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Human Behavior Modeling for Evacuation From Classroom Using Cellular Automata

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ABSTRACT Understanding and simulating human behavior during the evacuation is essential in cognitive computing, which can be used to guide pedestrians to evacuate quickly and to avoid a potential hazard. In this paper, we propose a model to simulate the human behavior for evacuation from a classroom. Specifically, first, we give an improved evacuation model based on cellular automata, which consists of the static floor field and the dynamic floor field. Then, we present the detailed algorithms for calculating both the floor fields. The static floor field is calculated using an A-star algorithm, which can be used to solve the evacuation environments with and without obstacles. The dynamic floor field is calculated based on the impact of the number of pedestrians in each exit area on evacuation. Finally, the calculation method of pedestrian movement probability and the model evolution rules are given. The simulation experiments using our model have been conducted, and comparisons between our model and some state-of-the-art evacuation models are also conducted. The experimental results show that the model is effective and can reproduce the evacuation experiments conducted by students well. The model is expected to yield the optimal evacuation plan from the indoor environment.

INDEX TERMS Cognitive computing, human behavior, modeling, evacuation, cellular automata.

I. INTRODUCTION

Cognitive computing aims to mimic the functioning of the human brain and help to improve human decision-making, and it has been widely used in data intelligence [1], brain-computer modeling [2], and healthcare [3]. As an important component of cognitive computing, understanding and simulating human behavior during the evacuation has gained more attention in recent years [4]–[6]. In pedestrian-intensive environments, if pedestrians are improperly evacuated, it will cause crowding, falling and stampede accidents, which seriously threaten people's safety and health. It is a necessary work to construct a reasonable evacuation model to simulate and understand human behavior, which will be applied to help pedestrians to evacuate safely and protect human health for different evacuation environments [7].

Researchers have proposed several evacuation models to understand and simulate human behavior for evacuation. Those models can be divided into two main categories: macroscopic evacuation models and microscopic models [8]. Macroscopic models ignore the differences between individuals and take pedestrians as a whole, and the pedestrians can be treated as the flow of water in the pipeline [9]–[11]. Xiong *et al.* [12] proposed a model that simulates the phenomenon of pedestrian flow self-organization in opposite pedestrian flow. Tian *et al.* [13] introduced a two-dimensional lattice hydrodynamic model of traffic, which extends the bidirectional pedestrian lattice fluid dynamics model [14] to two-dimensional bidirectional pedestrian flow. Microscopic models represent each pedestrian individually, which can reflect individual properties such as

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walking velocity and the interactions between pedestrians. Microscopic models include social force model [15], [16], centrifugal force model [17], optimal velocity model [18], lattice gas evacuation model [19], [20] and cellular automaton model [21]–[25]. Zheng *et al.* [21] proposed a dynamic parameters cellular automaton, the model is used to simulate the behavior of passenger in subway. Kirchner and Schadschneider [22] presented an evacuation model, which uses bionics to describe the interaction between pedestrians. Yuan and Tan [23] used the results of reliability analysis to simulate evacuation from a room full of smoke.

Although those evacuation models can simulate human behavior for evacuation, some of those models still exist the following two limitations. Some evacuation models only consider the case of no obstacles in the room [22]–[24]. In fact, obstacles in the room are common in the evacuation environment. Meanwhile, the number of pedestrians in the exit area is a very important factor for evacuation [24], [25], but the factor is rarely studied in those models.

In this paper we propose a model based on cellular automata to study the human behavior in evacuation from a classroom. The model consists of the static floor field and the dynamic floor field. We use A-star algorithm to calculate the static floor field and consider the dynamic impact of the number of pedestrians in the exit area on evacuation. In addition, simulation experiments have been conducted. The experiment results show that the number of pedestrians in the exit area is an important factor for evacuation and our model can reproduce the evacuation experiments conducted by students well.

II. EVACUATION MODEL

In this section, we first describe the evacuation model based on cellular automata. Then we propose the algorithms for calculating the model's static floor field and dynamic floor field. Finally, we give the method of calculating transition probability and the evolution rules of the model.

A. MODEL DESCRIPTION

In our model, we divide the room into two-dimensional square cells. Each cell is 0.5m×0.5m with three states: empty, occupied by a pedestrian and occupied by an obstacle. Obstacles include the wall, the furniture, the household appliance, and so on. As shown in Figure 1a, we use the Moore neighborhood, and a pedestrian can only have two options each time: stay unmoved or move to one of the eight neighbors cells. The next movement of a pedestrian is based on the transition matrix, as shown in Figure 1b, which is determined by the evolution model consisting of the static floor field and the dynamic floor field.

The static floor field reflects the influence of the room's structure and obstacles on evacuation, and it will stay unchanged during the evacuation. The dynamic floor field is updated simultaneously with time steps, and in this paper we consider the dynamic impact of the number of pedestrians in the exit area on evacuation.

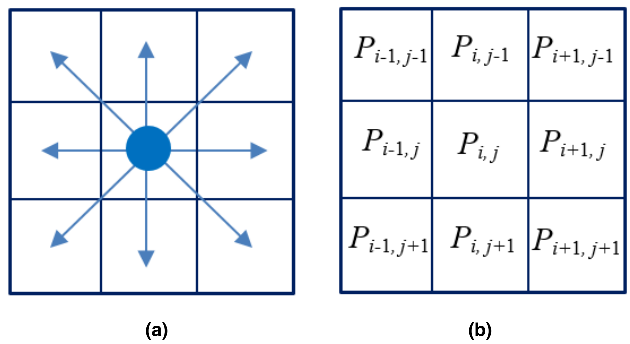

FIGURE 1. (a) Potential direction of pedestrian movement. (b) Matrix of movement probability.

B. STATIC FLOOR FIELD CALCULATION

A-star algorithm is used to find the path, and it simulates human's pathfinding well in the known environment. A-star algorithm is widely used in the robot path planning and aircraft navigation [26], but it is rarely used in calculating the static floor field of the evacuation model. In this section, we use A-star algorithm to calculate the static floor field.

Assume that there are N exits $Exit_1, Exit_2, \ldots Exit_N$ in a room and the length and width of the room are $L \times 50$cm and $W \times 50$cm, respectively. Let $C_{i,j}$ denote a cell in the room with $1 \leq i \leq L$ and $1 \leq j \leq W$. Let $C_{xend,yend}$ denote the cell at $Exit_i$ with $1 \leq i \leq N$. Let $Path_1, Path_2, \ldots, Path_N$ denote the paths form $C_{i,j}$ to $Exit_1, Exit_2 \ldots Exit_n$, respectively. Let $L_1, L_2, \ldots L_N$ denote the lengths of $Path_1, Path_{2}, \ldots Path_N$, respectively. The following formulas are used in our algorithm.

$$F(C_{x,y}) = G(C_{x,y}) + H(C_{x,y}) \tag{1}$$

$$G(C_{x,y}) = D + G(C_{xpar,ypar}) \tag{2}$$

$$H(C_{x,y}) = 10 \times (|x - x_{end}| + |y - y_{end}|) \tag{3}$$

where,

$C_{x,y}$ represents the current cell;

$C_{xpar,ypar}$ represents the parent of $C_{x,y}$;

$F\left(C_{x,y}\right)$ denotes the movement cost of the path from $C_{i,j}$ to $C_{xend,yend}$ and constrained to go through $C_{x,y}$;

$G\left(C_{x,y}\right)$ denotes the movement cost of the path from $C_{i,j}$ to $C_{x,y}$; if the pedestrian moves horizontally or vertically, then D is equals to 10; otherwise, D is equals to 14;

$H\left(C_{x,y}\right)$ denotes the estimated cost movement of the path from $C_{x,y}$ to $C_{xend,yend}$.

In addition, two empty lists called the open list and the closed list are used to store cells. Let $S_{i,j}$ be the static floor field value of the cell $C_{i,j}$, and we could use Algorithm 1 to calculate $S_{i,j}$.

Now we give an example to illustrate Algorithm 1. The structure of the room is shown in Figure 2a, which has two exits. We first find each cell's two paths form the cell to the two exits (see Figure 2b), next calculate the length of these two paths, after find the minimum path value from the

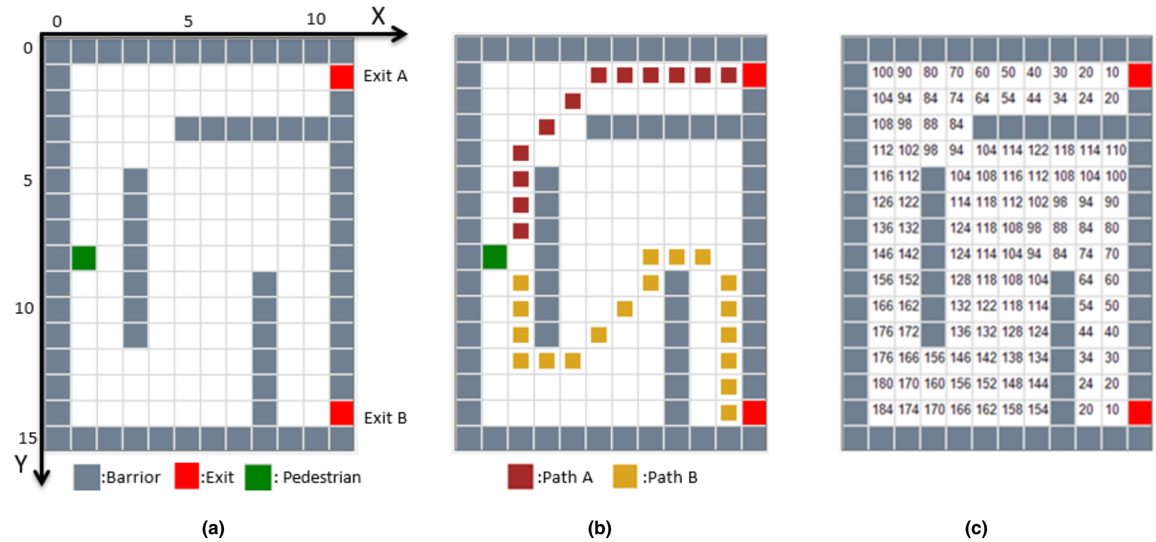

FIGURE 2. **(a) An example of an evacuation room. (b) The two paths to the two exits of the pedestrian. (c) Minimum path value for each cell.**

Algorithm 1 Calculating Static Floor Field Based on A-Star Algorithm for a Room

Input: the obstacles in the room
Output: the static floor field of the room

Step 1: If the state of $C_{i,j}$ is empty or occupied by a pedestrian, then go to Step 2; otherwise, $S_{i,j}$ is *Null* and return.
Step 2: Find $Path_1, Path_2, \ldots Path_N$ and calculate $L_1, L_2, \ldots L_N$. The procedures of finding $Path_i$ and calculating L_i are as follows, with $1 \leq i \leq N$.
Step 2.1: Calculate and record G, H, and F cost of $C_{i,j}$, and add $C_{i,j}$ to the open list.
Step 2.2: **While** the open list is not empty
Step 2.3: Find the cell with minimum F in the open list and add the current cell to the closed list.
Step 2.4: **For** each of the 8 cells adjacent to the current cell, denoted by $C_{xa,ya}$.
Step 2.5: **If** $C_{xa,ya}$ is not in the closed list and the state of $C_{xa,ya}$ is not occupied by an obstacle. **Then**
Step 2.6: **If** $C_{xa,ya}$ is not in the open list **Then**
Step 2.7: Calculate and record G, H and F cost of $C_{xa,ya}$ using formula (2), (3) and (1), respectively. Make the current cell the parent of $C_{xa,ya}$. Add $C_{xa,ya}$ to the open list.
Step 2.8: **Else**
Step 2.9: Calculate G_{new} cost of $C_{xa,ya}$ using formula (2). If $G_{new} < G$, then $G = G_{new}$, recalculate and record H and F cost of $C_{xa,ya}$ using formula (3) and (2) respectively, and make the current cell the parent of $C_{xa,ya}$.
Step 2.10: **End If**
Step 2.11: **End If**
Step 2.12: If $C_{xend,yend}$ in the open list, which indicates that $Path_i$ has been found, then P_i is marked *have-path* and go to Step 2.16 and Step 2.17.
Step 2.13: **End For**
Step 2.14: **End While**
Step 2.15: If the open list is empty and $Path_i$ is not marked *have-path,* then $Path_i$ is marked *no-path* and set $L_i = +\infty$.
Step 2.16: If $Path_i$ is marked *have-path*, then obtain the path and calculate L_i.
Step 2.17: Work backwards from $C_{xend,yend}$, go from each cell to its parent cell until reach $C_{i,j}$, and then obtain the path. Calculate L_i according to the path.
Step 3: Find the minimum value of $L_1, L_2, \ldots L_N$, denoted by $MinL_{i,j}$.
Step 4: Find the maximum value of all the$Minl_{i,j}$ of the room, denoted by $MaxL$, with $1 \leq i \leq RL$ and $1 \leq j \leq RW$.
Step 5: Obtain $S_{i,j} = MaxL - MinL_{i,j}$.

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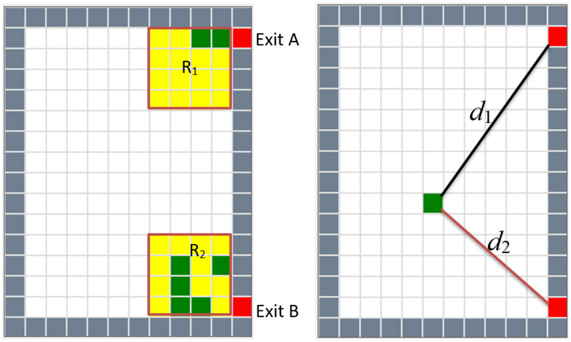
two paths, then record minimum path value for each cell (see Figure 2c), and finally can obtain the room's static floor field by Step 4 and 5 of Algorithm 1.

C. DYNAMIC FLOOR FIELD CALCULATION

In this section we give an algorithm for calculating the dynamic floor field. We consider the dynamic impact of the



(a) (b)

FIGURE 3. (a) An example of evacuation cost of pedestrians in exit area. (b) An example of evacuation cost of a pedestrian to an exit.

number of pedestrians in the exit area on evacuation, and use $D_{i,j}$ to denote the dynamic floor field. We first give the following definitions which will be used in the algorithm for calculating the dynamic floor field.

(1) Exit area is defined as the rectangular area near the exit. The size of the exit area can be adjusted according to the evacuation room. As shown in Figure 3a, the exit areas of exit A and exit B are R_1 and R_2, respectively.

(2) Evacuation cost of pedestrians in an exit area is defined as the sum of the distance from pedestrians in the exit area to the exit, and it denoted by V_E. As shown in Figure 3a, the evacuation cost of pedestrians in R_1 is the sum of the distance from the two pedestrians in R_1 to exit A. The evacuation cost of pedestrians in R_2 is the sum of the distance from the five pedestrians in R_2 to exit B.

(3) Evacuation cost of a pedestrian to an exit is defined as the Euclidean distance from the pedestrian to the exit, and it is denoted by V_P. As shown in Figure 3b, the evacuation cost of the pedestrian P to exit A and exit B, denoted by $V_{P,A}$ and $V_{P,B}$ are d_1 and d_2, respectively.

(4) The cost of pedestrian choosing an exit, denoted by V_S, is defined as follows:

$$V_S = k_1 V_E + k_2 V_P \tag{4}$$

where, k_1 and k_2 represent the sensitive factor of V_E and V_P, respectively. In this paper we set $k_1 = 1$ and $k_2 = 1$.

Now we give the following algorithm, which is used to calculating the dynamic floor field of a room of two exits.

In Step4 of Algorithm 2, parameter V_L and V can be set according to the evacuation room. Algorithm 2 can calculate a pedestrian's dynamic floor field at time t, and we can obtain all pedestrians' dynamic field at time t by calculating each pedestrian's dynamic field using Algorithm 2.

D. TRANSITION PROBABILITY CALCULATION

After calculating the static floor field and the dynamic floor field according to Algorithm 1 and Algorithm 2, we can obtain the pedestrian's movement probability $P_{i,j}$ using to the following formulas:

$$P_{i,j} = N \exp\{\mathrm{k}_s S_{i,j} + \mathrm{k}_D D_{i,j}\}\alpha_{i,j}(1 - n_{i,j}) \tag{5}$$

Algorithm 2 Calculating a Pedestrian's Dynamic Floor Field at Time t

Input: the pedestrian's position at time t
Output: the dynamic floor field of the pedestrian

Step 1: Set the size of the exit area for the two exits.
Step 2: Calculate the evacuation cost of the two exit areas, denoted by $V_{E,1}$ and $V_{E,2}$.
Step 3: Calculate evacuation cost of a pedestrian to the two exits, denoted by $V_{P,1}$ and $V_{P,2}$.
Step 4: Calculate the cost of pedestrian choosing the two exits using formula (4), denoted by $V_{S,1}$ and $V_{S,2}$. Calculate the absolute difference between $V_{S,1}$ and $V_{S,2}$, denoted by V_G.
Step 5: **IF** the pedestrian is not in the two exit area and $V_G > V_L$. **Then**
Step 6: Find the exit with the smaller value of V_S form the two exits, denoted by E_{LOW}
Step 7: Find the cell that is the closest to E_{LOW} from the nine cells of the pedestrian possible to move, denoted by U.
Step 8: Set the value of dynamic floor field of cell U to V, and set the value of dynamic floor field of the other night cells to 0.
Step 9: **End If**

$$N = [\sum_{(i,j)} \exp\{\mathrm{k}_s S_{i,j} + \mathrm{k}_D D_{i,j}\}\alpha_{i,j}(1 - n_{i,j})]^{-1} \tag{6}$$

where,

$S_{i,j}$ and $D_{i,j}$ denote the static floor field and the dynamic floor field, respectively;

k_S and k_D denote the sensitive factor of the static floor field and the dynamic floor field, respectively;

$n_{i,j}$ represents the factor of pedestrian occupancy; if the position of the cell is occupied by a pedestrian at time t, then $n_{i,j}$ is equal to 0; otherwise, $n_{i,j}$ is equal to 1;

$\alpha_{i,j}$ represents the factor of obstacle occupancy; if the position of the cell is occupied by the obstacle at time t, then $\alpha_{i,j}$ is equal to 0; otherwise, $\alpha_{i,j}$ is equal to 1;

N represents normalization coefficient.

In formula (4) and (5), we can adjust the values of k_S and k_D to control the influence of $S_{i,j}$ and $D_{i,j}$ on $P_{i,j}$.

E. MODEL EVOLUTION RULES

The model uses the parallel update rules, and pedestrians satisfy the following evolution rules during the evacuation from time t to t + 1.

(1) With the movement probability calculated by the formula (5) and (6), a pedestrian moves to a next cell with the maximum probability to the target position at time t + 1. If there are multiple choices with the same probabilities, then the pedestrian will randomly select a position with a uniform probability at time t + 1.

(2) When multiple pedestrians compete for the same target position at the same time, the system randomly selects one

TABLE 1. Comparison of key evacuation data for Experiment 1.

Data Sources	The number of pedestrians choosing Exit A	The number of pedestrians choosing Exit B	The maximum evacuation time of Exit A (s)	The maximum evacuation time of Exit B (s)	Average evacuation time (s)
Experiment 1	18	22	9.0	8.5	5.4
Simulation experiment 1 using Liu's model [25]	18	22	9.7	10.4	5.8
Simulation experiment 1 using our model	18	22	8.4	9.6	5.2

TABLE 2. Comparison of key evacuation data for Experiment 2.

Data Sources	The number of pedestrians choosing Exit A	The number of pedestrians choosing Exit B	The maximum evacuation time of Exit A (s)	The maximum evacuation time of Exit B (s)	Average evacuation time (s)
Experiment 2	18	22	7.0	6.5	4.2
Simulation experiment 2 using Liu's model [25]	18	22	7.8	7.0	4.9
Simulation experiment 2 using our model	18	22	7.0	6.8	3.8

of the pedestrians to move to the target position with equal probability at time t + 1, and the remaining pedestrians remain do not move.

(3) If two pedestrians simultaneously take the position occupied by the other as the target position at time t + 1, then the two pedestrians will exchange positions; otherwise, they will remain unmoved.

(4) When a pedestrian moves to an exit, the pedestrian will be removed from the room at time t+1, namely the pedestrian successfully completed evacuation.

(5) When all pedestrians in the room have successfully completed evacuation, namely there are no pedestrians in the room, the simulation ends.

III. EXPERIMENTAL RESULTS AND DISCUSSION

To validate efficiency of our proposed model, we use our proposed model to simulate the evacuation experiments conducted by Liu *et al.* [25], and compare key data of experiments. The model's algorithms were coded in the C# programming language. The computation was performed on a computer with a processor of Dual-core 2.6GHz, main memory 4G and operation system Microsoft Windows 8 64bit.

A. EVACUATION EXPERIMENT DESCRIPTION

Liu *et al.* [25] organized 40 students to conduct two evacuation experiments in a classroom, and these students were between 20 and 23 years old. The two experiments are called Experiment 1 and experiment 2, respectively. The classroom is divided into 27 × 23 grids, and the size of each grid is 50cm × 50cm. The classroom has two exits, and each exit has two doors. In the following statement, we use "pedestrian" to stand for "student". We assume that each time step in the model costs 0.2 s, which is the same as Liu's model [25]. The initial distribution of the two experiments are described as follows.

Experiment 1: Figure 4a shows the initial distribution of the classroom and the pedestrians in Experiment 1. There are only one door open for each exit.

Experiment 2: Figure 5a shows the initial distribution of the classroom and the pedestrians in Experiment 2. There are two doors open for each exit.

B. SIMULATION EXPERIMENTAL RESULT

The parameters of our model to simulate Experiment 1 and Experiment 2 are set as follows: $k_S = 1, k_D = 1, V = 25$ and $V_L = 4$. As shown in Figure 4a and Figure 5a, we set rectangular areas R_1 and R_2 as two exit areas. Since some rules of the model are based on probability, we run 10 times for each simulation experiment to ensure the reliability of the results, namely our result is an average value of 10 times' runs.

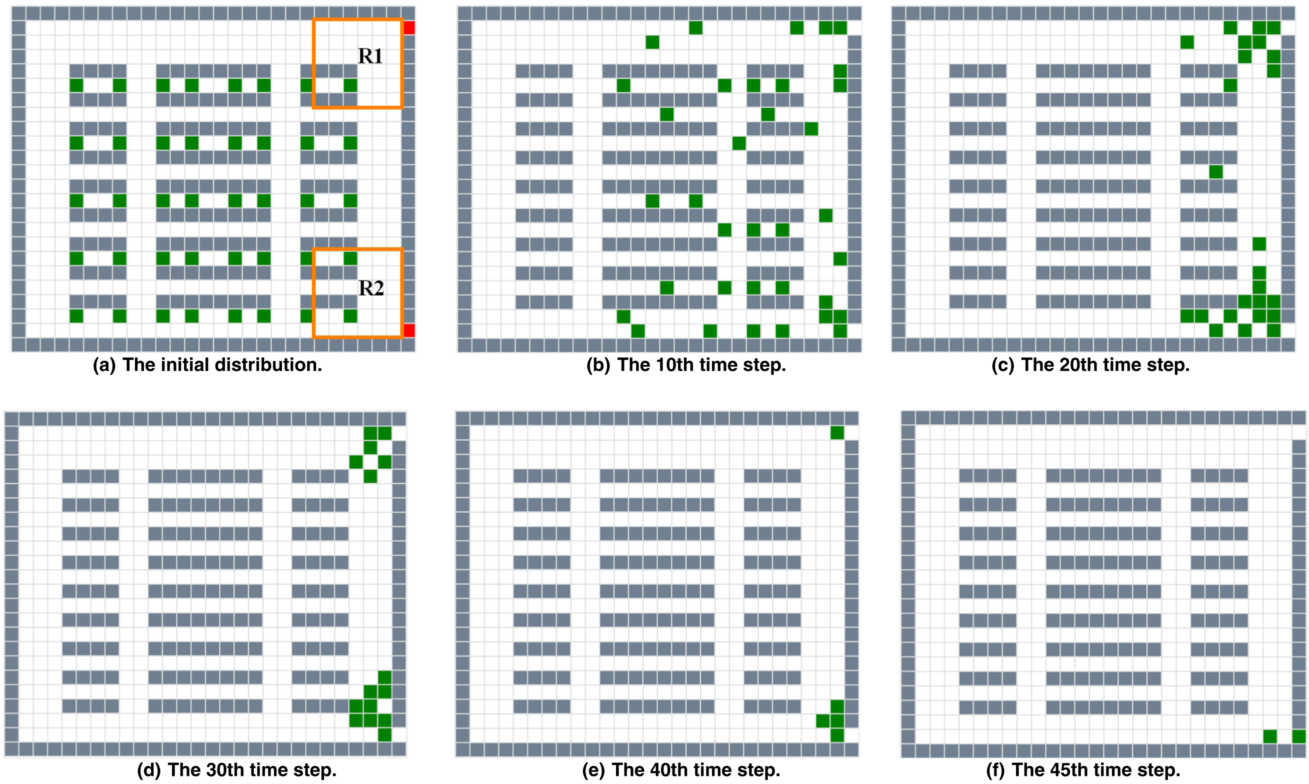
Table 1 shows the key evacuation data which are derived from Experiment 1 conducted by students, simulated Experiment 1 using Liu's model and simulated Experiment 1 using our model. Table 2 shows the key evacuation data which are derived from Experiment 2 conducted by the 40 students, simulated Experiment 2 using Liu's model [25] and simulated Experiment 2 using our model.

Figure 4 shows the snapshots at the 10th, 20th, 30th, 40th, and 45th time steps of the simulations for Experiment 1 using our model in a simulation experiment. Figure 5 shows the snapshots at the 5th, 10th, 15th, 20th, and 30th time steps of the simulations for Experiment 2 using our model in a simulation experiment.

C. DISCUSSION

In the previous section, we give the experimental results of the simulation evacuation. Now we analyze the experimental results as follows.

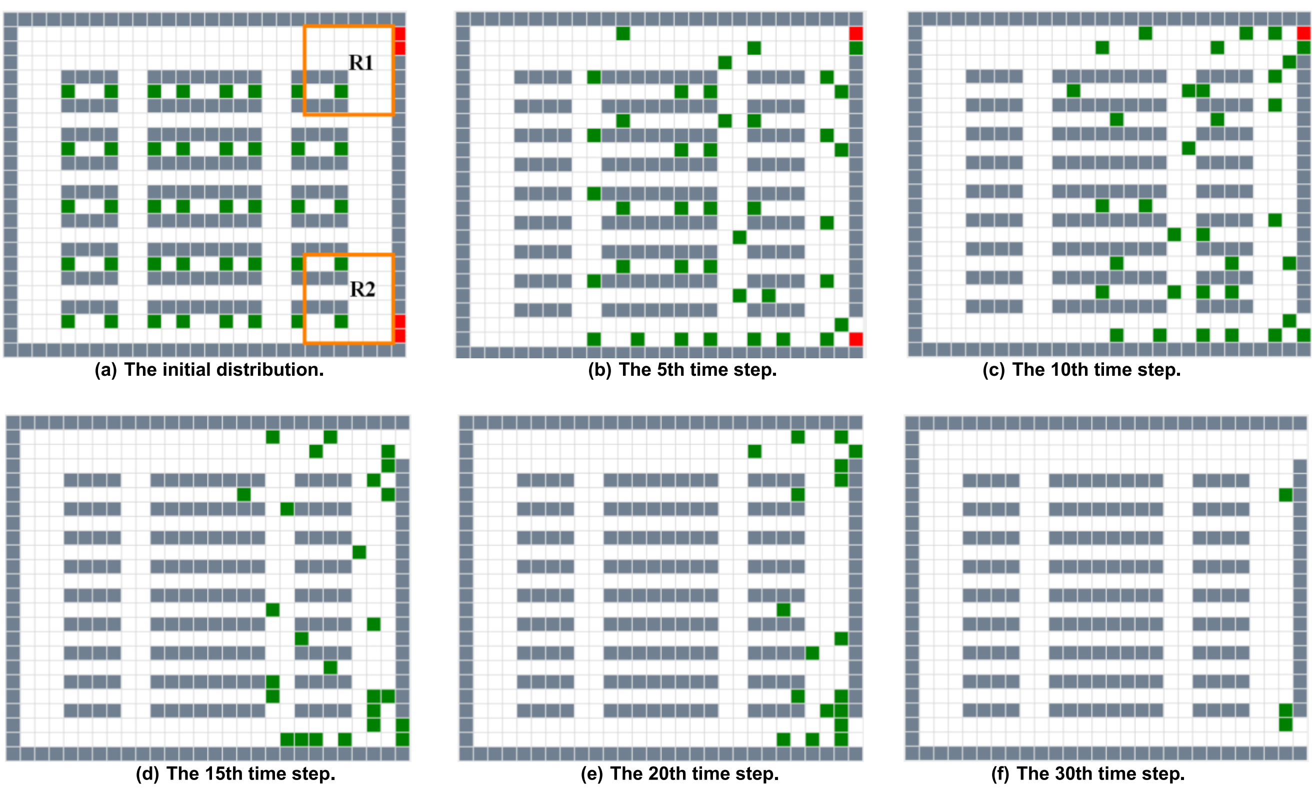
(1) Our model can reproduce the evacuation experiments conducted by students well. As shown in Table 1 and Table 2, the number of pedestrians choosing the two exits in simulation experiments using our model is the same as that in experiments conducted by students. The maximum evacuation time for two exits and the average evacuation time in simulation experiments using our model are well fitted to that in experiments conducted by students.



(a) The initial distribution. (b) The 10th time step. (c) The 20th time step.

(d) The 30th time step. (e) The 40th time step. (f) The 45th time step.

FIGURE 4. The initial distribution of the classroom for Experiment 1 and the snapshots at the 10th, 20th, 30th, 40th, 45th time steps of the simulation using our model for Experiment 1.



(a) The initial distribution. (b) The 5th time step. (c) The 10th time step.

(d) The 15th time step. (e) The 20th time step. (f) The 30th time step.

FIGURE 5. The initial distribution of the classroom for Experiment 2 and the snapshots at the 5th, 10th, 15th, 20th, 30th time steps of the simulation using our model for Experiment 2.

In addition, compared to the experiments conducted by students and the simulation experiments using Liu's model, simulation experiments using our model can evacuate pedestrians in a shorter average evacuation time.

(2) The number of pedestrians in each exit area is also an important factor for pedestrians to choose to evacuate the exit in the evacuation. When the gap of the cost of a pedestrian choosing exit between two exits reach the threshold, the pedestrian will consider to evacuate from the exit with a fewer pedestrians in that exit area.

We believe that our evacuation model can be applied to derive the reasonable evacuate plan to prevent from the indoor environment and protect human health. In addition, our evacuation model may be guide pedestrians to improve human decision-making during evacuation.

The limitations of our model should be acknowledged. In our evacuation model, we ignore the factors which affect the field of pedestrian's view, such as smoke and fire. If those factors exist in evacuation, our model needs to be improved.

An important direction for future work might be to study the relationship between the desks layout of the classroom and the time of evacuation from the classroom using our evacuation model, which may help us to select a reasonable layout to evacuate quickly from the classroom. Another future research work is to extend our model and apply it for evacuation form other indoor environments, such as the conference hall.

IV. CONCLUSION

We propose an evacuation model based on cellular automata that is used to simulate the human behavior during evacuation from a classroom. In our model two factors affecting evacuation are considered: the room's obstacles and the number of pedestrians in each exit area. The factor of room's obstacles is represented by the static floor field that is calculated using A-star algorithm. The factor of the number of pedestrians in each exit area represented by the dynamic floor field, and the algorithm for calculating the dynamic floor field is also given in this paper. In addition, we give the method of calculating pedestrian movement probability and the evolution rules of the model. Our model can be used to handle the two evacuation environments with and without obstacles. Two simulation experiments and some experimental comparisons have been conducted. Our model can reproduce the evacuation experiments conducted by students well and evacuate pedestrians in a shorter average evacuation time. The experiment results show that the number of pedestrians in the exit area is an important factor for evacuation, and our model is effective and superior.

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