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Crowd Hybrid Model for Pedestrian Dynamic Prediction in a Corridor

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ABSTRACT The pedestrian dynamic prediction is of great theoretical significance to provide information to staff in public buildings for decision makings. Based on the conservation law of mass and the social force model, the crowd hybrid model, in which the heterogeneity of pedestrians from the microscopic level is considered, is established to predict the dynamic characteristics of pedestrian flow in a corridor. In this model, the corridor is divided into multiple calculation black boxes in which the number of pedestrians is conserved, and the adopted density-outflow data via social force model is required to be saved in the data base in advance. The crowd dynamics in the corridor is studied, and simulation results indicate that the pedestrian density and motion state, i.e., free state and jamming state, can be predicted. The proposed crowd hybrid model combines the advantages of both macroscopic pedestrian movement model with less computation and microscopic pedestrian movement model considering the detailed interactions of individuals. This hybrid modeling method is especially suitable for the pedestrian dynamic prediction in a corridor where a camera or laser cannot satisfy the requirements of monitoring.

INDEX TERMS Pedestrian flow, social force model, density prediction, hybrid pedestrian movement model.

I. INTRODUCTION

Corridors occupy important roles in public buildings, e.g. subway stations, airports, or stadiums. With the increase of people's travel demand, the study on pedestrian movement in the corridor has attracted much attention in the last few decades. Especially, the bidirectional pedestrian flow dynamic in the straight corridor is a research focus as its self-organization phenomenon of lane formation [1], [2]. Generally, the bidirectional pedestrian flow can form into three motion states [3], i.e., the free state when lane formation may occur, the coexisting state, and the jamming state when breakdown phenomenon [4] may be triggered. When breakdown phenomenon occurs, overcrowded pedestrians are bound to reduce the traffic rate and even cause the potential disaster like stampede. In order to avoid this happening, it appears that the evaluation and prediction of pedestrian motion state in advance is very important. With the development of computer simulation technology, many pedestrian dynamics models have emerged and achieved great progress for further evaluating evacuation efficiency [5].

Generally speaking, pedestrian dynamics model can be roughly divided into fast but behaviorally questionable macroscopic models and slow but highly precise microscopic models. Macroscopic models, treating the pedestrian flow at a level of aggregation [6], are usually built as the fluid dynamics or gas dynamics [7]. In the macroscopic model, the crowd system is usually described by the flow density and its average motion speed [8]. Some contributions about the macroscopic pedestrian movement model are presented in [9]–[11]. In contrast to the macroscopic model, the microscopic models consider pedestrians as independent individuals with respect to detailed behaviors, which are the state of the art for computer simulation of pedestrian dynamics [12]. The typical microscopic models mainly contain cellular automata model with the grid-based motion decision [13]–[15], the social force model (SFM) considering the physical and psychological forces [16], NOMAD model incorporating a strategic decision making process [17], the game theory model maximizing each pedestrian's utility [18], and the agent-based model with virtual agents [19]. The detailed comparisons

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between the macroscopic model and the microscopic model are presented in [20].

Each pedestrian movement model usually has its own characteristics. The macroscopic model mainly focuses on the global information of pedestrian flow, meanwhile some precisions of the individual interactions are overlooked. The microscopic model mainly focuses on individual behaviors, whilst the calculation amount inevitably increases which could further cause the reduction of real-time performance especially for the large scale crowd. In recent years, hybrid pedestrian movement model emerges as required. The hybrid model refers to the combination of two or more different pedestrian movement models. This model can give full play to the advantages of the selected models, but the model construction process is complex and its solution is also difficult. So far, there is still no model which could be able to completely simulate crowd movements in reality, as the pedestrian movement involves many internal and external factors. Borrmann *et al.* [21] combined the macroscopic dynamic network flow model and the microscopic cellular automata model through the two-way coupling technology. In this hybrid method, the output of one model was fed back to the other model which thereby established a control cycle. Therefore, The predicted evacuation time error was reduced to a certain extent. Hanseler *et al.* [11] proposed a load hybrid model, combing the Hughes model and the cellular automata model, for crowd dynamics in the public pedestrian-friendly area, which can reflect the simultaneous and potential conflict propagation among multiple pedestrian groups. Wang *et al.* [22] introduced a two-time-scale hybrid model to describe crowd dynamics in a typical unidirectional environment. In this model, the analysis of pedestrian movements can be carried out rigorously by using properties of stability of network system and stochastic approximations.

Actually, the research on understanding and further predicting pedestrian dynamics in public buildings especially with complex structures, such as airport, metro stations, stadiums, etc., is rather difficult. Take the pedestrian flow in the metro hub station as an example, the real-time prediction of pedestrian density in the corridor during the rush hours is a very important task for the crowd management, which will become more important if the pedestrian flow is bidirectional that is extremely prone to breakdown. Therefore, how to predict pedestrian dynamics in the corridor such as density and motion states seems to be particularly important. Xue *et al.* [23] studied the collaboration behaviors in the bidirectional pedestrian flow through experiments in order to improve the accuracy of the cellular automata model. Li *et al.* [24] investigated the influence of psychological tension on the bidirectional flow via an extended cellular automaton model. Zhang *et al.* [2] studied lane formation and overtaking behavior of pedestrians in the heterogeneous bidirectional flow based on the modified social force model. Yang *et al.* [25], [26] pointed out that the heterogeneity in pedestrians can affect the bidirectional flow dynamics. However, the above studies on the bidirectional pedestrian flow mainly focused on the specific behaviors of the flow from a microscopic perspective. It is impossible to predict the crowd's future dynamic characteristics, which is very important for the formulation of crowd control measures. Basically, the investigation of pedestrian flow dynamics based on microscopic model is more suitable for exploring some specific behavior details, but is not the best choice to predict traffic flow with strong real-time requirement. Therefore, one of the main contributions in this paper is to propose a hybrid method to solve the problem of pedestrian flow state prediction with high real-time performance, in order to control inflows in advance which could help avoiding congestions. This hybrid model can not only give full play to the advantages of microscopic model such as SFM in describing individual habits, gender, heterogeneity and other detailed behaviors, but also give play to the characteristics of macroscopic model with less computation.

The structure of this paper is as follows. It continues with the description of the SFM in section II. Section III presents the modeling method for the crowd hybrid model, where the concept of calculation black box is proposed to compute its inner density. The verification of the proposed hybrid model is given in section IV. After analyzing the simulation results, the key discoveries are reviewed in section V.

II. DESCRIPTION OF THE SFM

The SFM [27] of Helbing *et al.* expressed by Eq. (1) indicates that pedestrians are driven by the desired force, $\vec{f}_i^0$; the interaction force between pedestrians i and j, $\vec{f}_{ij}$; and the interaction force between pedestrian i and walls w, $\vec{f}_{iw}$.

$$m_i \frac{d\vec{v}_i(t)}{dt} = \vec{f}_i^0 + \sum_{j(\neq i)} \vec{f}_{ij} + \sum_{w} \vec{f}_{iw}, \tag{1}$$

$$\vec{f}_i^0 = m_i \frac{v_i^0(t)\vec{e}_i^0 - \vec{v}_i(t)}{\tau_i}, \tag{2}$$

$$\begin{aligned} \vec{f}_{ij} &= A_i \exp\left[\left(r_{ij} - d_{ij}\right)/B_i\right]\vec{n}_{ij} \\ &\quad \times \left(\lambda_i + (1-\lambda_i)\frac{1+\cos(\varphi_{ij})}{2}\right) \\ &\quad + kg\left(r_{ij} - d_{ij}\right)\vec{n}_{ij} + \kappa g\left(r_{ij} - d_{ij}\right) \triangle v_{ji}^t \vec{t}_{ij}. \end{aligned} \tag{3}$$

$$\begin{aligned} \vec{f}_{iw} &= A_i \exp[(r_i - d_{iw})/B_i]\vec{n}_{iw} + kg(r_i - d_{iw})\vec{n}_{iw} \\ &\quad + \kappa g(r_i - d_{iw}) \triangle v_{wi}^t \vec{t}_{iw}. \end{aligned} \tag{4}$$

Here, m_i is the mass of pedestrian i, and $\vec{v}_i(t)$ is the actual walking velocity at time instant t. The desired force $\vec{f}_i^0$ shows pedestrians' aspiration to obtain the desired velocity, where v_i^0 is the desired speed and $\vec{e}_i^0$ is the desired walking direction. τ_i is the adaptation time to adjust the current velocity to the desired velocity. $\vec{f}_{ij}$ defines the pedestrian's psychological tendency to steer away from others and the physical force that occurs when the distance between two pedestrians d_{ij} is less than the sum of these two pedestrians' radii $r_{ij} = r_i + r_j$. A_i is the interaction strength and B_i is the range of the repulsive interactions. $\vec{n}_{ij} = (n_{ij}^1, n_{ij}^2) = (\vec{r}_i - \vec{r}_j)/d_{ij}$ is the normalized

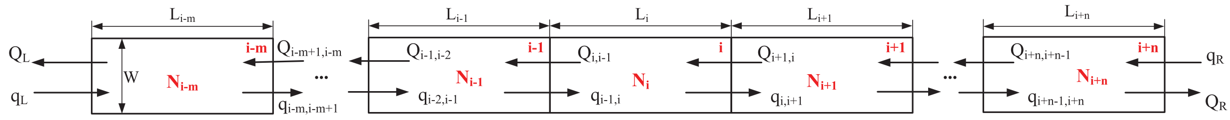


FIGURE 1. The diagram of the calculation black boxes in the straight corridor.

TABLE 1. Parameters in the SFM.

Symbol	m (kg)	A_i (N)	B_i (m)	κ (kg/(m · s))	k (kg/s^2)
Value	80	2000	0.08	240000	120000

vector pointing from pedestrian j to i, and $\vec{r}_i$ is the position of pedestrian i. $\cos(\varphi_{ij}) = -\vec{n}_{ij} \cdot \vec{e}_i$, and $\vec{e}_i = \frac{\vec{v}_i}{\|\vec{v}_i\|}$. $0 \leq \lambda_i \leq 1$, which introduces an anisotropic effect of pedestrians' vision field on the motion. Assume that $\lambda = 0.3$ for all pedestrians in this paper, therefore pedestrians in front of the current pedestrian have larger impacts on him or her than people behind. We refer readers to [1] to learn more about this vision field. k is the body compression coefficient, and κ is the coefficient of the sliding friction. $\vec{t}_{ij} = (-n_{ij}^2, n_{ij}^1)$ is the tangential direction, and $\triangle v_{ji}^t = \left(\vec{v}_j - \vec{v}_i\right) \cdot \vec{t}_{ij}$ is the velocity difference along the tangential direction. The function $g(x)$ is zero if pedestrians do not touch each other ($d_{ij} > r_{ij}$), otherwise it is equal to the argument x. $\vec{f}_{iw}$ is defined analogously as Eq. (4) shows.

In order to make the pedestrian flow heterogeneous, this paper assumes that pedestrians' reaction time τ uniformly distributes between 0.15 s and 0.50 s with its deviation 0.05 m, and radius r uniformly distributes between 0.250 m and 0.300 m with its deviation 0.025 m, respectively. Pedestrian's desired velocity, however, meets the normal distribution with expectation 1.37 m/s and standard deviation 0.2 [4]. The other parameters of the original SFM are specified in TABLE 1.

III. THE CROWD HYBRID MODEL

In order to monitor and predict pedestrian dynamics in the corridor, especially in the complex shape of the corridor such as a S-bend, this paper proposes a hybrid modeling method based on the microscopic SFM and the law of mass conservation. In this hybrid model, the corridor is divided into multiple calculation black boxes. The calculation black box here means that we do not know any parameter of the flow inside the box except the initial pedestrian density. The length of the calculation black box not only relates to the curvature of the corridor but also relates to the purpose of monitoring. If the curvature of the corridor is large, the length of the box will be relatively short. Furthermore, the shorter the calculation black box is, the detailed information inside the corridor we get.

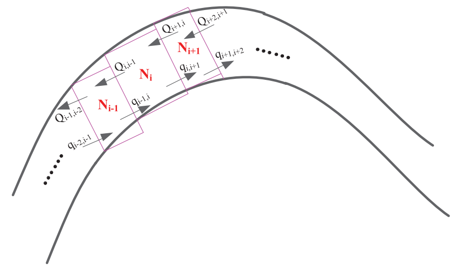


FIGURE 2. The diagram of the calculation black boxes in the curved corridor.

Figure 1 gives a section of the straight corridor with multiple calculation black boxes. For the curved corridor shown in Fig. 2, it could be thought that the corridor is also made up of rectangular calculation black boxes. At this time, the length and width of the box should be determined according to the curvature of the corridor, in order to improve the accuracy of the prediction. For the section of corridor with a large curvature, there are differences in the width of adjacent calculation black boxes. Pedestrian flow parameters in each box can also be calculated step by step according to inflows and outflows of adjacent boxes. Therefore, the principle of pedestrian dynamic prediction in the curved corridor could be similar to that in the straight corridor. It is worth noting that additional prediction errors may exist for some sections of corridors with large curvatures, because of the error between the size of the partitioned rectangle calculation black box and the actual size of the corridor. However, the method in this paper provides a way of thinking for the prediction study of pedestrian dynamics in curved corridors. This paper only takes a straight corridor as an example to study the feasibility of the proposed model. We will also discuss the applicability of the proposed method for the curved corridors in our near future work.

In this paper, the pedestrian flow in the calculation black box of Fig. 1 can be either the unidirectional flow or the bidirectional flow. Specially, the unidirectional flow can be regarded as a bidirectional flow if the inflow from one side of the corridor is zero.

In Fig. 1, for the calculation black box i, we define $N_i(t)$ as the number of pedestrians at time instant t, $Q_{i,i-1}(t)$ and $q_{i,i+1}(t)$ are defined as the outflows from the left and right sides of the calculation black box i, respectively. $q_{i-1,i}(t)$ and $Q_{i+1,i}(t)$ are defined as the inflows from the left and right sides of the calculation black box i, respectively. The number of pedestrians at time instant $t+1$ in the calculation black box i based on the conservation law of mass, therefore, can be updated by

$$\begin{aligned} N_i(t+1) &= min(N_{i,full}, max(N_i(t) \\ &\quad - (Q_i(t) - q_i(t)) \cdot W_i \cdot \Delta T, 0)), \\ Q_i(t) &= Q_{i,i-1}(t) + q_{i,i+1}(t), \\ q_i(t) &= q_{i-1,i}(t) + Q_{i+1,i}(t). \end{aligned} \tag{5}$$

where $N_{i,full}$ is the maximum threshold number of pedestrians in the calculation black box i. In this paper, the maximum threshold density in each calculation black box is 5.4 $\mathrm{p/m^2}$ [28]. When the calculation black box reaches the threshold density, pedestrians are not allowed to enter the calculation black box because of the limited physical boundary of each box, until the density is lower than this maximum threshold density. $Q_i(t)$ is the total outflow value coming out from both sides of the calculation black box i, and $q_i(t)$ is the total inflows into the calculation black box i. $\Delta T = 1$ s, W_i is the width of the calculation black box i.

The outflow of pedestrians from the left side of the calculation black box i, $Q_{i,i-1}(t)$, is updated by comprehensively considering the outflow data of the microscopic SFM based on the current density, the number of pedestrians in the calculation black box i ensuring enough pedestrians to go outsides, and enough spaces in the calculation black boxes $i-1$ and $i+1$ to let pedestrians swarm into:

$$\begin{aligned} Q_{i,i-1}(t) &= min(Q'_{i,i-1}(t), Q''_{i,i-1}(t), Q'''_{i,i-1}(t)), \\ Q'_{i,i-1}(t) &= (Q^{up}_{i,i-1}(\rho,t) - Q^{down}_{i,i-1}(\rho,t)) \cdot r(1) + Q^{down}_{i,i-1}(\rho,t), \\ Q''_{i,i-1}(t) &= \frac{a_R}{a_L + a_R} \cdot \frac{N_i(t)}{W_i \cdot \Delta T}, \\ Q'''_{i,i-1}(t) &= max(\frac{a_R}{a_L + a_R} \cdot \frac{N_{i-1,full} - N_{i-1}(t)}{W_i \cdot \Delta T}, 0). \end{aligned} \tag{6}$$

Here, $\rho = \frac{N_i(t)}{W_i \cdot L_i}$, L_i is the length of the calculation black box i. $r(1)$ is a random constant between 0 and 1. $Q^{up}_{i,i-1}(\rho,t)$ and $Q^{down}_{i,i-1}(\rho,t)$ are obtained from statistical data of a large number of simulation results by using the SFM. It is worth noting that when determining the outflow data under a certain density according to the simulation results of the SFM, we randomly choose a value between the maximum $Q^{up}_{i,i-1}(\rho,t)$ and the minimum $Q^{down}_{i,i-1}(\rho,t)$. Furthermore, $a_L : a_R$ stands for the ratio of the inflow from the left side to the inflow from the right side of the corridor.

The outflow of pedestrians from the right side of the calculation black box i, $q_{i,i+1}(t)$, is updated analogously, which is given by

$$\begin{aligned} q_{i,i+1}(t) &= min(q'_{i,i+1}(t), q''_{i,i+1}(t), q'''_{i,i+1}(t)), \\ q'_{i,i+1}(t) &= (q^{up}_{i,i+1}(\rho,t) - q^{down}_{i,i+1}(\rho,t)) \cdot r(1) + q^{down}_{i,i+1}(\rho,t), \\ q''_{i,i+1}(t) &= \frac{a_L}{a_L + a_R} \cdot \frac{N_i(t)}{W_i \cdot \Delta T}, \\ q'''_{i,i+1}(t) &= max(\frac{a_L}{a_L + a_R} \cdot \frac{N_{i+1,full} - N_{i+1}(t)}{W_i \cdot \Delta T}, 0). \end{aligned} \tag{7}$$

By the same token, we can obtain $q_{i-1,i}(t)$ and $Q_{i+1,i}(t)$. Note that the inflows from the leftmost and rightmost sides of the corridor are respectively q_L and q_R, which are controllable and known in this paper. Besides, $q_L : q_R = a_L : a_R$.

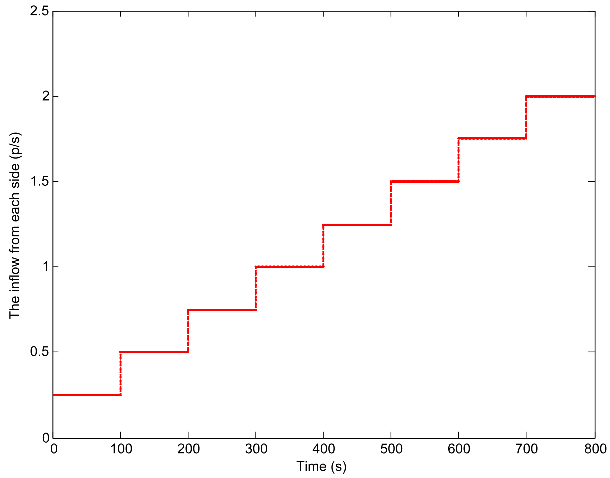
In the case of $a_L : a_R \neq 1{:}1$, this modeling method for N ($N > 1$) calculation black boxes can not be directly used when breakdown phenomenon [4], [26] occurs. The reason for this is the calculation black boxes adjacent to the congested one can not meet the basic assumption that the ratio of inflows from both sides of the corridor is $a_L : a_R$. At this time, we can treat this N calculation black boxes as one calculation black box ignoring the detailed initial density of each calculation black box. We, therefore, can obtain the information in the N-in-1 calculation black box. The shortage of the N-in-1 method is that the detailed information in each calculation black box cannot be obtained. Generally, when density is predicted to approach the density of breakdown, staff in buildings should control the inflow in a timely manner.

Based on the crowd hybrid model proposed in this paper, we should first obtain the initial information of pedestrian density in each calculation black box, then determine the value of outflow according to Eqs. (6)-(7). The density at time instant $t+1$ in each calculation black box, therefore, can be predicted according to Eq. (5). After that the density at time instant $t+2$ can be further achieved using the prediction method. Analogously, the density information at time instant $t+K$ can be predicted. Therefore, the density information can be predicted which is very important for the regulation of pedestrian flow into the corridor. Once the predicted density in the near future exceeds a preset value, staff can divert the crowd in advance according to the specific circumstances. It is worth noting that if the pedestrian flow in the corridor is bidirectional, the motion state, namely the free motion state and the jamming state even breakdown, can further be determined.

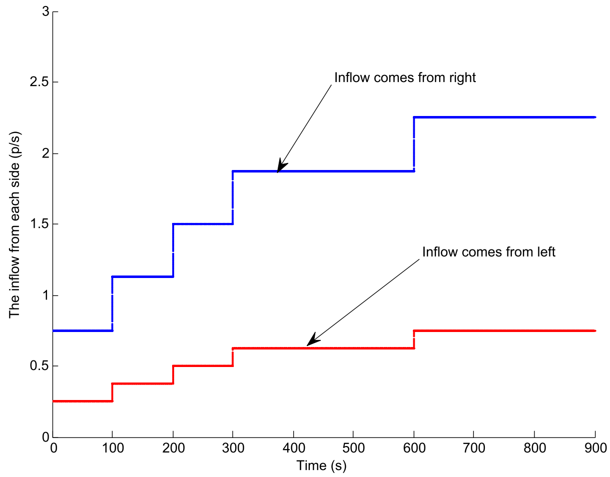
This crowd hybrid modeling method combines the advantages of both the macroscopic and the microscopic pedestrian movement models, which not only considers the interactions among pedestrians when using the outflow data of the microscopic SFM choosing from the data base but also reduces the computational complexity after obtaining the outflow data. We can save multiple simulation results of density-outflow in different cases based on the SFM into the data base ahead of schedule, and use the corresponding density-outflow data from the data base when adopting the proposed model. Therefore, the real-time performance of our model is improved significantly. Generally, for the crowd containing N pedestrians, the calculation amount when using the SFM is $O(N^2)$, while the calculation amount when using the proposed hybrid method is $O(1)$.

IV. VERIFICATION OF THE CROWD HYBRID MODEL

The study on the verification of the proposed hybrid model is a very necessary work. Firstly, the relationship between density and outflow is simulated based on the SFM, meanwhile the crowd motion states are obtained, then two scenarios are set to demonstrate the validity and feasibility of this hybrid model.



(a) $q_L : q_R$=1:1.



(b) $q_L : q_R$=1:3.

FIGURE 3. The inflow patterns over time.

A. THE RELATIONSHIP BETWEEN DENSITY AND OUTFLOW

Take two flow cases of the bidirectional crowd for example. One case is that the ratio of inflows from both sides of the corridor is 1:1, the other case is that the corresponding ratio is 1:3, as shown in Fig. 3. With the increase of time, the influx of pedestrians from both sides of the corridor increases.

After applying the SFM, we can obtain the relationship between pedestrian density and outflow, then the motion state of bidirectional pedestrian flow can be judged. It is worth noting that the simulated bidirectional flow when using the SFM moves in a corridor whose size is 10 m $\times$ 4 m.

Figure 4(a) shows the statistical density-outflow data of 100 times repeated simulations using the SFM and its corresponding fitting curve, when $q_L : q_R = 1{:}1$. In reality, not each outflow is the same under the same density of pedestrians. Figure 4(b) gives the range of 95 % confidence intervals for the fitting curve in Fig. 4(a), which could reflect the difference values in outflow under the same density. From Fig. 4, we can observe that the outflow from the corridor increases as the pedestrian density in the corridor increases from 0 to a critical value. However, the outflow begins to drop as the density exceeds this critical value. Note that the outflow is set to be 0 when the pedestrian density is 0.

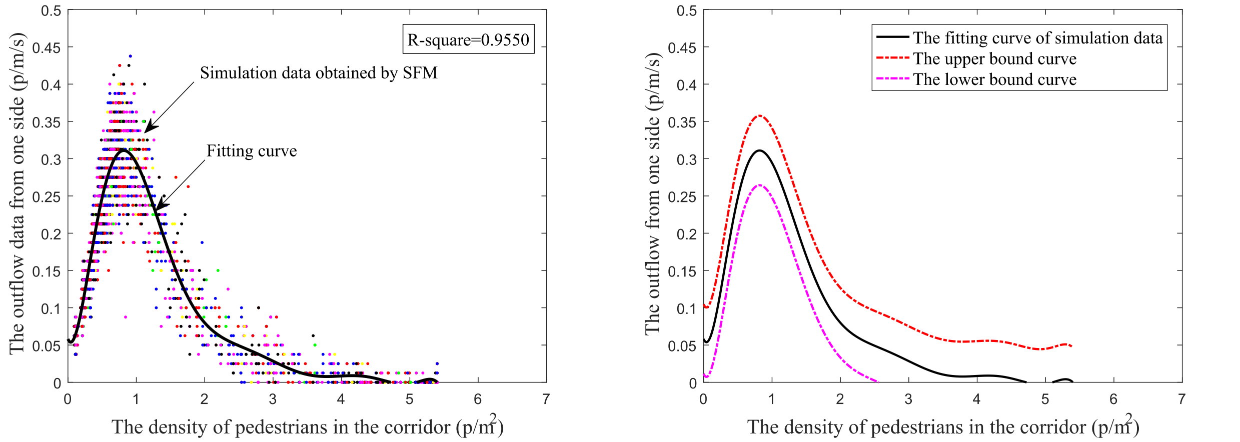
When fitting statistical data of simulation results, the fitting method of least square is adopted in this paper. Furthermore, R-square, which is the square of the correlation between the sampling data and the fitting value, is used to assess the goodness-of-fit. This R-square value belongs to 0 to 1. The closer it is to 1, the better the fitting will be. This paper gives the R-square value for each fitting in the figure in order to illustrate the feasibility of our fittings.

Analogously, Fig. 5 shows the density-outflow relationship, when $q_L : q_R = 1{:}3$. Note that the results in Fig. 5 are also based on 100 times repeated simulations using SFM. Figure 5 reflects that the difference of inflows from each side of the corridor can result in different outflows at different ends, both of which have a close relationship.

When using the proposed crowd hybrid model, the required density-outflow data can be achieved from Figs. 4 and 5. For example, if $q_L : q_R = 1{:}3$, $Q^{up}_{i,i-1}(\rho, t)$ and $Q^{down}_{i,i-1}(\rho, t)$ should be read from Fig. 5.

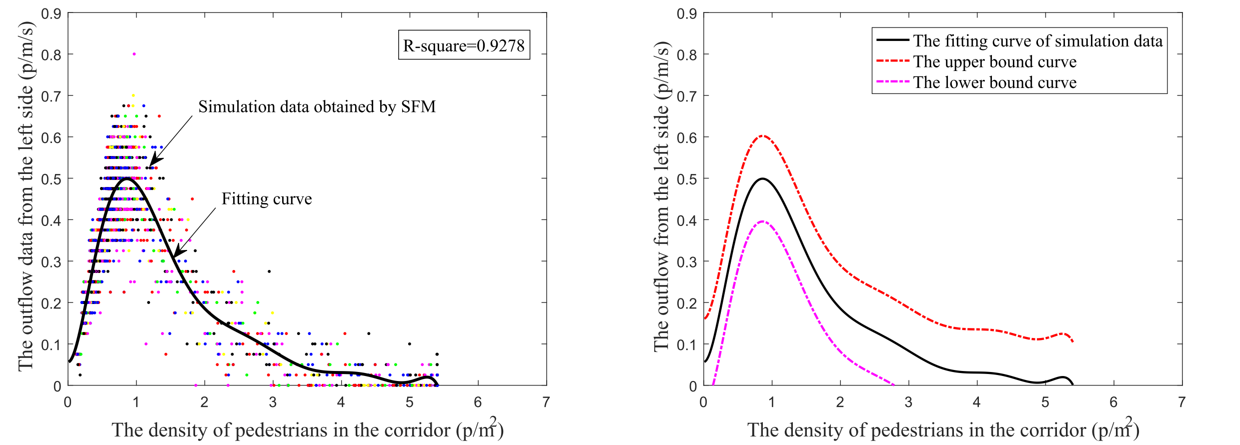
Motion states of the bidirectional pedestrian flow can be further determined after predicting the density. The bidirectional flow exists three states which are the free motion state, the coexisting state and the jamming state, respectively [3]. Jamming occurs when pedestrians cannot keep speeds in the desired walking directions, which may further lead to a temporary or total standstill that indicates breakdown [4]. In [4] and [26], breakdown is defined as: In the bidirectional pedestrian flow, at least N' pedestrians are with small walking speeds in the 5 consecutive seconds. Here, we set this threshold speed is V' m/s. In our study, we classify the coexisting state for convenience of study as the free motion state. The main purpose of studying the change of motion states is to determine whether to enter the jamming state, which is a very important message for the staff of public buildings. Jamming in this paper, similarly, is assumed to be that at least N pedestrians walk very slowly with the speeds that are lower than V m/s in the 5 consecutive seconds.

Figures 6 and 7 show the statistical data of the density and outflow in the free motion state and the jamming state of the bidirectional flow, which are obtained by 100 simulation experiments, and also gives the fitting curves of the corresponding data when $q_L : q_R = 1{:}1$. In Note that $N = 20$ and $V = 0.4$ in Fig. 6, and $N = 20$ and $V = 0.4$ in Fig. 7. In Fig. 6, the red dot represents the pedestrian flow is in the free motion state, while the blue dot represents the pedestrian flow is in a jamming state. Through observing Fig. 6, we can find that there is a small density interval around 0.6 p/m^2, in which the motion state of the pedestrian flow is uncertain.

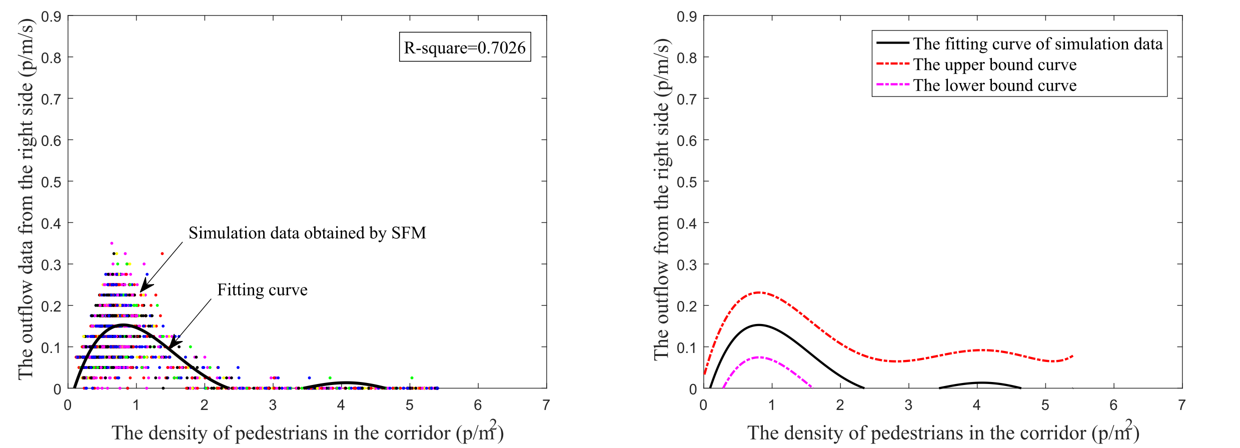


(a) The simulation data of pedestrian density in the corridor and outflow from a side obtained by SFM, and the corresponding fitting curve. (b) The fitting curve of pedestrian density and outflow, and the corresponding threshold curves with 95% confidence intervals.

FIGURE 4. The pedestrian outflow from a side versus density in the corridor ($q_L : q_R$ = 1:1).



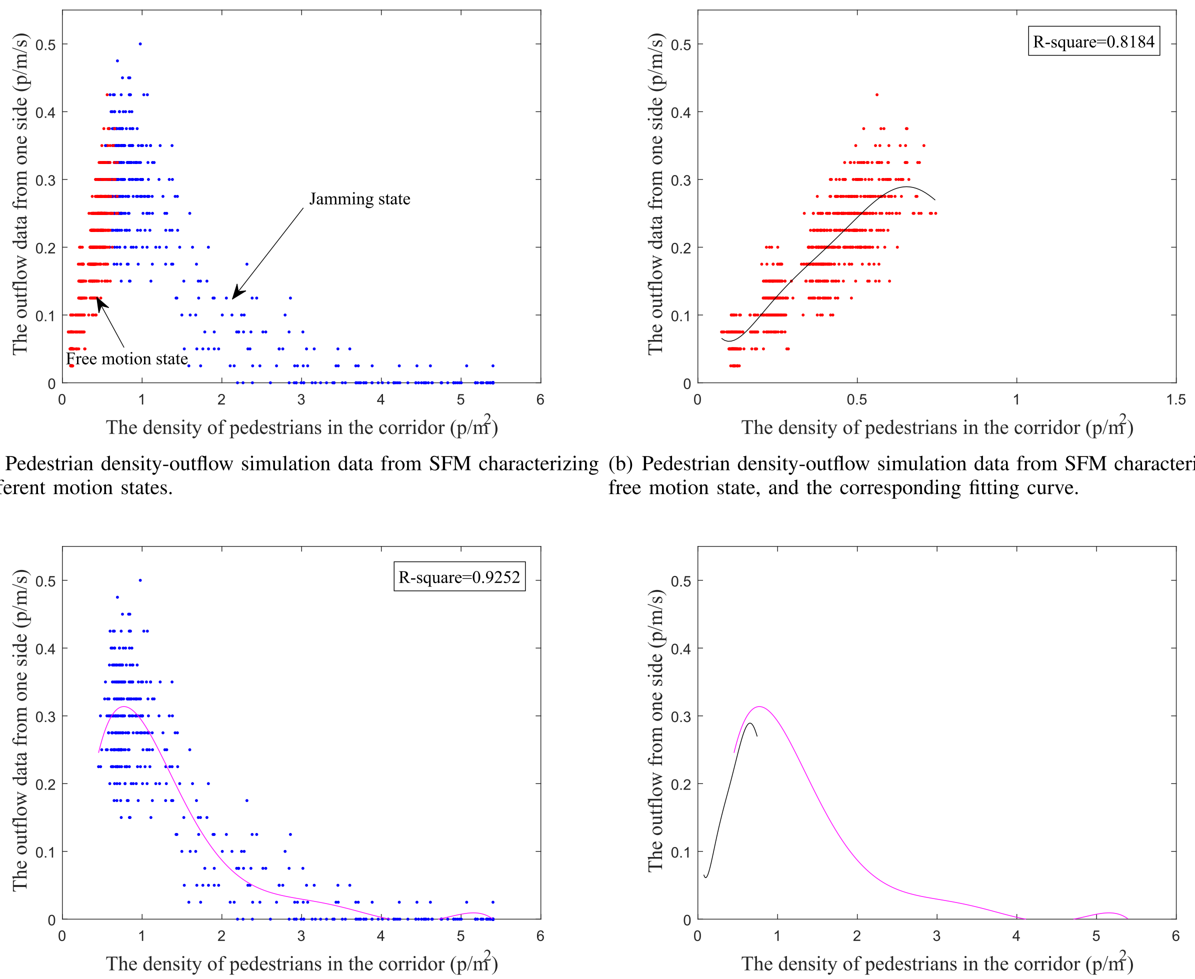
(a) The simulation data of pedestrian density in the corridor and outflow from the left side obtained by SFM, and the corresponding fitting curve. (b) The fitting curve of pedestrian density and outflow from the left side, and the corresponding threshold curves with 95% confidence intervals.



(c) The simulation data of pedestrian density in the corridor and outflow from the right side obtained by SFM, and the corresponding fitting curve. (d) The fitting curve of pedestrian density and outflow from the right side, and the corresponding threshold curves with 95% confidence intervals.

FIGURE 5. The pedestrian outflow versus density in the corridor ($q_L : q_R$ = 1:3).

Figure 7 shows that both red and blue dots may appear near the pedestrian density of 1 p/m^2. However, compared with Fig. 6, the length of the overlapping density interval by red and blue dots in Fig. 7 is shorter and the corresponding



(a) Pedestrian density-outflow simulation data from SFM characterizing different motion states.
(b) Pedestrian density-outflow simulation data from SFM characterizing free motion state, and the corresponding fitting curve.
(c) Pedestrian density-outflow simulation data from SFM characterizing jamming state, and the corresponding fitting curve.
(d) The fitting curves of pedestrian density-outflow simulation data from SFM characterizing different motion states.

FIGURE 6. The analysis of motion states (N = 20, V = 0.4).

density value is larger. This may be due to the higher requirements for jamming conditions, that is, at least 60 pedestrians are required to meet the speed value of less than 0.2 m/s at the same time.

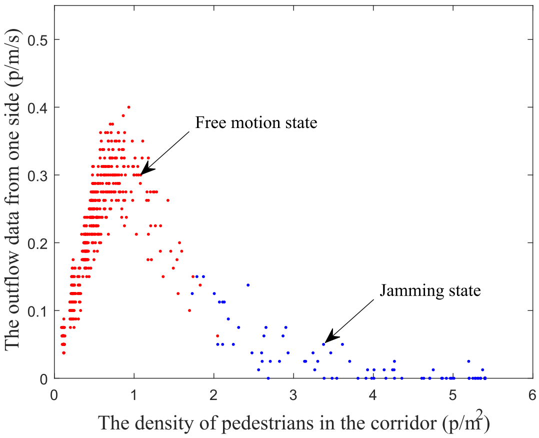
Figure 8 further shows the overlapping area of Fig. 6, from which we can conclude that both the blue dot and the red dot exist in the interval [0.45 p/m^2, and 0.75 p/m^2]. Particularly, red dots are slightly more in the interval [0.45 p/m^2, 0.6 p/m^2], which means the probability of pedestrian flow in the free motion state is greater. Meanwhile, blue dots are in the majority in the interval [0.6 p/m^2, 0.75 p/m^2], which means pedestrian flow is more likely to be congested.

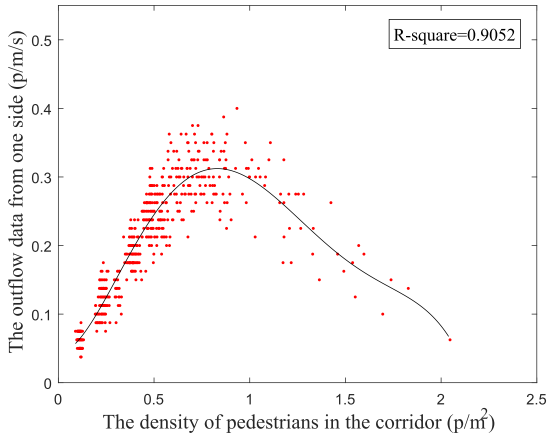
Therefore, when the pedestrian density in the corridor is determined, the motion state of the pedestrian flow can be determined except for a short density overlapping interval. This indicates that managers in public places need to start controlling inflows before reaching the critical chaotic density in order to improve the traffic rate of corridor.

B. MODEL VALIDITY ANALYSIS

Model validation is a very important task. In this paper, two scenarios shown in Fig. 9 are investigated in this paper to verify the validity and feasibility of the proposed hybrid model. One is that there exists single calculation black box which is named after scenario 1, and the other is that there are three calculation black boxes which is named after scenario 2. Under these two scenarios, pedestrian flow dynamics are studied under $q_L : q_R = 1{:}1$ and $q_L : q_R = 1{:}3$, respectively. Assuming that in the initial state, there is no obstacle in the calculation black box.

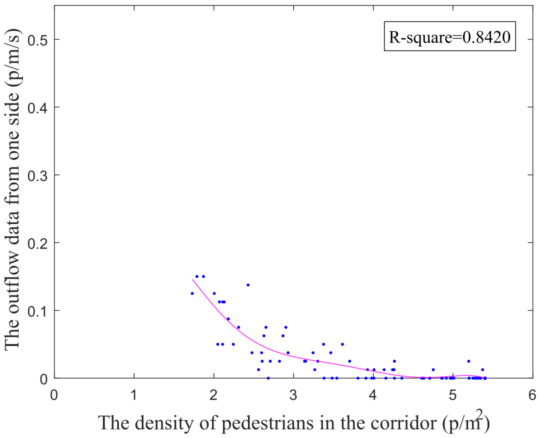
Figure 10 shows the comparison results of pedestrian density over time between using the SFM and using our hybrid model when $q_L = q_R = 1$ p/s. Figure 10(a) reflects that the densities of pedestrians obtained by using the hybrid model can remain stable around 0.5 p/m^2 after a few seconds in scenario 1 whether the initial density is 0.25 p/m^2 or 1 p/m^2, which are almost identical with the results obtained

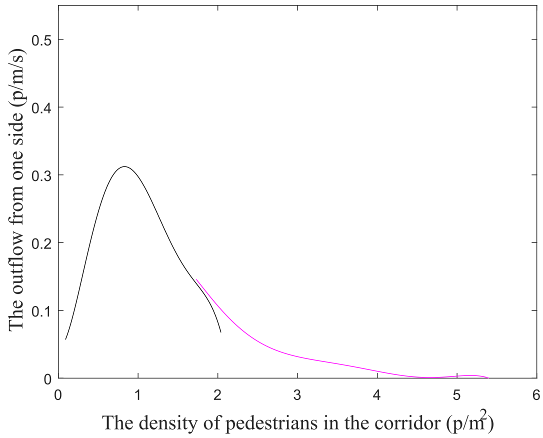




(a) Pedestrian density-outflow simulation data from SFM characterizing different motion states.

(b) Pedestrian density-outflow simulation data from SFM characterizing free motion state, and the corresponding fitting curve.





(c) Pedestrian density-outflow simulation data from SFM characterizing jamming state, and the corresponding fitting curve.

(d) The fitting curves of pedestrian density-outflow simulation data from SFM characterizing different motion states.

FIGURE 7. The analysis of motion states (N = 60, V = 0.2).

by using the SFM. Similarly, Figure 10(b) verifies the validity of the hybrid model in scenario 2 by comparing the density results which reach a steady-state value also around 0.5 p/m^2. The value of steady-state pedestrian density in the corridor relates to the size of inflow, and is independent of initial density. It is worth noting that the simulation results in Fig. 10 are the mean values of 10 times repeated simulations.

Figure 11 shows the comparison results of pedestrian density varying with time between using the SFM and using the hybrid model when $q_L = 0.25$ p/s and $q_R = 0.75$ p/s. From this figure, we can also verify the validity and feasibility of the proposed model through a very good coincidence with the results of the SFM. Even though the initial density in each calculation black box in Fig. 11(b) is different from the steady-state value, the density in each box can reach a stable value after a period of time. Besides, the steady-state value in Fig. 11 is around 0.25 p/m^2 whether in scenario 1 or in scenario 2 when $q_L : q_R =$ 1:3.

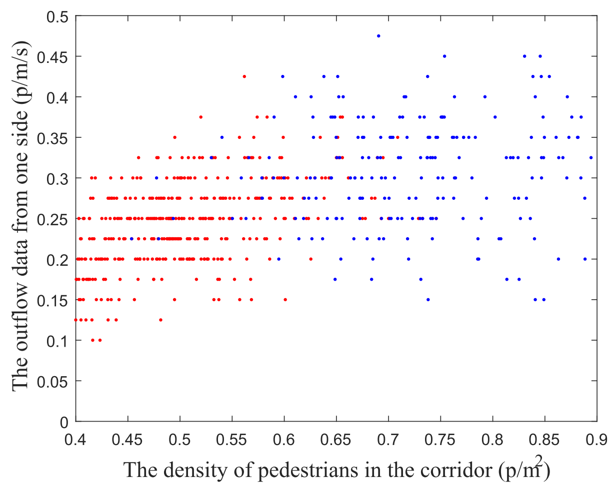
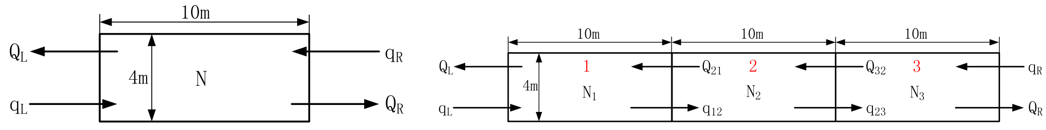


FIGURE 8. The overlapping area (N = 20, V = 0.4).

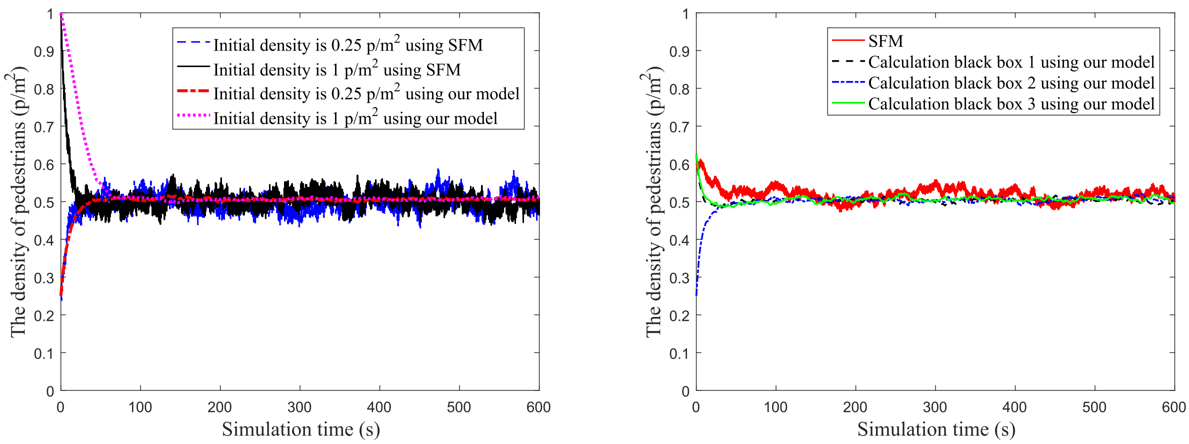
In summary, the hybrid model proposed in this paper could not only predict the pedestrian density in the corridor but



(a) Scenario 1.

(b) Scenario 2.

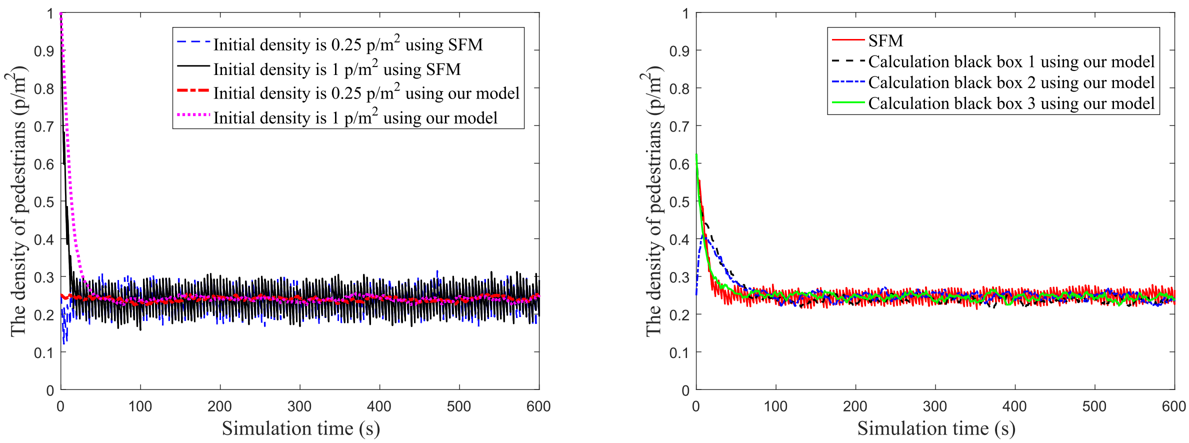
FIGURE 9. **The layouts of two investigated scenarios.**



(a) The comparison results for scenario 1.

(b) The comparison results for scenario 2.

FIGURE 10. **The comparison results of pedestrian density versus simulation time between using the SFM and using the hybrid model ($q_L = q_R = 1$ p/s).**



(a) The comparison results for scenario 1.

(b) The comparison results for scenario 2.

FIGURE 11. **The comparison results of pedestrian density versus simulation time between using the SFM and using the hybrid model ($q_L = 0.25$ p/s, $q_R = 0.75$ p/s).**

also could further judge the motion state of the pedestrian flow.

V. CONCLUSION

This paper mainly focuses on studying the hybrid modeling method for predicting pedestrian dynamics, which is very important for the managerial staff of pedestrian flow in public buildings. By considering the heterogeneity of pedestrians, a crowd hybrid model is presented based on the SFM and the conservation law of mass. The most obvious advantage of this hybrid method is that it not only takes account of detailed behaviors and habits of pedestrians but also consumes less computation. In the proposed hybrid model, the corridor is divided into multiple calculation black boxes, and the density-outflow data using the SFM should be saved in the data base in advance. The motion states are also investigated which could be determined in most of the density intervals. Two scenarios are set, namely one calculation black box and three calculation black boxes, under two different compositions of inflows respectively to verify the validity and feasibility of the crowd hybrid model. By comparing the simulation results, we can conclude that the prediction result of the hybrid method for the straight corridor has a very good coincidence with that of the SFM.

Although pedestrian dynamic prediction is investigated through the proposed hybrid model, the validity of the model is checked only in the straight corridor. The accuracy of this hybrid model for the curved corridor still requires further study in our future work.

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