Agent-based Microscopic Pedestrian Interaction with Intelligent Vehicles in Shared Space

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ABSTRACT

Looking out for pedestrians has long been one of the most important issues for intelligent vehicles. Sometimes, intelligent vehicles have to cope with a large crowd of pedestrians. This is extremely common in shared spaces such as campus, shopping mall, or transportation station. In this paper, a vehicle-pedestrian interaction simulator is introduced to help intelligent vehicles, especially automated vehicles in The Smart Mobile Operation: OSU Transportation Hub (SMOOTH), achieve better decision making and local path planning. This simulator integrates different characteristics of pedestrians, and is capable of easily configuring and simulating different scenarios. Fundamental simulations have been completed to verify the simulator effectiveness for a pilot four-passenger golf cart. The results show that the simulator can effectively reflect the interaction behavior between vehicles and pedestrians.

CCS CONCEPTS

•Applied computing →Transportation; •Computing methodologies →Modeling and simulation;

KEYWORDS

pedestrian interaction; intelligent vehicle; shared space; simulation modeling; OSU SMOOTH

ACM Reference format:
Dongfang Yang, Arda Kurt, Keith Redmill, and Ümit Özgüner. 2017. Agent-based Microscopic Pedestrian Interaction with Intelligent Vehicles in Shared Space. In *Proceedings of The 2nd Workshop on Science of Smart City Operations and Platforms Engineering, Pittsburgh, PA USA, 21 April 2017 (SCOPE 2017),* 6 pages.
DOI: http://dx.doi.org/10.1145/3063386.3063766

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1 INTRODUCTION

Pedestrians are ubiquitous and regarded as the most vulnerable users in the public transportation. Pedestrian safety, especially nowadays, has become more challenging than before due to the increasing complexity of transportation systems, which are composed of different structures such as roads, intersections, crosswalks, and shared spaces, and of various participants, such as cars, buses, trucks, motorcycles, bikes, pedestrians, and even rollerblades. According to the traffic safety facts from NHTSA [3], in 2014, 4,884 pedestrians were killed and an estimated 65,000 were injured in traffic crashes in the United States. This means that, on average, a pedestrian was killed every 2 hours and injured every 8 minutes. There is a 2-percent increase from 4,779 pedestrian fatalities in 2013. And from 2005 to 2014, the percentage of total traffic fatalities that are pedestrians increased from 11% to 15%. Thus, it is urgent to take actions to improve pedestrian safety.

It is widely acknowledged that intelligent vehicles will be popular and play an essential role of daily life in the near future. One major reason of developing intelligent vehicles is to improve transportation safety. Unlike traditional cars, pedestrian avoidance in intelligent vehicles is accomplished by vehicle intelligence instead of drivers' action. Therefore, to improve pedestrian safety, interpreting pedestrian behavior in a way that the vehicle intelligence can understand is extremely necessary and promising.

Shared space or shared zone is one representative scenario where interactions between vehicles and pedestrians always happens. Here, the term interaction means how vehicle and pedestrian would react when they encountered with each other. Pedestrians might appear in different densities with unpredictable collective behavior, making pedestrian avoidance more difficult. Thus, introducing intelligent vehicles in shared spaces is a very suitable solution to improve pedestrian safety. Projects exploring intelligent vehicles travelling at shared zones have already been popular for several years. Since September 2012, a European project CityMobil2 [2] has been setting up a pilot platform for automated road transport systems that are made up of vehicles operating without drivers and providing service in areas of low or dispersed demand. Its first demonstration has been done in 2016. LUTZ Pathfinder Project [9] is another project under Transport Systems Catapult in UK developing driverless pods in public streets. It also finished a trial on pavements around Milton Keynes train station in October 2016. To provide a more customized transportation service, especially on campus, OSU SMOOTH [10] proposed by The Control and Intelligent Transportation Research (CITR) lab at the Ohio State University (OSU) has been developing first mile/last mile intelligent vehicles for campus transportation service since 2014. One pilot test has been conducted in summer 2015. For all those intelligent vehicles, understanding pedestrian behavior is one of the core missions. And there is still room to explore better understanding of pedestrian behavior.

Pedestrian behavior analysis has been studied for more than two decades. Back in 1995, a famous pedestrian interaction model, the social force model, was proposed by D. Helbing and P. Molnar [4], and it is generally regarded as the most efficient model for pedestrian behavior analysis. Some studies for intelligent transportation systems have already applied social force model into pedestrian behavior analysis for general cases [7] and for specific applications [1]. From the aspect of intelligent vehicles, when interaction happens, it is not enough to simply avoid or yield to pedestrians. Pedestrians might have additional behavior in presence of intelligent vehicles rather than normal ones. For example, H. Kidokoro et al. demonstrated that intelligent robots might attract more people due to its novelty, and possibly blocking the passage [6]. To solve this problem, they proposed a pedestrian simulation method that applied social force model and is capable of anticipating pedestrian behavior. Although this study focuses on service robots traveling inside a shopping mall, it does provide an approach to integrate pedestrian behavior analysis into intelligent units. On the other hand, recently, a study about pedestrians interacting with a normal-sized car at a signalized intersection has demonstrated the feasibility of applying social force model into normal-sized intelligent vehicless instead of smaller-size intelligent robots [11]. Thus, with the idea of simulation method and the potential of incorporating normal-sized vehicle, this study proposed a vehicle-pedestrian interaction simulator for normal-size intelligent vehicles. The simulator can help intelligent vehicles to make more efficient and safe path planning in shared spaces.

The CITR group at OSU has worked on exploring pedestrian interaction behaviors related to intelligent vehicles and transportation systems for several years. In 2013, E. Adamey et al. [1] conducted an agent-based passenger modeling study for intelligent public transportation based on both social force model and hybrid state machines. This passenger model was successfully applied into simulation scenarios such as passenger loading and unloading at a bus station. One limit is that this study only assumes pedestrians as point-mass particles. To improve this, in 2015, R. El Helou [5] proposed a modified pedestrian interaction model based on social force, in which pedestrians' sizes and personal characteristics are considered. Pedestrians in this model are capable of properly avoiding moving obstacles, but not yet specifically designed for intelligent vehicles. This study, based on previous exploration, further improved the pedestrian interaction model and integrated it in the vehicle-pedestrian simulator.

The remaining paper is organized as follows. A description of OSU SMOOTH is presented in section 2. The model framework of the vehicle-pedestrian interaction simulator is detailed in section 3, including pedestrian behavior modeling and vehicle dynamics and control. Next, simulation results are analyzed in section 4. Finally, conclusions are drawn and future work is discussed in section 5.

2 OSU SMOOTH

The vehicle-pedestrian simulator is initially designed for the project, The Smart Mobile Operation: OSU Transportation Hub (SMOOTH) at The Ohio State University, but it is also applicable to general pedestrian behavior analysis in shared spaces. SMOOTH is a solution to improve the transportation of the first mile (from starting point to a public transportation access point) and the last mile (from transportation terminals to the final destination), especially for the elderly, or people with limited mobility or disability [10]. Fig. 1 shows the configuration of OSU SMOOTH concept design servicing OSU campus. It primarily consists a transportation hub, several automated vehicles, and a mobile-first web-based application. The transportation hub is responsible for vehicle scheduling, route planning, infrastructure sensor data processing, communication, and web hosting. Three pilot automated vehicles equipped with SMOOTH techniques are a motorized wheelchair, a single-person mobility scooter, and a four-passenger golf cart, as shown in Fig. 2. The web-based application is available to all smart device, where users can log into their accounts and schedule an automated vehicle for service.

This study mainly focuses on improving automated vehicles in OSU SMOOTH, specially on pedestrian behavior prediction and avoidance. It is divided into two phases: (1) the modeling, simulation and analysis of vehicle-pedestrian interaction, and (2) the development and implementation of local path planning or pedestrian avoidance algorithm in the automated vehicle. This paper generally covers phase 1. Phase 2 is still under exploration and is planned to be done around Summer 2017.

3 MODEL FRAMEWORK

The overall framework for detecting and avoiding pedestrians on an automated vehicle is shown in the gray block of Fig. 1, in which the vehicle-pedestrian interaction simulator plays an essential role. First, sensors such as LIDAR, radar, cameras, ultrasonic and GPS, and communication approaches such as V2V and V2I recognize the surrounding environment. Once the received data is processed, information including each pedestrian's position, velocity and potential destination can be identified and made available to the vehicle-pedestrian interaction simulator. Although in reality, it would be difficult to obtain such exact information due to occlusions and sensor noises. Here we simply assume that all pedestrian information is available because precise pedestrian detection is beyond the scope of the study. With pedestrian information, pedestrian behaviors (possible moving trajectories) are simulated based on current configurations of both pedestrians and the vehicle. Using the simulation results, vehicle motion planner can determine more reliable and efficient local reactive decisions and perform real-time local path planning, which is a complement or an addition to global path planning. Both global and local path plannings constitute the high-level controller, hence vehicle control is achieved and the corresponding action is executed.

The following subsections will describe details of the vehicle-pedestrian interaction simulator. This includes how the pedestrian

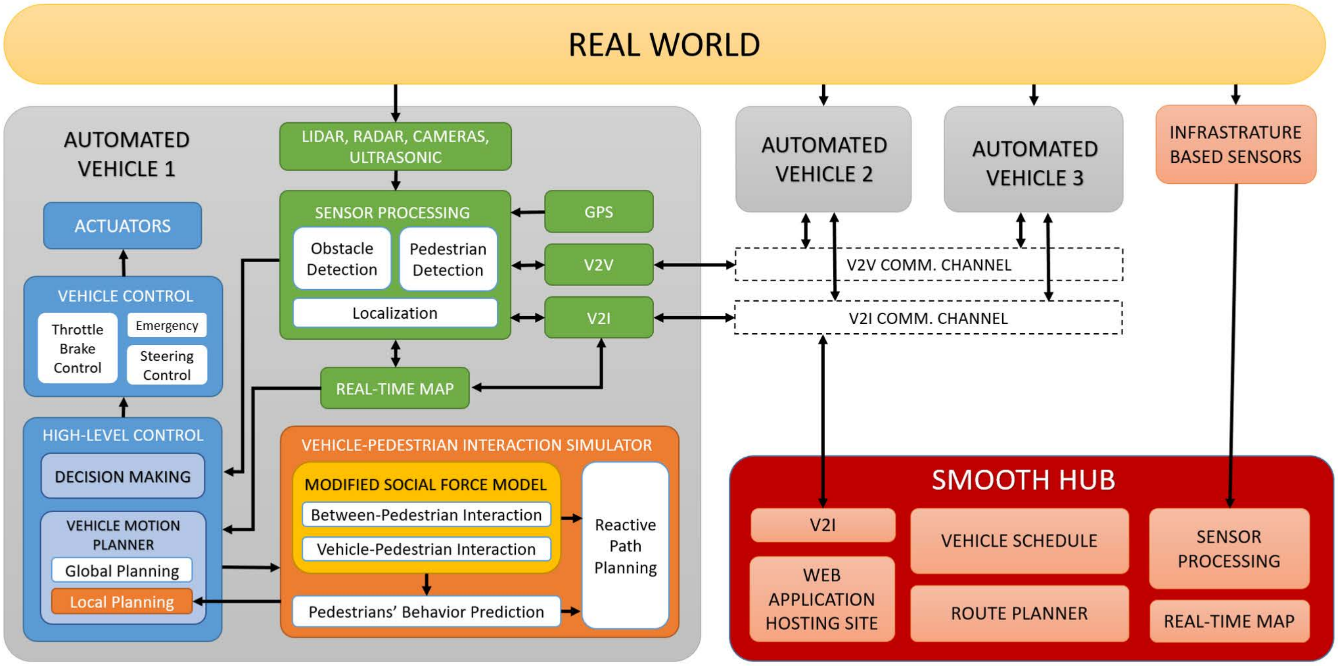

Figure 1: Configuration of SMOOTH and the vehicle-pedestrian simulator on an automated vehicle.


(a) Motorized wheelchair (b) Single-person mobility scooter

(c) Four passenger golf cart

Figure 2: Pilot automated vehicles

interaction model is constructed, what kind of dynamic model and controllers are applied for the vehicle, and how the vehicle-pedestrian interaction algorithm is currently designed for the simulation of the shared space scenario.

3.1 Pedestrian Behavior Modeling

The most acknowledged model for pedestrian interaction analysis is social force model [4]. Compared with other two major models, magnetic force model and cellular automata, social force model can represent pedestrian interaction in a microscopic view and in a continuous space. In this study, the modified social force model in [5] is further improved in the aspect of environment effect to be applicable to interaction between pedestrians and intelligent vehicles in shared space. Pedestrian dynamics is governed by Newton's second law of motion:

$$\frac{d^2\vec{r}}{dt^2} = \frac{d\vec{v}}{dt} = \frac{\vec{F}_{total}}{m} \qquad (1)$$

where $\vec{r}$ and $\vec{v}$ denote the pedestrian position and velocity, respectively. The total experienced force $\vec{F}_{total}$ is divided into two classes. One is external force representing effect of collision and friction. The other is internal force, including three types: the destination force driven by destination, the social force influenced by surrounding pedestrians, and the environment force determined by other objects in the environment. They are generalized as the equation:

$$\vec{F}_{total} = \vec{F}_{ex} + \vec{F}_{in} = (\vec{F}_{col} + \vec{F}_{fri}) + (\vec{F}_{des} + \vec{F}_{soc} + \vec{F}_{env}) \qquad (2)$$

The first four forces are illustrated in Fig. 3. Collision force $\vec{F}_{col}$ is a repulsion force experienced by the reference pedestrian when another pedestrian gets extremely close, e.g., physically touching or pushing. It is a counter force from the adjacent pedestrian, and the effect of all surrounding pedestrians is superimposed together. Friction force $\vec{F}_{fri}$ is generated when two pedestrians are walking toward each other, and brushing past. It points in the opposite direction of the other pedestrian's walking velocity. Similarly, the

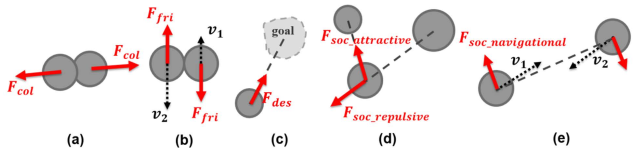

Figure 3: Illustration of first four forces: (a) collision force; (b) friction force; (c) destination force; (d)(e) social force

effect of all surrounding pedestrians is added. Destination force $\vec{F}_{des}$ only considers the reference pedestrian's state and destination. It is generated by a feedback controller fed by reference pedestrian's current position, current speed, and destination. Social force $\vec{F}_{soc}$ considers the target pedestrian' subjective reaction to surrounding pedestrians. It consists of social repulsive or attractive force and social navigational force. Social repulsive or attractive force integrates the desire of keeping away from some pedestrians (stinky or nasty people) and that of keeping close to certain people (family or group leader). Social navigational force deals with the pedestrian's active avoidance to others when possible collision is anticipated. All the modeling details of above forces can be found in [10].

The last force, environment force $\vec{F}_{env}$, is more complicated than others. It manages all effect from surrounding environment except pedestrians. This effect could come from walls, road edges, flower stands, etc., and the most important one, moving vehicles. This study mainly concerns interaction between vehicles and pedestrians. So it is assumed that vehicle effect is the only one in the environment force. In [5] this force is viewed as the effect similar to a pedestrian but with quite different characteristics. But this is applicable only when the vehicle is small, round and slow. Considering vehicle's shape, in [11] the author modeled the vehicle effect as an ellipse effect field. It was successfully applied in the pedestrian behavior analysis at an intersection, but not yet applied for interaction between pedestrians and intelligent vehicles in shared space. This study further improved the modeling of vehicle effect to make it suitable for scenarios related to intelligent vehicles.

Fig. 4 shows the repulsive effect $\vec{F}_{rep}$ from a vehicle to the pedestrian. Two points, the rear point of the vehicle $\vec{P}_{rear}$, and the expected front point $\vec{P}_{expected}$, are defined as the two foci of the ellipse. The distance between $\vec{P}_{expected}$ to $\vec{P}_{front}$ is calculated based on the vehicle's current velocity. The faster the vehicle, the longer the distance between two foci. The position of a pedestrian near the vehicle defines a point on this ellipse, through which the ellipse is calculated. Based on the ellipse, the vehicle effect force can be calculated, with its direction perpendicular to the tangent line of the ellipse, and its magnitude by the equation:

$$\vec{F}_{rep} = k_1 exp(-k_2 b)\vec{n} \tag{3}$$

where b is the length of semi-minor axis of the ellipse, k_1, k_2 are parameters, and $\vec{n}$ is the direction vector.

3.2 Vehicle Dynamics and Control

In the simulation, the vehicle motion is described by a linearized bicycle model and the lane following (steering) maneuver is achieved by the look-ahead steering control [8]. Way-points for look-ahead steering control are predefined so that the study can focus on pedestrian behavior analysis for certain scenarios. Longitudinal speed regulation policy is illustrated in Fig. 5. The speed is regulated via a proportional controller based on the distance from the vehicle to the closest pedestrian inside the field of view (FOV). Two threshold distances, d_{slow}, d_{stop}, are set as shown in the figure. Four types of desired speeds are defined: forward speed $v_{forward}$, turning speed v_{turn}, yielding speed for pedestrians v_{yield}, and no speed v_{stop}. Once the closest distance d_{v2p} is found, the desired speed v_d is determined by the following equation:

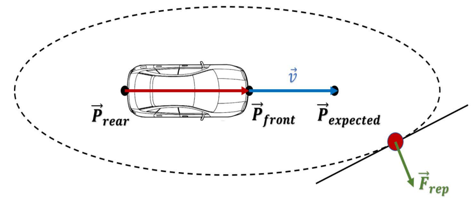

Figure 4: Ellipse effect force from vehicle

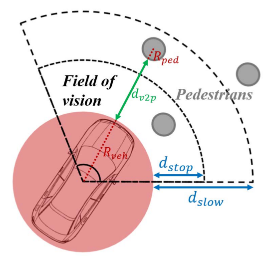

Figure 5: Vehicle longitudinal speed regulation

$$v_d = \begin{cases} v_{forward}, & d_{v2p} > d_{slow} \text{ with no steering} \\ v_{turn}, & d_{v2p} > d_{slow} \text{ with steering} \\ v_{yield}, & d_{stop} < d_{v2p} < d_{slow} \\ v_{stop}, & d_{v2p} < d_{stop} \end{cases} \tag{4}$$

This algorithm is sufficient for testing the reliability of the pedestrian-vehicle interaction model. Currently, it does not consider advanced actions such as taking a detour to bypass pedestrians, which will be explored in the near future. The preliminary testing result and analysis are presented in next section.

4 SIMULATION AND PRELIMINARY RESULT

In this study, the simulation considered a shared space environment. It is done in three steps. Step 1 only considered the interaction among pedestrians. This verified the effectiveness of inter-pedestrian modeling. Step 2 investigated some basic scenarios, in which a group of pedestrians are walking from an initial point to the destination, while the vehicle is traversing the center area of pedestrians from different directions. Step 3 explored a more complex scenario, which contains two groups of pedestrians with different initial points and goals, and involves a vehicle that would steer aside when it reached the center area of pedestrians. In the simulation, the sizes of pedestrians are randomly generated according to people's average size. Other characteristics, such as social force sensitivity, are determined based on individual size.

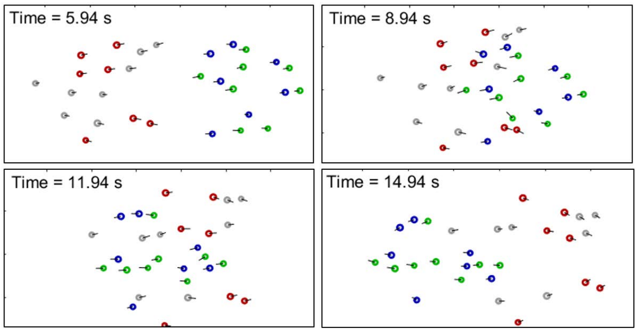

Figure 6: Simulation of pedestrian interaction

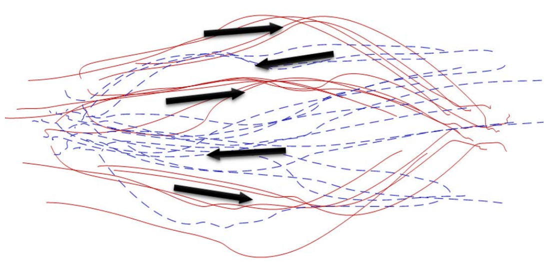

Figure 7: Trajectories of pedestrian interaction

4.1 Pedestrian Interaction

The main purpose of simulating interaction among only pedestrians is to adjust model parameters and validate the effectiveness of the modified social force model. After multiple trials, a set of effective parameters is obtained. The model performance with these parameters is evaluated in the scenario where two groups of pedestrians walk toward each other. This is a common way to verify the feasibility of pedestrian interaction model. For each group, pedestrians with slightly different desired velocities are randomly initiated in a rectangular area on one side, with the destination on the other side. Fig. 6 shows the visualization result of this scenario. This result displayed a proper walking avoidance pattern when pedestrians encountered with others. Fig. 7 shows trajectories of pedestrians in this simulation. It clearly demonstrates lane formation, which is a typical phenomenon in real world.

4.2 Basic Vehicle-Pedestrian Interaction

In this simulation, a group of 20 pedestrians (10 with higher speed and 10 with lower speed) are going to interact with a slow-moving vehicle (running at a maximum speed of 15mph, with the control policy provided in section 3) from three directions: left/right side, front, and back. Pedestrians are randomly initiated in a rectangular area at the southwest corner with the destination at the northeast corner. Fig. 8 displays the simulation results of side interaction, back interaction and front interaction. These three simulations verified the feasibility of the model by showing reasonable vehicle-pedestrian interaction behavior. For example, in each setting, when the vehicle was approaching, pedestrians who anticipated a possible collision turned aside or around to avoid the moving vehicle, even if they might push or squeeze other pedestrians. The simulation

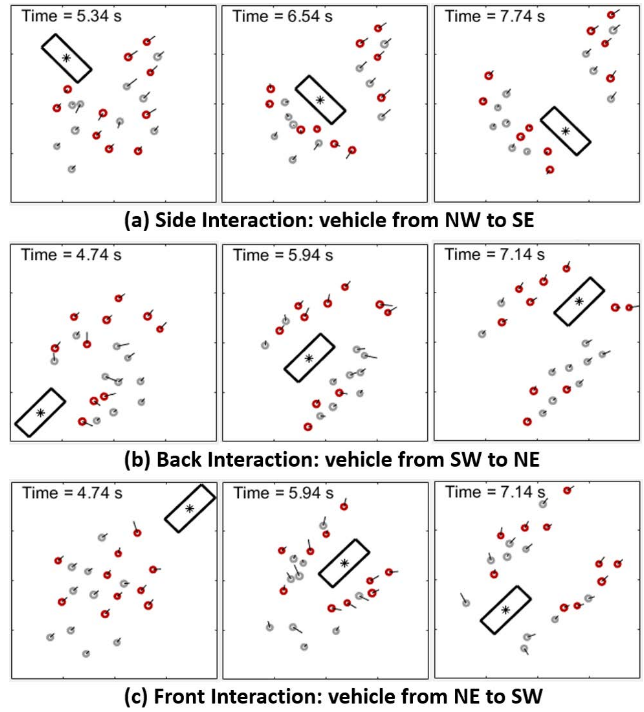

Figure 8: Simulation of basic vehicle-pedestrian interaction

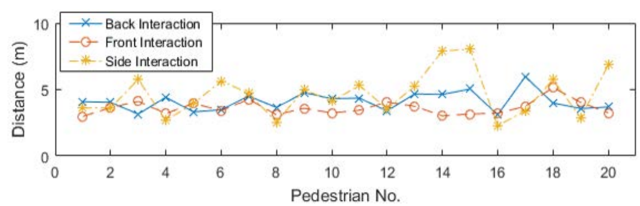

Figure 9: Closest distances to vehicle: basic scenario

also recorded the closest distance between each pedestrian and the vehicle, as shown in Fig. 9. The result shows that, during the simulation, each pedestrian's closest distance to the vehicle is larger than 2 meters, which demonstrated that each pedestrian was always maintaining a safe distance to the vehicle.

4.3 Advanced Vehicle-Pedestrian Interaction

A more complex scenario is constructed to validate the model efficiency. Two groups of pedestrians are designed to walk to cross each other, one from southwest to northeast, the other from southeast to northwest. They are initiated in a similar way to the previous setup. The vehicle movement is designed to first travel from southwest to northeast until it reaches the center of pedestrians. At the center of pedestrians, the vehicle turns right, changes its direction to southeast, and drives toward southeast. This scenario covers basic elements in shared-space situations. Fig. 10 shows that pedestrians react properly to the turning vehicle. In Fig. 11, convolved trajectories in the center demonstrates that pedestrians made more complex turning actions to avoid the vehicle. Fig. 12

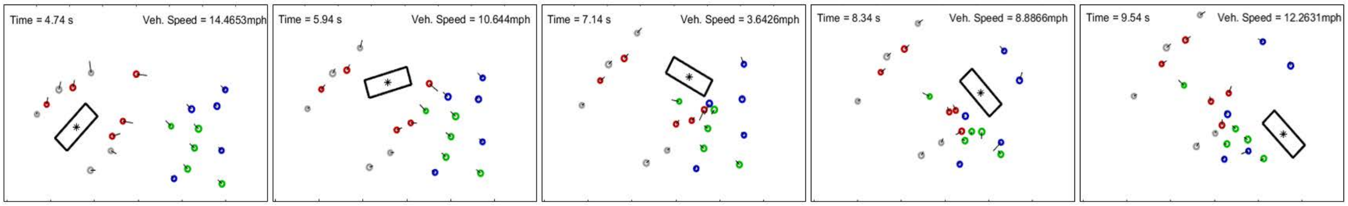

Figure 10: Simulation of advanced vehicle-pedestrian interaction

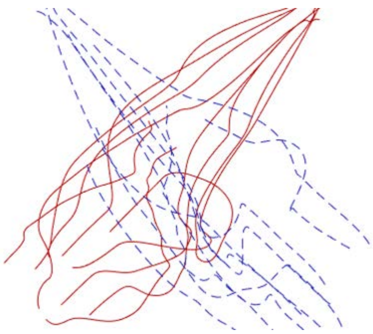

Figure 11: Pedestrian trajectories (dashed lines from SE to NW, solid lines from SW to NE) in advanced scenario

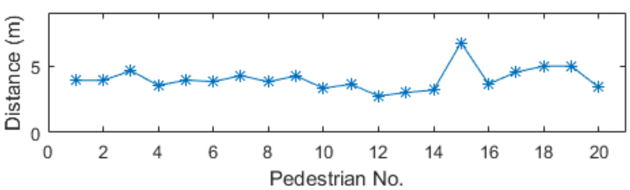

Figure 12: Closest distances to vehicle: advanced scenario

displays the pedestrians' closest distances to the vehicle, which indicates that each pedestrian was always maintaining a safe distance to the vehicle. The overall simulation verified the effectiveness of the vehicle-pedestrian model.

5 SUMMARY AND FUTURE WORK

This paper presented a method and a tool, vehicle-pedestrian interaction simulator, to analyze pedestrian behavior in shared space, and consequently help intelligent vehicles such as automated vehicles in OSU SMOOTH make more accurate and efficient decisions and improve local path planning. The simulator can reflect interaction between pedestrians and intelligent vehicles in shared space under various configurations. It can also be extended to provide a variety of other useful information for intelligent vehicles. The preliminary result demonstrated the feasibility of this model/simulator.

The proposed simulator has two major merits. First, pedestrians are considered as agents with different characteristics, which makes the interaction closer to real world. In the future, characteristics such as unique repulsive or attractive force and different responses to the vehicle can be specifically and easily added. Second, scenarios can be easily constructed and modified by changing the vehicle's configuration and pedestrians' initial points and destinations. Thus, vehicle paths generated by different path planning algorithms can be easily tested and hence improved.

One possible improvement is that currently the parameters of the interaction model are determined by subjective judgement. Although subjectively determined parameters are good enough for pedestrian behavior analysis and useful for vehicle path planning, it is always worth validating the parameters in a probabilistic and statistical way based on ground truth data.

Developing and testing more advanced pedestrian avoidance algorithms would be the next step to improve pedestrian safety in shared spaces, in which elastic band theory would be one candidate. After all necessary simulations are completed and verified, using this simulator, the automated vehicle will be able to achieve a better pedestrian avoidance. Consequently, the vehicle-pedestrian simulator will be implemented and tested on a pilot OSU SMOOTH equipped four-passenger golf cart.

ACKNOWLEDGMENTS

This study was partially supported by the NSF under the CPS Program (Award #1528489 and #1446735), and partially by the US DoT under the UTC Program (Award #DTRT13-G-UTC47).

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