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Cognition-Driven Traffic Simulation for Unstructured Road Networks

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Abstract Dynamic changes of traffic features in unstructured road networks challenge the scene-cognitive abilities of drivers, which brings various heterogeneous traffic behaviors. Modeling traffic with these heterogeneous behaviors would have significant impact on realistic traffic simulation. Most existing traffic methods generate traffic behaviors by adjusting parameters and cannot describe those heterogeneous traffic flows in detail. In this paper, a cognition-driven traffic-simulation method inspired by the theory of cognitive psychology is introduced. We first present a visual-filtering model and a perceptual-information fusion model to describe drivers' heterogeneous cognitive processes. Then, logistic regression is used to model drivers' heuristic decision-making processes based on the above cognitive results. Lastly, we apply the high-level cognitive decision-making results to low-level traffic simulation. The experimental results show that our method can provide realistic simulations for the traffic with those heterogeneous behaviors in unstructured road networks and has nearly the same efficiency as that of existing methods.

Keywords unstructured road network, traffic simulation, cognition-driven, heterogeneous

1 Introduction

Unstructured road networks are road networks in which traffic features (e.g., topological structures, traffic signs, and traffic accidents) change dynamically. These changes occur frequently and they are unpredictable [1,2], challenging drivers' cognitive and decision-making abilities and leading to various heterogeneous traffic behaviors. It is a daunting task to model these heterogeneous traffic behaviors and generate a realistic traffic flow in these networks.

Existing traffic-simulation methods mainly focus on physical-based and data-driven traffic simulations [3–8]. In physical-based traffic simulations, heterogeneous traffic behaviors are generated by simply adjusting parameter values [9]. In data-driven traffic simulations, the richness of heterogeneous traffic-behavior simulations is mainly determined by data quality. These methods cannot offer detailed traffic simulations in unstructured road networks. Scholars in the field of traffic psychology have analyzed the psychological changes of drivers in unstructured road networks by considering driving experience, gender, and personality characteristics [10–14]; however, most of these studies focused on driver aptitude tests. They usually do not show mathematical descriptions. Therefore, it is difficult to directly use them in traffic simulations.

To tackle the aforementioned challenges, in this paper we introduce a cognition-driven traffic-simulation method inspired by the theory of cognitive psychology. The framework of our method is shown in Fig.1. There are three processes in our method: the heterogeneous cognitive process, the heuristic decision-making process, and the low-level-traffic simulation process. We

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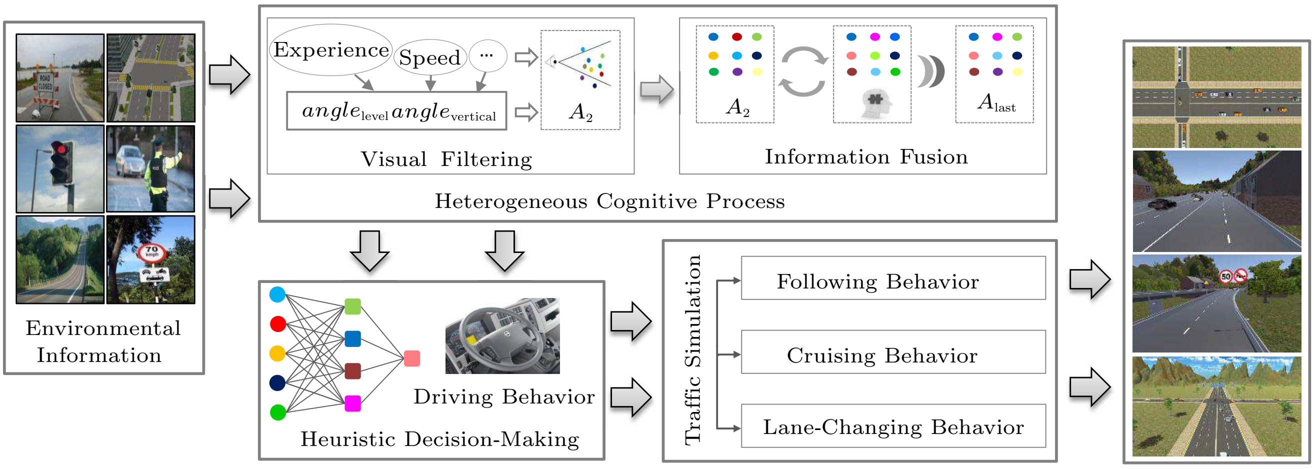


Fig.1. Framework of our method.

first introduce a visual-filtering model that considers driving speed and experience, and an information-fusion model that considers the environment familiarity of the driver to model the heterogeneous cognitive process. We then use logistic regression to model the heuristic decision-making process based on the above cognitive results. Finally, we apply the high-level cognitive decision-making results to a low-level traffic simulation and introduce an integrated traffic-simulation model that considers environments, drivers and vehicles. Specifically, the input data of our method are environmental-information sets and their spatial locations. In the heterogeneous cognitive process, input data are environmental information, and output data are environmental information finally perceived by drivers. In the heuristic decision-making process, input data are the environmental information that is finally perceived by drivers, and output data are the corresponding driving decisions. In the low-level traffic simulation process, input data are drivers' driving decisions and vehicle properties, and output data are vehicles' final behavior. We outline efficiency analysis to demonstrate the merits of our method. We also demonstrate that our method could successfully reconstruct traffic flows in typical unstructured road networks.

The main contributions of this paper are as follows.

1) *Modeling the Relationship Between Environments and Drivers.* A heterogeneous cognitive process and a heuristic decision-making process are introduced to model the relationship between environmental information and driving behaviors in unstructured road networks. They can simulate heterogeneous driving behavior in detail.

2) *Modeling the Relationship Among Environments, Drivers, and Vehicles.* The high-level cognitive decision-making results are applied to low-level traffic simulation, and an integrated traffic-simulation model is presented, considering drivers, vehicles, and environments. It can successfully reconstruct traffic flows in unstructured road networks.

3) *High Efficiency.* The proposed method has high computational efficiency. It has nearly the same efficiency as that of classical traffic simulations.

The rest of the paper is organized as follows. We describe related work in Section 2. In Section 3, the method of cognition-driven traffic simulation is outlined in detail. In Section 4, experimental evaluation is presented. Finally, the conclusions are given in Section 5.

2 Related Work

Our work is a cross-section of research in the fields of both traffic simulations and traffic psychology. In this section, we give a brief review of prior work, first in traffic simulations, and then in traffic psychology.

2.1 Traffic Simulation

With the increasing volume of traffic data and software tools capable of modeling urban scenes, much research has been conducted on traffic simulations in the field of computer graphics[3–8, 15–22]. The microscopic method is a famous traffic-simulation method where each vehicle is regarded as an agent, and a set of rules are employed to generate natural traffic behaviors. Car-following models are typical microscopic models. In the car-following models, vehicles make decisions (acceleration or deceleration) according to a variety of factors, such as the state of vehicles in front of them in the current lane, speed limits, and road conditions[23]. Other models, such as the generalized force model (GFM) proposed by Helbing and Tilck [23], and the intelligent-driver model (IDM) proposed by Treiber *et al.* [24] can also simulate many different traffic conditions well. These models mainly focus on physical-based traffic simulations. They simulate multiple traffic behaviors in unstructured road networks by simply adjusting the values of model parameters. Xu *et al.* [25] introduced the Smog Full Velocity Difference Model (SMOG-FVDM) to simulate how the weather affects drivers' behaviors. Lin *et al.* [26] presented an agent-based approach to animate microscopic mixed traffic involving cars and motorcycles in unstructured road networks. There are few descriptions about drivers' heterogeneous cognitions. Some data-driven traffic-simulation methods have also been proposed [4, 19, 20]; however, the richness of heterogeneous traffic-behavior simulations in these methods is mainly determined by data quality.

2.2 Traffic Psychology

Currently, scholars in the field of traffic psychology mainly analyze driving behaviors from the aspects of driving experience [10, 11], gender [12–14, 27, 28], in-car interference [29–31], weather, and climate [32]. However, little research has been aimed at simulating driving behaviors in unstructured road networks. There are still some important theoretical achievements. For example, according to the theory of anchoring effect, different drivers may show different driving behaviors due to their different environment familiarities [33, 34]. In addition, according to the theory of the chameleon effect, there are herd behaviors between nearby vehicles, especially when environmental information is insufficient [10]. The abilities of drivers' herd behaviors are determined in some ways by their driving experiences [35]. These theories focus on drivers' aptitude tests and do not introduce mathematical descriptions; thus, they cannot be directly used for traffic simulations.

In the field of cognitive science, there are some well-known cognitive models, such as the Adaptive Character of Thought-Rational (ACT-R) model and the State, Operator and Result (SOAR) model, which model human cognitive processes [36]. Most of these models have a series of complex processes, and it is difficult to use these models for traffic simulations due to their complexity and large time consumption.

In summary, in the field of traffic psychology, there are few efficient mathematical models for driving-behavior simulations in unstructured road networks.

3 Cognition-Driven Traffic Simulation

Vehicles move along lanes under drivers' control. Drivers make reasonable decisions by perceiving the surrounding environmental information, and then drive their vehicles safely and smoothly. In this section, we give detailed descriptions of the three processes in our method.

3.1 Heterogeneous Cognitive Process

About 90% of the information that drivers perceive from the environment is obtained from vision [37]. Therefore, our cognitive process focuses on visual perceptions.

Let the traffic environmental-information set be $D = (\boldsymbol{X}_1, \boldsymbol{X}_2, ..., \boldsymbol{X}_N)$, where N represents the maximum amount of traffic environmental information, and $\boldsymbol{X}_j (j \in [1, N])$ is the j-th information set, the elements of which are mutually exclusive (for example, red/green/yellow light). It is described as follows:

$$\boldsymbol{X}_j = (d_{1j}, d_{2j}, ..., d_{m_j j})^{\mathrm{T}}, \tag{1}$$

where m_j represents the number of elements, and $d_{ij} (i \in [1, m_j])$ represents the probability of occurrence of the i-th element in the j-th information set in environments. $d_{ij} \in [0, 1]$ and $\forall j$, $\sum_{i=1}^{i=m_j} d_{ij} = 1$.

It is easy to prove that D is not a matrix and that it is difficult to operate it in our subsequent simulations. To facilitate the computation process of the simulations, we give the matrix form of D here: $\boldsymbol{A} = (d_{ij})_{M \times N}$, where $M = \max\{m_1, m_2, ..., m_N\}$ and $d_{ij} \equiv 0$ $(j \in [1, N], i \in (m_j, M])$.

We then introduce a visual-filtering model and an information-fusion model to model the heterogeneous cognitive process. The pipeline of the cognitive process is shown in Fig.2. $\boldsymbol{A}$ is the matrix form of the traffic environmental-information set. In the visual-filtering model (Subsection 3.1.1), we first obtain $\boldsymbol{A}_1$, which describes the environmental information located in the driver's visual field. We then get $\boldsymbol{A}_2$, which describes the environmental information captured by drivers' vision. In the information-fusion model (Subsection 3.1.2), we obtain $\boldsymbol{A}_{\text{last}}$, which describes the environmental information that is finally perceived by drivers.

3.1.1 *Visual Filtering Model*

Environmental information enters drivers' perception systems through their vision. Drivers with different levels of driving experience use different methods to capture environmental information. Considering the complexities of our method, in this paper we only take into account situations in which drivers drive at daytime when the sky is bright. Driver stadia are consistent in our simulation. Next, we model how to determine drivers' horizontal and vertical visual angles.

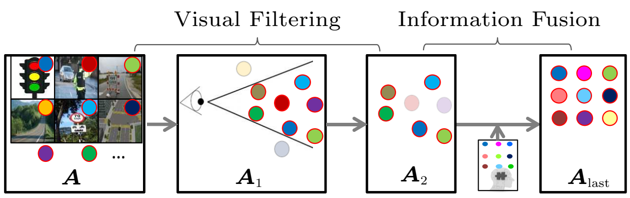


Fig.2. Pipeline of heterogeneous cognitive process.

Drivers with more driving experience have broader visual fields and more effective searching methods compared with those of inexperienced drivers [38–40]. We use the following formulas with a curve-fitting method to model the relationship between drivers' horizontal/vertical visual angles and their driving speed and experience according to the datasets created by Yuan [41]:

$$angle_{\text{level}} = \omega_1(a_1 \times v^{b_1} + c_1), \tag{2}$$
$$angle_{\text{vertical}} = \omega_1(a_2 + b_2 v + c_2 v^2), \tag{3}$$

where $angle_{\text{level}}$ represents the horizontal visual angle, $angle_{\text{vertical}}$ represents the vertical visual angle, and v represents vehicle speed. a_1, b_1, c_1, a_2, b_2, c_2 are constant. $a_1 = -0.633\,7$, $b_1 = 1.088$, $c_1 = 136.6$, $a_2 = 149.5$, $b_2 = -0.201\,4$, and $c_2 = -0.005\,2$. ω_1 describes the driving experience, $\omega_1 \in (0, 1]$. The value of ω_1 is determined by the driver's experience: if the driver has rich driving experience, we let $\omega_1 \equiv 1$. If the driver does not have driving experience, we let $\omega_1 \propto 0$ (for example, $\omega_1 \equiv 0.01$). Otherwise, we let $\omega_1 \in (0, 1)$ randomly.

Environmental information in $\boldsymbol{A}$ cannot be perceived by drivers if it is out of the drivers' visual field. The visual frustum constructed by $angle_{\text{level}}$ and $angle_{\text{vertical}}$ is used to clip $\boldsymbol{A}$ and obtain $\boldsymbol{A}_1$. Obviously, $SUM(\boldsymbol{A}_1) \leqslant SUM(\boldsymbol{A})$, and $SUM(\bullet)$ is the sum of the matrix elements.

In general, inexperienced drivers' visual-filtering processes are disorderly on some level. A driver with better skills can obtain more environmental information, even though they have the same visual frustum. In this paper, in order to simulate the differences between drivers with different levels of experience, we let the information captured by drivers be $\boldsymbol{A}_2 = (\overline{d}_{ij})_{M\times N}$, and

$$\boldsymbol{A}_2 = \boldsymbol{A}_1\boldsymbol{B}. \tag{4}$$

Here $\boldsymbol{B} = \boldsymbol{B}_{N\times N}$ is a diagonal matrix, the value of each diagonal element is randomly either 0 or 1, and $SUM(B) = \lfloor \omega_1 N \rfloor$, where ω_1 is the same as that in (2) and (3). It is easy to prove that the value of each element in $\boldsymbol{B}$ is determined by drivers' skills. More elements are set to 1 if the driver had better experience. Considering that our method is used for traffic simulations, which give low-level descriptions of drivers, we let each element in $\boldsymbol{B}$ randomly be either 0 or 1 for simplicity. It is also easy to prove that the interpretation of (4) is simply and randomly filtering environmental information in $\boldsymbol{A}_1$, and drivers with better skills can obtain more environmental information after the filtering of (4).

3.1.2 Information-Fusion Model

From the viewpoint of traffic psychology, the information perceived by drivers is mainly from their vision and their memories. Therefore, some environmental information entering a driver's vision may not be perceived by them, and some environmental information that does not enter drivers' vision may be perceived by drivers because of their memories. The reason for this is that there is a process of information fusion [42]. The famous Fuzzy-Logic Model of Perception (FLMP) [43] provides an information-fusion method by integrating scene and feature information. Here, we use it to simulate the perception process of information fusion about environmental information.

For the i-th element in the j-th information set in $\boldsymbol{A}_2$, c_{ij} describes the probability of occurrence of the i-th element in the j-th information set in the driver's memory. According to the FLMP model, the probability that the driver perceives this information is as follows:

$$p_{ij} = \begin{cases} \dfrac{\overline{d}_{ij}\times c_{ij}}{(\overline{d}_{ij}\times c_{ij}) + (T_{\overline{d}_{ij}} \times K_{\overline{d}_{ij}})}, & \text{if } c_{ij} \neq 0, \\ \overline{d}_{ij}, & \text{if } c_{ij} = 0, \overline{d}_{ij} \neq 0, \\ c_{ij}, & \text{if } \overline{d}_{ij} = 0, \end{cases} \tag{5}$$

where $T_{\overline{d}_{ij}} = 1 - \overline{d}_{ij}$, $K_{\overline{d}_{ij}} = 1 - c_{ij}$, and $\overline{d}_{ij}$ is the element of $\boldsymbol{A}_2$, which was described in Subsection 3.1.1.

Then the final information that a driver finally perceives is $\boldsymbol{A}_{\text{last}} = (p_{ij})_{M\times N}$. The amount of information that drivers finally perceive may not be the same as the amount of information captured by drivers after visual filtering. Sometimes the former is larger because of supplements from drivers' memory, and sometimes the latter is larger because there is a conflict between the information in drivers' memories and the information captured by drivers after visual filtering.

3.2 Heuristic Decision-Making Process

Let the decision set be $\boldsymbol{Q} = (q_1, q_2, ..., q_S)$, where S represents the total number of decisions, q_i $(i \in [1, S])$ represents the i-th decision, and $q_i \in \{y_1^i, y_2^i, ..., y_t^i\}$. $y_1^i, y_2^i, ..., y_t^i$ represent mutually exclusive decisions (for example, acceleration, deceleration, uniform speed and stopping).

According to cognitive psychology, people usually make decisions through a simple heuristic process [44]. The logistic-regression model is used to obtain drivers' final decisions based on the above perception results (shown in Fig.3):

$$P(q_i = y_j^i) = \frac{\mathrm{e}^{\beta_{00} + \sum\limits_{i=1}^{M}\sum\limits_{j=1}^{N}\beta_{ij}p_{ij}}}{1 + \mathrm{e}^{\beta_{00} + \sum\limits_{i=1}^{M}\sum\limits_{j=1}^{N}\beta_{ij}p_{ij}}},$$

where $P(q_i = y_j^i)$ means the probability that $q_i = y_j^i$. p_{ij} is the element of $\boldsymbol{A}_{\text{last}}$, and β_{ij} $(i \in [0, M], j \in (0, N])$ is calculated by maximum likelihood estimation. The input data of the estimation are the environmental information finally perceived by drivers and the corresponding driving decisions. It is difficult to collect the data in practice. In this paper, we collect them in a virtual evaluation system. Testers entered virtual cars in virtual scenarios, and their horizontal and vertical visual angles are not modeled and are given randomly to exclude errors of cognitive processes. Those testers watched their surrounding environment, and then checked the environmental information that they finally perceived ($\boldsymbol{A}_{\text{last}}$) and their corresponding driving decisions ($\boldsymbol{Q}$).

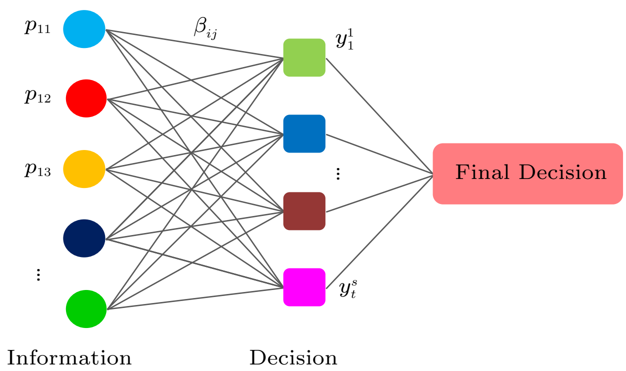


Fig.3. Drivers' heuristic decision-making process.

3.3 Integrated Traffic-Simulation Process

Drivers drive vehicles according to the above driving decisions. There are mainly three driving behaviors: following, cruising, and lane-changing behavior. In this paper, the classical IDM model [24] is used to model the following behavior and the integrated lane-changing model proposed by Wang *et al.* [17] is used to model lane-changing behavior. Let vehicle acceleration under a driver's cognition be a_{inf}, which is equal to the vehicle's comfortable acceleration, 0, and maximum deceleration, if the driver's decision is to accelerate, maintain uniform decelerate, and stop, respectively. Then, vehicle acceleration a in the three behaviors above is as follows.

1) *Following Behavior.* Following behavior is responsible for controlling a vehicle to maintain a safe distance between it and the leader vehicle in the lane and avoid collisions with the leader vehicle. Let the vehicle's acceleration obtained by IDM be a_{IDM}; then,

$$a = \min\{a_{\text{inf}}, a_{\text{IDM}}\}.$$

2) *Cruising Behavior.* In cruising behavior, there are no leader vehicles. Drivers drive vehicles according to the acceleration obtained by their cognition, that is,

$$a = a_{\text{inf}}.$$

3) *Lane-Changing Behavior.* Lane-changing behavior is motivated by lane-changing necessity. There are mainly two types of lane-changing necessities.

• Discretionary lane change that is motivated by a preference. For example, a driver changes lane to increase speed.

• Mandatory lane change that is motivated by transit requirements. For example, a lane is closing.

Once there is a feasible lane-changing trajectory, and the vehicle has begun to change its lane, its acceleration is as follows:

$$a = \min\{a_{\text{inf}}, a_{\text{lane\_change}}\},$$

where $a_{\text{lane\_change}}$ is the acceleration determined by the integrated lane-changing model [24].

4 Experimental Evaluation

In this section, we offer some comparisons of our method and SMOG-FVDM presented by Xu *et al.* [25], which is similar to ours. We also used our method to reconstruct traffic simulations in typical unstructured road networks.

First, we created a virtual evaluation system. The amount of traffic environmental information was 20 ($N \equiv 20$ in Section 3). We obtained 100 data groups from the virtual evaluation system and then used SPSS (Statistical Product and Service Solutions) software① to compute the value of β_{ij} ($i \in [0, M], j \in (0, N]$) according to the descriptions in Subsection 3.2. Note that it only took very little time to finish the computation (a few seconds).

4.1 Comparison Results

In this paper, we introduced a cognition-driven traffic-simulation method to describe drivers' heterogeneous behaviors in unstructured road networks. In our model, different drivers had different parameter values. It was difficult to obtain them from existing open datasets (for example, NGSIM (Next Generation Simulation)② and LiDAR (Light Detection and Ranging) [45]), thereby we could not perform some validations for traffic simulations using real-word data. We used our method and SMOG-FVDM to construct an intersection scenario with improper traffic-light positioning. We then compared their simulation results.

The scenario with improper traffic-light positioning depicted traffic behavior in an intersection where traffic lights were located at the center. There were three traffic lanes, and drivers could not perceive traffic signals in the westbound nearside lane. We simulated this scenario using our method and SMOG-FVDM. In our simulation, westbound-green-light duration in the intersection was 30 s, the expected speed of traffic flows was 6 m/s, and the maximum expected acceleration was 2.7 m/s^2. We also clipped drivers' visual region through (2) and (3) (Subsection 3.1.1).

Fig.4 shows some simulation snapshots gotten by our method. Four snapshots in this figure were time-ordered in one traffic signal cycle. Blue and red-bordered translucent cones were used to describe the visual fields of drivers in the westbound nearside lane. In Fig.4(a), the westbound traffic light was red. The leading yellow vehicle in the westbound nearside lane remained still at the stop line. We can see that the light was out of the driver's visual field. In Fig.4(b), the westbound traffic light turned green. Leading vehicles in the westbound inner two lanes moved. However, the yellow vehicle in the nearside lane remained still.

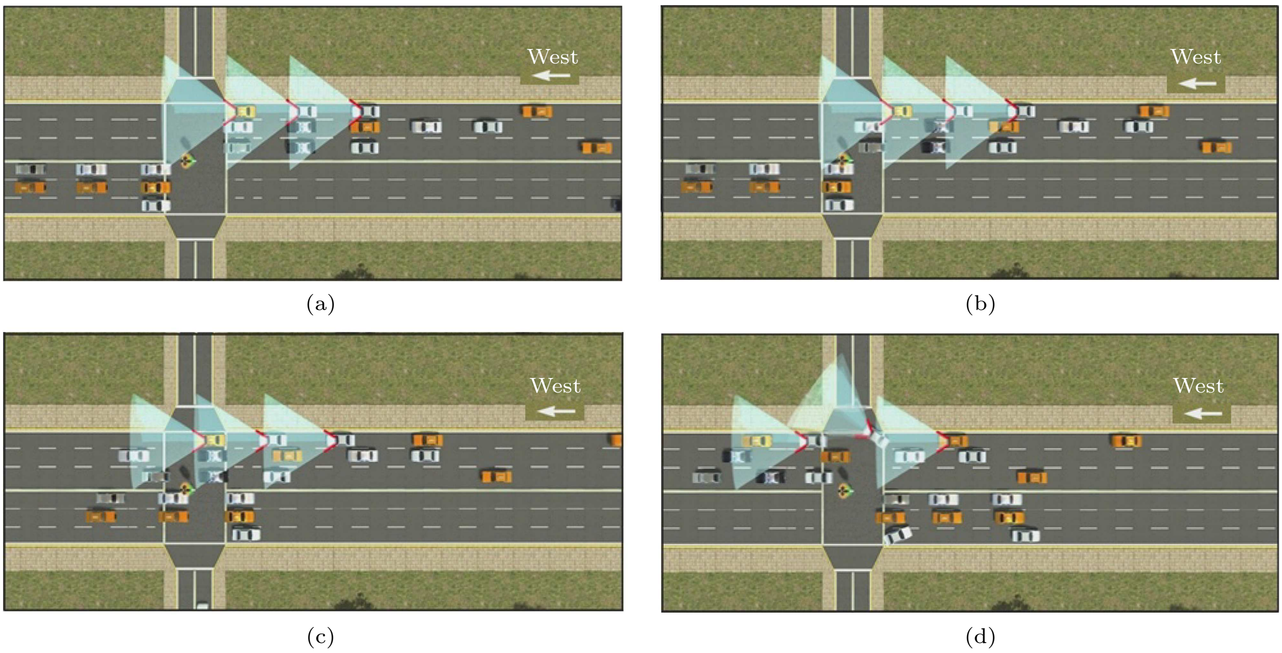


Fig.4. Snapshots of traffic simulation using our method in intersection with improper traffic-light positioning. Blue and red-bordered translucent cones are drivers' visual fields. (a)–(d) are four time-ordered snapshots. (a) The 86th frame. (b) The 99th frame. (c) The 114th frame. (d) The 134th frame.

①Spss I N C. SPSS version 16.0. Chicago, IL: SPSS Incorporated, 2007.

②FHWA, U.S. Department of Transportation. NGSIM—Next Generation SIMulation, July 2012. http://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm, July 2020.

The reason was that the light was out of the drivers' visual field and the drivers could not perceive the light changes (filtering by (2) and (3)). After a few seconds, they saw their neighbors' movements and then started to go ahead (Fig.4(c)). The reason was that, in our method, drivers begin to move if they perceive both of the following types of environmental information: there is a red light ahead, and vehicles in the neighboring same-direction lanes are moving ahead.

Fig.5 shows some simulation snapshots using SMOG-FVDM. Four snapshots in this figure were time-ordered in one traffic signal cycle. We could not obtain the visual fields of drivers in this model. In Fig.5(a), all westbound vehicles remained still at the stop line because the westbound traffic light was red. In Fig.5(b), the westbound traffic light turned green. All westbound vehicles began to go ahead, which was inconsistent with the fact that drivers in the westbound nearside lane could not perceive traffic signals and would have a delayed response.

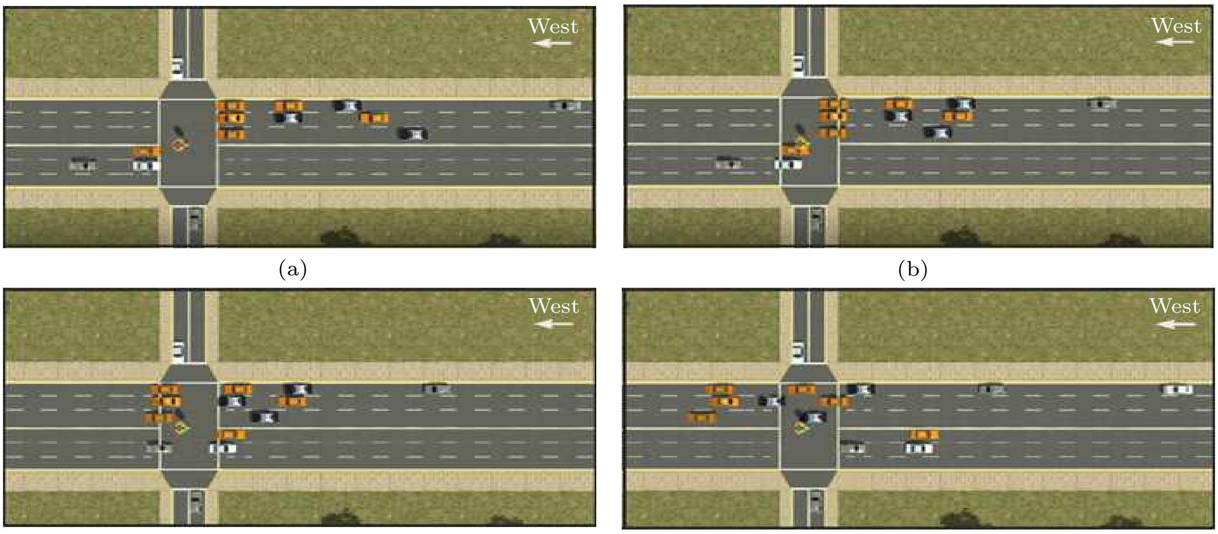
Fig.6 shows how the average speed of traffic-flow changes as a function of time in the westbound nearside lane.

4.2 Scenarios

To demonstrate the benefits of our method, we used it to reconstruct some typical traffic scenarios (Fig.7 and Fig.8), including an intersection in which a traffic sign was missing, unexpected damaged lanes, on-and-off ramp, and roundabout. Next, we mainly describe the following two scenarios. Other scenarios are highlighted in our supplementary video[3].

1) *An Intersection in Which a Traffic Sign Is Missing*. In this intersection, vehicles could turn right and go ahead in the nearside lane. However, there were no apparent hanging signs in easy-to-see places. We modeled the traffic behavior of drivers who were familiar or unfamiliar with the environmental conditions (changed the value of c_{ij} in (5)). Fig.9 shows some snapshots of the situation in which drivers were familiar with the environmental conditions. Figs.9(a)–9(d) were four time-ordered snapshots. Fig.10 shows some snapshots of the situation in which drivers were unfamiliar with environmental conditions, and Figs.10(a)–10(d) are also four time-ordered snapshots. It could be observed that there was high usage of the nearside lane when all drivers were familiar with the environmental conditions. When drivers were not familiar with them, they tried to change the lane to a neighboring lane. There were few vehicles in the nearside lane although there was a heavy traffic jam in the neighboring lanes. The reason for this was that drivers that were unfamiliar with environmental conditions did not know that they could drive ahead in the nearside lane. The outcome is highlighted in the supplementary video.

2) *Unexpectedly Damaged Lanes*. In this traffic scenario, there was a damaged point in the westbound



(a) (b) (c) (d)

Fig.5. Snapshots of traffic simulation using SMOG-FVDM in intersection with improper traffic-light positioning. (a)-(d) are four time-ordered snapshots. (a) The 86th frame. (b) The 98th frame. (c) The 113th frame. (d) The 128th frame.

[3]https://youtu.be/kxvsmZxTPWE, July 2020.

nearside lane and the lane was temporarily closed. We modeled the traffic behaviors of drivers who had much or little experience (changed the value of ω_1 in (2)–(4)).

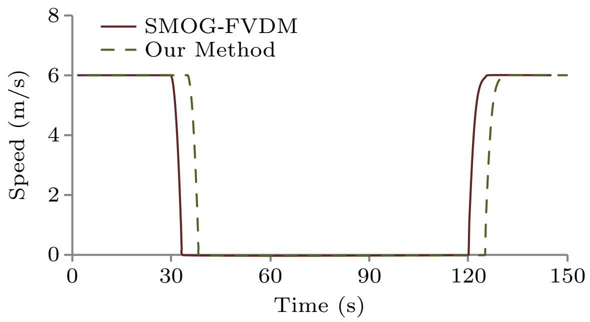


Fig.6. Average speed of traffic-flow changes in westbound nearside lane.


Fig.7. Traffic-intersection simulations.


Fig.8. Traffic country-road simulations.

Fig.11 shows snapshots of the situation in which drivers had much experience. In this figure, four snapshots were time-ordered. Vehicles that were in a lane-changing process are circled by red rectangles in the westbound nearside lane. In Fig.11(a), the leading vehicle in the lane began to change lanes when it was far away from the damaged point (yellow-line segment in the snapshot shows the distance between vehicles that began to change lanes and damaged point). The vehicle continued its lane-changing process (Fig.11(b)), and then the driver of the following vehicle saw the lane-changing behavior and also began to change lanes (Fig.11(c)). The reason was that the experienced driver could perceive all of the following three types of environmental information after visual filtering by (4): traffic was free; it was far away from on-and-off ramps; its

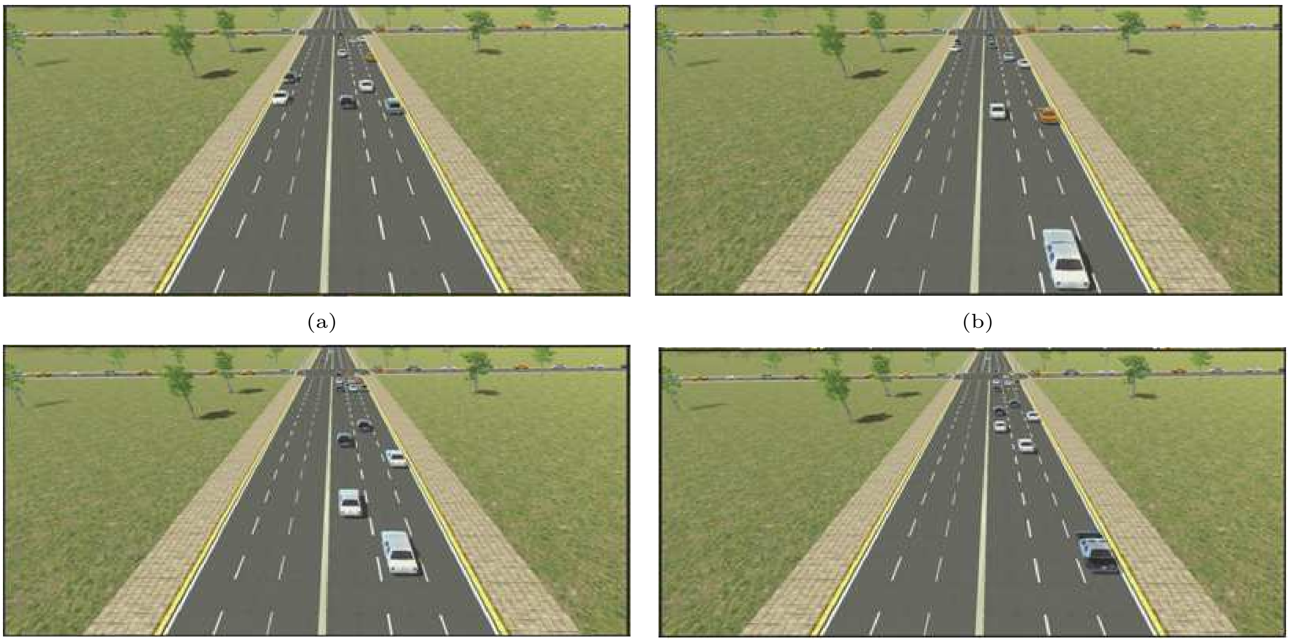

(a) (b) (c) (d)

Fig.9. Snapshots of situation in which drivers were familiar with environmental conditions. (a)–(d) are four time-ordered snapshots. (a) The 94th frame. (b) The 135th frame. (c) The 180th frame. (d) The 200th frame.

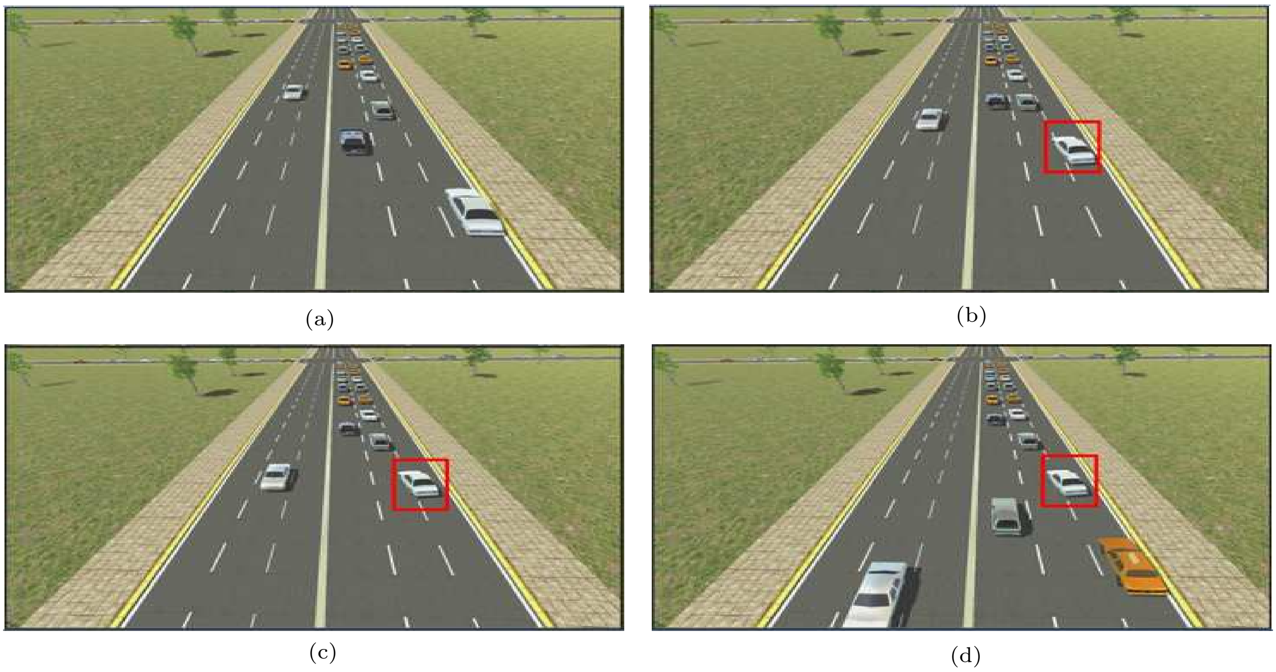


Fig.10. Snapshots of situation in which drivers were unfamiliar with environmental conditions. (a)–(d) are four time-ordered snapshots. (a) The 64th frame. (b) The 73rd frame. (c) The 82nd frame. (d) The 96th frame. Vehicles that were in a lane-changing process are circled by red frames.

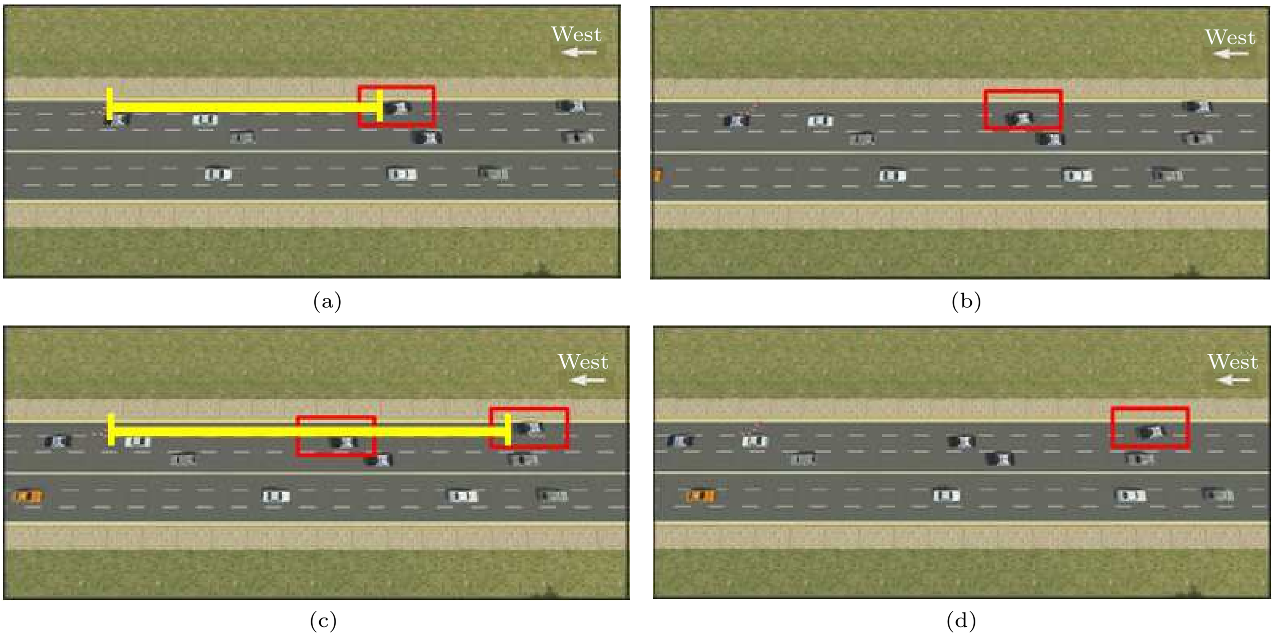


Fig.11. Snapshots of situation in which drivers were experienced. (a)–(d) are four time-ordered snapshots. (a) The 80th frame. (b) The 89th frame. (c) The 93rd frame. (d) The 96th frame. Vehicles that were in a lane-changing process are circled by red rectangles in the westbound nearside lane. Yellow-line segments show the distance between vehicles that began to change lanes and damaged point.

leading vehicles were in the middle of a lane-changing process, which would lead to a lane-changing process. Therefore, the vehicle changed lanes much farther away from the damaged point compared with its leading vehicle.

Fig.12 shows snapshots of the situation in which drivers had little experience. Four snapshots were time-ordered in this figure. Vehicles that were in the middle of a lane-changing process are circled by red rectangles in the westbound nearside lane. In Fig.12(a), the lead-

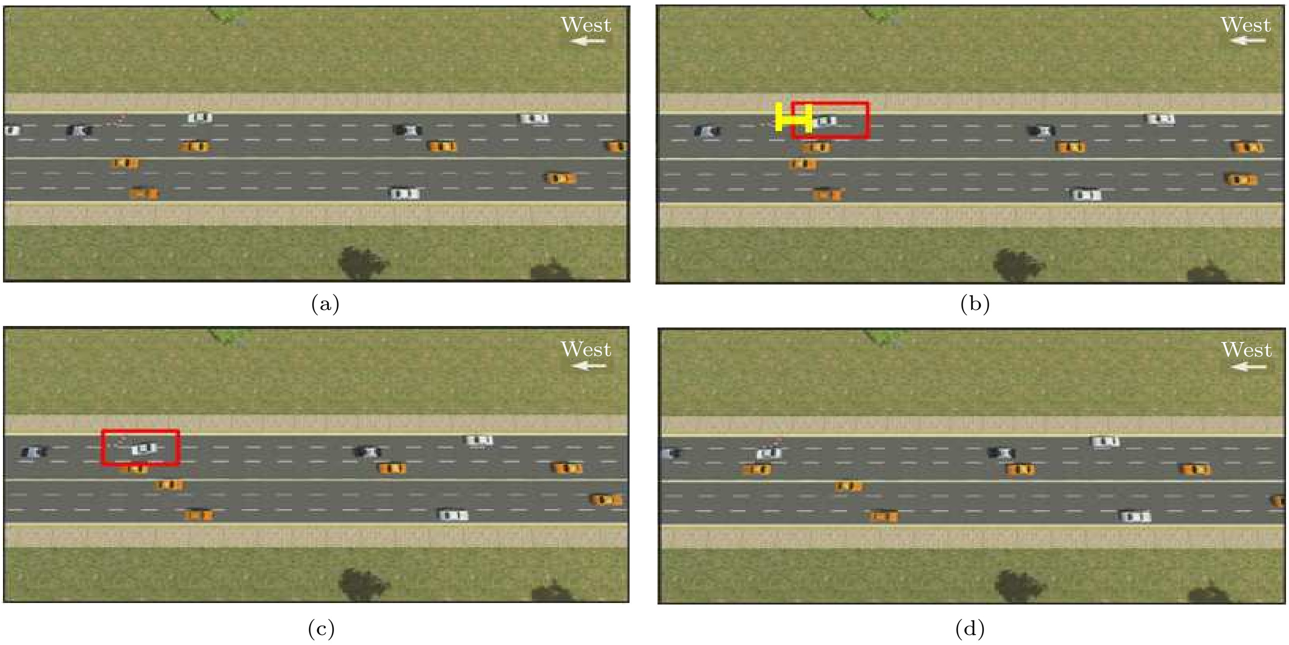


Fig.12. Snapshots of situation in which drivers were inexperienced. (a)–(d) are four time-ordered snapshots. (a) The 80th frame. (b) The 86th frame. (c) The 90th frame. (d) The 93rd frame. Vehicles that were in a lane-changing process are circled by red rectangles in the westbound nearside lane. Yellow-line segment shows the distance between vehicles that began to change lanes and damaged point.

ing vehicle in the lane did not change lanes when it was near the damaged point. It began to change lanes when it was close to the point (in Fig.12(b), yellow-line segment in the snapshot shows the distance between vehicles that began to change lanes and the damaged point). The drivers in the following vehicles could have been able to see the lane-changing behavior, but they did not begin to change lanes (Fig.12(c)). The reason is that an inexperienced driver considered that the lane-changing process of their leading vehicles was not an important type of environmental information, which no longer existed after filtering by (4). Drivers could not make a decision to change lanes in a situation in which traffic was free and far away from on-and-off ramps. Then, drivers with little experience always changed lanes after seeing the damaged point.

4.3 User Study

We used the simulation results of these three traffic scenarios described in Subsection 4.1 and Subsection 4.2 (intersection with improper traffic-light positioning, intersection in which a traffic sign is missing, and unexpectedly damaged lanes) for a user study on intuition. We surveyed a number of volunteers who had driving licenses to obtain their total driving mileage, and then divided them into three groups according to their total driving mileage: more than 10 000 kilometers, less than 100 kilometers, and all the others. In this paper, we did not model gender, age, etc. Therefore, we do not take them into account here. We randomly chose 25 volunteers from the first group and let them be drivers with much experience. We then randomly chose 25 volunteers from the second group and let them be drivers with little experience. In one scenario, a volunteer entered the virtual scenarios through virtual devices and had a first-person view of a virtual driver. They watched the vehicle's behavior and then graded it according to their intuitions. There were three possible grades: good, medium, and bad. If most of the vehicle's behavior was consistent with the volunteer's intuitions, then the grade was good; if almost all of the vehicle's behaviors were different from the volunteer's intuitions, then the grade was bad; otherwise, the grade was medium. Fig.13 shows the results. Our simulation results agreed to some degree with what happens in real life.

4.4 Performance-Scaling Comparison

The performance of this method was quantitatively analyzed and its performance was evaluated. The method includes visual-filtering, perceptual-process, and drivers' heuristic decision-making modeling, and traffic simulation based on drivers' scene cognition. Theoretically, compared with existing traffic-simulation methods, the method in this paper also includes the process of drivers' scene cognition. There is matrix computing in this process; according to (1) in Section 3, most of the matrices in the proposed method are sparse. To achieve high runtime efficiency, a six-tuple was used to compress the matrices. Matrix multiplications were transformed into the multiplication operation of some elements which is defined in Subsection 3.1 in the six-tuple. Let the number of those elements be N'. N' may be far less than N in many specific scenarios, thereby computing drivers' scene-cognitive modeling is inexpensive.

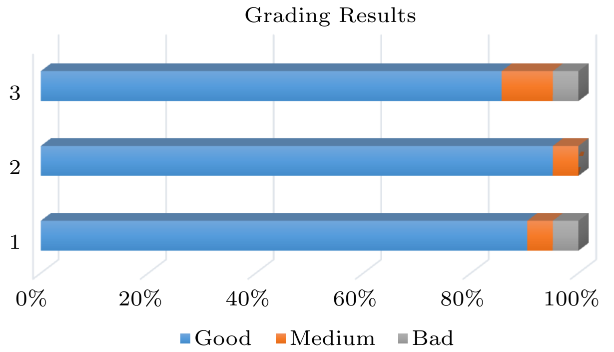


Fig.13. Results of our user study. (1–3) Scenarios of intersection with improper traffic-light positioning, unexpectedly damaged lanes, and intersection in which a traffic sign is missing, respectively.

The efficiency of the proposed model was demonstrated through two experiments to better evaluate the performance of our method. Results were collected on a work station with an Intel® Core 8 Xeon® CPU E31240 with a 3.4 GHz processor and 4.0 GB of RAM.

4.4.1 Impact of Driver Scene Cognition Modeling

Traffic behaviors were modeled by adding drivers' cognitive simulations to a traditional traffic method using the IDM model [24] for car-following simulations, and the all-in-one (AIO) model [17] for lane-changing simulations (called the IDM + AIO method). We compared the computational time of our method with that of the IDM + AIO method. Here, the amount of environmental information was $[0, N/3]$ for each simulation.

Results are shown in Fig.14. As shown, our method had nearly the same efficiency as that of the IDM + AIO method.

4.4.2 Effect of Environmental-Information Amount

According to analysis in the first paragraph of Subsection 4.3, amount of environmental information N' increases the complexity of our method. In this subsection, we discuss how N' affects compute time. There were nearly 50 000 vehicles in our simulation. Fig.15 shows the increase in computation time with an increasing N', As shown, computing time negligibly increased as N' increased. Specifically, there were only a few milliseconds of additional overhead despite $N' = 10$. In fact, it was practically impossible for so many environmental messages to exist in a traffic scenario.

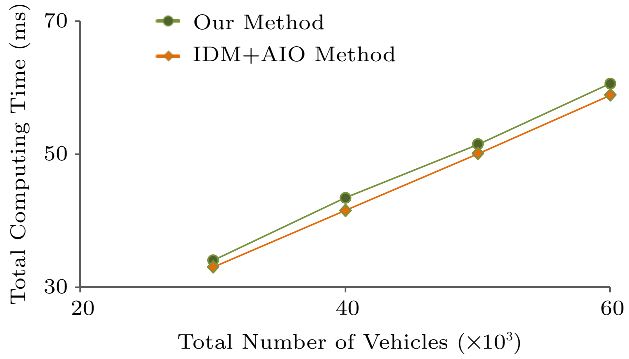


Fig.14. Total computing time as a function of number of vehicles.

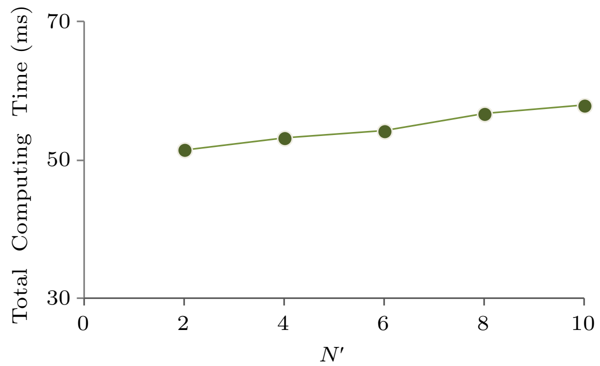


Fig.15. Total computing time as a function of N'.

5 Conclusions

In this paper, a cognition-driven traffic-simulation method inspired by the theory of cognitive psychology was introduced. Through the creative transformations of drivers' cognitive processes in a traffic-simulation framework, this method created a computational relationship of environment-driver-vehicle in the traffic-simulation framework. The experimental results showed that it could successfully reconstruct various kinds of heterogeneous traffic flows in unstructured road networks that existing methods cannot do. In the future, we aim to combine our method with SMOG-FVDM [25] to simulate smoggy and rainy scenarios. We also aim to create traffic datasets including each driver's driving-experience and environment-familiarity information.

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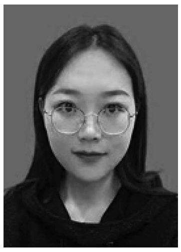

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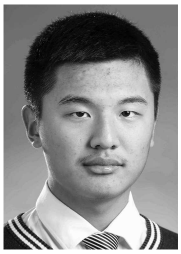

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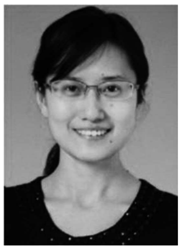

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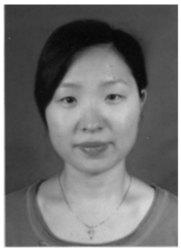

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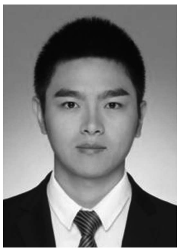

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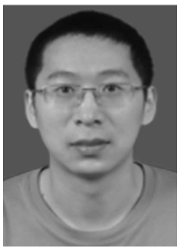

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