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SPECIAL ISSUE PAPER

Vehicle–pedestrian interaction for mixed traffic simulation

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ABSTRACT

Simulation of real-world traffic scenarios is widely needed in virtual environments. Different from many previous works on simulating vehicles or pedestrians separately, our approach aims to capture the realistic process of vehicle–pedestrian interaction for mixed traffic simulation. We model a decision-making process for their interaction based on a gap acceptance judging criterion and then design a novel environmental feedback mechanism for both vehicles' and pedestrians' behavior-control models to drive their motions. We demonstrate that our proposed method can soundly model vehicle–pedestrian interaction behaviors in a realistic and efficient manner and is convenient to be plugged into various traffic simulation systems. Copyright © 2015 John Wiley & Sons, Ltd.

KEYWORDS
microscopic simulation; vehicle–pedestrian interaction; traffic simulation; crowds

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1. INTRODUCTION

Simulation of road traffic has received increasing attention in recent years. Vehicles and pedestrians are two important entities in traffic environments. They have inseparable relations and complex interactions in the real world. Accurately modeling the interaction between vehicles and pedestrians in transportation networks is important to traffic safety and future development of urban environments. In addition, simulation of such mixed traffic flows also makes more realistic virtual urban environment.

In computer graphics community, vehicles and pedestrians have been always studied separately. There are a vast amount of literature on modeling and simulating traffic flows or pedestrian crowd dynamics, using either agent-based microscopic or continuum-based macroscopic methods. However, all the studies were carried out under the assumption of ideal traffic environments. Modeling of the non-ideal real-world traffic scenarios still remains a less explored research topic. For example, several traffic simulation tools (such as VisSim [1]) have involved vehicle–pedestrian interaction in micro-simulations. However, their methods just specify the moving priority to one conflicting side, which is oversimplified and less realistic.

In this paper, we propose a novel microscopic method for vehicle–pedestrian mixed flow simulation to model their realistic interaction. We first present a decision-making process for their interaction and then an action process to drive their motions, which introduces environmental feedbacks into their own behavior control models. To the best of our knowledge, our approach is the first reported work in modeling vehicle–pedestrian interaction behaviors in traffic simulation and pedestrian crowd simulation.

In the decision-making process, we present a gap-acceptance judging criterion to dynamically determine the pedestrian's behavior (walk or wait) in current surrounding traffic environment. During the simulation, vehicles and pedestrians need to know how to pass through each other safely based on their decisions. Therefore, they treat each other as the environmental influence and compute the feedback to themselves. Finally, the feedbacks are added into their original behavior control models to drive their motions.

Our method has three main contributions: (i) it provides a complete solution for vehicle–pedestrian mixed flow simulation; (ii) it introduces a new gap-acceptance judging criterion for the pedestrian's decision-making process; and (iii) it introduces a novel environmental feedback mechanism for both vehicles' and pedestrians' behavior control models. Our approach can produce vehicle–pedestrian mixed flow simulation scenarios with realistic interaction

(a) (b) (c)

Figure 1. Example vehicle–pedestrian interaction results simulated by our approach.

between the two kinds of entities. Figure 1 shows several simulation results using our method.

The rest of the paper is organized as follows. Section 2 describes the related work on traffic simulation and crowd animation. Section 3 presents our method in detail. The simulation results and performance analysis are described in Section 4. Finally, we conclude the paper and discuss the future work in Section 5.

2. RELATED WORK

In this section, we give a brief overview of prior work related to crowd modeling and traffic simulation.

2.1. Crowd Modeling

Many different techniques [2–6] have been proposed for modeling the motion of multiple human agents in a crowd. The primary task in this problem is to compute each agent's path towards its goal while avoiding collisions with obstacles and other agents and reproducing natural human behaviors.

Rule-based approaches are commonly used to model complex crowd behaviors. It can be dated back to the seminal work of Reynolds [7,8] who demonstrated emergent flocking and other behaviors from several effective steering rules. Other techniques for local navigation use force-based models including the social force model (SFM) [9] and Hi-DAC (High-Density Autonomous Crowds) [10]. These approaches use complex forces between agents to accurately model their local interactions. Geometric formulations based on velocity obstacles [11] also have been used to model local collision avoidance behaviors.

Some researchers have introduced psychological factors into crowd simulation to create realistic heterogeneous crowd behaviors. Durupinar et al. [12] and Guy *et al.* [13] used personality traits to model heterogeneous behaviors and traffic behaviors [14]. Based on these works, Kim *et al.* [15] used stress modeling to simulate the dynamic nature of human behaviors when responding to various environmental situations.

2.2. Traffic Simulation

In traffic behavior modeling, several macroscopic models were developed, including the LWR model (by Lighthill, Whitham and Richards) [16], the PW model (by Payne and Whitham) [17,18], and the ARZ model (by Aw, Rascle and Zhang) [19,20]. They treated traffic as a kind of continuum, using partial differential equations to describe its evolution over time. On the other hand, agent-based microscopic methods treat each vehicle as a discrete autonomous agent governed by specific rules. Gerlough [21] summarized a set of car-following rules about traffic simulation. Later, many variations and extensions have been developed including the optimal velocity model [22] and the intelligent driving model (IDM) [23].

In computer graphics community, Sewall *et al.* [24] extended the ARZ model to correctly handle lane changes, merges, and traffic behaviors because of changes in speed limit. Shen and Jin [25] proposed a new agent-based model by combining IDM with a flexible lane-changing model mainly for the purpose of vivid traffic animation. Sewall *et al.* [26] presented a hybrid traffic model to integrate macroscopic continuum and microscopic agent-based methods for large-scale traffic animation.

Recently, several approaches have been proposed for data-driven traffic visualization. Researchers presented approaches to visualize vehicle traffic reconstructed directly from temporal-spatial data available from existing in-road sensors on the road networks [27,28]. Chao *et al.* [29] proposed a video-based approach to learn drivers' specific driving characteristics for traffic reconstruction and sample-based traffic animation.

3. OUR METHOD

Our approach aims to model the real-world interaction process between vehicles and pedestrians for their mixed flow simulation. Their interactions may happen in a road that has no signaled control or in a street that allows both vehicles and pedestrians to travel. The pedestrians have conflicts with vehicles when they cross the road, as no signals exists to separate pedestrians and vehicles in this case.

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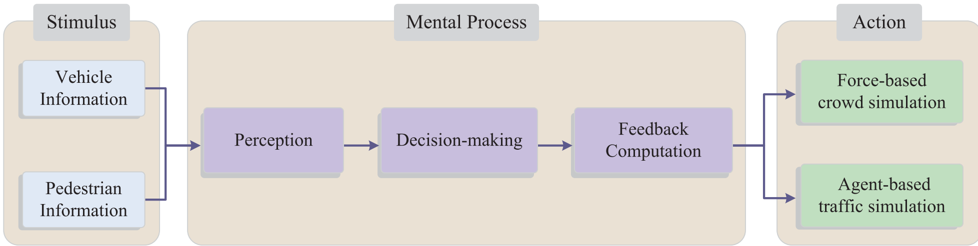


Figure 2. The pipeline of our approach for modeling the interaction between vehicles and pedestrians.

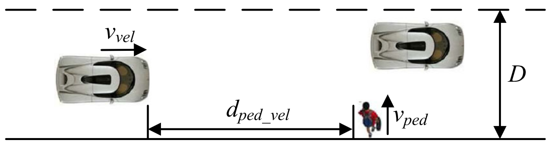


Figure 3. The illustrative relationship between a pedestrian and the involved vehicles.

Figure 2 illustrates the pipeline of our approach. A complex traffic simulation can be perceptually viewed as a dynamic interaction process driven by continuous sensor stimuli, involved with psychological, mental, and behavioral reactions. For vehicle–pedestrian interaction, the pedestrian perceives the surrounding traffic environment where the current states of his/her neighboring pedestrians, and oncoming vehicles are his/her stimuli. Based on the perception, the pedestrian makes a walk-or-wait decision based on a safety judging criterion. If walking, the mutual feedback of the pedestrian and the involved vehicle is computed. All the above are finished in the mental process. In the action process, the environmental feedback mechanism is introduced into the behavior control models of the pedestrians and vehicles.

3.1. Decision-making Process

A pedestrian's interaction with vehicles are conducted per lane. The pedestrian needs a decision-making process to judge whether the current vehicle gap can satisfy his or her safe crossing. The relationship between the pedestrian and the involved vehicles is illustrated in Figure 3. We use gap acceptance [30] as the judging criterion of pedestrians' safety crossing. Both the pedestrian's predicted crossing time t_{ped} and the vehicle's estimated passing time t_{veh} are computed. Only when t_{ped} is less than t_{veh}, the pedestrian can cross the road safely. Otherwise, the pedestrian needs to wait for the next longer vehicle gap. Formally, the pedestrian's decision-making model is

$$\begin{cases} t_{\text{ped}} \geq t_{\text{veh}}, & \text{wait} \\ t_{\text{ped}} < t_{\text{veh}}, & \text{walk} \end{cases} \tag{1}$$

The pedestrian's predicted crossing time t_{ped} can be computed using Equation (2):

$$t_{\text{ped}} = \frac{D}{v_{\text{ped}}} + t_a + t_b, \tag{2}$$

where D is the width of the lane that the pedestrian need to cross, and v_{ped} is his or her walking speed. t_a and t_b are two empirical parameter values to denote the pedestrian's reaction time and the safe time after crossing in case of the next oncoming vehicle, respectively.

The vehicle's estimated passing time t_{veh} can be calculated using Equation (3):

$$t_{\text{veh}} = \frac{d_{\text{ped\_veh}}}{v_{\text{veh}}}, \tag{3}$$

where $d_{\text{ped\_veh}}$ is the distance between the pedestrian and the oncoming vehicle; v_{veh} is the vehicle's current velocity.

3.2. Feedback to Behavioral Models

Analogous to the real-world decision making process, when pedestrians make their walking decisions, they need to ensure they can pass through the vehicle flow safely; a similar reasoning for vehicles also holds. Their mutual influence is quantified and introduced as environmental feedback into their behavior control model in our approach.

Pedestrian's Behavior: We use the SFM [9] to describe individual pedestrian behaviors. The original SFM suggests that the motion of a pedestrian i can be described by the combination of a driving force $\boldsymbol{f}_i^0$ that reflects the pedestrian's motivation to move in a given direction at a certain desired speed, a repulsive force $\boldsymbol{f}_{ij}$ describing the effects of interactions with other pedestrians j, and $\boldsymbol{f}_i^{\text{obs}}$ describing the repulsive effects of obstacles.

In our approach, to take into account the interactions between vehicles and pedestrians, we extend the original SFM by formulating a new interaction term $\boldsymbol{f}_i^{\text{veh}}$ to describe the vehicle's influence to the pedestrian i's behavior as follows:

$$\frac{d\boldsymbol{v}_i}{dt} = \boldsymbol{f}_i^0 + \boldsymbol{f}_{ij} + \boldsymbol{f}_i^{\text{obs}} + \boldsymbol{f}_i^{\text{veh}} \tag{4}$$

$\boldsymbol{f}_i^{\text{veh}}$ is treated as the pedestrian i's perceived level of stress from surrounding road traffic. The involved oncoming vehicle is referred to as a position stressor that provides a source of stress for the pedestrian i. Formally, we define the intensity of a stressor I_p as

$$I_p = \left| p_{\text{ped}} - p_{\text{veh}} \right|, \tag{5}$$

where p_{ped} and p_{veh} denote the positions of the pedestrian and the vehicle, respectively.

In order to define the perceived amount of stress experienced by the pedestrian, we adapt Stevens' psychophysical power law [15]. It states the relationship between the perceived intensity of the stress and the physical measurement of the stimulus intensity. Applying it to our problem, it has the following form:

$$\boldsymbol{f}_i^{\text{veh}} = k I_p^2 \boldsymbol{n}_i^{\text{veh}}, \tag{6}$$

where k is a constant scale factor. $\boldsymbol{n}_i^{\text{veh}}$ is the two-dimensional unit vector pointing from the vehicle to the pedestrian i.

It should be noted that, $\boldsymbol{f}_i^{\text{veh}}$ is a slightly backwards force at the beginning of walking, which causes the pedestrian i's slight deceleration behavior. After passing through the vehicle, the pedestrian accelerates based on the forwards force $\boldsymbol{f}_i^{\text{veh}}$. This kind of behavior pattern is in line with the pedestrian's psychological behavior and often observed in the real world.

Vehicle's Behavior: To model vehicles' driving behavior, we use the IDM [23] as their behavior control model. It is a microscopic car-following model. The driver's decision of accelerating or decelerating depends on its current driving speed v, the relative speed Δv, and gap distance s to its leader (that is, the vehicle immediately in front of it on the same lane). The relationship between the involved vehicles is illustrated in Figure 4.

Intelligent driving model defines the vehicle's acceleration as follows:

$$a_{\text{IDM}} = a\left[1 - \left(\frac{v}{v_0}\right)^4 - \left(\frac{s^*}{s}\right)^2\right], \tag{7}$$

and

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}. \tag{8}$$

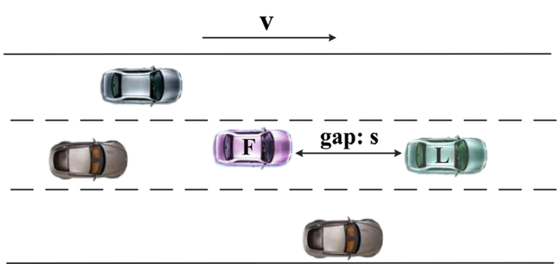


Figure 4. The relationship between the involved vehicles: the leader (*L*), the follower (*F*) and their gap *s*.

As shown in Equation (7), the acceleration a_{IDM} can be divided into two parts: the first part $a_{\text{acc}} = a\left[1 - \left(\frac{v}{v_0}\right)^4\right]$ indicates free acceleration towards a desired velocity v_0, while the second part $a_{\text{dec}} = -a\left(\frac{s^*}{s}\right)^2$ represents a braking deceleration strategy based on the current gap s and the desired minimum gap to the preceding vehicle s^*. IDM shows a stable crash-free dynamics with an intelligent braking strategy.

The parameters $(a, b, v_0, T \text{ and } s_0)$ are constant for each vehicle, which describe its basic driving capability. a and b are the maximum acceleration and comfortable braking deceleration, respectively; v_0 is the desired free-flow velocity; T is the desired safety time headway; and s_0 is jam space headway.

In a vehicle–pedestrian mixed flow simulation, when a pedestrian successfully cuts in the gap between two vehicles, the original IDM is insufficient to describe vehicles' behaviors in this situation because of the different behavior patterns between pedestrians and vehicles. Take the aforementioned into consideration; we add the pedestrian's information into the original IDM, which has the following form:

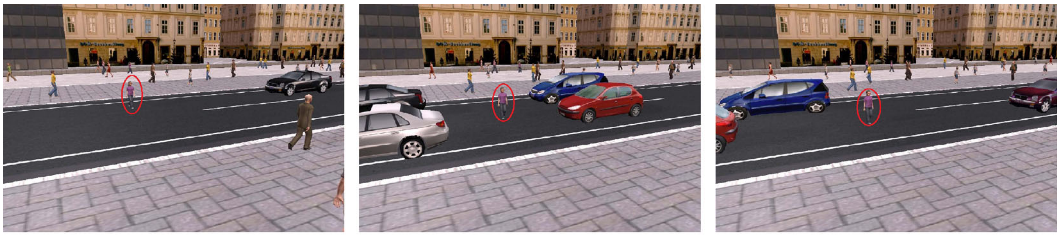
$$a_{\text{veh}} = a_{\text{IDM}} - b * \left(\frac{t_{\text{veh}}}{t_{\text{ped}}}\right)^n \tag{9}$$

Here, a_{veh} is the vehicle's acceleration in response to the pedestrian's behavior; b is the driver's habitual deceleration mentioned earlier; n is the deceleration exponent; t_{veh} and t_{ped} are, respectively, the pedestrian's predicted passing time and the vehicle's estimated passing time, which can be calculated using Equations (2)–(3).

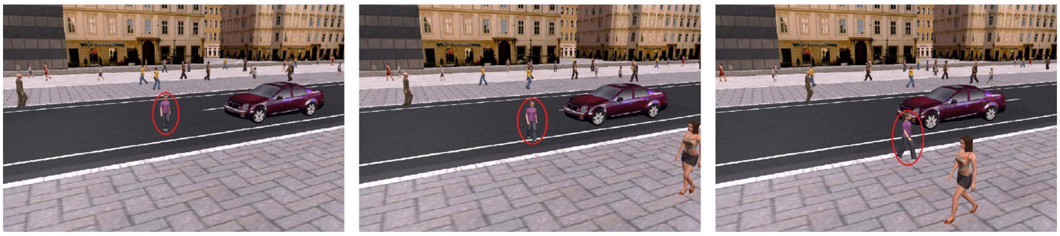
4. RESULTS

We tested our vehicle–pedestrian interaction approach on an unsignaled road that allows both vehicles and pedestrians to travel. Figure 1(a)–(c) show the mixed traffic scenarios depicted in our companion video. Figure 5(a)–(f) show the interaction between vehicles and pedestrians in detail. As Figure 5(a) shows, when no vehicles or the oncoming vehicle is far from the crossing pedestrian (in red ellipse), the pedestrian will walk directly. On the other hand, when the gap between the pedestrian and the oncoming vehicle is not proper for the pedestrian to cross, he/she will wait until a new safe gap occurs (Figure 5(b) and (c)). During the pedestrian crossing movement, the involved vehicle decelerates for safety, and the pedestrian passes through the road quickly (Figure 5(d)–(f)).

We performed qualitative and quantitative comparisons between our simulation results and the simulation results without considering vehicle–pedestrian interaction. One of the simulation scenarios is that a pedestrian (in yellow t-shirt) wants to cross a road that has no signaled control when a black car is oncoming. As illustrated in Figure 6(a), the pedestrian and the oncoming car did not

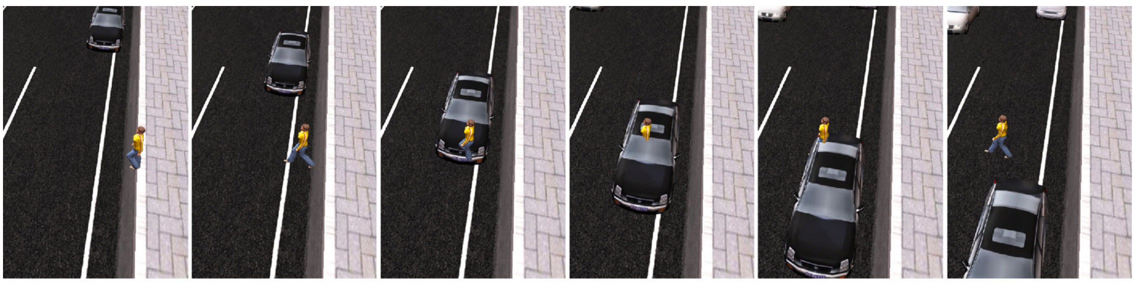


(a) $500th$ frames (b) $600th$ frames (c) $650th$ frames

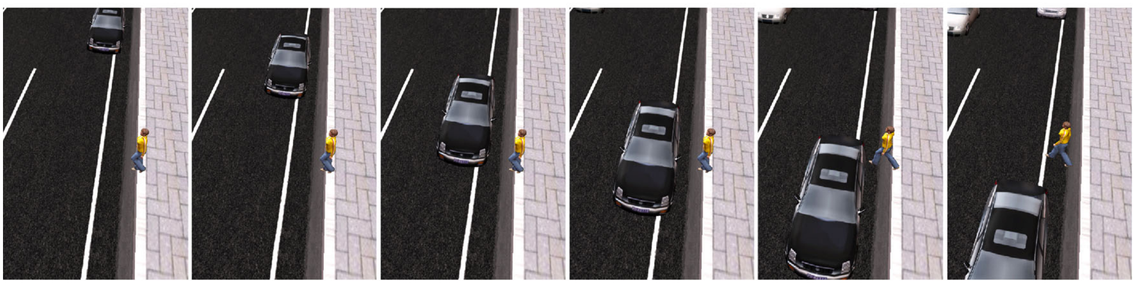


(d) $680th$ frames (e) $720th$ frames (f) $770th$ frames

Figure 5. Snapshots of a pedestrian's (in red ellipse) crossing behavior and the interaction with the oncoming vehicles during this time. (a) 500th frames, (b) 600th frames, (c) 650th frames, (d) 680th frames, (e) 720th frames, and (f) 770th frames.



(a)



(b)

Figure 6. Snapshots of a pedestrian's behavior and the oncoming vehicle's motion: (a) without pedestrian–vehicle interaction and (b) using our interaction detection and action methods.

consider each other and did not change their own motions, which led to the collision and penetration in the simulation results. This should be avoided in real-world scenarios. The simulation results using our method is presented in Figure 6(b). When the pedestrian perceives an oncoming car, he or she will not walk until finding a safe gap to cross. During the action process, the pedestrian speeds up to cross the road for safety, and the car brakes gently to let the pedestrian go first. The whole process conforms to the real-world situation.

To better understand the performance of our technique, in Figure 7, we show the comparison of the velocities of both the pedestrian and the involved car between our method and a method without modeling pedestrian–vehicle

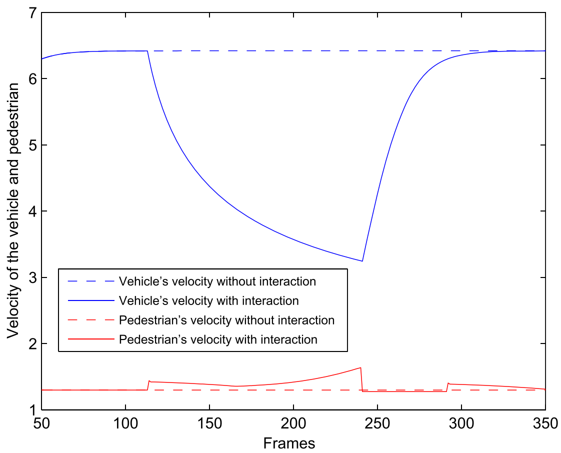


Figure 7. The comparison of the velocities of both the pedestrian and vehicle between our method and a simulation method without modeling pedestrian–vehicle interaction.

Table I. Computational time per frame of our method.

Pedestrians #	Vehicles #	Time (ms)
150	100	2.1
600	280	11.8
900	340	20.6
1200	400	27.4

interaction. We can see the car's obvious deceleration (the blue solid lines) and the pedestrian's acceleration (the red solid line) in the interaction period. They quickly go back to their original status after interaction.

Table I shows the computational time of our approach when it is used to simulate pedestrian–vehicle mixed traffic flows. The timings were recorded on a 3.1 GHz Inter i5 processor. In all the cases, our approach can run in real-time on an off-the-shelf computer, which shows that our approach adds negligible overhead to the simulation runtime. It can be straightforwardly plugged into various existing traffic simulation systems.

In addition, the empirical values of some parameters used in our experiments are shown in Table II. It is noteworthy that the parameter values reported in Table II may not be optimal for other mixed traffic simulation cases because their values fundamentally depend on specific environment settings and the personality characteristics of both pedestrians and vehicles [29]. In this paper, we initialize them to empirical values for all individuals because it is not the main focus of our work.

5. DISCUSSION AND CONCLUSION

We introduce a novel method for vehicle–pedestrian mixed flow simulation, which includes the decision-making process for pedestrian–vehicle interaction and the

Table II. Parameter values used in our experiments.

Param	Value	Description
t_a	1.5s	Pedestrian's reaction time
t_b	1s	Pedestrian's safe time after crossing
k	0.012	Scale factor for stress model
n	2	Vehicle's deceleration exponent

feedback-intrigued action process. The pedestrian makes a gap-acceptance judgement according to the instantaneous states of oncoming vehicles and will not walk until finding a sufficiently safe gap. In the action process, we consider the mixed traffic characteristics, that is, the vehicle and the pedestrian are influenced in a mutual manner. Their behaviors are driven by a feedback-incorporated behavior control model. To the best of our knowledge, in the computer graphics community, this is the first reported result on modeling mixed traffic flow characteristics and simulating vehicle–pedestrian interaction.

In real life, humans' decision-making and action process are far more complex than our current model. Our algorithm uses a simple gap acceptance criterion for pedestrians' decision-making process. The SFM and the intelligent driver model in our approach can be replaced by other microscopic behavior control models, such as RVO for pedestrians' motions. In addition, pedestrians and vehicles' specific behavior characteristics can be introduced to generate heterogeneous crowd behaviors.

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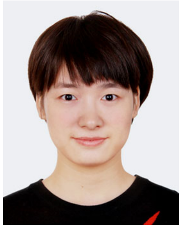

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