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On the Use of a Pedestrian Simulation Model with Natural Behavior Representation in Metro Stations

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Abstract

Rapid urbanization in many large cities in China makes metro station an integral part of metropolitan people's daily life. High density of crowds in metro stations would cause serious congestion problems and pose threats to pedestrian safety. Because of the heterogeneous and complex properties of pedestrians, traditional approaches face difficulties in predicting future pedestrian flow patterns. The use of agent-based simulation approach makes it possible to naturally reproduce various pedestrian behaviors in different scenarios. This paper presented an agent-based microscopic pedestrian simulation model—CityFlow, which was proved to be flexible in revealing most important pedestrian behaviors in metro stations by several simulation cases. The model applications can provide implications in evaluation of design proposals of metro facilities.

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1. Introduction

With strong tendency of re-urbanization and quick expansion of public transit networks in China, there is a heavy use of public transit especially the faster service like metro, which makes transit nodes overcrowded. High density of crowds in metro stations would cause serious congestion problems as well as pose threats to pedestrian safety. Therefore, understanding of crowd dynamics and pedestrian behavioral characteristics is vital. Because of the

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heterogeneous and complex properties of pedestrians, traditional approaches face difficulties in predicting future pedestrian flow patterns. Recently, with advancements in computer technology, pedestrian simulation models can be served as useful tools. They commonly fall into two categories: macroscopic models and microscopic models. Macroscopic models usually simulate pedestrian crowd as a continuous flow by describing the dynamics of macroscopic variables (e.g., density, velocity, and flow), in which the movement mechanisms are usually derived from some classical fluid dynamics theories or queuing theories¹. However, the main drawback of macroscopic models is that behavioral factors of individuals are greatly simplified or largely neglected. In microscopic models, simulation environment can be represented in detail and every pedestrian is treated as an individual by considering certain spatial interactions with the environment and other pedestrians.

Most existing microscopic simulation modeling approaches can be divided into three categories: force-based models, cellular automata (CA) models and agent-based models. In force-based models, pedestrian movement is driven by different forces which can be calculated by Newtonian mechanics. The most well-known example is the Social-Force (SF) model proposed by Helbing², which has been further developed to simulate panic situations by interpreting social psychology issues³. The major challenge in designing the force-based models is the appropriate force representations of internal motivations and external influences of various environmental factors on pedestrian movements. Nay, thinking and decision making of individuals are also difficult to be interpreted by mathematical equations only⁴. CA models divide the space into uniformly distributed cells and pedestrians have to choose a neighboring cell to move or remain in the current one at each time step according to transition probabilities. To make the CA model more intelligent, Schadschneider introduced the concept of “floor field” to modify the transition probabilities and simulate interactions between the pedestrians and the geometry of the environment⁵. Though only simple rules are used in the floor field and CA models, it is sufficient to reproduce various pedestrian behaviors, including pedestrian group behavior⁶, herding/clogging at bottlenecks in evacuation⁷, lane formation and jamming transition in pedestrian counter flow⁸, and pedestrian dynamic exit selection behavior⁹, etc. However, the model suffers from some deficiencies mainly caused by the discreteness of the model, indicating the dilemma between finer discretization including both space and time and computational complexity of the model¹⁰. The Agent-based modeling (ABM) approach is designed to integrate human thinking and decision making process with crowd simulation. In ABM, each pedestrian is modeled as an intelligent and autonomous agent who may have capabilities to self-sense, interact and adapt to complex dynamic environments. ABM has gained tremendous momentum in pedestrian behavior modeling and simulation because of its advantages in handling heterogeneous agents and the recent significant enhancements in computation power. Moreover, it also exhibits great flexibility in combination with other modeling methods. For example, integrating with CA to simulate pedestrian locomotion behaviors while keeping high computation efficiency^{11,12}, in combination with the discrete choice model to simulate the long-term behaviors at the strategic, tactical and the operational levels^{13,14}, and coupling with the SF model to reveal individual behaviors in evacuations, such as competitive, grouping and herding¹⁵.

Although modeling and simulating pedestrian movement has been attempted in previous decades, how pedestrian behaviors can be appropriately represented and realistically reproduced in different environments still remain as unsolved issues. In this paper, we present an agent-based microscopic pedestrian simulation model that can integrate various pedestrian behaviors and be configured for different scenarios. This paper is structured as follows. The next section describes the presented model, including environment representation, agent design and an overview of pedestrian behavior implementation. The third section analyzes the most important pedestrian behaviors in metro stations with several simulation cases. In the fourth section, a model application on evaluation of design proposals of metro facilities is conducted.

2. Agent-based crowd movement modeling

This section presents the agent-based microscopic pedestrian simulation model— ‘CityFlow’, which is further developed by authors based on a previous framework¹⁶. In specific, various intelligent attributes have been introduced to agents to explicitly and naturally reproduce pedestrian behaviors for different environments.

2.1. Environment representation and agent design

The building space in the simulation is represented in a network approach by dividing the geometry into “zones” connected to one another by “connections” (an example can be found in Fig. 3(a)). It is worth mentioning that in the network graph, a node (zone) contains features such as type, capacity and crowding condition, while an arc does not indicate the actual trajectories that pedestrians would generate but a virtual link between zones representing features of this route, including distance, direction, etc. Pedestrian in the simulation model is regarded as a self-adapted agent and represented by a circle (the diameter is set to be 0.4m in the model, which is the typical body size of a person) with several intelligent attributes:

(1) A view range is set to effectively guide locomotion, such as avoiding collisions with obstacles and other pedestrians in the immediate space. As suggested in the study¹³, the view angle is set as 170° and discretized into sub angles to reduce the computational burden without losing accuracy. The depth of the view range is set to 3m in the model, however, it can be changed to adapt to different situations as suggested in the study¹⁷;

(2) An attention range is set to interact with the visual attractors in the built environment. As suggested in the study of Chen¹⁸, the angle of attention range is 120° and the depth of range is 10m;

(3) Internal status is individual-based, including planned activities and internal demands. For example, a pedestrian may plan to visit shops (planned activity) for cosmetics (internal demands);

(4) Cognition is a higher-order process, resting on a foundation of knowledge acquired from early exploration of the environment, including individual’s knowledge and memory of the environment.

2.2. Pedestrian behavior implementation

Similar to most pedestrian simulation modes, pedestrian behaviors in CityFlow are implemented at three levels, as shown in Fig. 1.

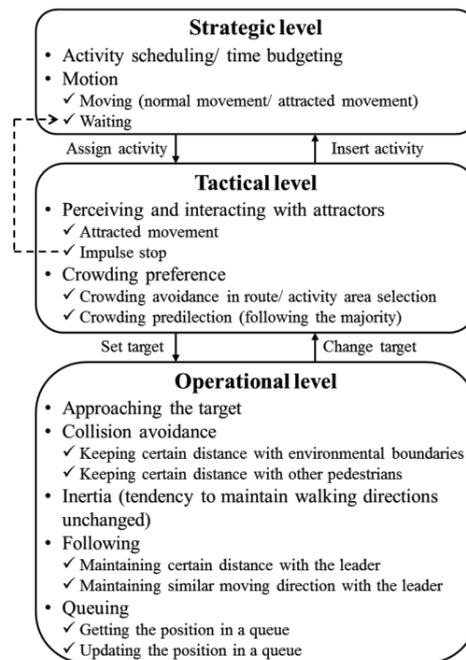


Fig. 1. Pedestrian behavior effects in CityFlow.

Specifically, the strategic level deals with trip nature determining, activity scheduling and time budgeting of individuals. At the tactical level, individuals need to determine trip destination and routes consisting of a sequence

of regional perceivable targets. Since each individual is set to have an attention range and is able to dynamically perceive attractors according to his/her internal demands. When an attractor is attractive enough and matches the pedestrian's demands, "impulse stop" behavior can be performed. Specifically, the pedestrian will change his/her current regional target into the attractor (and stop for a while), which will ultimately alter the pedestrian's activity schedule at the strategic level. In terms of the relative presence of other pedestrians (crowding) in space, different individuals may have varied responses. Under some circumstances, pedestrians may prefer following the majority, such as evacuating from an unfamiliar environment. On the other hand, pedestrians will choose a place or a route with lower congestion level¹⁹, such as choosing counter with shortest queue in the bank. According to the regional target set by modules at a higher level, pedestrian locomotion is simulated at the operational level. It mainly deals with detailed movement processes, with consideration of the approaching the target, collision avoidance and inertia (the tendency to maintain walking directions unchanged). Moreover, following and queuing behavior effects are also included in this study.

Furthermore, the communications between modules at different levels are highly important, especially the responses to "commands" from modules at lower levels. For example, when the target is reached at the operational level, the message will be conveyed back to the tactical level and the next regional target will be assigned until the destination is reached. As soon as the pedestrian approaches the destination, the module at the strategic level will be informed and then a command will be given based on the activity execution and time budget of the pedestrian.

3. Pedestrian behavior analyses

In the operational level, the agent moves step by step toward the regional target while considering a series of behavior effects. As described before, the view range angle (θ) is discretized into N sub-angles by every $\Delta\theta$. That is, $\Delta\theta = \theta/N$ and the angle of a possible movement direction k can be denoted as $\theta_k = k \cdot \Delta\theta$, $k \in (0, N)$. The decision to choose direction k is made by a utility maximization approach, calculated through formula (1).

$$a = \theta_k | U_a = \max\{U_k = \omega_e \cdot E_k + \omega_o \cdot O_k + \omega_p \cdot P_k + \omega_a \cdot A_k + \omega_i \cdot I_k + \varepsilon\}, k \in (0, N) \quad (1)$$

where E_k represents behavior of approaching the target, O_k represents behavior of keeping certain distance with environmental boundaries, P_k represents that the pedestrian tries to keep certain distance with other pedestrians, A_k represents the pedestrian tries to avoid potential collision with others in the moving direction, and I_k represents the effect of inertia during walking process. Detailed descriptions and formulas of above behavior effects can be found in a previous study of the authors¹⁶. Once a direction is chosen, the agent can move forward one step with proper movement speed, which considers both the available movement distance, density of the view range as well as the desired speed of the agent.

3.1. Queuing and waiting behavior

Queuing and waiting behaviors are commonly observed inside metro stations. Queuing phenomenon includes passengers waiting in front of specific facilities (e.g., Automatic Fare Collection Gates, Add Value Machine (AVM), and the train doors). And in some transfer metro stations or those connecting with shopping areas of Hong Kong, a great number of waiting pedestrians can be observed. They prefer stopping at some particular positions inside metro stations, such as the corner area, area nearby walls and area along the railings that separate the paid and un-paid area, etc⁴. But it is suggested that these standing pedestrians may block walking pedestrians and thereby have a profound influence on entire pedestrian dynamics²⁰. Thus natural representations of these pedestrian behaviors (queuing and waiting) cannot be neglected in simulation of pedestrian crowd movement in metro stations. Fig. 2(a) shows a simulation snapshot of part of a metro station, in which, queuing pedestrians in front of AVM and waiting pedestrians along railings and walls can be observed.

In our study, we model the waiting behavior by introducing the concept of "waiting areas". Specifically, waiting areas can be considered as intermediate targets for particular pedestrians who include waiting behavior in their trips. As introduced before, pedestrian's route consists of a sequence of regional targets in our model. When the pedestrian approaches the nearest regional target before waiting area where he/she intends to stop, an arbitrary

location within this area is chosen as the next target. After stopping at this location for a short time, the pedestrian moves toward the next scheduled regional target after waiting area (see Fig. 2(b)).

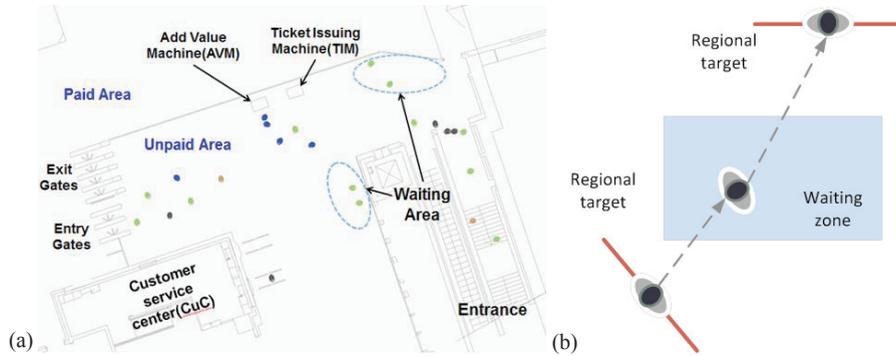


Fig. 2. Simulation of pedestrian’s queuing and waiting behavior in part of a metro station: (a) simulation snapshot; (b) illustration on modeling of pedestrian waiting behavior in CityFlow.

3.2. Dynamic target choice behavior

The dynamic target choice behavior relates to pedestrian’s navigation decisions. It is one of the most important aspects of realistically modelling pedestrian movements. The attention range is used to perceive environment at more remote distance when comparing with pedestrian’s view range, and travel cost including crowdedness can be explicitly considered for target decision at tactical level. For example, pedestrians usually would choose the train door with less waiting pedestrians to queue up, causing nearly an even distribution of pedestrians in front of train doors on the platform. In order to illustrate the described behavior, a simple notional simulation scenario is used, as shown in Fig. 3(a). In this case, 100 agents were generated from entry line, as soon as an agent approached the decision zone (zone 3), it would choose an exit to leave the environment. The main selecting criteria include crowding condition of specific exit zone and distance from its decision point to corresponding connection linking with that exit zone, calculated through formula (2). Fig. 3(b) and 3(c) show agent distribution in the scenario at certain time step and the aggregated moving trajectories of all the agents in the simulation, respectively.

$$TC_t = \omega_c \cdot C_t + \omega_d \cdot D_t, t \in (0, M) \tag{2}$$

where TC_t is the travel cost of a pedestrian from decision zone to exit zone t , C_t represents the crowding level of the exit zone, and D_t is the distance from current location of a pedestrian to the corresponding connection linking with that exit zone. Then the connection which links to the exit zone with least traveling cost will be chosen as the next target.

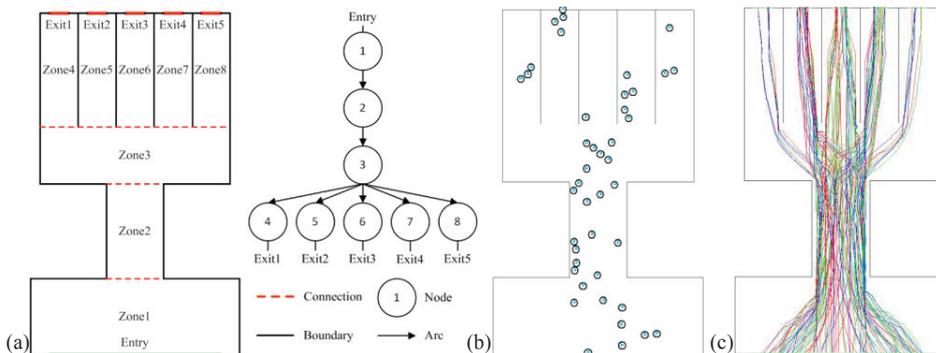


Fig. 3. Simulation on dynamic target choices of agents: (a) network graph of simulation scenario; (b) simulation snapshot; (c) aggregated moving trajectories.

We also recorded the agent number in each exit zone against time and the accumulated number of agents passing through each exit by time. We can see periodic change of each curve and reciprocal relationship among curves in Fig. 4(a), indicating pedestrians’ dynamic adjustments of exit choices. Theoretically, all the agents would choose the shortest route consisting of zone 1-2-3-6 if the predictive least cost routing strategy was adopted. In this test, agents had to make target choices according to present instantaneous environment condition (see the study of Tong and Wong²¹ for reactive dynamic user equilibrium principle). Specifically, most agents still chose to use this route and Exit 3 was the most favorable one among exits, followed by Exit 2, and Exit 4. Because of the symmetric distribution of exit locations, Exit 1 and Exit5 had similar patronages, so were Exit 2 and Exit 4 (see Fig. 4(b)).

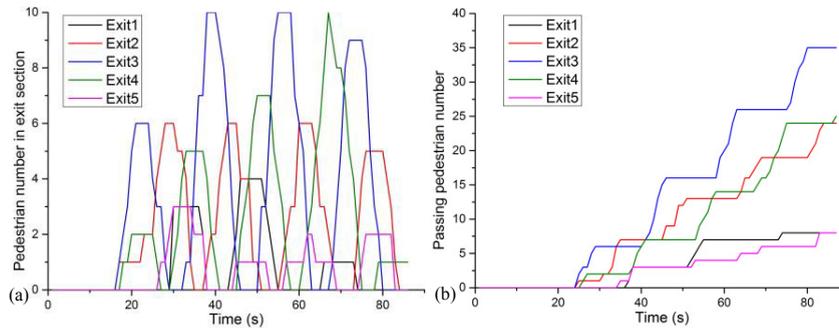


Fig. 4. Pedestrian number changes by time: (a) pedestrian number in each exit section; (b) pedestrian number passing through each exit.

The metro stations are an integral part of metropolitan people’s daily life. The stations also have a great variety of usages such as shops, banks, fast food kiosks, exhibitions, etc. Thus pedestrians moving in the stations may not only head towards the train but also take other activities. For passengers, metro shops can be served as attractors, and “impulse stop” at the shop is usually caused by individual interactions between a pedestrian and the attractor. Specifically, we assume the pedestrian in our model has its specific internal demand, and after dynamically examining the characteristics of an attractor during movement, he/she would finally decide whether to take “impulse stop”, which may influence his/her activity scheduling at tactical level. And the detailed descriptions on modeling of pedestrian’s “impulse stop” behavior using CityFlow can be found in a previous study of the authors²².

4. Model application

With proper consideration of pedestrian behavior, pedestrian simulation models can be served as useful tools for designers to compile efficient settings of metro stations. A notional study of metro station entrance area is used to demonstrate the influence of station entrance orientation design on surrounding pedestrian flow efficiency. In this study, boundary conditions for two cases are the same except that orientations of the station entrances are diverse. Specifically, station entrance faces the street in Case A and station entrance locates back to the street in Case B (see Fig. 5(a) and 5(b)).

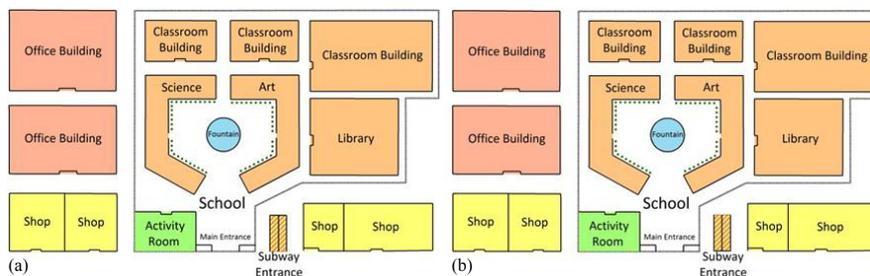


Fig. 5. A notional scenario of station entrance area considering different entrance orientations: (a) Case A in which station entrance faces the street; (b) Case B in which station entrance locates back to the street.

In the scenario, during afternoon peak hours, we assume most people leave different buildings and some rush into the metro station to use the train service and thus the congestion level surrounding the station entrance would be high. Fig. 6(a) and 6(b) show simulation snapshots of Case A and Case B, respectively. In the simulations, dark yellow dots represent pedestrians who would enter the metro station and use the transit service, blue dots represent those who would not use metro service, and dark dots are pedestrians exit the metro station from the specific entrance. When simulation runs steadily in the above two cases, the density map showing the congestion level of pedestrian flows are obtained, in which the density classification in different colors is in accordance with the Level-of-Service concept proposed by Fruin²³. Fig. 6(c) and 6(d) show crowding level of Case A and Case B, respectively. But it can be observed that congestion level of the main street of Case B is relieved in certain extent when comparing to that of Case A.

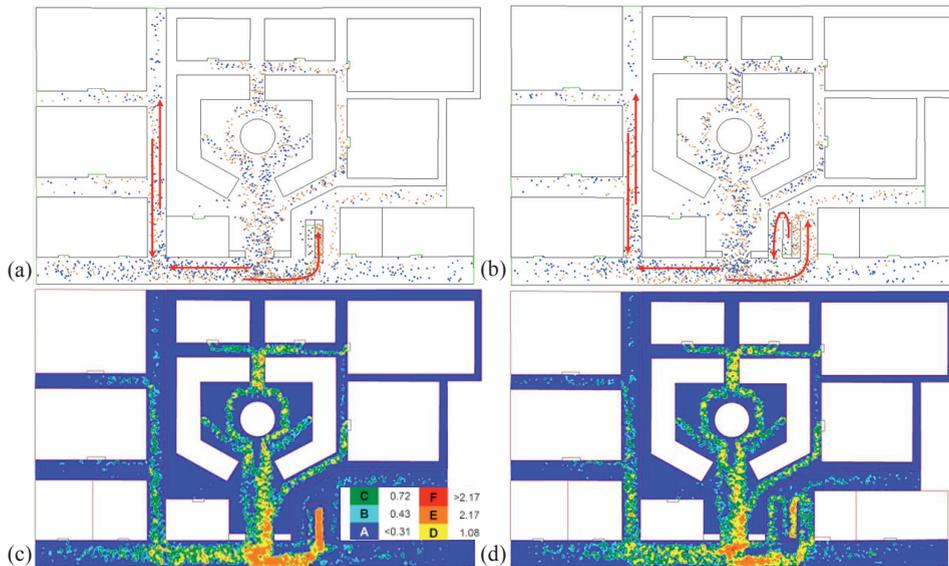


Fig. 6. Simulation snapshots and density map showing crowding level of pedestrian flows (a) simulation snapshot of Case A; (b) simulation snapshot of Case B; (c) density map of Case A; (d) density map of Case B.

5. Concluding remarks

This paper demonstrated the use of a simulation model—CityFlow for studying pedestrian behaviors in complex environments. The building space of simulation environment was represented as a network structure in the model. The pedestrians were represented as agents in circle shapes with several intelligent attributes, including view range, attention range, internal status and cognition. Various pedestrian behaviors in the model were implemented at three levels. In the operational level, pedestrian movement was simulated mainly considering behavior effects of approaching the target, collision avoidance and inertia. Besides, other commonly observed pedestrian behaviors inside metro stations such as queuing and waiting behaviors were presented. In the tactical level, dynamic target choice effect was examined with a simple notional simulation scenario, revealing some natural behaviors in metro stations. For example, the phenomenon of nearly even distribution of passengers in front of train doors on the platform. Moreover, an application has been used to demonstrate the model capacity in evaluating detailed design proposals of metro facilities. To conclude, CityFlow was proved to be a flexible platform for pedestrian flow simulation in metro stations, with natural consideration of various pedestrian behaviors. However, pedestrian behaviors are highly complex because of their heterogeneous characteristics and differences in actual walking performances across circumstances and across cultures. Due to the heterogeneity and complexity of pedestrians as well as a lack of empirical data, different view ranges and attention ranges between agents, pedestrian group behavior will be considered in future studies. Although the simulation model in this study covers most important

behaviors at the tactical and the operational levels, some behaviors especially those at the strategic level are unconsidered. Thus the combination of the presented model and the activity-based model which is behaviorally sound in pedestrian activity choice at the strategic level is recommended.

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