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Blind PCN: A Novel Blind Guidance Method Based on Ensemble Learning

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ABSTRACT: According to the estimate made by the World Health Organization on the situation of blind people, it is estimated that the number of people with visual defects in the world will reach about 25 million by 2030. The increasing number of blind people has become one of the serious social and public problems. The quality of life of blind people has been paid more and more attention. In the world, the blind navigation in public places still remains in the traditional blind guidance facilities, especially the indoor navigation tools and technologies for the blind are still relatively scarce, and most of the time can only rely on the guidance of normal people. The guidance of normal people costs a lot of manpower and is not in line with the pace of modern society's pursuit of a high standard of life. So, it is very valuable to study an indoor navigation system for this society.

KEYWORDS: blind guidance, indoor navigation, indoor navigation system.

I. INTRODUCTION

At present, there are two main blind navigation technologies, namely ultrasonic navigation and GPS navigation. The former uses the principle of ultrasonic distance measurement to inform the blind user whether there is an obstacle ahead and the distance of the obstacle to prevent the blind from being injured. This method only has the ability to perceive obstacles and cannot provide the blind with correct walking route instructions. This method has limited contribution to the blind. GPS navigation generally uses intelligent electronic equipment to locate the specific location of the blind, and uses the voice system of electronic equipment to broadcast the path to the blind. Compared with ultrasonic navigation, this method is more intelligent, and it is more helpful to travel outdoors, but the accuracy of GPS navigation is not enough for indoor conditions, which has great disadvantages. The problem of indoor blind track prediction and obstacle avoidance is far from being solved, and the problem of safe walking has become a major problem to be solved for blind people. The blind person needs auxiliary equipment to send out motion instructions for him/her during walking. For example, the blind person hears "left", "right" or other instructions at a certain position during walking, and then follows this instruction to walk. When he/she reaches the next position, he/she accepts the corresponding correct instructions again, and finally reaches the destination safely. The motion trajectory of blind people is an important basis for generating motion instructions. We propose a spatiotemporal model for trajectory prediction and a command obstacle avoidance algorithm for blind people's indoor travel tasks. In addition, it is very important to give instructions to the blind to avoid obstacles in real time. However, in reality, we cannot always know the purpose of blind people. A more realistic way is to learn track patterns through track sequences in the past. It is often necessary to further predict the instructions that the blind people will receive through online methods, and deduce their short-term or medium-term trajectory. Our goal is to enable early warning or effective preventive measures to be triggered in advance when the monitoring system has a key decision-making system in real time, so as to reasonably help the blind people walk safely on the correct track. How to realize the command prediction of the blind person's position and how the blind person can avoid indoor static objects accurately and reach the destination safely are the focus of this paper [1-7].

Command prediction for blind people is challenging research. One of the challenges researchers face in predicting human motion is how to adapt these technologies to the context of motion. We propose a real-time prediction method for blind instructions. The real-time performance of this method can well solve many practical problems. The main contributions of this work are as follows:

(i) We propose an instruction prediction method. First of all, we have complete blind track information and blind track information. Our method can find out the position that the blind person wants to reach on the blind track according to the movement track of the blind person over a period of time and the position of the blind person, and get the instructions that the blind person should be given at the current position according to the position to be reached in the future.

(ii) In view of the above research, we propose a blind path command prediction model (BlindPCN). It is used for blind people in indoor scenes to receive command prediction and trajectory prediction tasks. BlindPCN is mainly composed of two parts, which are the spatial convolution layer used to extract the spatial feature information of track points and the TCN used to calculate the temporal dependence. In addition, we adopt the integrated learning method, which can combine the advantages of different models and has strong stability.

(iii) We propose a set-based method and an ensemble learning method to solve the problem of uneven distribution of data sets leading to discrete model results and improve the prediction accuracy. We conducted cross validation on the data set, and used the typical spatiotemporal model, traditional recurrent neural network and traditional machine learning method as the baseline for validation. After trying to optimize the parameters of all baselines, the experimental results show that our method and model are optimal (all experimental results are the average of the results of multiple rounds of training).

II. RELATED WORK

During the whole journey of the blind person, the spatial position of the blind person has a significant impact on the prediction of the command, and the spatial position can be expressed explicitly by the motion trajectory. Therefore, the motion trajectory prediction of the blind person is an important basis for generating the motion command.

Under the catalysis of massive data, some researchers began to use deep learning algorithms for relevant research. In the data-driven prediction task, Liu et al. introduced a work of RNN [8-13], and proposed a global prediction model called spatiotemporal recurrent neural network (ST-RNN) to predict the next direction of users. Space and time are divided into discrete units to generate time-specific and distance-specific transformation matrices. For each specific time value in a time unit and for each specific space value, the corresponding transformation matrix is calculated. Unlike ST-RNN, we mainly predict instructions based on location information, so we focus on spatial information, build local and global prediction factors in our model, and extract the spatial features of all blind people's historical tracks and indoor scene planning tracks respectively.

Bartoli et al. considered the environment context by providing the short- and long-term memory model (LSTM) of the distance between the target pedestrian and the static object in space, and the context between people in the form of grid map, or the hidden coding of neighbors. Lee et al. predicted pedestrian motion by sampling and planning trajectory from conditional variational automatic coder. They grade the trajectory according to the future interaction, so as to select the most reasonable trajectory, and consider the environment by using convolution neural network to encode it in the occupied grid graph. Based on the current two works, we change the track of the blind into the form of grid, subdivide and automatically code the grid, and then perform convolution operation to improve the strength of space features and strengthen the environment context. We also code the instructions, and construct the form of digital representation of the command state, which is more conducive to the prediction of the model, and improve the accuracy and speed of prediction. Make the prediction instructions serialized more precise. In addition to neural network, Gaussian process based on reinforcement learning method is also proposed to predict pedestrian environment. The above methods have the advantages of intuition, low complexity and strong theory, but the generalization ability of the model is weak. More importantly, the above methods can only simulate the short-term response of pedestrians, and cannot take into account the long-term location information. Especially in the field of instruction prediction for indoor blind people, there are few achievements.

Lv et al. applied time convolution network (TCN) to the field of trajectory prediction for the first time. A convolution layer in the model can calculate the deeper trajectory space characteristics required by the time network layer, and has higher accuracy and training speed, and enhances the weight of nonlinear trajectories. The whole local estimation layer replaces the traditional linear method. Our model also uses the advantages of TCN to embed the captured grid features, the blind historical track features and the spatial features of the planned track [14-18].

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How to obtain adaptive path instructions while maintaining system efficiency, Holscher et al. proposed a two-stage method to learn hierarchical pathfinding strategy, using hierarchical reinforcement learning (HRL). Based on the mechanism of cognitive landmarks, we combine multiple continuous instructions into a more compact higher-order instruction (so-called spatial block), which is more convenient to guide blind people through the whole process. Andrea proposed a natural language generation model, which uses structured and grammatically correct path instructions under the background of providing indoor path instructions. Cuay á huitl proposed a method of fast reinforcement learning path instruction strategy. This method decomposes the problem into sub-problems, so as to learn low-level behaviors in advance (before user-machine interaction), and learn high-level behaviors at runtime, and finally generate instructions for high-level behaviors. We believe that the grammatically

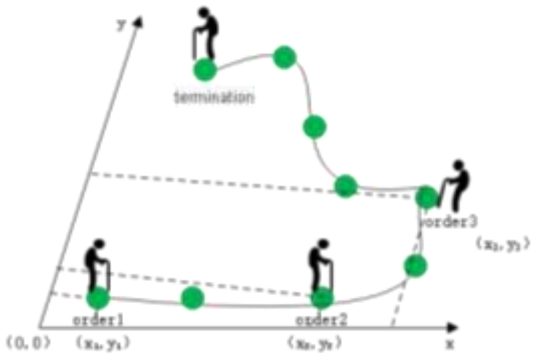

Figure1. The corresponding commands.

III. EXPERIMENTATION

We designed three data-driven methods to complete the task of indoor blind walking command prediction. These include the command prediction based on the track of abscissa and ordinate, the command prediction based on the combination of original blind track and track, and the command prediction method based on grid map. The first is based on abscissa and ordinate. The abscissa and ordinate represent the real track of the blind. In this method, as shown in Figure 1, fix a moving scene in the room, and fix the starting point of the blind person to= (x1, y1). If you maintain a state during the moving process, the command provided is "No Action", and the command to go straight forward is "Approaching". If you want to turn left or right, provide other instructions. Our task is to predict what instructions the blind person should receive in the corresponding space position in the real scene. (x1,y1),(x2,y2),... The corresponding commands are structured commands are only for normal people, so instead of using natural language processing modules, we choose simple commands that are friendly to the blind.

Integrated learning completes the learning task by constructing and combining multiple learners. First, a base learner is trained from the initial training set, and then the sample distribution is adjusted according to the performance of the base learner, so that the training samples that the previous base learner did wrong receive more attention in the future, and then the next base learner is trained based on the adjusted sample distribution; Repeat until the number of base learners reaches the specified value, or the whole integration result reaches the exit condition, and then combine these learners with weights. Based on the Bagging method, we use the bootstrap method to sample 9 data sets from the overall data set, and learn a model from each data set. The final prediction results are obtained by using the output of the six models.
O1, O2, As shown in Figure 1. In addition, in the field of machine learning, different evaluation indicators have different dimensions and units. In order to eliminate the dimensional impact between indicators, we need to standardize data so that we can compare data indicators. Since the abscissa and ordinate of the position of the blind are floating point numbers with a small range of changes, we use the data standardization method.

Because the blind person walks slowly, the abscissa and ordinate of the track change slightly with the time step, and the position of the blind person changes gently. Therefore, we add the calculation method of dividing the trajectory points into grid labels. In addition, in order to reduce the computational complexity of the grid point planning method, this paper uses the multi-resolution grid representation of free configuration space. Conceptually, if any part of the linear element centred on the grid point encounters an obstacle, the grid point is considered an obstacle. In order to improve the performance of obstacles, an obstacle unit can be subdivided into smaller units. Each dimension of the original unit can be divided into two parts, forming a sub-unit of 2 to the nth power. Any unit containing obstacles can continue to split until the appropriate maximum resolution. The advantage of this representation method is that only the space close to the obstacle is improved to high resolution, while the space far away from the obstacle is still represented by rough resolution. This allows the path planner to use the minimum step length to pass through the messy space, while using the large step length to pass through the wide space. As shown in Figure 2.

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Figure 2. The subunits.

IV. FRAMEWORK

This paper designs a model (BlindPCN) that can train, evaluate and predict the walking commands of blind people. BlindPCN is mainly composed of three blocks, including space convolution module, time convolution module and integrated learning block. The spatial convolution block is mainly used to calculate the spatial distribution of the original route and the blind track. The time convolution block is mainly used to calculate the time recursive characteristics of blind data. The integrated learning block is mainly used to reduce the global error and local error of the prediction results. If the blind lane is a straight line, there are only two commands "straight ahead" and "stop". However, due to the influence of turning and obstacle distribution, the driving route is usually a complex curve. This makes it particularly important to capture the spatial relationship of positions in the feature extraction process of command prediction. Therefore, it is necessary to extract another round of features from the track and enhance the weight of the local curve of the blind track before the time series prediction, instead of directly using the standardized position data. First, the data of abscissa and ordinate are fused to calculate the features of spatial correlation. A convolution layer in the model can calculate the deeper trajectory space characteristics required by the time network layer, and has higher accuracy and training speed, and enhances the weight of nonlinear trajectory. The global local estimation layer replaces the traditional linear method. Our model also uses the advantages of TCN to embed the captured grid features, the blind historical track features and the spatial features of the planned track. Recursive neural network has played a great role in the field of time series data prediction. However, traditional recurrent neural networks (RNN, LSTM, GRU, etc.) only involve single-step calculation methods. Single-step calculation has two disadvantages, that is, the complexity of the calculation process is high and the long-term prediction performance is low. Time convolution network (TCN) is based on the idea of convolution neural network and parallelization, which overcomes the two inherent shortcomings of traditional recurrent neural network. For blind instruction prediction, TCN uses causal convolution to associate all historical location points of the track with the instructions predicted in the future. The use of extended convolution can make the hidden layer obtain a larger receptive field, thus establishing the high-dimensional timing characteristics of the blind track and command, and finally using the SoftMax layer to predict the final command. For the data structure designed in this paper, a time convolution block with five hidden layers is constructed to calculate the time characteristics. Each hidden layer has an expansion factor, and each factor is an exponential growth of 2. The maximum is calculated according to specific parameters. The role of TCN is mainly reflected in the following three aspects: it retains all track and grid historical information of the blind, and uses causal convolution to calculate long-term historical information. Expansive convolution is used to expand the receptive field of the convolution process. The cavity factor, Division, changes exponentially. When the model performs deep calculation, there will not be too large receptive field resulting in local information loss. It is completely composed of convolution network and uses multi-layer residual structure to replace the gating structure.

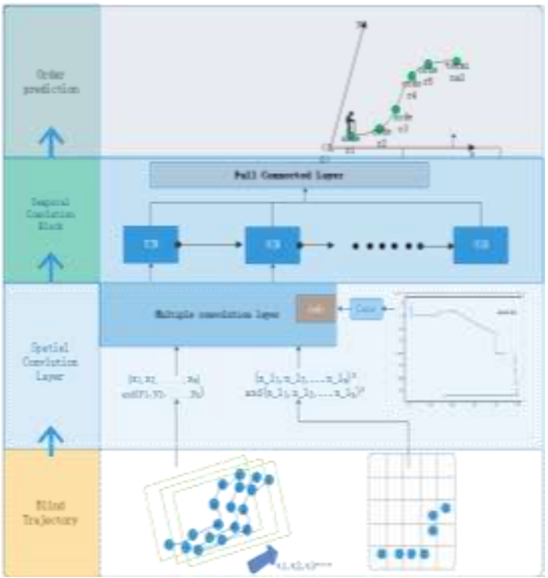

Figure3. The framework.

In order to verify the performance of the model on the premise of ensuring that the results are scientific, this paper uses traditional recursive networks (LSTM, GRU), Atr+LSTM, Atr+GRU models with attention mechanism, and TCN to carry out comparative experiments on complex spatiotemporal models.

(1) LSTM: The traditional recurrent neural network (RNN) model is difficult to learn the long-distance dependence of the input sequence. The LSTM and its variant gated cyclic unit models have largely compensated for the loss caused by the gradient disappearance by adding gating mechanism.

(2) Atr+LSTM: On the basis of LSTM, spatial attention is added, which increases the probability value of spatial attention distribution (attention weight) of the model.

(3) GRU:GRU is a better variant of LSTM network. Compared with LSTM, GRU has fewer parameters, simpler structure and faster training speed.

Indicators	GRU	Atr+GRU	LSTM	Atr+LSTM	TCN	Atr+TCN	BlindPCN
Accuracy	35%	40%	44%	49%	65%	72%	81%
Precision	34%	44%	44%	48%	63%	78%	79%
Recall	32%	33%	37%	43%	60%	71%	78%

V. CONCLUSION

For the field of blind navigation in indoor scenes, in this paper, we propose a network for indoor blind command prediction. The network consists of three parts: the space layer used to calculate the deep spatial features, the time layer used to calculate the recurrence relationship of the trajectory in time, and the integrated learning module used to reduce the global error. In order to solve the problem that traditional convolution computation is not dependent on feature space at the spatial level, we build Spatial composed of extended convolution. TCN is adopted in the time layer and applied to the field of time trajectory prediction. The integrated learning module replaces the traditional SoftMax method and reduces the error caused by local prediction by using the idea of taking the mode of the model prediction results from the trained multiple models. The experimental results show that the model network has high accuracy in long-term prediction.

However, in the process of long-term prediction, the distribution of roads and obstacles should be considered in the prediction of indoor areas. In addition, the factors such as the actual changes of blind people's actions and the implementation of instructions for blind people should also be considered. Because the speed and position of the blind person after executing a single different command may not match the speed and position in the plan. Future research will not only focus on solving the above problems, but also investigate the impact of other indirect factors on the blind person's track and command, including the response time of the blind person to execute the command, and the standardization of the action.

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