Multiple Destinations Pedestrian Model using an Improved Social Force Model

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Abstract

Social Force Model is extensively used to represent pedestrian movements. This model comprises several force terms. One of the terms describes the force that is required to move to the destination. The manner to select a destination in such a model is not specified and this model is generally used for one destination. In the real world, however, the desired destination of a pedestrian is observed to change over time. Therefore, in this research, we formulate a constantly changing destination selection process and model pedestrian movement when there are multiple destinations by improving Social Force model.

1 Introduction

Social Force Model [1][2] is known as a model representing pedestrian movement in a crowd. In this model, the pedestrian movement is formulated by defining a social force that applies to pedestrians, such as the force required to go to the destination and the force required to maintain a certain distance from other pedestrians and obstacles. The destination is considered to be immutable; however, in reality, the destination often changes over time. For example, when you go to workplaces or shopping malls where you visit frequently, the destination is obvious. Conversely, you cannot determine the destination accurately when you go to an event for the first time or in case of sudden evacuation due to a disaster; therefore, the destination may change from moment to moment. In fact, during a large-scale evacuation drill conducted at the New National Theater in Japan (2014), the choice of destination of the entire pedestrians was observed to alter owing to the mistakes of a few people. In this study, we formulate an ever-changing destination selection thereby extend Social Force Model and propose a pedestrian movement model wherein the destination which the pedestrian desired to move changes over time. In addition, we simulate the phenomenon that was observed during the evacuation drill at the New National Theater.

2 Related Work

Recently, pedestrian movement models have been studied to examine the crowd behavior for danger avoidance and migratory behavior by primarily using Cellular Automaton Model [3][4] and Social Force Model.

Cellular Automaton Model divides the space into lattice cells and considers the movement of pedestrians as to be movement between the cells. In this model, the cells in which the pedestrian moves are limited to four directions, referred to as the von Neumann neighborhood, or to eight directions, referred to as the Moor neighborhood, surrounding the cell in which the pedestrian is located. While it is easy to simulate the behavior of pedestrians in a crowd, it is difficult to produce human-like movements because the model is simple. In addition, the destination of the pedestrian is given; furthermore the group to which the pedestrian belongs and the intentions of each pedestrian are not considered.

Conversely, Social Force Model [1][2] proposed by Helbing et al. assumes that the forces from other pedestrians and environments act on each pedestrian and the movement of the pedestrians is formulated using these forces. Several models have been proposed as an extension of Social Force Model. For example, Moussaïd et al. calculated the traveling direction that does not contain any obstacles, such as other pedestrians and walls, and that travel without detouring as far as possible to the destination, and incorporates it in Social Force Model, whereby more natural pedestrian movement is reproduced [5]. However, Social Force Model simulates unconscious behaviors, such as maintaining a certain distance from other pedestrians and obstacles, and it cannot model the pedestrians' conscious destination selection. Line of sight can be used as a substitute expression for pedestrian consciousness. However, estimating the line of sight using videos is difficult. Some studies have been conducted to estimate the directions of the body [6][7] or of the head [8][9]; however, the following questions remain. Does the pedestrian actually look in the direction in which the body or head is facing? Even if the pedestrian observes something, does the pedestrian perceive it? While monitoring large-scale movements, it is costly to have all pedestrians wear a device such as an eye-tracker to measure the line of sight. Therefore, using the information concerning the line of sight is difficult. Another model that expresses conscious behavior has been proposed by Tamura et al. [10]. They defined the three pedestrian actions such as free walk, avoid, and follow, and assumed that the pedestrian decides 'which action to select' from the relationship with other pedestrians. Even though

Tamura et al. were able to achieve the movement of pedestrians more naturally by setting a subgoal in accordance with the pedestrian's intention, they considered the final destination to be immutable. However, in case of events such as fireworks festivals and evacuations, the destination may be ambiguous and likely to change. In a study conducted by Yamaguchi et al. [11], to predict the destinations using the past trajectory points, a model was proposed that was able to reproduce the pedestrian behavior even in case of multiple destinations. However, as the destination varied from moment to moment, the information that was contained in the past trajectory points may not be useful at times.

In this study, we formulate a process to determine the pedestrian's destinations without using any information from the line of sight or the past trajectory points. Further, we extend Social Force Model to enable the selection different destinations over time. Consequently, our proposed model can simulate natural pedestrian movement in real situations. Additionally, an evacuation guidance experiment was conducted for 1,300 people, and the validity of the model can be evaluated by comparing the measurement data that was obtained from the trajectories of the pedestrians, which were extracted from the fixed camera data, with the simulation result.

3 Social Force Model

In [1], Helbing et al. defined four forces that were applied to a pedestrian: the force required to go to a destination, the force required to maintain a certain distance from other pedestrians, the force to take a certain distance from an obstacle, and the force that attracts toward other pedestrians and objects as illustrated in Figure 1. Helbing et al. proposed Social Force Model comprising these forces and defined the force $\boldsymbol{F}_i(t)$ for a pedestrian i at a time t as

$$\boldsymbol{F}_i(t) = \boldsymbol{F}_{i,d} + \sum_{j \neq i} \boldsymbol{F}_{i,j} + \sum_{k} \boldsymbol{F}_{i,k} + \sum_{l} \boldsymbol{F}_{i,l}. \quad (1)$$

These four forces will be explained in turn below.

3.1 Force required go to the destination

The force that is required to advance at the desired speed to a destination can be defined by

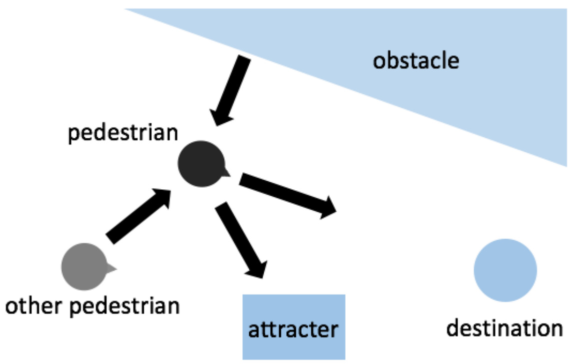


Figure 1: Forces acting on pedestrians

$$\boldsymbol{F}_{i,d}(t) = \frac{v_i^0 \boldsymbol{e}_i(t) - \boldsymbol{v}_i(t)}{\tau_i}, \quad (2)$$

where $\boldsymbol{e}_i(t)$ is the direction vector to the destination, $v_i^0 \boldsymbol{e}_i(t)$ is the desired speed, $\boldsymbol{v}_i(t)$ is the velocity vector, and τ_i is the relaxation time. When the final destination is $\boldsymbol{r}_i^0$ which comprises a series of several points, $\boldsymbol{r}_i^0$ can be represented as $\boldsymbol{r}_i^0 = \{\boldsymbol{r}_i^1, \cdots, \boldsymbol{r}_i^G\}$. If the destination at time t is $\boldsymbol{r}_i^g$ and the current position is $\boldsymbol{r}_i(t)$, $\boldsymbol{e}_i(t)$ can be defined as a unit vector given by

$$\boldsymbol{e}_i(t) = \frac{\boldsymbol{r}_i^g - \boldsymbol{r}_i(t)}{||\boldsymbol{r}_i^g - \boldsymbol{r}_i(t)||}. \quad (3)$$

3.2 Force required to maintain a certain distance from other pedestrians

When pedestrian i and pedestrian j are close to each other, a certain distance should be maintained so that they do not colide with each other. This force can be defined by

$$\boldsymbol{f}_{i,j} = A_1 \exp\left(\frac{-b_{i,j}}{B_1}\right) \boldsymbol{n}_{i,j}, \quad (4)$$

where A_1 and B_1 are the parameters, $b_{i,j}$ is the distance between the pedestrian i and the pedestrian j, and $\boldsymbol{n}_{i,j}$ is the unit vector of the direction of the pedestrian i from the pedestrian j.

A pedestrian i may be less affected by a pedestrian j who is located behind in the moving direction. The angle threshold ϕ is constant that used to determine whether the pedestrian j is behind the pedestrian i. Therefore, the weight w can be defined as:

$$w_{i,j}(\boldsymbol{e}, \boldsymbol{f}) = \begin{cases} 1 & (\text{if} - \boldsymbol{e} \cdot \boldsymbol{f} \geq ||\boldsymbol{f}|| \cos\phi), \\ c & (\text{otherwise, where } 0 < c < 1). \end{cases} \quad (5)$$

Thus, the following equation can be derived:

$$\boldsymbol{F}_{i,j} = w_{i,j}(\boldsymbol{e}, \boldsymbol{f}) \boldsymbol{f}_{i,j}. \quad (6)$$

3.3 Force required to maintain a certain distance from the obstacles

Similarly, a pedestrian i maintains a certain distance to avoid colliding with an obstacle k such as a nearby wall or door. This force can be given by

$$\boldsymbol{F}_{i,k} = A_2 \exp\left(\frac{-b_{i,k}}{B_2}\right) \boldsymbol{n}_{i,k}, \quad (7)$$

where A_2 and B_2 are the parameters, $b_{i,k}$ is the distance between the pedestrian i and the obstacle k, and $\boldsymbol{n}_{i,k}$ is the unit vector in the direction of the pedestrian i from the obstacle k.

3.4 Force that attracts toward to other pedestrians and objects

A pedestrian may be attracted to other pedestrians such as friends and family members and various objects, including shops and tourist sights. This is different from the force that is required to maintain a certain distance from other pedestrians and obstacles because, the force of attraction weakenes as time passes.

4 Extended Social Force Model

4.1 Pedestrian movement model

The pedestrian movement model proposed in this study is an extension of the multiple destinations selection that is based on Social Force Model. The force that attracts toward to other pedestrians and objects that are mentioned in Social Force Model is assumed to influence the destination selection; therefore, we integrate the multiple destinations selection into the term of the force required to go to the destination. In summary, in this study, we consider the following three forces: the force required to go to a destination, the force required to maintain a certain distance from other pedestrians, and the force required to maintain a certain distance from an obstacle. The proposed model includes a formulation of the process that is used to determine the destination as depicted in Eq. (8). This model separately considers two forces: 1) the force required to go to the destination in accordance with the intention of the pedestrian, “Which destination to select”, and 2) the force required to maintain a certain distance from other pedestrians/obstacles, which causes unconscious behavior that is irrelevant to the intention of the pedestrian. Therefore, this model can express movements that reflect the pedestrians’ intent with a “simple” model.

$$\boldsymbol{F}_i(t) = \boldsymbol{F}_{i,d} + \sum_{j \neq i} \boldsymbol{F}_{i,j} + \sum_{k} \boldsymbol{F}_{i,k}. \tag{8}$$

$\boldsymbol{D}_i(t) \in \{\boldsymbol{d}_1, \boldsymbol{d}_2, \cdots, \boldsymbol{d}_N\}$ is the destination selected by pedestrian i at time t. To apply this to Social Force Model, Eq. (3) is extended to Eq. (9).

$$\boldsymbol{e}_i(t) = \frac{\boldsymbol{D}_i(t) - \boldsymbol{r}_i(t)}{||\boldsymbol{D}_i(t) - \boldsymbol{r}_i(t)||}. \tag{9}$$

The equations of the other forces are the same.

4.2 Formulation of multiple destinations selection

The probability that the pedestrian i selects the destination $\boldsymbol{d}_n$ is $p_{i,n}$ and the final destination $\boldsymbol{D}_i(t)$ can be represented by

$$\boldsymbol{D}_i(t) = \boldsymbol{d}_{\hat{n}},\ \hat{n} = \max_n \{p_{i,n}, n = 1, 2, \cdots, N\}, \tag{10}$$

where $p_{i,n}$ comprises two terms. The first term, $x_{i,n}$, represents the confidence of the pedestrian i to go to $\boldsymbol{d}_n$. The second term, $y_{i,n}$, represents the confidence to go to the destination $\boldsymbol{d}_n$ when influenced by other pedestrians. α_i is the degree of to be influenced by other pedestrians and $p_{i,n}$ can be expressed by

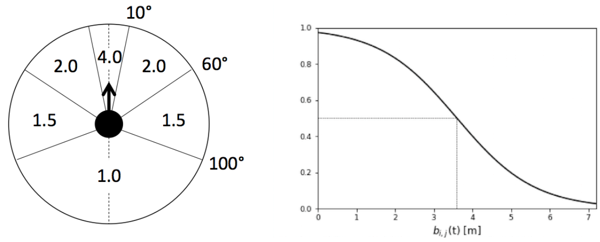
$$p_{i,n} = (1 - \alpha_i) x_{i,n} + \alpha_i y_{i,n}(t), \tag{11}$$

where $x_{i,n}$ and $y_{i,n}(t)$ satisfy the following conditions:

$$x_{i,1} + x_{i,2} + \cdots + x_{i,N} = 1, \tag{12}$$

$$y_{i,1}(t) + y_{i,2}(t) + \cdots + y_{i,N}(t) = 1. \tag{13}$$

While $x_{i,n}$ is a constant that does not change with time, $y_{i,n}(t)$ changes according to the relationship with other pedestrians with time, and can be defined by the following equation:



(a) Angle weight

(b) Distance weight

Figure 2: Positional weight

$$\bar{y}_{i,n}(t) = \sum_{j \neq i} \beta_{i,j} \gamma_{i,j}(t) h_{j,n}(t), \tag{14}$$

$$y_{i,n}(t) = \frac{\bar{y}_{i,n}(t)}{\sum_n \bar{y}_{i,n}(t)}, \tag{15}$$

where $\beta_{i,j}$ is the degree of familiarity of pedestrian i with pedestrian j that takes a maximum value of 10 if pedestrians i and j are intimate, but is otherwise 1, and $\gamma_{i,j}(t)$ is a weight defined by the positional relation, such as the angle and the distance between pedestrians i and j. For the angle, we define $f(\theta_{i,j}(t))$, which returns the value that depicted in Figure 2a for the angle $\theta_{i,j}(t)$ of pedestrians i and j. As the angle thresholds, 60° for both left and right, depicts the range that is simultaneously visible, whereas right and left 100° is the threshold that is required to consider the weak influence from other pedestrians who are located as behind a pedestrian defined in Helbing’s document [1]. In addition, we consider that the influence of the direction of movement will increase, and we set the weight to 2 times for left and right 10°. For the distance, we define the sigmoid function $g(b_{i,j}(t))$ that is represented in Eq. (16) for the distance $b_{i,j}$ between pedestrians i and j. In [12], the range of the social space that affects people is defined as 3.6[m]; therefore, the sigmoid is set so that the weight is halved in 3.6[m]. The inclination is set so as to gradually decrease depending on the distance.

$$g(b_{i,j}(t)) = \frac{1}{1 + \exp(b_{i,j}(t) - 3.6)}. \tag{16}$$

Using these relations, $\gamma_{i,j}(t)$ is defined as the product of the weights $f(\theta_{i,j}(t))$ on the angles and the weights $g(b_{i,j}(t))$ on the distance as follows:

$$\gamma_{i,j}(t) = f(\theta_{i,j}(t)) g(b_{i,j}(t)), \tag{17}$$

where $h_{j,n}(t)$ is 1 if the pedestrian j goes to the destination $\boldsymbol{d}_n$ and is 0 otherwise.

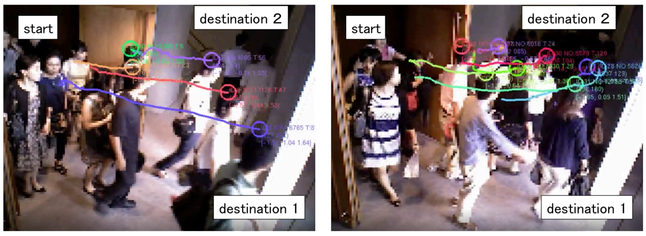
5 Experiments

5.1 Datasets

Data measured in an evacuation drill of 1,300 people that was conducted at the New National Theater in 2014 were used to evaluate the proposed model. The pedestrians’ movements were measured with RGB-Depth cameras using the method of [13]. Figure 3 and Figure 4 depict the examples of pedestrian movements at two locations. In this study, we use two-dimensional coordinate data projected from the three-dimensional coordinates onto the floor plane, as depicted in Figure 5.

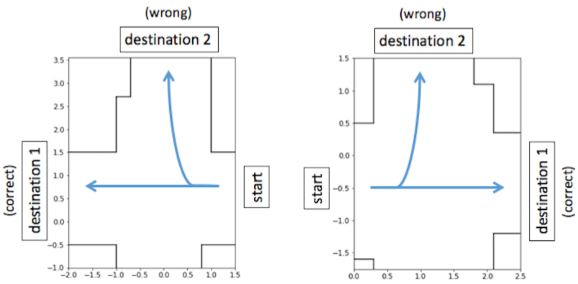
(a) Movement to destination 1 (b) Movement to destination 2

Figure 3: Location 1



(a) Movement to destination 1 (b) Movement to destination 2

Figure 4: Location 2



(a) Location 1 (b) Location 2

Figure 5: Two-dimensional space of the measurement environment. The obstacles are indicated by black lines. The number represents the distance, and the unit is[m]

At location 1, it is accurate to select destination 1. Two people mistakenly selected destination 2; however, the entire pedestrian flow did not alter. At location 2, it is accurate to select destination 1. However, several people in the front mistakenly selected destination 2; consequently, almost all the following people were influenced and selected destination 2. We examine whether these two phenomena can be reproduced using the proposed model.

5.2 Simulation of datasets

Here are the parameters used in the experiment. v_i^0 is the average value of the speed of each pedestrian calculated from the measurement data, $A_1 = 4$, $B_1 = 0.4$, $\phi = 100$, $c = 0.2$, $A_2 = 3$, and $B_2 = 0.2$.

The relaxation time τ_i, confidence $x_{i,n}$, degree of to be influenced α_i, and familiarity $\beta_{i,j}$ were determined from the captured video and the measurement data. In this situation, there are two destinations, so there are $x_{i,n}$ and $y_{i,n}$ for each of the two destinations.

For the primary pedestrians who chose the wrong destination, the actual measurement data were used. The initial positions of all the pedestrians were the same as the coordinates of the measurement data. While the probability of selecting a destination is approximately 0.5, a pedestrian is set to go to an intermediate point that is located between destination 1 and 2.

Location 1

Figure 6 depicts the measurement data for the primary pedestrian who chose the wrong destination at location 1. The parameters of each pedestrian are presented in Table1. The measurement data of a representative pedestrian and the simulation results of the proposed model are depicted in Figure 7.

Pedestrian ID38 is familiar with pedestrian ID37; therefore, pedestrian ID38 followed pedestrian ID37 and selected destination 2. Additionally, for a while, pedestrian ID45 could not decide which destination to selecte but finally selected destination 1. According to a visual evaluation, our proposed model was able to reproduce all 49 of the pedestrians' movements (100%), including the above mentioned phenomena.

Figure 8 depicts the flows of the measurement data and the simulation results at a particular time. It is possible to reproduce the fact that the flow moving to destination 1 does not alter even if there is a pedestrian who selects destination 2.

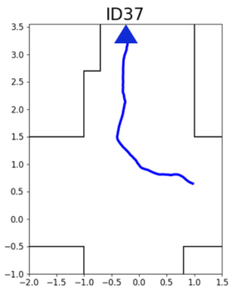
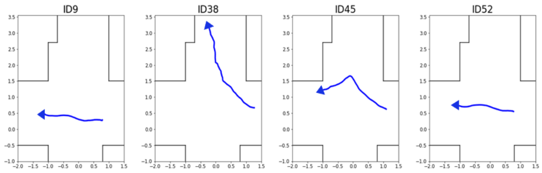


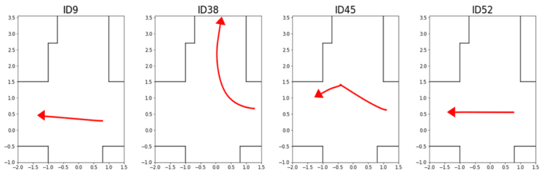
Figure 6: Measurement data of the primary pedestrian who selected the wrong destination at location 1

Table 1: parameters of each pedestrian at location 1

ID	9	38	45	52
τ	0.5	0.5	0.1	0.5
α	0.5	0.5	0.13	0.5
x_1	0.5	0.5	0.45	0.5
x_2	0.5	0.5	0.55	0.5
β (friendly pedestrian's ID)	1	10 (37)	1	1

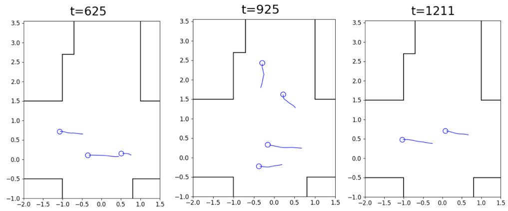


(a) Measurement data

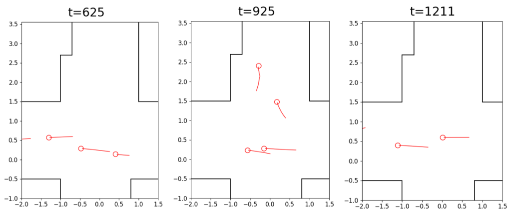


(b) Simulation results

Figure 7: Measurement data and simulation results of the representative pedestrians at location 1



(a) Measurement data



(b) Simulation results

Figure 8: Measurement data and simulation results of the pedestrian flow at location 1

Location 2

Figure 9 depicts the measurement data for the main pedestrians who chose the wrong destination at location 2. The parameters of each pedestrian are presented in Table2. The measurement data for the representative pedestrians and the simulation results of the proposed model are depicted in Figure 10.

Pedestrian ID4 is familiar with pedestrian ID5; therefore, pedestrian ID4 changed destination from destination 1 to destination 2 when pedestrian ID5 moved to destination 2. Pedestrian ID8 was influenced by the other pedestrians and changed destination from destination 1 to destination 2. Furthermore, pedestrian ID11 selected destination 2 owing to the influence of pedestrian ID10, who was moving nearby. Pedestrian ID13 selected destination 2 due to influence of the high familiarity with pedestrian ID10. According to the visual evaluation, our proposed model can reproduce the movement of 42 out of 44 pedestrians (95.5%).

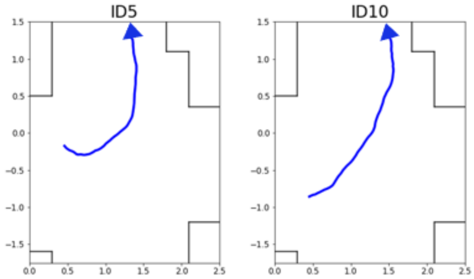


Figure 9: Measurement data of the primary pedestrian who selected the wrong destination at location 2

Table 2: parameters of each pedestrian at location 2

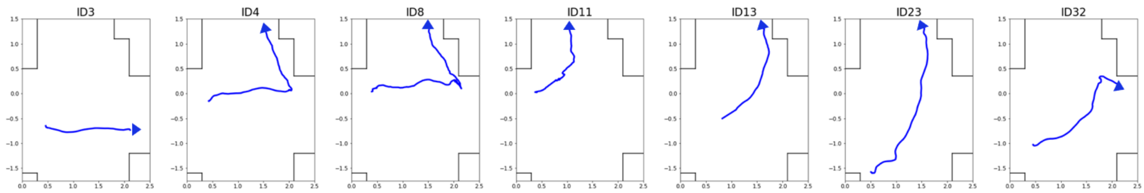
ID	3	4	8	11	13	23	32
τ	0.5	0.1	0.1	0.5	0.5	0.5	0.1
α	0.5	0.5	0.6	0.5	0.5	0.5	0.3
x_1	0.5	0.4	0.35	0.2	0.5	0.5	0.8
x_2	0.5	0.6	0.65	0.8	0.5	0.5	0.2
β (ID)	1	10 (5)	1	1	10 (10)	1	1

The two pedestrians whose movements could not be reproduced were pedestrians ID8 and ID32.

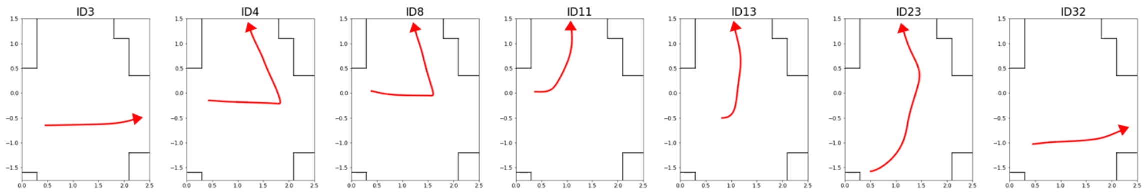
The trajectories of the measurement data of pedestrian ID8 and the simulation result are similar. However, for a long time, this pedestrian stopped and thought about the destination that should be selected. Changes in the coordinates x, y with respect to time t are depicted in Figure 11. During the time from $t = 100$ to $t = 200$, the value of x, y in the measurement data did not change. This indicates that the pedestrian could not rapidly decide about the destination. However, during the simulation, it was impossible to reproduce this movement of not being able to determine the destination for a long time.

Pedestrians ID32 changed its destination from destination 2 to destination 1 en route; however, this situation could not be reproduced by the simulation. Figure 12 depicts the results while changing the degree of be influenced α. Even when α is changed, pedestrian ID32 in the simulation selected only destination 1 or 2, and the situation of changing destination could not be reproduced. According to the video recorded with RGB-D cameras, pedestrian ID32 was influenced by the movement of the other pedestrians to destination 2 and moved toward destination 2. However, for some reason, the pedestrian's confidence in going to destination 1 increased, and pedestrian ID32 switched destinations. In the proposed model, the confidence of the pedestrians to move to their own destinations does not change with time, and it is set to remain constant. Considering that confidence is a function of time, it is possible that the variation in confidence could be reproduced; however, in this case, the model would become complicated.

Figure 13 depicts the flow of the measurement data and of the simulation results at various times. The model can reproduce the fact that the flow that was moving to destination 1 switched midway and finally changed to destination 2.

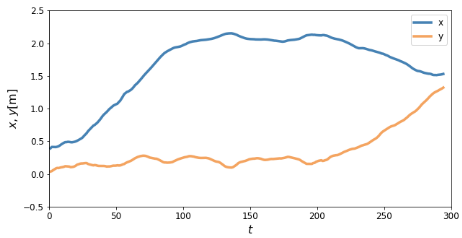


(a) Measurement data

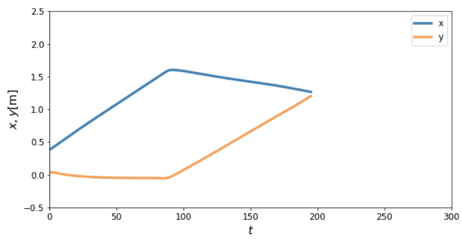


(b) Simulation data

Figure 10: Measurement data and simulation results of the representative pedestrians at location 2

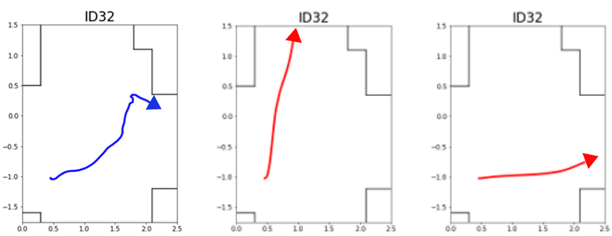


(a) Measurement data



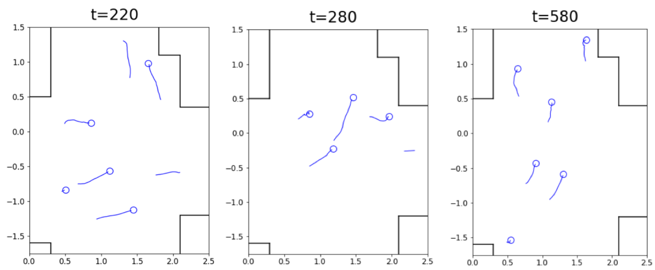
(b) Simulation results

Figure 11: Measurement data and simulation results of pedestrian ID8

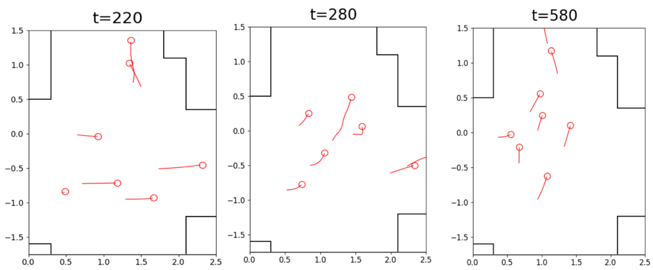


(a) Measurement data (b) $\alpha = 0.3$ (c) $\alpha = 0.4$

Figure 12: Measurement data and simulation results of pedestrian ID32



(a) Measurement data



(b) Simulation results

Figure 13: Measurement data and simulation results of pedestrian flow at location 2

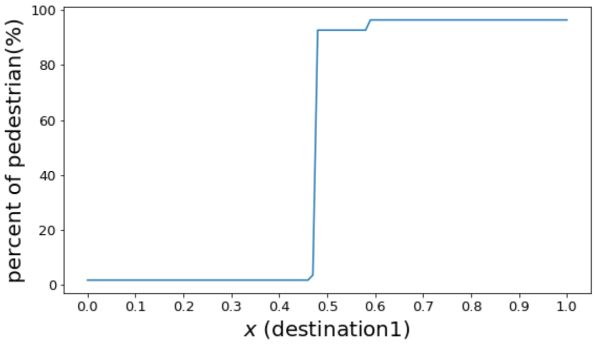


Figure 14: The proportion of the pedestrians who finally moved to destination 1

5.3 Difference in pedestrian movement with confidence

Experiment 1 demonstrated that the movement of pedestrians could be reproduced with high probability using the proposed model. At location 2, several pedestrians chose the wrong destination that influenced the pedestrians behind them to also select destination 2. Therefore, we examined the manner in which pedestrian movement changes when the confidence is changed. We changed pedestrian's confidence to destination 1 from 0 to 1. For the remaining parameters, we used the parameters of the model used in Experiment 1.

The percentage of pedestrians who finally moved to destination 1 while changing the pedestrian's own confidence to destination 1 from 0 to 1 is depicted in Figure 14. While the certainty exceeds a certain value (0.48), nearly all the pedestrians were observed to select destination 1. Therefore, if all the pedestrians have a confidence higher than a half, nearly everyone selects the accurate destination even if there are some people who mistakenly select the inaccurate destination. Therefore, it is necessary to increase the confidence degree via guides such as signboards.

6 Conclusion

In this study, we formulated an ever-changing destination-selection process and extended Social Force Model to model the movement of pedestrians when the destination changes. The proposed model reproduced the phenomenon of the changing destination-selection process during the evacuation drill of the New National Theater. If it is possible to increase the confidence via the guidance of a signboard or an assistant, an evacuation from a large facility can be accurately performed using the correct route. Therefore, it should be possible to realize optimal pedestrian navigation by examining the manner in which the design of a signboard and the position of a guidance member affects the degree of confidence.

Acknowledgments

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