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A Hybrid Model for Simulating Crowd Evacuation

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ABSTRACT

Macroscopic and microscopic models are typical approaches for simulating crowd behaviour and movement to simulate crowd and pedes-trian movement, respectively. However, the two models are unlikely to address the issues beyond their modelling targets (i.e., pedestrian movement for mi-croscopic models and crowd movement for macroscopic models). In order to solve such problem, we propose a hybrid model integrating macroscopic model into microscopic model, which is capable of taking into account issues both from crowd movement tendency and individual diversity to simulate crowd evacuation. In each simulation time step, the macroscopic model is executed first and generates a course-grain simulation result depicting the crowd move-ment, which directs microscopic model for goal selection and path planning to generate a fine-grain simulation result. In the mean time, different *level-of-detail* simulation results can also be obtained due to the proposed model containing two complete models. A synchronization mechanism is proposed to convey simulation results from one model to the other one. The simulation results via case study indicate the proposed model can simulate the crowd and agent behaviour in dynamic environments, and the simulation cost is proved to be efficient.

Keywords: Crowd simulation, Hybrid modelling, Microscopic model, Macroscopic model, Cellular automation

I INTRODUCTION

Macroscopic and microscopic approaches are currently two main mod-elling techniques for crowd simulation. The microscopic model, such as the meth-ods used in [1–5], emphasizes the issues of individual characteristics, including pedestrian's psychological and social behaviors, communication amongst pedestrians, and individual decision making processes. With the ability to describe individual issues, microscopic models can generate a fine-grain simulation result. Since microscopic methods only consider issues about each individual, it can only reflect the individual behaviour and movement pattern. Global and local crowd information is scarcely reflected in the same model. Whereas, macroscopic meth-ods (e.g., in [6–8]) focuses on the movement features of the whole crowd. It can generate a simulation result reflecting the tendency and movement pattern about the whole crowd, which is what the microscopic methods lack. However, macro-scopic methods are hardly to produce a fine-grain simulation result to reflect the individual diversities in simulation, due to its lack of consideration of individual issues.

In evacuation scenarios, pedestrian moves not only based on her/his own desire, but also subject to the crowd movement tendency as well as environment constraints. Regarding this, the model for simulating crowd evacuation needs to reflect crowd characteristics of both global movement tendency and individ-ual behaviour, which can be obtained by macroscopic and microscopic models, respectively. The combination of these two models is hence a natural idea to achieve this objective. Existing work has attempted to combine di®erent mod-els together to build a *hybrid model*. The existing hybrid models mainly fall into three categories. Methods like [8–10] build their models by adopting partial microscopic and macroscopic model into di®erent layers, which essentially fall into microscopic approach. Another type, like the one proposed in [11], incor-porates both complete macroscopic and microscopic models and executes them inter-changeably. However, the macroscopic model can only be executed when crowd movement is mostly stable (or becomes stable eventually), and the two models have no interactive communications during the same simulation time step. The third type, as proposed in [12], adopts a complete microscopic and macroscopic model and executes them simultaneously by applying them to dif-ferent parts of the environment. However, global and individual issues can not be simultaneously reflected for any simulation area.

This paper proposes a hybrid model for simulating crowd evacuation to exploit the integrated advances in macroscopic and microscopic method. Is-sues like environmental and global crowd movement pattern are simulated by macroscopic model. Whereas, the microscopic model only simulates how agent makes decision and moves directed by the simulation result from the macroscopic model. In each simulating time step, the macroscopic model is first executed. The microscopic model then accesses simulation results from the macroscopic model, and each agent makes a further individual movement decision, according to the global information as response. At the end of each simulation time step, the macroscopic model updates the initial parameters, according to the simula-tion results by the microscopic model and ends the current simulation time step. An interactive synchronization method is also proposed to conduct information exchange and synchronization between two models. Existing macroscopic or microscopic methods can only reflect either global crowd movement pattern or individual diversity, due to the limitations of the two types models. The proposed hybrid model in this paper, by contrast, is able to simulate both macroscopic and microscopic patterns, by executing the two models sequentially.

The simulation of crowd evacuation benefits from the proposed model by the following contributions:

1. The model integrates a microscopic model and a macroscopic model and executes them sequentially in one time step.
2. The microscopic model is proposed to simulate how an agent is a®ected by the crowd movement pattern and thus to generate a fine-grain simu-lation result with individual diversity.
3. Simulation performance is improved by the macroscopic model resulting in a global path planning which is not dependent on crowd size.
4. As a by-product, the simulation is able to obtain di®erent *Level-of-Detail* results by exclusive execution of either macroscopic or the whole hybrid model.

The rest of the paper is organized as follows: the existing related work is summarized in Section 2. How the macroscopic model is integrated into the microscopic model is depicted in Section 3. Experiment results given via case studies are represented in Section 4. The proposed model is evaluated and analyzed in Section 5. The paper is concluded in Section 6.

II RELATED WORK

This section gives a brief summary of existing related work for crowd simulation. Models for crowd simulation can be categorized in terms of modelling granularity of crowd that reflects in the grain of simulation result.

2.1 Microscopic Models

One of the typical methods to model and simulate large scale human crowd evacuation is to use the agent-based model (a kind of microscopic method), in which each pedestrian in the crowd is simulated individually. It is based upon the assumption that pedestrians have distinct characteristics and make decisions depending on personal desires. For example, [13)] adopted the social comparison theory in the crowd behavior and [1)] also employed a multi-agent based frame-work to demonstrate emergent human social behaviors, for instance, competing, queuing, and herding. Several collision avoidance methods were proposed, like the rule-based flocking model,[14, 15)] velocity-obstacles-based formulation.[5, 16, 17)] There are a number of models accounting for more sophisticated variants, like motion dynamics,[18)] sociological factors,[19)] psychological e®ects,[20, 21)] situation-guided control,[22)] and cognitive and behavioural models.[23, 24)]

Another type of microscopic approach simulates individual movement by employing *particle system* models, which considers individuals as a set of homo-geneous entities. It treats crowd as a discrete set of homogeneous particles, and simulates pedestrians as particles in the physical world. The typical method is Helbing's social force model.[2)] The motions of individuals were usually influenced by some global laws based on physical or socio-psychological forces. Some global emerging phenomena such as jamming and flocking were generated in simulation results.

2.2 Cellular Automata

Cellular Automata (CA) model [25, 26] is an important branch of microscopic model for crowd simulation. The environment in CA model is abstracted as discreet cells with equal size, and each individual is treated as a particle moving from one cell to a neighboring cell subjected to some local transition rules among neighboring cells. The CA model either reflects and imitates individual level details or macroscopic movement pattern depending on its considering issues.

Models aiming at microscopic level attempts to simulate the behaviour and movement of pedestrians.[27] aimed at individual-level features to reflect and imitate individual intelligence.[28] presented a CA model for pedestrian dynamics, which applied bionics approach to describe the interaction between pedestrians using ideas from chemotaxis.

Models aiming at macroscopic level attempt to simulate the whole movement pattern of the crowd. [29] used floor field for the CA model to reflect macroscopic and environmental issues for crowd evacuation.[30] presented a CA model based on lattice gas, which is usually used in macroscopic model. With this scheme, it was able to reflect the macroscopic pattern of crowd movement. [31] used a so-called floor filed to simulate collective phenomena like lane formation, flow oscillations at doors. The floor field is still a macroscopic method to describe the global feature of crowd movement.

Methods presented in [32] are the example to obtain both macroscopic and microscopic pattern of pedestrian and crowd movement in a CA model, which is derived from [28]. It introduced a vector-based particle filed to represent the macroscopic pattern. However, this method is based on the approach of particle system, which is hard to reflect real pedestrian's behaviour and movement.

2.3 Macroscopic Models

The individual behavior is constrained by the whole movement of the crowd. The higher the pedestrian density is, the more the individual will follow the average movement of the crowd. Regarding this, macroscopic models, such as those in [6, 7, 33, 34], studied the principles of crowd movement and simulate the movement pattern of the whole crowd instead of simulating each individual in the crowd. The basic idea of these macroscopic models is to model a crowd as continuous flow of fluid. Due to the inherent nature of flow-based models, they neglected the features and diversities of individuals. In this sense, flow-based models are mainly useful in estimating the flow of movement/evacuation process for huge and dense crowds.

2.4 Hybrid Approaches

It is obvious that the advances of macroscopic and microscopic models are complementary. Aiming at exploiting the advances of both models, some existing work attempts to combine the two types of models. Methods used in [8–10] adopted part of modules from both the macroscopic and microscopic models and combine them into a single model. The basic idea was to divide the model into two layers: a set of governing equations are applied from the macroscopic model at the top layer. This performed the role of the cognitive module which results in the overall movement pattern of whole crowd. Based on this result, the movement of each individual was simulated by a simplified m icroscopic model at the bottom layer. For example, in [8], a macroscopic model was used at the crowd level to generate simple rules to govern the movement of individuals; while a microscopic model simulated collision avoidance for each individual. Since the methods mentioned above still need to execute a complete microscopic model for every individuals in the crowd, the simulation eÿciency significantly decreases as the crowd size increases. Additionally, it is still constrained by the limitation of the macroscopic model. If the adopted macroscopic method is not applicable for a specified crowd, the whole model will not be a pplicable. Essentially, these type hybrid methods are still microscopic models.

In contrast to the aforementioned methods, we previously proposed a multi-resolution modelling[11] approach, which attempted to combine both macro-scopic and microscopic models. The approach of this method was to make the two models work iteratively: the macroscopic model governs the simulation when the crowd movement is stabilized; if there is an event which makes the crowd movement unstable, the simulator will switch to the microscopic mode and choose the microscopic model to simulate the crowd movement. Finally, the simulation adopted the macroscopic model once the crowd movement became stable again. This method is suitable for simulating crowds whose movement remains mostly stable. It can also avoid the limitation of the macroscopic model, because part of crowd, for which the macroscopic model is not applicable, can be simulated by the microscopic model. However, it only aims to generate a multi-resolution simulation result, and the global issues are not reflected in the microscopic model.

III PROPOSED HYBRID MODEL SPECIFICATION

In order to integrate a macroscopic model into a microscopic model, the proposed hybrid model contains three modules: 1) a macroscopic model sim-ulating crowd movement subject to global and environmental scenarios; 2) a microscopic model simulating each pedestrian's movement in the crowd under the direction of the simulation result generated by the macroscopic model; and 3) a synchronization module charging the convey of the simulation result from one model to the other one.

Simulation time is divided into discrete equal time intervals as simula-tion time step, each of which both models are executed sequentially depicted as follows:

step 1 With the initial information collecting from the result of the microscopic

model in the last time step, the macroscopic model executes at the begin-ning of current time step and then generates a course-grain simulation result reflecting the crowd movement tendency.

step 2 The synchronization module provides the functions of accessing the simulation result of the macroscopic model for the microscopic model.

step 3 The microscopic model is then triggered to execute based upon the crowd movement tendency and density generated from *step 1*. The generated simulation result is considered as the final result of the hybrid model in the current time step.

step 4 The synchronization module transfers the agent's position to crowd density as the initialization of the macroscopic model. After this, the simulation of the current time step ends and go to *step 1* for the execution of the next time step.

Detail designs of these modules are introduced in the following subsections.

3.1 Simulation Environment Specification

A typical environment for crowd evacuation includes accessible moving areas, exit and obstacle. The whole continuous simulation environment is divided into square cells with equal size. Both the macroscopic and microscopic models share this specification for the model execution.

In real life, a pedestrian may not choose its moving path exactly according to the ideal path, especially for those without familiar knowledge of the environment. That's why sign board always appears in complicated environment to help pedestrians to find the desired goal efficiently. Taking into account this, information tags are added into the simulation environment at specified cells. These tags make an agent to know the full knowledge of the simulation environment, which implies that the agent is able to follow the shortest path generated by the macroscopic model (introduced in the next subsection).

3.2 Macroscopic Model

A continuum model, derived from [35], is applied as the macroscopic model for the proposed hybrid model, which considers the crowd as a whole with symmetric dynamic features. The model describes how crowd selects velocity (i.e., magnitude and direction of velocity) and how crowd moves with the selected velocity (i.e., the density distribution). The simulation result of the model is presented as crowd density and velocity distribution.

[1] Crowd speed selection

Assuming the magnitude of crowd velocity, i.e., the speed of crowd movement, is related to the crowd density around only. A speed-density relationship proposed in [7] is applied in the macroscopic model, as shown in Equation 1.

$$f(\rho) = \begin{cases} A, & \rho \le \rho_t \\ A\sqrt{\dfrac{\rho_t}{\rho}}, & \rho_t < \rho \le \rho_c \\ A\sqrt{\dfrac{\rho_t \rho_c}{\rho_m - \rho_c}\dfrac{\sqrt{\rho_m - \rho}}{\rho}}, & \rho_c < \rho \le \rho_m \end{cases} \quad (1)$$

where ρ represents the crowd density around the agent, and the typical values of ρ_t, ρ_c, ρ_m, and A are set as 0.8m^{-2}, 2.8m^{-2}, 5.0m^{-2}, and 1.4m/s respectively in [7]. Actually, the parameter A here represents the agent's *preferred speed*. The density information is collected from the result by the microscopic model through calculating the average density for each cell in the simulating environment.

[2] Determination of crowd moving direction

Here we assume that a crowd prefers to arrive at the destination as fast as possible, which implies that the crowd selects a shortest path to move along. A scalar field, called *position field*, is used to generate the shortest path. The value of each element in the position filed, $\phi(x, y)$, records a value for each cell in the simulation environment, where (x, y) is the coordinate of the cell location. The value means the travelling time from current location to an exit along the shortest path. The value is assigned to 0 and positive infinity for cells in part of an exit and obstacle, respectively. Values for the other cells are assigned as positive values, which are determined during the model execution. The value change of the position field along a detected shortest path should be the fastest amongst all the possible paths, which can be formalised as Equation 2:

$$\vec{d}(x, y) // - \nabla\phi(x, y) \tag{2}$$

where // indicates the directions of the two vectors are parallel, and $vecd(x, y)$ represents the movement direction at Point(x, y). In other words, the direction of crowd movement always follows the opposite direction of the gradient of the position field. With this relationship, the time for crowd movement per unit distance can then be presented as

$$t(x, y) = |\nabla\phi(x, y)| \tag{3}$$

where $t(x, y)$ is the time per unit distance at location (x, y) calculated by $1/v(x, y)$. Here, density is not considered, which is an issue of the microscopic model. Hence, $v(x, y)$ can be any positive value. By solving the partial differential equation, the values of position field of all cells are determined. The numerical solution to this equation follows the method proposed in [36].

[3] Generation of crowd movement

The continuum model assumes that crowd movement is governed by the following *conservative equation*, which is a typical *Navier-Strokes* equation:

$$\partial\rho(x, y, t)/\partial t + \nabla \cdot (\mathbf{v}(x, y, t)\rho(x, y, t)) = 0 \tag{4}$$

where $\mathbf{v}(x, y, t)$ and $\rho(x, y, t)$ is the velocity vector and crowd density at Point(x, y) for simulation time t, respectively. With this formula, the distribution of crowd density at simulation time $t+1$ can be obtained with the information of velocity and density distribution at simulation time t. The magnitude and direction of velocity are determined by Equations 1 and 3. By using numerical method proposed in [35], the crowd density distribution in each simulation time step is then generated.

3.3 Microscopic Model

We propose a CA-based model to simulate how an agent moves in a simulation environment with the emphasis on how an agent selects cell, being aware of the impact from crowd movement. Each agent holds a property set defined in Equation 5

$$\begin{aligned} S = \{x, y, H, v_x, v_y, \rho \\ sight, \theta, w_{dir}, w_{pos}, w_\rho\} \end{aligned} \tag{5}$$

where x and y represent the agent's current position; H reflects the agent's current healthy status; v_x and v_y holds current magnitudes of the agent's velocity along x and y coordinates, respectively; ρ represents the density at the current cell including point (x, y); $sight$ means the agent's maximum distance of eye sight, and θ means half of the maximum angle the agent can see from its current position (shown in Fig. 1); the following three parameters are weight factors reflecting how the agent's behaviour is affected by external factors from either crowd or environment issues, i.e., w_{dir} (crowd movement), w_{pos} (position) and w_ρ (density).

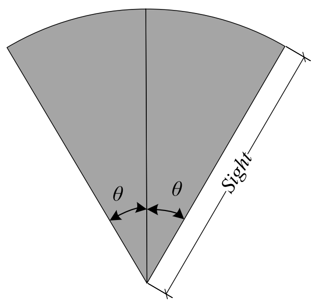


Fig. 1 Description for an Agent's Eye Sight

We first propose the transition rules for the CA-based model . An integration of these rules are proposed to determine each agent's position and velocity during each simulation time step.

[1] Transition rules

The agent's movement depends not only on its own desire, but also on crowd movement. We propose the following transition rules for the CA-based microscopic model to reflect how the agent selects cell based upon the simulation result of the macroscopic model with the issues of position field, density distribution, and crowd movement. In order to evaluate candidate cells, we introduce *cell attraction* for each rule to quantify the evaluation metric.

Rule 1: Agent movement by position field. Ideally, an agent follows the moving direction generated by Equation 2, if it is fully aware of the information of the simulation environment. Otherwise, the agent observes the movement of crowd around and makes a similar decision for the selections of goal and moving path. In order to simulate such behaviour, we define a *position* *attraction* to depict how the agent is directed by the position field, defined in Equation 6.

$$P_k = \frac{\phi_{max} - \phi_k}{\phi_{max} - \phi_{min}} \tag{6}$$

where k is the indicator for the neighbouring cell of the agent currently standing; P_k represents the position attraction from the cell k; ϕ_{max} represents the maximum value of ϕ amongst all cells inside the agent's eyesight (with the exception of infinity of ϕ); ϕ_{min} is the minimum value of ϕ inside the agent's eyesight; ϕ_k is the value of ϕ at cell k. The agent prefers to move towards the neighbouring cell with a higher value of P_k calculated by this formula. Once the agent catches sight of a information tag thus to have the full knowledge of environment information, it will take the shortest path generated by the macroscopic model. In this case, 1 is assigned to position attraction of the neighbouring cell along the shortest path, and 0 to the other neighbouring cells.

Rule 2: Agent movement by density distribution. The agent may make a detour when encountering a dense area. We introduce a cell attraction Den_k to reflect such a behaviour, defined in Equation 7.

$$Den_k = \frac{\rho_{max}(t+1) - \rho_k(t+1)}{\rho_{max}(t+1) - \rho_{min}(t+1)} \tag{7}$$

where t and $t+1$ represents the current and next simulation time steps; $\rho_{max}(t+1)$ and $\rho_{min}(t+1)$ is the maximum and minimum densities inside the agent's eyesight; and $\rho_k(t+1)$ is the density at cell k. The macroscopic model provides the density information.

Rule 3: Agent movement by crowd movement When a pedestrian moves into a high density area, her/his movement mainly constrained by the crowd movement, which is a typical phenomenon described by *social comparison theory.*[13)] Another cell attraction is proposed to simulate this behaviour, defined in Equation 8.

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

where p_{dir_k} is the attraction of the neighbouring cell k; $dir(k)$ defines the direction from the current cell pointing to cell k; $S_{dir(k)}$ represents the number of cells in the agent's eyesight where the crowd moves along the direction $dir(k)$; $\sum\limits_{i=1}^{m} S_{dir(i)}$ counts up the number of cells along all the m directions. The neighbouring cells may be occupied by obstacles, which leads to the decrease of number of crowd moving direction. Hence, the maximum value of m is 8. The crowd moving direction can be calculated by the velocity distribution from the macroscopic model.

[2] Generation of agent movement

In order to integrate the transition rules defined in Equations 6, 7 and 8, and to evaluate the candidate cells, we propose the integrated cell attraction to evaluate all candidate cells, defined in Equation 9.

$$V_k = w_{pos_k} P_{pos_k} + w_{\rho_k} Den_k + w_{dir_k} P_{dir_k} \tag{9}$$

where V_k means the value of the cell attraction of cell k. Here, three weight factors are introduced, i.e., w_{pos_k}, w_{ρ_k} and w_{dir_k}, representing the impact of position, density and crowd movement on agent movement, respectively. The three weight factors holds the constrains defined in Equation 10, i.e., the sum of them equals to 1.

$$w_{pos_k} + w_{\rho_k} + w_{dir_k} = 1 \tag{10}$$

The agent always prefers to move towards the neighbouring cell with the largest value of the cell attraction, V_k. Since a cell can hold only one agent in the CA model, agents may competes for the same cell during the simulation. The competition rule is defined in Equation 11, and the agent with the largest value of $competition_i$ wins the competition and moves into the cell in the next time step.

$$competition_i = \frac{H_i}{cost_i} \tag{11}$$

where i discriminates agent i, H_i is its health degree, and $cost_i$ describes the cost of the agent i moving from the current to the targeted cell. H_i reflects the agent's characteristic of age and strength. An adult holds a higher value of H_i than a child and the elderly. The cost of movement $cost_i$ is set as follows: 1 is assigned if the current and targeted cell share an edge, and 1.414 if the two cells only share a vertex. Once an agent fails to select its preferred cell, it competes for another neighboured cell with a smallest deviation.

The cell selection determines the agent's moving direction. Its speed is figured out according to the density-speed relationship defined in Equation 1. If an agent cannot select a cell to move, it will reduce its speed to move to the edge of the current cell. On the other hand, if the agent's speed is not fast enough to arrive at the selected cell, it should remain at the current cell. In both scenarios, the agent's position will still be updated according to the selected velocity.

3.4 Synchronization between Models

The simulation results of the two models are reused for one another, which raises two issues for the synchronization mechanism between models. One issue is how to convey the simulation result to the microscopic model; the other is how to initialize the macroscopic model with the results of the CA-based model.

For the first issue, a synchronization module provides read-only methods for the microscopic model to access position field, density distribution and velocity distribution. Each of them is stored in one (position field and density distribution) or two (velocity distribution) 2-dimensional array(s). Since both models share the environment discretization, the value of each element in those arrays can be directly used as corresponding information for a specified cell.

As for the latter issue, the synchronization module needs to convert the agent position from the result of the microscopic model to crowd density as the initial value of the parameter $\rho(x, y)$ in Equation 4. The determination of crowd density for a specified cell follows the steps below:

1. Count the number of agents, $number$, in the cells which are inside the eyesight of an imaginary agent locating at the centre of the specified cell.
2. Calculate the area size of cells in the agent's eyesight.
3. The crowd density at the specified cell is then calculated as $number/size$.

IV CASE STUDY

In this section, several cases are studied by using the proposed hybrid evacuation model to simulate crowd evacuation scenarios. The section starts with a simple scenario first, where a common phenomenon of crowd movement is found. The function of density attraction is also evaluated in this section. After this, an indoor scenario is conducted and the simulation results show how an agent moves around the environment governed by the hybrid model.

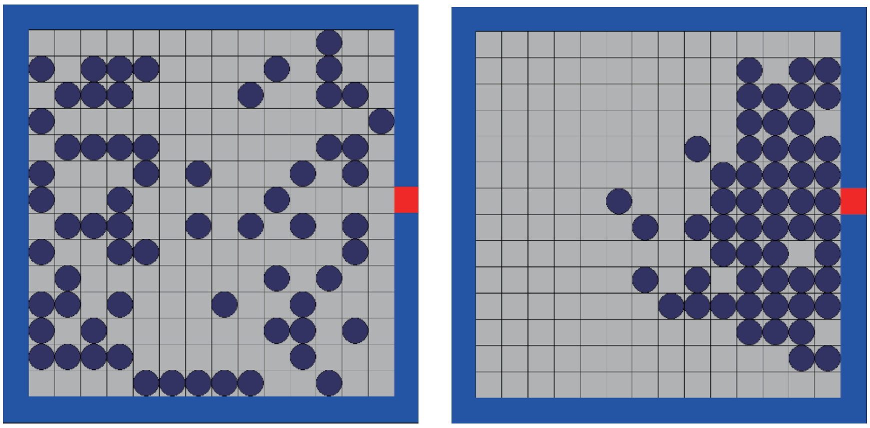
Without additional description, the environment is divided into cells by the size of $0.4 \times 0.4m$, and simulation time step is set as $0.5s$. As for the value assignment of weight factors defined in Equation 9, there are two sets of assignments. If there are no information tagging inside the agent's eyesight, the weight factor of position should be dominant amongst the three factors. Regarding this, the value is set as 0.7, and w_{dir_k} and w_{ρ_k} is set as 0.2 and 0.1, respectively. On the other hand, if there is no guide tag in the agent's eyesight, the crowd movement should be dominant (the value is set as 0.7), and w_{ρ_k} and w_{pos_k} is set as 0.2 and 0.1, respectively. As for the agent eyesight, θ is set as $\pi/4$ and $sight$ as $8m$.

4.1 Scenario I

The simulation environment is specified as follows (illustrated in Fig 2a): 1) the environment size is set to $6.4 \times 6.4m$; 2) the initial number of agents is 64; 3) the environment is surrounded with obstacles (colored with blue); and 4) only one exit is in the environment locating at the right side of the environment (colored with red). The environment specification aims to simulate the real scenario with a narrow moving space and few exit.

All agents desire to evacuate as soon as possible via the only exit. How-ever, the exit occupies only one cell, which means at most one agent can access the exit in each simulation time step. Hence, it can be expected that the density around the exit will be very high, which is observed in the simulation result shown in Fig 2b. Furthermore, the shape of agent positions near the exit is a approximate semicircle. Similar shape can also be found in the literature.[2] This phenomenon is compatible with the empirical observations, and comparable to intermittent clogging found in granular flows through funnels or hoppers.[37, 38]

Based on this scenario, a further experiment is conducted with another desired speed. Previously, the desired speed of agent is set as $1.4m/s$ for the parameter A in Equation 1. Another value of A is set as $2.5m/s$. The time for evacuation simulation is compared with both desired speeds. The simulation



(a) Simulation Time Step=0 (b) Simulation Time Step=30

Fig. 2 Simulation Results of Scenario I: Scenario of Narrow Space for Evacuation

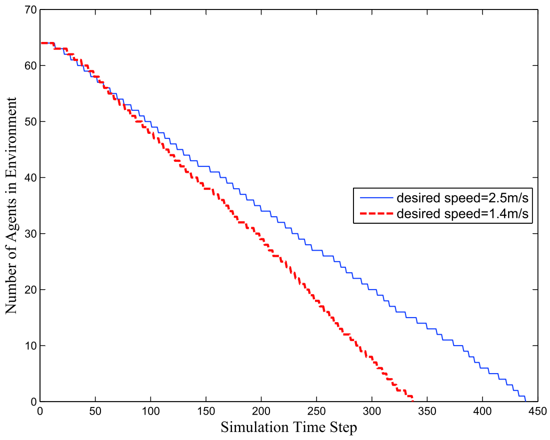


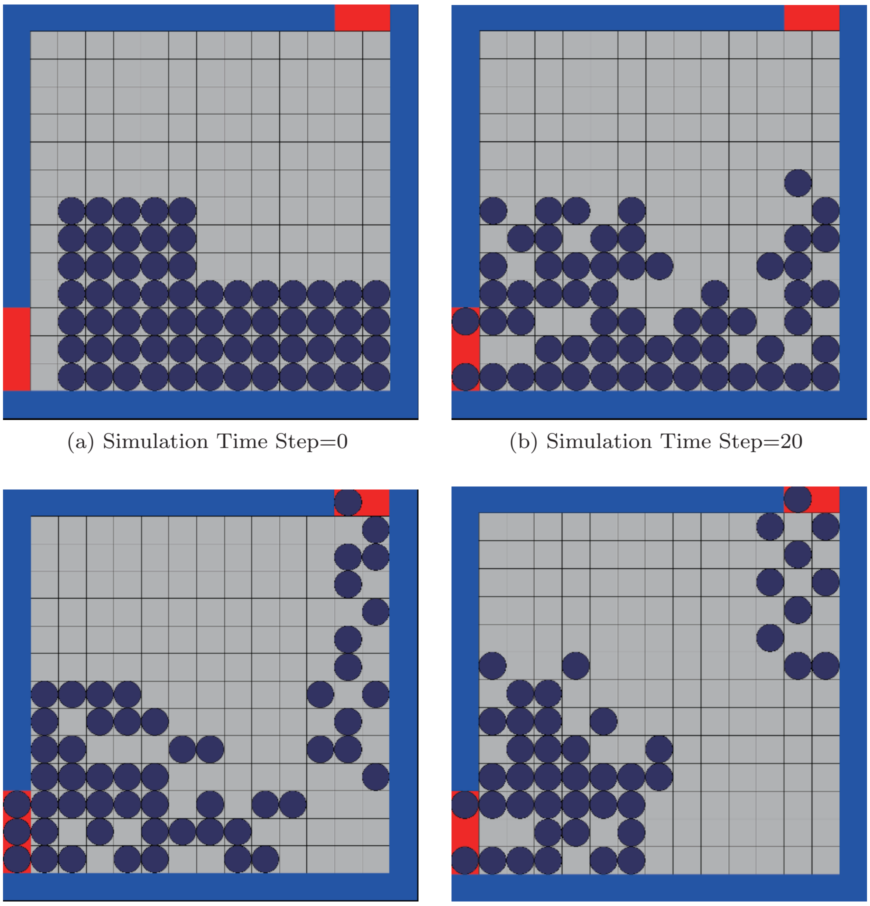
Fig. 3 Comparison of Agent Number with Different Desired Speed (Scenario I)

results is shown in Fig. 3. It can be observed that the evacuation time for the desired speed setting as $2.5m/s$ is around 22.2% slower than that setting as $1.4m/s$. The simulation results show another empirical observation called *faster-is-slower*, which is also observed in [2)].

Through the found phenomena from the simulation results, the proposed hybrid model is proved to be holding the capability of simulating crowd evacuation.

4.2 Scenario II: Evaluation for Density Attraction

In this subsection, a scenario is designed to evaluate how density attrac-



(a) Simulation Time Step=0

(b) Simulation Time Step=20

(c) Simulation Time Step=40

(d) Simulation Time Step=60

Fig. 4 Scenario II: Evaluation for Density Attraction

tion works in the model. The simulation is specified as follows: the environment contains two exits located at the left and top of the environment, with environment size of $6 \times 6m$; and 63 agents are initially in the environment, mainly locating at the bottom of the environment, as shown in Fig. 4a.

Without density attraction, agents at bottom-right should choose the exit at the left side due to shorter distance to exit. As the density attraction works, some agents choose another exit to avoid the high density area, which can be observed from the simulation results illustrated in Fig. 4b- 4d, which is compatible to empirical phenomenon in real life.

4.3 Scenario III: Evaluation for Information Tagging

The function of information tagging is evaluated through a scenario defined in Fig. 5. Initially, there are 60 agents in the environment and two exits

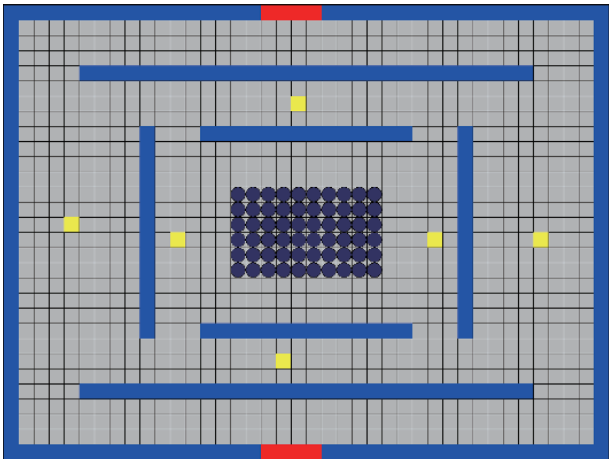


Fig. 5 Initial Status for Evaluation of Information Tagging

located at the top and bottom of the boundary of the environment (with red color). Information tags are labelled with yellow color, which helps an agent to be aware of the nearest exit immediately once it comes into the agent's eyesight. The environment is bounded with obstacles, and there are also several obstacles inside the environment.

Two experiments are conducted based on the scenario with and without information tagging, respectively. Fig. 6 shows the number of agents in the environment during the simulation process. At the beginning of the simulation (before simulation time step 103), agent numbers in the two experiments are the same and kept unchanged, which indicates that there is no agent leaving the environment. As simulation time elapses, the number of agent in environment of the two experiments become different. Experiments with information tagging always holds a smaller agent number than that without information tagging. This indicates that agents without information tagging need more time to evacuate due to moving along a longer path; by contrast, agents with the help of

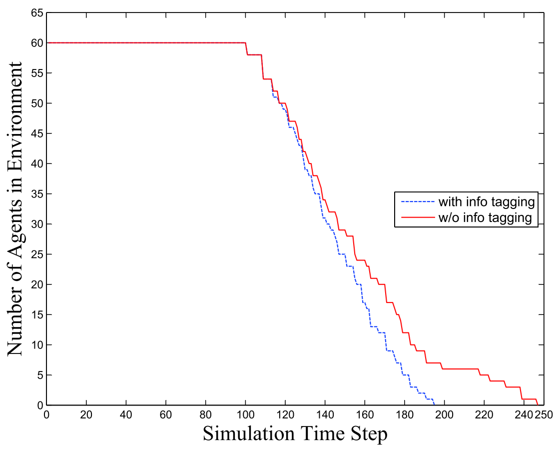


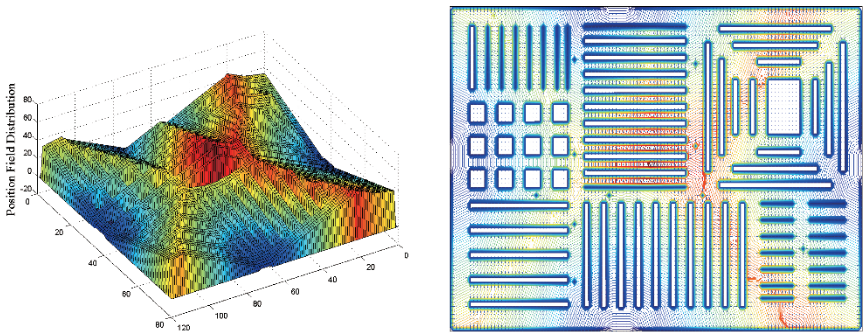
Fig. 6 Simulation Results for Hybrid Model with and without Information Tagging

information tagging is able to find the desired path towards an exit immediately once they catch sight of cells tagged with guiding information. That's why the simulation with information tagging completes the simulation earlier than the other one. Another reason is that unfamiliar agents follow the crowd movement which shorten the evacuation time for the whole crowd. The simulation time costed by the experiment with information tagging around 22.6% faster than the one without information tagging.

4.4 Scenario IV: An Indoor Scenario for Crowd Evacuation

An indoor scenario is designed to validate how a crowd/agent is governed by the proposed hybrid model to evacuate from the environment. The environment size is set as $120 \times 80m$, surrounded by obstacles (colored with blue). There are 4 exits (colored with red) allocated at each boundary. The other obstacles inside the environment are also labelled with blue color, and cells with yellow color represent information tags. This specification derives from a supermarket layout.

Initially, there are 1000 agents uniformly distributed around the environment (shown in Fig. 9a). The initial position field and density distribution by the macroscopic model are shown in Fig. 7a and 8a, respectively. The position field determines how the crowd chooses a path towards an exit to evacuate from the current location. Fig. 7a illustrates that cells with highest value of position field is located at the center of the environment due to the distance to any exit. It can also be found that some cells are with negative value of position field, which means these cells are inside obstacle (as a substitution for the original positive infinity). Fig. 7b shows the information collected from the result of the macroscopic model, depicting the contour of the position field around the environment and the opposite direction of gradient of position field. It indicates the moving direction of crowd at any specified location towards an selected exit. Fig. 8a represents the density distribution around the defined environment, and negative

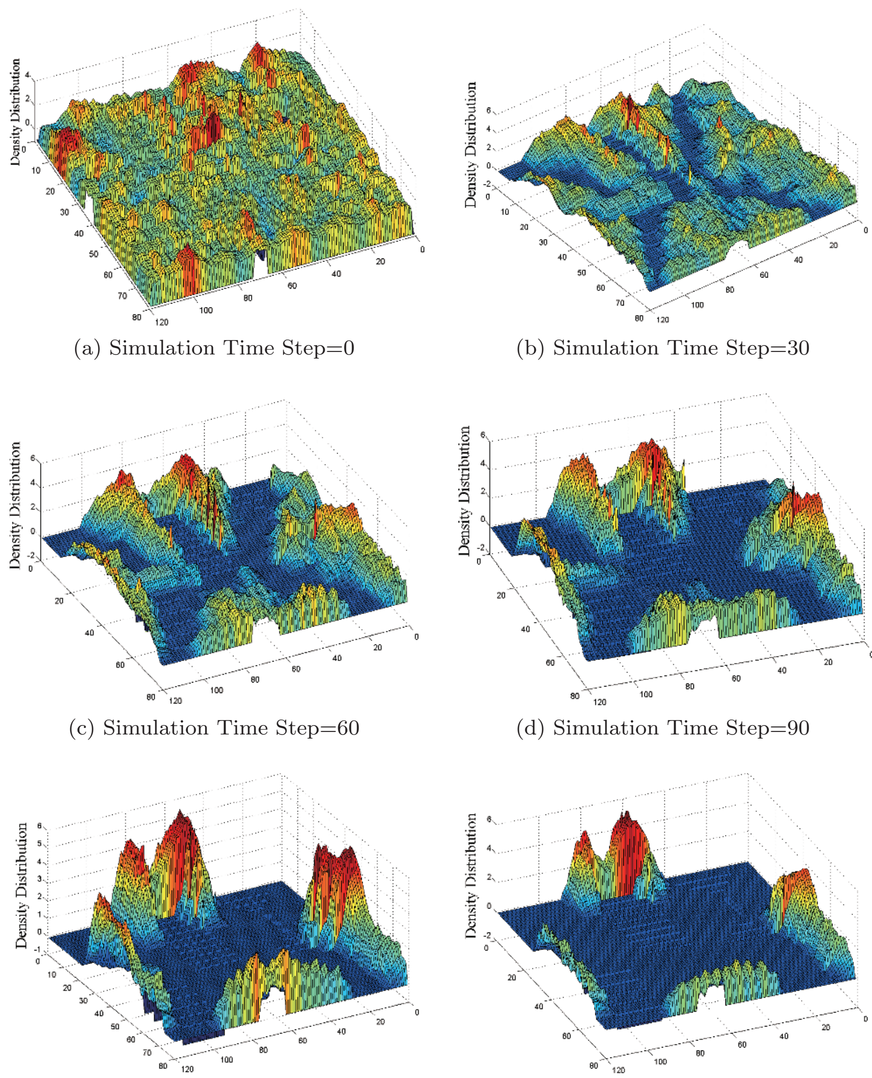


(a) Position Field Distribution of Scenario IV by Macroscopic Model

(b) Position Field Description of Scenario IV: Contour and Opposite Direction to its Gradient

Fig. 7 Position Field Distribution and Crowd Movement Direction values also represent cells in obstacles. Actually, the position field is static and does not change during the simulation once the environment is assigned. The crowd density distribution is dynamic reflecting how the crowd moves governed by the macroscopic model.

Fig. 8b - 8f show the crowd density distributions at simulation time steps 30, 60, 90, 150 and 240 by the macroscopic model, respectively. Fig. 9b - 9f



(a) Simulation Time Step=0

(b) Simulation Time Step=30

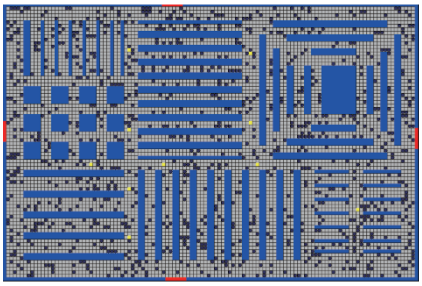
(c) Simulation Time Step=60

(d) Simulation Time Step=90

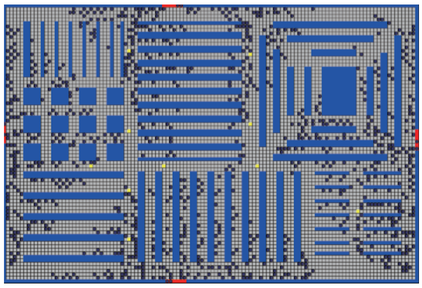
(e) Simulation Time Step=150

(f) Simulation Time Step=240

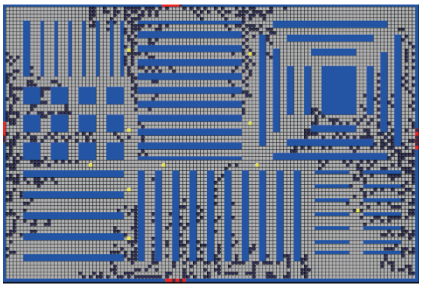
Fig. 8 Density Distribution for Scenario IV at Different Simulation Time Step Governed by Macroscopic Model



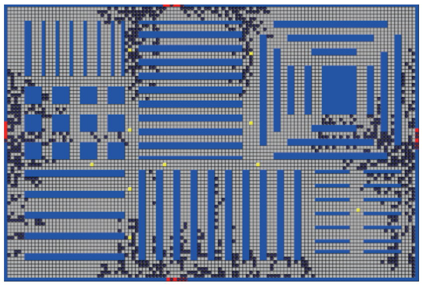
(a) Simulation Time Step=0



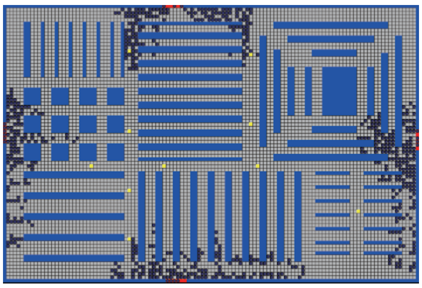
(b) Simulation Time Step=30



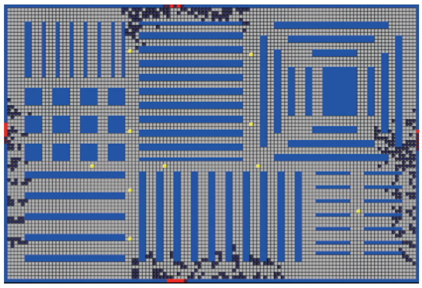
(c) Simulation Time Step=60



(d) Simulation Time Step=90



(e) Simulation Time Step=150



(f) Simulation Time Step=240

Fig. 9 Simulation Results of Scenario IV: Crowd Evacuation in an Indoor Environment

illustrate the simulation results at simulation time steps 30, 60, 90, 150 and 240, respectively. As simulation time step elapse, crowd densities around the exits becomes higher gradually. This means most of agents have arrived at the areas around the exit. However, the capacity of exit for an agent moving through is fixed, agents need to wait or decrease its speed for moving through. At simulation time step 240, the density around exits becomes lower (shown in Fig. 9f), this is due to the decrease of the agent number inside the environment.

4.5 Scenario V: Evaluation for Agent in Different Types

An crowd can contain several types of agents. In this section, the simulation evaluates how different types of agents move in the environment defined in Scenario IV. Initially, there are three types of agents, i.e., adult, child and the elderly, all with the number of 250, uniformly distributed around the environment. The snapshot for the initial status is shown in Fig. 10. The value of H used in Equation 11 is set as 1, 0.8 and 0.6 for adult, child and the elderly, respectively. As for the desired speed defined in Equation 1, the value of A is set as 1.4, 1.1 and $0.84m/s$ for adult, child and the elderly, respectively.

The number of agents left in the environment over simulation steps is shown in Fig. 11. From the simulation result, it can be observed that the agent with the type of adult moves at the fastest speed and the number of them drops to 0 first amongst the three agent types, whereas the agent with the type of the elderly moves at the slowest speed. On the other hand, it can also be found the curve representing for the adult number drops more sharply than the other two types, which indicates that adults can move quick and swiftly in the

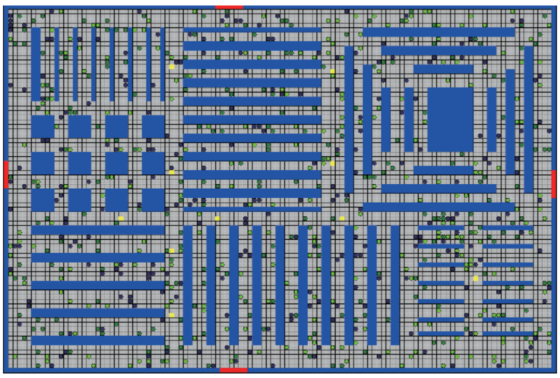


Fig. 10 Initial Status of Scenario V

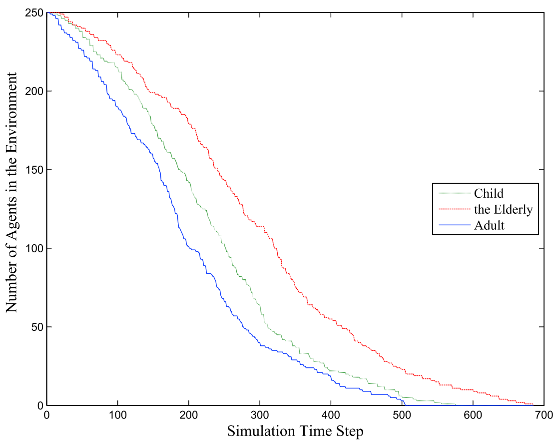


Fig. 11 Comparisons in Agent Number in Environment for Different Agent Types

environment when they compete for the same cell with the other two types. The reason falls in the following two aspects. Agents with the type of adult hold the highest competition factor H (defined in Equation 11), so that they have a highest privilege to move into the selected cell. It is also due to the fact that the adult holds a highest desired speed, and moves faster than the other two types. Hence, agents with the type of adult will first complete the evacuation process.

V MODEL EVALUATION

In this section, the proposed model is evaluated through the model ex-ecution performance and comparison analysis with existing typical microscopic and macroscopic models.

5.1 Performance Evaluation

We apply the scenario defined in Section 4.4 to evaluate the performance of the simulation model. Three experiments are conducted, with initial agent number of 1000, 800 and 600 respectively, uniformly distributed around the environment. The simulation platform is a desktop configured with Intel i5 CPU, 4GB memory, and 1TB disk.

The simulation cost over simulation time step is reported in Fig. 12. In the performance point of view, the simulation process can be roughly divided into three stages: it starts with a lower cost, then increases to a peak, and it drops gradually to 0 when approaching the end of simulation. This is due to different agent location distributions around the environment in different stages. At the beginning of the simulation, agents are distributed uniformly and there is no areas with very high density. So agents can move around the environment freely. As simulation time elapses and agents moving towards their selected exits, the density of some areas become higher. Such higher density indicates that the agent needs to observe and analyze more agents' movement in its eyesight to calculate Equation 8. This is why the time for each simulation time step increases

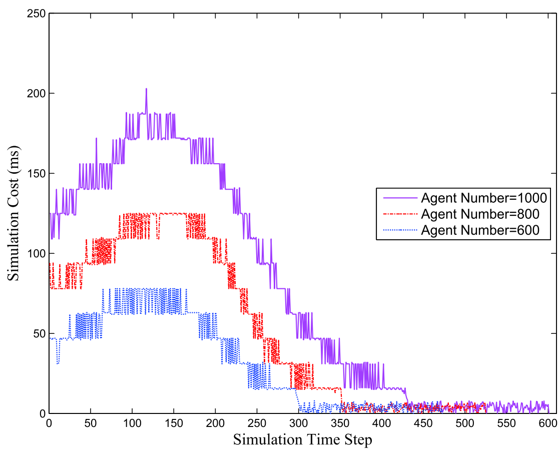


Fig. 12 Simulation Performance Comparison with Different Crowd

in the second stage. As agent leaves the environment and the number of agents decreases, the time for each simulation time step decreases. This is obvious due to the decrease of the number of model executions. When the simulation time drops to 0, it means the evacuation process has completed.

For the three experiments, the maximum time for simulating each agent is similar, which is around $0.17ms$. This indicates that the increase in agent number will not result in a sharp performance drop. It also indicates that the proposed model has a good scalability for simulating crowd evacuation process.

5.2 Comparisons with Existing Work

The proposed hybrid model integrates a macroscopic model into a microscopic model, which directs agents to follow the crowd movement pattern as well as reflecting individual behaviour. In this subsection, we make an comparison analysis with other typical crowd simulation models.

Helbing's social force model[2)] is a typical microscopic model for crowd simulation. As shown in Fig. 3, the simulation result of the proposed model is similar to the result by using Helbing's model. However, it aims at modelling pedestrian's behaviour and movement by social force, which makes it hard to reflect the global movement pattern of the crowd. As for our model, the microscopic model can access the crowd information, like position field, density distribution and velocity, from the simulation result of the macroscopic model. With them, crowd movement pattern can be easily reflected in the microscopic model, which reflects in the following aspects:

a Fig. 4 shows how an agent can avoid a high density area;

b Agents unfamiliar with the simulation environment can follow the crowd movement to complete the simulation result, shown in Fig. 6.

The model proposed in the literature[35)] is a typical continuum model, from which the macroscopic model in our hybrid model is derived. However, it can only provide simulation results to illustrate the density and velocity distribution over simulation time step. Our model also generates such results to describe the crowd movement as reported in Figs. 7 and 8. In addition, our proposed model can reflect individual diversity. For example, agents familiar and unfamiliar with the environment specification are described by the information tagging due to a complete CA-based model introduced in the hybrid model. In addition, the model can simulate different types of pedestrians, i.e., adult, child and the elderly.

As a by-product, the proposed model has the ability to provide different *Level-of-Detail* (LOD) simulation results. This is because the hybrid model consists of two complete models with different simulating granularity. The model provides a fine-grain simulation result with the executions of the macroscopic and microscopic models, sequentially. On the other hand, the model can also switch off the execution of the microscopic model, which results in a course-grain simulation result from the macroscopic model.

Finally, the model provides a good scalability of crowd size due to the efficient performance of model execution, as indicated in Fig. 12. The main reason of this is due to the eÿcient performance of execution of the macroscopic model, which is independent on the crowd size of resolving the Equations 3 and 4. It is well known that the cost of microscopic model increases sharply with the crowd size. With the macroscopic result, the CA-based microscopic model is not necessary to build a complicated path planning module, which causes the microscopic model relatively simple and thus to obtain an eÿcient model execution performance.

VI CONCLUSIONS

This paper proposes a hybrid model to simulate human crowd in dynamic environments. The macroscopic model simulates crowd movement tendency. For the microscopic model, it directs how an agent selects its movement direction and speed, under the constraints by macroscopic model. The two models share and exchange simulation results, so that they can reflect t he c urrent s tate of environment and crowd movement. Case study is also conducted for the pro-posed model, and the simulation results indicate that the proposed hybrid model can reflect the characteristic of human and crowd movement, with eÿcient and scalable simulation performance.

In the future, some external and individual factors could be further added into the model, such as fire a nd e motion. I n o rder t o i mprove t he simulation eÿciency, parallel and distributed simulation techniques can also be applied to the simulation. The execution of the macroscopic model may be processed by GPGPU, and the microscopic model may be executed by either GPGPU or high performance cluster. In this case, synchronization and load balancing should be further considered.

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