Article:

Zhou, Z, Wang, Y, Liu, R orcid.org/0000-0003-0627-3184 et al. (3 more authors) (2022) Short-Term Lateral Behavior Reasoning for Target Vehicles Considering Driver Preview Characteristic. IEEE Transactions on Intelligent Transportation Systems, 23 (8). pp. 11801-11810. ISSN 1524-9050

https://doi.org/10.1109/TITS.2021.3107310

Short-term Lateral Behavior Reasoning for Target Vehicles Considering Driver Preview Characteristic

Zhisong Zhou, Yafei Wang, *Member, IEEE,* Ronghui Liu, Chongfeng Wei,
Haiping Du, *Senior Member, IEEE,* Chengliang Yin

***Abstract*—A timely understanding of target vehicles (TVs) lateral behavior is essential for the decision-making and control of host vehicle. Existing physical model-based methods such as motion-based method and multiple centerline-based method are generally constructed based on TV pose and longitudinal velocity, and tend to ignore TV preview driving characteristic and other useful information such as lateral velocity and yaw rate. To address these issues, a driver preview and multiple centerline model-based probabilistic behavior recognition architecture is proposed for timely and accurate TV lateral behavior prediction. Firstly, a driver preview model is used to describe vehicle preview driving characteristic, and TV preview lateral offset and preview lateral velocity are calculated with TV states and road reference information. Then, the preview lateral offset and preview lateral velocity are combined with multiple centerline model for TV lateral behavior reasoning based on the interacting multiple model-based probabilistic behavior recognition algorithm. With this method, TV preview driving characteristic and lateral motion states are combined for precise TV lateral behavior description. Furthermore, to predict short-term lateral behavior, a preview lateral velocity-dependent transition probability matrix model constructed with Gaussian cumulative distribution function is proposed. Simulation and experimental results show that the proposed method considering vehicle preview driving characteristic predicts TV lateral behavior earlier than the conventional method.**

***Index Terms*—Autonomous vehicles, driver preview model, behavior reasoning, lateral behavior.**

I. Introduction

WITH the development of advanced sensing and communication technologies, autonomous vehicles have received much attention recently for their potential benefits on road safety and traffic efficiency [1]–[3]. For autonomous driving, the controlled autonomous vehicle is generally defined as the host vehicle (HV), and the vehicles surrounding the HV that affect the decision and planning of the HV are defined as the target vehicles (TVs). For a vehicle system including HV and TVs, the comprehensive understanding of TV lateral behavior is essential for HV decision and control. For example, in [4], the cut-in intention of nearby vehicles are predicted and considered in HV trajectory tracking control. The lateral motions of surrounding vehicles are predicted and then integrated into threat assessment algorithm of the decision-making system in [5]. In [6], TV lane change behavior are estimated and then combined in the car-following control. Methods for TV lateral behavior recognition can be classified into two categories, data-driven and physical model-based methods. For data-driven methods, vehicle driving data is collected for model training, and then the learned models are able to recognize vehicle lateral behavior. In [7], the hidden Markov model is trained with trajectory snippets and used for behavior recognition. By training the parameters of Bayesian network with collected driving data, drivers' intention can also be well identified in [8]–[10]. In [11], the multi-class support vector machine is trained for maneuver classification. Recently, with the rapid development of deep learning methods, they have also been widely used for TV behavior identification. For example, in [12], the lane change intention is predicted based on the convolutional neural network and Long Short-Term Memory network with visual information. In [13], the vehicle maneuvers are classified using artificial neural networks. Although the above mentioned data-driven methods have been widely accepted and can achieve good performance, the physical meaning of the data-driven models is unclear, and their performance is highly dependent on the quality and quantity of training data sets [14]–[16]. In this way, the development of high-accuracy physical model-based methods is also essential for TV lateral behavior reasoning. For physical model-based methods, motion model and multiple centerline model are two widely adopted models for describing TV lateral behavior. For motion model-based method, TV lane keeping and lane changing behaviors are generally modeled base on different vehicle kinematics models such as constant acceleration model and constant turn rate and acceleration model, and then these models are combined based on the interacting multiple model (IMM) method for behavior probability updating with detected TV pose. For example, in [17], the constant velocity lane keeping, constant acceleration lane keeping, constant velocity lane changing and constant acceleration lane changing models

Manuscript received November 10, 2020; revised June 8, 2021; accepted August 01, 2021. The research is supported by National Natural Science Foundation of China under Project 52072243, Sichuan Science and Technology Program under Project 2020YFSY0058 and SJTU-LEEDS Sustainable Cities Joint Living Lab Programme. *(Corresponding authors: Yafei Wang; Chengliang Yin.)*

Z. Zhou, Y. Wang, and C. Yin are with the School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China (e-mail: zhouzhisong1993@sjtu.edu.cn; wyfjlu@sjtu.edu.cn; clyin1965@sjtu.edu.cn).

R. Liu is with the Institute for Transport Studies, University of Leeds, Leeds LS2 9JT, U.K. (e-mail: R.Liu@its.leeds.ac.uk).

C. Wei is with the School of Mechanical and Aerospace Engineering, Quen's University Belfast, Belfast, BT7 1NN, U.K.(e-mail: weichongfeng@gmail.com).

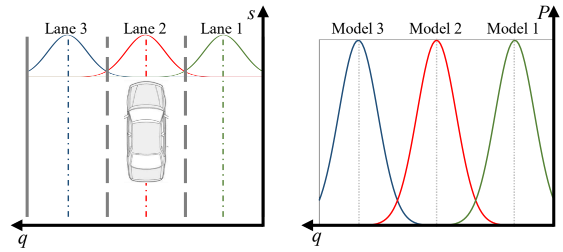
H. Du is with the School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, Wollongong, NSW 2522, Australia (e-mail: hdu@uow.edu.au)

are adopted for TV behavior modeling, and the IMM filter is used for behavior reasoning with the detected vehicle pose in road curvilinear coordinate system. Considering the limitations of the number of dynamic models for motion model-based method, TV lateral behaviors are modeled based on the lateral offsets of road centerlines in multiple centerline model-based method, and then the model probabilities are updated with TV lateral offset and lateral velocity in road curvilinear coordinate system [18]. However, due to the limitations of the existing simplified physical models, useful information such as TV lateral velocity and yaw rate, which contain significantly different features in lane keeping and lane changing processes, have not been used for model probability updating in both of these two methods [13]. Besides, driver preview driving characteristic which is common in path following control have not been considered for TV lateral behavior reasoning [19]. Therefore, to accurately describe TV lateral behavior, these two aspects mentioned above should be considered in the design of physical model-based lateral behavior reasoning architecture.

This study aims to estimate TV short-term lateral behaviors, including lane change left (LCL), lane keeping (LK) and lane change right (LCR), which are defined based on a single lane change process. To provide timely and accurate prediction of these short-term lateral behaviors, a driver preview and multiple centerline model-based probabilistic behavior recognition architecture is proposed. At first, a driver preview model is adopted for the description of vehicle preview driving characteristic, and the preview lateral offset and preview lateral velocity in road curvilinear coordinate system are calculated with TV states and road reference information. Then, these two measurements combined with TV multiple certerline model are used for lateral behavior prediction with the IMM-based probabilistic behavior detection algorithm. With this driver preview and multiple centerline model-based probabilistic behavior recognition architecture, TV preview driving characteristic and lateral motion states including lateral velocity and yaw rate are used for TV lateral behavior reasoning. Furthermore, for the identification of short-term lateral behavior, a new dynamic transition probability matrix (TPM) directly constructed based on the Gaussian cumulative distribution function (CDF) with the preview lateral velocity is proposed in this study to speed up the behavior recognition process. The contributions of this study are two folds.

1) Different from the conventional multiple centerline model-based method without considering TV preview driving characteristic, a driver preview and multiple centerline model-based probabilistic behavior recognition architecture is proposed in this study for TV lateral behavior reasoning. With this proposed method, TV lateral velocity and yaw rate which contain significantly different features in lane keeping and lane changing processes are used for TV lateral behavior describing, and TV lateral behavior can be predicted earlier than the conventional method.

2) For the prediction of TV short-term lateral behavior, a new dynamic TPM model constructed based on the Gaussian CDF with preview lateral velocity is proposed in this study to speed up the behavior recognition process.



(a) Lane model (b) Model Probability

Fig. 1. TV multiple centerline model. (a) the solid and dotted lines represent lane markers, and the dash-dotted lines represent the centerlines that vehicle tends to follow. (b) the blue, red and green curves represent the probability distribution of these three centerline models in (a).

The remainder of this article is organized as follows, in section II, TV multiple centerline model is given and problems for lateral behavior reasoning are formulated. Driver preview model and TV lateral behavior reasoning architecture are given in section III. Simulation and experimental results are presented in section IV. In section V, this study are concluded.

II. Target Vehicle Lateral Behavior Modeling and Problem Formulation

In this section, TV multiple centerline model is presented at first. Then, problems of TV short-term lateral behavior reasoning are formulated.

A. Target Vehicle Multiple Centerline Model

To describe TV lateral behavior, two typical physical models are generally adopted, motion model and multiple centerline model. For motion model, TV lateral behaviors such as lane keeping and lane changing are modeled based on different kinematics models [17]. For multiple centerline model, TV trajectory is considered based on vehicle maneuvers, and the multiple lane centerlines are considered as the paths that TV tends to follow [18]. In this study, the multiple centerline model is selected as the basic model for TV lateral behavior reasoning. On a road with multiple lanes, a centerline model is constructed for each lane, and the TV lateral offset of the centerline model follows the Gaussian distribution with respect to the centerline. Then, these models can be unified as the multiple centerline model (1).

$$q_k^i = \bar{q}_k^i + w_k^i \tag{1}$$

where q_k^i is TV lateral offset, $\bar{q}_k^i$ is lateral offset of the i_{th} centerline, $w_k^i \sim N(0, \theta_w^2)$ represents zero-mean normal distribution with variance θ_w^2, in which θ_w^2 is set as $(W/4)^2$ to cover the lane by two-sigma variance. W is lane width. $i > j$ indicates that i_{th} lane is on the left side of j_{th} lane.

As can be seen in Fig. 1 (a), a road with three lanes is given and the corresponding centerlines are presented. For this scene, a multiple centerline model with three sub-models are constructed to describe TV lateral position on the road. In Fig. 1 (b), the probability distribution of TV lateral offset corresponding to these three sub-models is shown.

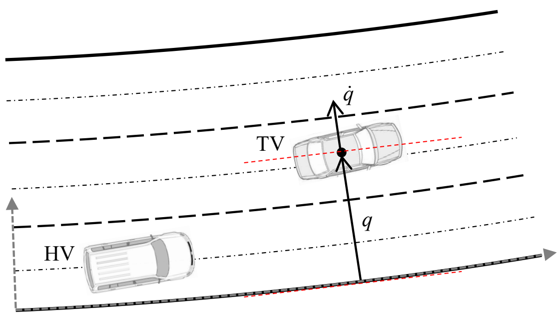


Fig. 2. TV lateral behavior recognition based on TV lateral offset and lateral velocity in road curvilinear coordinate system.

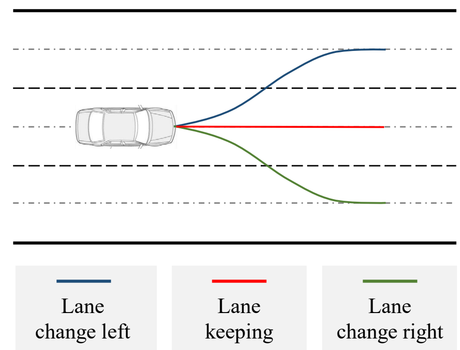


Fig. 3. TV lateral behavior classification: LK, LCL and LCR

B. Problems Formulation

To apply multiple centerline model for TV lateral behavior reasoning, the IMM estimator is adopted and TV lateral offset q shown in Fig. 2 is used for model probabilities update [18]. Considering that only lateral offset q cannot provide timely prediction, lateral velocity $\dot{q}$ in the road curvilinear coordinate system is introduced to the TPM to speed up the prediction process. For a more accurate and timely TV short-term lateral behavior reasoning, the following two problems should be addressed.

1) The Description of TV Lateral Behavior Considering Lateral Motion States and Preview Driving Characteristic: TV state measurements are essential for lateral behavior reasoning. For example, in [7], the position and their corresponding instantaneous velocity in ground plane coordinate system are adopted as features for the training of hidden Markov models. In [13], aimed at TV maneuver reasoning, the features of yaw angle, yaw rate, lateral velocity and lateral acceleration in lane changing and lane keeping processes are compared. In [17], the detected TV pose in road curvilinear coordinate system is used for TV motion tracking and behavior reasoning. For lateral behavior recognition, TV state measurements can be divided into two categories:

1) **Pose-related states:** TV pose including position and orientation, and the road reference information.

2) **Motion-related states:** TV longitudinal velocity, lateral velocity and yaw rate.

Remark 1: Pose-related and motion-related states such as lateral offset and lateral velocity in the road curvilinear coordinate system can also be obtained based on the above mentioned information via coordinate transformation.

In [18], TV lateral offset q and lateral velocity $\dot{q}$ in the road curvilinear coordinate system are used for lateral behavior recognition in multiple centerline model-based method. TV lateral motion states such as lateral velocity and yaw rate have not been employed for probability updating. However, these TV lateral motion states are important features to characterize vehicle lateral behavior [13]. To promote the performance of TV lateral behavior recognition, the description of TV lateral behavior with TV lateral velocity and yaw rate should be considered.

On the other hand, considering the response delay of the driver and the vehicle, the driver should look forward in front of the vehicle for a certain distance to stably control the vehicle, and this control characteristic of the driver is called the driver preview [20]. For vehicle path following control, the driver preview driving characteristic is ubiquitous. For example, in [19], a driver perception and steering control model presents that drivers minimize the bearing angle to a aim point located 0.25-0.75s ahead. In [21], the preview optimal curvature model is chosen to reflect the driver preview driving characteristic. However, current physical model-based methods for TV lateral behavior recognition neglect this characteristic. To accurately describe TV lateral behavior, this preview driving characteristic should also be considered.

2) The Design of Dynamic TPM for Short-term Lateral Behavior Recognition: Aiming at different autonomous driving applications, there are much different lateral behavior definitions. For example, in [7], to emphasize the motion relationship between HV and TV, TV lateral behaviors are defined as overtake and cut-in. In [18], for long-term TV lateral behavior prediction, lane keeping, lane-change and double lane-change are considered on a road with three lanes. Different from the definition of long-term TV lateral behavior that regards two consecutive lane changes as a double lane change behavior, we dedicate to estimating TV short-term lateral behavior in this study, and as can be seen in Fig. 3, TV short-term lateral behaviors are classified into three categories including LK, LCL and LCR. The set of TV lateral behaviors is given as

$$B = \{LK, LCL, LCR\} \tag{2}$$

Based on this definition, the TPM for multiple centerline model can be represented as

$$TPM = \begin{bmatrix} \pi_{11} & \pi_{12} & 0 & \cdots & 0 \\ \pi_{21} & \pi_{22} & \pi_{23} & \cdots & 0 \\ 0 & \pi_{32} & \pi_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \pi_{NN} \end{bmatrix} \tag{3}$$
$$\text{where} \quad \pi_{ij} = 0 \quad (|i-j| > 1)$$

π_{ij} indicates the transition probability from the i_{th} lane model to the j_{th} lane model, and the following relationship should be satisfied

$$\pi_{ij} = P[L_k = j | L_{k-1} = i] \quad \text{where} \sum_j \pi_{ij} = 1 \tag{4}$$

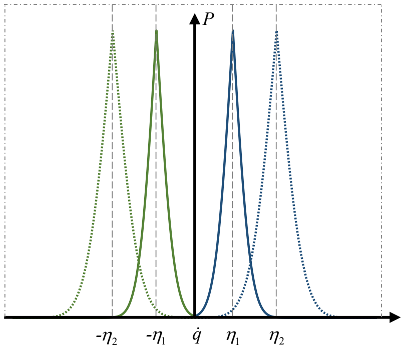


Fig. 4. The increments of the conventional lateral velocity-dependent dynamic TPM. The solid lines indicate the increment of single lane change while the dashed lines for double lane change.

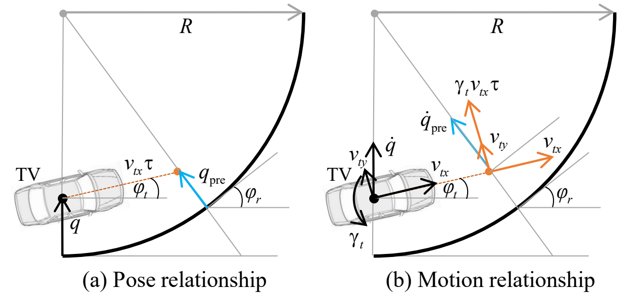


Fig. 5. TV driver preview model. (a) shows the pose relationship between the preview point and current vehicle pose. (b) gives the relationship between the motion of the preview point and vehicle current motion states.

Generally, the TPM is established based on the Markov assumption as a constant matrix. In [18], to detect TV lateral behavior rapidly, TV lateral velocity $\dot{q}$ in the road curvilinear coordinate system is introduced. For LCR, $i \geq j$, and TV lateral velocity $\dot{q}$ is negative and below a certain threshold λ_{ij}. For LCL, $i < j$, TV lateral velocity $\dot{q}$ is positive and above a certain threshold λ_{ij}. Then, for TV lateral behavior, the model transition criteria considering TV lateral velocity $\dot{q}$ is defined as

$$\begin{cases} \dot{q} - \lambda_{ij} \leq 0 (i \geq j) \\ \dot{q} - \lambda_{ij} > 0 (i < j) \quad \text{where} \quad \lambda_{ij} \sim N(\eta_{ij}, \sigma_{ij}^2) \end{cases} \tag{5}$$

where λ_{ij} represents the model transition criteria for lane changing. η_{ij} and σ_{ij}^2 is the mean and variance of λ_{ij}. Then, a dynamic TPM is designed as

$$\pi_{0,ij}(\dot{q}) = \begin{cases} \pi_{ij}^{ini} + \Phi(\dot{q}, \eta_{ij}, \sigma_{ij}^2) & \dot{q} - \eta_{ij} \leq 0 \\ \pi_{ij}^{ini} + [1 - \Phi(\dot{q}, \eta_{ij}, \sigma_{ij}^2)] & \dot{q} - \eta_{ij} > 0 \end{cases} \tag{6}$$

where π_{ij}^{ini} is the initial constant model transition probability. $\pi_{0,ij}(\dot{q})$ is the lateral velocity dependent model transition probability and it should be normalized to satisfy equation (4). $\Phi(\dot{q}, \eta_{ij}, \sigma_{ij}^2)$ denotes the Gaussian CDF.

As can be seen in Fig. 4, the solid and dashed lines represent the probability increments in single and double lane changing processes respectively. It can be found that when the absolute value of TV lateral velocity approaching η_2, the increments for double lane changing increase while the increments for single lane changing decrease, and TV is regarded as tending to conduct double lane changing maneuver. However, this study aims to predict TV short-term lateral behaviors and double lane changing process can be separated into two short-term single lane changing processes. To predict short-term lateral behavior, a new dynamic TPM should be designed.

III. Driver Preview Model and Target Vehicle Lateral Behavior Reasoning

A. Target Vehicle Driver Preview Model

As can be seen in Fig. 5, TV driver preview model is selected to consider driver preview driving characteristic. In Fig. 5(a), the pose relationship is shown, and the preview lateral offset q_{pre} is given as

$$\begin{aligned} q_{pre} &= \frac{q + v_{tx}\tau sin(\varphi_t) - R(1 - cos(\varphi_r))}{cos(\varphi_r)} \\ &= \frac{q + v_{tx}\tau sin(\varphi_t) - 2R sin^2(\frac{\varphi_r}{2})}{cos(\varphi_r)} \end{aligned} \tag{7}$$

where v_{tx} is TV longitudinal velocity, φ_t is the vehicle heading angle relative to the road reference. φ_r is the difference between the heading angle of the road reference in the preview point and current position. τ is the preview time. R is the road radius. Considering that R is much larger than the preview distance $v_{tx}\tau$ and lateral offset q, the relative angle φ_r is approximately equal to

$$\varphi_r = \frac{v_{tx}\tau}{R - q} = \rho v_{tx}\tau \tag{8}$$

where ρ is the road curvature.

Then, the preview lateral offset q_{pre} in road curvilinear coordinate system is simplified as

$$q_{pre} = q + v_{tx}\tau sin(\varphi_t) - \frac{(v_{tx}\tau)^2\rho}{2} \tag{9}$$

To model TV lateral motion of the preview point, we must understand that this lateral motion is affected by TV longitudinal velocity v_{tx}, lateral velocity v_{ty} and yaw rate γ_t. Then, as can be seen in Fig. 5(b), TV preview lateral velocity $\dot{q}_{pre}$ in the road curvilinear coordinate system is given as

$$\begin{aligned} \dot{q}_{pre} &= (v_{ty} + \gamma_t v_{tx}\tau) cos(\varphi_r - \varphi_t) - v_{tx} sin(\varphi_r - \varphi_t) \\ &= (v_{ty} + \gamma_t v_{tx}\tau)[cos(\varphi_r)cos(\varphi_t) + sin(\varphi_r)sin(\varphi_t)] \\ &\quad - v_{tx}[sin(\varphi_r)cos(\varphi_t) - cos(\varphi_r)sin(\varphi_t)] \end{aligned} \tag{10}$$

Considering that φ_r and φ_t are close to zero and equation (8), TV preview lateral velocity $\dot{q}_{pre}$ is simplified as

$$\begin{aligned} \dot{q}_{pre} &= v_{ty} + \gamma_t v_{tx}\tau + v_{tx} sin(\varphi_t) - v_{tx} sin(\varphi_r) \\ &= v_{ty} + \gamma_t v_{tx}\tau + v_{tx} sin(\varphi_t) - \rho v_{tx}^2\tau \end{aligned} \tag{11}$$

With TV preview lateral offset q_{pre} and preview lateral velocity $\dot{q}_{pre}$ in road curvilinear coordinate system, TV preview driving characteristic is considered for TV lateral pose and motion description. Besides, TV longitudinal-lateral states including lateral offset q, heading angle φ_t, longitudinal velocity v_{tx}, lateral velocity v_{ty} and yaw rate γ_t are combined and used

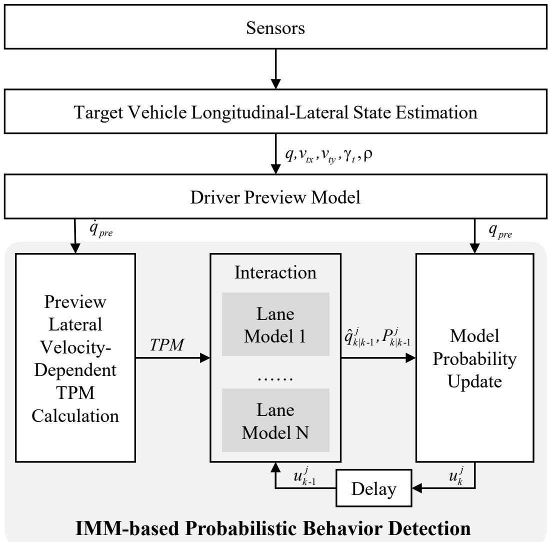


Fig. 6. The driver preview and multiple centerline model-based probabilistic behavior recognition architecture.

for TV future position and motion description using equations (9) and (11).

B. IMM-based Probabilistic Behavior Reasoning

In Fig. 6, TV lateral behavior recognition architecture is presented. Based on the measurements obtained by sensors such as radar, LiDAR, vision system and vehicle to vehicle communication, TV longitudinal-lateral states can be measured or estimated [22], [23]. Then, TV lateral offset q, longitudinal velocity v_{tx}, lateral velocity v_{ty}, yaw rate γ_t and road curvature ρ are available for the calculation of TV preview lateral offset q_{pre} and preview lateral velocity $\dot{q}_{pre}$ with the driver preview model. At last, IMM-based probabilistic behavior detection algorithm is used for TV lateral behavior recognition [18]. The main steps of this algorithm are summarized as following.

1) Interaction (Mixing): The mixing probability $\mu^{ij}_{k|k-1}$ represents the i_{th} lane model was in effect at time $k-1$ given that the j_{th} lane model is in effect at time k and it is written as

$$\mu^{ij}_{k|k-1} = \frac{\pi_{ij}(\dot{q}_{pre})\mu^i_{k-1}}{\mu^j_{k|k-1}} \tag{12}$$

where $\pi_{ij}(\dot{q}_{pre})$ represents the preview lateral velocity-dependent transition probability from the i_{th} to j_{th} lane model. μ^i_{k-1} is the i_{th} model probability at time $k-1$ obtained by equation (20) and the predicted model probability $\mu^j_{k|k-1}$ is calculated by

$$\mu^j_{k|k-1} = \sum_i \pi_{ij}(\dot{q}_{pre})\mu^i_{k-1} \tag{13}$$

Then, the mixed lateral offset and covariance are calculated based on the above mentioned multiple centerline models as

$$\hat{q}^j_{k|k-1} = \sum_{i=1} \bar{q}^i_{k-1} u^{ij}_{k|k-1} \tag{14}$$

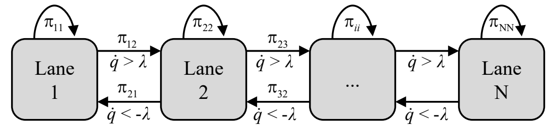


Fig. 7. Model transition relationship of the multiple centerline models.

$$\begin{aligned} P^j_{k|k-1} = &\sum_{i=1} u^{ij}_{k|k-1}\{\theta^2_w + [\bar{q}^i_{k-1} - \hat{q}^j_{k|k-1}] \\ &\cdot [\bar{q}^i_{k-1} - \hat{q}^j_{k|k-1}]^T\} \end{aligned} \tag{15}$$

2) Model Probability Update: To consider vehicle preview driving characteristic, the measurements of TV preview lateral offset z_k is obtained based on the driver preview model for TV lateral behavior reasoning and they can be given as

$$z_k = q_{pre,k} + v^q \tag{16}$$

where $v^q \sim N(0, \theta^2_q)$ is used to describe the measurement noise. θ^2_q is the variance of v^q.

Then, the measurement residual r^j_k and its corresponding covariance S^j_k are described as

$$r^j_k = z_k - \hat{q}^j_{k|k-1} \tag{17}$$

$$S^j_k = P^j_{k|k-1} + \theta^2_q \tag{18}$$

Based on the measurement residual and its covariance, the model probability of each lane model is updated with

$$\Lambda^j_k = N(r^j_k, 0, S^j_k) = \frac{1}{\sqrt{2\pi|S^j_k|}} exp\{-\frac{(r^j_k)^2}{2S^j_k}\} \tag{19}$$

$$u^j_k = \frac{\Lambda^j_k u^j_{k|k-1}}{\sum_{i=1}\Lambda^i_k u^i_{k|k-1}} \tag{20}$$

where Λ^j_k is the likelihood function of model j at time k.

With the IMM-based probabilistic behavior detection algorithm, the probabilities of multiple centerline models are updated.

C. Preview Lateral Velocity-Dependent TPM for Short-term Lateral Behavior Recognition

In this study, LCL, LCR and LK are defined for TV short-term lateral behavior recognition. In Fig. 7, the transition relationship of these multiple centerline models is given and the model transition criteria is presented in equation (5) . To predict TV short-term lateral behavior, a new preview lateral velocity-dependent dynamic TPM is designed as

$$\pi_{0,ij}(\dot{q}_{pre}) = \begin{cases} \pi^{ini}_{ij} + b[1 - \Phi(\dot{q}_{pre}; \eta_{ij}, \sigma^2_{ij})] & (i > j) \\ \pi^{ini}_{ij} + b\Phi(\dot{q}_{pre}; \eta_{ij}, \sigma^2_{ij}) & (i < j) \end{cases} \tag{21}$$

where b is the amplitude of the increments. The Gaussian CDF $\Phi(x; \eta_{ij}, \sigma^2_{ij})$ with mean η_{ij} and variance σ^2_{ij} is given as

$$\Phi(x; \eta_{ij}, \sigma^2_{ij}) = \int_{-\infty}^{x} \frac{1}{\sigma_{ij}\sqrt{2\pi}} exp\{-\frac{(x-\eta_{ij})^2}{2\sigma^2_{ij}}\}dx \tag{22}$$

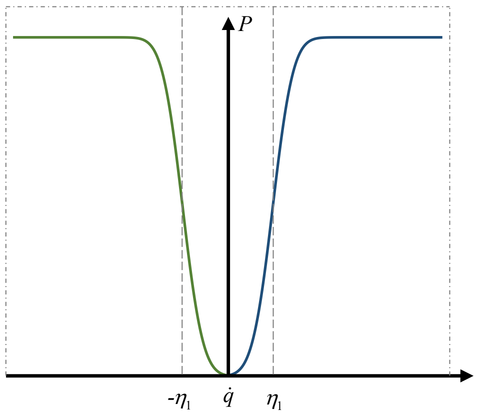


Fig. 8. The increment of the designed lateral velocity-dependent dynamic model transition probability

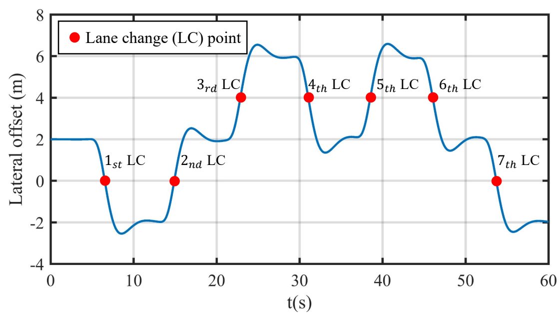


Fig. 9. Target vehicle lateral offset in simulation. These red dots are the lane change points.

To make the designed preview lateral velocity-dependent TPM satisfies equation (4), a normalization procedure is required and denoted as

$$\pi_{ij}(\dot{q}_{pre}) = \frac{\pi_{0,ij}(\dot{q}_{pre})}{\sum_{j=1}^{N} \pi_{0,ij}(\dot{q}_{pre})} \tag{23}$$

In Fig. 8, the increments of the designed TPM are shown. When the absolute value of the preview lateral velocity $\dot{q}_{pre}$ closes to zero, a small increment is added to the transition probability for lane changing. When the absolute value of the preview lateral velocity increases, the corresponding transition probability increment also gradually increases to a constant. Compared with existing lateral velocity-dependent TPM presented in Fig. 4, the proposed one is more suitable for TV short-term lateral behavior recognition.

IV. Simulation and Experimental Results

A. Simulation

To verify the effectiveness of the proposed method for TV short-term lateral behavior recognition, Carsim-simulink co-simulation is conducted. In the test, TV performs a continuous lane change process and Fig. 9 plots TV lateral offset. TV longitudinal velocity is given in Fig. 10. In this study, we assume that TV longitudinal-lateral states have been obtained, and they are modeled based on the true value with Gaussian noise in the simulation. The preview time τ of the proposed method is set as 1s.

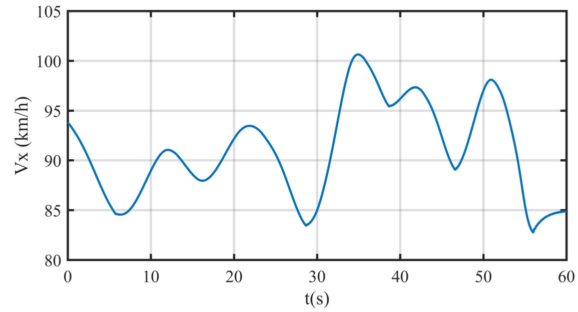


Fig. 10. Target vehicle longitudinal velocity in simulation.

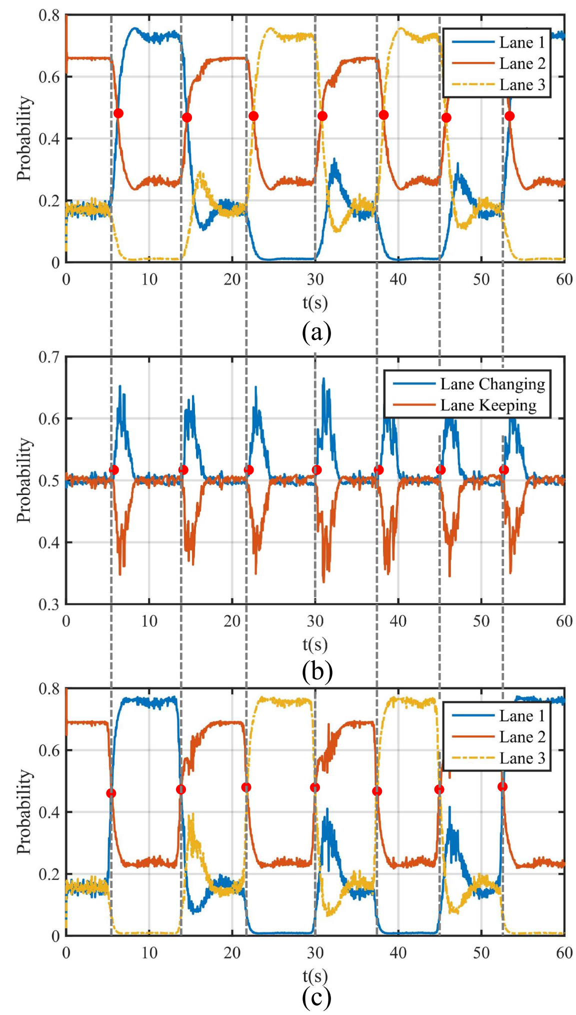


Fig. 11. The model probabilities in simulation. (a) Model probabilities of the conventional multiple centerline model-based method. (b) Model probabilities of the conventional motion model-based method. (c)Model probabilities of the proposed driver preview and multiple centerline model-based method. The red points are the predicted lane changing points in each lane changing process. The gray dashed lines are aligned with the predicted lane change points of the proposed method for comparison with the predicted points of these two traditional methods.

In this study, the proposed method with driver preview model is compared with the conventional motion model-based method [17] and multiple centerline model-based method [18]. For the conventional motion model-based method, TV motion

TABLE I
THE COMPARISON OF ADVANCE TIME BETWEEN THE CONVENTIONAL AND PROPOSED METHODS IN SIMULATION.

Lane change process	Conventional multiple centerline model-based method (s)	Conventional motion model-based method (s)	Proposed method (s)
1_{st} LC	0.326	0.726	**1.086**
2_{nd} LC	0.299	0.779	**1.019**
3_{rd} LC	0.346	0.786	**1.106**
4_{th} LC	0.213	0.813	**1.053**
5_{th} LC	0.244	0.964	**1.084**
6_{th} LC	0.330	0.970	**1.050**
7_{th} LC	0.313	0.953	**1.033**

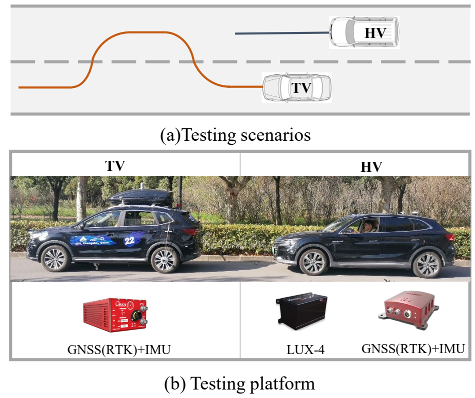


Fig. 12. HV-TV testing system.

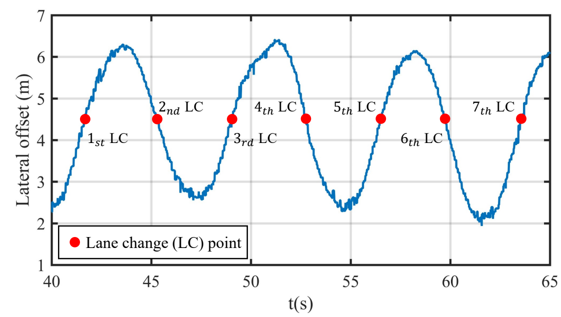


Fig. 13. TV lateral offset in experiment. These red dots are the lane change points.

are modeled by four motion models including the constant velocity lane keeping, constant acceleration lane keeping, constant velocity lane changing and constant acceleration lane changing models. In this study, TV lateral behaviors need to be identified, and these four models are divided into two categories: lane keeping models and lane changing models. Then, the probabilities of the lane keeping and lane changing models are obtained, and TV lateral behavior is inferred.

In Fig. 11, the model probabilities of these three methods are given. In Fig. 11(a), the model probabilities of the conventional multiple centerline model-based method are shown. The blue, red and yellow curves are the predicted probabilities of each lane model. The intersections of the two curves with higher probabilities are the predicted lane change points, which are indicated by red dots. In Fig. 11(b), the probabilities of the conventional motion model-based method are given. The blue and red curves are the probabilities of the lane changing models and lane keeping models, respectively. As the lane keeping models can be regarded as a special case of the lane changing models without lateral motion, the probabilities of the lane keeping and lane changing models fluctuate around 0.5 during the lane keeping processes. Considering this situation, the lane changing behavior is recognized when the probabilities of the lane changing models are greater than the probabilities of the lane keeping models by a certain threshold. The predicted lane change points of the conventional motion model-based method are indicated by the red dots in Fig. 11(b). The model probabilities of the proposed method are plotted in Fig. 11(c), and the blue, red and yellow curves are the predicted probabilities of each lane models. The red dots are the predicted lane changing points of the proposed method. In Fig. 11, the gray dashed lines aligned with the predicted lane change points of the proposed method are added in these figures to compare the time sequence of the predicted lane change points of different methods in each lane change process. Comparing these lane change points in these three figures, it is found that the proposed method predicts TV lateral behavior earlier than the conventional two methods. To quantify the performance of these three methods, as can be seen in Fig. 9, the points where TV cross the lane edge are defined as the lane change points, and the corresponding time is defined as the crossing time t_c. In Fig. 11, the time of these predicted lane change points are defined as the prediction time t_p. The difference of these two time is defined as the advance time of behavior prediction, and it is represented as

$$t_a = t_c - t_p. \tag{24}$$

Table I shows the advance time of these three methods, and it is found that the conventional multiple centerline model-based method predicts TV lateral behavior about 0.2-0.4s in advance. The conventional motion model-based method predicts TV lane changing behavior about 0.7-1.0s in advance, while the proposed method considering TV preview driving characteristic achieves about 1.0-1.1s in advance. In each lane changing process, the advance time of the proposed method is greater than that of the two conventional methods, which shows that the proposed method can predict TV lateral behavior earlier than the two conventional methods.

B. Experimental Results

In this study, a HV-TV testing platform presented in Fig. 12 is adopted to verify the effectiveness of the proposed method. In this system, the ground truth of HV and TV states are obtained based on the GNSS(RTK)+IMU system. We assume that vehicle-to-vehicle communication is possible between HV and TV, and a Lux-4 Lidar is mounted in HV to detect TV and road reference. Based on the sensor configuration, TV longitudinal-lateral states are measured and estimated based on the methods proposed in [22], [23]. Then, TV lateral

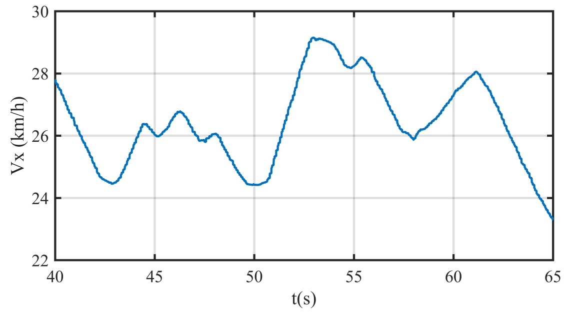


Fig. 14. TV longitudinal velocity in experiment.

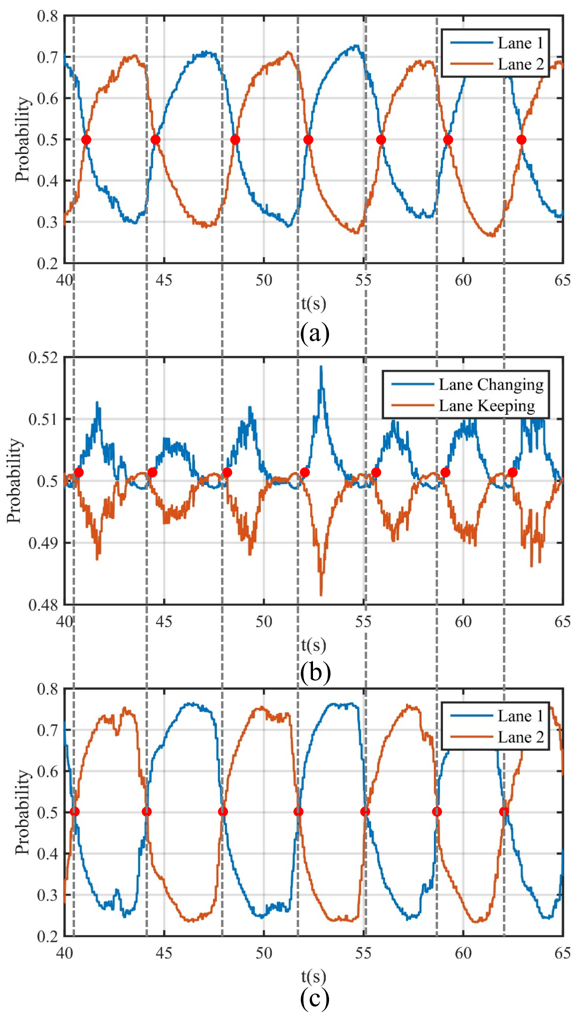


Fig. 15. The model probabilities in experiment. (a) Model probabilities of the conventional multiple centerline model-based method. (b) Model probabilities of the conventional motion model-based method. (c)Model probabilities of the proposed driver preview and multiple centerline model-based method. The red points are the predicted lane changing points in each lane changing process. The gray dashed lines are aligned with the predicted lane change points of the proposed method for comparison with the predicted points of these two traditional methods.

offset q, longitudinal velocity v_{tx}, lateral velocity v_{ty}, yaw rate γ_t and road curvature ρ are available for TV lateral behavior recognition. This study focuses on TV lane change behavior recognition. To include more lane-changing scenes, TV performs a continuous lane change process in a two-lane road. Fig. 13 shows TV lateral offset relative to the road reference, and it is found that TV changes lanes 7 times, and the red dots represent the points where the TV crosses the edge of the lane. Instead of running at a constant speed, the TV was randomly controlled by the driver, making the test more in line with the real driving scene, and Fig. 14 plots TV longitudinal velocity. In [24], driver preview time is discussed based on field tests, and $\tau = 1s$ is used in this study for TV lateral behavior recognition.

TABLE II
THE COMPARISON OF ADVANCE TIME BETWEEN THE CONVENTIONAL AND PROPOSED METHODS IN EXPERIMENT.

Lane change process	Conventional multiple centerline model-based method (s)	Conventional motion model-based method (s)	Proposed method (s)
1_{st} LC	0.559	0.957	**1.120**
2_{nd} LC	0.719	1.079	**1.200**
3_{rd} LC	0.516	0.917	**1.157**
4_{th} LC	0.478	0.759	**0.959**
5_{th} LC	0.638	0.959	**1.477**
6_{th} LC	0.520	0.641	**1.079**
7_{th} LC	0.759	1.240	**1.639**

Fig. 15(a) shows the predicted lane probabilities of the conventional multiple centerline model-based method without considering driver preview driving characteristic. In Fig. 15(b), the probabilities of the lane changing and lane keeping models of the conventional motion model-based method are shown. Fig. 15(c) gives the model probabilities of the proposed method considering driver preview driving characteristic. Comparing the predicted lane change points in these three figures, it is found that the proposed method predicts TV lateral behavior earlier than the two conventional methods. To quantify the performance of these three methods, the advance time is calculated and given in Table II. In Table II, it is found that the conventional multiple centerline model-based method predicts the lane change behavior about 0.4-0.8s in advance. The conventional motion model-based method predicts the lane changing behavior about 0.6-1.3s in advance. The proposed method achieves about 0.9-1.6s in advance. For each lane change process, the advance time of the proposed method is greater than the other two methods, which shows that the proposed method can predict TV lane change behavior earlier than the two conventional methods.

V. Conclusion

TV lateral behavior reasoning plays a key role in the safe and effective decision-making and control of HV, and the physical model-based behavior reasoning method is so important that should be carefully investigated. Existing physical model-based methods generally neglect TV preview driving characteristic and lateral motion states such as TV lateral velocity and yaw rate. To predict TV lateral behavior accurately and timely, a driver preview and multiple centerline model-based probabilistic behavior recognition architecture was proposed in this study. Firstly, the driver preview model was selected to describe TV preview driving characteristic. Then, the driver preview and multiple centerline modes were combined based on the IMM-based probabilistic behavior recognition algorithm for TV lateral behavior detection with TV preview lateral offset and preview lateral velocity. For TV short-term lateral behavior reasoning, a preview lateral velocity-dependent TPM constructed based on Gaussian CDF was proposed to consider LCL, LCR and LK behaviors defined in this study. Simulation and experiments were conducted and the results showed that the proposed method considering TV preview driving characteristic can predict TV lateral behavior earlier than the conventional method. In the future, the proposed method can be combined with the existing lane changing decision models and data-driven models shown in [12], [13], [25] to consider more traffic information to better identify TV lateral behavior.

References

[1] Y. Huang, H. Ding, Y. Zhang, H. Wang, D. Cao, N. Xu, and C. Hu, "A motion planning and tracking framework for autonomous vehicles based on artificial potential field elaborated resistance network approach," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 2, pp. 1376–1386, 2020.

[2] C. You, J. Lu, D. Filev, and P. Tsiotras, "Autonomous planning and control for intelligent vehicles in traffic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2339–2349, 2020.

[3] C. Chen, T. Xiao, T. Qiu, N. Lv, and Q. Pei, "Smart-contract-based economical platooning in blockchain-enabled urban internet of vehicles," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 6, pp. 4122–4133, 2020.

[4] Y. Chen, C. Hu, and J. Wang, "Human-centered trajectory tracking control for autonomous vehicles with driver cut-in behavior prediction," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 8461–8471, 2019.

[5] C. Xu, W. Zhao, and C. Wang, "An integrated threat assessment algorithm for decision-making of autonomous driving vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2510–2521, 2020.

[6] Y. Zhang, Q. Lin, J. Wang, S. Verwer, and J. M. Dolan, "Lane-change intention estimation for car-following control in autonomous driving," *IEEE Transactions on Intelligent Vehicles*, vol. 3, no. 3, pp. 276–286, 2018.

[7] N. Deo, A. Rangesh, and M. M. Trivedi, "How would surrounding vehicles move? a unified framework for maneuver classification and motion prediction," *IEEE Transactions on Intelligent Vehicles*, vol. PP, no. 99, pp. 1–1, 2018.

[8] A. Koenig, T. Rehder, and S. Hohmann, "Exact inference and learning in hybrid bayesian networks for lane change intention classification," *2017 IEEE Intelligent Vehicles Symposium (IV)*, pp. 1535–1540, 2017.

[9] G. Xie, H. Gao, L. Qian, B. Huang, K. Li, and J. Wang, "Vehicle trajectory prediction by integrating physics- and maneuver-based approaches using interactive multiple models," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 7, pp. 5999–6008, 2018.

[10] T. Rehder, A. Koenig, M. Goehl, L. Louis, and D. Schramm, "Lane change intention awareness for assisted and automated driving on highways," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 2, pp. 265–276, 2019.

[11] C. Wissing, T. Nattermann, K. Glander, and T. Bertram, "Trajectory prediction for safety critical maneuvers in automated highway driving," *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 131–136, 2018.

[12] R. Izquierdo, A. Quintanar, I. Parra, D. Fernández-Llorca, and M. A. Sotelo, "Experimental validation of lane-change intention prediction methodologies based on cnn and lstm," *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pp. 3657–3662, 2019.

[13] A. Benterki, M. Boukhnifer, V. Judalet, and C. Maaoui, "Artificial intelligence for vehicle behavior anticipation: Hybrid approach based on maneuver classification and trajectory prediction," *IEEE Access*, vol. 8, pp. 56 992–57 002, 2020.

[14] R. Rai and C. K. Sahu, "Driven by data or derived through physics? a review of hybrid physics guided machine learning techniques with cyber-physical system (cps) focus," *IEEE Access*, vol. 8, pp. 71 050–71 073, 2020.

[15] D. Yang, L. Zhu, Y. Liu, D. Wu, and B. Ran, "A novel car-following control model combining machine learning and kinematics models for automated vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 6, pp. 1991–2000, 2019.

[16] S. K. Singh, R. Yang, A. Behjat, R. Rai, S. Chowdhury, and I. Matei, "Pi-lstm: Physics-infused long short-term memory network," *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)*, pp. 34–41, 2019.

[17] K. Jo, M. Lee, J. Kim, and M. Sunwoo, "Tracking and behavior reasoning of moving vehicles based on roadway geometry constraints," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 2, pp. 460–476, 2017.

[18] J. Kim and D. Kum, "Collision risk assessment algorithm via lane-based probabilistic motion prediction of surrounding vehicles," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–12, 2017.

[19] K. van der El, D. M. Pool, M. R. M. van Paassen, and M. Mulder, "A unifying theory of driver perception and steering control on straight and winding roads," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 2, pp. 165–175, 2020.

[20] M. Abe, *Vehicle handling dynamics: theory and application*, 2015.

[21] B. Zhu, Z. Liu, J. Zhao, Y. Chen, and W. Deng, "Driver behavior characteristics identification strategies based on bionic intelligent algorithms," *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 6, pp. 572–581, 2018.

[22] A. Almagambetov, S. Velipasalar, and M. Casares, "Robust and computationally lightweight autonomous tracking of vehicle taillights and signal detection by embedded smart cameras," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 6, pp. 3732–3741, 2015.

[23] Z. Zhou, Y. Wang, H. Du, Q. Ji, J. Hu, and C. Yin, "Sub-full model-based heterogeneous sensor fusion for lateral state estimation of preceding target vehicles," *IEEE/ASME Transactions on Mechatronics*, vol. 25, no. 3, pp. 1335–1345, 2020.

[24] D. Xing, X. Li, X. Zheng, Y. Ren, and Y. Ishiwatari, "Study on driver's preview time based on field tests," *2017 4th International Conference on Transportation Information and Safety (ICTIS)*, pp. 575–580, 2017.

[25] Z. Zheng, "Recent developments and research needs in modeling lane changing," *Transportation Research Part B: Methodological*, vol. 60, pp. 16–32, 2014.

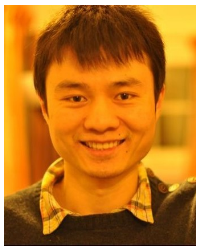
Zhisong Zhou was born in Anhui, China, in 1993. He received the B.S. degree in mechanical engineering from Shandong University, Shandong, China, in 2015, and is currently working toward the Ph.D. degree with the School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China.

His research interests include estimation and control of the connected and automated vehicles.

Yafei Wang (M'12) received the B.S. degree in internal combustion engine from Jilin University, Changchun, China, in 2005, the M.S. degree in vehicle engineering from Shanghai Jiao Tong University, Shanghai, China, in 2008, and the Ph.D. degree in electrical engineering from The University of Tokyo, Tokyo, Japan, in 2013.

From 2013 to 2016, he was a Postdoctoral Researcher with The University of Tokyo. He is currently a Associate Professor with the School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai, China. His research interests include state estimation and control for connected and automated vehicles.

Ronghui Liu received the B.S. degree from Peking University, China, and the Ph.D. degree from Cambridge University, U.K. She is currently a Professor with the Institute for Transport Studies, University of Leeds, U.K. Her main research interest lies in developing traffic micro-simulation models to analyze the dynamic and complex travel behavior and interactions in transport networks.



Chongfeng Wei received his Ph.D. degree in mechanical engineering from the University of Birmingham, Birmingham, U.K., in 2015. He is currently a lecturer at Queen's University Belfast, UK.

His current research focuses on Human-centric Autonomous Driving and including Human-like Automated Vehicle Control and Human-centric Decision Making, Motion Planning and Control for Intelligent Vehicles.

Haiping Du (M'09-SM'17) received the Ph.D. degree in mechanical design and theory from Shanghai Jiao Tong University, Shanghai, China, in 2002.

He was a Research Fellow with the University of Technology Sydney, Ultimo, NSW, Australia, from 2005 to 2009, and was a Postdoctoral Research Associate with Imperial College London, London, U.K., from 2004 to 2005 and the University of Hong Kong, Hong Kong, from 2002 to 2003. He is currently a Professor with the School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, Wollongong, NSW, Australia. His current research interests include vibration control, vehicle dynamics and control systems, robust control theory and engineering applications, electric vehicles, robotics and automation, and smart materials and structures.

Chengliang Yin was born in Inner Mongolia, China, in 1965. He received the M.S. and Ph.D. degrees in vehicle engineering from Jilin Industrial University, Changchun, China, in 1996 and 2000, respectively.

He is currently a Full Professor with Shanghai Jiao Tong University, Shanghai, China, where he is also the Vice-Dean of the Institute of Automotive Engineering and the Vice-Director of the National Engineering Laboratory for Automotive Electronic Control Technology. His research interests include the control of automotive electronics and electric vehicles, particularly research and development of hybrid electric vehicles.