A Simulation Study on the Effect of Individuals' Uncertain Behaviors in Indoor Evacuation

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Abstract—**Simulation study on indoor evacuation has gained tremendous attention in recent years. How to portray the effect of individuals' uncertain behaviors on the evacuation procedure remains a research challenge. In this study, an agent-based simulation of general indoor evacuation scenarios has been developed. Each individual is modelled as an autonomous agent driven by a weight-based decision-making mechanism. The environment is modelled as a combination of a grid-based map and potential fields. The simulation focuses on the uncertain interactions among individuals, small groups of individuals, and between the individuals and the environment. Experimental results indicate that pedestrians escaping as a single group in a similar manner may not be an effective scheme in indoor evacuation and the uncertainty in individual behaviors has significant influences on the evacuation procedure.**

Keywords- Evacuation; Crowd Modelling & Simulation; Behavior; Agent

I. INTRODUCTION

Emergency evacuation has long been a problem faced by many government agencies, sociologists, physicists, and computer scientists. A lot of existing works are based on the data extracted from emergency evacuations in the real world [5][7][16] or experiments [1][3][20]. Simulation study on emergency evacuation has gained tremendous attention in recent years. For example, routing algorithms have been studied in [11], which views an evacuation procedure as a path-finding problem. There are also some works concerning the effect of individual's speed [4], and the outputs prove some common knowledge, such as "faster-is-slower". More works have been carried out to investigate the decision-making mechanism and individuals' behaviors in emergency evacuation scenarios [1-7][15][17].

Most works of evacuation modelling & simulation (M&S) are either flow-based or individual-based. Flow based approaches ignore the individuality of the crowd [21], thus unable to characterize effect of the uncertain behaviors of some individuals [2]. Individual-based approaches normally model the crowd as a collection of individuals [6]. For example, individuals were modeled as homogeneous entities with no intelligence [22] and no entity exhibits abnormal behavior under the control of the same rules.

As the main trend of individual-based approaches, agent-based models represent individuals using intelligent and autonomous agents [2][8][14][15], which can independently make decisions. Most agent-based approaches focus on defining the rule of an individual's behavior and then applies the rule to all individuals of the whole simulated crowd [8][9][13]. In other words, in most agent-based evacuation simulation, individuals are only copies of the same template and "abnormal" individuals have been largely ignored [7][11].

During emergency evacuation in the real world, the behavior of an individual is affected by many factors , such as strength, reaction speed, emotion, other individuals around him/her, and the environment etc [5][7][13][14]. These factors operate on individuals in a complicated manner. The effect of the same factor may vary for different individuals. Existing approaches have been able to produced significant simulation results including individual and collective behaviors which can be observed in evacuation scenarios in the real world. However, following the above approaches, the effects of individuals' uncertain behaviors remain unclear and research along this direction is rare.

In this study, we proposed a general modelling & simulation framework for indoor evacuation scenarios, which focuses on the uncertain interactions among individuals (pedestrians), small groups of individuals, and between the individuals and the environment. This study adopts agent-based model to represent an individual using an agent (see section III for detailed design). The model focuses on a mechanism to drive agents' movement. An environment is modelled to provide information of pedestrian's density within it and information ("weight") that an agent can referred to for direction selection. A density-based algorithm is proposed to determine an agent's speed. A weight-based scheme makes decision for an agent to choose direction. The interactions between agents, especially conflicts, are handled by the algorithm as well. An agent interacts with other agents in a small group(s) by making tradeoff between the effect of density fields and the tendency to following other groups.

Experiments have been performed using our simulation framework to study a general indoor evacuation scenario to investigate the uncertain behaviors of individuals, in particular the uncertainty for an agent following a group or avoiding an area where dense pedestrians exist. The simulations successfully reproduced uncertain behaviors of a few individuals observable in real evacuation scenarios. From the simulation study, we found that pedestrians escaping as a single group in a similar manner may not be the most efficient scheme and the uncertainty in individual behaviors has significant influences on the evacuation process

The remainder of the article is organized as follows. Section II introduces the environment modelling approach. Section III describes the design of agents and the model for agent's movement. Section IV presents experiments of simulating a general indoor evacuation scenario and the experimental results. Section V concludes the paper with a summary and a proposal for future work.

II. ENVIRONMENT MODELING

This study models an environment as a combination of a map and associated fields. A map describes the physical properties of the environment, such as accessible areas. The fields include (1) a static field that describes the position information referred to by the agents to find exists, and (2) a dynamic field describing the density of pedestrians.

A. *The Map of an Environment*

This study abstracts an environment's physical properties using a map. As shown in Figure 1, the map consists of a grid of cells (squares). Four types of cells are defined here: accessible area (grey), exit (red), obstacle (blue), and sign of guidance (yellow). Agents are only allowed to move in cells of accessible areas and exits, and each cell can only be exclusively occupied by one agent. An agent who moves into a cell of exit is considered successfully escaped from the environment and will be removed from the simulation scenario. No entry to obstacles or signs of guidance is permitted. A sign of guidance can pass agents routing information to nearby exits.

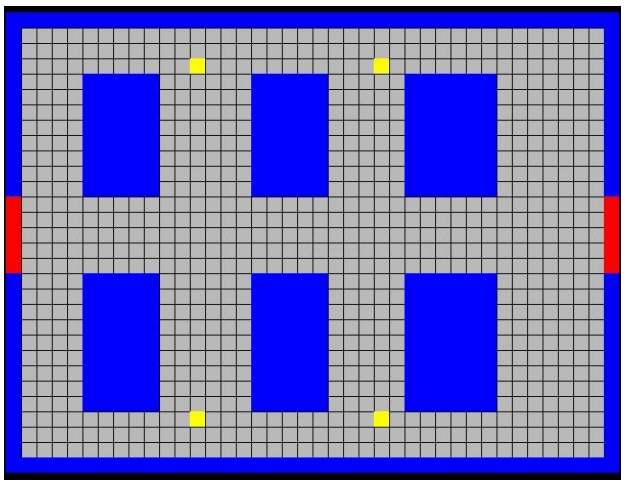


Figure 1. An exmpale of an enviroment's map

B. *Position Potential Field*

Each cell of the map is associated with a position property governed by a potential field. The potential field [14] denotes the distance to the nearest exit cell from a given position, which means the best path for an agent to route to the exit. The position potential field is a discrete 3D function (shown in Figure 2). An instance of such a field is basically a matrix consists of numeric values each associated to a specific cell, written as the cell's "position potential". In particular, the position potential of cells within an obstacle is specified as -2, which is invalid. Obviously, all exit cells have a position potential of 0, which is the lowest valid value. Figure 2 illustrates a position potential field corresponding to the environment's map as shown in Figure 1.

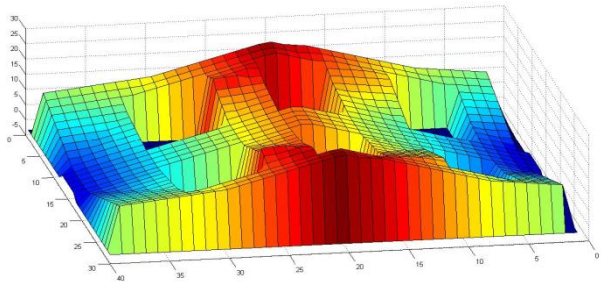


Figure 2. An example of position potential field

All position potentials are normalized to fit the use for agent's weight-based decision-making mechanism (See section III for details), and a normalized position potential is set between 0 and 1 conforming to formula (1).

$$p_g = \frac{p_{\max} - p_c}{p_{\max} - p_{\min}} \qquad (1)$$

where p_c is the distance to the nearest exit cell, p_{min} and p_{max} are the minimum and maximum values of the position potential field. The value of p_{min} is 0 (the exit), and the value of p_{max} is the cell farthest from any exits. p_g is the normalized position potential of the current cell. A p_g of a small value means the cell is far from any exit. The resulted position potential field remains static during the whole simulation process.

C. *Density Field*

A cell is also associated with a density field which describes the density of pedestrians around the cell. A density field is also a matrix same as a position potential field. The density of a cell k is denoted by ρ_k, which can be calculated by formula (2)

$$\rho_k = \frac{N_k}{N \times a^2} \qquad (2)$$

where N is the total number of cells around cell k within a given scope (e.g., a circle with radius of 5 in our experiments), N_k is the number of agents in these cells, and a is the edge length of a cell (see Figure 3).

Figure 4(a) shows an example of an evacuation simulation scenario at simulation time t, which uses dots to represent

agents. The corresponding density field is given in Figure 4(b). Distribution of the pedestrians changes with the evolvement of the simulation process. As a result, the density field is dynamic and subject to the activities of pedestrians in contrast to the static position potential field. The density of each cell is also normalized to a relative density value $D_{(k)}(t)$ between 0 and 1 with formula (3).

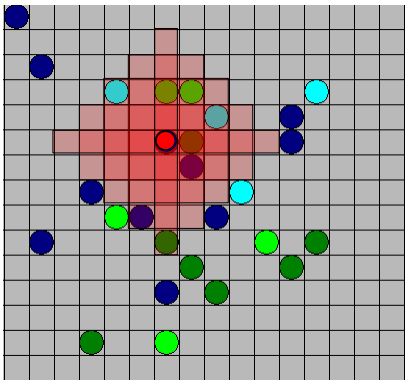
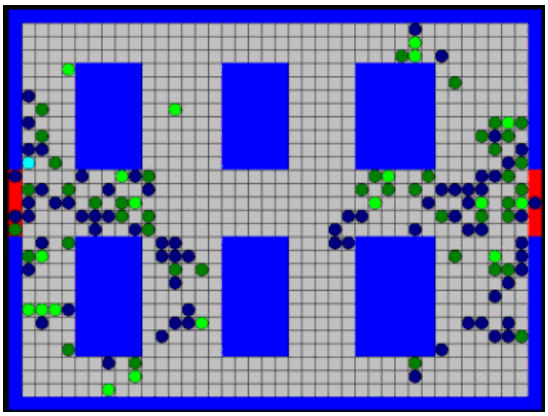


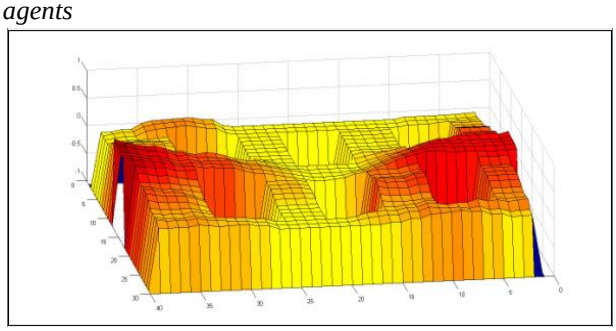
Figure 3. The density of the red area is considered as the density of the cell in the middle, which is marked by a blue dot.

$$D_{(k)}(t) = \frac{\rho_{\max} - \rho_k(t)}{\rho_{\max} - \rho_{\min}} \tag{3}$$

where ρ_k is the density value of cell k at time t, ρ_{max} and ρ_{min} are the maximum and minimum values of the whole density field. A $D_{(k)}(t)$ of a small value means the pedestrians on cell k are dense.



(a) A simulation scenario at time t with dots representing agents



(b) The corresponding density field at time t

Figure 4. An simulated evacuation scene and its density field

III. Individual Modelling

This section introduces the design of agents. The agent model focuses on the underlying mechanism of agent movement. Agent movement basically concerns speed and direction. Speed is basically influenced by the density field. An agent chooses its direction under the control of a weight-based decision-making scheme.

A. *Agent's Properties*

As presented in Figure 5, an agent has four fundamental properties, i.e., position, velocity, health status, and weights. *Position* (*x*, *y*) is simply the current cell the agent locates; *health* is the agent's health status which can influence the agent's behavior when collision is likely to occur; The agent's compound property *velocity* defines (1) *direction*, i.e., the direction of last movement, (2) v which denotes the agent's current speed, and (3) v_{max}, i.e., the highest speed the agent can achieve. Each agent maintains a set of weights, namely W_{pos}, W_{dir} and W_{den}, which are key parameters that determine the movement of the agent. The weight-based decision-making method will be covered in the next subsection.

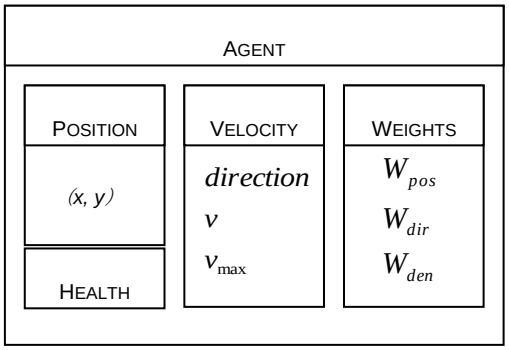


Figure 5. Agent properties

B. *Agent Movement*

The movement of an agent is about its speed and direction.. Agent's movement follows the cellular automation model, which means an agent can only move in the unit of cells and the agent can stop or move to one of the eight neighbor cells.

1) *Speed*

The speed v is determined by a segmented function written as formula (4).

$$v = \begin{cases} v_{\max}, \rho \in [0, \rho_t) \\ v_{\max}\sqrt{\dfrac{\rho_t}{\rho}}, \rho \in [\rho_t, \rho_c] \\ v_{\max}\sqrt{\dfrac{\rho_t \rho_c}{\rho_{\max} - \rho_c}}\sqrt{\dfrac{\rho_{\max} - \rho}{\rho}}, \rho \in (\rho_c, \rho_{\max}] \end{cases} \tag{4}$$

where ρ represents the density of the pedestrians around the agent, ρ_t and ρ_c are two thresholds in connection with density, and ρ_{max} is the maximum density.

The model is time stepped and evolves in multiple identical time frames with each representing a time unit in the real world according to users' need. A timing system is designed in the context of cellular automation model to realize various speeds of agents in the simulation [14][19]. Apparently, an agent can choose to move to one of the eight cells around or stay on its current cell in each round of movement. The timing system let an agent move one cell in n time units, n is a natural number. The maximum speed an agent can achieve is one cell per time unit. The value of m is calculated as the follows.

Given the time interval Δt, and the length of the cell Δl. The speed v is determined by formula (5).

$$v = \frac{s}{t} = \frac{p \times \Delta l}{q \times \Delta t} = \frac{p}{q} \times \frac{\Delta l}{\Delta t} \tag{5}$$

Assume n is an integer close to the value of q/p, we have formula (6).

$$v = \frac{p}{q} \times \frac{\Delta l}{\Delta t} \approx \frac{1}{n} \times \frac{\Delta l}{\Delta t} \tag{6}$$

2) Weight-based Method for Deliberation on Direction

How an agent determines the moving direction is an important issue. In this study, an agent selects one of the eight cells around it via a weight-based decision-making method.

From an agent's perspective, the method calculates the "attraction values" of the eight cells using the three types of weights. Then these cells are sorted as a queue according to their attraction values. The larger the attraction value is, more likely the corresponding cell will be selected.

a) Calculating Cell Attraction Values

Here an attraction value is defined for an agent to choose the eight cells around it. For an agent x next to cell k, the attraction value $V_{(k)}$ of the cell from the agent's perspective is given by formula (7).

$$V_{(k)} = W_{pos(k)} \times p_{g(k)} + W_{den} \times D_{(k)} + W_{dir(k)} \times P_{dir(k)} \tag{7}$$

where $p_{g(k)}$ is the position potential, $D_{(k)}$ is the density, and $P_{dir(k)}$ reflects the percentage of agents who are moving towards cell k from all agents moving towards x's eight neighbor cells, which can be calculated by formula (8).

$$P_{dir(k)} = \frac{S_{dir(k)}}{\sum_{i=1}^{8} S_{dir(i)}} \tag{8}$$

$S_{dir(k)}$ is the number of agents moving toward the direction k within agent x's sight. The cell i with the largest S_{dir} means most agents within agent x's sight are moving towards that cell. If agent x moves to cell i, the agent is considered tending to "follow the largest group". The three factors, i.e., position potential, density, and tendency to follow a large group, drives the agent's decision with the moderation of three weights of the agent denoted by W_{pos}, W_{dir}, and W_{den}. The value of the three weights conforms to formula (9).

$$W_{pos(k)} + W_{den} + W_{dir(k)} = 1 \tag{9}$$

The weights are an agent's inherent properties and they vary from agent to agent. An agent who has a large W_{den} tends to follow a group of pedestrians. If W_{pos} dominates, the agent tends to route to the nearest exit. If W_{den} dominates, the agent tends to avoid dense cells and choose to move to areas with fewer pedestrians. The weights of an agent may also change under certain conditions. For example, when an agent observes a sign of guidance, its W_{pos} may turn very large, and it generally follows the shortest path to the nearest exit. When an agent senses one of the exits in its sight, it adjusts W_{pos} to 1 to ignore other factors but position potential.

The $V_{(k)}$ values of the eight cells around agent x are eventually sorted for its reference, and the cell with the largest $V_{(k)}$ has the highest probability to be selected for x's next movement.

b) Decision-Making for Cell Selection

After the eight neighbor cells are sorted, the next step is to commit the selection and implement the decision. An agent normally takes to cell with the highest attraction value, i.e., the best move after deliberation on the agent's own initiative.

Once the cell cannot be reached, a strategy in real world rules: people will choose the second best move rather than just remaining still. Before commit the move, an agent (x) examines the accessibility of each cell. If the target cell is occupied by another agent y, agent x may compete with y for the cell. Agent x has a probability of P_{swap} to win the competition and swaps its cell with agent y conforming to formula (10).

$$P_{swap} = H_c \times \frac{1-\rho_t}{1-\rho_c} \times \frac{\rho_c}{\rho_t} \tag{10}$$

where H_c is the health status of agent x, ρ_c is current cell's density, and ρ_t is the target cell's density. Agent x generates a random number between 0 and 1. When this number is smaller than or equals to P_{swap}, agents x and y will swap their cells. If agent x loses the competition, it assesses the next best cell in the queue and so on. If competition is required for all of the eight cells and agent x cannot win any competition, it has to remain in the current cell.

IV. Experiments and Results

Experiments have been performed using an evacuation scenario illustrated in Figure 6, which consists of a typical indoor environment with 400 individuals randomly distributed in the scenario at the beginning. The objective of the simulation experiments is to examine the contradiction between an agent's tendency to "follow the largest group" , the tendency "to avoid dense pedestrians", and the tendency "to follow the shorted path to exit", which is basically the uncertainty of an agent's behavior. The three tendencies are reflected by W_{dir} , W_{den} , and W_{pos} (see Section III.B.2 for more details) respectively. We can

disable each types of tendency by adjusting the corresponding weight to 0.

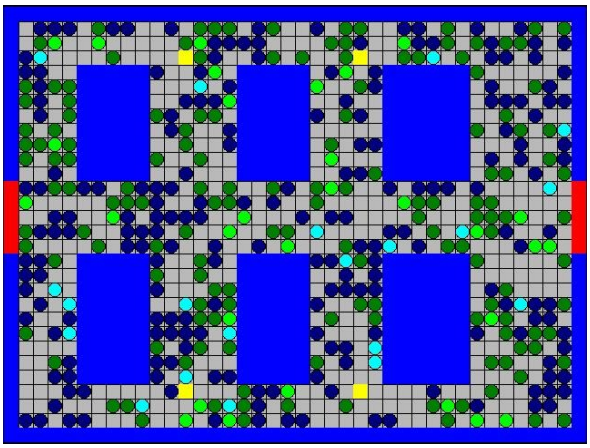


Figure 6. The scenario for individual behavior experiment

A. *Experimental Results*

Four different sets of tests have been performed with different settings of weight. Table 1 shows the weight settings in each test, marked as "A", "B", "C", and "D". In test set A, all agents are assigned a W_{pos} = 1 with two other weights disabled through the whole simulation, which represents an ideal situation of routing using optimal path. In all other tests, agents are initialized with two different settings, in which test set B disables W_{den} and test set C disables W_{dir}. When sensing a sign of guidance, an agent's weights will change to: (1) W_{pos} = 0.9, W_{dir} = 0.1 in test sets B and C; (2) W_{pos} = 0.9, W_{dir} = 0.05, and W_{den} = 0.05 in test set D; when sensing an exit, an agent's weights will change to W_{pos} = 1 in all test sets.

TABLE I. DIFFERENT SETTINGS OF AGENT WEIGHTS IN FOUR SETS OF TEST

Test A. W_{pos} dominates

Initialization / Weight	400 agents in the whole simulation
W_{pos}	*1*

Test B. W_{den}:0; Sensing guidance W_{pos}:0.9, W_{dir}:0.1; Sensing exit W_{pos}:1

Initialization / Weights	280 agents	120 agents
W_{pos}	*0.8*	*0.4*
W_{dir}	*0.2*	*0.6*

Test C. W_{dirs}:0; Sensing guidance W_{pos}:0.9, W_{dir}:0.1; Sensing exit W_{pos}:1

Initialization / Weights	280 agents	120 agents
W_{pos}	*0.8*	*0.4*
W_{den}	*0.2*	*0.6*

Test D. Sensing guidance W_{pos}:0.9, W_{dir}:0.05, W_{den}:0.05; Sensing exit W_{pos}:1

Initialization / Weights	280 agents	120 agents
W_{pos}	*0.8*	*0.4*
W_{den}	*0.1*	*0.3*
W_{dir}	*0.1*	*0.3*

Each test set has been executed for tens of times. The experimental results are presented in Figure 7, which records the number of pedestrians remaining in the environment (y-axis) against simulation time (x-axis) in the four sets of tests.

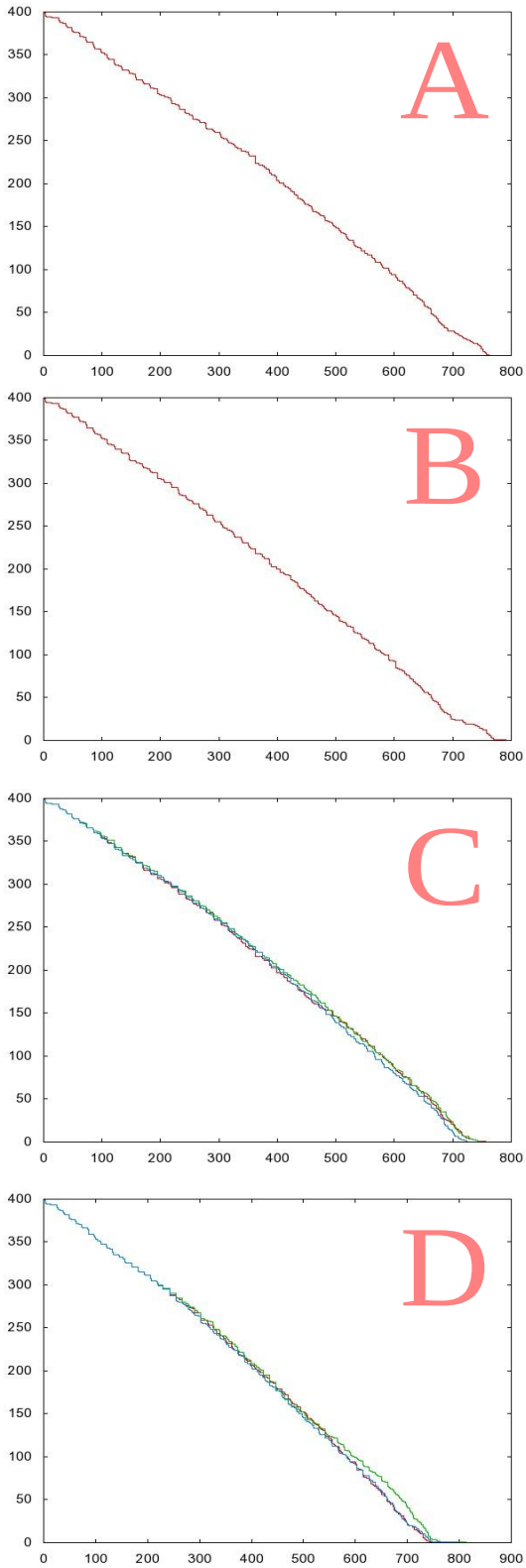


Figure 7. Experimental results with various settings of agent weights

In test sets A and B, the errors of results obtained in different runs are ignorable, and the average results are presented in Figures 7(a) and 7(b). Results obtained in test sets C and D vary significantly in different runs, and the former and the later have errors of 4.1% and 8.2% respectively. The maximum, minimum, and the averaged results are provided in Figures 7(c) and 7(d). The final evacuation times are reported in Table II.

TABLE II. TIME OF EVACUTION IN DIFFERENT TEST SETS

Evacuation time / Test set	averaged	min	max
A	*763*	*N/A*	*N/A*
B	*791*	*N/A*	*N/A*
C	*746*	*725*	*756*
D	*797*	*746*	*813*

Figures 8 and 9 present two snapshots of the simulation process of test set D, in which the agents with uncertain behaviors are highlighted using circles.

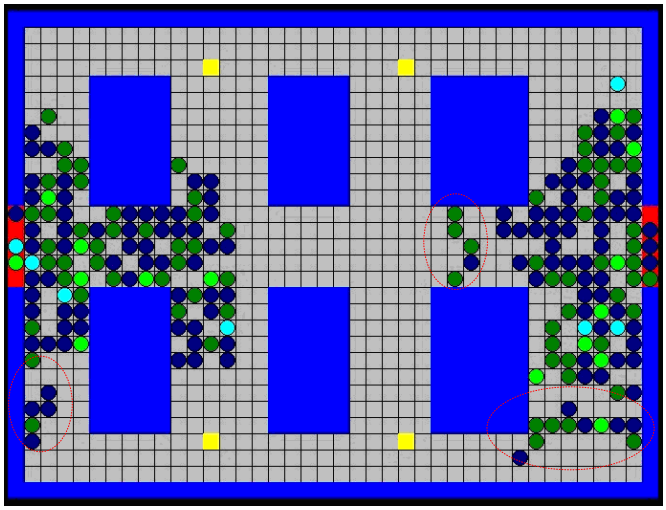


Figure 8. A snapshot in the middle of the evacuation simulation

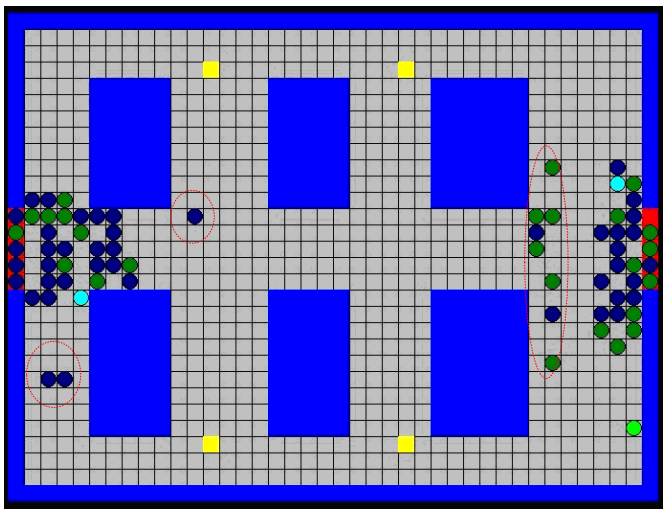


Figure 9. A snapshot at the end stage of the evacuation simulation

B. *Analysis*

The averaged evacuation time in test B is the longest in the four test sets. This is because agents always tend to follow the largest group, and the densities of the cells around agents are high and this leads to a very low speed of agents. This observation well matches the phenomena in real evacuations.

The averaged evacuation time in test set C is much shorter than the others. In this test set, agents have no tendency to follow a large group. The densities of pedestrians close to exits remain much smaller than those in other test sets. There is a much smaller probability for congestion to occur. Although some agents lag behind pedestrians close to exits, they can reach the maximum speed at the end stage of the simulation. The resulted averaged speed is still high. The overall effect is that the evacuation progresses smoother than in the other test sets.

In test set A, the strategy for always selecting the shortest path to an exit is applied to each agent. Although an agent moves to the exit in the shortest distance, there often exist congestions as agents always compete for cells in its shorted path to the exit. This effect compromises the advantage of shortening distances for agents.

In test set D, agents start to exhibit uncertain behaviors in the second half of the simulation procedure. As shown in Figure 9, a few agents after the group of pedestrians at exit do not move toward the exit but in the opposite direction towards the areas of low density. These agents wonder in a small area. When the exits are no longer congested, they begin to move into the exits.

Test set D enables agents the tendency to avoid dense cells in contrast to test set B, the evacuation procedure in the former test set is much more uncertain. There exist a few agents (highlighted in Figures 8 and 9) with uncertain behaviors in test set D and they may take a much longer time to evacuate than others, which are reflected by the near-flat end parts (span over 60 time units) of the curves shown in Figure 7(D).

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we introduced an agent-based modelling and simulation framework for indoor evacuations. The objective is to enable a general method and a platform to investigate the effect of individuals' uncertain behaviors in various indoor evacuation scenarios. The main research issues include environment modelling and decision-making of agent's movement.

The proposed approach models an environment as a combination of a map and a couple of fields associated to the map. The map defines the physical space for agent's movement using a grid of cells of four types. A potential field is suggested to quantify the property of each cell in connection with the exits of the environment. Another density field is defined to describe the dynamic density of pedestrians around each cell against simulation time. The two fields are referred to as the external factors that can physically influence/constrain agent's movement.

A weight-based decision-making scheme is proposed to drive agent's moving direction. The scheme concerns the interaction of three factors for an agent: (1) the tendency of following a large group, (2) the tendency to avoid dense pedestrians, and (3) the tendency to exit in a shorted path. Our approach also handles the competition for the same position between different agents.

Experiments have been carried out using the simulation framework to examine the contradiction between an agent's different tendencies when selecting moving direction, which is basically the uncertainty of an agent's behavior. The simulation successfully reproduced the uncertain behaviors of individuals during evacuation in real life. The simulation outputs indicates that the existence of individuals with uncertain behavior, even in a small number, can make an indoor evacuation procedure unstable. The results of evacuation time indicate that pedestrians escaping as a single group may not be the most efficient scheme.

In the future, we aim to extend the current model to accommodate more social factors in the real evacuations to establish a more comprehensive simulation framework. In addition, we plan to adopt modern cyberinfrastructure to support scenarios with extra-large scales and huge crowds.

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