 100, the sequence length is 5, the batch_size is 10, the learning_rate learning rate is 0.01, and the dropout_rate is 0.35.

4.5. Definition of loss function

In this study, LSTM weights are trained by back propagation(BP) loss function. The smaller the difference between the actual coordinates and the predicted coordinates is, the more accurate the positioning results are. Therefore, we choose the loss function as mean square error(MSE). The calculation formula is as follows :

$$MSE = \frac{1}{n}\sum_{i=1}^{n}((x_p - x_i)^2 + (y_p - y_i)^2) \tag{14}$$

where (x_i, y_i) is the real coordinates of reference point sample i, (x_p, y_p) is the estimated coordinates of reference point sample i, and n is the number of samples.

5. Experiments

This section has two main aspects. On the one hand, the PGSE expansion algorithm proposed in this paper is verified. Firstly, the UJIndoorLoc public dataset and the experimental hardware and software environment are introduced. Then, the sparse data are expanded. Finally, the similarity between the expanded data and the original data is compared from the two perspectives of Euclidean distance and Chebyshev distance, and the effectiveness of the PGSE expansion algorithm is verified. On the other hand, the LSTM localization algorithm is verified. Firstly, the experimental environment, data acquisition and processing are introduced, and then the basic parameters of LSTM are introduced and some comparative experiments are carried out. Finally, the application of PGSE in fingerprint database localization verifies the applicability of PGSE extension algorithm to time information data.

5.1. Verification of PGSE extension algorithm based on public datasets

5.1.1. Dataset setting

The UJIndoorLoc dataset [44] is a multi-architectural multi-floor WiFi fingerprint database published by Universitat Jaume I of Spain in 2014. The UJIndoorLoc dataset is collected by more than 20 users on the UJI Riu Sec campus with 25 different types of mobile devices. The campus covers an area of 108 703 m^2, mainly including 3 buildings. The first two buildings have 4 layers, and the third building has 5 layers, as shown in Fig. 6. The number of dataset reference points is 933.

Table 2
UJIIndoorLoc database attributes.

Number	Attributes
001–520	RSSI levels
521–523	Real world coordinates of the sample points
524	BuildingID
525	SpaceID
526	Relative position with respect to SpaceID
527	UserID
528	PhoneID
529	Timestamp

Table 3
Some examples of UJIIndoorLoc database.

Number	Attributes
001–520	−97, …,+100
521	−7594.7...
522	4 864 983.9...
523	3
524	0
525	111
526	2
527	11
528	13
529	1 370 340 142

The UJIIndoorLoc dataset contains 19 938 samples for training, 1111 samples for testing, and a total of 21 049 sampling points. As shown in Table 2, each record in the dataset contains 529 attributes. The first 520 attributes are RSSI signal values for wireless APs. The following nine attributes are building number, space number, relative position of space number, latitude and longitude, number of users, equipment number and measurement timestamp. The UJIIndoorLoc dataset instance shows in Table 3. Because there are too many reference points in the UJIIndoorLoc dataset, we only use the data of 98 reference points in the upper part of the third building in Fig. 6 for experiments.

5.1.2. Selection of AP

The UJIIndoorLoc dataset has 520 APs, and most APs in the dataset are invalid data. Therefore, APs need to be screened. The paper mainly uses the AP selection algorithm based on PCA, and 74 effective APs are obtained after selection. To verify the accuracy of AP selection algorithm based on PCA, we use Recursive Feature Elimination (RFE) based AP selection algorithm to filter AP again. The main idea of AP selection algorithm based on RFE is to delete one or more of the weakest features by recursively constructing the training model of RSSI and coordinates until reaching the specified number of features. The experimental results show that the results of the two AP selection algorithms are consistent, and the final results are 74 APs.

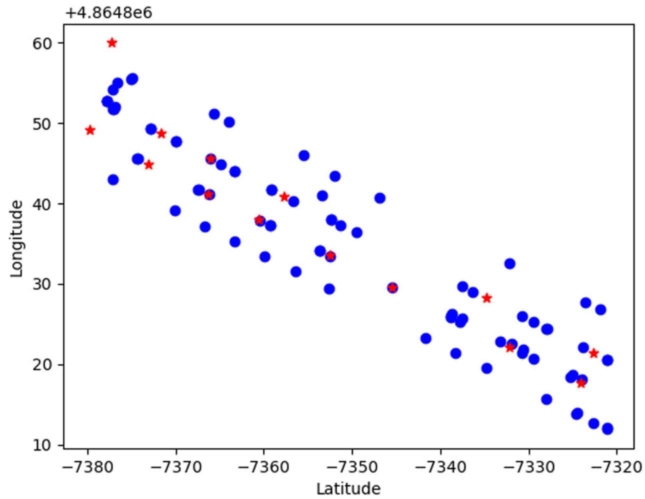

Fig. 7. The map of UJI Riu Sec campus sample expansion.

5.1.3. Data expansion results

Expand the sparse samples on the collected data of the third building. There are 98 reference points in the original data. Here, the data of 14 reference points are used to predict the data of other 84 unsampled points, as shown in Fig. 7, in which the red star represents the selected 14 reference points and the blue circle represents other unsampled points.

5.1.4. Data similarity measurement

To compare the similarity of numerical properties, we use Euclidean distance and Chebyshev distance to calculate the similarity of the expanded dataset to the original dataset.

We often use Euclidean distance to judge the distance between two vectors. Its formula is as follows:

$$sim(v_1, v_2) = \sqrt{(v_{11} - v_{21})^2 + (v_{12} - v_{22})^2 + \cdots + (v_{1n} - v_{2n})^2} \tag{15}$$

where v_1 and v_2 represent two vectors described by numerical attributes, n is the dimension of vector. Here n is the number of AP is 74.

Chebyshev distance is defined as the maximum absolute value of the difference between two vectors. The formula is as follows :

$$sim(v_1, v_2) = \max_i (|v_{1i} - v_{2i}|) \tag{16}$$

where v_1 and v_2 represents the two vectors described by the numeric properties, $\max_i$ represents the maximum value of all numeric differences.

The similarity of RSSI signal values corresponding to 84 reference points in the expanded dataset and the original dataset is shown in Fig. 8. We can know that the maximum Euclidean distance between the two datasets is 146, and the minimum Euclidean distance is 32. For $n \times 74$ dimensional datasets, the two datasets are very similar. In addition, from the Chebyshev distance of the two datasets, the maximum distance of a single data is 95, the minimum distance is 14, and the average distance is 38, which can also verify that the two datasets are very similar. By comparing the similarity of two datasets, the effectiveness of PCA-GPR sparse sample expansion algorithm PGSE is further verified.

Table 4
Some examples of reading room data.

WiFi name	MAC address	RSSI levels	X	Y
IMUDGES Pro	d4:a1:48:a4:87:3c	−83	1	1
network	f4:83:cd:91:16:62	−82	2	1
NETGEAR	00:0f:b5:35:32:a4	−48	3	1

Table 5
Reading room database attributes.

Index	Attribute
01–22	RSSI levels
23	X
24	Y

5.2. LSTM-based localization algorithm validation

In the experiment, the average localization error (ALE) is used to measure the positioning performance. The distance formula between two points calculated by Euclidean distance is as follows:

$$d(i, k) = \sqrt{(x_i - x_p)^2 + (y_i - y_p)^2} \tag{17}$$

where i and p are the real points and prediction points, respectively.

The smaller the average localization error is, the better the positioning performance is. We calculate the average distance $\overline{d}$ as ALE.

$$\overline{d} = \frac{1}{n}\sum_{i=1}^{n} d(i, p) \tag{18}$$

5.2.1. Experimental data

During the experiment, a large-scale database containing location tags is needed to evaluate the properties of localization. In this experiment, we choose the third floor reading room of Inner Mongolia University Library [45]. As shown in Fig. 9, the reading room covers nearly 1000 m^2, including 57 bookshelves about 2 m high and some large and long tables and chairs. The space is divided into regular grids with an interval of 1 m, with a total of 938 reference points.

Next, we collect data at each reference point with a mobile phone in the reading room. The collected data includes WiFi name, MAC address, RSSI level, X and Y five attributes. Part of the collected data are shown in Table 4.

Then, we process the collected data and establish a WiFi fingerprint database. The training database has 727 sampling points, each sampling point includes 22 wireless access points, coordinate points (X, Y), test data 158 sampling points. In order to ensure the independence of the data, the training data and test data are collected respectively, and the data are collected at each reference point by uniform walking. The properties of the reading room database are shown in Table 5.

5.2.2. Data generation

Training data are collected at 727 reference points; test data is collected in 158 test points. The collected data is stored in the form of text on line, each line data includes AP name, AP MAC address, RSSI signal value. Firstly, read the data, get the MAC address of all APs, and number the MAC address; then rearrange the RSSI signal value of each AP according to the number; because RSSI value range is generally between [−90 dBm, −30 dBm], for missing data, use −100 dBm to fill. A 22-dimensional array of signal values m is then obtained, which represents the RSSI signal value received by the i AP. The coordinates (x_i, y_i) of the

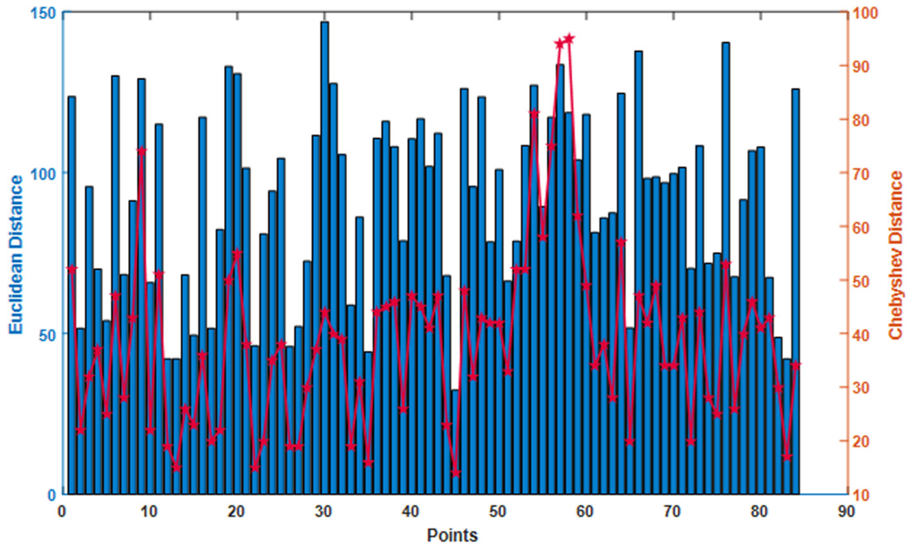

Fig. 8. The result of similarity calculation.

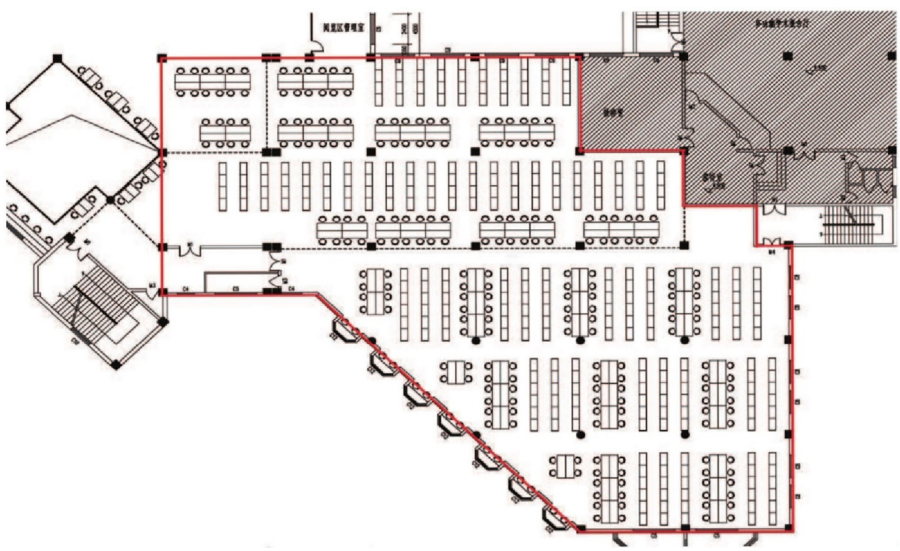

Fig. 9. The floor plan of reading room.

reference point are appended to the tail of the corresponding $R_i = [r_1, r_2, \ldots, r_{22}]$ to form a new data $[R_i, x_i, y_i]$. Finally, all the new data are combined to construct the corresponding training database and test database.

5.2.3. Sequence length selection

Different sequence length will have different effects on the localization results. In order to explore the influence of the input sequence length on the localization accuracy, we have tested different sequence lengths, and the corresponding localization error is shown in Fig. 10. It can be seen from the figure that when the sequence length is 5, the average localization error of the test dataset is 3.91 m, and the running time is medium, which is one of the optimal localization results in all sequence lengths. Combined with the actual situation, due to the bookshelf, desks and chairs, the effective length of the sequence is limited. In summary, this paper sets the sequence length to 5, that is, at most, only the data of the past four moments are used for calculation.

5.2.4. Layer selection

Because LSTM is based on time series, so it is difficult to parallel computing, the increase of layers will bring exponential growth of time and memory overhead. When the number of layers reaches 3, the adjacent two layers will disappear, and the convergence effect and efficiency will also decrease sharply. In order to explore the influence of layers on positioning accuracy, different layers are tested, and the corresponding localization error is shown in Fig. 11. It can be seen from the graph that when the number of layers is 2, the average positioning error of the test dataset is 3.07 m. When the number of layers is 1 and 3, the corresponding average localization error exceeds the number of layers 2. When the number of layers is 2, the running time is medium and the positioning performance is the best, so the number of layers is 2.

5.2.5. Training cycle selection

The training period is used to control the number of neural network learning on the training set. In different training cycles, the learning ability of neural network to data is different. In order to explore the influence of different training periods on

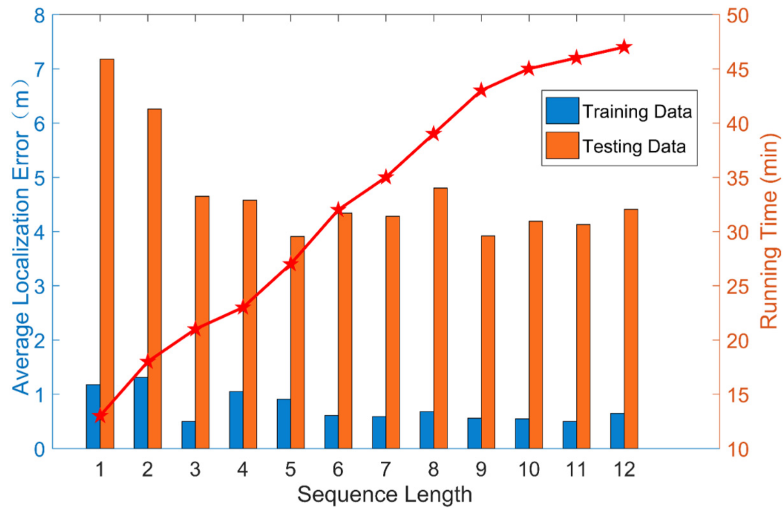

Fig. 10. The average localization error and running time of different sequence lengths.

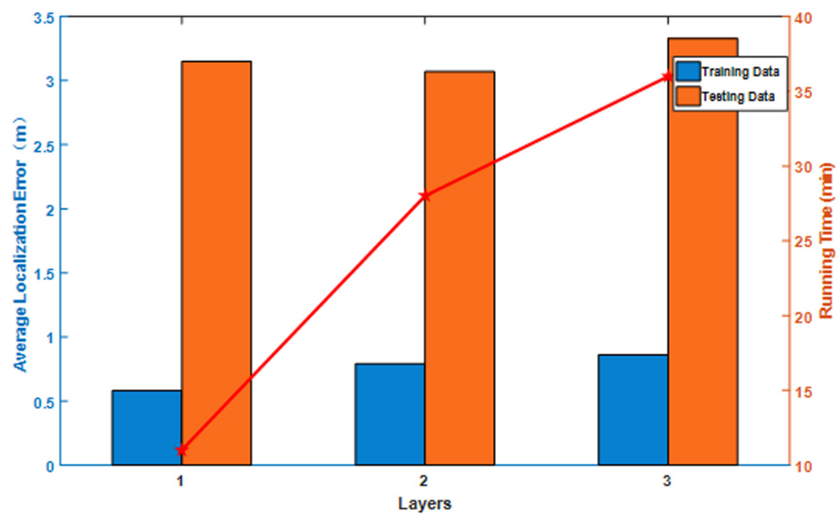

Fig. 11. The average localization error and running time of different layers.

positioning accuracy, different training periods are tested, and the corresponding localization error is shown in Fig. 12. It can be seen from the middle year of the figure that when the training cycle is 100, the average localization error of the test dataset is 3.03 m, and the running time is medium. Other training cycle localization errors are more than 3.2 m. Considering the positioning accuracy and running time, the training cycle of 100 can achieve the optimal effect, and can avoid underfitting and overfitting.

5.2.6. Experimental results

We compared the localization algorithms based on different machine learning methods, and used the LSTM localization method in different scenarios. Validation of LSTM algorithm and scene applicability.

Comparison of the results of different machine learning methods: The Localization errors generated by different localization methods are shown in Table 6, and their CDFs are shown in Fig. 13. It is obvious that LSTM is superior to the other six localization methods. The probability of localization error within 10 m of LSTM localization algorithm is 92%, while the probability of localization error within 10 m of DNN, KNN, SVM, DecisionTree, RandomTree and ExtraTree is about 28%. As can be seen from Table 6, the average localization error of LSTM is 3.2 m, while the average localization error of the other 6 methods is more than 10 m. Overall, the localization effect of LSTM is better than that of other methods.

Table 6
Location results of different machine learning methods.

Method	Average localization error (m)
LSTM	3.2
DNN	14.8
KNN	16.8
SVM	16.8
DecisionTree	17.3
RandomTree	16.2
ExtraTree	15.9

Comparison of LSTM in different scenarios: The original data is collected at a uniform speed. Considering real life scenarios, there will be various situations. So in order to further explore the robustness of LSTM, we resampled the original data and constructed new data. Resampling includes the following methods: random, interval and random+interval. Original is the raw data, without re-sampling; Random: For each point, we use a random number to determine whether to sample the point or not; Interval-2: re-sampling at 2 intervals each time; Interval-4: re-sampling at 4 intervals each time; Mix-2 : Use interval of 2

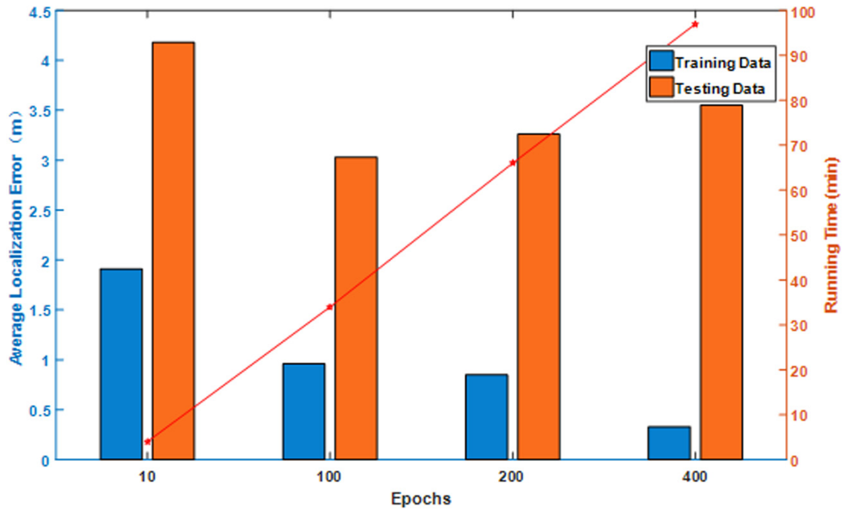

Fig. 12. The average localization error and running time of different epochs.

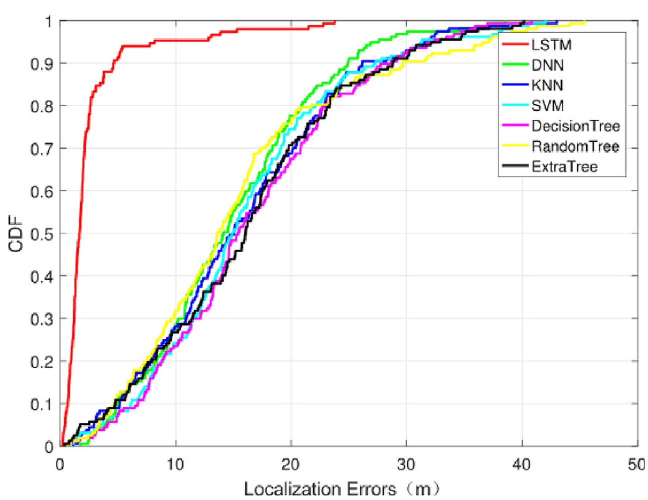

Fig. 13. Location results of different machine learning methods.

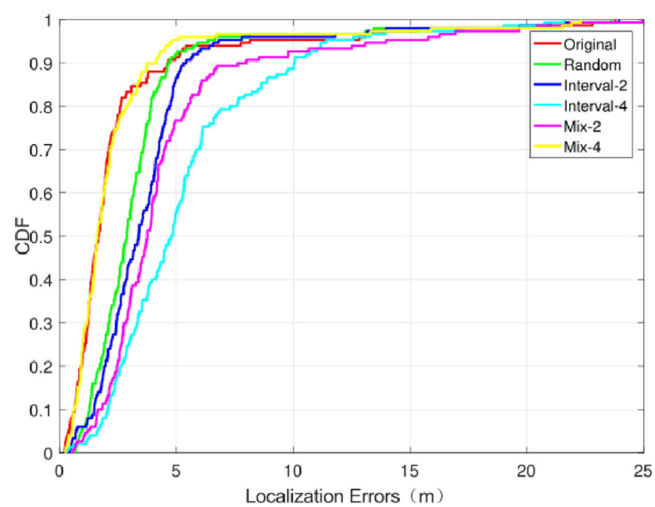

Fig. 15. The comparison of LSTM in different scenarios.

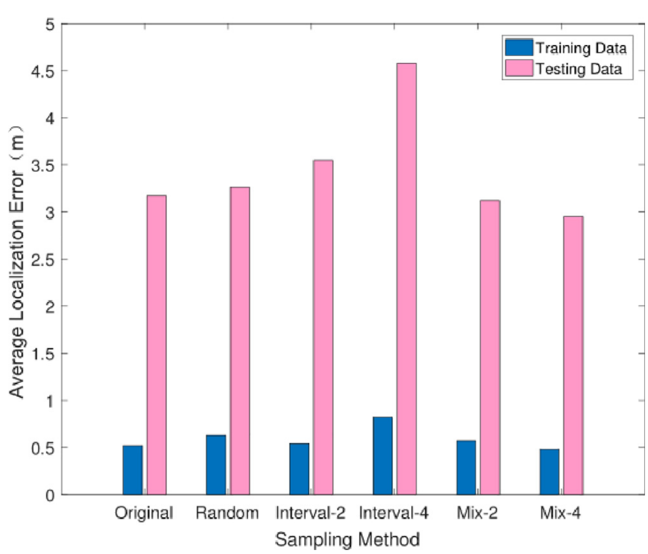

Fig. 14. The comparison of LSTM in different scenarios.

and random sampling combination ; mix-4 : Use interval of 4 and random sampling combination. Through the above methods, we can obtain data in different localization scenarios, and use these new data to validate the localization performance of LSTM. The location error of different localization scenarios as show in Fig. 14, and their CDFs are illustrated in Fig. 15. It can be seen that the localization error of most scenarios is about 3 m, and only one scenario is about 4.5 m.

5.3. Application of PGSE algorithm in fingerprint location

5.3.1. Sample expansion

The PGSE sparse sample expansion algorithm is used to expand the sparse sample based on the original data. There are 727 reference points in the original data. Here, the data of 61 reference points are used to predict the data of other 994 unsampled points at an interval of 1 m, as shown in Fig. 16. The red stars are the selected 61 reference points, and the blue circles represent other unsampled points. After data expansion, there are 1056 data.

5.3.2. Comparison of different localization algorithms

Different positioning algorithms are used to locate the fingerprint database formed by the expanded samples. The average

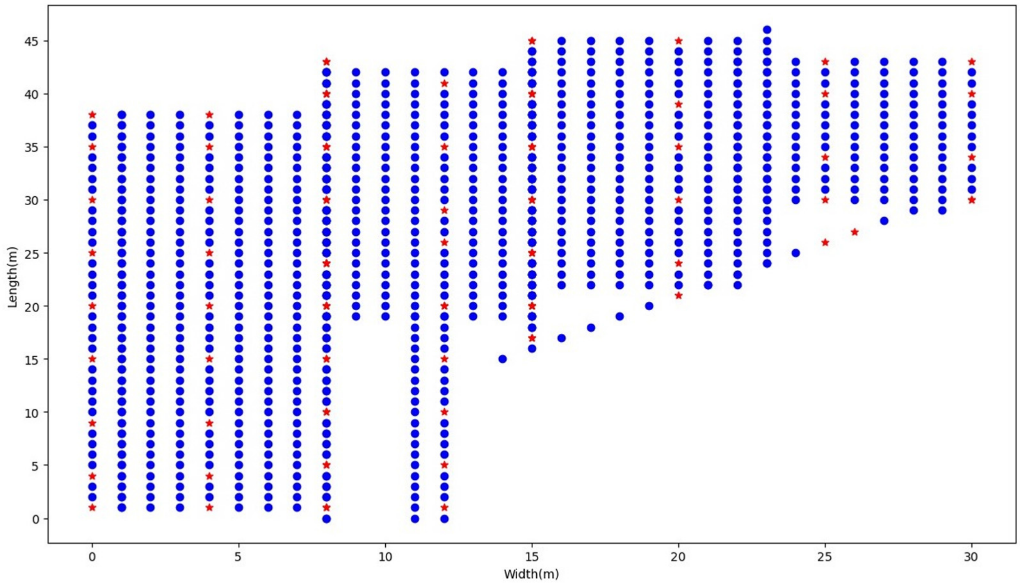

Fig. 16. The library reading room sample expansion map.

Table 7
Average localization errors of different positioning algorithms under extended samples.

Method	Average localization error (m)
LSTM	4
DNN	15.2
KNN	17.1

positioning errors of different positioning algorithms under the expanded samples are shown in Table 7. Obviously, the localization error of LSTM localization algorithm is about 4 m, which is only 0.8 m away from the original data, while the localization error of other positioning algorithms has increased to varying degrees. For the total area of the positioning area of nearly 1000 m^2, only the data of 61 reference points are used to expand the data of the whole region. Although the localization error is increased by 0.8 m, the cost of manual acquisition is greatly reduced, which is acceptable in practical application. This also verifies that the PGSE expansion algorithm can expand the data with temporal information.

6. Conclusion

In the paper, we propose an automatic sparse samples expansion algorithm PGSE based on PCA-GPR. The AP is selected PCA, and the relationship between the position coordinates of the sampled reference point and the RSSI signal value is modeled by GPR. The trained Gaussian normal distribution model is used to predict the RSSI signal value on the unsampled reference point, and the fingerprint database is further expanded. Experiments were carried out using the UJIIndoorLoc dataset, and the effectiveness of the PGSE algorithm was verified by comparing the similarity of the data. In particular, we also applied PGSE in fingerprint-based localization to verify the applicability of PGSE expansion algorithm to data with temporal information. We also propose a WiFi fingerprint-based indoor localization method based on LSTM. The average positioning error of library database is 3.2 m, which is better than the other six methods. For scenes with different motion speeds, the positioning results of LSTM are relatively stable. Therefore, WiFi-RSSI localization method based on LSTM has accuracy and adaptability in indoor localization.

AP screening method can be further optimized. The current AP is mainly based on the idea of PCA, only using the AP with high contribution rate, which may bring some errors. In the future, AP selection can be further studied, and AP combinations with improved positioning accuracy may be found. In the future, further research can be done on the localization of corner points to improve the positioning accuracy.

CRediT authorship contribution statement

Bing Jia: Conceptualization, Methodology, Resources, Funding acquisition, Writing – original draft, Writing – review & editing, Investigation, Formal analysis. **Wenling Qiao:** Investigation, Data curation, Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Zhaopeng Zong:** Writing – review & editing, Implementation. **Shuai Liu:** Validation, Formal analysis, Conceptualization, Writing – review & editing, Writing – original draft, Investigation. **Mohammad Hijji:** Formal analysis, Writing – review & editing, Writing – original draft, Validation, Investigation. **Javier Del Ser:** Conceptualization, Writing – review & editing, Writing – original draft. **Khan Muhammad:** Conceptual review and editing, Revision review, Writing – review & editing, Supervision, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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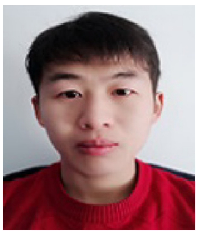

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