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Dynamic Game-Theoretic Risk Assessment for Vehicle-Pedestrian Interaction With Perception Uncertainty

Jie Zhao

School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China. E-mail: zhaojie14@buaa.edu.cn

Shengkui Zeng

School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China. E-mail: zengshengkui@buaa.edu.cn

Jianbin Guo

School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China. E-mail: guojianbin@buaa.edu.cn

Haiyang Che*

School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China. E-mail: chehaiyang@buaa.edu.cn

Pedestrians, as vulnerable road users, critically influence traffic safety and efficiency through their interactions with autonomous vehicles. Perception biases in judging vehicle distance and approaching velocity often lead to unsafe behaviors (e.g., risky crossing). However, existing studies based on game theory did not consider pedestrians' cognitive bias and sensor bias. To address this gap, we propose a dynamic risk assessment framework that integrates perceptual uncertainties. The model quantifies the effects of pedestrian visual biases and sensor noise, establishing an incomplete information game with Bayesian belief predication. The proposed model considers pedestrians' limited reasoning capacity characterized by two-stage discrete decision, while vehicles perform real-time observation and adjustment through continuous belief prediction. Dynamic conflict risk is evaluated by statistically analyzing the probability of mutual non-yielding between both agents at the second decision stage. Simulation experiments validate the model's efficacy, with results demonstrating its superior capability in reflecting real-world conflict risk.

Keywords: dynamic risk assessment, incomplete information game, bayesian belief predication, perception uncertainties.

1. Introduction

Pedestrian traffic safety has emerged as a global public health concern in recent years. According to World Health Organization statistics, pedestrians account for 21% of global road traffic fatalities [1]. Unsignalized crosswalks, characterized by ambiguous right-of-way rules, represent high-risk scenarios for pedestrian-vehicle conflict [2]. Of particular significance, the rapid adoption of autonomous driving technologies has disrupted traditional interaction protocols among traffic participants, substantially amplifying the complexity and uncertainty of human-vehicle interactions [3]. This critical challenge underscores the urgent need for advanced dynamic risk assessment models to enhance decision-making frameworks for autonomous vehicles (AVs).

Existing research predominantly focuses on pedestrian behavior prediction and risk quantification methodologies. Early scholars such as Yue et al. [4] established pedestrian trajectory prediction frameworks using Markov random walk models with active safety enhancement functions. With advancements in sensing technologies, Zhang et al. [5] proposed a collision warning algorithm integrating wheel velocity sensors and vision systems. Notably, breakthroughs in deep learning have facilitated the adoption of Transformer architectures [6], long-short term memory networks [7], and deep Q-networks [8] for pedestrian intent recognition. However, current approaches predominantly employ unidirectional prediction paradigms that neglect complex vehicle-pedestrian interactions, which may lead to systematic overestimation or underestimation of conflict risk.

To address these limitations, game theory has become a predominant tool for modeling traffic conflict, with extensive applications in vehicle-vehicle [9-11] and vehicle-pedestrian interaction modeling under autonomous driving conditions. Chen et al. [12] simulated AV-pedestrian conflict at mid-block crosswalks using Stackelberg game theory, while Nan et al. [13] characterized dynamic game processes through hybrid Nash equilibrium solutions. Nevertheless, traditional game-theoretic approaches relying on perfect information assumptions fail to capture cognitive limitations in real-world scenarios. Bayesian game-theoretic frameworks address this challenge through prior probability distributions, enabling incomplete information interaction modeling. Deng et al. [14] developed a lane-changing aggressiveness assessment model using Bayesian games, and Adamova et al. [15] incorporated road environment parameters into Bayesian game models for multi-factor risk quantification. Current studies focus on decision-layer uncertainty while neglecting perception-layer error propagation, and lacking systematic modeling of agent cognitive constraints. Pedestrian misjudgment of vehicle distance and approach velocity constitutes a contributing factor to traffic conflict [16]. At the same time, vehicle sensors are prone to measurement errors due to environmental interference [17]. Constrained by limited temporal and computational resources, pedestrians struggle to derive optimal strategies in real time. The coupling effects of these three dimensions frequently result in model mismatch issues in conventional frameworks when addressing complex scenarios. To overcome these challenges, this paper proposes a novel conflict risk assessment framework for developing more accurate real-world behavioral models. Specifically, the framework characterizes agent perception and cognition processes through a situational awareness (SA) model. The sensor degradation models and pedestrian visual bias functions are incorporated into perception level. At the cognitive level, the probability of behavior prediction is quantified by a discrete choice model. Finally, Bayesian Nash equilibrium is solved at the decision level to realize dynamic risk assessment. Conflict risk is quantified as the probability of mutual non-yielding between interacting agents at the second decision stage.

The main contributions are summarized as follows: (1) A hierarchical uncertainty propagation model that synchronously captures the coupling mechanism between perceptual biases and decision-game interactions, facilitating more authentic simulations. (2) A two-stage integrated perception-cognition-decision architecture with a dynamic conflict risk assessment model. The proposed methodology facilitates more realistic simulations of pedestrian-vehicle interaction modeling and provides theoretical support for advancing decision-making systems in autonomous driving.

The remainder of this paper is organized as follows: Section 2 describes the problem and presents the model framework. Section 3 details the proposed risk assessment methodology. Section 4 provides comprehensive simulation analyses and discussions. Conclusions are drawn in Section 5.

2. Model Framework

This section describes the application scenarios and model framework necessary for solving the problem.

2.1. Problem Statement

At unsignalized or unguided locations, AV-pedestrian interactions constitute a dynamic decision-making process that fundamentally represents a game-theoretic competition over constrained spatiotemporal resources. A simplified scenario of vehicle and pedestrian interaction is shown in Fig. 1. Autonomous systems exhibit superior computational power and rapid response mechanisms, while human have a preference of interaction at undefined times [18]. Therefore, vehicle interacts at a fixed time step and pedestrian is considered to interact at two different moments. The first moment is when the pedestrian is at the curb; and the second moment is when the pedestrian is approaching the conflict area. Subject to delay and risk cost constraints, at these two moments, pedestrian can choose to cross the road or not, and AV can choose to yield or not. We focus on the conflict phenomenon where both parties still fail to yield at the second moment due to the game between pedestrian and AV.

During the gaming process, pedestrian can experience velocity and distance perception bias, while the degradation of vehicle sensor performance can also lead to errors in the measured data. The accumulation of such uncertainties will trigger variables in the decision-making process of both parties, thus increasing the possibility of conflict between pedestrian and vehicle. Therefore, this paper proposes a risk assessment model that takes cognitive bias and sensor performance degradation into account, aiming to prevent potential conflict between pedestrian and vehicle and to improve the safety of road transportation.

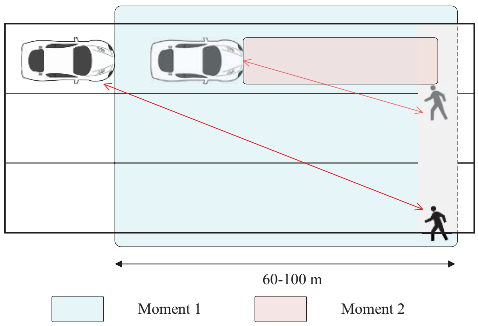

Fig. 1 Conflict scenarios between the AV and the pedestrian

2.2. Framework Description

The framework architecture is illustrated in Fig. 2. This model comprises three integrated modules: a SA model, a decision model and a motion model. The objective of the SA model is to characterize the perception and judgment process of pedestrian and AV during crossing scenarios. This process is influenced by human cognitive ability and the performance and reliability of the sensor. The decision model formalizes yielding behaviors through a Bayesian Nash equilibrium framework, where pedestrian and vehicle iteratively update their strategies based on inferred intentions. The motion model determines the microscopic movements of vehicle and pedestrian in two stages. The subsequent sections elaborate on each component in detail.

3. Methodology

In this section, we investigate a risk assessment method of pedestrian crossing conflict. First, we describe the definition and details of each model. Then, we develop a new algorithm to assess the conflict probability of pedestrian and AV based on Monte Carlo (MC) simulation.

3.1. *SA Model*

The SA model aims to characterize the cognitive processes of pedestrian and vehicle, guided by Endsley's renowned three-level SA theory [19]. Level 1 SA involves perceiving real-time statuses and relevant attributes of critical environmental elements. Level 2 SA synthesizes unrelated Level 1 SA elements to establish comprehensive system understanding. Level 3 SA subsequently projects future system states through prediction based on this synthesized awareness.

3.1.1. *Perception Modeling*

During the perception phase, vehicle type, pedestrian gender, and motion parameters are acquired by either the vehicle or the pedestrian. In this paper, we focus on the cognitive bias and sensor performance degradation on the motion parameters, i.e., position and velocity.

A nonlinear mapping exists between subjective human distance perception and physical reality, where within the visible range, humans tend to underestimate actual distances. The Gilinsky Equation [20], derived through mathematical analysis and experimental validation, is expressed as follows:

$$\frac{d_{judge}}{d_{actual}} = \frac{A}{A + d_{actual}} \tag{1}$$

where d_{judge} and d_{actual} are the judging distance and the true distance respectively; and A represents the maximum perceptual distance limit under given conditions, which is taken as 74 meters according to the literature.

Pedestrian systematically underestimates high-velocity vehicles while demonstrating overestimation tendencies for low-velocity vehicles under rainy conditions. Field experiments in natural traffic environments, integrating pedestrian behavioral observations with vehicular kinematic data, sun et al. [16] revealed the velocity perception bias relationship formalized as:

$$v_{bias} = 0.47 v_{actual} - 16.10 - 2.17 I\{rainy\} \tag{2}$$

where v_{bias} denotes velocity estimation deviation, v_{actual} is the true velocity, and $\{\bullet\}$ represents weather state, which is 1 on rainy days and 0 on sunny days.

Sensor degradation modeling is implemented through stochastic perturbations of actual variables. Specifically, position and velocity measurements are perturbed by random sampling from normal distributions with means equal to true values and standard deviations equal to the actual value multiplied by a perturbation parameter. Formally, observed pedestrian velocities and distances are derived from the following distributions:

$$d_{veh,est} \sim N\left(d_{actual}, \left(\delta \cdot d_{actual}\right)^2\right) \tag{3}$$

$$v_{veh,est} \sim N\left(v_{actual}, \left(\delta \cdot v_{actual}\right)^2\right) \tag{4}$$

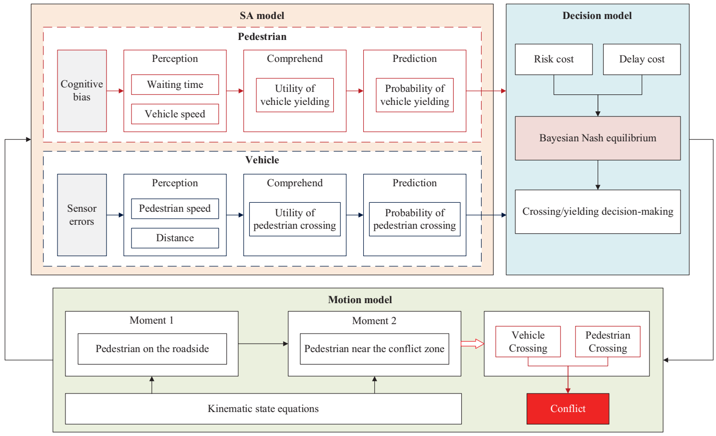

Fig. 2 The proposed framework of AV-pedestrian conflict risk assessment

where $d_{veh,est}$ and $v_{veh,est}$ are the distance and velocity estimation, d_{actual} and v_{actual} are the true distance and velocity, and δ represents perturbation parameter.

3.1.2. *Comprehend and Prediction Modeling*

In the comprehension and prediction phase, vehicle intelligence system or pedestrian estimates the belief of the other party's behavioral choices. In this paper, discrete choice model is used for modeling. In particular, a binary logistic regression model is used, which is a better choice for modeling and analyzing binary variables [21]. The belief estimates are obtained by means of probabilities, is calculated as follows:

$$P(Y=1|U)=\frac{1}{1+e^{-U}} \tag{5}$$

where Y is a binary variable with $1=cross$ and $2=yield$, and p represents the estimated probability of crossing behavior by the counterpart, with yielding probability $1-p$. U is the subject's utility reflecting how pedestrian and vehicle characteristics shape behavioral expectations. This utility can be expressed as a function of multi-dimensional decision factors as follows:

$$U=\alpha+\sum_{i}^{m}\beta_i x_i \tag{6}$$

where x_i denotes explanatory variables obtained from the perception phase, β_i are their corresponding weights, and α is an intercept term. The comprehension phase enables vehicle to derive pedestrian crossing utilities and pedestrians to obtain vehicle yielding utilities through interpretation of perceptual variables, with model parameterization based on datasets from [22]. Parameter estimation using 698 pedestrian-vehicle interaction cases reveals statistically significant influences ($p<0.05$). The corresponding model parameters are provided in Table 1.

During the prediction phase, agents probabilistically forecast opposing behaviors using these utility functions. These probability estimates serve as critical inputs to the subsequent decision model.

Table 1 Parameters of pedestrian and vehicle utility models in the comprehend phase [22]

Factor	**First interaction**	**Second interaction**
The utility model of pedestrian (cross)		
Constant	-0.57	-1.52
Male pedestrian	0.58	1.15
Walking velocity	1.13	0.48
Vehicle velocity	-0.02	-0.02
waiting time	-0.04	-0.07
The utility model of vehicle (yield)		
Constant	-1.42	-1.77
Vehicle distance	-0.02	-0.03
Vehicle velocity	0.14	0.08
Heavy vehicle	-0.24	-0.58
Walking velocity	0.03	0.05

3.2. *Decision Model*

The instantaneous decisions of pedestrian and vehicle are determined by a decision model formulated within a Bayesian game-theoretic framework. Agents optimize their strategies by analyzing probability distributions of opponents' behavioral types to maximize expected payoffs. The game model comprises the following components:

- The set of players: $N=\{1,2,\cdots,n\}$, where 1 denotes the pedestrian and 2 denotes the AV.
- Action space: $A=\{A_1,A_2,\cdots,A_n\}$, represents the strategic option space for player i. Pedestrian choose whether or not to cross the road $A_1=\{a_{11}=cross,a_{12}=wait\}$, and AV chooses whether to yield $A_2=\{a_{21}=cross,a_{22}=yield\}$.
- Type space: $T=\{T_1,T_2,\cdots,T_n\}$. The uncertainty that a player cannot be sure of the choices of the other players stems from the existence of different types of benefits for the players. Pedestrian type $T_1=\{aggressive,conservative\}$, and AV type $T_2=\{safe,risky\}$.
- Confidence functions: $p_i(t_{-i}|t_i)$, which describes player i's belief estimate of the possible types t_{-i} of the other participants, given his own type t_i. For pedestrian $P_1=\{p_{safe}=p_{yield},p_{risky}=1-p_{yield}\}$, and for AV $P_2=\{p_{radical}=p_{cross},p_{risky}=1-p_{cross}\}$.
- Payoff functions: $u_{ij}(a_1,\cdots,a_{ij},\cdots,a_n|t_i)$. Player i chooses the payoff of strategy a_{ij} under type t_i.

The payoff is linked to player types and their selected actions. The probability distributions over player types are derived from the outputs of the SA model. p_{yield} represents the pedestrian's belief about the AV's likelihood of yielding, i.e., the probability that the interacting AV is safety-oriented. p_{cross} denotes the AV's belief about the pedestrian's propensity to cross, i.e., the probability that the interacting pedestrian exhibits risk-aggressive behavior. The payoffs are defined by two key metrics: a) safety metrics, quantified as the perceived potential collision risk $k={}^{1}\!/_{TTC}$, and TTC is the time-to-collision of vehicle. b) efficiency metrics, which indicates the cost of delay due to yielding, equal to the time it takes for a pedestrian to cross the street or the time it takes for a vehicle to cross.

The final payoff matrices for vehicles and pedestrians are composed according to their decisions as well as the appropriate risk and delay cost, as shown in Table 2. The values of the parameters were obtained from the literature [23]. a is the weight, and c is the multiplier on the delay cost due to the loss of time due to emergency braking in the case where both choose to cross the street.

Following the computation of payoff matrices, Bayesian Nash equilibrium requires that for any player i and each possible type t_i, the optimal action a_i^* maximizes the expected payoff given belief distributions over opponents' types. The equilibrium decision pairs $a^*=(a_1^*,a_2^*)$ for pedestrian and vehicle are derived by solving:

$$\max_{a_{ij}\in A_i}\sum_{t_{-i}}\sum_{a_{-i}}u_{ij}(a_{-i},a_{ij}|t_i)\,p(t_{-i}|t_i)$$

Table 2 Payoff matrices of decision model [23]

	Pedestrian cross	Pedestrian wait
Vehicle cross	$-k-act_1,-k-act_2$	$k+at_1,k-at_2$
Vehicle yield	$k-at_1,k+at_2$	$k-at_1,k-at_2$

3.3. *Motion Model*

The agents' positions, velocities, and accelerations are updated temporally through kinematic models based on executed decisions. Given the exclusion of lane-changing behavior in this study, pedestrian and vehicle motions are modeled through simplified kinematic state equations:

$$s(t+1)=s(t)+v(t)\Delta t+\frac{1}{2}a(t)\Delta t^2 \tag{7}$$

$$v(t+1)=v(t)+a(t)\Delta t \tag{8}$$

where Δt is the discrete time step.

To formalize movement patterns and interaction mechanisms, we establish the following moving rules and interaction protocols for pedestrian and vehicle.

When choosing to cross the road, vehicle accelerate to its maximum velocity at a certain acceleration, while pedestrian accelerate at toward maximum walking velocity. When yielding is selected, the vehicle's deceleration is set to slow to the edge of the sidewalk according to (9) and the pedestrian comes to a direct stop.

$$a(t) = -v(t)^2 / 2s(t) \tag{9}$$

The proposed interaction protocol accounts for heterogeneous decision capabilities. AV execute real-time decisions due to the powerful computational capabilities and fast response time, while human agents exhibit phased decision-making constrained by biological limitations. Specifically, pedestrians only reassess decisions at two critical temporal nodes. If both agents choose to yield, the system initiates a renewed perception-cognition-decision cycle. For instance, when mutual deceleration behaviors are detected, the game-theoretic interaction reinitializes with updated state parameters.

3.4. *Conflict Risk Assessment*

The inherent uncertainties arising from human cognitive biases and sensors degradation render pedestrian-vehicle interactive decisions probabilistic until a steady-state distribution is reached. Therefore, the safety in this scenario varies with the decision distribution until it remains stable. To evaluate conflict risk, we define the risk metric as the steady-state probability that both pedestrians and vehicles will not yield. First, pedestrian and vehicle with different initial states are generated. Then, the interaction trajectories are simulated by iteratively applying the SA model, decision model, and motion model. Finally, the number of times that both sides do not yield at the second moment is counted as the conflict risk value. Based on the above steps, we develop Algorithm 1 to calculate the risk metric.

Algorithm 1: Conflict Risk Assessment

Input: L : lane dimensions, vehicle/pedestrian types, dimensions, speed distributions
Output: Conflict probability

Initialize simulation parameter: Δt , N
for $n = 1$ **to** N **do**
  initialize vehicle and pedestrian states randomly
  perceive x_0, v_0 $\leftarrow$ uncertainty sampling
  compute the belief $p_{yield,0}^{ped}, p_{cross,0}^{veh}$
  compute the payoff metrics
  a_0^{veh}, a_0^{ped} $\leftarrow$ agents get their decisions
  x_t, v_t $\leftarrow$ agents update dynamics by rules
  if $a_0^{veh} = yield$ & $a_0^{ped} = wait$ **then**
    update decisions a_t^{veh}, a_t^{ped}
  end
  if $y > L$ **then**
    update decisions $a_{t+1}^{veh}, a_{t+1}^{ped}$
  end
  if $a_{t+1}^{veh} = cross$ & $a_{t+1}^{ped} = cross$ **then**
    $n_{conflict} \leftarrow n_{conflict} + 1$
    break
  end
  conflict probability $\leftarrow$ $P[n] = n_{conflict}/n$
end
return *conflict probability*

4. Simulation Analysis

This paper uses an actual physical size design environment of the Jianshe First Road in Wuhan, China [24], to simulate the conflict scenario between pedestrian and AV.

4.1. *Simulation Setup*

In the simulation environment, the location is set up as a two-lane unidirectional roadway with a width of 3 meters for each lane. Percentage of heavy vehicles (e.g., buses) is 12%. The initial settings for vehicle and pedestrian are shown in Table 3.
The vehicle's longitudinal distance (60 to 100 meters) is set based on an acceptable time interval for pedestrian (e.g., 7 seconds [25]) and current speed. Following the initialization of vehicle and pedestrian, the simulation initiates their interaction at first moment. Based on the proposed interaction protocol, their states are determined by their respective SA, decision and motion models. This iterative process continues until either agent make their decision in the second moment or the vehicle successfully passes the intersection. Finally, 10,000 simulations of vehicle-pedestrian interactions are performed for statistical analysis.

Table 3 Initial set of simulation environment [24]

Parameter	Value
Light vehicle length	4.5*m*
Light vehicle width	1.8*m*
Heavy vehicle length	10.0*m*
Heavy vehicle width	2.5*m*

Initial position of vehicle	$(U(-100,-60),4.5)m$
Initial velocity of vehicle	$N(7.5,2^2)m/s$
Initial position of pedestrian	$(0,U(-2,0))m$
Initial velocity of pedestrian	$N(1.38,0.27^2)m/s$
Maximum vehicle velocity	$9.7\,m/s$
Maximum pedestrian velocity	$2\,m/s$
Maximum acceleration rate	$2\,m/s^2$
Perturbation parameter	0.3

4.2. *Result*

The probability of conflict between pedestrian and vehicle with or without perception bias is shown in Fig. 3. We find that the probability of conflict is higher in the presence of uncertainty than in the absence of it. This indicates that judgment errors caused by perception biases are more likely to cause traffic conflict.

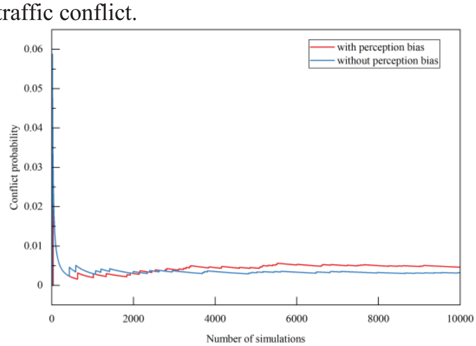

Fig. 3 Conflict probability of simulation cases

The traditional surrogate safety measures, TTC is used as a baseline method to demonstrate the validity of the model [26]. The results indicate that TTC significantly overestimates the presence of conflict phenomena, as shown in Table 4. This is because it quantifies conflict by using the immediate speed and direction of the road users at the current moment without considering the interaction between pedestrian and vehicle, i.e., it fails to capture the evasive behavior of vehicle and pedestrian.

In order to discuss the reliability of the model, we perform a sensitivity analysis for different levels of degradation to see its effect on the conflict probability. The values of the perturbation are set to 10%, 30% and 50%, while other variables remain unchanged. The results are shown in Fig. 4. It can be noticed that the higher the degradation, the higher the conflict probability. This is due to the underestimation of the collision risk due to the large measurement error of the vehicle.

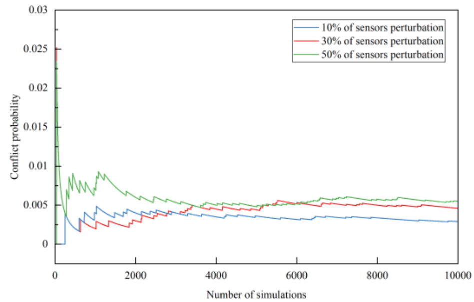

Fig. 4 Sensitivity analysis results for different levels of degradation

Table 4 The Comparison Between the Proposed Model and TTC

Method	**Conflict probability**
Proposed model	0.0042
TTC	0.0091

5. Conclusion

In this study, we propose a conflict risk assessment model for unsignalized crosswalks that accounts for human perception and cognitive limitations alongside sensor degradation characteristics, establishing more realistic and systematic interaction model compared to conventional game-theoretic approaches. Furthermore, we introduce an asynchronous interaction protocol addressing the heterogeneous decision-making capabilities between humans and autonomous systems, coupled with a MC-based risk quantification algorithm. Extensive simulations validate the methodological feasibility, revealing that perception biases correlate with elevated pedestrian-vehicle conflict risk. Future work will extend the framework to model multi-vehicle and multi-pedestrian following behaviors through multi-agent systems, addressing complex traffic scenarios with enhanced fidelity.

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