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# A Conflict Decision Model Based on Game Theory for Intelligent Vehicles at Urban Unsignalized Intersections

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**ABSTRACT** This article proposed a novel conflict decision model for intelligent vehicles based on game theory with analyzing the interaction behaviors between vehicles at urban unsignalized intersections. The proposed model can help intelligent vehicles cross intersections safely and more efficiently. Firstly, we developed an inference model for types of interactions among vehicles based on fuzzy logic. Then, the driving data was collected at urban unsignalized intersections by subgrade sensors and a retrofit intelligent vehicle and it was used in verifying the proposed inference model. After that, a conflict decision model considering safety, efficiency and comfort for intelligent vehicles based on game theory, was proposed to select the optimal driving strategies. Finally, a simulation and verification platform was built using Matlab/Simulink & Prescan. And the validity and effectiveness of the model were proved by simulation experiments. The results show the decision model can effectively help vehicles avoid conflicts and save their time spent in crossing intersections by 15 percent.

**INDEX TERMS** Intelligent vehicle, urban unsignalized intersection, decision-making model, game theory, conflict resolution.

## I. INTRODUCTION

Intelligent vehicles have drawn increasing attentions in recent years and many researchers have made great achievements about them. Due to the complexity of traffic at urban environments, it is of great significance to resolve conflicts among traffic participants at urban unsignalized intersections. Nowadays, researchers have employed methods like gap acceptance model, conflict table algorithm and vector graph algorithm to solve the conflicts. However, these models just explained the passing priorities of vehicles crossing the intersections, ignoring the interactions between intelligent vehicles and other traffic participants.

Scholars at home and abroad have put more focus on the interactions between intelligent vehicles and human-driving vehicles recently. Arda *et al.* [1] established a decision-making model of intelligent vehicles based on Finite State Machine (FSM) to predict the vehicle behaviors in scenarios of intersection. Zyner *et al.* [2] proposed a system with Recurrent Neural Network to infer drivers' intentions at the roundabout. Xiong *et al.* [3] and Song *et al.* [4] proposed a prediction method of driving intentions of surrounding vehicles based on HMM to realize the cooperative control among vehicles at intersections. In these researches, the accuracy of predicting drivers' intentions is limited by the quality of the collected data and the decision-making process of vehicles has not been quantified.

With the good performance in solving complex problems, game theory is widely used in conflict resolution among vehicles. It can quantify vehicles' decision-making process to ensure that they could always select optimal actions at each moment. Wang *et al.* [5] developed a prediction method for lane-changing and car-following based on optimal control and dynamic game theory in the scenarios of highway.

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Bouderba and Moussa [6] applied a dilemma game in unsignalized intersections and studied the impacts of the adopted method on the traffic capacity. This model employed game theory to study the microscopic traffic flow in intersections. Sasinee *et al.* [7] established a decision-making model in a unsignalized intersection in presence of selfish and irrational vehicles. In this article, the opponent vehicle is preset to be aggressive, ignoring the diversity of drivers.

In [8], [9], we have conducted researches on the decision-making process of intelligent vehicles in complex urban environments. To overcome the problems mentioned above, This article proposed a decision-making model based on game theory for intelligent vehicles to resolve conflicts, the contributions are listed as:

(1) A decision-making model based on game theory for intelligent vehicles at urban unsignalized intersections is proposed with the considerations of driving safety, efficiency and comfort.

(2) The validity and effectiveness of the model are verified by Matlab/Simulink & Prescan. The results show the model can provide help intelligent vehicles pass through intersections more efficiently.

The remainder of this article is organized as follows: Section II describes the methodologies and the data acquisition process in this article. Section III analyzes the interaction behaviors between vehicles at urban intersections and proposes a decision-making model for intelligent vehicles based on game theory. The simulation verification platform to evaluate the effectiveness and reliability of the proposed model is introduced in Section IV. In Section V, conclusions and future works are presented.

## II. METHODS AND DATA

### A. METHODS

#### 1) FUZZY LOGIC INFERENCE

Fuzzy logic inference is a classical method that can imitate the inference modes of the human brain to deal with uncertain systems by using fuzzy sets and fuzzy rules, which is widely applied in logic control modeling, software engineering and computer science researches. A fuzzy logic inference controller consists of inputs, outputs, membership functions and fuzzy control rules:

$$F = (I, O, M, R) \tag{1}$$

where: $I$ and $O$ refer to the input variables and output variables of uncertain systems, respectively, $M$ refers to the membership functions, which can convert the inputs $I$ into the fuzzy variables which can be recognized by the system, $R$ refers to the fuzzy reference rules, which are mapping relationships from inputs to outputs based on the experience of experts.

#### 2) GAME THEORY

Game theory is a mathematical method to study the competitive phenomena and it considers the predictive behaviors and actual behaviors of individuals in the game [10]–[12]. With the advantage of considering the information interactions between players, it is suitable for the decision making of intelligent vehicles at urban intersections. A game process consists of players, actions, information, strategies, payoffs, results, and equilibrium. And players, strategies and payoffs are three basic elements (Fig. 1).

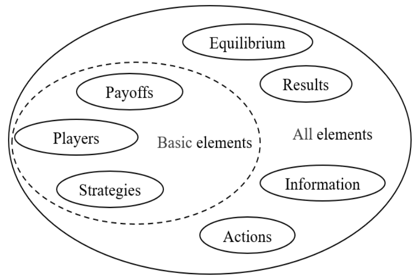



**FIGURE 1.** The elements of game theory.

(1) Players: The decision makers in the game. Players maximize their utility values by choosing optimal actions or strategies.

(2) Actions: The decision variables of a player at a certain moment in the game. Generally, $a_i$ represents a specific action of the $i$th player, and $A_i = \{a_i\}$ represents a set of all actions available for the $i$th player to choose.

(3) Information: The understandings of game-related knowledge obtained by players in the game.

(4) Strategies: The action rules of players with given information. Generally, $s_i$ represents a specific strategy of the $i$th player, and $S_i = \{s_i\}$ represents the set of all strategies available for the $i$th player to choose.

(5) Payoffs: The utility values obtained by a player under specific strategies, commonly known as the revenue function.

(6) Results: The indicators that can draw the interests of game analysts, such as balanced strategy combinations, balanced action combinations, balanced payoff combinations.

(7) Equilibrium: The optimal strategies of all players, which is generally represented as: $S^* = \{s_1^*, s_2^*, \ldots, s_i^*, \ldots, s_n^*\}$. where, $s_i^*$ is the optimal strategy of the $i$th player.

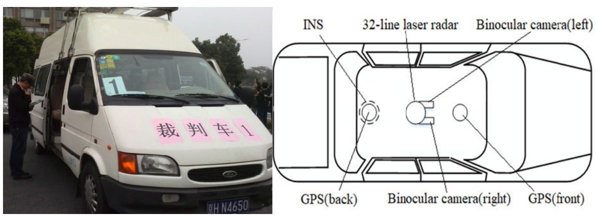
#### 3) NASH EQUILIBRIUM

Generally, the solution of a static game with complete information is called Nash equilibrium, which is a strategy set that cannot achieve a better situation by changing the players' actions in the game [10]–[12]. This means that there is no strategy set superior to the Nash equilibrium. In a game $G$ with $n$ players, $s_i'$ and $s_i''$ refer to the two strategies can be selected by a player, $s_{-i}$ refers to the strategies of other players. When (2) is satisfied, we call that strategy $s_i'$ is obviously better than strategy $s_i''$. When (3) is satisfied, the strategy set $S^* = \{s_1^*, s_2^*, \ldots, s_i^*, \ldots, s_n^*\}$ is called a Nash equilibrium of $G$.

$$u_i(s_i', s_{-i}) > u_i(s_i'', s_{-i}) \tag{2}$$

$$u_i(s_i^*, s_{-i}^*) > u_i(s_i, s_{-i}^*), \quad \forall s_i \in S_i, \ \forall i \tag{3}$$

(a) Acquisition process of subgrade data




(b) The FORD retrofit vehicle and layouts of sensors

**FIGURE 2.** Data acquisition.

where, $s_i$ refers to the strategy selected by $i$th player and $s_1^*$ represents the optimal one, $S_{-i}^* = \{s_1^*, \ldots, s_{i-1}^*, s_{i+1}^*, \ldots, s_n^*\}$ refers to the strategy set of other players, $u_i$ refers to the payoff of $i$th player under given strategy set.

### *B. DATA*

The data used in this article was collected by a subgrade camera and a retrofit referee vehicle in the 2017-2018 World Intelligent Driving Challenge (WIDC). The symmetric exponential moving average method (sEMA) was adopted to smooth the training data [13].

#### 1) SUBGRADE DATA ACQUISITION

The subgrade data collecting process is as follows:

(1) Use map software to calibrate the reference points. Select 5 (at least 5) reference points in the video interface one after another. The red dots represent the reference points marked manually, and the blue ones are the image coordinates of these reference points, which are transformed by their geodetic coordinates. Once the red dots and blue dots coincide, the coordinate calibration can be regarded as accurate. The processing is shown in Fig. 2(a).

(2) Add the vehicle ID. The trajectories of intelligent vehicles and human-driving vehicles are extracted, including positions, velocities, accelerations, etc., to analyze the behaviors of vehicles. The partial trajectory data of vehicles at the intersection are shown in Table 1, including longitudinal and lateral coordinates, velocities, accelerations.

#### 2) VEHICLE DATA ACQUISITION

The vehicle data were collected by the FORD referee vehicle, which was equipped with several kinds of sensors (Fig. 2(b)). The binocular cameras and LIDAR can detect, track and localize dynamic objects. The outputs of the fusion algorithm are positions of vehicles.

## III. THE DECISION-MAING MODEL BASED ON GAME THEORY

### *A. RESEARCH ON INTERACTION BEHAVIORS BETWEEN VEHICLES*

Researching interaction behaviors between vehicles is helpful for understanding dynamic traffic scenarios and can further improve the legitimacy of decision-making models for intelligent vehicles. The interaction types between intelligent vehicles (IV) and human-driving vehicles (HD) are determined by the crossing intentions of IV and the driving types of HD.

#### 1) CROSSING INTENTIONS

The crossing intentions are mainly determined by the pressure $P$ and the time difference $T_c$ in conflicts. A fuzzy inference model for crossing intentions is established with $P$, $T_c$ as the inputs and crossing intentions of vehicles as the outputs.

##### *a: PRESSURE*

When vehicles approach the conflict point, the conflict pressure $P$ increases and the probability of crossing will increase too. Assuming that the effective communication range at the intersection is 150m, the pressure $P$ is set as 0 when the vehicles are on the boundary of this area. $P$ is defined as:

$$P = 1 - \frac{L_i(t)}{150} \tag{4}$$

where, $L_i$(t) refers to distance of the $i$th vehicle to the conflict point. The range of $P$ is empirically set as {0.1, 0.3, 0.5, 0.7, 0.9} and the fuzzy set is represented as {very small (VS), small (S), medium (M), large (L), large (VL)}.

##### *b: TIME*

The collision possibilities among vehicles should be considered when intelligent vehicles cross unsignalized urban intersections. The time difference $T_c$ between the two vehicles passing through the conflict point is used to evaluate the risk levels of collisions, which is defined as:

$$T_c = \left| \frac{L_1(t)}{v_1(t)} - \frac{L_2(t)}{v_2(t)} \right| \tag{5}$$

where, $L_1(t)$ and $L_2(t)$ refer to the distances of IV and HD to the conflict point, respectively, $v_1(t)$ and $v_2(t)$ refer to the velocities of IV and HD, respectively. The range of time difference $T_c$ is empirically set as {0, 3, 5, 7, 10} and the fuzzy set is {VL, L, M, S, VS} as defined above.

**TABLE 1. Partial trajectory data of vehicles at the intersection.**

| Global Time/s | $x$/m | $y$/m | $v_x$/(m/s) | $v_y$/(m/s) | $a_x$/(m/s$^2$) | $a_y$/(m/s$^2$) |
|---|---|---|---|---|---|---|
| **Intelligent vehicle** | | | | | | |
| 27:40.9 | 0 | -40.0000 | -0.4413 | 1.0545 | 0.0024 | -0.0762 |
| 27:41.0 | 0 | -39.7506 | -0.4410 | 1.0445 | 0.0027 | -0.0987 |
| 27:41.1 | 0 | -39.5025 | -0.4407 | 1.0318 | 0.0016 | -0.1199 |
| 27:41.3 | 0 | -39.2556 | -0.4406 | 1.0166 | -0.0014 | -0.1389 |
| 27:41.4 | 0 | -39.0100 | -0.4409 | 0.9992 | -0.0057 | -0.1557 |
| 27:41.5 | 0 | -38.7656 | -0.4418 | 0.9799 | -0.0109 | -0.1704 |
| 27:41.6 | 0 | -38.5225 | -0.4433 | 0.9590 | -0.0164 | -0.1829 |
| **Human-driving vehicle** | | | | | | |
| 27:40.9 | -50.0000 | 0 | -0.1460 | 0.1640 | -0.0823 | 0.0103 |
| 27:41.0 | -49.5000 | 0 | -0.1558 | 0.1652 | -0.0800 | 0.0094 |
| 27:41.1 | -49.0000 | 0 | -0.1653 | 0.1663 | -0.077 | 0.0081 |
| 27:41.2 | -48.5000 | 0 | -0.1744 | 0.1672 | -0.0733 | 0.0062 |
| 27:41.3 | -48.0000 | 0 | -0.1830 | 0.1678 | -0.0688 | 0.0038 |
| 27:41.5 | -47.5000 | 0 | -0.1911 | 0.1682 | -0.0637 | 0.0011 |
| 27:41.6 | -47.0000 | 0 | -0.1985 | 0.1682 | -0.0582 | -0.0015 |

**TABLE 2. Fuzzy logic rules of crossing intentions (IV).**

| Crossing intentions | | Pressure $P$ | | | | |
|---|---|---|---|---|---|---|
| | | VL | L | M | S | VS |
| Time $T_c$ | VL | VH | VH | H | L | L |
| | L | H | H | H | L | L |
| | M | M | M | M | L | L |
| | S | L | L | L | VL | VL |
| | VS | VL | VL | VL | VL | VL |

**TABLE 3. Fuzzy logic rules of driving types (HD).**

| Driving types | | Velocity $v$ | | | | |
|---|---|---|---|---|---|---|
| | | VL | L | M | S | VS |
| Acceleration $a$ | L | I | I | I | O | O |
| | M | I | I | O | C | C |
| | S | I | I | O | C | C |

Similarly, the crossing intentions of IV can be devided into {very high(VH), high(H), medium(M), low(L), very low(VL)}. Based on these analysis, the corresponding fuzzy logic rules are empirically listed in Table 2. The larger $P$ is and the larger $T_c$ is, the more possible IV tends to cross. On the contrary, the smaller $P$ is and the smaller $T_c$ is, the less likely IV crosses.

### 2) DRIVING TYPES

The willingness that vehicles accept or reject the crossing requests from other vehicles varies with different driving types. With the velocity and acceleration of HD as inputs, a fuzzy inference model for driving types is established based on experts' experience. In this article, the driving types are divided into 3 types {conservative(C), ordinary(O) and impulsive(I)}, and the vehicle velocity' and acceleration' fuzzy sets are {VL, L, M, S, VS}, {L, M, S} respectively. The fuzzy logic rules are shown in Table 3.

### 3) FUZZY INFERENCE PROCESS

Based on the crossing intentions of IV and the driving types of HD, a fuzzy inference model for interaction types among vehicles is established to infer the cooperation levels between the two vehicles, as shown in Fig. 3. Their cooperation levels are discretized as {H, M, L}, corresponding to cooperative relationship, unclear relationship and competitive relationship, respectively. The fuzzy logic rules of interaction model for vehicles are shown in Table 4.

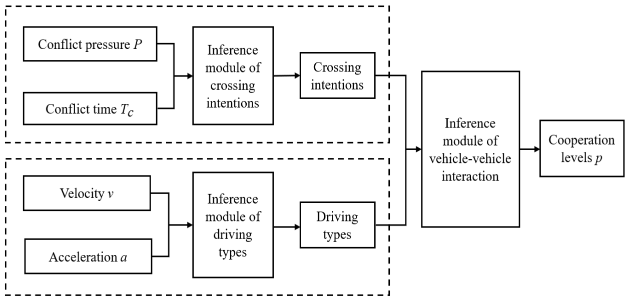



**FIGURE 3. The work process of interaction model for vehicles.**

**TABLE 4. Fuzzy logic rules of cooperation levels.**

| Cooperation levels | | Crossing intention | | | | |
|---|---|---|---|---|---|---|
| | | VH | H | M | L | VL |
| Driving types | C | H | H | H | M | M |
| | O | H | H | M | M | M |
| | I | L | L | L | L | M |

The fuzzy logic surface of the interaction model is shown in Fig. 4. Furtherly, the cooperation levels $p$ between vehicles are discretized as three specific values:

$$\text{cooperation levels between vehicles} = \begin{cases} 1 & 0 < p \leq 0.4 \\ 2 & 0.4 < p \leq 0.7 \\ 3 & 0.7 < p \leq 1 \end{cases} \tag{6}$$

where: 3, 2 and 1 represent the cooperative relationship, unclear relationship and competitive relationship, respectively.

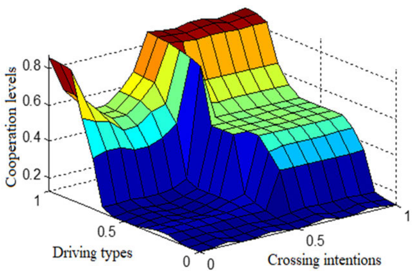



**FIGURE 4.** Fuzzy logic surface of interaction model for vehicles.

By predicting the cooperation levels between vehicles, their interaction behaviors under mixed traffic conditions are analyzed and it provides a basis for decision-making models of intelligent vehicles at urban unsignalized intersections.

### B. ANALYSIS OF CONFLICTS AT URBAN UNSIGNALIZED INTERSECTIONS

Fig. 5(a) shows the conflicts between intelligent vehicles and other vehicles at intersections, where $C_{\mathrm{ABCD}}$ refers to the conflict area, HD and IV refer to the human-driving vehicle and the intelligent vehicle, respectively. When IV enters the conflict area, the decision-making model based on game theory is established to avoid collisions in space by controlling vehicles crossing the intersections at different times. This article only focuses on the conflicts between motor vehicles. The conflicts between vehicles and non-motor vehicles or pedestrians will be discussed in future work.

To explicitly discuss the decision-making model, some assumptions are made as follows:

(1) Vehicles are all equipped with V2V systems so that they can obtain the driving characteristics of other vehicles, which lays the foundation for the establishment of game theory model.

(2) Players in the game make decisions simultaneously.

In order to efficiently analyze the conflicts between IV and HD, EPET(Estimating Post Encroachment Time) [14] is employed, which is a vital index to depict the collisions between vehicles with any angle. It is defined as time difference between the former vehicle leaving the conflict area and the latter one entering the area, as shown in Fig. 5(b).

$$\mathrm{EPET}=\mathrm{f}(x)=\begin{cases} |T_{\mathrm{IV1}}-T_{\mathrm{HD2}}|, & T_{\mathrm{HD1}}\leq T_{\mathrm{IV1}}\leq T_{\mathrm{HD2}} \\ |T_{\mathrm{IV2}}-T_{\mathrm{HD1}}|, & T_{\mathrm{IV1}}\leq T_{\mathrm{HD1}}\leq T_{\mathrm{IV2}} \end{cases} \tag{7}$$

where, $T_{\mathrm{HD1}}$ refers to the time when HD enters the conflict area, $T_{\mathrm{HD2}}$ refers to the time when HD leaves the conflict area, $T_{\mathrm{IV1}}$ refers to the time when the IV enters the conflict area, $T_{\mathrm{IV2}}$ refers to the time when IV leaves the conflict area. When $T_{\mathrm{IV1}} > T_{\mathrm{HD2}}, T_{\mathrm{HD1}} > T_{\mathrm{IV2}}$ are satisfied, there is no conflict among the two vehicles and they can cross the intersection with original driving mode. On the contrary, the conflicts among vehicles exist and they have to cross with cooperative driving mode.

### C. DECISION-MAKING MODEL BASED ON GAME THEORY

By analyzing the decision process of human drivers crossing intersections with conflicts, the conflict problem is simplified as a two-player game model. Four basic elements are as follows [15]:

(1) The players set in the game is:

$$C = \{C_1, C_2\} \tag{8}$$

where: $C_i$ refers to the $i$th players, HD and IV are two players in this model.

(2) The strategy set of all players is:

$$S = \{S_1, S_2\} \tag{9}$$

where: $S_i$, $i = 1, 2$ refers to driving strategy set of vehicle $C_i$, which is consisted of a series of driving strategies at different timesteps $s_i$, $i = 1, 2, \ldots,$ n.

(3) $U_i$ refers to the expected utility value obtained by vehicle $C_i$, which is not only related to its own strategy, but also to the strategy of another vehicle. Therefore, the utility value of vehicle $C_i$ is represented as $U_i(s_1, s_2)$. Where: $s_i$ refers to the strategy taken by vehicle $C_i$ (i.e.$s_i \in S_i$).

(4) A game with two vehicles can be represented as $G = C, S, U$. If the strategy set $S^* = \left\{s_1^*, s_2^*\right\}$ is a Nash equilibrium, the following must be satisfied:

$$U_i(s_i^*, s_{-i}^*) \geq U_i(s_i, s_{-i}^*), \quad \forall s_i \in S_i,\ i = 1, 2 \tag{10}$$

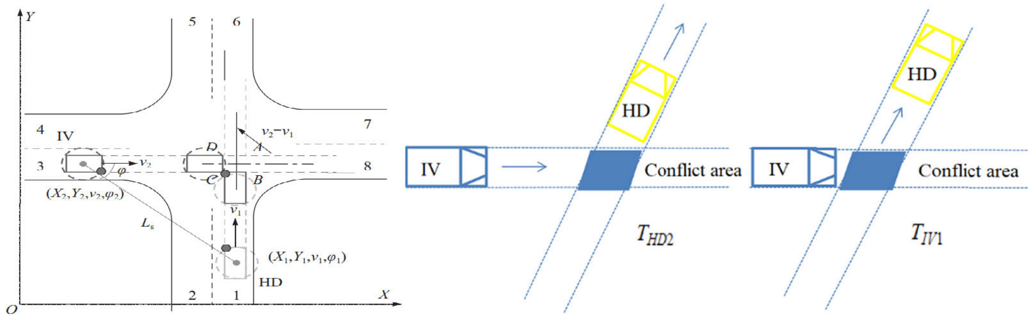
where, $s_i^*$ refers to the optimal strategy selected by vehicle $C_i$, $s_{-i}^*$ refers to the strategy of another vehicle, $U_i$ refers to the utility value of vehicle $C_i$, $S_i$ refers to the strategy set of vehicle $C_i$.

#### 1) REVENUE FUNCTION SELECTION

The driving revenue is represented by the utility value $U$ in the proposed model, which is not only related to current conditions of vehicles, but also to the potential conflict levels between them. Therefore, the safety revenue, efficiency revenue and comfort revenue are comprehensively combined to define the driving revenue in this section.

##### a: SAFETY

The safety mainly refers to the factors that can increase the severity of the conflicts between vehicles, which is represented by the time difference $\Delta T$ between the two vehicles arriving at the conflict point. The smaller the $\Delta T$ is, the smaller the driving revenue is. Otherwise, the larger the $\Delta T$ is, the larger the driving revenue is. Considering the influence of driving types on the driving strategies, the safety revenue




(a) Description of conflicts at intersections (b) The principle of EPET

**FIGURE 5. (a) Description of conflicts at intersections (b) The principle of EPET.**

is set as follows:

$$\begin{cases} U_{safe} = u\left(\Delta T\right) = \exp\left(\Delta T\right) \\ \Delta T = \left|T_1 - T_2\right| = \left|\left\{\left[\left(\dfrac{v_1\left(t\right)}{a_1\left(t\right)}\right)^2 + 2\left(\dfrac{L_1\left(t\right)}{a_1\left(t\right)}\right)\right]^{\frac{1}{2}} - \dfrac{v_1\left(t\right)}{a_1\left(t\right)}\right\}\right. \\ \qquad \left. - \left\{\left[\left(\dfrac{v_2\left(t\right)}{a_2\left(t\right)}\right)^2 + 2\left(\dfrac{L_2\left(t\right)}{a_2\left(t\right)}\right)\right]^{\frac{1}{2}} - \dfrac{v_2\left(t\right)}{a_2\left(t\right)}\right\}\right| \\ i = 1, 2; \quad t = 1, 2, \ldots, N \end{cases} \tag{11}$$

where: $u(\cdot)$ refers to normalization, $v_i(t)$, and $a_i(t)$ refer to the velocity and acceleration of the $i$th vehicle, respectively, $L_i(t)$ refers to the distance of the $i$th vehicle to the conflict point.

#### *b: EFFICIENCY*

The efficiency refers to that vehicles expect to cross intersections as quickly as possible to avoid the time delay caused by decelerating or waiting. The efficiency revenue is set as:

$$\begin{cases} U_{efficence} = u(\Delta v_i) \\ \Delta v_i = v_i(t+1) - v_i(t) \\ \qquad = a_i(t) \cdot \Delta t, \quad t = 1, 2, \ldots, N \end{cases} \quad i = 1, 2 \tag{12}$$

where, $u(\cdot)$ refers to normalization, $\Delta v_i$ refers to the velocity change of $i$th vehicle during the time difference $\Delta t$.

#### *c: COMFORT*

The longitudinal acceleration change $|\Delta a|$ is mainly considered to calculate the comfort revenue, the comfort revenue is set as:

$$\begin{cases} U_{comfort} = u(\Delta a_i) \\ \Delta a_i = \left|a_i(t+1) - a_i(t)\right|, \quad t = 1, 2, \ldots N \end{cases} \quad i = 1, 2 \tag{13}$$

where: $u(\cdot)$ refers to normalization. $\Delta a_i$ refers to the acceleration change of $i$th vehicle during the time difference $\Delta t$.

Therefore, the comprehensive driving revenue is consisted of safety revenue $U_{safe}$, efficiency revenue $U_{eff}$ and comfort revenue $U_{com}$, which is defined as:

$$U = \alpha U_{safe}(\Delta T) + \beta U_{efficence}(\Delta v_i) + \gamma U_{comfort}\Delta v_i(\Delta a_i) \tag{14}$$

where: $\alpha, \beta, \gamma$ refer to the weights of the safety revenue, efficiency revenue and comfort revenue respectively, $\alpha + \beta + \gamma = 1$. Then the whole problem can be expressed as: To solve the Nash equilibrium of the model (e.g. the optimal driving strategies) to maximize the overall driving revenue based on (14).

### 2) COOPERATIVE DECISION-MAKING PROCESS OF VEHICLES

The cooperative decision-making process of HD and IV at urban intersections filled with potential conflicts is shown in Fig. 6. And the decision-making model outputs the optimal driving strategies of the two vehicles, as shown in (15):

$$\begin{cases} S_1 = \left\{a_1^{(1)}, a_2^{(1)}, \cdots, a_n^{(1)}\right\} \\ S_2 = \left\{a_1^{(2)}, a_2^{(2)}, \cdots, a_n^{(2)}\right\} \end{cases} \tag{15}$$

A series of deceleration or acceleration actions are included in the optimal strategies, which decide whether the two vehicles yield or speed up to pass through the intersection.

## IV. EXPERIMENT AND COMPARISON

A simulation platform based on Prescan and Matlab/Simulink has been built to evaluate the effectiveness and reliability of the proposed model.

### *A. SIMULATION AND VERIFICATION PLATFORM*

Prescan is a simulation environment for developing advanced driver assistant systems (ADAS) and intelligent vehicle (IV) systems. It is a platform that can be used to build 3D traffic virtual scene, generate vehicles, pedestrians, traffic lights and other control modules. Prescan comes up with a powerful graphics preprocessor, a high-end 3D visualization viewer, and a connection to standard MATLAB /Simulink. It is composed of various main modules, some of these main modules represent a specific world and multiple sensors are simulated in the Sensor World.

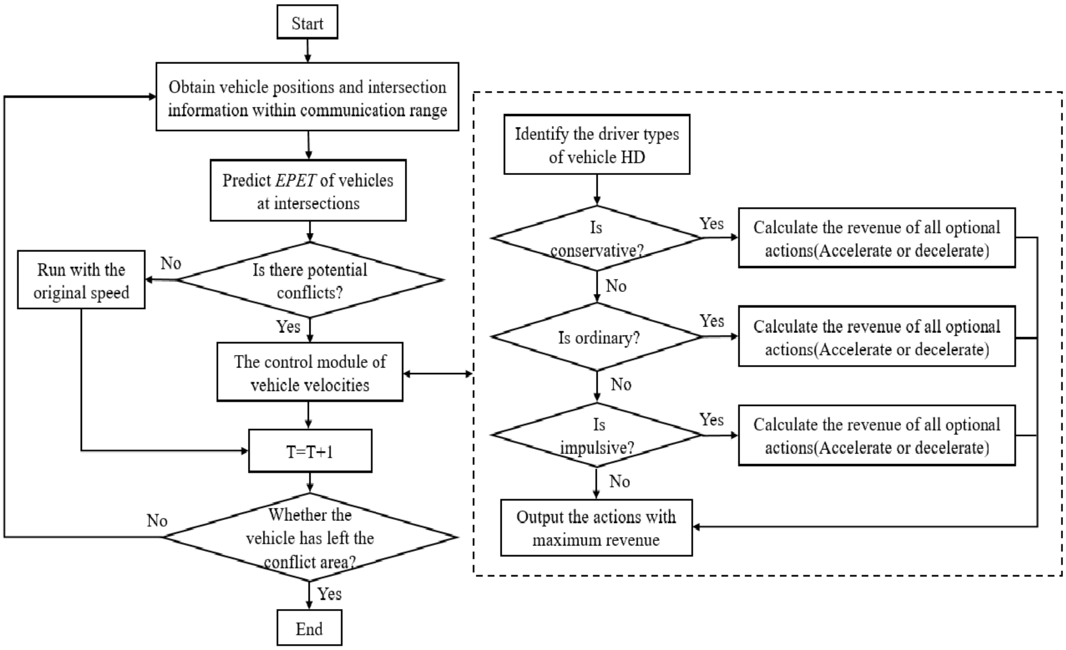
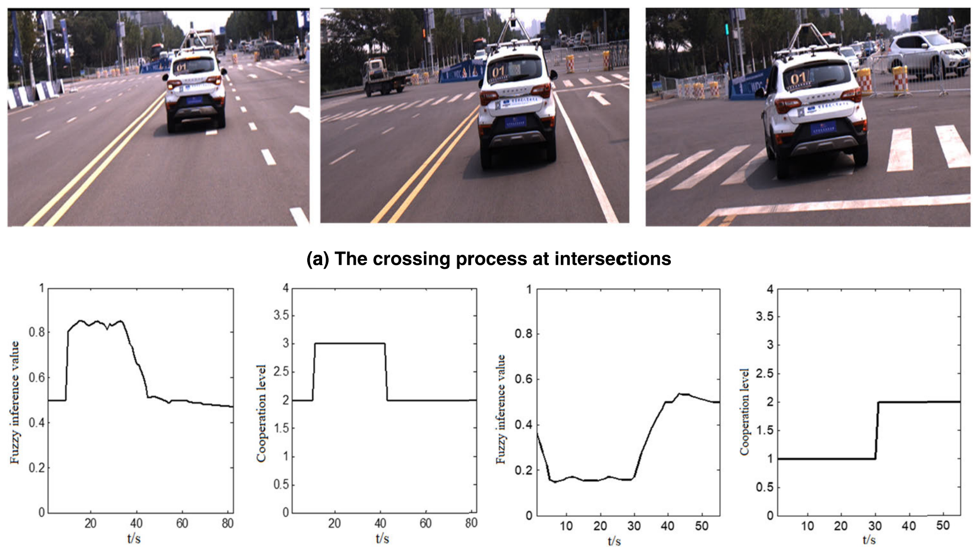



**FIGURE 6.** **The cooperative decision-making process of IV and HD.**




(a) The crossing process at intersections

(b) Inferred cooperation levels in Group A

(c) Inferred cooperation levels in Group B

**FIGURE 7.** **(b) Inferred cooperation levels in Group A (c) Inferred cooperation levels in Group B.**

### *B. VERIFICATION OF INTERACTION BEHAVIORS BETWEEN VEHICLES*

In this section, driving data at real urban intersections (Fig. 7(a)) are collected to verify the effectiveness and reliability of the interaction model for vehicles. Two groups of driving data with successful crossing (Group A) and unsuccessful crossing (Group B) are respectively collected to infer the cooperation levels between vehicles (Fig. 7(b-c)). The results show that the cooperation levels between the vehicles in Group A is higher to ensure they all can pass through the intersection successfully and efficiently.

To further verify the accuracy of the interaction model, 120 groups of crossing data at intersections are collected by a subgrade camera to infer the cooperation levels between HD and IV (Fig. 8). It can be seen the model can correctly classify most of the interaction behaviors with an accuracy of 91.6%. The results show that intelligent vehicles have the abilities to understand human behaviors, which provides theoretical

**TABLE 5.** Utility values of different driving strategies.

| Time/s | HD: acceleration IV: acceleration | HD: deceleration IV: acceleration | HD: acceleration IV: deceleration | HD: deceleration IV: deceleration |
|---|---|---|---|---|
| 1 | -0.3658, -0.0525 | **0.4886, 0.2000** | -0.7414, -0.0780 | 0.1960, 0.2000 |
| 2 | -0.3659, -0.0211 | **0.4352, 0.2300** | -0.7119, -0.0612 | 0.1685, 0.2000 |
| 3 | -0.3658, 0.0050 | **03175, 0.2300** | -0.6880, -0.0344 | 0.1212, 0.2000 |
| 4 | -0.3658, 0.0230 | **0.2300, 0.2300** | -0.6400, -0.0026 | 0.0664, 0.2000 |
| 5 | -0.3659, 0.0415 | **0.0891, 0.2300** | -0.5035, 0.0270 | -0.0650, 0.2000 |
| 6 | -0.3657, 0.1163 | -0.1422, 0.2300 | -0.4626, 0.0552 | **-0.1045, 0.2000** |
| 7 | -0.3230, 0.1794 | -0.2925, 0.2300 | -0.3908, 0.0820 | **-0.2161, 0.2000** |
| 8 | **-0.0140, 0.3605** | -0.2158, 0.2300 | -0.2380, 0.0138 | -0.2856, 0.2000 |
| 9 | **0.2315, 0.2856** | -0.2037, 0.2300 | -0.1240, 0.2985 | -0.4050, 0.2000 |
| 10 | **0.3892, 0.1120** | -0.2060, 0.2300 | -0.4830, 0.4982 | -0.9305, 0.7130 |

**(The bold data represents the utility values of optimal driving strategies at each timestep)**

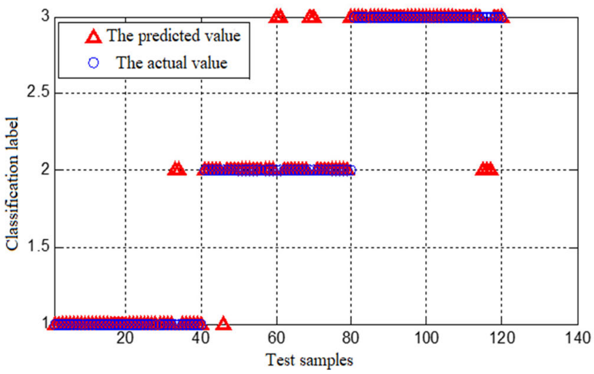



**FIGURE 8.** Predicted results of interaction model for vehicles.

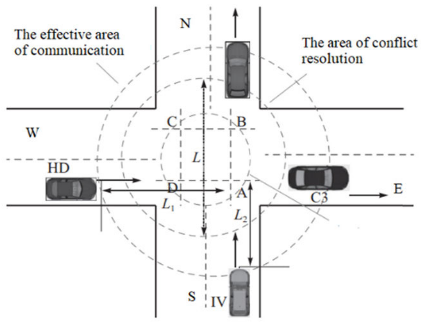



**FIGURE 9.** Traffic scenario at urban intersections.

support for the collaboration between human-driving and intelligent vehicles.

### C. VERIFICATION OF DECISION-MAKING MODEL BASED ON GAME THEORY

The above experimental results show that the collaboration between human-driving and intelligent vehicles can be achieved at complex traffic conditions. In this section, a decision-making model based on game theory for intelligent vehicles is established to improve traffic efficiency at urban unsignalized intersections.

#### 1) SCENARIO SETTING

The traffic scenarios have been built by Prescan, showed as Fig. 9. And the initial conditions of the two vehicles are $X_1 = (L_1, v_1, a_1) = (40, 12.5, 0)$, $X_2 = (L_2, v_2, a_2) = (40, 12.5, 0)$ respectively. The maximum velocity allowed at intersections should meet $v_{\max} \leq 15$ m/s. Assuming that safety is the most significant index in the crossing process, the weights $\alpha, \beta, \gamma$ of the revenue function are select as 0.5, 0.3, 0.2, respectively in this article.

#### 2) THE RESULTS ANALYSIS IN CROSSING PROCESS

The crossing process can be represented as $G = S_1, S_2; U_1, U_2$, where, $U_1$ and $U_2$ refer to HD and IV respectively, $S_1$ and $S_2$ refer to the strategies taken by them respectively. To simplify the decision-making model, the longitudinal acceleration $a$ is divided into 6 certain values (e.g. $a = \pm 1.5, \pm 1.0, \pm 0.5\}$m/s2) according to driving types (conservative, ordinary, impulsive). During the crossing process at the intersection, the two vehicles always select the driving strategies that can maximize their utility values. Assuming that the driving types of HD and IV are conservative- conservative, the utility values of HD and IV in 4 various driving strategy sets are shown in Table 5. The utility values of optimal driving strategies at each timestep are marked as bold data. During $t = 1 \sim 6$s, the optimal strategies for HD and IV are deceleration-acceleration. When $t = 6$s, they all decelerate to ensure safety as IV reaches the conflict point earlier. After $t = 8$s, IV has passed through the conflict point, indicating that the conflicts among them have been resolved and their optimal driving strategies turn into acceleration-acceleration, as shown in Fig. 10(a).

Similarly, the optimal driving strategies of the two vehicles under other driving types are shown in Fig. 10(b-f). $T_{\text{cross}}$ refers to the crossing time of vehicles, which defined as the moment when the last vehicle leaves the conflict point. The results show that IV can adjust its own driving strategies based on the behaviors of HD and the crossing time $T_{\text{cross}}$ varies when they have different driving types.

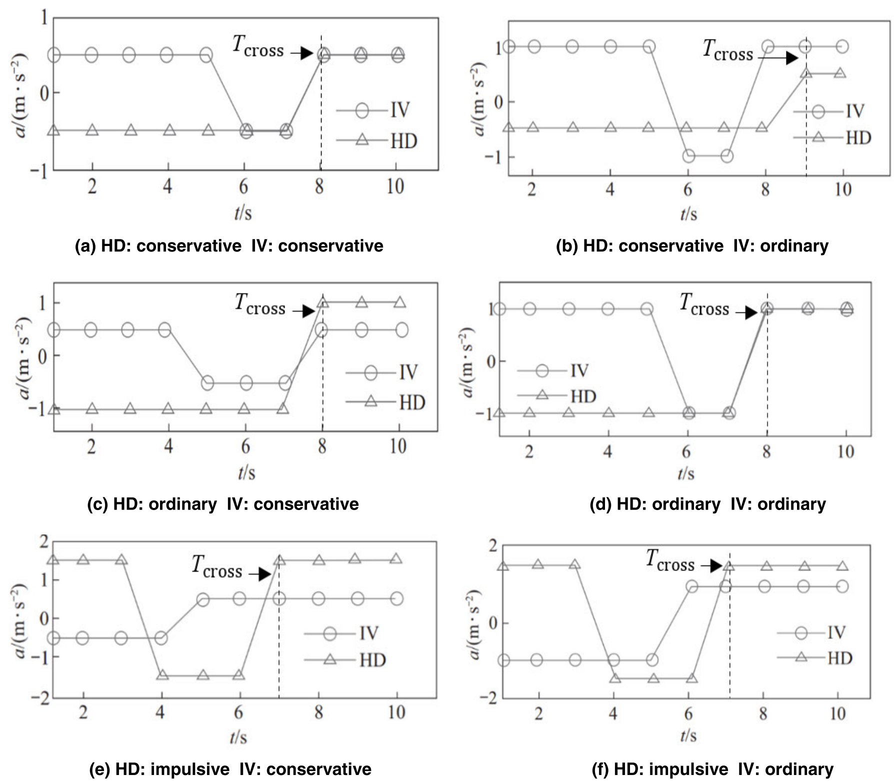



**FIGURE 10.** **The optimal driving strategies of the two vehicles under different driving types.**

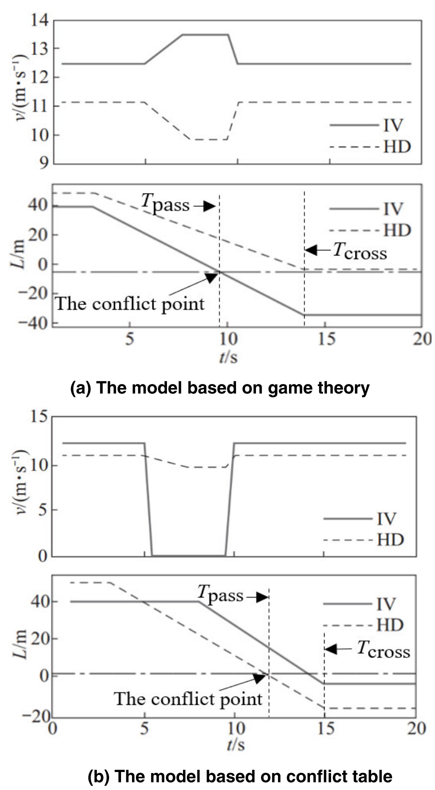



**FIGURE 11.** **(b) The model based on conflict table.**

### 3) THE RESULTS ANALYSIS WITH COMPARED MODEL

To further verify the efficiency of the proposed model, the decision-making model based on the conflict table [16] is compared with it. The results show the position and velocity changes of the two vehicles to the conflict point (Fig. 11(a-b)). $T_{pass}$ refers to the moment that the first vehicle arrives at the conflict point and $T_{cross}$ is same defined as above. The results show that IV can adjust its own velocities to accelerate through the conflict point instead of waiting for HD passing firstly in the proposed model. Compared with the model based on conflict table, it can decrease $T_{pass}$ by 20 percent and $T_{cross}$ by 15 percent (Table 6), respectively, which can obviously improve the traffic efficiency at urban unsignalized intersections.

**TABLE 6.** **The results of the two decision-making models.**

| Model | Model based on game theory | Model based on conflict table |
|---|---|---|
| $T_{pass}$/s | 9.5 | 12.1 |
| $T_{cross}$/s | 12.8 | 15.0 |

## V. CONCLUSION AND FUTURE WORKS

In order to help intelligent vehicles cross urban unsignalized intersections more safely and efficiently, this article proposed a decision-making model based on game theory for intelligent vehicles, which considers the complexity of traffic and interaction behaviors between vehicles at urban intersections. The main conclusions are listed as follows:

(1) The interaction behaviors between vehicles in scenarios of intersection-crossing are studied and it provides theoretical

basis for the decision-making of intelligent vehicles at urban unsignalized intersections. The decision-making model based on game theory and the optimal driving strategies under the Nash equilibrium are developed with the consideration of driving safety, efficiency and comfort.

(2) By conducting a series of simulation experiments, the reliability and effectiveness of the decision-making model are verified. The results show the model can significantly reduce the crossing time of vehicles at intersections.

The decision-making process of intelligent vehicles is influenced by many other factors. The impacts from pedestrians, non-motor vehicles, road structure types and traffic flow density will be studied and discussed in future work.

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