MICROSCOPIC DECISION MODEL FOR PEDESTRIAN ROUTE CHOICE AT SIGNALIZED CROSSWALKS

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ABSTRACT

In this paper, two-tier mathematical models were developed to simulate the microscopic pedestrian decision-making process of route choice at signalized crosswalks. In the first tier, a discrete choice model was proposed to predict the choices of walking direction. In the second tier, an exponential model was calibrated to determine the step size in the chosen direction. First, a utility function was defined in the first-tier model to describe the change of utility in response to deviation from a pedestrian's target direction and the conflicting effects of neighboring pedestrians. A mixed logit model was adopted to estimate the effects of the explanatory variables on the pedestrians' decisions. Compared with the standard multinomial logit model, it was shown that the mixed logit model could accommodate the heterogeneity. The repeated observations for each pedestrian were grouped as panel data to ensure that the parameters remained constant for individual pedestrians but varied among the pedestrians. The mixed logit model with panel data was found to effectively address inter-pedestrian heterogeneity and resulted in a better fit than the standard multinomial logit model. Second, an exponential model in the second tier was proposed to further determine the step size of individual pedestrians in the chosen direction; it indicates the change in walking speed in response to the presence of other pedestrians. Finally, validation was conducted on an independent set of observation data in Hong Kong. The pedestrians' routes and destinations were predicted with the two-tier models. Compared with the tracked trajectories, the average error between the predicted destinations and the observed destinations was within an acceptable margin.

Keywords: Pedestrian decision model, Pedestrian route choice, Bi-directional pedestrian movements, Discrete choice model, Random-parameter model, Panel data

1 INTRODUCTION

Walking is an environmentally friendly mode of transportation. A better understanding of the decision-making processes of individual pedestrians when interacting with others would help to improve microscopic simulation of pedestrian movements and would thus allow more accurate prediction of their behavior in different situations. This in turn would help to assess the effectiveness of management measures on pedestrian-related traffic, such as crowd movements in mass gatherings (Batty et al. [1], Kluepfel [2]), passenger flows in mass transport terminals (Jia et al. [3], Schultz et al. [4]), and pedestrian crossing movements at signalized crosswalks (Zeng et al. [5], Lee et al. [6]).

Because signalized junctions are the most common type of traffic junction in densely populated cities, observational survey is a practical, straightforward, and reliable approach by which to study pedestrian movements there. To assess the macroscopic characteristics of pedestrian flows, Knoblauch et al. [7] conducted field studies on walking speed and start-up times at signal-controlled intersections in four urban areas in the United States. Lam et al. [8] conducted surveys on bidirectional pedestrian flows at signalized crosswalks in Hong Kong and investigated the relationships between speed and flow under different conditions. Xie et al. [9] observed pedestrian crossing flows at a busy crosswalk in central Hong Kong and suggested that the walking speed of bidirectional pedestrian streams is also influenced by the angle of intersection between the two flows. Xie and Wong [10] further extended their study on four-directional pedestrian streams at another crosswalk in Hong Kong and proposed a mathematical model to represent multidirectional pedestrian flow movements. Petritsch et al. [11] collected field data from the United States and developed a level of service model based on a series of pedestrian perception factors and junction geometric factors. Yang et al. [12] and Li et al. [13] estimated pedestrian delay at signalized intersections based on a field study in Xi'an. Although analyses of pedestrian-related safety issues are usually based on historical data, observational studies are still beneficial for measurement of pedestrian exposure (Knoblauch et al. [14]) and for evaluation of electronic devices' distracting effects on pedestrians as they cross junctions (Nasar et al. [15]). Therefore, it is appropriate to develop a microscopic model of pedestrian movements based on observational survey data.

In recent decades, typical models have been proposed to model pedestrian behavior at the microscopic level. The cellular automaton model and the lattice model were both introduced from vehicle traffic models. Blue and Adler adopted the cellular automaton model to simulate unidirectional [16], bidirectional [17], and four-direction [18] pedestrian flows based on a set of behavioral rules that determine the occupancy of neighborhoods. As CA models enable pedestrian movements to be approximated by setting rules for behavior, researchers have used this approach to perform microsimulation experiments investigating the operational conditions and performance of a variety of walking facilities. For example, Yue et al. [19] produced CA models of bidirectional pedestrian flow with different directional split ratios, taking pedestrian habits into consideration. Fang et al. [20] and Yang et al. [21] investigated whether pedestrians in different countries preferred to move left or right in cases of counter-flow. Lee and Lam [22] used observational survey data to derive rules for pedestrian behavior and calibrate and validate a simulation model for bidirectional pedestrian flow at signalized crosswalks, using the speed-flow relationship obtained in a previous study [8]. Abdelghany et al. [23] developed a microsimulation assignment model of multidirectional pedestrian movements in crowds, and used the model to evaluate the performance of different operational conditions in a prayer hall in Mecca, Saudi Arabia.

The lattice model is an analog for pedestrian flow as a gas or fluid. Muramatsu et al. [24] adopted the lattice gas model to describe pedestrian counter flow in a two-dimensional system. Helbing et al. [25] and Isobe et al. [26] adopted the lattice gas model to simulate pedestrian movements during an evacuation. In addition to using the analogy of gas and fluid, Helbing and Molar [27] proposed a "social force" model to represent several factors that influence the pedestrians' decision making. Furthermore, Hoogendoorn and Bovy [28] considered that pedestrian predict the behavior of other pedestrians based on their observations on the surrounding pedestrians, and hence suggested that walking can be represented as a differential game and pedestrian may aware of the walking strategies of others. Hoogendoorn and Daamen [29] further amended the model with anisotropy and finite reaction times as important aspects of walking behavior, and establish the approach to the calibration of experimental pedestrian trajectory data. Qu et al. [30] incorporated a heuristic function into the force-based model and suggested an effective algorithm to find approximate optimal pedestrian walking direction.

While CA models, lattice-gas models and social force models represent pedestrian movements with certain rules and predict their behavior in a deterministic approach, the discrete choice model has been commonly adopted to model pedestrian route choices in a probabilistic way. Antonini et al. [31] and Robin et al. [32] proposed a model to describe the short-term individual responses regarding route choice in the presence of other pedestrians. A cross-nested logit model was formulated because they considered the walking direction choice and the decision to change walking speed to be correlated. An error component was then introduced to change the model's error structure, and thus the mixed nested logit model was formulated. This approach considered 33 different alternatives and resulted in well statistically fit in model calibration and recovered comparable choice histogram in the validation. However, it divided the area around a pedestrian into 33 strips and only predicted which one he/she would go at the next step, i.e. the exact position of pedestrian will not be predicted. Rather than considering walking direction and speed at different levels of a nested logit model, Guo et al. [33] developed a microscopic pedestrian-simulation model that updated the pedestrians' positions at discrete time steps. A multinomial logit model was proposed to combine the choice of direction and the time step. As a one-step approach, all pedestrians were assumed to behave in the same way with the same preference in direction choice and avoidance of possible collisions.

Besides the above studies on pedestrian moving behavior at step level, discrete choice model has also been adopted to simulate pedestrian destination choices at link level. Dijkstra et al. [34] proposed a multi-agent approach to utilize behavioral principles for simulating pedestrian activity in shopping environments, and particularly focused on impulse and non-impulse chopping behavior. Borgers et al. [35] used this approach to model pedestrian movements at street segments. The destination choices include shops and other terminus, and the independent variables include type of shop, distance and tendency to visit a shop. Considering that pedestrian may not take all attributes into account in reality, Zhu and Timmermans [36] suggested principles of bounded rationality, i.e. pedestrians may have heterogeneous decision styles and rules so that they may decide only based on a subset of attributes.

In this study, we investigated pedestrian movements and their interactions in crossing signalized intersections, developed and calibrated an estimable model for pedestrian route choice at signalized crosswalks at microscopic level. We considered the choice of walking direction and the determination of step size sequentially. A two-tier modeling approach was proposed to simulate the microscopic pedestrian decision-making process on the choice of route at signalized crosswalks. In the first tier, a discrete choice model was proposed to estimate the choice of walking direction. It is followed by the second tier with an exponential model for capturing the step size change in response to the spacing change between pedestrians. Given the heterogeneity across the pedestrian samples, a random-parameter multinomial logit model (mixed logit) was adopted to address inter-pedestrian heterogeneity. Furthermore, because repeated observations of each pedestrian are made through the trajectory, panel data were adopted to ensure that the random parameters remained constant for individual pedestrians.

2 DATA

2.1 Description

In this study, a video data set collected in a previous study of bidirectional pedestrian flow at signalized crosswalks (Xie et al., [9]) was used to provide walking trajectory data to develop our model. The selected site was the signalized intersection between the Queen's Road Central and D'Aguilar Street in Central District, Hong Kong. The crosswalk was at the Queen's Road Central, which is a one-way, two-lane road. The size of the crosswalk was 17.5 m in length and 7.5 m in width. The cycle time of the intersection was 120 seconds, and there was a 15-second pedestrian phase in each cycle.

As described by Xie et al. [9], a 2-second period in the middle of each pedestrian phase was extracted to capture pedestrian interactions when the two streams had fully mixed. The pedestrian movements were tracked every 0.2 s; therefore, the trajectory of an individual pedestrian consisted of 10 positions. The first point was regarded as the origin, and the last was regarded as the destination. In this study, 1457 trajectories including 11,656 observations were extracted to develop the model, and the average speed was 1.21 m/s. An additional data set collected at the same site, with 5376 observations from 672 trajectories, was used for validation later in the study (Table 1).

[Insert Table 1 here]

2.2 Classification of direction choices

To investigate pedestrians' decisions on walking direction, the choices of direction must be defined. According to our observations, a pedestrian chooses any forward direction rather than stepping backward in more than 90% of cases. Therefore, the possible movement directions of a pedestrian at P_i were defined as shown in Figure 1 (labeled 1 to 10). The angles between the 10 directions and the target direction are $-\pi/2$, $-3\pi/8$, $-\pi/4$, $-\pi/8$, 0, $\pi/8$, $\pi/4$, $3\pi/8$, $\pi/2$, and π, respectively. The red arrow represents the pedestrian's target direction (from the origin to the destination). However, when affected by conflicting pedestrians, the subject pedestrian at P_i may choose to move in one of the 10 directions to avoid potential conflicts. As shown in Table 2, nearly 60% of observations indicate a strong preference for maintaining the target direction, and about 85% of observations maintain directions within $3\pi/16$ (33.75°) of the target direction (i.e., direction choices 4, 5, and 6). In addition, because directions 1, 2, 3, and 4 are actually symmetric with the directions 9, 8, 7, and 6, respectively, both directions in each symmetrical pair have the same degree of deviation from the target direction. The numbers of observations that fall on both sides of the target direction for each pair are roughly the same, which reveals that pedestrians have no significant preference for using either side of the target direction.

[Insert Figure 1 here]
[Insert Table 2 here]

Because pedestrians are inclined to walk with a smaller deviation from the target direction while not being sensitive to which side of it they use, it is reasonable to categorize the 10 possible movement directions according to the degree of deviation from the target direction as shown in Figure 2 (labeled 1 to 6).

[Insert Figure 2 here]

2.3 Interaction with potential conflicting pedestrians

In addition to the preference on directions, the movements of surrounding pedestrians also influence one's decision on the choice of route when walking in crowds. In this study, pedestrians who were closer than 2 m were generally considered to have possible conflicts. According to a preliminary investigation, a neighboring pedestrian P_j that enters the 90° visual cone in front of subject pedestrian P_i would be significantly aware of P_i and would influence the decision regarding the choice of route (Figure 3). To specify the effect induced by the surrounding pedestrians, a potential conflict point Q for P_i and P_j was estimated on the basis of their speeds at the preceding steps. The distance between the current position of P_i and Q was measured as S_{ijn} for P_i chooses a particular direction n, as shown in Figure 3.

[Insert Figure 3 here]

Based on the categories of direction choices defined in Figure 2, the observations of potential conflicts with surrounding pedestrians were identified, and their average distance to the estimated conflict points are listed in Table 3.

[Insert Table 3 here]

As shown in Table 3, although more than 80% of pedestrians who maintained their target directions (category 1) encountered no potential conflicts, about half of those who adjusted their walking directions (categories 2 to 6) had potential conflicts with surrounding pedestrians. In addition, the average distance to the estimated conflict point was greater than 0.8 m for categories 1 and 2, which deviate less from the target direction. However, this distance dropped to a level comparable to the width of the human body, about 0.5 to 0.6 m (Transportation Research Board, [37]), for categories 3 to 6. The greater the deviation from the target direction, the closer the subject pedestrian comes to the estimated conflict point, and some would finally choose to step backward to avoid the imminent collision (category 6, 0.47 m). This finding implies that pedestrians are sensitive to potential conflicts with others and would rather change directions to maintain a comfortable distance. Therefore, the trade-off between the willingness to maintain the target direction and the avoidance of potential conflicts should be taken into account in the model formulation.

3 METHODS

To develop a model that accurately represents pedestrian route choice behavior, a logical decision-making process must be defined and simulated with the use of a two-tier modeling approach. It is reasonable that a pedestrian would first decide upon a direction and then adjust the step size to optimize the utility. Therefore, multinomial logit models are adopted to evaluate the choice of walking direction, and an exponential function is used to determine the step size.

3.1 Choice of walking direction

Utility function

The multinomial logit model is a practical discrete choice model whose framework is based on the random utility theory. A commonly adopted expression of the utility of the n^{th} alternative for the i^{th} individual is

$$U_{in} = \sum_{k=1}^{p} \beta_k X_{ik} + \varepsilon_{in} \tag{1}$$

where X_{ik} is the k^{th} observable characteristics for the i^{th} individual, β_k $(k = 1, \ldots, p)$ are the estimable parameters, and ε_{in} is the random error term.

In this study, the utility of each choice of direction is estimated on the basis of the deviation from the target direction and the conflict induced from the surrounding pedestrians. As mentioned in Section 2.2, the direction choices were divided into six categories according to the degree of deviation from the target direction. Therefore, X_{i1}, X_{i2}, X_{i3}, X_{i4}, and X_{i5} are a set of dummy variables that represent categories 1 to 5, respectively, with the corresponding parameters β_1, β_2, β_3, β_4, and β_5. The parameter of category 6 is normalized to zero to allow parameter estimation. As mentioned in Section 2.3, the distance from the current position of pedestrian i to the estimated conflict point with pedestrian j for direction n was measured as S_{ijn}, and the value for estimating this conflict is defined as the critical spacing

$$X_{i6} = \mathrm{Min}(S_{ijn}), i \neq j \tag{2}$$

Finally, the utility of the n^{th} direction for the i^{th} pedestrian is

$$U_{in} = \sum_{k=1}^{6} \beta_k X_{ik} + \varepsilon_{in} \tag{3}$$

Standard multinomial logit (MNL) model

The simplest way to estimate the function and determine the direction choice probabilities is to adopt the standard multinomial logit model. The probability that the i^{th} pedestrian chooses to walk in the n^{th} direction out of the 10 direction choices is

$$P_{in} = \frac{\exp(U_{in})}{\sum_{m=1}^{10} \exp(U_{im})} = \frac{\exp(\sum_{k=1}^{6} \beta_k X_{ik})}{\sum_{m=1}^{10} \exp(\sum_{k=1}^{6} \beta_k X_{ik})} \tag{4}$$

By adopting the standard multinomial model for the choice of walking directions, the decision made by each pedestrian at each step was regarded as an individual observation, and parameters **β** are assumed to be constant for all individuals, i.e., a fixed-parameter model.

Mixed multinomial logit (ML) model

As noted in the previous section, the same set of parameters **β** are applied to all individuals with the standard MNL. However, a general concern in the model specification is the possible random variation in the effects of the explanatory variables across observations. To address this problem, the mixed multinomial logit model is an alternative that provides flexibility for **β** to vary over observations with the mixing distribution q (**β**|**φ**) (Washington et al., [38]); the probability function then becomes

$$P_{in} = \int \frac{\exp[\boldsymbol{\beta}_\mathbf{i}\mathbf{X}_\mathbf{in}]}{\sum_m \exp[\boldsymbol{\beta}_\mathbf{i}\mathbf{X}_\mathbf{im}]} q(\boldsymbol{\beta}_\mathbf{i} \mid \boldsymbol{\varphi}) d\boldsymbol{\beta}_\mathbf{i} \tag{5}$$

Particularly for this study, because the direction choices for all pedestrians are the same, to address the heterogeneity across individual observations, the mixed logit model can be expressed in a random-parameter structure as

$$\begin{aligned} P_{in} &= \frac{\exp(U_{in})}{\sum_{m=1}^{10}\exp(U_{im})} = \frac{\exp(\sum_{k=1}^{6}\beta_{ik}X_{ik})}{\sum_{m=1}^{10}\exp(\sum_{k=1}^{6}\beta_{ik}X_{ik})} \\ \beta_{ik} &= \beta_k + \varphi_{ik} \end{aligned} \tag{6}$$

where φ_{ik} is randomly distributed.

Mixed logit model with panel data (MLP)

As mentioned in Section 2.1, repeated observations of a particular pedestrian were made as he or she walked along the trajectory. It is more appropriate to account for the correlation among observations that belong to the same decision maker (Ortuzar and Willumsen, [39]). A practical method is to treat the parameters **β** as varying among pedestrians while remaining constant over the whole route as he or she walked. Therefore, the repeated observations for each pedestrian were grouped as a set of panel data. According to Train [40], a mixed logit panel probability that accommodates such inter-respondent heterogeneity while assuming intra-respondent homogeneity in tastes was given as

$$P_{i\mathbf{n}} = \int \prod_{t=1}^{T} \frac{\exp[\boldsymbol{\beta}_{\mathbf{i}} \mathbf{X}_{\mathbf{in_t t}}]}{\sum_m \exp[\boldsymbol{\beta}_{\mathbf{i}} \mathbf{X}_{\mathbf{imt}}]} q(\boldsymbol{\beta}_{\mathbf{i}} \mid \boldsymbol{\varphi}) d\boldsymbol{\beta}_{\mathbf{i}} \tag{7}$$

where $P_{i\mathbf{n}}$ is the probability that the i^{th} pedestrian makes the sequence of direction choices as $\mathbf{n}=\{n_1,\ldots,n_T\}$ over T repeated observations. $\mathbf{X}_{\mathbf{in_t t}}$ are the explanatory variables of the chosen direction n_t to the pedestrian i at time t.

NLOGIT 5 software was used to estimate the models mentioned above. The estimation of the random parameters was based on the simulated maximum likelihood approach with 100 Halton draws.

3.2 Step size

In addition to the choice of walking direction, step size is the other component of the pedestrian route-choice model. It is natural that a pedestrian would adjust the length of his or her step to avoid possible conflicts with others as he or she walks. Assuming a free flow speed of u_f, at which a pedestrian can walk freely without being affected by any other pedestrians, an exponential term is used to represent the decrease in walking speed in response to the conflicting effects induced by surrounding pedestrians. The model for estimating the instantaneous speed is then formulated as

$$u_{\mathrm{i}} = u_f (1 - \exp(\alpha (X_{\mathrm{i}6} + \beta))) \tag{8}$$

where X_{i6} is the critical spacing defined in Section 2.3, i.e., the distance to the closest estimated conflict point in the chosen direction (Equation 2), and α and β are the coefficients.

As defined in Section 2.3, only neighboring pedestrians who are closer than 2 m to the subject pedestrian and fall within the 90° visual cone would be considered to have conflicting effects on the subject pedestrian (Figure 3). Therefore, the value of X_{i6} was set at 2 m as a default for all observations that involved no such conflicting pedestrians.

4 RESULTS

4.1 Estimation of the walking direction choice model

NLOGIT 5 was used to estimate the standard multinomial logit model, the mixed logit model, and the mixed logit model with panel data; the results are shown in Table 4. The parameter estimates of all modeling approaches are significant at the 1% level for the five dummy variables that represent the direction choice categories. All models are consistent for the preference of direction choices. The pedestrians are inclined to maintain their target directions, and the utility decreases as the deviation increases from the target direction. However, when conflicting pedestrians are nearby, some may choose to give way directly to either side or even step backward (categories 5 and 6) than to keep moving forward along an ambiguous direction (categories 3 and 4) that is neither close to the target nor sufficient to avoid the potential conflict.

In contrast, the coefficient of the critical spacing X_6 became negative in the standard multinomial model, whereas the same coefficients were positive and significant at the 1% and 5% levels in the mixed logit model and the mixed logit model with panel data, respectively. As revealed from the results of the likelihood-ratio test, heterogeneity exists across individual pedestrians in response to the change in the explanatory variables. The positive values are also consistent with our observation from the data shown in Table 3, i.e., pedestrians would likely switch from the preferred target direction when they encounter conflicting pedestrians within a short distance. Therefore, the estimates of the latter two models are considered to be more reliable because they address heterogeneity and because the parameters are significant at acceptable levels. This finding indicates that the presence of a conflicting pedestrian reduces the utility of the corresponding direction for the subject pedestrian. Closer spacing means that the collision may occur sooner; however, inter-respondent heterogeneity exists among pedestrians in response to such a spacing change.

In terms of goodness-of-fit, the mixed logit model with panel data, with the lowest AIC value and the largest McFadden adjusted pseudo R^2, is considered to have the best fit among the three models. The statistics of the likelihood-ratio test are 192.58 and 727.66, respectively, which are both greater than χ^2 (6, 99%) = 16.81, which indicates that the standard multinomial logit model is rejected in favor of the mixed logit model and the model with panel data.

[Insert Table 4 here]

4.2 Estimation of the step size model

As proposed in Section 3.2, the step size is estimated with an exponential function of the critical spacing X_{i6}. As shown in Table 5, all parameters are significant at the 5% level. The free flow speed u_f is 1.306 m/s, which is similar to the value calibrated by Xie et al. [9] with observational data collected from the same site. It is also consistent with the observational mean walking speed (75.38 m/min, or 1.26 m/s) reported by Lam et al. [8] in a commercial area in Hong Kong. The other two parameters, α and β, are the coefficients; α is negative and indicates that the pedestrians would reduce their step size if the estimated critical spacing decreased. With no other pedestrians around, the subject pedestrian can walk freely at the free flow speed; however, the speed decreases with the spacing. The R^2 value of 0.062 and the MAPE of 31.1% indicate that the data points did not perfectly fit the model due to the short time interval between each data point (0.2 s); however, it still showed the general trend of how pedestrians interact with others and adjust their step size.

[Insert Table 5 here]

4.3 Test on the angle of view

As mentioned above, a preliminary test was conducted before adopting the 90° visual cone as the pedestrian visual field in Section 2.3 and later in Section 3.2. The horizontal binocular visual limit in humans is generally considered to be 120° (Stidwill and Fletcher, [41]). Using the same set of data, tests were conducted for different angles between 60° and 120° at 10° intervals. The lowest AIC value (30299.2) was achieved at a visual field of 90° (Figure 4). Therefore, we decided that the neighboring pedestrians in such a visual field would be aware of the subject pedestrian and would influence his or her decision-making process.

[Insert Figure 4 here]

5 VALIDATION

As mentioned in Section 2.1, another set of tracked pedestrian walking trajectories was used for model validation. Because the focus of this study was to develop a microscopic decision model of pedestrian route choice, the validation was conducted directly by predicting the walking route to the destination on the basis of the pedestrian's origin and the given positions of other pedestrians over the 10 frames.

For the choice of walking direction, the probabilities that the i^{th} pedestrian would choose each of the 10 directions were computed with the proposed model. Rather than assuming that the pedestrian would always choose the direction with the highest probability, a random number between 0 and 1 was generated for each step and the corresponding direction was drawn from the cumulative density function. The instantaneous speed was directly computed with the proposed step size model using the critical spacing of the i^{th} pedestrian on each direction at the t^{th} frame. The process was repeated frame by frame over 2 s. Finally, the predicted destination was then compared with the tracked one, and the error between them was taken as ε_i for the i^{th} pedestrian. The 672 trajectories resulted in a mean of 0.260 m and a standard deviation of 0.182 m, which is about half of the widely accepted human body width (0.5 to 0.6 m; Transportation Research Board, [37]). A comparison between observed and predicted sampled trajectories is shown as Figure 5.

[Insert Figure 5 here]

6 CONCLUSIONS

This paper proposes a two-tier modeling approach for simulation of the microscopic pedestrian decision-making process on the choice of routes at signalized crosswalks. The model results regarding pedestrian route choice were validated with the use of observation data collected from a signalized crosswalk in Hong Kong. In the first tier, a random-parameter multinomial logit model was used to model the choice of direction. In the second tier, an exponential model was calibrated to further determine the step size. Each parameter in the calibrated results was statistically significant.

In the first tier, the walking direction choice model indicates that pedestrians would probably walk in the most desirable target direction. However, if conflicting pedestrians are encountered, they would rather give way (either to one side or backward) than move on in a deviated direction. In addition, the estimated spacing change between the surrounding pedestrians also influences the utility of a pedestrian to choose a walking direction.

In estimating the walking direction choice model, the mixed logit model (random parameter) was found to be superior in addressing inter-pedestrian heterogeneity and thus gave better results than the standard multinomial logit model. The application of panel data was shown to be a practical way to control the random parameter as a constant for an individual pedestrian.

In the second tier, the model of the step size formulated the manner in which pedestrians would adjust their step size according to the presence of conflicting pedestrians. The nearer the potential conflict point, the slower is the walking speed. Finally, it was shown that two-tier models can work together to effectively reproduce the observed routes and destinations of pedestrian movements.

Rather than giving a set of fixed rules to simulate pedestrian movements, the proposed model represents pedestrian movements in a probabilistic approach, and accounts for heterogeneities among pedestrians with a simple and estimable form. Further validation with data from other sites would be beneficial for future application of the model. The model would be helpful in estimating pedestrian crossing time and capacity of signalized crosswalks, hence provide useful information for planning and geometric and signal design of the intersections. Besides, pedestrian movements at other walking facilities, especially crowded areas such as metro facilities and shopping malls, can also be investigated with the proposed model or its extended forms in future.

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TABLE 1. Summary of data.

	Calibration Set	Validation Set
Total number of trajectories	1,457	672
Total number of observations	11,656	5,376
Average walking speed (m/s)	1.21	1.24
Maximum walking speed (m/s)	3.22	3.06
Minimum walking speed (m/s)	0.13	0.10
Standard deviation of walking speed (m/s)	0.41	0.65

TABLE 2. Distribution of direction choices.

Direction	Observations	Percentage
1	283	2.4%
2	10	0.1%
3	145	1.2%
4	1582	13.6%
5 (Target direction)	6856	58.8%
6	1625	13.9%
7	151	1.3%
8	17	0.1%
9	242	2.1%
10 (Backward)	745	6.4%

TABLE 3. Observations with potential conflicts.

Category	1	2	3	4	5	6
Total number of observations	6856	3207	296	27	525	745
Number of observations with potential conflicts	1141	1299	138	13	249	399
Percentage of observations with potential conflicts	16.64%	40.51%	46.62%	48.15%	47.43%	53.56%
Average distance to the estimated conflict point (m)	0.85	0.81	0.62	0.58	0.56	0.47

TABLE 4. Estimates for the direction choice models.

	MNL	ML	MLP
Variables			
Direction category 1, X_1	2.2502 ***	2.3694 ***	2.3410 ***
Direction category 2, X_2	0.7941 ***	0.8568 ***	0.8642 ***
Direction category 3, X_3	−1.6020 ***	−1.6267 ***	−2.0039 ***
Direction category 4, X_4	−4.1166 ***	−4.7053 ***	−5.7424 ***
Direction category 5, X_5	−1.0243 ***	−1.0682 ***	−2.6120 ***
Critical spacing, X_6	−0.7864 ***	2.9098 ***	0.6954**
Goodness-of-fit			
No. of observations	11656	11656	11656
No. of parameters, K	6	12	12
Log likelihood at zero, $LL(\mathbf{0})$	−26838.93	−26838.93	−26838.93
Log likelihood at convergence, $LL(\boldsymbol{\beta})$	−15501.44	−15405.15	−15137.61
AIC	31014.90	30834.30	30299.20
McFadden's adjusted pseudo R^2	0.422	0.426	0.436
Likelihood-ratio test *(vs. Standard MNL)*			
$\chi^2 = -2\left[LL(\boldsymbol{\beta}_{MNL}) - LL(\boldsymbol{\beta}_{ML})\right]$		192.58	727.66
Degrees of freedom		6	6
Significance level		< 0.01	< 0.01

*Note: ***, **, * = significance at 1%, 5%, 10% level.*

TABLE 5. Estimates for the step size model.

Parameter	Estimate	Standard Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
u_f	1.306	0.017	1.273	1.338
α	−1.234	0.181	−1.588	−0.880
β	0.817	0.144	0.535	1.098
R^2	0.062			
MAPE	31.1%			

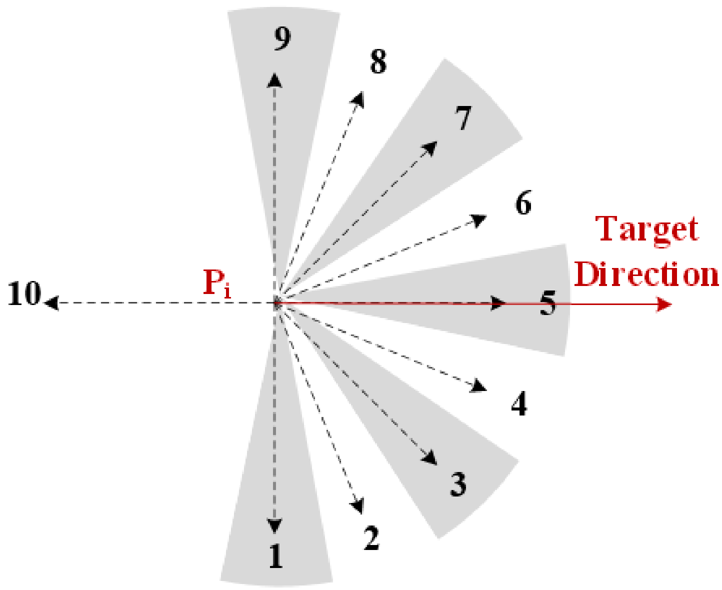

FIGURE 1 Possible movement directions

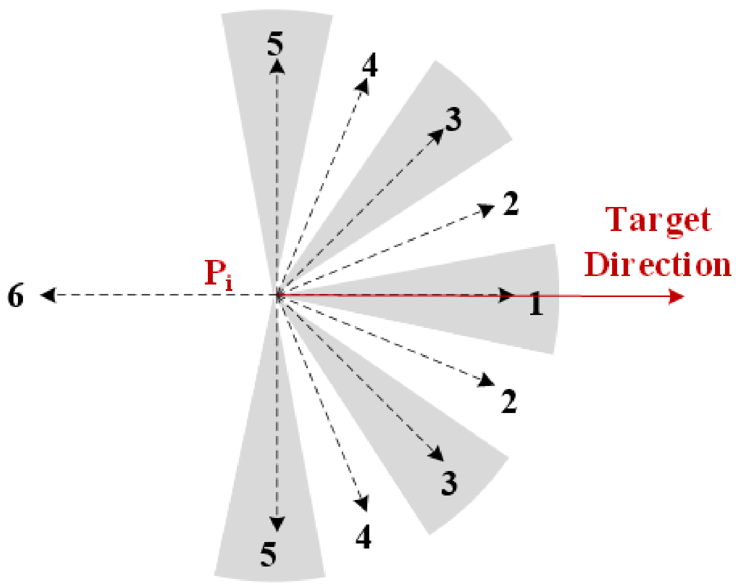

FIGURE 2 Categories of direction choices

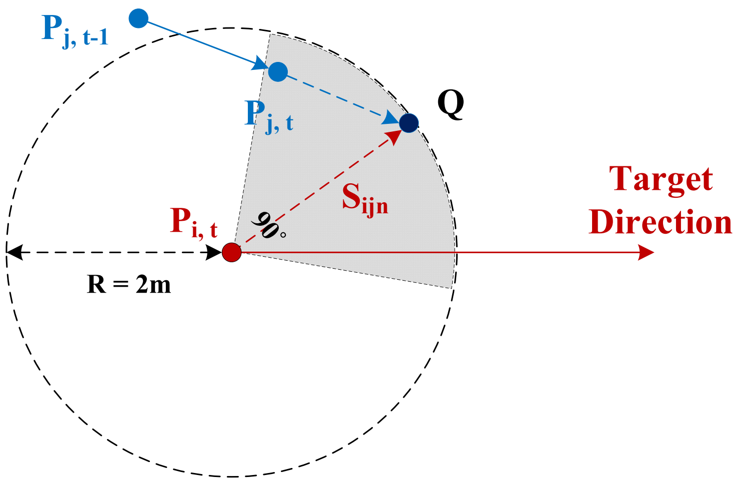

FIGURE 3 Potential conflicting with surrounding pedestrians

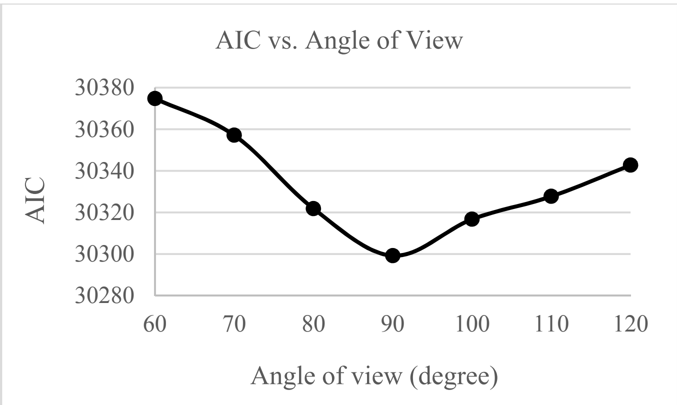

FIGURE 4 The AIC values for different angles of view

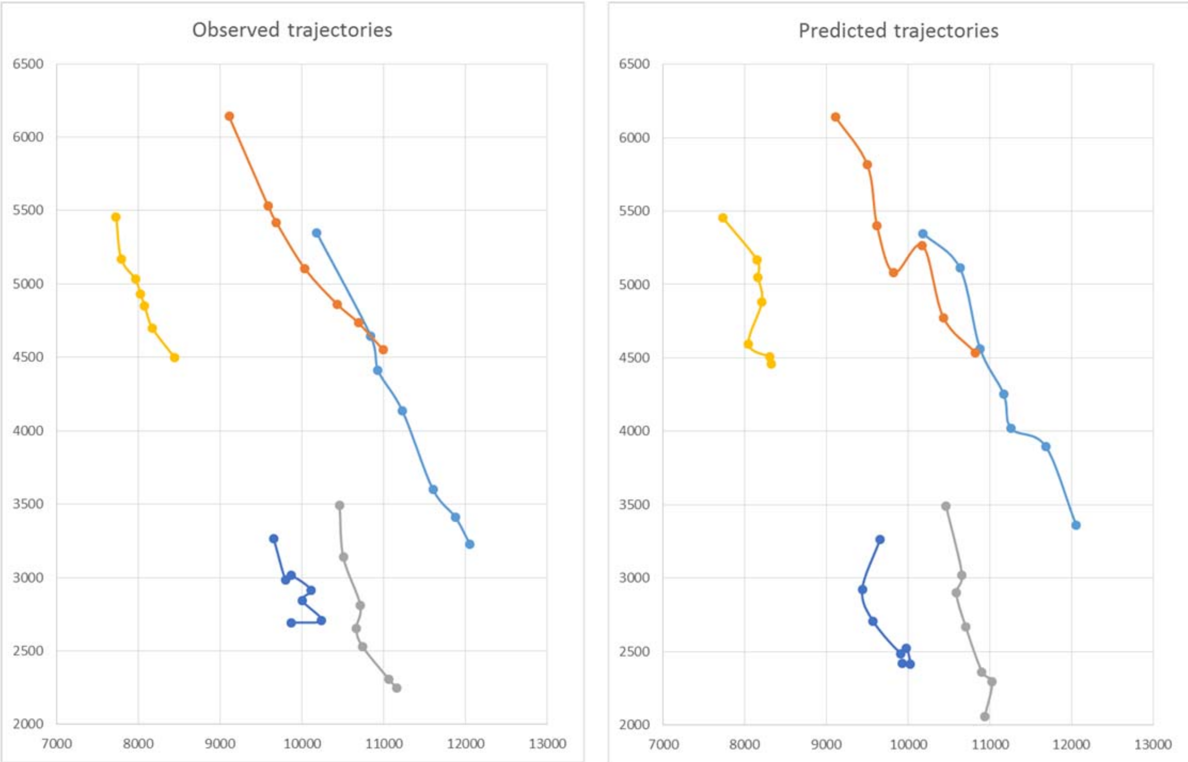

FIGURE 5 Comparison between observed and predicted trajectories