Research Article

Modeling and Simulation of Departure Passenger’s Behavior Based on an Improved Social Force Approach: A Case Study on an Airport Terminal in China

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The unprecedented growth of passenger throughput in large airport terminals highlights the importance of analyzing passengers’ movement to achieve airport terminal’s elaborate management. Based on the theory of original social force model, video data from a departure hall of a large airport terminal in China were analyzed to summarize passengers’ path planning characteristics. Then, a double-level model was established to describe passengers’ path planning behaviors. At the decision level of the proposed model, the avoiding force model including common avoiding force and additional horizontal avoiding force was established on the basis of setting time and space limitations for taking avoiding action and was used to describe passengers’ path planning in close-range space. At the tactical level of the proposed model, the route and node choice models were established to describe passengers’ path planning in long-range space. In the route choice model, a distribution of intermediate destination areas was proposed, with detouring distance, pedestrian density, speed difference, and pedestrian distribution considered in choosing an intermediate destination area. In the node choice model, the walking distance, the quantity of people waiting, and luggage were considered in choosing a check-in counter or security check channel. The main parameters of the proposed model were confirmed according to video data. Simulation results show that the proposed model can simulate departure passengers’ path planning behaviors at an acceptable accuracy level.

1. Introduction

With the growth of passenger throughput, more airport terminals lack sufficient infrastructures to offer passengers efficient service. At the same time, huge passenger throughput may cause congestion in some parts of an airport terminal and lead to potential risk of security assurance [1, 2]. An important way to solve these problems is to dispatch and use the existing terminal facilities efficiently to organize the passengers sensibly.

An airport terminal is a complex infrastructure composed of many subsystems, such as check-in, security check, waiting in the airport lounge, and boarding [3]. Passengers are the main service targets of all these segments. Thus, analyzing passengers’ traffic behaviors is the basis for improving the terminal’s internal facility planning, resource allocation, and passenger organization. Among all the segments mentioned above, many departure passengers are accompanied by relatives and friends before security check, making pedestrians’ traffic behaviors in the departure hall more complex than other regions in the terminal. Therefore, focusing on departure passengers’ traffic behaviors before security check is significant to provide a decision-making basis for improving airport terminal’s internal facility planning, resource allocation, and passenger organization. To describe departure passengers’ path planning behaviors, we chose the social force model [4] as the basic theory given its previous application to describe pedestrian’s microscopic traffic behaviors in several different scenes.
Analyzing passengers’ microscopic traffic behaviors is the key to realizing airport terminal’s elaborate management of facility planning and passenger organization needs [5, 6]. Additionally, in the departure hall before entering the security check area, departure passengers’ avoiding, route, and node choice behaviors are different from those shown in other walking scenes due to the special layouts. Thus, this study analyzed passengers’ characteristic microscopic traffic behaviors in a departure hall based on a video of a large airport terminal in China. Then, a double-level model was established to describe passengers’ path planning behaviors for the first time. At the decision level, by defining passengers’ avoiding time and space limitations, the close-range avoiding behavior can be described quantificationally. At the tactical level, passengers’ long-range route and node choice behaviors were modeled. Finally, the simulation results were compared with video data to prove the proposed model’s accuracy.

The structure of this paper is as follows. Section 1 briefly introduces the research background. Section 2 presents the literature review. Section 3 introduces the original social force model’s theory. Section 4 describes our analysis of the departure passenger’s avoiding behavior in the departure hall and the design of the avoiding social force model as the decision-level path planning model. Section 5 details our analysis of departure passenger’s route and service facility choice behaviors in the departure hall and the establishment of the route and node choice social force model as the tactical-level planning model. Section 6 confirms the proposed model’s parameters according to video data and then compares the simulation results with video data to prove the proposed model’s effectiveness. Section 7 concludes the research findings and proposes further research suggestions.

2. Literature Review

Modeling and simulating the motion of passengers in a terminal departure hall is a valid approach. The models on pedestrian dynamics can be categorized as macroscopic and microscopic. Compared with the macroscopic models, which study the movement characteristics of the pedestrian flow, the microscopic models focus on the movement of each pedestrian and have been much more widely used in the pedestrian traffic research field. The most common microscopic simulation models include the cellular automata model [7] and the social force model [4]. In the automata model, pedestrians are assumed to be homogeneous [8], consequently ignoring pedestrian heterogeneity and preference. However, the social force model is a successful approach in the field of crowd dynamics [9, 10], in which the agents having personalized characteristics form a complex crowd dynamic system. The social force model in the form of various forces can not only simulate pedestrian’s microscopic movement but also describe the relationship between group behaviors. The simulation results largely fit the actual observation results and thus mainly explain why the social force model is chosen as the research method in this study.

In 1998, the social force model was first proposed by Dirk Helbing [4], which indicates that a pedestrian’s movement is determined by three kinds of social force, namely, self-driven, psychological repulsive, and attractive forces. Helbing et al. improved the model by considering physical force (friction and stress) in subsequent research [11, 12]. Since then, more researchers pay attention to pedestrian’s microscopic behaviors on the basis of the social force model. Their related studies can be divided into two categories: one only focuses on pedestrian’s decision-level behaviors and improves the theory of each social force; the other adds a tactical-level route and the destination choice model in which the original social force model was not mentioned before.

Pedestrian’s avoiding behavior is the main focus of research in path planning’s decision level. The original social force model’s psychological repulsive force could not show a pedestrian’s voluntary avoiding behavior; thus, further research improved social avoiding force’s form and mechanism [13–15]. For example, Wang et al. [16] proposed that pedestrians adjust their desired speed considering the position of exits, obstacles, and other pedestrians to facilitate their discovery of the quickest path to destination. Additionally, Xiao et al. [17] and Qu et al. [18] employed the Voronoi diagram to calculate the detour route of an agent. Based on the avoiding force’s prediction mechanism, pedestrians decide how to avoid conflicting objects by considering their relative positions when collision happens [19–21]. To sum up, the recent research about the social force model (shown in Table 1) puts emphasis on the pedestrian collision avoidance and the shortest detour route, to name a few.

Path planning’s tactical level includes pedestrians’ route and node choice behaviors. For pedestrians’ route choice behaviors, researchers tend to consider more factors which affect pedestrians’ choices. Walking time [22] and route length [23] are utilized as the evaluation indexes of the shortest path. Two major factors affect the route choice: (a) environmental and (b) personal factors. The most influential environmental factors are distances from destination [24], congestion degree [25], speed difference [26], and exit’s width [27, 28]. Apart from environmental factors, personal factors can also affect exit choice. The most influential personal factor is the familiarity of the decision-maker with the route [29]. Furthermore, physical ability (depending on the age or health), habits, and sociopsychological characteristics (e.g., direct or indirect risk perception, cultural background or training, and past experience) can affect route choice. The research on pedestrians’ node choice behavior showed a similar trend with route choice. For example, Zheng et al. [30] established the metro station’s exit choice model regarding distance, pedestrian density, and width of exit.

The research mentioned above was mainly applied in the outdoors and metro or railway stations and cannot be used to study pedestrian flow at airport terminal. In fact, the terminal departure hall and the above scenarios have common characteristics (e.g., the avoiding, route, and node selection behaviors). Thus, the studies can be extended to explore the pedestrian flow in the terminal departure hall. This research will propose a revised social force model
according to the motion characteristic of the pedestrians and companions in the terminal departure hall.

3. Social Force Model

The original social force model proposed by Helbing [4,11,12] indicates that pedestrians move according to three different kinds of social forces, namely, self-driven, psychological repulsive, and physical forces. A pedestrian’s movement is calculated by Newton’s second law considering the three kinds of social forces: self-driven force \( \vec{f}_{i}^b \), demonstrating the expectation of pedestrian \( i \) arriving at the destination, and “interaction forces” \( \vec{f}_{ij} \) and \( \vec{f}_{iw} \) from other pedestrians \( j \) and walls \( w \), respectively. The corresponding equations are given by

\[
m_i \frac{d\vec{V}_i}{dt} = \vec{f}_{i}^b + \sum_{i' \neq i} \vec{f}_{ij} + \sum_{w} \vec{f}_{iw} = m_i \left( \vec{V}_{i}^0 + \frac{\vec{t}_i}{t_i} (\vec{V}_{i}^0 - \vec{V}_i(t)) \right),
\]

where \( m_i \) is the mass of pedestrian \( i \), \( \vec{V}_i^0 \) is pedestrian \( i \)'s velocity at time \( t \), \( \vec{V}_{i}^0 \) is the value of pedestrian \( i \)'s desired velocity, and \( \vec{t}_i \) is the unit vector of pedestrian \( i \)'s desired velocity pointing from pedestrian \( i \)'s position to his/her destination.

\( \vec{f}_{ij} \) is the resultant force of psychological repulsive and physical forces from pedestrian \( j \) to \( i \), which can be calculated as follows:

\[
\vec{f}_{ij} = A_i \exp \left( \frac{r_{ij} - d_{ij}}{B_i} \right) \vec{n}_{ij} + k g (r_{ij} - d_{ij}) \vec{t}_{ij} + K g (r_{ij} - d_{ij}) \Delta V_{ij} \cdot \vec{t}_{ij},
\]

where \( A_i \) is the strength parameter and \( B_i \) is the range parameter. \( r_{ij} \) is the sum of pedestrian \( i \)'s radius \( r_i \) and pedestrian \( j \)'s radius \( r_j \), and \( d_{ij} \) is the distance between pedestrians \( i \) and \( j \). \( \vec{n}_{ij} \) is the unit vector pointing from pedestrians \( j \) to \( i \). \( k \) and \( K \) are the strength parameters of friction and press, respectively; \( \vec{t}_{ij} \) is the unit vector of the relative motion’s direction; and \( \Delta V_{ij} = (\vec{V}_i - \vec{V}_j) \cdot \vec{t}_{ij} \) is the tangential speed difference between pedestrians \( i \) and \( j \). \( g(x) \) is a piecewise function which can be calculated as follows:

\[
g(x) = \begin{cases} 
0, & d_{ij} > r_{ij}, \\
1, & d_{ij} \leq r_{ij}.
\end{cases}
\]

The resultant force \( \vec{f}_{iw} \), including wall \( w \) to pedestrian \( i \)'s psychological repulsive and physical forces has a similar form to the resultant force from pedestrians \( j \) to \( i \), which is given by

\[
\vec{f}_{iw} = A_i \exp \left( \frac{r_{iw} - d_{iw}}{B_i} \right) \vec{n}_{iw} + k g (r_{iw} - d_{iw}) \vec{t}_{iw} + K g (r_{iw} - d_{iw}) \Delta V_{iw} \cdot \vec{t}_{iw}.
\]

Figure 1 illustrates the interpretation of the social force model.

4. Departure Passengers’ Decision-Level Path Planning Model

Pedestrians’ decision-level traffic behaviors determine their walking direction and speed in a close range around themselves. For departure passengers, avoiding other pedestrians and obstacles in a close range is their decision-level path planning behavior. In this paper, close-range area refers to the small area around the passenger, where pedestrian avoiding behavior occurs, defined as a semicircular area with a radius of 1.5 m centered on the passenger. Here, the avoiding behavior includes not only avoiding collision with opposite pedestrians but also overtaking low-speed pedestrians walking ahead. This section first summarizes departure passengers’ avoiding behavior according to video data from a large airport terminal in China. Then, it establishes departure passengers’ avoiding social force model on the basis of the characteristics of their avoiding behavior.

4.1. Departure Passenger Avoiding Behavior’s Characteristics

In this part, we collect a 15 min (starting at 6 a.m.) video on March 21, 2018, from the surveillance camera installed on the east side of island C of a departure hall in a large airport terminal in China, to analyze and summarize passengers’ avoiding behavior. The video includes check-in area, queuing area before security check, and common walking area in the departure hall, with over 500 passengers involved in it. According to the analysis of the video data, we summarize passengers’ avoiding behavior characteristics as follows:

1. Passengers only avoid other pedestrians or obstacles in a close range.
2. Passengers only avoid other pedestrians or obstacles within their visual field.

| Table 1: Comparison of current research about the social force model. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                               | Basic model     | Repulsive force revision | Pedestrian collision avoidance | Detour |
| Helbing [4]                    | ✓               |                  |                  |                  |
| Helbing [11, 12]               | ✓               | ✓                |                  |                  |
| Wang [16]                      | ✓               |                  |                  |                  |
| Xiao [17]                      | ✓               |                  |                  |                  |
| Jia [14]                       | ✓               |                  |                  |                  |
| Qu [18]                        | ✓               |                  |                  |                  |
| Yamamoto [15]                  |                  |                  |                  | ✓               |
(3) Passengers’ avoiding action has different priorities; the sooner a potential conflict happens, the earlier they will take avoiding action.

(4) Passengers have the ability to anticipate potential collisions. They forecast their future positions and potential conflict objects. Then, they change their speed accordingly instead of merely keeping a distance from their conflict objects’ real-time location.

(5) Each passenger has a smallest personal demand space just a little larger than the space he/she occupies on the ground. The area of this space differs from person to person, but nearly all the passengers avoid others because they do not want others to enter their personal space.

According to the avoiding characteristics mentioned above, we first provide the time and space limitations of taking avoiding action and then establish departure passengers’ avoiding social force model.

### 4.2. Time and Space Limitations of Taking Avoiding Action

Given that passengers only avoid other pedestrians or obstacles in their visual field and are not far from themselves, we combine sight and distance to describe the space limitation of avoiding.

As shown in Figure 2, a passenger can possibly take avoiding action in such a sector area. In the sector area, the middle circle $P_i$ is passenger $i$. Defining that the space occupied by passenger $i$ is a circle area, the smallest personal demand space should be a circle area just a little larger than the area occupied by passenger $i$. Therefore, we use the concentric circle larger than passenger $i$ to describe his/her smallest personal demand space, with its radius represented by $r_i^0$. The angle of this sector is $180^\circ$, which represents a passenger’s range of vision. $l_i^0$ is the radius of the sector, which limits that a passenger will not avoid other objects farther than this distance to himself/herself. To summarize, a departure passenger’s space limitation of taking avoiding behavior can be represented as follows:

$$P_i^0 = \left\{ P_j \mid d_{ij} \leq l_i^0, \forall_{ij} \in \left[ -\frac{\pi}{2}, \frac{\pi}{2} \right] \right\}, \quad (5)$$

where $P_i^0$ is the set of other pedestrians and obstacles that will be possibly avoided by passenger $i$ according to the space limitation and $P_j$ represents pedestrian or obstacle $j$.

Based on the space limitation, we then confirm the time limitation of taking avoiding action. Given that passengers have the ability to anticipate potential collisions, we forecast their positions while in conflict by the following equation:

$$\| (\vec{x}_j + \vec{v}_j t) - (\vec{x}_i + \vec{v}_i t) \| = r_i^0 + r_j, \quad (6)$$

where $\vec{x}_i$ and $\vec{x}_j$ are the real-time locations of passengers $i$ and $j$, respectively, and $t$ is the time interval from the current moment to the time when potential collision happens.

Equation (6) indicates that if passengers $i$ and $j$ maintain their motion at the current moment, they will conflict with each other after time $t$. Here, passengers $i$ and $j$ conflicting with each other equals passenger $i$'s smallest personal space boundary tangents to the circle occupied by passenger $j$. In equation (6), $t$ is the unknown value, and the minimum positive root of equation (6) is the time interval to potential conflict. If equation (6) has no positive root, conflict will not happen; thus, passenger $i$ does not have to avoid. In addition, the smaller the $t$ is, the sooner the passenger $i$ will have to take avoiding action.

In summary, passenger $i$ will take avoiding action only if the time and space limitation are both qualified. Moreover, passenger $i$ will first avoid passenger $j$ with the smallest time interval to potential conflict.

### 4.3. Avoiding Social Force Model

According to departure passengers’ avoiding behavior characteristics mentioned in Section 4.1, passengers forecast future positions of themselves and potential conflict objects and change their speed accordingly. Thus, the direction of avoiding force should be from passenger $j$'s centroid to passenger $i$'s centroid at the potential conflict place. Moreover, the closer passenger $i$ is to his/her position while conflicting with passenger $j$, the stronger the avoiding force will be. Therefore, the avoiding social force can be measured as follows:

$$f_{soc}^i = A_i \exp \left( -\frac{d_{ij}}{B_i} \right) \overrightarrow{n}_{ij}, \quad (7)$$

where $d_{ij}$ is the distance from passenger $i$’s real-time location to his/her location when conflict happens and $\overrightarrow{n}_{ij}$ is the unit vector pointing from passenger $j$’s centroid to passenger $i$’s centroid at the potential conflict place.

Figures 3(a) and 3(b) show the differences between the original social force model’s repulsive force and the avoiding force model proposed in this paper. As shown in Figure 3(a), the original social repulsive force points from pedestrian $j$ to pedestrian $i$, making pedestrian $i$ take action to move away from $j$. By contrast, in Figure 3(b), our avoiding force model lets passenger $i$ walk faster to arrive at the potential conflict point earlier than $j$ to avoid conflicting with passenger $j$, and this action fits the true behavior of passengers in the departure hall.
Figure 3(c) shows a possible condition in which the avoiding force points to the opposite direction of passenger $i$'s velocity vector. According to observations from the departure hall’s video, a passenger will change his/her walking direction rather than merely decelerating. In such circumstances, we add a horizontal avoiding force to passenger $i$ to describe his/her flexible detouring behavior. The bigger the passenger $i$ and $j$’s velocity difference on $i$’s horizontal direction, the easier for passenger $i$ to detour; thus, the horizontal avoiding force should be smaller. Therefore, the accessional horizontal avoiding force can be calculated as follows:

$$f_{avo}^{ij} = \frac{C_i}{V_j \cdot \sin(\theta_{ij})},$$

where $C_i$ is the strength parameter of the accessional horizontal avoiding force and $\theta_{ij}$, $V_i$, and $V_j$ is the angle between passengers $i$ and $j$’s walking direction.

In summary, a passenger avoids his/her first conflicting object under the common avoiding force calculated by equation (7). If the common avoiding force is opposite to his/her walking direction, the accessional horizontal avoiding force calculated by equation (8) also exists.

5. Departure Passengers’ Tactical-Level Path Planning Model

Pedestrians’ tactical-level traffic behaviors determine their walking direction and speed in a long range in their walking scene. For departure passengers, the long-range area can be the entire terminal departure hall, and their tactical-level path planning behavior includes route and node choices (including check-in counters and security check channels). In our model, passengers’ tactical-level model determines their self-driven force by changing their temporary walking direction. This section first summarizes departure passengers’ route and node choice characteristics according to video data mentioned in Section 3 and then establishes departure passengers’ tactical-level route choice model.

5.1. Departure Passengers’ Route and Node Choice Characteristics. Combining on-the-spot study and analysis of video data, we summarize passengers’ route and node choice characteristics as follows:

1. Each passenger has a final destination in the departure hall, but their trajectories are not always direct to the destination. Instead, they often change their walking direction and approach the final destination gradually.
2. The factors that passengers consider while changing their walking direction include distance, pedestrian density, and speed difference. Passengers seemingly tend to reduce detour distance to achieve efficiency. They also tend to walk through areas where pedestrian density is low and speed difference is small to walk comfortably.
3. The nodes that passengers have to choose in the departure hall are service facilities including manual check-in counters, self-service check-in facilities, and...
security check channels. These facilities are usually distributed in line. Accordingly, passengers choose one from the same kind of facilities when entering relevant service segments.

(4) When choosing a manual check-in counter or security check channel, a passenger typically considers his/her distance to the facility and the number of passengers waiting for service in each queue. While walking to the queuing area, they cannot always know the number of people in the queue because people at the end of the queue may cover their front people. In such a circumstance, passengers tend to estimate the number of people waiting in the queue by observing the distribution of people and luggage at the end of the queue.

(5) Passengers waiting before a self-service check-in facility often distribute themselves similar to a sector: The first passenger using the facility occupies the sector’s vertex, while other waiting passengers behind him/her stand on his/her left or right and attempt to forecast when they can use the facility.

Among all the characteristics mentioned above, the first and second characters are related to route choice behaviors, and the rest are about passengers’ node choice. Based on these characteristics, we establish route and node choice models, respectively, in Sections 5.2 and 5.3.

5.2. Departure Passengers’ Route Choice Model. To describe passengers changing walking direction, we first set a series of intermediate destination areas and then model passengers’ temporary desired speed direction to simulate passengers’ gradual path planning behavior until they reach their final destination.

As shown in Figure 4, considering passengers’ visual field and average horizontal and vertical displacement, we distribute the walking area of the departure hall into a series of identical rectangles. Using $l_i^\text{right}$ to represent the distance between passenger $i$’s regard point and his/her real-time location when making long-range tactical decision, we define the length of the rectangle’s long side as half of $l_i^\text{right}$, and the length of the rectangle’s short side is adjusted according to passengers’ average horizontal displacement. In this circumstance, when passenger $i$ arrives at the lower boundary of a rectangle, he/she begins to choose one of the rectangles whose lower boundaries are collinear with the upper boundary of the rectangle he/she is standing on.

According to passengers’ route choice characteristics mentioned in Section 4.1, passengers tend to reduce detouring distance. Thus, the sum of the distance from passenger $i$’s location to an intermediate destination area and the distance from the same intermediate destination area to passenger $i$’s final destination should be as small as possible. At the same time, passenger $i$ tends to choose an intermediate destination area with low pedestrian density and small speed difference between him/her and others. Furthermore, other pedestrians’ distribution in an intermediate destination area also affects passenger $i$’s choice. If pedestrians in an intermediate destination area are not close to its lower boundary, passenger $i$ is more likely to choose this area. On the basis of these analyses, we use a cost function to measure the cost if passenger $i$ chooses intermediate destination area $j$:

$$U_j = \left( \frac{\omega_1 l_1 + \omega_2 l_2}{d_{i,\text{ele}}^i} \right)^{k_1} \times \left( \frac{\sum_{s \neq j} \left( \frac{\bar{v}_i - \bar{v}_s}{\bar{v}_i} \right) ^ k_2}{S_j} \right) \times \left( \frac{\rho_j}{S_{j1}} \right) ^{k_3}, \quad (9)$$

where $l_1$ and $l_2$ are the distances from passenger $i$’s location to an intermediate destination area’s lower boundary midpoint and the distance from the same intermediate destination area’s lower boundary midpoint to passenger $i$’s final destination, respectively. $\omega_1$ and $\omega_2$ are the weights of $l_1$ and $l_2$, respectively, which are used to guarantee that passenger $i$ will not keep being farther from his/her final destination when making temporary route choices (if passenger $i$’s route choice draws him/her away from the final destination, $\omega_1$ will decrease and $\omega_2$ will increase). $n$ is the number of pedestrians in the intermediate destination area $j$, $S_j$ is the area of walking space in intermediate destination area $j$, and $S_{j1}$ is the area of the rectangle formed by passenger $i$’s nearest pedestrian and the lower boundary of intermediate destination area $j$. $k_1$ to $k_3$ are the impact degree parameters of detouring distance, speed difference, pedestrian density, and pedestrian distribution, respectively.

Among the intermediate destination areas on the same horizontal line, passenger $i$ will choose the one with the smallest cost function value as his/her temporary destination area. On the basis of this choice, passenger $i$’s desired speed vector should be pointing from $i$’s real-time location to the midpoint of $i$’s nearest passable gap in the chosen rectangle given that pedestrians always tend to adjust their motion as slightly as possible.

5.3. Departure Passengers’ Node Choice Model. Departure passengers’ node choice can be seen as a kind of special route choice. Therefore, passengers’ node choice shares the same trigger mechanism with route choice behavior. In the departure hall, the nodes that passengers must choose are the service facilities including manual check-in counters, self-service check-in facilities, and security check channels. Considering that passengers typically choose one from the same kind of service facilities which are located in line, we discuss passengers’ choices of each kind of service facility, respectively.

When choosing a manual check-in counter, a passenger usually considers the distance he/she has to walk to reach the counter as well as the expected waiting time. For a certain counter, waiting time depends on the quantity of passengers and their luggage in the queue, because both printing boarding pass and checking luggage need time. However, clearly counting the number of people and bags is difficult for passengers out of the queue. In such a circumstance, passengers estimate the total number of people and the amount of luggage in the queue through the distribution of people and luggage at the tail of the queue. Therefore, we use a cost function to measure the cost if passenger $i$ chooses manual check-in counter $j$:
When choosing a security check channel, the factors considered by passengers are the same as those of manual check-in counter. Therefore, we use equation (10) to measure the cost if passenger $i$ chooses security check channel $j$.

Above all, passenger $i$ will choose a service facility with the smallest cost value among all service facilities of the same kind in line.

6. Model Simulation and Verification

In this section, we first propose our parameter settings and then compare the simulation results of the proposed model with relevant video data to show its effectiveness in simulating departure passengers’ path planning behaviors.

6.1. Parameter Settings. We simulated video data mentioned in Section 3 and also considered previous work to confirm the value of the proposed model’s main parameters. Table 2 provides each parameter’s symbol, description, and value.

6.2. Simulation and Verification of Passengers’ Avoiding and Route Choice Behavior. To simulate passengers’ avoiding and route choice behavior, we use a common walking area in the departure hall of a large airport terminal in China as the walking scene. As shown in Figure 5, the common walking area is cut out from the surveillance video. The dashed areas in this figure represent obstacles. The smaller one on the top of the figure is a billboard, and the bigger one in the middle of the figure is a parterre. The upper right corner is part of check-in counters’ dividing strips.

To record passengers’ location conveniently, we establish a plane Cartesian coordinate system on the scene. According to Figure 5, we set the lower left quarter as the origin of the coordinate system, and the lower boundary and left boundary are the $x$- and $y$-axes, respectively. Based on these settings, each point in the scene can be represented by 2D coordinates. According to the video data, we define the long side of the intermediate destination as equal to 2.5 m and the short side as equal to 1.5 m. Thus, the walking scene can be divided into $7 \times 3$ suppositional rectangles.

As examples, trajectories of thirteen passengers in this area were used to simulate passengers’ movement, and each passenger was given a number according to his/her entrance order. To show the effects of each part of the route choice cost function, we discuss the motion of three passengers (passengers 1, 6, and 13) who are amply affected by different factors and briefly summarize the results of the rest.

Passenger 1 entered the walking scene from the right of the billboard, with his trajectory nearly straight at the beginning. Then, he detoured a handcart which stands to the right of the parterre, with its ordinate equal to 4.25 and the maximum distance to the right boundary of the parterre equal to 0.5 m. After detouring, he slowly approached the parterre’s right boundary and finally sat down at the boundary where ordinate is equal to 2.387 m.
Figure 6 shows the comparison between the real trajectory and the emulational trajectory of passenger 1. The red line represents the real trajectory extracted from the video by Tracker, while the blue line represents the trajectory simulated by the proposed model (the places of abscissa and ordinate are exchanged to observe the trajectories conveniently). Qualitatively comparing the two trajectories, we can find that their overall trends are similar, and the places on $y$-axis when maximum abscissa appears are also adjacent, which indicated that the proposed model can simulate the passenger’s moving trend. Quantificationally analyzing the two trajectories, we find that when passenger 1 was entering the second row of intermediate destination areas, the coordinates of real trajectory were $(7.0027, 5.1045)$, while the corresponding coordinates of emulational trajectory were $(7.7971, 4.2255)$, which had an aberration smaller than half of passenger 1’s radius with emulational coordinates. Comparing with passenger 6’s motion, which was similar to passenger 1, but an obvious difference was that when passenger 6 was entering the second row of intermediate destination areas, four walking passengers occupied the intermediate destination area which had the smallest detouring distance for passenger 6. By contrast, when passenger 1 began to choose intermediate destination areas on the second row, no passenger was blocking his way.

Figure 7 shows the comparison between the real trajectory and the emulational trajectory of passenger 6. The red line represents the real trajectory extracted from the video by Tracker, while the blue line represents the trajectory simulated by the proposed model (the places of abscissa and ordinate are exchanged to observe the trajectories conveniently). Qualitatively comparing the two trajectories, we can find that the first half of the two trajectories is not superimposed but shows a similar trend. Maximum abscissa appeared at a similar place, and the values of maximum abscissa are also similar. The two trajectories’ latter half shows an accordant trend when approaching the destination. Thus, the proposed model can simulate the passenger’s moving trend. Quantificationally analyzing the two trajectories, we find that when ordinate approached 5m (which indicated that passenger 6 was entering the second row of intermediate destination areas), the coordinates of real trajectory were $(7.4669, 5.0029)$, and emulational trajectory were $(7.1712, 5.0534)$, which indicated that passenger 6 chose the intermediate destination area closest to the parterre’s right boundary both in reality and in simulation. Both real trajectory and emulational trajectory’s maximum abscissa appeared when ordinate was between 4.2 and 4.3 m, with their coordinates equal to $(8.267, 4.256)$ and $(8.2792, 4.2735)$, respectively, and the distance between these two coordinates was only 0.02 m. Moreover, passenger 6’s emulational maximum abscissa appeared at a similar vertical position to passenger 1, which indicates that the proposed model can simulate passenger’s close-range direction change after choosing an intermediate destination area. The only difference from real trajectory was that when the ordinate

| Symbol | Description                      | Value                           |
|--------|----------------------------------|---------------------------------|
| $\tau_1$ | Time consumption of changing velocity | 0.5 s                           |
| $l_0^i$  | Radius of avoiding behavior’s space limitation | 1.5 m                           |
| $A_i$    | Strength parameter of avoiding force | 200N                            |
| $B_i$    | Range parameter of avoiding force | 1.5 m                           |
| $C_i$    | Strength parameter of horizontal avoiding force | 40N                             |
| $k_1$    | Strength parameter of press       | $1.2 \times 10^3 \text{kg} \cdot \text{s}^{-2}$ |
| $k_2$    | Strength parameter of friction    | $2.4 \times 10^5 \text{kg m}^{-1} \cdot \text{s}^{-1}$ |
| $k_3$    | Impact degree parameter of distance in route choice | 2                               |
| $k_4$    | Impact degree parameter of speed difference in route choice | 1                               |
| $k_5$    | Impact degree parameter of density in route choice | 2                               |
| $k_6$    | Impact degree parameter of distribution in route choice | 1                               |
| $k_7$    | Impact degree parameter of distance in node choice | 1                               |
| $k_8$    | Impact degree parameter of waiting people in node choice | 1                               |

Figure 5: Common walking area used for simulation.

Table 2: Parameter settings.

![Figure 5: Common walking area used for simulation.](image)
was between 4.4098 and 4.6048 m, emulational trajectory’s abscissa decreased at nearly 0.2 m compared to the last point before it. This finding is due to the deviation of passenger 6’s self-driven force and avoiding force. When passenger 6 was not very close to the parterre, avoiding force did not exceed the self-driven force, thereby explaining the appearance of such phenomenon which was different from reality.

Passenger 13 started his motion in the middle of the billboard and the parterre and then walked to the parterre’s right side and detoured six static passengers who were standing in the two second-row intermediate destination areas closest to the parterre’s right side, before finally approaching slowly the parterre’s right side.

Figure 8 shows the comparison between the real trajectory and the emulational trajectory of passenger 13. The red line represents the real trajectory extracted from the video by Tracker, while the blue line represents the trajectory simulated by the proposed model (the places of abscissa and ordinate are exchanged to observe the trajectories conveniently). Qualitatively comparing the two trajectories, we can find that the two trajectories showed similar overall trend and maximum abscissa. In the horizontal movement part, two trajectories accord with each other well; in the vertical movement part, emulational trajectory seems to be closer to the parterre’s right side than the real trajectory. Qualitatively comparing the two trajectories, we can find that emulational trajectory’s maximum abscissa appeared at (9.2840, 5.2656). Under the same ordinate, real trajectory’s relevant abscissa was 9.296 m. The deviation of these two abscissae was only 0.012 m, which shows that the proposed
model can accurately simulate passengers’ maximum horizontal displacement when making route choices and avoiding others. After detouring the static passengers, the distance between the real and emulational trajectories was around 1.0 m. This finding holds because, in reality, passenger 13 nearly kept walking straight after detouring and suddenly changed his walking direction at the end of his motion. By contrast, the proposed model’s simulation results slowly moved close to his destination. Therefore, this deviation appears due to passenger 13’s personal walking habits.

Comparing the movement trends of passengers 1, 6, and 13, we can find that all of them moved under self-driven and avoiding forces. When passenger 1 began to choose an intermediate destination area on the second row, none of these areas was occupied by other pedestrians. Thus, he only needed to be concerned about the handcart to the right of the parterre and made small horizontal movement. When passenger 6 began to choose an intermediate destination area on the second row, the area which had the shortest detouring distance for passenger 6 was occupied by four moving pedestrians. Fortunately, the speed differences between passenger 6 and the four moving pedestrians were quite small, thereby preventing them from blocking passenger 6 if he chose this area. Thus, passenger 6’s route choice and avoiding behaviors were similar to those of passenger 1. When passenger 13 began to choose an intermediate destination area on the second row, the two intermediate destination areas with the shortest detouring distances were both occupied by static pedestrians, which made it difficult for passenger 13 to walk through them to reduce walking distance. Thus, passenger 13 showed large horizontal movement under self-driven and avoiding forces.

Furthermore, the other ten passengers’ deviations between real and simulation trajectories were all smaller than the radius of their occupied space on the ground, indicating that the proposed model can simulate passengers’ avoiding and route choice behaviors at an acceptable accuracy level.

6.3. Simulation and Verification of Passengers’ Node Choice Behavior. In this section, we simulate passengers’ node choice behavior in the queuing area before security check channels. As shown in Figure 9, the simulation scene is also cut out from the surveillance video of a large airport terminal in China. Passengers enter this area from the lower left quarter, and walking through the dashed area is not possible. While shooting this video, three security check channels were in use. From top to bottom, we number these channels from No. 1 to No. 3. To record passengers’ location conveniently, we establish a plane Cartesian coordinate system on the scene. According to Figure 9, we set the lower left quarter as the origin of the coordinate system, and the lower boundary and left boundary are the $x$- and $y$-axes, respectively.

The video showed fourteen passengers arriving at this queuing area at the same time. To record their node choices clearly, we number them from No. 1 to No. 14 according to their order of entering the simulation scene. Each passenger’s suitcase number is recorded in Table 3. At the same time, Table 4 shows each queue’s original information.

Among the fourteen passengers, passengers 2 to 5 were a group of people led by passenger 2, and all of them followed passenger 2’s choice. Other eleven passengers independently chose security check channels. Based on this circumstance, Table 4 presents the node choice comparison of reality and simulation results.

According to the results in Table 5, after all these passengers made their node choices, the numbers of passengers who chose channels 1 to 3 were five, four, and five, respectively; and these results are all the same in reality and simulation. Comparing each passenger’s node choice, we can find that only passengers 11 and 13’s emulational choices did not match their real choices. Therefore, the proposed model can simulate passengers’ node choices at an acceptable accuracy level.

Discussing the reason why such simulation results appeared, we find that after passengers 1 and 2 chose channel

![Figure 8: Comparison of passenger 13’s real and emulational trajectory.](image-url)
because it was close to them with not many waiting people, passengers 3 to 5 followed their leader and made the waiting people number of channel 3 exceed those of the other two channels. The following passenger, 6, chose channel 1 because it had the least waiting people at that moment. Considering that passenger 6 was not carrying a suitcase, passengers 7 and 8 still thought that they would not have to wait for a long time before channel 1. Accordingly, these two people also chose channel 1. At this moment, the number of waiting people before channel 1 exceeded that of channel 2; consequently, passengers 9 and 10 chose channel 2. Given that passengers 9 and 10 had no luggage, channel 2 could still attract passenger 11. When passenger 12 began to make a node choice, channel 1 had the least waiting people and suitcases; thus, passenger 12 chose channel 1. For passenger 13, waiting people and suitcases before each channel were nearly the same. Thus, passenger 13 chose channel 1 because it was closest to him. After passengers 12 and 13 chose

![Figure 9: Queuing area before security check used for simulation.](image)

| Passenger number | Suitcase number |
|------------------|----------------|
| 1                | 1              |
| 2                | 1              |
| 3                | 1              |
| 4                | 1              |
| 5                | 1              |
| 6                | 0              |
| 7                | 0              |
| 8                | 0              |
| 9                | 0              |
| 10               | 0              |
| 11               | 1              |
| 12               | 1              |
| 13               | 1              |
| 14               | 2              |

Table 3: Collection of passengers’ suitcase numbers.

| Channel number | Queue length (m) | Pedestrian density at the tail of the queue (person/m²) | Suitcase density at the tail of the queue (item/m²) |
|----------------|------------------|--------------------------------------------------------|---------------------------------------------------|
| Channel 1      | 0.4              | 1                                                      | 1                                                 |
| Channel 2      | 0.8              | 2                                                      | 2                                                 |
| Channel 3      | 0                | 0                                                      | 0                                                 |

Table 4: Original information of each queue.
channel 1, passenger 14 chose channel 2 because it was the closest channel to him with not many people waiting in it.

### 7. Conclusions

The original social force model lacks the description of pedestrians' tactical traffic behaviors, and passengers in airport terminal’s departure hall have their special traffic behavior characteristics. In this paper, we first analyzed passengers’ traffic behaviors in a departure hall according to video data from a large airport terminal in China and then established a double-level path planning model of departure passengers. In the proposed model, passengers’ decision-level path planning behaviors are described by passengers’ avoiding social force model, and passengers’ tactical-level path planning behaviors are described by passengers’ route and node choice models. Passengers’ avoiding force model uses common avoiding force and additional horizontal avoiding force to describe how they change their velocity and walking direction in close range. Passengers’ route and node choice models use cost functions to determine the direction of their desired speed to change their self-driven force and describe their walking direction changes in the long range. Simulation results show that the proposed model can simulate passengers’ path planning behaviors at an acceptable accuracy level in both common walking space and service facility choosing area of a departure hall. Based on such detailed description of departure passengers’ path planning behavior, airport terminal’s internal layout can be better planned. Simulation results of passengers’ trajectories can also help the managers in airport terminal determine the region where conflicts and walking direction changes are frequent to prepare adequate service and security management resource in time and achieve grid-based elaborate management.

The findings of this study can help the airport management department obtain a better grasp of the rules of passenger movement and aggregation in the terminal. The social force model of departure passengers proposed in this study can be applied to all aspects of terminal operation management:

- (1) Terminal facility planning: the main flow direction of passengers walking in the departure hall can be attained through the analysis using the route choice model. Moreover, the main flow direction of passengers between different origins and destinations can be used to evaluate the rationality of internal planning of departure halls.

- (2) Passenger safety management: the entire departure hall is divided into smaller areas. Under the joint action of self-driven and avoidance forces, passengers’ trajectories are simulated by the proposed double-level model. The change in passenger’s movement path in each area and the number and degree of conflicts with other passengers can be calculated [31, 32]. The area with large fluctuations and frequent conflicts is the area where local passenger safety management must be strengthened.

- (3) Service resource allocation: the allocation evaluation of check-in counters in the departure hall of a terminal is realized by the service node choice model of departure passengers.

Further research can be started in these regions: (1) extending surveillance video’s collecting area to analyze passengers’ desired velocity change in different parts of the departure hall; (2) extending passenger traffic behavior model from 2D to 3D world to model passengers’ reactions to information boards set in different parts of the departure hall.

### Data Availability

The raw/processed data required to reproduce these findings, such as surveillance videos, cannot be shared at this time as the data also form a part of an ongoing study. All figures and tables of this article can be shared.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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| Passenger number | Channel number choice in reality | Channel number choice in simulation |
|------------------|----------------------------------|-------------------------------------|
| 1                | 3                                | 3                                   |
| 2                | 3                                | 3                                   |
| 3                | 3                                | 3                                   |
| 4                | 3                                | 3                                   |
| 5                | 3                                | 3                                   |
| 6                | 1                                | 1                                   |
| 7                | 1                                | 1                                   |
| 8                | 1                                | 2                                   |
| 9                | 2                                | 2                                   |
| 10               | 2                                | 2                                   |
| 11               | 1                                | 2                                   |
| 12               | 1                                | 1                                   |
| 13               | 2                                | 1                                   |
| 14               | 2                                | 2                                   |
Authors’ Contributions

Y.Z. and J.L. participated in conceptualization; X.X. contributed to data curation; Y.Z., J.L., and D.K. carried out formal analysis; Y.Z. was responsible for funding acquisition and wrote the original draft; J.L. and D.K. were involved in methodology and validation; Y.Z. and Q.L. helped with project administration; X.X., Q.L., and J.M. were responsible for resources; and Y.Z., J.L., D.K., X.X., and Q.L. reviewed and edited the paper. All authors have read and agreed to the published version of the manuscript.

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