Deep Learning Localization Algorithm Integrating Attention Mechanism in Database Information Query

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***Abstract*—This study aims to solve the problems of traditional indoor car search positioning technology in terms of positioning accuracy and functionality. Based on database technology and deep learning technology, an LSTM model with attention mechanism was established. This model can simultaneously extract temporal and spatial features, and use attention mechanism for feature importance recognition. The entire positioning model has been designed as a triple functional entrance that includes positioning, car storage, and reverse car search, enhancing the user's coherent experience. The data results show that the root mean square error of the LSTM (Attention) model designed in the study is 0.216, and the variance is 0.092. Among similar positioning models, the index value is the smallest, while the CDF line rises the fastest and the maximum value is the highest. The research conclusion indicates that the LSTM (Attention) indoor positioning model designed in this study has better computational performance and can help users achieve more accurate positioning and vehicle navigation.**

Keywords*—*LSTM; attention mechanism; positioning; database

I. INTRODUCTION

Indoor vehicle positioning has always been a problem that many people need to solve in real life, and existing positioning technologies often have shortcomings such as significant positioning error and single positioning function. With the continuous maturity of the Internet of Things and intelligent computing technology, its application in the field of smart cities is also deepening. This comprehensive application based on life network interaction can be found in various aspects. Among them, deep learning technology, as an intelligent computing technology, has been widely applied and widely used [1-3]. Deep learning technology relies on database technology and modern network technology, utilizing network technology to achieve interaction between people and things, and utilizing database technology to store, manage, and update information [4-6]. As an intelligent computing technology based on human vision, attention mechanism can extract highly important target regions in global scenes, filter out impurities for the current task, and retain more important regions [7-9]. The main goal of this study is to use deep learning technology to solve the problem of vehicle positioning in the city, improve the accuracy and stability of positioning. This technology can not only be applied to indoor vehicle search, but also to many other indoor positioning problems, making it a positioning research of certain importance. In the future, this indoor vehicle positioning method based on database and deep learning technology can help people find parking spaces more conveniently, improving the efficiency and convenience of urban transportation. To achieve the research objectives, a LSTM model with attention mechanism was established based on database technology and deep learning technology. This model can simultaneously extract temporal and spatial features. On this basis, the entire positioning model has been designed as a triple functional entrance that includes positioning, car storage, and reverse car search, enhancing the user's coherent experience.

II. RELATED WORKS

With the maturity of intelligent computing technique, the utility of deep learning algorithms in various fields has gradually deepened. Bédard et al. [10] applied deep learning algorithms to the medical field, and constructed a mouse pattern of sodium dextran sulfate colitis through convolutional neural networks. The study mainly used medical slide pictures as the main samples to establish training dataset, and based on this network pattern is trained. The pattern can improve overall efficiency of medical compound screening. Yu et al. [11] applied the deep learning algorithm to the prediction of the operating load of the power system, and selected the short-term load prediction suitable for the machine learning scheme as the main research direction, and designed a deep learning pattern for the nonlinear problem. The pattern can significantly improve the prediction efficiency. Shen et al. [12] applied the convolutional neural network algorithm to the short-term prediction problem of subway traffic passenger flow, and combined the auto-encoder to perform convolutional coding summation to solve the passenger flow matrix problem. At the same time, the back-propagation strategy was used to solve the optimization problem of matrix weight parameters. It shows that the technique can predict more accurately than the traditional pattern, and the pattern has a significant influence on the forecast prediction of passenger flow between stations. Tang et al. [13] proposed a low-cost image acquisition strategy that combines UAVs with intelligent algorithms, through which researchers can conduct more efficient and low-cost ground image acquisition. The strategy mainly uses a convolutional neural network with 12 layers to layer and recognize images. The research results show that this strategy is less time-consuming and more accurate than other strategies, and is more suitable for ground sampling. Wang et al. [14] proposed a fault localization pattern based on multi-class features, which constructs a ranking pattern from the perspectives of depth pattern and breadth pattern, and explores the relationship between different features. It means pattern designed in the study has a greater performance advantage in early troubleshooting than the traditional pattern. This research also adopts the deep learning method to design the localization pattern. The research also integrates attention mechanism in the pattern design.

Attention mechanisms are used in different types of pattern designs. Zheng et al. [15] combined attention mechanism with 3D-network. By embedding the attention mechanism into the first level of the convolutional neural network, the band attention vector in the band selection process was learned, and then the plant Prediction of chlorophyll content. The research results show the pattern has higher classification accuracy than other types of patterns such as genetic patterns. Lai et al. [16] designed an attention application mechanism based on convolutional neural network that is, designing an excitation module after the convolutional layer of the convolutional neural network, and then forming an attention convolutional network pattern to emphasize important features. Research results show that the pattern can minimize the number of redundant candidates, thereby improving the efficiency of the pattern. Xiao et al. [17] combined an attention mechanism learning pattern with a bilinear efficiency network for the identification and classification of radar jamming signals. It shows that the bilinear network pattern based on the attention mechanism can extract signal features more efficiently and achieve the effect of automatic signal interference type classification. Wang et al. [18] proposed a temporal convolutional neural network pattern that combines soft threshold technology and attention mechanism, and applied it to the prediction of machine remaining life. The pattern does not need to perform overall feature preprocessing, but directly Multi-channel sensors for data input and retain valid features during feature extraction. It shows that the prediction performance of this pattern is more outstanding better than similar patterns. Shobana and Murali [19] designed an automatic review pattern based on attention mechanism for the difficult problem of manual review of online customer reviews. The pattern can perform abstract review through encoding-decoding and solve the problem of manual repetitive labor. The review efficiency of this pattern is more outstanding than that of similar patterns. This research designs a database-based indoor positioning pattern design. The pattern integrates the characteristics of the attention mechanism, making the indoor positioning more accurate and more practical.

III. Attention-LSTM Localization Pattern Design

A. *Attention-LSTM Car-Finding and Positioning Pattern Framework Design*

The indoor positioning pattern researched and designed is mainly based on the database-based position fingerprint indoor vehicle positioning pattern. The pattern mainly searches the data stored in the database and the position fingerprint in the positioning area through the fingerprint positioning strategy, and finally achieves indoor positioning. In order to adapt to the search strategy of fingerprint positioning, the pattern must have a certain intelligent learning ability, so as to ensure the accuracy and efficiency of the query in the query process. The research mainly combines the LSTM (Long Short-Term Memory) temporal network with attention mechanism to design the pattern for deep learning, and the pattern framework is mainly designed in combination with the main functional requirements of indoor car-finding and positioning. The Attention-LSTM car-finding and positioning pattern designed by the research can be mainly divided into three functional parts, namely, the car-finding navigation module, the vehicle temporary storage module and the reverse car-finding module formed according to the user's car-finding and positioning requirements. The specific functional flow of the car-finding navigation module and the vehicle temporary storage module is shown in Fig. 1.

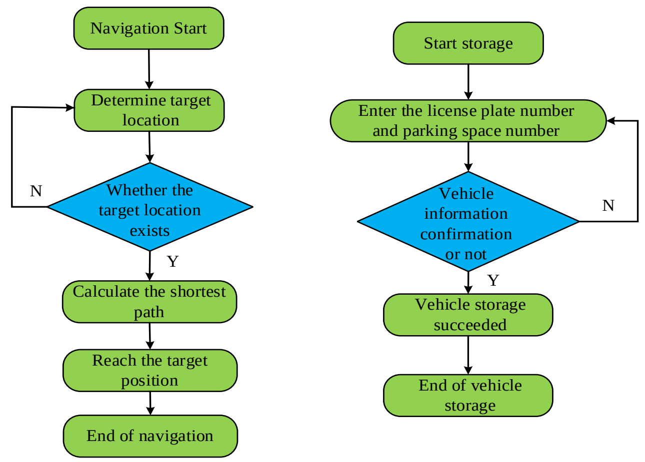

Fig. 1. Car search navigation module and vehicle temporary storage module.

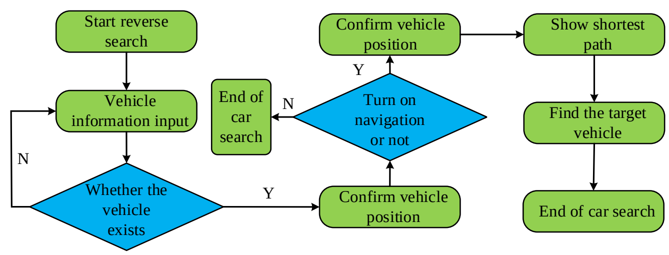

Fig. 2. Reverse car search module.

The sub-figure (a) in Fig. 1 describes the car-finding navigation module. The car-finding navigation module mainly serves to receive the user's query target signal, and to determine whether the query target position actually exists. Once the module determines that there is a target position, the A* (A-Star) algorithm can be used for shortest path navigation. The A* algorithm is a search algorithm for the shortest path. The algorithm converts the path planning into a graph search problem, and converts the overall search area into a set of two-dimensional map arrays to complete the transformation and search of elements in the area, and then converts the entire search area into a set of two-dimensional map arrays. After the search is completed, the shortest distance from the target starting point to the target destination will be displayed according to the distribution of obstacles in the map. The sub-picture (b) in Fig. 1 is the vehicle temporary storage module, which is mainly responsible for meeting the needs of users in the vehicle storage process. The corresponding location fingerprint can be formed, which is convenient for the user to perform subsequent reverse car search. The operation mode of the reverse car search module is shown in Fig. 2.

The reverse car-finding module is a module for car-finding and navigation based on the location fingerprint. In the pattern, the location fingerprint of the vehicle is mainly composed of two parts of information, namely vehicle information and positioning information. The search path associated with the location. Therefore, in the reverse car storage module, the pattern will first confirm the vehicle information to confirm whether the vehicle actually exists. After confirming the real existence of the vehicle, the pattern will further determine the vehicle location according to the search path. Once the vehicle position is determined successfully, the navigation part can be entered, and the shortest path navigation can be carried out through the A* algorithm. Since the indoor positioning of the pattern mainly adopts the indoor Bluetooth technology, it is necessary to arrange the Bluetooth beacons according to the indoor environment and the characteristics of the positioning algorithm. However, in this process, the strength evaluation of the received signal needs to be solved. The research mainly uses the logarithmic normal path pattern for evaluation. The evaluation of signal propagation distance and received signal strength variation, the specific calculation process is shown in Equation (1):

$$RSSI\left(d\right)=RSSI\left(d_0\right)-10*n*\lg\frac{d}{d_0}+N_\sigma \tag{1}$$

In Equation (1), the $RSSI$ received signal strength is d expressed, and the distance between the signal transmitter and the receiver is expressed. This distance is often expressed by the closest distance of signal propagation, which is the d_0 reference distance, the n attenuation factor, and N_σ the random noise.

B. Attention-LSTM Positioning Mechanism Design

Indoor positioning strategies based on deep learning patterns often use neural networks as a feature extraction tool, through which effective features of received signals are extracted, and location estimation is performed based on the features. However, when most neural network patterns perform feature extraction and position calculation, the calculation of position information lacks time, that is, the temporal continuity of signals in the positioning process cannot be fully calculated [20-21]. Therefore, when designing the indoor vehicle positioning mechanism, the research mainly selects the LSTM pattern as the basic positioning pattern. Unlike other neural networks, the LSTM pattern itself has a strong processing ability for time series. In the case of introducing the attention mechanism, its consideration Feature selection with screening is performed simultaneously with the dual features of spatial and temporal features, as shown in Fig. 3.

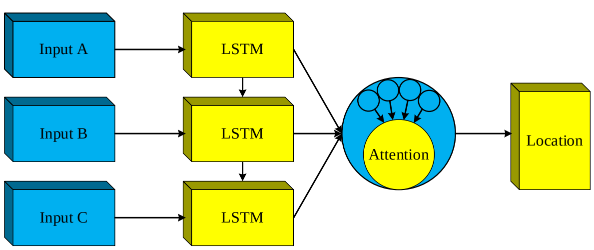

Fig. 3. Basic framework of the pattern.

Fig. 3 describes how the attention mechanism and the LSTM algorithm are combined in the overall pattern. The pattern will input information A, information B, and information C into the LSTM pattern respectively after receiving information A, informationl B, and information C. These three signals contain their own spatial characteristics, and they also have time domain continuous characteristics between each other. After the LSTM pattern extracts its features, it will be introduced into the attention mechanism module. The attention mechanism module will target the importance of the signal, and finally form an effective feature unit with temporal and spatial features. The feature unit is the main basis for calculating the position coordinates. The LSTM pattern itself is evolved based on the network pattern. The network pattern has specialized processing capabilities for sequence data. The calculation equation for single data is shown in Equation (2):

$$y=f\left(Wx+b\right) \tag{2}$$

In Equation (2), the cyclic network x performs a linear transformation on a single input value, and the linear transformation $Wx+b$ is expressed y as $f\left(\cdot\right)$ When facing a series of data, the calculation method of the network pattern state at the current moment is as shown in Equation (3).

$$s_t=f\left(U\cdot x_t+W\cdot s_{t-1}\right) \tag{3}$$

In Equation (3), U and W are all pattern parameters that need to be learned, x_t representing the input value at a certain moment, s_{t-1} representing the network state at a certain moment in the past, which t is a time expression. The calculation method of the pattern output value at the current moment is shown in Equation (4).

$$o_t=g\left(V\cdot s_t\right) \tag{4}$$

Equation (4) is V the pattern parameter that needs to be learned. The LSTM pattern adds a transfer state to the RNN pattern, as shown in Fig. 4.

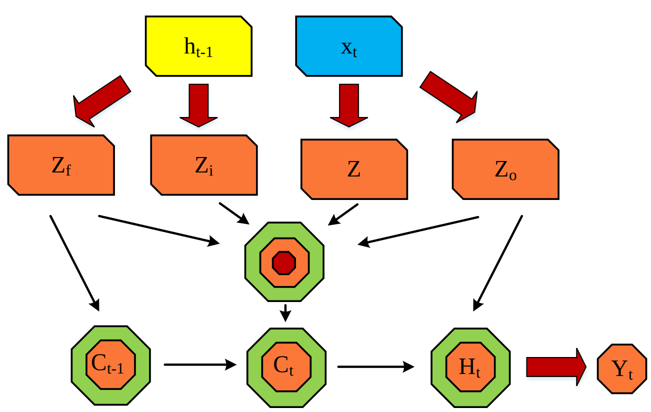

Fig. 4. LSTM pattern construction.

In Fig. 4, the input variable is composed of two different element states. The element states are combined to form a splicing vector, and the splicing vector forms four different types of outputs after four different operations, which are Z_f, Z_i, Z, Z_o, where Z_f, Z_i, Z_o are all three gated states, and Z represent the updated state value after the unit is updated. Z The calculation method is shown in Equation (5).

$$Z = \tan h\left(w\left[x_t, h_{t-1}\right]\right) \tag{5}$$

Weight parameter h_{t-1} is represented in Equation (5), and w, x_t respectively represent two different information states of the input variable. The calculation method of the forget gate Z_f is shown in Equation (6).

$$Z_f = \sigma\left(w_f\left[x_t, h_{t-1}\right]\right) \tag{6}$$

In Equation (6), the σ activation function is expressed. The input gate Z_i is calculated as shown in Equation (7).

$$Z_i = \sigma\left(w_i\left[x_t, h_{t-1}\right]\right) \tag{7}$$

Output gate Z_o is calculated as shown in Equation (8).

$$Z_o = \sigma\left(w_o\left[x_t, h_{t-1}\right]\right) \tag{8}$$

Under the attention mechanism, the pattern can extract information that is more critical to the current target from the global information. In a time-series-related environment, the influence of input elements at different times on output elements. At the same time, the attention mechanism change applies more attention to the input features with high influence. The flow of the LSTM (attention) localization pattern formed under the attention mechanism is shown in Fig. 5.

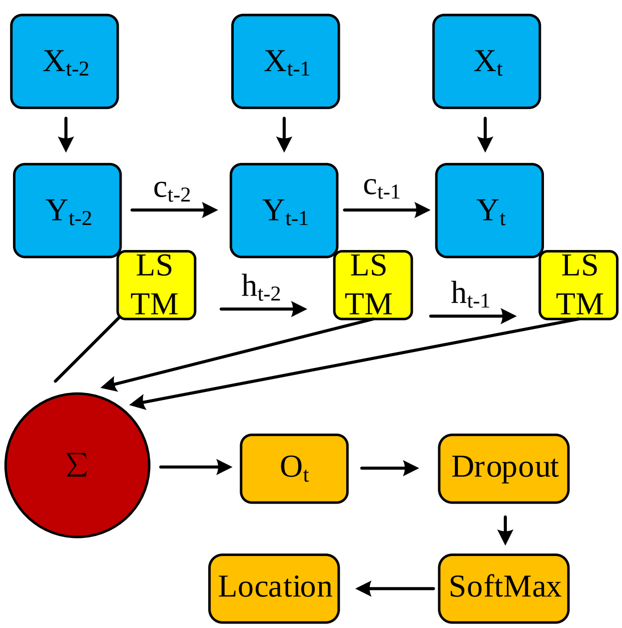

Fig. 5. Attention LSTM positioning pattern process.

Assuming that the input element values in Fig. 5 come from a given input sequence, and the vectors in the sequence are all one-dimensional vectors, the sequence is expressed as shown in Equation (9).

$$\begin{cases} X = \left[x_{t-2}, x_{t-1}, x_t\right] \\ x_i = \left[r_1, r_2, r_3, \cdots, r_k\right] \end{cases} \tag{9}$$

In Equation (9), x_{t-2}, x_{t-1} and x_t respectively represent the input signal at three consecutive time points, and t represent a certain moment, i represent the general name of different moments, and represent x_i a one-dimensional vector in the signal. After the NN structure operation of LSTM, the pattern will obtain the output vector Y, which is expressed as Equation (10).

$$\begin{cases} Y = \left[y_{t-2}, y_{t-1}, y_t\right] \\ y_i = v_1, v_2, v_3, \cdots, v_n \end{cases} \tag{10}$$

A one-dimensional vector is represented in Equation (10). y_i Under the action of the attention mechanism, the pattern will obtain the importance vector in this part ∂, and the specific equation is shown in Equation (11).

$$\begin{cases} \partial = \left[\alpha_{t-2}, \alpha_{t-1}, \alpha_t\right] \\ \alpha_i = \left[u_1, u_2, \cdots, u_n\right] \end{cases} \tag{11}$$

A one-dimensional vector is represented in Equation (11). α_i The final calculation equation of spatiotemporal features is shown in Equation (12).

$$o_t = \sum_{i=0}^{2} \alpha_{t-i} \odot y_{t-1} \tag{12}$$

The output network of the pattern is mainly composed of Droup level and SoftMax level. The Droup levelr is mainly used to solve the overfitting problem of the pattern, and the Droup leve randomly disconnects part of the network connection to prevent the occurrence of overfitting. The SoftMax layer is mainly used for multi-classification of the positioning problem, and the final position probability can be written in the form of Equation (13).

$$\sum_{i=0}^{n} P_i = 1 \tag{13}$$

In Equation (13), i represents the position, and P_i represents the probability of being located at the position. The final position of the pattern output can be expressed in two ways. The first way is the maximum probability way, as shown in Equation (14).

$$\begin{cases} p_t = \max(p) \\ position\_x = x_t \\ position\_y = y_t \end{cases} \tag{14}$$

The position in Equation (14) is $position = (position\_x, position\_y)$ expressed in terms of positioning coordinates. The second representation method is the weighted average representation method, as shown in Equation (15).

$$\begin{cases} position\_x = \sum_{i=0}^{n} p_i \cdot x_i \\ position\_y = \sum_{i=0}^{n} p_i \cdot y_i \end{cases} \tag{15}$$

IV. LSTM-CNN Positioning Pattern Positioning Effect Analysis

A. Pattern Performance Analysis

When analyzing the localization effect of the LSTM-CNN localization pattern, the research will analyze from the two perspectives of the LSTM-CNN pattern's operational performance and the pattern's localization effect. In the data analysis, the research mainly uses the underground garage on the first floor below ground as the main data collection site. In the study, the beacons were evenly arranged in the indoor environment, and the coordinate positions of the signals were recorded. After the data is obtained, 80% of the experimental data is training set, and the other 20% is test set. Since the LSTM pattern requires information sequence input, the research assumes that the order size is 3 when selecting the data set, so the available data sets are combined as shown in Table I.

Based on the data set setting, the research will explore whether adding attention mechanism to the pattern will affect the performance of the pattern. In the comparison process, the research uses four patterns: LSTM pattern, LSTM (Mean pooling) pattern, LSTM (Max pooling) pattern, and LSTM-attention pattern, the variance of four indicators to analyze, the specific data results are shown in Fig. 6.

TABLE I. DATA SET COMBINATION

Order size 1		Order size 2		Order size 3	
Signal order	Position representation	Signal order	Position representation	Signal order	Position representation
x_0	y_0	$[x_0,x_1]$	y_1	$[x_0,x_1,x_2]$	y_2
x_1	y_1	$[x_1,x_2]$	y_2	$[x_1,x_2,x_3]$	y_3
x_2	y_2	$[x_2,x_3]$	y_3	$[x_2,x_3,x_4]$	y_4
…	…	…	…	…	…
x_{n-1}	y_{n-1}	$[x_{n-2},x_{n-1}]$	y_{n-1}	$[x_{n-3},x_{n-2},x_{n-1}]$	the $_{n-1}$
x_n	the $_n$	$[x_{n-1},x_n]$	the $_n$	$[x_{n-2},x_{n-1},x_n]$	the $_n$

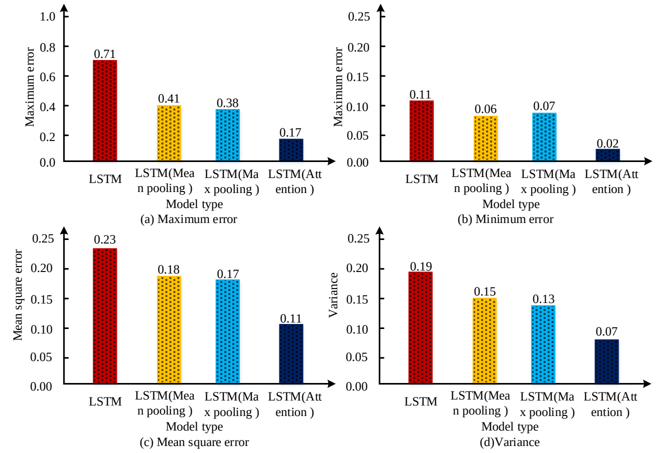

Fig. 6. Performance index comparison.

In Fig. 6, according to maximum error, the maximum error value of the data obtained by the LSTM pattern is 0.71, the max-error of data obtained by the LSTM (Mean pooling) pattern is 0.41, and the max-error of data obtained by the LSTM (Max pooling) pattern is 0.41. The maximum error value of the data obtained is 0.38, while the maximum error value of the data obtained by the LSTM-attention pattern designed by the research is 0.17. The max-error of the data obtained by the LSTM-attention pattern is the smallest, much less than The other three patterns; in terms of minimum error, the maximum error value of the data obtained by the LSTM pattern is 0.11, the maximum error value of the data obtained by the LSTM (Mean pooling) pattern is 0.06, and the data obtained by the LSTM (Max pooling) pattern. The maximum error value of the LSTM-attention pattern is 0.07, and the maximum error value of the data obtained by the LSTM-attention pattern designed by the research is 0.02. The min-error of the data obtained by the LSTM-attention pattern is also the smallest, much smaller than the other three. According to mean square error, the mean square error of the data obtained by the LSTM pattern is 0.23, the mean square error of the data obtained by the LSTM (Mean pooling) pattern is 0.18, and the mean square error of the data obtained by the LSTM (Max pooling) pattern. The mean square error is 0.17, and the mean square error of the data obtained by the LSTM-attention pattern designed by the research is 0.11. The mean square error of the data obtained by the LSTM-attention pattern is the minimum value, which is much smaller than the other three. In terms of variance, the variance difference of the data obtained by the LSTM pattern is 0.19, the variance of the data obtained by the LSTM (Mean pooling) pattern is 0.15, and the variance of the data obtained by the LSTM (Max pooling) pattern is 0.13, while The variance of the data obtained by the LSTM-attention pattern designed in the research is 0.07. It can be seen that the variance of the data obtained by the LSTM-attention pattern is the minimum value, which is much smaller than the other three patterns. In summary, the LSTM-attention pattern designed by the research has the smallest values in the four indicators of maximum error, minimum error, mean square error, and variance. LSTM pattern shows stronger capability in both accurate and stable performance. In addition, the research starts from the perspective of different order sizes of data input, analyzes the accuracy changes of the patterns under different order sizes, and uses the CDF (Cumulative Distribution Function) to compare the accuracy. The specific data differences are shown in Fig. 7.

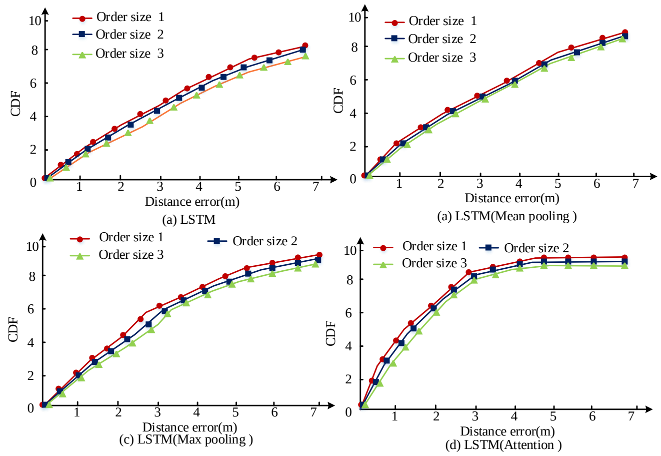

Fig. 7. Cumulative probability distribution function.

In Fig. 7, the CDF values of the order size 1, order size 2, and order size 3 of the LSTM pattern all show a uniform upward trend. When the distance error reaches 7, order size 1, order size 2. The CDF value of order size 3 reaches around 80%. It can be seen that the rising trend of CDF value is slow, and the highest CDF value does not reach 90%; order size 1, order size 2, order size of LSTM (Mean pooling) pattern 3 The CDF values of the three data order sizes also show an upward trend. Although the upward trend is also uniform, when the distance error reaches 7, the CDF values of order size 1, order size 2, and order size 3 reach more than 90%. It can be seen that The accuracy of the LSTM (Max pooling) pattern is better than that of the LSTM pattern; in addition, the CDF values of the order size 1, order size 2, and order size 3 of the LSTM (Max pooling) pattern also show an upward trend. The upward trend is faster than that of the LSTM (Mean pooling) pattern in the first half of the rise, and the speed of reaching the high CDF value area is faster. When the distance error reaches 7, the CDF values of order size 1, order size 2, and order size 3 are the same. When it reaches more than 90%, it can be seen that the accuracy of the LSTM (Max pooling) pattern is more outstanding than that of the LSTM (Mean pooling) attern; the LSTM-attention pattern designed by the study has three order sizes: 1, order size 2, and order size 3. The CDF values of the data order size all show an upward trend. It can be seen that the first half of the data line of the LSTM-attention pattern has the fastest upward trend, while the second half of the line has a relatively stable trend. When the distance error reaches 3, the order size is 1, the sequence The CDF values of length 2 and order size 3 both reach more than 90%, and are close to 100% when the distance error reaches 5. The overall precision of LSTM-attention pattern designed by the research is higher and the performance is better, indicating that the attention mechanism can indeed significantly improve the computing function of the LSTM pattern.

B. Quantitative Analysis of Positioning Effect

In the analysis of the positioning effect of the overall pattern, the research mainly adopts the method of comparing the positioning effects of different positioning patterns. First, the positioning accuracy and stability of different patterns are compared, and then the positioning and navigation routes are compared. The comparison of positioning accuracy and stability data is shown in Fig. 8.

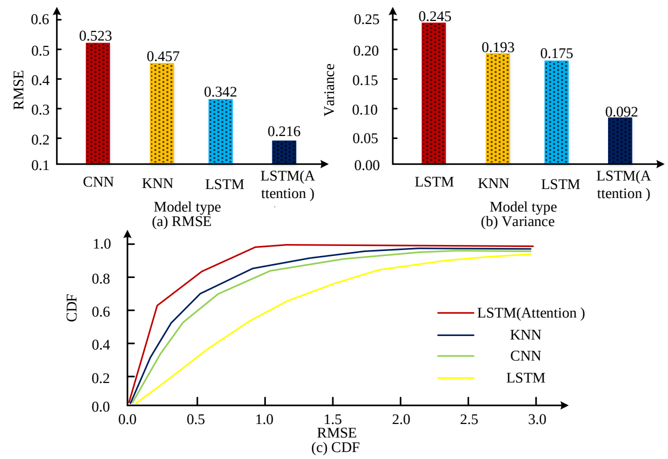

Fig. 8. Pattern comparison.

As can be seen from Fig. 8, accoting to root mean square error, the root mean square error of the CNN pattern is 0.523, the root mean square error of the KNN pattern is 0.457, the root mean square error of the LSTM pattern is 0.342, and the LSTM-attention pattern The root mean square error is 0.216. From the comparison, the root mean square error of the LSTM-attention pattern is the smallest; in terms of variance value, the variance value of the CNN pattern is 0.245, the variance value of the KNN pattern is 0.193, and the variance of the LSTM pattern is 0.193. The figure is 0.175, and the variance figure of LSTM-attention pattern is 0.092. From the comparison point of view, the variance figure of LSTM-attention pattern is the smallest; in terms of CDF value changes, it can be seen that among the four patterns, the fastest rising speed is LSTM. (Attention) pattern, and in the final accuracy effect presentation, the LSTM-attention pattern that shows the highest CDF value is also the LSTM-attention pattern, followed by the KNN pattern, the CNN pattern again, and the LSTM pattern. Although the KNN pattern and the CNN pattern show a higher rising speed and a better rising trend, they still show certain disadvantages compared with the LSTM-attention pattern designed by the research. Compared with else patterns, the LSTM-attention indoor positioning pattern designed by the research has higher positioning accuracy and positioning stability, and can reflect better results in practical applications. The research also compares the positioning and navigation routes of the four patterns, and the comparison results is Fig. 9.

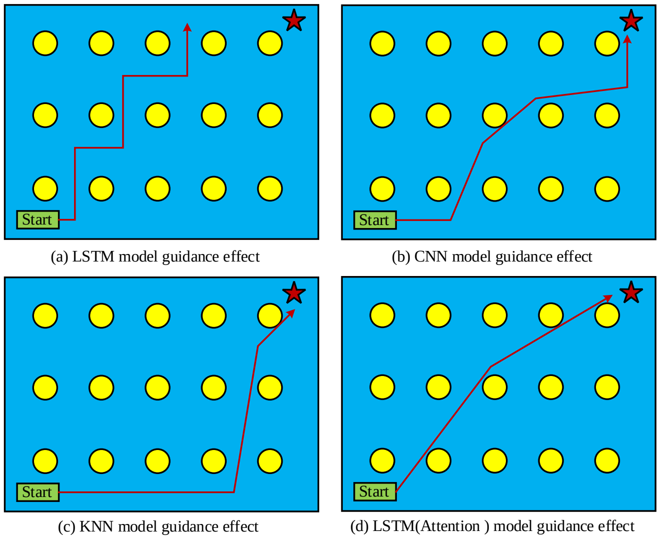

Fig. 9. Positioning and navigation effect.

In Fig. 9, the navigation route of LSTM pattern shows the shape of multiple right-angle corners, the overall navigation route is relatively complex, and the final navigation target point deviates and fails to reach the target point accurately. Both the positioning ability and the navigation ability are insufficient; the navigation route of the CNN pattern shows the form of right-angle corners and oblique interspersed routes. The overall navigation route is also more complicated, but the pattern locates the target point more accurately, and the final navigation route is completed. more precise guidance. However, it can be seen from the route planning that the route planning is redundant and not simple and direct; the navigation route of the CNN pattern also shows the form of right-angle corners and obliquely interspersed routes, and the overall route planning is simpler and more direct. It shows relatively accurate target point positioning ability; the navigation route of the LSTM-attention indoor positioning pattern designed by the research shows an accurate oblique interspersed route form. Among the four patterns, the navigation route form is the most concise, and finally reaches the target point accurately. It can be seen that compared with the other three positioning patterns, the LSTM-attention indoor positioning pattern designed in the study has the best positioning effect and navigation effect, and can obtain the best effect in actual indoor positioning and navigation.

V. Conclusion

To solve the issue of insufficient accuracy of indoor spatial positioning in traditional methods, an indoor positioning pattern with temporal and spatial characteristics is established based on LSTM pattern, and on this basis, the attention mechanism is integrated into the pattern, so that the pattern can Features are effectively screened, and features with higher importance are retained for more precise positioning and navigation. The research shows the LSTM-attention pattern designed in the study has higher index values of 0.17, 0.02, 0.11, and 0.07, in line with maximum error, minimum error, mean square error, and variance, respectively, than other LSTM patterns that do not incorporate the attention mechanism. The global operation effect of the LSTM-attention pattern is more outstanding. At the same time, the CDF data trend that the LSTM-attention pattern rises faster and the highest value is the highest. In addition, in terms of positioning and navigation effect, the root mean square error and variance of the LSTM-attention pattern designed by the study are 0.216 and 0.092 respectively, the index value is the smallest, the CDF curve rises the fastest, and the maximum value is the highest. The navigation route of the LSTM-attention pattern is the most direct and accurate. The LSTM-attention pattern is more stable and accurate than similar patterns, with better positioning and navigation effects.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

It is declared by the authors that this article is free of conflict of interest.

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