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Trajectory Study of Indoor Blind People

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Abstract
Worldwide, the field of indoor blind navigation assistance is becoming more and more prominent. In this paper, a comprehensive study of indoor blind trajectory and command navigation is carried out in two stages. First, in the data analysis stage of indoor blind trajectories, this paper analyzes the relationship between trajectories and instructions. Secondly, to study the relationship between instructions and blind behavior, the path separation index proposed in this paper reflects the error between the actual path and the planned path of the blind person while considering the position relationship and direction decision of the blind person. The results show that different instructions have different effects on blind behavior, and appropriately reducing the width of the road under the condition of ensuring the normal walking of blind people indoors can help stabilize the walking state of blind people.

Keywords: *Navigation assistive technology, Indoor trajectory, Blind behavior*

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I. INTRODUCTION

Worldwide, blind navigation in public places is still in the traditional blind navigation stage. In outdoor situations, there are mainly two kinds of navigation technologies for blind people, namely ultrasonic navigation and GPS navigation[1][2]. The former uses the principle of ultrasonic ranging to inform the blind whether there are obstacles ahead and the distance of the obstacles. This method only can perceive obstacles, cannot provide correct walking instructions for the blind and is of limited help to the blind[3]. For indoor situations, blind navigation tools and technologies are still relatively scarce, and most of them can only rely on human guidance. Safe walking indoors for the blind has become a major problem to be solved[5][6]. In the real world, blind people need assistive devices to issue movement instructions for them during walking[7]. To send the command more accurately, it is necessary to consider the influencing factors of the blind person's trajectory deviation after receiving the command under indoor conditions, such as the blind person's group avoidance behavior, collision avoidance behavior with indoor obstacles, the width of the road, and the blind person's response to different command signals. Factors such as varying degrees of response, the total length of trajectories, and random behavior of blind people[8][9].

This paper mainly studies the behavior of blind people at different nodes in the path, and the effect of instructions on the behavior of blind people indoors. In this paper, the path resolution metric is proposed to evaluate the degree of trajectory deviation. This paper examines the behavior of blind people after following instructions, such as group avoidance and herd movements, responses to obstacle boundaries, and analysis of path separation. The parameters of the developed model are then statistically calibrated, and the parameters are directly estimated from the observational data. Finally, model performance was verified by position, instantaneous speed, blind trajectory, and instruction compliance.

The main contributions of this study are summarized as follows.

i. This paper proposes the concept of path separation degree. To date, most studies have typically modeled blind trajectories with little consideration of the component of path deviation. The path separation model proposed in this study can truly estimate the deviation of the entire blind person's trajectory from the planned trajectory, and can also draw the overall process of guiding the blind person to walk. It provides new ideas for future research in the field of command navigation.
ii. This paper proposes a new type of positional relational model. Considering the road width and other influences, the factors such as path separation degree, command sensitivity, and compliance degree proposed in this study are added for the first time in terms of positional correlation. It is beneficial to quickly calculate the positional relationship of some nodes and establish the relationship between the position and other influencing factors.

II. SCHEME DESIGN AND ANALYSIS METHOD

2.1 Dataset

The data analyzed in this paper come from a three-story supermarket experimental base. During the experiment, 32 blind people were tested for instruction walking, and the time-stamped walking trajectories for each blind person in each layer and the corresponding received instruction information were provided. The time step of the complete trajectory is 500~1000s, with a total of 8097 pieces of data.

2.2 Blind location distribution

The location of the blind person is critical to their walking process. Because when the blind person deviates too far from the road at a certain moment, or the difference between the vector (the direction of the speed of the blind person and the magnitude of the speed) is too large, it is difficult to reach the exit of the road[10]. There are three stages for the blind to complete the indoor walking task, that is, listening to the instructions from the starting point, choosing the direction and walking according to the prompts of the instructions, and finally reaching the destination.

The analysis of the blind people's movement trajectories shows that the blind people's entrance positions and walking trajectories are affected by indoor obstacles, building geometry, previous passing positions, and the density of other pedestrians. Considering that the Weibull distribution [11] can represent various types of distributions, this paper establishes a probability density function based on the location distribution, as shown in the formula (1).

$$f(x;\alpha,\beta)=\frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1}e^{-\left(\frac{x}{\beta}\right)^{\alpha}}$$

$$\alpha=f(y_{1,1},y_{1,2},\dots\dots,y_{1,n})=\lambda_{1,1}y_{1,1}+\lambda_{1,2}y_{1,2}+\cdots\dots+\lambda_{1,n}y_{1,n}+\lambda_{1,n+1} \tag{1}$$

$$\beta=f(y_{2,1},y_{2,2},\dots\dots,y_{2,n})=\lambda_{2,1}y_{2,1}+\lambda_{2,2}y_{2,2}+\cdots\dots+\lambda_{2,n}y_{2,n}+\lambda_{2,n+1}$$

where $f(x;\alpha,\beta)$ is the probability density through the location distribution. x is the starting position of the blind. $y_{1,1}, y_{1,2}, \cdots\cdots, y_{1,n}$ are independent variables of influencing factors, such as the width of the road, the proportion of nearby obstacles, the length of the road from the start point to the endpoint, etc. $\lambda_{1,1}, \lambda_{1,2}, \cdots\cdots, \lambda_{1,n}$ are the model coefficients estimated using the maximum likelihood method.

2.3 Direction decision

The process of behavioral direction decision is similar to the path selection strategy. If the blind road is a straight line, there are only two instructions, "go straight" and "stop". However, due to the influence of obstacle distribution, the driving route is a complex curve. Blind people can only continue the previous command for some time. When receiving a new command, there will be a short error between the actual walking direction and the command planning direction. The behavior trend at a certain node means the continuation of the previous command. The real instantaneous speed and direction of movement at the time, indicate the direction indicated by the command.

2.4 Path separation

This paper focuses on analyzing the walking behavior of the blind according to the instructions. The walking speed of the blind is slow, the abscissa and ordinate of the trajectory change little with the time step, and the position of the blind changes slowly. Due to the insignificant changes in the position of the blind person per unit of time, we updated the original data and increased the timestamp. To reflect the error more intuitively between the actual path and the planned path of the blind, we propose the path separation degree. As shown in formula (2).

$$D(f)=\frac{exp(f)}{1+exp(f)}$$

$$F(n)=\sum_{i=1}^{n}\frac{1}{2}\sqrt{\left|X_{\alpha i}-X_{\beta i}\right|^2+\left|Y_{\alpha i}-Y_{\beta i}\right|^2+(V_{\alpha i}-V_{\beta i})\Delta t}+k_i\Delta t+Z_i \tag{2}$$

$$f(n)=\frac{F(n)}{\sum_{i=1}^{n}\sqrt{\left|X_{\alpha i}-X_{\beta i}\right|^2+\left|Y_{\alpha i}-Y_{\beta i}\right|^2}}$$

In addition to the position error of the node, the determinants of the path separation degree also include factors such as the width of the road and the instantaneous direction. The separation degree of the local path and the global path is compared by formula (2).

Among them, k_i represents the width coefficient of the road corresponding to the i-th node. The wider the road is, the larger the value of the width coefficient is, the easier the blind track is to deviate, and the higher the deviation of $F(n)$. Z represents other impact factors. X and Y respectively represent the horizontal and vertical coordinates of the two-dimensional coordinate system, α and β respectively represent the actual path and the planned path. $V_{\alpha i}$ and $V_{\beta i}$ represent the velocities on the real path and the planned path, respectively.

In this paper, the total deviation $F(n)$ is designed for the path separation degree to calculate the deviation of the true trajectory of the blind. The degree of path separation is not only related to the total amount of deviation, but also the path length of the node's trajectory. The design path separation degree can not only visually see the deviation degree of some nodes, but also obtain the deviation degree of the overall blind walking process. The average walking speed of blind people is 0.3~0.5 m/s. Due to a large amount of data, the interval between nodes is set to 4 seconds (s), and the distance between nodes is about 2 meters (m). $F(n)$ is the total amount of deviation, $f(n)$ is the degree of deviation.

2.5 Blind position relationship

Blind behavior is composed of the behavioral characteristics of each node, and there is a close relationship between each adjacent node. The work in Sections 3.1-3.6 paved the way for calculating the positional relationship of the blind. To constrain the range of some parameters in the position relation formula and calculate the position of the next node, this paper proposes a position relation formula as shown in formula (3).

$$\begin{aligned} P(x,f,D,S,F)_x &= f(\mathrm{x};\alpha,\beta) * [1\text{-}\mathrm{D}^{(\mathrm{i,i+1})}] * [x_i + S(i) * F(i) * V_i * Cos\theta_i * \Delta t_i] * C_i \\ P(x,f,D,S,F)_y &= f(\mathrm{x};\alpha,\beta) * [1\text{-}\mathrm{D}^{(\mathrm{i,i+1})}] * [y_i + S(i) * F(i) * V_i * Sin\theta_i * \Delta t_i] * C_i \end{aligned} \tag{3}$$

The two expressions in formula (3) represent the positional changes of the abscissa and the ordinate from the i node to the next i+1 node, respectively. $f(x;\alpha,\beta)$ represents the position distribution probability of node x, D represents the separation rate, S and F represent the sensitivity and compliance of blind people receiving instructions from this node, V represents the planned speed of this node, and θ represents the angle between the instantaneous speed and the planned speed, Δt_i represents the time difference between two adjacent nodes, C is the influencing factors such as group avoidance and obstacle distribution.

Through the local position change, we can deduce the global position relation, as shown in formula (4).

$$\begin{aligned} P(x,f,D,S,F)_x &= x_i + \sum_{i=1}^{n} \left\{ f(\mathrm{x};\alpha,\beta) * [1\text{-}\mathrm{D}^{(\mathrm{i,i+1})}] * [S(i) * F(i) * V_i * Cos\theta_i * \Delta t_i] * C_i \right\} \\ P(x,f,D,S,F)_y &= y_i + \sum_{i=1}^{n} \left\{ f(\mathrm{x};\alpha,\beta) * [1\text{-}\mathrm{D}^{(\mathrm{i,i+1})}] * [S(i) * F(i) * V_i * \mathrm{Sin}\theta_i * \Delta t_i] * C_i \right\} \end{aligned} \tag{4}$$

III. CONCLUSION

Indoor blind navigation and assistive technologies will continue to improve the quality of life for the visually impaired. We verified the performance of the model for issues such as instantaneous position, instantaneous velocity, blind trajectories, the possibility of collision with pedestrians, and obstacle avoidance. The enhancement of mainstream mobile technology functions, the advancement of computer vision processing algorithms, the miniaturization of electronic devices, and cutting-edge new medical interventions, and this paper, starting from the positional relationship and direction decision-making of the blind, proposes a path separation index, which is expected to further promote the navigation field. The development of indoor assisted navigation technology for the blind, thereby improving the safety of indoor walking for the blind.

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