Surrounding Vehicles' Lane Change Maneuver Prediction and Detection for Intelligent Vehicles: A Comprehensive Review

Ruitao Song and Bin Li

Abstract—**Identifying and evaluating the potential risks in the surrounding environment is critical for intelligent vehicles' safety and user experience. This paper provides a comprehensive overview of the state-of-the-art research on the surrounding vehicles' lane change maneuver prediction and detection. First, various driver behavior modeling and classification methods are reviewed and analyzed, which gives a general understanding of what the lane change maneuver is and how to predict or detect the lane change maneuver. Next, the primary sensing devices equipped on intelligent vehicles and their impacts on lane change inference systems are discussed. Then, a series of representative research works in recent years are selected, introduced, and compared regarding their input feature selection, inference algorithms, and performance evaluation methods. Finally, some potential future research directions are proposed. This paper aims to help the relevant researchers and institutions summarize the current studies on the surrounding vehicles' lane change maneuver inference and recognize its future development directions.**

Index Terms—**Autonomous driving, ADAS, lane change inference, target vehicle, driver intention.**

Nomenclature

ACC	Adaptive Cruise Control
ACU	Accuracy
AD	Autonomous Driving
ADAS	Advanced Driver-Assistance Systems
ADST	Adapting Deceleration to Safety Time
ANOVA	Analysis of Variance
ANN	Artificial Neural Networks
AUC	Area under the Curve
BN	Bayesian Network
CNN	Convolution Neural Network
DBN	Dynamic Bayesian Network
BDRNN	Bidirectional Recurrent Neural Network
DLC	Discretionary Lane Change
DSRC	Dedicated Short Range Communications
EEG	Electroencephalogram
GMMs	Gaussian Mixture Models
GNSS	Global Navigation Satellite Systems
GRU	Gated Recurrent Units
HD	High-Definition
HMM	Hidden Markov Models
LSTM	Long-Short Term Memory
MLC	Mandatory Lane Change
MLP	Multi-layer Perceptron
NBC	Naive Bayesian Classifier
NGSIM	Next Generation Simulation
PRE	Precision
TPR	True Positive Rate
FPR	False Positive Rate
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
SD	Standard-Definition
SPMDD	Safety Pilot Model Deployment Data
SVM	Support Vector Machine
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything

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(Corresponding author: Ruitao Song.)

The authors are with Aptiv Corporation, Troy, MI 48098 USA (e-mail: songrui1@msu.edu; editorialwork.bli@gmail.com).
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I. Introduction

In RECENT years, traffic safety has attracted increasing attention among researchers, industries, and government organizations. According to a report from the U.S. Department of Transportation, there were 36,560 people died in motor vehicle-related crashes in the U.S. in 2018 [1], which means there were about 100 deaths every day. Human error is involved in 94 to 96 percent of all motor vehicle crashes. Therefore, the autonomous driving technology has been attracting the interest of the researchers for decades.

The autonomous driving or advanced driver-assistance technology can be traced back to the basic safety features, like anti-lock brakes and cruise control, equipped on the vehicle in the last century. Beginning from this century, more advanced driver assistance technologies, like electronic stability control and lane departure warning, were being developed to further improve the safety and reduce the driver load, which also pave the way to autonomous driving technologies. The Society of Automotive Engineers (SAE) has defined six different levels of driver assistance technology advancements [2]. Level 0 features can only provide warnings and momentary assistance, e.g., blind-spot monitoring, emergency braking. Level 1 and 2 features are able to provide steering or/and brake/acceleration support to the driver. For Level 3 or higher systems, the drivers are not driving when these automated features are engaged. Level 3 autonomous driving features require the driver to take over and drive when the features request. And Level 4 features can drive the vehicle under some limited conditions, like on the highway, without drivers' taking over. Finally, Level 5 features can drive the vehicle everywhere in all conditions.

Higher-level autonomous driving technology requires better environment detection capabilities to identify the surrounding objects and the associated potential risks to the ego vehicle. For example, the adaptive cruise control (ACC) system needs to determine when the leading vehicle is going to cut-in or cut-out of the host lane. A typical autonomous vehicle platform of Level 3 or higher usually consists of the following parts: perception, localization, planning, and control. An example is shown in Fig. 1. Perception is used to detect the surrounding environment, including pedestrians, vehicles, traffic lights, traffic signs, etc., to avoid accidents while driving [3]. The objects around the ego vehicle are composed of both static and moving objects. Static objects do not change their position relative to the ground, while moving objects' position are changing. To prevent collisions with moving objects, the ego vehicle needs to not only identify the object's location at current time but also predict the object's future position. Usually, more attention should be put on the moving objects, since the uncertainty of their future position significantly affects the safety of the autonomous vehicle. Therefore, a prediction module is usually necessary for Level 3 or higher autonomous driving platform, as shown in Fig. 1, e.g., Waymo are putting a lot of effort into surrounding object's trajectory prediction [4]; Apollo developed by Baidu has a prediction module between the perception and planning module [5]; and the winner of the 2007 DARPA Urban Challenge, Boss, has the prediction functionality inside its perception module [6], [7]. The prediction functionality is sometimes also added into lower level driver assistant systems for better user experience, e.g., Honda introduced their intelligent Adaptive Cruise Control (i-ACC) to the market in 2015 [8]. I-ACC can predict if a vehicle is about to change from a neighboring lane to the lane of the ego vehicle, and thus react earlier than conventional ACC systems to ensure increased safety and comfort. A autonomous vehicle will have more knowledge of its surrounding environment/potential risk and make better decisions if accurate and early predictions of the surrounding vehicles' behaviors are available [9]. A variety of driving maneuvers have been studied, like lane keeping, lane changing, turning, stopping, etc. Among them, lane changing can happen in both urban and highway environments and attracted lots of attention. Car crashes often occur when traffic participants attempt to change the lanes [10]. Therefore, good predictions of the surrounding vehicles' lane change maneuvers will significantly improve intelligent vehicles' safety and passengers' comfort.

A. Motivation and Contribution

Lane change detection and prediction of the surrounding vehicles are critical for many features of the autonomous driving or advanced driver-assistance system (ADAS) on intelligent vehicles in a variety of scenarios. There are several review papers about driver or vehicle behavior prediction. Xing *et al.* [11] provide a comprehensive review on the driver lane change intention prediction for intelligent vehicles. However, this research focuses on the prediction of ego vehicle's behavior, which is very different from the prediction of the surrounding vehicle's behavior around the ego vehicle. A survey on motion prediction and risk assessment is provided for intelligent vehicles in [12]. In [13], a review of the deep learning-based vehicle behavior prediction algorithms is conducted. However, these studies do not specifically focus on surrounding vehicles' lane change maneuver prediction.

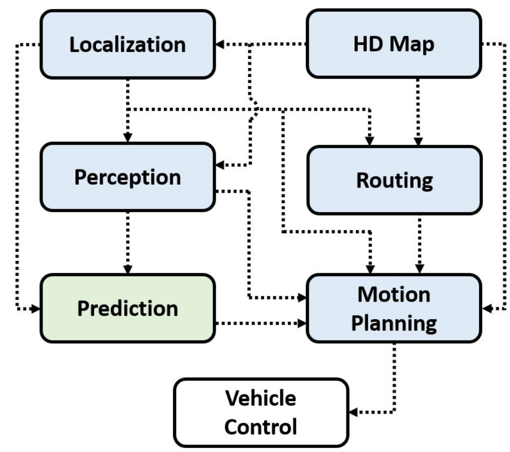

Fig. 1. Prediction module in general autonomous driving system architecture [5].

This paper aims to give the readers an overview of the state-of-the-art research on the surrounding vehicles' lane change inference for intelligent vehicles. We provide detailed discussion on the basic concepts of lane change prediction and detection to help the readers to have a better understanding of the problem itself and the subtle differences among the different research studies. Moreover, the reviewed studies are discussed in terms of sensing technology, inference algorithm, input/output type, etc.

The rest of the paper is organized as follows: First, the basic concepts of the lane change maneuver are introduced to show the complexity of lane change maneuver inference and most, if not all, of the factors that need to be considered. Second, the sensing and perception systems of intelligent vehicles are introduced, since the algorithm selection methods and inference performance are profoundly affected and limited by the vehicle's sensing ability. Then, the popular algorithms and validation methods for lane change maneuver inference are reviewed and analyzed. Some studies for ego vehicle's intention inference can also be used in surrounding vehicles' lane change maneuver inference. Therefore, some of these research works are also mentioned in this paper as a reference. Finally, some prospects of prediction and detection of surrounding vehicles' lane change are also introduced.

II. Basic Concepts and Problem Formulation

In this paper, the vehicle equipped with autonomous driving, ADAS systems, or wireless communication devices is referred

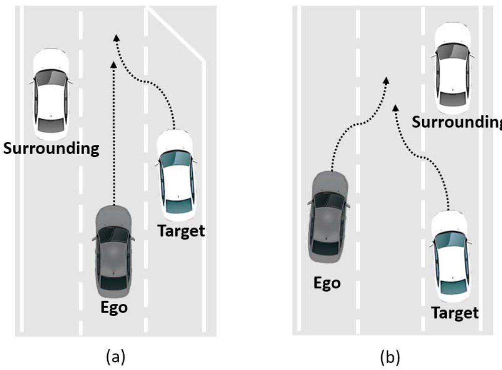

Fig. 2. Example scenarios where lane change inference is critical for the safety and comfort of the intelligent vehicle.

to as the intelligent vehicle and also the **ego vehicle**. The vehicles that are around and have impact on the ego vehicle are referred to as **surrounding vehicles**. Please note, the surrounding vehicles are not limited to the vehicles on the adjacent lanes or the ones directly in front or behind the ego vehicle. The vehicle whose lane change intention is being detected or predicted by the ego vehicle is called the **target vehicle**. Target vehicles are also surrounding vehicles.

Fig. 2 shows two examples when the lane change prediction and detection performance greatly affecting the safety and comfort of the intelligent vehicle. Fig. 2 (a) represents a scenario for the ACC system. The ACC system usually is able to follow the leading vehicle with a safe distance fairly well without driver's interference. However, it becomes challenging when another vehicle tries to cut-in in front of the intelligent vehicle from the adjacent lanes. If the ACC system fails to detect the lane change or cut-in situation early enough, the intelligent vehicle is likely to crash on the cut-in vehicle if the driver is not able to take over. Timely recognition of such situations can facilitate early and smooth reactions of the system and reduce hand-over situations [14]. Lane change intention prediction is also critical when the autonomous vehicle is trying to perform a lane change, as shown in Fig. 2 (b). The autonomous driving system needs to make sure that no other vehicles are going to change their lanes and move to the same range in the target lane the intelligent vehicle is going. Once such a vehicle is detected, the autonomous driving system should immediately abort the lane change if possible or perform other evasive maneuvers.

Maneuver detection is a process of analyzing whether a sequence of actions belongs to a particular maneuver. Maneuver prediction, on the other hand, refers to the prediction of the maneuver based on a set of incomplete sequence of actions before the execution of the maneuver. Due to the limited sensing ability, some intelligent vehicles are not able to predict the surrounding vehicles' lane change maneuver before the maneuver is executed. In many cases, the intelligent vehicle can only detect the lane change maneuver when the target vehicle is crossing or even crossed the lane marker [15]. To be more concise and accurate, this paper refers to both the prediction and detection of lane change maneuver as lane change maneuver inference.

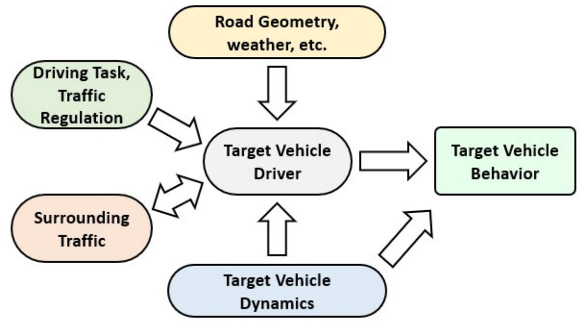

Fig. 3. Interaction between some of the main factors that affecting the target vehicle's behavior.

In this paper, the target vehicle is assumed driven by a human driver, which means that a human driver determines whether to make a lane change or not. The case where the target vehicle is driven by the autonomous driving system is not considered. Nevertheless, the discussion in this paper may also be useful for autonomous driving target vehicles, because most of the autonomous driving system is trying to mimic the human driver decision making process.

Since the target vehicle is controlled by a human driver, one needs to consider both the target vehicle itself and the driver during the lane change inference. On the one hand, the driver can change the behavior of the vehicle, as shown in Fig. 3; on the other hand, the status and dynamics of the vehicle also affects the decision of the driver, e.g., a driver usually won't make sharp turn when the vehicle speed is high due to safety and comfort issue. The behavior of the target vehicle is the consequence of both its driver's control input and the vehicle dynamics, where the driver plays in the dominant position especially for long-term vehicle behaviors. Therefore, identifying the driver's lane change intention can be considered somewhat equivalent to predicting the target vehicle's lane change maneuver. However, it needs to be noted that the driver's lane change intention comes first and the target vehicle's lane change maneuver is the result of that. Given the current sensing technology, it is usually not possible for the ego vehicle to directly detect the behavior of the driver inside the target vehicle. However, the driver's lane change intention is also affected by a lot of other factors, like the surrounding traffic, road geometry, traffic regulations, driver's destination, etc., as shown in Fig. 3. The ego vehicle can rely on these factors to predict the target vehicle's driver intention and thus its lane change maneuver along with the observed behavior of the vehicle.

In most of the studies, the prediction model only tells how likely the target vehicle is going to perform a lane change without information about when the lane change will happen. Although it is not always clearly stated in these studies, the predicted lane change maneuver should be happening within a reasonable period of time in the future, such as 5 or 10 seconds. The prediction result becomes very hard to use if the time is too long, because the downstream controller can hardly determine when to react to the possible lane change. Moreover, it is almost certain that a vehicle is going to make a lane change given a time duration long enough. However, if the prediction model can calculate accurately when the lane change will happen, it is almost always better to have a lane change prediction as early as possible.

A. Driver Behavior

Studying the formation, classification, and modeling of driver behaviors will provide valuable information and hints on how to predict the lane change maneuver. In general, drivers' behaviors can be classified as intended or unintended behaviors. Unintended behaviors can be caused by distractions and workload [16], multi-tasking [17], and fatigue [18], etc. In general, it is difficult to predict an unintended behavior well beforehand [19]. Because the driver's intention in the target vehicle is hard to predict, the lane change inference model mainly relies on the vehicle's behavior to 'detect' rather than to 'predict' the lane change. Fortunately, most of the lane change maneuvers belong to the intended behaviors. In [20], [21], a three-level hierarchy has been proposed to underlie cognitive control of driving. The three levels include strategic, tactical or maneuvering, and operational or vehicle control. The strategic level involves general trip planning, including setting trip goals (e.g., minimize time, avoid traffic), selecting routes, and evaluating the costs and risks associated with alternative trips. The maneuvering level involves the negotiation of common driving situations such as curves and intersections, gap acceptance in overtaking or entering the traffic stream, and obstacle avoidance. The operational level consists of the immediate vehicle control inputs, which are largely automatic action patterns (e.g., steering, braking, shifting).

The three decision-making levels can also be considered as three intentional levels. The lower level decisions are aligned with higher-level decisions. Different levels of decisions also require different knowledge and time to make [22]. For example, a general trip plan can be made in advance. Maneuver-level decisions take place in seconds according to the immediate driving environment. The lane change maneuver belongs to the category of tactical level driving tasks affected by the strategic level decisions and determines the operational level decisions. Therefore, the lane change maneuver inference can be performed within each driver's decision level. Once the strategic level decisions are known, one can tell how likely and when a lane change will be performed to complete the strategic level task. Similarly, once the sequence of operational level driving behaviors is detected, one can tell whether the vehicle is performing a lane change or not.

To predict the lane change, researchers need to distinguish the lane change from other maneuvers. Then the maneuver inference algorithm can evaluate which maneuver is most likely to be or being executed. In most of the research, the vehicle is in a multi-lane road environment without considering intersections or traffic lights. The drivers' maneuver or vehicle behavior can be generally simplified and defined as lane change and lane keeping. Driggs *et al.* defined three modes: lane keeping, lane changing and preparing to lane change [23]. Many research works also considered the left and right lane change separately [24]–[26]. Some of the research further divided the surrounding vehicles' maneuver into more classes. For example, six maneuver classes were defined for highway driving in [27]. Deo *et al.* defined ten maneuver classes for vehicle motion on freeways in the ego vehicle's frame of reference: lane passes, overtakes, cut-ins, and drift into ego lane [28]. Schreier *et al.* defined the following maneuvers: follow road, follow vehicle, target brake, lane change, turn, and trash maneuver class [29]. To avoid defining too many maneuvers, Bahram *et al.* suggested using a finite set of basic maneuvers to approximate the infinite number of possible movements a driver is able to perform on the highway, and proposed the lateral basic maneuver set to be: lane keeping, left and right lane change [30]. In this framework, overtakes can be decomposed to left/right lane change, lane keeping, and right/left lane change; and merges can also be classified as lane changes where the ending lane can be considered as the reason for the lane change, as shown in Fig. 2. Although it is almost certain that a vehicle is going to change lanes before the lane end point, but when the lane change will happen still remains unknown and requires prediction. In general, how to classify the driving maneuvers depends on how the researchers would like to model or infer the lane change maneuver. Introducing more maneuver classes can simplify the modeling process for each maneuver. However, too many maneuver classes will make the whole model over complicated. There should be a trade-off between the simplicity of each maneuver model and the number of maneuver models.

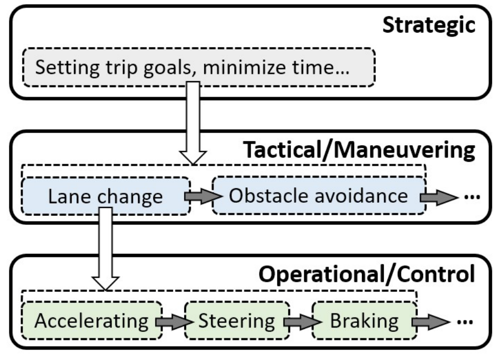

Fig. 4. Three-level hierarchical classification of driver behaviors.

Lane change can be classified as mandatory lane change (MLC) and discretionary lane change (DLC) [31]. MLC happens when the driver must leave the current lane, and DLC happens when the driver performs lane change to improve driving conditions. For instance, the driver needs to change to a certain lane to complete some strategic level driving task even there is more traffic in that lane. If only traffic conditions are considered, false lane change prediction can occur. Similarly, an MLC can be anticipated if the car is driving on a lane that will end very soon. Leonhardt *et al.* [32] grouped the lane change events into different types according to the causes of the lane change, such as slow leading vehicle, return lane, static obstacle, etc. They also reported the slow leading vehicle is the most frequent situation observed in their data set. This classification helps the researchers evaluate the possible input features for lane change inference and select the most important ones for better inference performance.

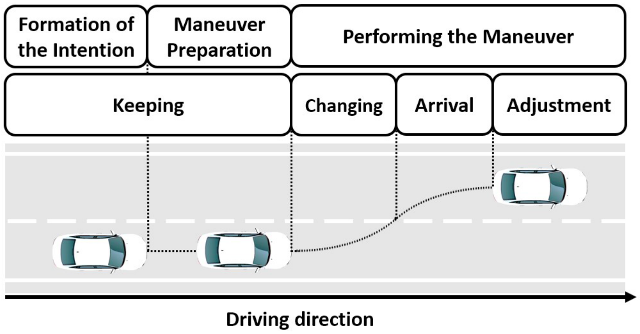

Fig. 5. Illustration of a typical lane change process.

B. Lane Change Modelling

There are three consecutive phases that can be aspired to be detected in order to conclude on the driver's intention of a lane change maneuver [32]. They are the formation of the intention, preparation of the maneuver, and performing the maneuver. While driving, the driver continuously evaluating the nearby environment and surrounding traffic conditions. Once another lane is available and more preferable, the driver will have the intention to drive to that lane. In the second phase, the driver will double-check the surrounding environment to ensure safety. Finally, the driver starts to perform the lane change, which results in observable changes of the vehicle's status and movement parameters. In this method, the lane change maneuver is divided into sub-phases according to the driver's intention. Some other works do so mainly based on the behavior of the vehicle. In [33], the lane change maneuver was divided into four phases: keeping, changing, arrival, and adjustment, which is similar to that in many other research [11]. In general, a typical lane change process can be modeled, as shown in Fig. 5.

According to the research about the driver behaviors during lane change [34]–[36], the lane change trajectories can be fitted by polynomial curves. Eshelman *et al.* [37] and Nelson [38] both explored the use of a single polynomial to describe an ideal lane change maneuver path. The polynomial can be of any power, but high order polynomials increase complexity and computation time [39]. Many research works directly used the lane change model to detect the lane change maneuver, as will be introduced in Section IV.

The lane change inference can be performed during different phases of the lane change process. If the inference model is able to identify the lane change before the target vehicle performing the maneuver, it is usually considered as lane change 'prediction'. Otherwise, it is usually considered as lane change 'detection'. Different inputs can be used during different phases. During the formation of the intention, the driving task, surrounding traffic can be used; when the target vehicle is performing the maneuver, the target vehicle's state of motion can be used. Extracting and evaluating features from the early stage of the lane change process generally leads to early detection but low classification accuracy, which will be discussed in Section IV. For example, the surrounding traffic speed can be used to provide an early lane change prediction, as shown in Table II, since this feature belongs to the formation of the intention stage.

III. Sensing and Environment Perception

The sensing ability of intelligent vehicles directly affects how to develop the lane change inference system and its performance. The environment perception mainly consists of the surrounding traffic, road information, and other environment perception. The surrounding traffic refers to pedestrians, vehicles, motorcycles, etc. The road information consists of the lane geometry, marker types, traffic signs, etc. Other environmental information, such as traffic lights, weather conditions, also have a great impact on the driver behavior [40].

A. Sensing Devices on Intelligent Vehicles

The key components of intelligent vehicles are sensing devices. The sensors on an intelligent vehicle can be generally divided into two groups: internal vehicle systems and external world sensing [41]. The internal vehicle systems are mainly used to provide the ego vehicle's status, like yaw rate, speed, etc. These systems do not directly detect the external world but provide many inputs utilized by the autonomous driving systems. For example, the resolution of Global Navigation Satellite Systems (GNSS) can be increased using data from IMU. To be noted, these sensors are critical when predicting the ego vehicle's lane change driven by human driver. The external world sensing will be mainly discussed in this paper since the focus of this paper is the surrounding vehicles' behavior inference. The main types of external world sensing devices that can be part of intelligent vehicles are cameras, Lidars, Radars, Ultrasonic sensors, GNSS, and wireless communication [40], [42], [43]. Different kinds of environment information can be detected by different sensing devices. The surrounding traffic is usually detected by cameras, Radars, and Lidars. The road geometry is usually obtained from cameras, and High-Definition (HD) maps. Sometimes, the surrounding traffic can also help to estimate the road geometry [44]. The same environment information can come from different sensing sources. For example, the surrounding vehicle can be detected by cameras and Radars; the traffic light can be identified by the vehicle-to-infrastructure (V2I) communication and cameras. In this case, sensory fusion can be applied to improve measurement [45].

While perception in autonomous vehicles is achieved with many sensing systems, cameras were among the first types of sensors to be used and are currently the primary choice for car manufacturers [42]. Current production vehicles mainly utilize them for lane departure and lane keeping algorithms [41]. Stereo vision is the application of two or more cameras to provide the fidelity necessary to distinguish the depth and height of objects. The challenge for cameras is the sensitivity to the low intensity of light. So, its performance is usually limited at night [43].

Radars are integrated into vehicles for different purposes like ACC, blind-spot warning, collision warning, and collision avoidance. Utilizing the Doppler effect, they also provide speed as a direct output. Radars are used for

TABLE I
COMPARISON OF MAIN TECHNOLOGIES FOR ENVIRONMENT SENSING

Criteria	**Lidar**	**Radar**	**Camera**	**US**[a]	**V2X**[b]
Short range detection (0-1m)	Med[c]	Med	Med	Good	Good
Mid range detection (1-30m)	Good	Good	Good	Med	Good
Long range detection (>30m)	Med	Good	Poor	Poor	Good
Angular accuracy	Good	Med	Good	Poor	-
Velocity accuracy	Poor	Good	Poor	Poor	Good
Distance accuracy	Good	Poor	Poor	Good	Good
Operation in adverse weather	Poor	Good	Poor	Med	Good
Operation at night	Good	Good	Poor	Good	Good
Delay	Good	Good	Good	Good	Poor

[a] US: Ultrasonic sensor
[b] V2X: HD map is also included here.
[c] Med: Medium

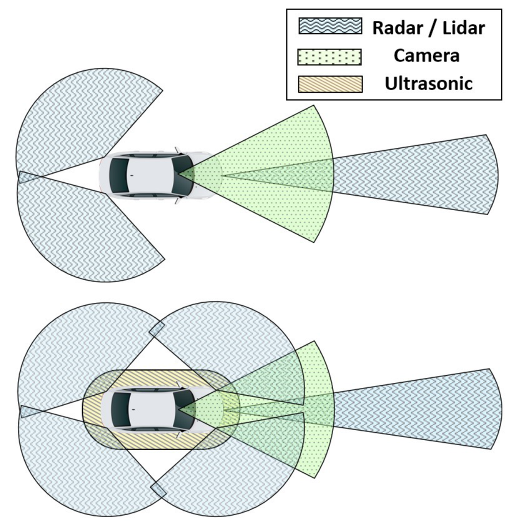

Fig. 6. Examples of sensors layout on intelligent vehicles.

both near and far obstacle detection. Generally, the typical Radar system is a trade-off between range and field of view. For example, a typical system used for ACC has a range of approximately 150-meters and a field of view of approximately 20 degrees [41]. Radar is usually less affected by weather conditions [43].

Lidar uses an infrared laser beam to determine the distance between the sensor and a nearby object. Most current Lidars use light in the 900nm wavelength range, although some Lidars use longer wavelengths, which perform better in rain and fog [42]. Although Lidar systems tend to be more accurate than Radar, they typically have higher costs and require additional packaging space that prohibits their use. Also, Lidar systems generally are not as accurate as Radar systems for detecting speed.

Ultrasonic systems tend to be the cheapest of the technologies discussed. However, they are typically affected by blockage or disturbances more than Radar systems based on the physics of operation described above [41]. It is usually used to detect short distances at low speed [45].

GNSS is based on the utilization of a receiver and antenna that communicate with various satellites to triangulate the absolute vehicle position. Vehicle-to-everything (V2X) communication is the passing of information from a vehicle to any entity that may affect the vehicle. V2X consists of different types of communications: vehicle-to-vehicle (V2V), V2I, etc. V2V is direct communication between multiple vehicles. V2I technologies capture vehicle-generated traffic data, wirelessly providing information such as advisories from the infrastructure to the vehicle that inform the driver of safety, mobility, or environment-related conditions. Compared with the Standard-Definition (SD) map, HD map allows vehicles to locate itself more precisely and to build a more detailed model of the surrounding environment [46]. Nowadays, the development of HD maps enables vehicles to access additional road and traffic information. Table. I summarized the strengths and weaknesses of different sensing devices mentioned in this section.

B. Sensors Layout and Detection Capability

The ADAS or autonomous driving system detects the surrounding environment by fusing the outputs of different sensing devices. Depending on the system's functionality or autonomous level, different sensor layouts can be implemented for different systems. Fig. 6 shows two examples of the sensor layout. The top one is usually utilized for L2 systems. This kind of system usually has ACC and lane keeping assistant functionality. Some of them have Radars or other sensors mounted on the rear of the vehicle to detect the vehicles in the blind spot. Honda Sensing [47] and Toyota Safety Sense [48] systems are two examples of the ADAS systems using a similar sensor layout, as shown in the upper plot. The sensor layout in the lower plot in Fig. 6 can be used for higher-level autonomous driving system due to the improved sensing ability. The actual sensor setup varies a lot among systems developed by different research groups and companies. Some systems use more cameras for environment detection, like Tesla's AutoPilot [49]. Other systems rely more on Radar or Lidar, like Waymo Driver [50]. The sensor type and sensor layout greatly impact the design and performance of the surrounding vehicle's lane change detection and prediction system.

For systems with similar sensor layout as shown in the upper plot in Fig. 6, it is difficult to detect the vehicles driving in front of the ego vehicle in the adjacent lanes due to the limited coverage of the sensors' field of view, especially when the vehicles are longitudinally close to the ego vehicle. This situation is sometimes called as close cut-in. In this case, the lane change maneuvers usually cannot be predicted before the lane change starts. The ego vehicle can usually only detect the lane change of the target vehicle during the middle or later stage of the lane change maneuver when the target vehicle enters the sensor's field of view and is close or crossing the lane marker. When the target vehicle is detected close or crossing the lane marker, it is almost certain that it is cutting in. Therefore, how to improve the perception performance becomes very important to detect the lane change maneuver. Morizane *et al.* [51] used the camera with a wide-angle lens to detect a cut-in vehicle from an adjacent lane near the ego vehicle. To further improve the cut-in detection performance, Choi *et al.* [15] applied a part-based vehicle detection approach that detects a vehicle by combining the detected tires. According to the authors, the proposed method can build a cut-in warning system with a high true warning rate of 98.6% and low latency.

Higher-level autonomous driving systems have much better surrounding environment detection ability. The additional sensors are able to detect the surrounding vehicles before they are performing lane change maneuvers. Lee *et al.* [52] developed a sensor fusion module that combined the measurements from Radar and camera sensors to provide relative positions and relative velocities from the ego vehicle to target vehicles in neighboring lanes. A simplified bird's eye view is fed into a Convolution Neural Network (CNN) to predict the vehicle's lane change intention. In [33], Woo *et al.* mounted six Lidars around the ego vehicle to detect the surrounding vehicles' position and speed. Many research works did not specify the sensor setup but assumed that the ego vehicle has the ability to detect all the relevant surrounding vehicles with enough accuracy [26], [53].

Most of the research work uses on-board sensors like cameras, Radar, and Lidar for environment detection. Problems arise when other vehicles are outside the field of view of these sensors or blocked by other surrounding vehicles [54]. The limited detection range of these sensors also poses a constraint on the time the ego vehicle has to react to a lane change maneuver. V2X provides another way to improve the detection of surrounding vehicles. Although these vehicles may not have direct impact on the ego vehicle, it may affect the target vehicle's behavior. Sakr *et al.* [55] proposed a machine learning based approach to detect lance changes of remote vehicles using V2V data received at the ego vehicle via DSRC. Ma *et al.* [56] also used the V2V communication to improve the detection accuracy of the speed and position of the target vehicle. Moreover, according to [57], researchers even suggested improving ACC safety in cut-in scenarios by V2V communication where the cut-in vehicle transmits a clear message of lane changing (an equivalent of 'turning light') to the following vehicle at the instant it starts to make lane changing. However, the disadvantages due to the high cost of the required infrastructure, the scalability problem of the networks, and the related security issues make its industrialization very difficult [58]. To the best of our knowledge, there is no dedicated research and study in this area yet. But, this could be a promising research topic in the future. In addition, the HD map provides a very useful and high-quality resource for detecting the surrounding road geometry. For example, the road curvature and distance to highway exit considered in [24] can be obtained directly from the HD map.

IV. Lane Change Maneuver Inference

The lane change inference system requires multiple techniques such as data fusion, perception, data processing, etc. As shown in Fig. 7, the 'data fusion & perception' module fuses all the signals captured from the sensing devices and obtains all the surrounding traffic and other environmental information. Then the variables in the ego vehicles' coordinate system are converted into the target vehicles' coordinate system and processed into features that can be consumed by the inference algorithm. Finally, the lane change inference algorithm provides the inference results to the downstream modules.

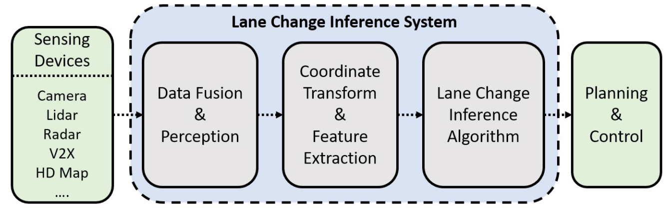

Fig. 7. Architecture of a typical lane change maneuver inference system.

A. Inputs for Lane Change Maneuver Inference

During each phase of the lane change maneuver, different inputs can be used to predict or detect the driver's behavior. The inputs can be further divided into three groups according to their resources: environment context, driver behavior, the status of the vehicle.

1) Environment Context: Environment context around the surrounding vehicle is the primary reason for the driver to do the lane change. Therefore, it is the primary input during the intention formation phase shown in Fig. 5. Environment context can be further classified into two groups: the dynamic environment and static environment.

- The dynamic environment refers to the movable or moving neighboring traffic, such as pedestrians, vehicles, motor-cycles;
- The static environment mainly includes the road/terrain information, traffic signs, weather condition, etc.

Environment information is usually only available on vehicles equipped with sensors for the higher-level autonomous driving system. Due to the difficulty of capturing and its complex nature, the environment context input is not intensively studied until recent years as advanced sensing or connected vehicle technologies are being developed. This information mainly belongs to the formation of intention stage shown in Fig. 5 and influences the strategical level driver decisions shown in Fig. 4. Therefore, inference systems using this information usually can detect the lane change maneuver early.

Zhang *et al.* used four neighboring vehicles' along with the target vehicle' information to predict the lane change maneuver of the target vehicle [59]. The information used is the longitudinal relative speed and distance between the target and its neighboring vehicles. Leonhardt *et al.* evaluated the lane change prediction using the similar inputs [32]. The authors used the Adapting Deceleration to Safety Time (ADST), calculated in Eq. 1, to quantify the occupancy of the possibility and likelihood of the lane change.

$$a_{ADST_{v_0}} = \frac{\left(v_{E_0} - v_0\right)^2}{2\left(v_0 t_{Safety} - s_0\right)} \tag{1}$$

where s_0 and v_0 are the distance and velocity of the neighboring vehicle; v_{E_0} is the velocity of the target vehicle; and t_{Safety} is a striven safety time [60]. In contrast, Woo *et al.* [61] borrowed the potential field method often used for robot navigation to calculate whether a lane change is advantageous or not, depending on the relative distance and speed between target and its neighboring vehicles. Wissing *et al.* used Sigmoid function to model the lane change probability reflecting the benefit and feasibility of a lane change maneuver [53]. Some other research directly utilizes the neighboring traffic's status and feeds it into the classification algorithm. Dou *et al.* [62] considered the lead and lag vehicles in target lane, in a highway lane drop scenario.

Some research used more neighboring vehicles around the target vehicle and more properties (like speed history) associated with each neighboring vehicle [25], [63]. Dai *et al.* [64] considered the closest six neighbours around the target vehicle. In [65], [66], the three closest vehicles in the target vehicle's current and two adjacent lanes were used for prediction. Altch *et al.* [67] even considered nine vehicles to improve the prediction performance. Instead of considering a fixed number of vehicles, some studies only consider the vehicles within some certain distance [68]–[70].

Ideally considering more vehicles can improve the prediction performance. However, in practical application, the states of the surrounding vehicles are not always available due to sensor blockage or limitations. The sensor outputs for the partially blocked or far-away vehicles are subject to large noise. And this noise can lead to false predictions.

Static environment information is another stimulus to the lane change intention. As the HD map is becoming a trend for autonomous vehicles, more information about the road will become available. The lane marker type, available lanes on the sides of the target vehicle, road curvature, elevation, distance to the highway exit, and speed limit were considered in [24], [71]–[73]. Das *et al.* also considered the weather information [73]. It was observed that there were significant differences among different weather conditions for most of the parameters, such as speed, longitudinal acceleration, and deceleration during lane changes. Considering weather conditions can also improve classification accuracy.

2) Status of the Vehicle: For ego vehicle driver intention detection, many signals available through the Control Area Network (CAN) are used, such as steering wheel angle and brake/gas pedal position. However, these signals are usually unavailable for detecting the surrounding vehicle's intention. Depending on the different sensor setup of the intelligent vehicle, various properties of the surrounding vehicles' status can be detected. The widely used signals are longitudinal/lateral position, speed, acceleration of the target vehicle [33], [74]. These variables can be based on different coordinate systems: the ego vehicle's coordinate system and the road coordinate system. Some research assumes that the ego vehicle is driving along the centerline of a straight lane, where the surrounding vehicles' properties are similar in both coordinate systems. However, once such an assumption is not valid, the surrounding vehicles usually need to be considered in the road coordinate (or curvilinear coordinate) system. The projection of the surrounding vehicles onto the road coordinate system requires the road/marker information coming from the HD map, cameras, or other sensing devices. Most of the research considered the target and surrounding vehicles' properties in road coordinate system [24]–[26], [75]

In [26], [28], [54], [76]–[78], not only the current values of the vehicle status were considered, but the track history of the values were also used to improve the lane change inference performance. The lane change maneuver is regarded as a dynamic process. The time-series data was sent to the algorithms such as the Dynamic Bayesian Network, the Hidden Markov Model (HMM), or the Long-Short Term Memory (LSTM). Although the track history can provide more information about the vehicles, it requires the sensing system having stable detection of the objects for a longer period of time. This is hard to achieve in some cases due to sensor limitations or blockage.

The turn signal is a practical solution for drivers' lane change intention inference [79]. However, this signal can also be used for other behavior, such as specific direction turning [80]. Many researchers have conducted studies demonstrating problems in the sensitivity of the turn signal as an indicator for lane changes [81]–[83], especially for inferring the traditional ego vehicle driver lane change intention. However, as more sensors and HD maps are becoming available for AD vehicles, the turn signal can be used with other information, like road type, to improve its sensitivity for lane change prediction.

3) Driver Behavior: The driver's behavior, like eye and head movement, is widely used to detect the driver's intention of the ego vehicle. Due to the sensor limitation, it is hard to use these signals to predict the surrounding vehicle's intention. However, with the development of relevant technologies, such as V2V communication, these signals may be available in the future. The driver behavior signals mainly including the eye and head movement of the driver [84]–[86]. Some other body behavior signals, like electroencephalogram, foot, hand, and body gestures, were also utilized for ego vehicle driver intention inference [87]–[91].

4) Feature Selection: There is a lot of research about driver intention prediction. Meanwhile, a large number of different variables or parameters are used as the inputs for the lane change inference system. The parameters are also known as situation features [75]. As sensing technologies keep being developed, the number of available features is also increasing. Consequently, selecting the most critical features as the inputs becomes an increasingly important topic when developing the lane change inference system. The objective of feature selection is three-fold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data [92].

Schlechtriemen *et al.* [24] proposed the use of Area under the Curve (AUC) of the Receiver Operating Characteristic (ROC) to evaluate each feature [93]. The prediction power for each feature is defined as:

$$AUC_t(t_m) = AUC_{total}(F^{t=t_m}) \tag{2}$$

TABLE II
PART OF THE FEATURES EVALUATED IN [24], [32], [94] FOR LANE CHANGE INFERENCE

Feature[a]	**Time to LC**[b]	**Effect Size**[c]	**Importance**[d]
Lane Accessibility	0∼25(s)	0.78	-
Fro. Dis.	0∼2(s)	0.24	0.01
Fro. - Rel. Vel.	0∼2(s)	0.29	0.01
Adj. Fro. - Dis.	0∼25(s)	0.53	0.013
Adj. Fro. - Rel. Vel.	0∼25(s)	0.55	0.012
Adj. Rea. - Dis.	6∼25(s)	0.64	0.013
Adj. Rea. - Rel. Vel.	0∼20(s)	0.65	0.012
Tar. - Vel.	0∼10(s)	0.66	0.011
Tar. - Yaw Rate	0∼2(s)	0.2	-
Tar. - Indicator	0∼2(s)	0.78	-
Tar. - Lat. Pos.	0∼2(s)	0.32	-

[a] Fro.: Front Vehicle; Tar.: Target Vehicle; Adj. Fro.: Adjacent Front Vehicle; Adj. Rea.: Adjacent Rear Vehicle; Dis.: Distance; Rel. Vel.: Relative Velocity; Lat. Pos.: Lateral Position.
[b] lane change time is defined as the moment when the vehicle's longitudinal axis passed the lane marking [32].
[c] the weighted overall effect size taking into account the total number of the lane change type [32].
[d] the importance value calculated in [94].

where F is the feature vector, t_m denotes the time before a lane marker is crossed, and AUC_{total} is defined as:

$$AUC_{total} = \sum_{c \in M} AUC_c \cdot p(c) \tag{3}$$

where M is the aggregate of the maneuvers, and $p(c)$ is the corresponding probability. According to the equations, the prediction power also considers how early a lane change maneuver can be predicted using each feature as the input. As expected, it is found different features contribute differently at the different times prior to the lane change [24]. This method requires the output from the maneuver classifier, which means the results are also affected by the classifier algorithm. Some other researchers evaluated the feature's ability to predict lane changes by a statistical approach: the analysis of variance (ANOVA) [32], [94]. Similarly, the time before lane changes is also considered in the evaluation. Leonhardt *et al.* [32] divided the data into two sets: lane change and lane keeping. The null hypothesis H_0 is assessed by calculating the p-value to determine whether the difference between the expectation values of the two data sets of a feature is statistically significant, where H_0 states that the two populations' expectations are equal. Unlike the AUC method mentioned above, ANOVA method does not rely on the output of the classification algorithm. Researchers are able to select the features before selecting a certain classification algorithm. It only reflects how each feature is correlated with the lane change maneuver. Das *et al.* [73] chose the Boruta algorithm because it utilizes 'all-relevant' feature selection method that allows selecting all features related to the outcome feature. Table. II shows some of the features studied in [24], [32], [94]. The 'Time to LC' reflects how early the corresponding feature can be used to predict the lane change. The values are obtained by combining all the time intervals, evaluated in [32], with effect size larger than 0.5.

Besides evaluating which features can provide the most prediction power, studying the combinations of features also plays an important role to improve the prediction performance according to [95]. Huang *et al.* evaluated different combinations of feature selection by applying Entropy analysis, where the entropy correlation coefficient is calculated. It was found that certain feature combinations can actually harm the system's uncertainty level [95]. Therefore, when selecting the input features for the system, certain combinations should be avoided.

B. Outputs of Lane Change Maneuver Inference

The outputs of the surrounding vehicles' lane change maneuver inference can be in different forms. The simplest and most widely used method is the binary type output. This kind of approach outputs a flag telling whether the associated vehicle is going to or is performing a lane change. The binary output is simple for the downstream controllers to use but provides less information about the likelihood of the lane change. Another kind of output also tells the probabilities of the lane change and other maneuvers depending on the maneuver classes definition. In this case, the downstream controller is able to react differently according to the lane change probability [96]. For example, in [27], [97], the likelihood of each predefined maneuvers were predicted. Readers can refer to Table. IV for the output types for some selected papers.

The time to lane change is a significant variable for the downstream controllers to plan the ego vehicle's movement. However, the time to lane change is usually not a direct output of the lane change inference system. Nevertheless, most of the research evaluated how early the inference system can identify a future lane change [59], [71], [72], [98]. There is also some research that especially studies the time to lane change after a future lane change maneuver is already identified [99], [100].

C. Algorithms for Lane Change Maneuver Inference

The algorithms used for lane change inference can be generally divided into two different approaches: the model-based and machine learning approaches. In recent years, the machine learning approaches are becoming very popular in this field, and can be further classified into generative and discriminative approaches. The generative approaches are more suitable for multi-target algorithms, while the discriminative approaches are mainly used for single-target algorithms [19]. As one of the machine learning techniques, the neural networks can be either generative or discriminative models depending on their structures. However, due to their popularity, the neural networks are classified as a separate group in this paper, as shown in Fig. 8.

1) Model-Based Approach: The first approach is based on a set of driver behavior models. The system continuously runs several versions of the behavioral models in parallel. Each model embodies a different driver maneuver, like lane change and lane following. The system gathers observable data from the driver and compares each model's simulated behavior with the driver's actual observed behavior. Then some similarity metric is used to determine the best matching model and thus

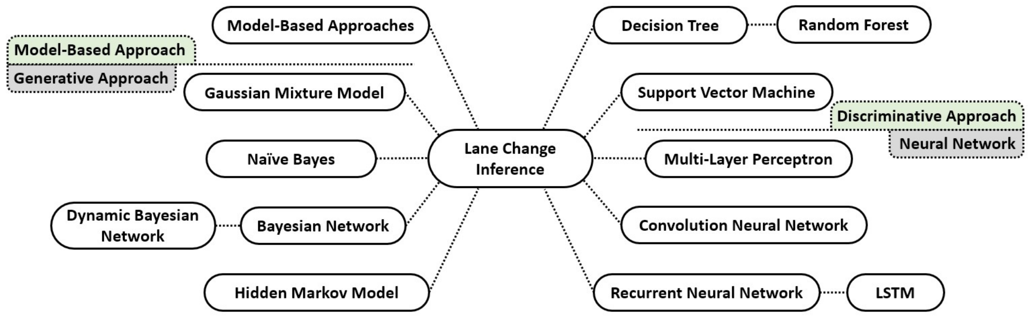

Fig. 8. A summary of popular algorithms used for lane change inference systems.

infers the driver's most likely current intention [101], [102]. This kind of approach puts a lot of effort into developing the driver models. The classification methods sometimes are based on some machine learning algorithms.

Another approach tries to model the driver's decision-making process. It is usually based on the assumption that drivers are always choosing the maneuvers that can give the best balance between safety and comfort. How good a particular maneuver can be is usually formulated as a cost function. The cost of all the possible maneuvers of the target and its surrounding vehicles will be calculated. The predicted maneuver will give the smallest cost. For example, Sorstedt *et al.* approximated the driver as an optimal controller according to a cost function reflecting safety, comfort, and preferred speed [103]. Lawitzky *et al.* predicted the drivers' maneuvers by evaluating the collision probability of all the interacting vehicles. It was assumed that the drivers locally optimize their trajectories based on the estimation of the intention of the surrounding drivers [104]. However, this approach leads to exponential growth with the number of vehicles [105]. To solve this problem, Schwarting *et al.* checked the maneuver combinations in a recursive way, where only pairs of vehicles were considered instead of all vehicles at once [105]. Schlenoff *et al.* applied a similar approach which also used the short term vehicle state prediction obtained based on the vehicle dynamics [106].

The model-based approach generally has good interpretability and can provide long-term predictions. However, the tuning of the cost functions or similarity metrics is usually challenging. Moreover, the assumption that all vehicles will try to avoid collisions may not be true in some situations [107]. Some dangerous lane change may not be predicted due to the fact that the drivers' decisions are based on imprecise perceptions and information [108]. Moreover, in the above mentioned studies, it was assumed that all the drivers could be described by the same model. In reality, drivers have different driving styles that lead to different behaviors. How to accurately identify the driver's driving style remains a challenging problem.

2) Generative Approach: Generative approaches are widely used for lane change inference.The Bayesian Network imitates human like-reasoning and decision making [14], [29], [74]. In some research, when assuming all features are mutually conditional independent, one of the most straightforward

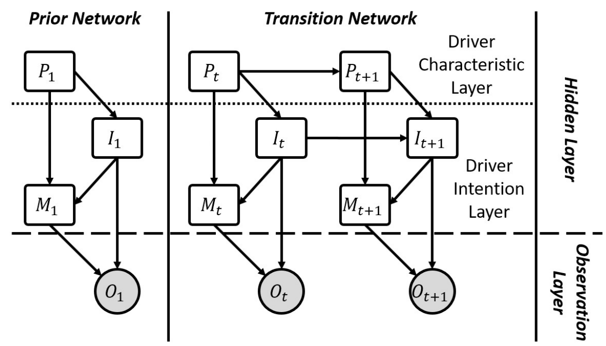

Fig. 9. The Dynamic Bayesian Network used in [76]. The nodes in the network represent variables and the connections between nodes in the form of arrows represent conditional distribution. The prior network defines the connection between the nodes at the first time, and the transition network defines the connection between the time t and the time $t+1$.

Bayesian Networks, the Naive Bayesian Classifier, can be used [74]. The Bayesian Network computes and analyzes at each time step without using the history data. Some research considers the driving as a dynamic process, and extend the Bayesian Network to Dynamic Bayesian Network [76], [109]. Since the driver intention is greatly affected by driver characteristic, Liu *et al.* [76] also considered the driver characteristic in the Bayesian Network, as shown in Fig. 9. As a method to improve the efficiency for exploring receptive structure patterns, the Object-oriented Bayesian Network was adopted in [75]. HMMs, which can be considered a type of Dynamic Bayesian Network, is another way of modeling time series data [28], [110], [111]. In [59], the continuous HMMs integrated with the Gaussian Mixture Models were used to model the lane change and lane keeping behavior.

3) Discriminative Approach: Unlike the generative approach, the discriminative approach does not need to model the dependencies between evidence variables. In [33], [112], Support Vector Machine (SVM) was used to estimate the driver's intention while applied to trajectory prediction. Kumar *et al.* [113] used a Bayesian Filter on top of the multi-class classifier in order to improve the reliability of the predictions. It was expected that the smoothing introduced by the filter will reduce the rate of false alarms and missed detections. In [114], a Bayesian extension to the SVM, called a relevance vector machine, was used to discriminate between

TABLE III
COMPARISON OF DIFFERENT TYPES OF POPULAR ALGORITHMS USED FOR LANE CHANGE INFERENCE SYSTEMS

Algorithms	Strength	Weakness
Model-Based Approach	•Very good interpretability. •Usually requires less data than the other algorithms to build the model.	•Model is based on some assumptions that may not always be true. •There is usually no standard method for tuning.
Generative Approach	•Usually have good interpretability. •Most of the algorithms can provide probabilistic output.	•Need to model dependencies in the data.
Discriminative Approach	•Parameters are optimized for the classification problem, so usually have better classification performance.	•Usually can only output binary results. •Poor interpretability.
Neural Network	•Due to its popularity, there are many methods and toolboxes available to use.	•Rely on large data set. •Interpretability is usually no good.

lane change and lane keeping. Hu *et al.* [115] presented a decision tree based method for maneuver prediction between braking or lane changing in cut-in scenarios. In some research, a large number of features were used to analyze the driver intention. It is hard to assume independence between the features. Moreover, the data set is highly affected by noise and outliers. To solve this problem, Random Forest algorithm was used to classify the driver intention [25], which was an ensemble of several decision trees. In general, the discriminative approach optimizes its model parameters for the classification problem itself rather than describing the lane change process.

4) Neural Network: The Neural Network is another group of algorithms being widely used. Probabilistic Multi-Layer Perceptron (MLP) was proposed for lateral motion prediction in [116]. Based on a set of representative trajectories for each target lane, the MLP model provides probabilities of how likely a vehicle will follow each trajectory and each lane with high-speed data sets. In [117], a Convolutional Neural Network (CNN) was used with MobileNetV2 [118] as the feature extractor. Lee *et al.* proposed an approach to infer traffic participants' lane-change-intentions based on a CNN for enhancing ACC [52]. Some other studies also chose CNNs to predict vehicle behaviors [119]–[121]. Recurrent Neural Network (RNN) is different from a typical neural network by containing feed-back connections [122]. This makes RNN suitable for time-series problems [11]. The typical RNNs lack the interpretability of the probabilistic graphical methods [123], like Bayesian Network. To solve the problem, Patel *et al.* [63] proposed a composite RNN model by adopting Structural Recurrent Neural Networks to learn factor functions and take advantage of both the high-level structure of graphical models and the sequence modeling power of RNNs. The problem of RNNs is that the input decays or increases exponentially over time, which causes problems in training. An Long-Short Term Memory (LSTM) uses a gating system to overcome this problem [124]. An LSTM has the property of remembering a value for an arbitrary length of time, allowing it to overcome the vanishing gradient problem [122]. Therefore, LSTM is widely used in driver intention prediction [26], [125]–[127]. Deo *et al.* [26] proposed an LSTM model for both vehicle maneuver and trajectory prediction for the case of freeway traffic. Using the surrounding vehicle's track histories, the LSTM network provides the probabilities of lateral and longitudinal maneuver classes as shown in Fig. 10, where lane change is one of the lateral maneuvers. In [72], Scheel *et al.* added an attention layer on top of the LSTM network to improve both the inference performance and interpretability. Some studies combined different neural networks to achieve better performance. For example, the LSTM and CNN were used together in [128], [129].

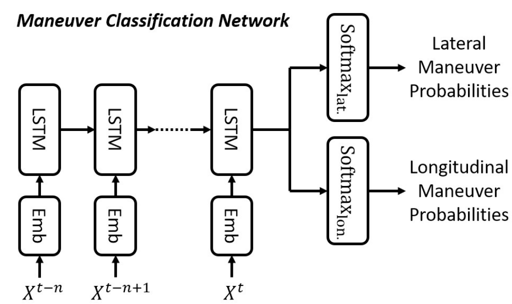

Fig. 10. The maneuver classification LSTM network used in [26]. $[x^{t-n}, \ldots, x^{t-1}, x^{t}]$ is the input tensor of track histories of the target vehicle.

In general, the model-based and generative approaches have better interpretability than the other approaches. The discriminative approach usually has good classification performance because its model parameters are specifically optimized for classification. However, it usually cannot provide lane change probabilities. The neural network usually requires an extensive data set to train, but various tools are available to facilitate the development process. The strengths and weaknesses of different approaches are summarized in Table. III. The algorithms used by some selected papers are listed in Table IV.

V. VALIDATION AND EVALUATION

A. System Validation

Most lane change inference systems are validated by real-world driving data collected by the corresponding researchers who designed the systems. This requires the research group to have their own test vehicles equipped with all the necessary sensors, data acquisition, and processing systems. Although this validation method is persuasive and trustworthy, it requires lots of effort to set up the test vehicles. Therefore, some of the research work is validated using

TABLE IV
SELECTED RESEARCH WORKS IN RECENT YEARS FOR SURROUNDING VEHICLE'S LANE CHANGE MANEUVER INFERENCE

Paper	Main Sensors	Input Type	Algorithm	Output Type	Validation
[26]	-	vehicle status	LSTM	probability	NGSIM
[75]	-	vehicle status	Object-Oriented Bayesian Networks	probability	vehicle test
[28]	camera, Radar, Lidar	vehicle status	HMM	probability	vehicle test
[30]	camera, Radar, Lidar, Ultrasonic	vehicle status, traffic	Model with Bayeisan Classifier	probability, binary	vehicle test
[33]	laser scanner	vehicle status	SVM	binary	NGSIM
[24]	camera, Radar	vehicle status, road geomitry	Naïve Bayesian Gaussian Mixture	binary	vehciel test
[29]	-	vehicle status, environment	Bayesian Network	probability	Simulation
[98]	camera, Lidar	vehicle status, environment	HMM	binary	vehciel test
[62]	-	vehicle status, traffic, lane drop	SVM, Artificial Neural Networks (ANN)	binary	NGSIM
[25]	camera	vehicle status, environment	Random Forest	binary	vehciel test
[116]	-	vehicle status	MLP	probability	NGSIM
[52]	camera, Radar	vehicle status,	CNN	binary	vehciel test
[71]	-	vehicle status, environment	Dynamic Bayesian Network	binary	NGSIM
[53]	camera, Radar	vehicle status, traffic	Situation based Probability Estimation, SVM	probability	vehciel test
[63]	camera, Radar, Lidar, HD map	vehicle status, environment	Structural RNN	binary	vehciel test
[59]	-	vehicle status, traffic	HMM GMM	probability, binary	NGSIM
[14]	laser scanner, camera	vehicle status	Probabilistic Network	binary	vehciel test
[61]	-	vehicle status, traffic	Potential Field, SVM	binary	NGSIM
[72]	camera, Radar	vehicle status, traffic, road	Attention Network, LSTM	binary	NGSIM, vehicle test
[94]	-	vehicle status, traffic	Random Forest	binary	NGSIM
[130]	Radar and camera	vehicle status	HMM	probability binary	vehicle test
[131]	-	vehicle status,	Decision Tree	binary	SPMD
[132]	-	vehicle status, traffic	Multilayer Perceptron	binary	NGSIM
[133]	-	vehicle status, traffic	LSTM	binary	NGSIM
[109]	Radar and camera	vehicle status	Object-Oriented Bayesian Network	probability binary	vehicle test
[55]	V2V	vehicle status, road geomitry	SVM, Decision Trees, Random Forest	binary	vehicle test
[76]	-	vehicle status	Dynamic Bayesian Network	probability	highD
[134]	-		CNN, LSTM	binary	PREVENTION
[135]	camera, Radar	vehicle status,traffic	Gaussian Process Neural Networks	probability	vehicle test
[136]	-	vehicle status	LSTM	binary	highD
[73]	Radar, camera, map	vehicle status, traffic, road, weather	Random Forest, SVM, ANN, XGBoost	binary	SHRP2

simulation platforms [29]. Another option is to validate the system using publicly available real-world datasets, such as Next Generation Simulation (NGSIM), highD, PREdiction of VEhicles iNTentIONs (PREVENTION), Safety Pilot Model Deployment Data (SPMD) [131], and Strategic Highway Research Program (SHRP2) [73]. The NGSIM US Route 101 (US-101) and Interstate 80 (I-80) Freeway datasets are widely used in many research works. The datasets are collected by the vision-based highway monitoring systems. Each dataset consists of real freeway traffic trajectories captured at 10Hz over 45 minutes, segmented into three 15-minute periods. These periods represent the buildup of congestion, or the transition between uncongested and congested conditions, and full congestion during the peak period. The HighD dataset used in [76], [136] is very similar to the NGSIM. It uses a drone to record the traffic in a segment of highway [137]. These datasets reduce the effort of setting up the testing platform and performing the data collection and help different researchers easily compare their algorithms' performance. However, the datasets are not collected from the perspective of intelligent vehicles, so final onboard predictions deserve further verification [71]. Some researchers used the dataset captured in the ego vehicle's perspective, like the PREVENTION dataset used in [134]. The PREVENTION dataset is collected from 6 sensors of different nature (Lidar, Radar, and cameras), which provides both redundancy and complementarity, using an instrumented vehicle driven under naturalistic conditions [138].

B. Performance Evaluation Metrics

In case of the binary output, the lane change maneuver inference results can be classified into four categories [24], [30], [109], [134]:

- True Positive (TP): lane change maneuvers correctly inferred as lane change
- False Positive (FP): lane keeping maneuvers incorrectly inferred as lane change
- True Negative (TN): lane keeping maneuvers correctly inferred as lane keeping
- False Negative (FN): lane change maneuvers incorrectly inferred as lane keeping

Using the above four categories, the classification performance for typical classifiers can be generally evaluated by the following metrics:

- Precision (PRE): the fraction of correct classification of corresponding lane change out of all events predicted to be lane change,

$$PRE = \frac{TP}{TP + FP} \tag{4}$$

- True positive rate (TPR), also known as Recall: the fraction of correct classification of corresponding lane change out of all actual lane change events,

$$TPR = \frac{TP}{TP + FN} \tag{5}$$

- False positive rate (FPR), also known as fall-out: the fraction of incorrect classification of corresponding lane change out of all actual lane keeping events,

$$FPR = \frac{FP}{FP + TN} \tag{6}$$

  Since the lane change inference system is a continuously predicting the vehicles' lane change maneuvers, it is not straightforward to calculate the number of TN events. False positive per time period is sometimes used instead [114], [139].

Sometimes, accuracy (ACU) is also used for measuring the classification performance. It is the fraction of correctly classified maneuvers out of all predicted maneuvers,

$$ACU = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

However, for imbalanced test data set where lane keeping samples are way more than lane change samples, the accuracy can be misleading [24], [30]. Because even a classification algorithm predicting every measured sample of a vehicle as lane keeping would lead to high accuracy.

For a particular inference system, its classification performance can often deliberately be biased towards one of the metrics mentioned above by only changing the threshold used in the inference system [140]. There is always a trade-off between these metrics. For example, the TPR can usually be improved at the cost of FPR. For some systems, the desired FPR is zero [33]. Then the PRE and TPR need to be sacrificed. Considering the trade-off effect, the F1-score is widely used to evaluate the classification performance of the lane change inference system with certain threshold choice. It can be interpreted as a weighted average of the precision and recall values:

$$F1 = 2 \cdot \frac{PRE \cdot TPR}{PRE + TPR} \tag{8}$$

The F1-score can also be changed by adjusting the threshold value without modifying the other part of the inference system. As a method to evaluate the classification performance of the lane change inference system without considering the threshold, the area under Receiver Operating Characteristic (ROC) curve (AUC-ROC) is widely calculated [95]. The ROC curve is a graphical representation of the trade-off between the TPR and FPR. A greater AUC-ROC means a better average performance [93]. Similarly, the area under the Precision-Recall curve can also be used, where the Precision-Recall curve shows the precision as the function of recall.

Besides the classification performance mentioned above, the researchers also need to consider how early the inference system can predict the lane change. For AD systems, it is essential to predict the lane change of the surrounding vehicle as early as possible. It is another metric to compare the performance of different inference systems. Usually, the time to lane change is used as the indicator to show the capacity of predicting the lane change maneuver in advance,

$$\tau_{LC} = t_{LC} - t_I \tag{9}$$

where t_I is the time when the lane change inference system first judges that the target vehicle would change lane. t_{LC} is the moment of the target vehicle performing the lane change maneuver. Its definition varies among different research works. Woo *et al.* [33] defined it as the moment when the target vehicle crosses the centerline. In other research, the lane change time is defined as the moment when the target vehicle crosses the lane marker [71]. There is usually a trade-off between the time to lane change and the classification performance. The researchers have to balance them. Julian *et al.* [25] shown that, by adjusting the threshold, the FPR can be greatly reduced while the time to lane change is also shortened.

VI. Challenges and Future Works

A. Improving Sensing Ability

Due to the limited sensing ability, some previously developed lane change inference systems can only detect the lane change when it has already been executed. It is even more challenging when surrounding vehicles perform the lane change maneuver outside the sensors' field of view, like the close cut-in scenario discussed in the previous sections. Some techniques can be applied to improve the performance without additional sensors, such as the part-based vehicle detection approach used in [15]. A more straightforward way to improve inference performance is to use more sensing devices to extend the field of view and detect more useful variables. For example, the V2X communication and HD map have been considered and used by more researchers for lane change inference in recent years. Although the additional sensors have their limitations and increase the cost, more research is needed to explore their potential for lane change inference.

B. Measurement Noise Handling

The inputs for the lane change maneuver inference system come from multiple sensors equipped on the intelligent vehicle. Different sensors have their limitations on environment detection as discussed in Section III. A variety of techniques are being applied on intelligent vehicles to improve the resolution, accuracy, and reliability of the perception output [141], [142], such as Kalman filters and Particle filters, etc. However, the sensing noise and uncertainty cannot be eliminated completely. Moreover, as more features, like environment context, are introduced for lane change inference to advance the prediction time, the measurement noise is becoming larger. Different inputs also have different noise levels. How to utilize the input signals according to their noise levels requires further study and research. Some previous research tried to model the sensor uncertainty while developing the lane change inference system. For example, Kasper *et al.* considered the sensor noise as Gaussian distribution and modeled the uncertainty by a Bayesian network class [75]. However, the amount of similar research is limited. The effect of the measurement noise on the performance of the lane change inference system is not intensively studied in the previous research. More dedicated analysis is needed to study how the measurement noise affects the inference results and how to improve the inference performance with input noise.

C. Comprehensive Environmental Interactive Model

The input features for lane change inference can come from different stages of the lane change process shown in Fig. 5. Each feature contributes to the final driver's decision in a different way. The previous research mainly studied the relationship between the input features and output behavior by statistical analysis of the driving data without much investigation about their inherent inner and inter-connections. More comprehensive environmental interactive models are needed to capture the mathematical relationship between the features and driver's decisions, especially the strategical and tactical decisions. Moreover, most of the previous research only studied the lane change inference in the highway environment without lane split, merge, etc. When a more complicated situation is considered, like in the urban road, more comprehensive environment models are required. For example, Geng *et al.* tried to tackle this problem by adaptively using scenarios-specific models when predicting the driver's behavior in urban environments [98].

Weather is another factor that can greatly impact the lane change inference system. The effect of different weather conditions is twofold: they can affect the quality of the data captured by the sensing devices as discussed in Section III and also the drivers' behavior performing the lane change maneuvers. El Faouzi *et al.* found that rain conditions impact the time headway between vehicles [143]. Heavy snow can reduce the free flow speed by as much as 30∼40% [144]. Das *et al.* found that the lane change classifiers did not maintain similar performance under different weather conditions. Their detection accuracy was increased after including the weather as one of the input features [73]. Therefore, modeling the effect of weather conditions is another way to reduce their impact on lane change inference systems' performance.

VII. Conclusion

The accurate lane change inference of the surrounding vehicles plays a critical role in keeping the intelligent vehicle safe and comfortable. This paper focuses on constructing a comprehensive review of the techniques and research in this field. The lane change decision comes from the interaction between the driver and the environment. Therefore, a variety of driver behaviors and lane change modeling studies are reviewed, which are useful for the design of the inference system and the selection of input features. According to the reviewed research papers, using input features from different lane change stages can lead to different performance. As the source of all the inputs, various sensing devices equipped on intelligent vehicles are reviewed and compared regarding their sensing abilities and impacts on the lane change inference system. As the key part of this review, the algorithms and validation methods for lane change maneuver inference are sincerely discussed and analyzed. In addition, some potential future research directions are also proposed as a reference for further studies of the lane change inference of surrounding vehicles for higher-level autonomous driving.

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References

[1] *Early Estimate of Motor Vehicle Traffic Fatalities for the First 9 Months (Jan–Sep) of 2019. 2019*. Accessed: Mar. 30, 2020. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812874
[2] S. O.-R. A. V. S. Committee *et al.*, "Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles," SAE Int., Warrendale, PA, USA, Tech. Rep. J3016B_201806, 2018.
[3] V. M. Raju, V. Gupta, and S. Lomate, "Performance of open autonomous vehicle platforms: Autoware and apollo," in *Proc. IEEE 5th Int. Conf. Converg. Technol. (I CT)*, Mar. 2019, pp. 1–5.
[4] Z. Zhang, J. Gao, J. Mao, Y. Liu, D. Anguelov, and C. Li, "STINet: Spatio-temporal-interactive network for pedestrian detection and trajectory prediction," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2020, pp. 11346–11355.
[5] H. Fan *et al.*, "Baidu Apollo EM motion planner," 2018, *arXiv:1807.08048*. [Online]. Available: http://arxiv.org/abs/1807.08048
[6] C. Urmson *et al.*, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 425–466, 2008.
[7] C. Urmson *et al.*, "Autonomous driving in traffic: Boss and the urban challenge," *AI Mag.*, vol. 30, no. 2, p. 17, Feb. 2009.
[8] M. Kleinehagenbrock *et al.*, "Introduction of intelligent adaptive cruise control (i-ACC): A predictive safety system," in *Proc. 3rd Int. Symp. Future Act. Saf. Technol. Toward Zero Traffic Accidents (FAST-Zero)*, 2015, pp. 649–655.
[9] J. Li, W. Zhan, Y. Hu, and M. Tomizuka, "Generic tracking and probabilistic prediction framework and its application in autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 9, pp. 3634–3649, Sep. 2020.
[10] J.-S. Wang and R. R. Knipling, *Lane Change/Merge Crashes: Problem Size Assessment and Statistical Description*. Washington, DC, USA: US Department of Transportation, National Highway Traffic Safety Administration, 1994.
[11] Y. Xing *et al.*, "Driver lane change intention inference for intelligent vehicles: Framework, survey, and challenges," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4377–4390, May 2019.
[12] S. Lefèvre, D. Vasquez, and C. Laugier, "A survey on motion prediction and risk assessment for intelligent vehicles," *ROBOMECH J.*, vol. 1, no. 1, pp. 1–14, Dec. 2014.

[13] S. Mozaffari, O. Y. Al-Jarrah, M. Dianati, P. Jennings, and A. Mouzakitis, "Deep learning-based vehicle behavior prediction for autonomous driving applications: A review," *IEEE Trans. Intell. Transp. Syst.*, early access, Aug. 4, 2020, doi: 10.1109/TITS.2020.3012034.

[14] I. Dagli, G. Breuel, H. Schittenhelm, and A. Schanz, "Cutting-in vehicle recognition for ACC systems-towards feasible situation analysis methodologies," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2004, pp. 925–930.

[15] K. Choi and H. G. Jung, "Cut-in vehicle warning system exploiting multiple rotational images of SVM cameras," *Expert Syst. Appl.*, vol. 125, pp. 81–99, Jul. 2019.

[16] L. S. Angell *et al.*, "Driver workload metrics task 2 final report," Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep. DOT-HS 810635, 2006.

[17] J. Levy, H. Pashler, and E. Boer, "Central interference in driving: Is there any stopping the psychological refractory period?" *Psychol. Sci.*, vol. 17, no. 3, pp. 228–235, Mar. 2006.

[18] Q. Wang, J. Yang, M. Ren, and Y. Zheng, "Driver fatigue detection: A survey," in *Proc. 6th World Congr. Intell. Control Autom.*, vol. 2, 2006, pp. 8587–8591.

[19] A. Doshi and M. M. Trivedi, "Tactical driver behavior prediction and intent inference: A review," in *Proc. 14th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2011, pp. 1892–1897.

[20] J. A. Michon, "A critical view of driver behavior models: What do we know, what should we do?" in *Human Behavior and Traffic Safety*. Boston, MA, USA: Springer, 1985, pp. 485–524.

[21] H. Van der Molen and A. Botticher, "Risk models for traffic participants: A concerted effort for theoretical operationalizations," *Road Users Traffic Saf.*, pp. 61–82, 1987.

[22] T. A. Ranney, "Models of driving behavior: A review of their evolution," *Accident Anal. Prevention*, vol. 26, no. 6, pp. 733–750, Dec. 1994.

[23] K. Driggs-Campbell and R. Bajcsy, "Identifying modes of intent from driver behaviors in dynamic environments," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst.*, Sep. 2015, pp. 739–744.

[24] J. Schlechtriemen, A. Wedel, J. Hillenbrand, G. Breuel, and K.-D. Kuhnert, "A lane change detection approach using feature ranking with maximized predictive power," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2014, pp. 108–114.

[25] J. Schlechtriemen, F. Wirthmueller, A. Wedel, G. Breuel, and K.-D. Kuhnert, "When will it change the lane? A probabilistic regression approach for rarely occurring events," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2015, pp. 1373–1379.

[26] N. Deo and M. M. Trivedi, "Multi-modal trajectory prediction of surrounding vehicles with maneuver based LSTMs," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 1179–1184.

[27] N. Deo and M. M. Trivedi, "Convolutional social pooling for vehicle trajectory prediction," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jun. 2018, pp. 1468–1476.

[28] N. Deo, A. Rangesh, and M. M. Trivedi, "How would surround vehicles move? A unified framework for maneuver classification and motion prediction," *IEEE Trans. Intell. Vehicles*, vol. 3, no. 2, pp. 129–140, Jun. 2018.

[29] M. Schreier, V. Willert, and J. Adamy, "Bayesian, maneuver-based, long-term trajectory prediction and criticality assessment for driver assistance systems," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 334–341.

[30] M. Bahram, C. Hubmann, A. Lawitzky, M. Aeberhard, and D. Wollherr, "A combined model- and learning-based framework for interaction-aware maneuver prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 6, pp. 1538–1550, Jun. 2016.

[31] T. Toledo, H. N. Koutsopoulos, and M. E. Ben-Akiva, "Modeling integrated lane-changing behavior," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1857, no. 1, pp. 30–38, Jan. 2003.

[32] V. Leonhardt and G. Wanielik, "Feature evaluation for lane change prediction based on driving situation and driver behavior," in *Proc. 20th Int. Conf. Inf. Fusion (Fusion)*, Jul. 2017, pp. 1–7.

[33] H. Woo *et al.*, "Lane-change detection based on vehicle-trajectory prediction," *IEEE Robot. Autom. Lett.*, vol. 2, no. 2, pp. 1109–1116, Apr. 2017.

[34] D. D. Salvucci and A. Liu, "The time course of a lane change: Driver control and eye-movement behavior," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 5, no. 2, pp. 123–132, Jun. 2002.

[35] W. Yao, H. Zhao, P. Bonnifait, and H. Zha, "Lane change trajectory prediction by using recorded human driving data," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2013, pp. 430–436.

[36] M. Werling, J. Ziegler, S. Kammel, and S. Thrun, "Optimal trajectory generation for dynamic street scenarios in a frenet frame," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2010, pp. 987–993.

[37] R. Eshleman and S. Desai, "Articulated vehicle handling," United States Dept. Transp., Washington, DC, USA, Tech. Rep. DOT-HS-800673, 1972.

[38] W. Nelson, "Continuous-curvature paths for autonomous vehicles," in *Proc. Int. Conf. Robot. Autom.*, 1989, pp. 1260–1264.

[39] K. M. Marshek and N. H. Sledge, Jr., "Comparison of ideal vehicle lane-change trajectories," *SAE Trans.*, vol. 106, pp. 2004–2027, Jan. 1997.

[40] D. Bevly *et al.*, "Lane change and merge maneuvers for connected and automated vehicles: A survey," *IEEE Trans. Intell. Vehicles*, vol. 1, no. 1, pp. 105–120, Mar. 2016.

[41] J. Z. Varghese *et al.*, "Overview of autonomous vehicle sensors and systems," in *Proc. Int. Conf. Oper. Excellence Service Eng.*, 2015, pp. 178–191.

[42] J. Kocic, N. Jovičić, and V. Drndarević, "Sensors and sensor fusion in autonomous vehicles," in *Proc. 26th Telecommun. Forum (TELFOR)*, Nov. 2018, pp. 420–425.

[43] C. Ilas, "Electronic sensing technologies for autonomous ground vehicles: A review," in *Proc. 8TH Int. Symp. Adv. TOPICS Electr. Eng. (ATEE)*, May 2013, pp. 1–6.

[44] T. B. Schon, A. Eidehall, and F. Gustafsson, "Lane departure detection for improved road geometry estimation," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2006, pp. 546–551.

[45] F. Rosique, P. J. Navarro, C. Fernández, and A. Padilla, "A systematic review of perception system and simulators for autonomous vehicles research," *Sensors*, vol. 19, no. 3, p. 648, Feb. 2019.

[46] H. Chu, L. Guo, B. Gao, H. Chen, N. Bian, and J. Zhou, "Predictive cruise control using high-definition map and real vehicle implementation," *IEEE Trans. Veh. Technol.*, vol. 67, no. 12, pp. 11377–11389, Dec. 2018.

[47] Honda Motor Company Ltd. (2020). *Honda Sensing*. [Online]. Available: https://automobiles.honda.com/sensing

[48] Toyota Motor Corporation. (2020). *Toyota Safety Sense*. [Online]. Available: https://www.toyota.com/safety-sense/

[49] Tesla. (2020). *Tesla Autopilot*. [Online]. Available: https://www.tesla.com/autopilot

[50] Waymo LLC. (2020) *Introducing the 5th-Generation Waymo Driver: Informed by Experience, Designed for Scale, Engineered to Tackle More Environments*. [Online]. Available: https://blog.waymo.com/2020/03/introducing-5th-generation-waymo-driver.html

[51] H. Morizane, H. Takenaga, Y. Kobayashi, and K. Nakamura, "Cut-in vehicle recognition system," in *Proc. IEEE/IEEJ/JSAI Int. Conf. Intell. Transp. Syst.*, Oct. 1999, pp. 976–980.

[52] D. Lee, Y. P. Kwon, S. Mcmains, and J. K. Hedrick, "Convolution neural network-based lane change intention prediction of surrounding vehicles for ACC," in *Proc. IEEE 20th Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2017, pp. 1–6.

[53] C. Wissing, T. Nattermann, K.-H. Glander, C. Hass, and T. Bertram, "Lane change prediction by combining movement and situation based probabilities," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 3554–3559, Jul. 2017.

[54] L. Xin, P. Wang, C.-Y. Chan, J. Chen, S. E. Li, and B. Cheng, "Intention-aware long horizon trajectory prediction of surrounding vehicles using dual LSTM networks," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 1441–1446.

[55] A. H. Sakr, G. Bansal, V. Vladimerou, and M. Johnson, "Lane change detection using V2V safety messages," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 3967–3973.

[56] Z. Ma, Q. Huo, X. Yang, and X. Zhao, "Safety cruise control of connected vehicles using radar and vehicle-to-vehicle communication," *IEEE Syst. J.*, vol. 14, no. 3, pp. 4602–4613, Sep. 2020.

[57] J. Piao and M. McDonald, "Advanced driver assistance systems from autonomous to cooperative approach," *Transp. Rev.*, vol. 28, no. 5, pp. 659–684, Sep. 2008.

[58] V. Paruchuri, "Inter-vehicular communications: Security and reliability issues," in *Proc. ICTC*, Sep. 2011, pp. 737–741.

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

[60] K. Bengler, J. Drüke, S. Hoffmann, D. Manstetten, and A. Neukum, "UR: BAN human factors in traffic," in *Approaches for Safe, Efficient Stress-Free Urban Traffic*. Wiesbaden, Germany: Springer, 2018.

[61] H. Woo *et al.*, "Dynamic potential-model-based feature for lane change prediction," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2016, pp. 000838–000843.

[62] Y. Dou, F. Yan, and D. Feng, "Lane changing prediction at highway lane drops using support vector machine and artificial neural network classifiers," in *Proc. IEEE Int. Conf. Adv. Intell. Mechatronics (AIM)*, Jul. 2016, pp. 901–906.

[63] S. Patel, B. Griffin, K. Kusano, and J. J. Corso, "Predicting future lane changes of other highway vehicles using RNN-based deep models," 2018, *arXiv:1801.04340*. [Online]. Available: http://arxiv.org/abs/1801.04340

[64] S. Dai, L. Li, and Z. Li, "Modeling vehicle interactions via modified LSTM models for trajectory prediction," *IEEE Access*, vol. 7, pp. 38287–38296, 2019.

[65] Y. Hu, W. Zhan, and M. Tomizuka, "Probabilistic prediction of vehicle semantic intention and motion," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 307–313.

[66] W. Ding, J. Chen, and S. Shen, "Predicting vehicle behaviors over an extended horizon using behavior interaction network," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 8634–8640.

[67] F. Altche and A. de La Fortelle, "An LSTM network for highway trajectory prediction," in *Proc. IEEE 20th Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2017, pp. 353–359.

[68] X. Li, X. Ying, and M. C. Chuah, "GRIP: Graph-based interaction-aware trajectory prediction," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3960–3966.

[69] W. Ding and S. Shen, "Online vehicle trajectory prediction using policy anticipation network and optimization-based context reasoning," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 9610–9616.

[70] F. Diehl, T. Brunner, M. T. Le, and A. Knoll, "Graph neural networks for modelling traffic participant interaction," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2019, pp. 695–701.

[71] J. Li, B. Dai, X. Li, X. Xu, and D. Liu, "A dynamic Bayesian network for vehicle maneuver prediction in highway driving scenarios: Framework and verification," *Electronics*, vol. 8, no. 1, p. 40, Jan. 2019.

[72] O. Scheel, N. S. Nagaraja, L. Schwarz, N. Navab, and F. Tombari, "Attention-based lane change prediction," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 8655–8661.

[73] A. Das, M. N. Khan, and M. M. Ahmed, "Detecting lane change maneuvers using SHRP2 naturalistic driving data: A comparative study machine learning techniques," *Accident Anal. Prevention*, vol. 142, Jul. 2020, Art. no. 105578.

[74] V. Popescu and S. Nedevschi, "Cut-in maneuver recognition and behavior generation using Bayesian networks and fuzzy logic," in *Proc. IEEE 8th Int. Conf. Intell. Comput. Commun. Process.*, Aug. 2012, pp. 123–130.

[75] D. Kasper *et al.*, "Object-oriented Bayesian networks for detection of lane change maneuvers," *IEEE Intell. Transp. Syst. Mag.*, vol. 4, no. 3, pp. 19–31, Aug. 2012.

[76] J. Liu, Y. Luo, H. Xiong, T. Wang, H. Huang, and Z. Zhong, "An integrated approach to probabilistic vehicle trajectory prediction via driver characteristic and intention estimation," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3526–3532.

[77] A. Zyner, S. Worrall, and E. Nebot, "Naturalistic driver intention and path prediction using recurrent neural networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 4, pp. 1584–1594, Apr. 2020.

[78] S. H. Park, B. Kim, C. M. Kang, C. C. Chung, and J. W. Choi, "Sequence-to-sequence prediction of vehicle trajectory via LSTM encoder-decoder architecture," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 1672–1678.

[79] D. K. Grimm, "Method for detecting or predicting vehicle cut-ins," U.S. Patent 7 444 241, Oct. 28, 2008.

[80] J. Tang, F. Liu, W. Zhang, R. Ke, and Y. Zou, "Lane-changes prediction based on adaptive fuzzy neural network," *Expert Syst. Appl.*, vol. 91, pp. 452–463, Jan. 2018.

[81] K. Schmidt, M. Beggiato, K. H. Hoffmann, and J. F. Krems, "A mathematical model for predicting lane changes using the steering wheel angle," *J. Saf. Res.*, vol. 49, p. 85-e1, Jun. 2014.

[82] R. Ponziani, "Turn signal usage rate results: A comprehensive field study of 12,000 observed turning vehicles," SAE Tech. Paper 2012-01-0261, 2012.

[83] S. E. Lee *et al.*, "A comprehensive examination of naturalistic lane-changes," United States Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep. DOT-HS 809702, 2004.

[84] Y.-M. Jang, R. Mallipeddi, and M. Lee, "Identification of human implicit visual search intention based on eye movement and pupillary analysis," *User Model. User-Adapted Interact.*, vol. 24, no. 4, pp. 315–344, Oct. 2014.

[85] T. Pech, P. Lindner, and G. Wanielik, "Head tracking based glance area estimation for driver behaviour modelling during lane change execution," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 655–660.

[86] A. Doshi and M. Trivedi, "Investigating the relationships between gaze patterns, dynamic vehicle surround analysis, and driver intentions," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2009, pp. 887–892.

[87] C. Tran, A. Doshi, and M. M. Trivedi, "Modeling and prediction of driver behavior by foot gesture analysis," *Comput. Vis. Image Understand.*, vol. 116, no. 3, pp. 435–445, Mar. 2012.

[88] R. K. Tiwari and S. Giripunje, "Design approach for EEG-based human computer interaction driver monitoring system," *Int. J. Latest Trends Eng. Technol.*, vol. 3, no. 4, pp. 250–255, 2014.

[89] N. Das, E. Ohn-Bar, and M. M. Trivedi, "On performance evaluation of driver hand detection algorithms: Challenges, dataset, and metrics," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst.*, Sep. 2015, pp. 2953–2958.

[90] Y. Xing *et al.*, "Identification and analysis of driver postures for in-vehicle driving activities and secondary tasks recognition," *IEEE Trans. Computat. Social Syst.*, vol. 5, no. 1, pp. 95–108, Mar. 2018.

[91] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," *Sensors*, vol. 12, no. 2, pp. 1211–1279, 2012.

[92] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *J. Mach. Learn. Res.*, vol. 3, pp. 1157–1182, Jan. 2003.

[93] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognit. Lett.*, vol. 27, no. 8, pp. 861–874, Jun. 2006.

[94] N. Motamedidehkordi, S. Amini, S. Hoffmann, F. Busch, and M. R. Fitriyanti, "Modeling tactical lane-change behavior for automated vehicles: A supervised machine learning approach," in *Proc. 5th IEEE Int. Conf. Models Technol. Intell. Transp. Syst. (MT-ITS)*, Jun. 2017, pp. 268–273.

[95] X. Huang, "Driver lane change intention recognition by using entropy-based fusion techniques and support vector machine learning strategy," M.S. thesis, Dept. Mech. Ind. Eng., Northeastern Univ., Boston, MA, USA, Dec. 2012.

[96] A. Carvalho, A. Williams, S. Lefevre, and F. Borrelli, "Autonomous cruise control with cut-in target vehicle detection," in *Proc. Adv. Vehicle Control, 13th Int. Symp. Adv. Vehicle Control (AVEC)*, Munich, Germany, Sep. 2016, pp. 93–99.

[97] H. Cui *et al.*, "Multimodal trajectory predictions for autonomous driving using deep convolutional networks," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 2090–2096.

[98] X. Geng, H. Liang, B. Yu, P. Zhao, L. He, and R. Huang, "A scenario-adaptive driving behavior prediction approach to urban autonomous driving," *Appl. Sci.*, vol. 7, no. 4, p. 426, Apr. 2017.

[99] C. Wissing, T. Nattermann, K.-H. Glander, and T. Bertram, "Probabilistic time-to-lane-change prediction on highways," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 1452–1457.

[100] Z. Yan, K. Yang, Z. Wang, B. Yang, T. Kaizuka, and K. Nakano, "Time to lane change and completion prediction based on gated recurrent unit network," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2019, pp. 102–107.

[101] D. D. Salvucci, H. M. Mandalia, N. Kuge, and T. Yamamura, "Lane-change detection using a computational driver model," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 49, no. 3, pp. 532–542, Jun. 2007.

[102] L. Bi, X. Yang, and C. Wang, "Inferring driver intentions using a driver model based on queuing network," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2013, pp. 1387–1391.

[103] J. Sorstedt, L. Svensson, F. Sandblom, and L. Hammarstrand, "A new vehicle motion model for improved predictions and situation assessment," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 4, pp. 1209–1219, Dec. 2011.

[104] A. Lawitzky, D. Althoff, C. F. Passenberg, G. Tanzmeister, D. Wollherr, and M. Buss, "Interactive scene prediction for automotive applications," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2013, pp. 1028–1033.

[105] W. Schwarting and P. Pascheka, "Recursive conflict resolution for cooperative motion planning in dynamic highway traffic," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 1039–1044.

[106] C. Schlenoff, R. Madhavan, and Z. Kootbally, "PRIDE: A hierarchical, integrated prediction framework for autonomous on-road driving," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2006, pp. 2348–2353.

[107] D. S. Gonzalez, "Towards human-like prediction and decision-making for automated vehicles in highway scenarios," Ph.D. dissertation, Dept. Robot., Université Grenoble Alpes, Grenoble, France, 2019.

[108] R. Sukthankar, S. Baluja, and J. Hancock, "Evolving an intelligent vehicle for tactical reasoning in traffic," in *Proc. Int. Conf. Robot. Autom.*, vol. 1, 1997, pp. 519–524.

[109] G. Weidl, A. L. Madsen, S. Wang, D. Kasper, and M. Karlsen, "Early and accurate recognition of highway traffic maneuvers considering real world application: A novel framework using Bayesian networks," *IEEE Intell. Transp. Syst. Mag.*, vol. 10, no. 3, pp. 146–158, Jun. 2018.

[110] Z. Ghahramani, "An introduction to hidden Markov models and Bayesian networks," in *Hidden Markov Models: Applications in Computer Vision*. Singapore: World Scientific, 2001, pp. 9–41.

[111] H. Berndt, J. Emmert, and K. Dietmayer, "Continuous driver intention recognition with hidden Markov models," in *Proc. 11th Int. IEEE Conf. Intell. Transp. Syst.*, Oct. 2008, pp. 1189–1194.

[112] H. M. Mandalia and M. D. D. Salvucci, "Using support vector machines for lane-change detection," in *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, vol. 49, no. 22. Los Angeles, CA, USA: Sage, 2005, pp. 1965–1969.

[113] P. Kumar, M. Perrollaz, S. Lefevre, and C. Laugier, "Learning-based approach for online lane change intention prediction," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2013, pp. 797–802.

[114] B. Morris, A. Doshi, and M. Trivedi, "Lane change intent prediction for driver assistance: On-road design and evaluation," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2011, pp. 895–901.

[115] M. Hu, Y. Liao, W. Wang, G. Li, B. Cheng, and F. Chen, "Decision tree-based maneuver prediction for driver rear-end risk-avoidance behaviors in cut-in scenarios," *J. Adv. Transp.*, vol. 2017, pp. 1–12, Jan. 2017.

[116] S. Yoon and D. Kum, "The multilayer perceptron approach to lateral motion prediction of surrounding vehicles for autonomous vehicles," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2016, pp. 1307–1312.

[117] N. Djuric *et al.*, "Uncertainty-aware short-term motion prediction of traffic actors for autonomous driving," vol. 2, 2018, *arXiv:1808.05819*. [Online]. Available: http://arxiv.org/abs/1808.05819

[118] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 4510–4520.

[119] S. Hoermann, M. Bach, and K. Dietmayer, "Dynamic occupancy grid prediction for urban autonomous driving: A deep learning approach with fully automatic labeling," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2018, pp. 2056–2063.

[120] W. Luo, B. Yang, and R. Urtasun, "Fast and furious: Real time end-to-end 3D detection, tracking and motion forecasting with a single convolutional net," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 3569–3577.

[121] S. Casas, W. Luo, and R. Urtasun, "IntentNet: Learning to predict intention from raw sensor data," in *Proc. Conf. Robot Learn.*, 2018, pp. 947–956.

[122] A. Zyner, S. Worrall, J. Ward, and E. Nebot, "Long short term memory for driver intent prediction," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 1484–1489.

[123] A. Jain, A. R. Zamir, S. Savarese, and A. Saxena, "Structural-RNN: Deep learning on spatio-temporal graphs," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 5308–5317.

[124] K. Kawakami, "Supervised sequence labelling with recurrent neural networks," Ph.D. dissertation, Dept. Comput. Sci., Tech. Univ. Munich, Munich, Germany, 2008.

[125] A. Zyner, S. Worrall, and E. Nebot, "A recurrent neural network solution for predicting driver intention at unsignalized intersections," *IEEE Robot. Autom. Lett.*, vol. 3, no. 3, pp. 1759–1764, Jul. 2018.

[126] A. Jain, A. Singh, H. S. Koppula, S. Soh, and A. Saxena, "Recurrent neural networks for driver activity anticipation via sensory-fusion architecture," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2016, pp. 3118–3125.

[127] O. Olabiyi, E. Martinson, V. Chintalapudi, and R. Guo, "Driver action prediction using deep (Bidirectional) recurrent neural network," 2017, *arXiv:1706.02257*. [Online]. Available: http://arxiv.org/abs/1706.02257

[128] T. Zhao *et al.*, "Multi-agent tensor fusion for contextual trajectory prediction," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 12126–12134.

[129] M. Schreiber, S. Hoermann, and K. Dietmayer, "Long-term occupancy grid prediction using recurrent neural networks," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 9299–9305.

[130] D. Lee, A. Hansen, and J. K. Hedrick, "Probabilistic inference of traffic participants' lane change intention for enhancing adaptive cruise control," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 855–860.

[131] C. Wang, J. Delport, and Y. Wang, "Lateral motion prediction of on-road preceding vehicles: A data-driven approach," *Sensors*, vol. 19, no. 9, p. 2111, May 2019.

[132] Z. Shou, Z. Wang, K. Han, Y. Liu, P. Tiwari, and X. Di, "Long-term prediction of lane change maneuver through a multilayer perceptron," 2020, *arXiv:2006.12769*. [Online]. Available: http://arxiv.org/abs/2006.12769

[133] T. Han, J. Jing, and U. Özgüner, "Driving intention recognition and lane change prediction on the highway," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2019, pp. 957–962.

[134] 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," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3657–3662.

[135] M. Krüger, A. S. Novo, T. Nattermann, and T. Bertram, "Probabilistic lane change prediction using Gaussian process neural networks," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3651–3656.

[136] V. Mahajan, C. Katrakazas, and C. Antoniou, "Prediction of lane-changing maneuvers with automatic labeling and deep learning," *Transp. Res. Rec.*, vol. 2674, Jul. 2020, Art. no. 0361198120922210.

[137] R. Krajewski, J. Bock, L. Kloeker, and L. Eckstein, "The highD dataset: A drone dataset of naturalistic vehicle trajectories on German highways for validation of highly automated driving systems," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 2118–2125.

[138] R. Izquierdo, A. Quintanar, I. Parra, D. Fernández-Llorca, and M. A. Sotelo, "The PREVENTION dataset: A novel benchmark for PREdiction of VEhicles iNTentIONs," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 3114–3121.

[139] A. Doshi, B. T. Morris, and M. M. Trivedi, "On-road prediction of driver's intent with multimodal sensory cues," *IEEE Pervas. Comput.*, vol. 10, no. 3, pp. 22–34, May 2011.

[140] M. Kubat and S. Matwin, "Addressing the curse of imbalanced training sets: One-sided selection," in *Proc. ICML*, vol. 97, Jul. 1997, pp. 179–186.

[141] M. B. Alatise and G. P. Hancke, "A review on challenges of autonomous mobile robot and sensor fusion methods," *IEEE Access*, vol. 8, pp. 39830–39846, 2020.

[142] T. Nicosevici, R. Garcia, M. Carreras, and M. Villanueva, "A review of sensor fusion techniques for underwater vehicle navigation," in *Proc. Oceans MTS/IEEE Techno-Ocean*, vol. 3, Nov. 2004, pp. 1600–1605.

[143] N.-E. El Faouzi, O. de Mouzon, and R. Billot, "Toward weather-responsive traffic management on French motorways," *Transp. Res. Circular*, vol. E-C126, pp. 443–456, Jun. 2008.

[144] T. Hou, H. S. Mahmassani, R. M. Alfelor, J. Kim, and M. Saberi, "Calibration of traffic flow models under adverse weather and application in mesoscopic network simulation," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2391, no. 1, pp. 92–104, Jan. 2013.

Ruitao Song received the B.Eng. degree in automation from Northwestern Polytechnical University, Xi'an, China, in 2011, the M.S. degree in mechatronics from the Université de Technologie de Compiègne, Compiègne, France, in 2013, and the Ph.D. degree in mechanical engineering from Michigan State University, East Lansing, MI, USA, in 2018.

He is currently working with Aptiv Corporation, Troy, MI, USA. His research interests include advanced control design, decision-making, motion planning, and motion prediction for autonomous driving.

Bin Li received the Ph.D. degree in mechanical engineering from Shanghai Jiao Tong University. He is currently working with Aptiv Corporation, Troy, MI, USA, focusing on ADAS/AD algorithm/software development, verification and validation of vehicle motion control, environment sensing, and vehicle state estimation. He has over 15 years' research and industry experience in ADAS/autonomous driving, active safety, vehicle dynamics, and motion control with over 50 research articles published. He has been an active organizer for SAE World Congress and ASME conferences since 2015. He serves as an Associate Editor for *International Journal of Vehicle Autonomous Systems*, *SAE International Journal of Commercial Vehicles*, and *SAE International Journal of Passenger Cars- Electronic and Electrical Systems*.