Driver Lane Change Intention Inference for Intelligent Vehicles: Framework, Survey, and Challenges

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***Abstract*—Intelligent vehicles and advanced driver assistance systems (ADAS) need to have proper awareness of the traffic context, as well as the driver status since ADAS share the vehicle control authorities with the human driver. This paper provides an overview of the ego-vehicle driver intention inference (DII), which mainly focuses on the lane change intention on highways. First, a human intention mechanism is discussed in the beginning to gain an overall understanding of the driver intention. Next, the ego-vehicle driver intention is classified into different categories based on various criteria. A complete DII system can be separated into different modules, which consist of traffic context awareness, driver states monitoring, and the vehicle dynamic measurement module. The relationship between these modules and the corresponding impacts on the DII are analyzed. Then, the lane change intention inference system is reviewed from the perspective of input signals, algorithms, and evaluation. Finally, future concerns and emerging trends in this area are highlighted.**

***Index Terms*—Intelligent vehicle, ADAS, lane change, driver intention, parallel driving.**

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I. Introduction

MORE than 80% of traffic accidents were caused by driver errors [1]–[3]. Until now, various passive safety systems like airbags and seat-belts have played a significant role in the protection of the driver and passengers. Although these techniques have saved millions of lives, they are not designed to prevent accidents from happening but to protect the passengers after the accidents [4], [5]. Instead of minimizing the injuries after the accidents, many efforts have been devoted to the development of safer and more intelligent systems such as the ADAS techniques so that the accidents can be prevent from happening. ADAS techniques like Adaptive Cruise Control (ACC), lane departure avoidance (LDA), lane keeping assistance (LKA), and side warning assistance (SWA) can assist the driver in making right decisions and reducing their workloads [6]–[8]. However, these systems usually make decisions without taking driver intended maneuver into consideration. A driver is in the center of the Traffic-Driver-Vehicle (TDV) loop, who makes decisions and interact with other road users by controlling the vehicle. Hence, understanding driver intention and behaviors are beneficial to driver safety, vehicle drivability, and traffic efficient.

From the cognitive psychology perspective of view, intention refers to the thoughts that one has before the actions [9]. Accordingly, driver intention is the attitude towards performing a series of future vehicle control actions. Three aspects determine the human intention: the attitude towards the behavior, subjective norm and the perceived behavior control [10]. Bratman defined the intention as the main attitude that directly influences future actions [11]. Also, Heinze described a triple level architecture of the intentional behavior, which consists of intended level, activity level, and state level [12].

Within the human-machine-interaction (HMI) scope [13], intention refers to the thoughts or attitudes towards an on-going action. Accordingly, intention recognition is the process of understanding whether the on-going activities of the agent are goal-oriented or not, and what is the goal behind these specific actions. Bonchek and Elisheva proposed a cognitive model with two core components, which were intention detection and intention prediction [14]. Intention detection is a process of analyzing whether a sequence of actions has underlying intention. Intention prediction, on the other hand, refers to the prediction of the intentional goal based on a set of incomplete sequence of actions. The intention inference and reasoning make people intelligent and enable them to be effectively involved in interpersonal activities and communications. A human can recognize other's intention based on their observation and the learned social knowledge. From the HMI perspective of view, only when a robot can recognize human intention based on their own observations can they be viewed as an intelligent agent [15]–[23]. Regarding the intelligent vehicles, it is still difficult to learn how to infer human intention accurately and collaborate with the driver efficiently since most of the most of current intelligent vehicles lack the ability of self-learning and knowledge summarizing by themselves.

The reasons for developing the DII technique are multi-folds. One of the primary motivations is to improve driving safety. Inferring the driver intention can better assess the potential risks. Since a large amount of accidents are caused by human errors, misbehavior, cognitive and judgment errors [2], [24], [25], monitoring and correcting the driver intention in time are critical to the ADAS. Also, intention recognition enables the ADAS to avoid making conflict decisions with the driver [26]. As ADAS share the control authorities with the driver, it is essential for the ADAS to recognize the driver intention and not operate against the driver's will. Driver intention inference enables the ADAS to assist the driver and focus on the corresponding traffic context perception as early as possible.

Furthermore, intention inference system will contribute to the development of automated vehicles. DII system can be used to modeling the driver intention and generate human-like decision-making system. Concerning the level-three automated vehicles (SAE international standard, J3016), accurate driver intention prediction will contribute to a smoother and safer transition between the driver and the autonomous vehicle controller [27]–[29]. When level-three automated vehicle working in the automated driving mode, all the driving tasks are handled by the vehicle. However, once an emergent situation occurs, it must disengage and give the driving authority back to the driver. The vehicle can determine whether the driver is ready to take over or not by assessing their intention in advance.

The contribution of this study can be summarized as follow. First, a state-of-art literature review for driver lane change intention is proposed. The LCII system is categorized based on different criteria. Second, the critical time flow of the DII with different driver behaviors is introduced. This leads to a comprehensive understanding of the architecture of intention inference system. Finally, future works and challenges of DII are proposed, and a parallel driver intention inference system is introduced.

This paper is organized as follow. In Section II, general human intention mechanisms and the classification methods for the DII systems are reviewed. In Section III, the time-flow of the LCII system is introduced, and literature on LCII are reviewed from different perspective of views. In Section IV, future works and research are discussed. Finally, the paper is concluded in Section V.

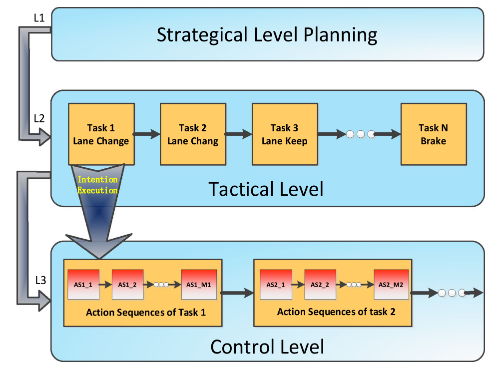

Fig. 1. Driver intention classification based on the time constant.

II. Driver Intention Classification

Driver intention can be classified into different categories based on different criteria. For example, it can be classified according to the motivation, time-scale, and the vehicle control direction. Among these, the two most straightforward classification ways are based on the time-scale of the intention and the driving directions.

A. Time-Scale Based Driver Intention Classification

Michon stated that the cognitive structure of human behavior in the traffic environment is a four-level hierarchical structure, which consists of road user, transportation consumer, social agent, and psycho-biological organism [30]. Among these, the road user level is directly related to the drivers and can be further divided into three sub-levels: strategical, tactical, and operational level (also known as control level), respectively, as shown in Fig. 1. The three cognitive levels can be viewed as three intentional levels based on time-scale characteristics. Strategy level defines the general plan of a trip such as the trip route, destination, and risk assessment, etc. The time constant is at least in minutes or even longer. At this moment, the driver considers transport mobility and comfortable issues, which is a long time-scale problem. Regarding the tactical level, the driver will make a short-term decision and control the vehicle to negotiate the prevailing circumstance. Tactical intentional maneuvers can consist of a series of operational maneuvers to finish the short-term tactical goals such as the turning, lane changing, and braking maneuvers [31].

The control commands must meet the strategy that are defined in the strategical level. The control intention is the shortest maneuver among the three and stands for the will to remain safe and comfortable. The time constant of the control action is generally in milliseconds. Also, Salvucci *et al.* concluded that lane change was not merely a control procedure, but also incorporated a set of critical aspects of driving such as lower level controls [32]. For example, lane change maneuver can contain a series of short-term driving behaviors like the acceleration and deceleration in the longitudinal direction and the steering wheel control in the lateral direction.

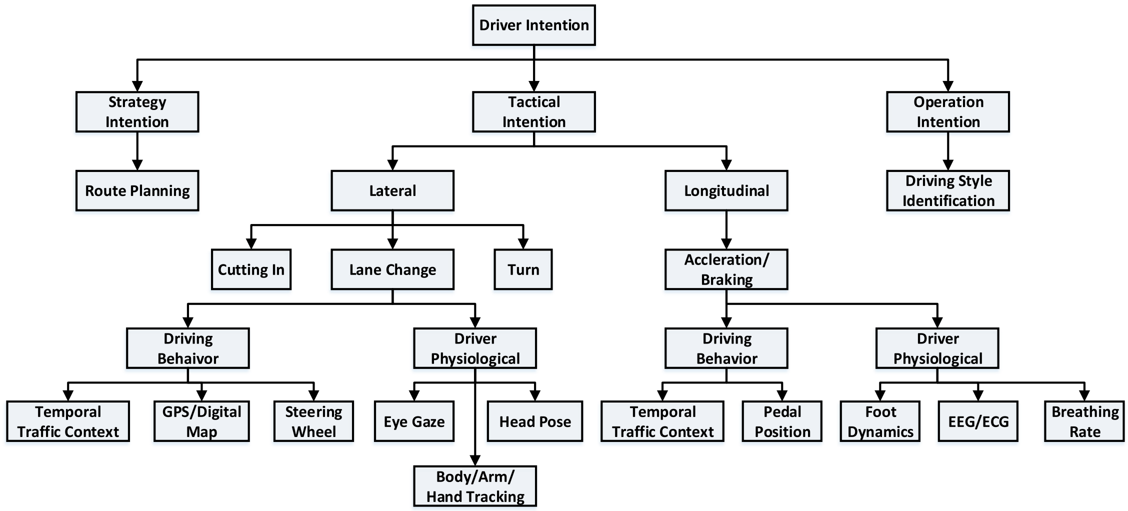

Fig. 2. Taxonomy of driver intention systems.

A driver model, namely, Adaptive Control of Thought-Rational cognitive architecture was developed in [33]. Like the three-level architecture given by [30], the integrated driver model is divided into another three components, which are control, monitoring, and decision-making module. The control component is similar to the control level in [30], which is responsible for the perception of the external world and transfer the control signals to the vehicle. The monitoring component keeps aware of the surrounding situation and context by periodically perceiving and analyzing. The decision-making component, which has the same function with Michon's tactical level, makes tactical decisions for each maneuver according to the awareness of the current situation and the information gathered from the control and monitoring module. One significant advantage of the cognitive driver model is the incorporation of the built-in features are useful for human ability imitation. A taxonomy of driver intention classification is depicted in Fig. 2.

B. Directional-Based Driver Intention Classification

The longitudinal and lateral motion are two basic directions for underground vehicles. Driver's longitudinal behaviors contain braking, acceleration, starting, and lane keeping, etc. While the lateral intentions are normally more complicated than the longitudinal intention dues to the complex interaction with surrounding vehicles.

Regarding the longitudinal intention, most of the previous studies focus on braking intention recognition [34]. Haufe *et al.* proposed a driver braking intention prediction using EEG (electroencephalograph) and EMG (electromyography) signals [35]. Similarly, Khaliliardali *et al.* proposed a driver intention prediction model to determine whether the driver will go ahead or stop based on the brain-computer-interface (BCI) technique [36]. McCall and Trivedi integrated the DII into an intelligent braking assistance system [37]. A sparse Bayesian learning algorithm was used to infer the driver's braking intention. Trivedi *et al.* predicted the driver's braking intention by directly monitoring the foot gesture through cameras [38], [39]. They showed

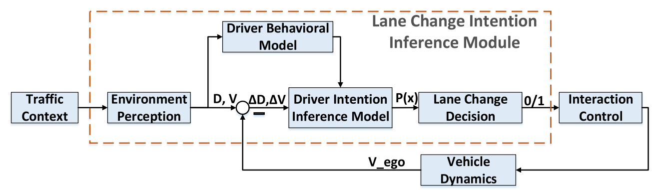

Fig. 3. Driver lane change intention inference framework.

that the driver foot gesture estimation plays a vital role in the vehicle longitudinal control and the usage of vision-based foot tracking is more straightforward and accurate. [40], [42] provided the braking intention estimation methods at intersections. Takahashi *et al.* predicted the deceleration intent during downhill road [41].

In addition, tactical maneuvers usually consist of a series of sub-control maneuvers. Some of the existing studies focus on the analysis of multiple tactics rather than a single tactical task based on the utilization of machine learning methods. It was mentioned that discriminative machine learning models are more suitable for binary intention classification, while generative methods contribute to a higher intention detection accuracy for the multi-intention inference tasks [43]–[46].

III. DRIVER INTENTION INFERENCE METHODOLOGIES

A. Architecture of Driver Intention Inference System

DII system is an integration of multiple techniques such as perception, data fusion and synchronization, model learning and model inference. According to the existing studies, DII system mainly contains the following modules: traffic context perception module, vehicle dynamic module, driver behavior recognition module, and driver intention inference module.

In Fig. 3, the traffic context information is captured by the environment perception block. This block captures the road and traffic context and outputs the position information of the ego-vehicle. By integrating the environment perception module with vehicle dynamic data through the CAN bus or the Ethernet, the

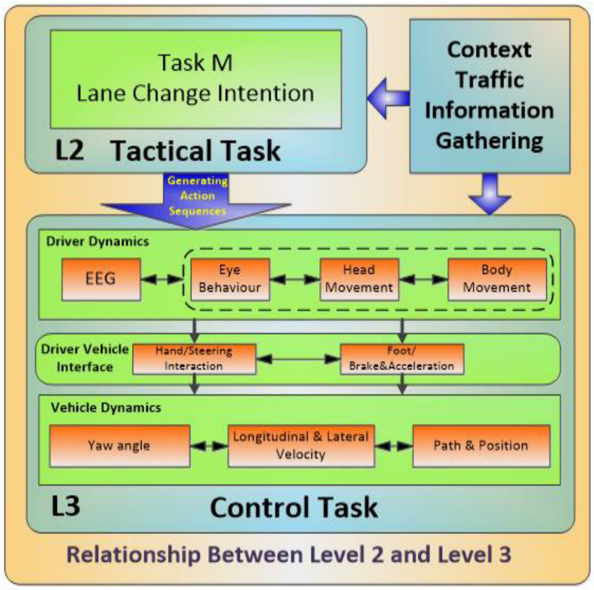

Fig. 4. Relationship between tactical intention and control intention.

relative distance, velocity, and future motion of the ego-vehicle and the surrounding vehicles can be obtained. The traffic and vehicle dynamic data will be fed into the inference module along with the driver behavior information. The driver behavioral information usually contains driver head rotation, eye gaze, and body movement, etc. Next, the intention inference model will calculate the probability of a lane change intention based on the integrated information. Like the human driver, the final output of the lane change decision module is a binary value which indicates a specific lane change decision. After the lane change decision is activated, the interaction module models the driver hand and foot dynamics as well as the dynamics of vehicle control interface.

The relationship between the tactical intention and the control intention concerning the driver-vehicle-interaction is explicitly illustrated in Fig. 4. Fig. 4 contains three parts namely the traffic context perception, tactical intention unit, and control units. Specifically, in the third level, three layers are defined. The upper layer is driver dynamics, which represent the checking and monitoring behavior of the driver. In this part, the most common dynamics are the brain dynamics that are measured by the EEG device, eye gaze behavior, head movement, and body movement (hand, body, and foot dynamics, etc.). The driver-vehicle-interaction layer will be activated once the lane change decision is made. Finally, vehicle control signals are fed into the lowest vehicle control layer.

B. *Inputs for Driver Intention Inference System*

The driver is in the center of the TDV loop. The signals from the TDV loop that used for driver intention inference can be classified into three categories. The standard inputs for the DLII system are summarized in Table I.

1) Traffic Context: Traffic context is the primary stimuli to the driver intention. A better understanding of the surrounding

TABLE I
COMMON INPUT SIGNALS AND SENSORS USED FOR DRIVER INTENTION INFERENCE

Sensor Sources	Sensor Categories
Traffic	Current ego-vehicle position (collected with GPS and digital map), Relative distance, velocity and acceleration concerning the front and surrounding vehicles (collected with cameras, radar or Lidar).
Vehicle	CAN bus signals (including steering wheel angle, steering wheel velocity, brake/gas pedal position, velocity, heading angle, etc.)
Driver	Cameras (Head rotation, gaze direction, foot dynamics). EEG, EMG, Heart rate, etc.

traffic context will improve the intention inference accuracy. For instance, a lane change maneuver usually occurs when encountering a low speed front vehicle or a rear vehicle is approaching with fast speed. Different kinds of sensors can be used to capture the surrounding traffic context, such as the camera, radar, and Lidar systems [47]–[50]. Bernt *et al.* designed a Hidden Markov Model (HMM) based intention classifier which takes the distance to the next turn, the street curvature, and street type from the digital map as the algorithm inputs [51]. Rafael *et al.* predicted the lane change maneuvers on highways with GPS/IMU sensors to collect the vehicle position [52]. One of the advantages of the GPS is that it gives the location and time information in unfavorable weather conditions when the camera and radar system cannot work. In [53], McCall and Trivedi proposed a preliminary work that focuses on the lane change events. Radar and video devices are used to obtain the forward, rear, and side information. Meanwhile, cameras were also used to monitor the driver foot gesture and head movement. The work in [54] concentrated on the lane change intention prediction according to the sensory data, which contains the lane information given by a lane tracker, the vehicle velocity, lateral position and its derivation, and the steering wheel angle.

2) Vehicle Dynamics: Vehicle dynamic information such as steering wheel angle, brake pedal position, and velocity is the direct response to the control actions from the driver. Hence, these signals have been widely adopted for driver intention identification in the past. Vehicle data are usually collected from the CAN bus, which enables a large amount of data collection with high transfer speed [49], [51], [57]. Schmidt *et al*. proposed a lane change intention recognition method based on the construction of an explicit mathematical model of the steering wheel [55]. In [56], [57], driver lane change/keep intention inference systems were proposed on a driving simulator with the collection of vehicle dynamic information. In [58], an intention recognition method with artificial neural networks (ANN) was proposed. CAN bus data and driver gaze information was collected and fed into the ANN. However, since vehicle dynamic information is the response to the driving actions, they give delayed information compared with driver behavior data and traffic context information in the intention inference tasks. In general, vehicle dynamic information cannot provide advanced information for intention prediction. However, they still useful for the intention

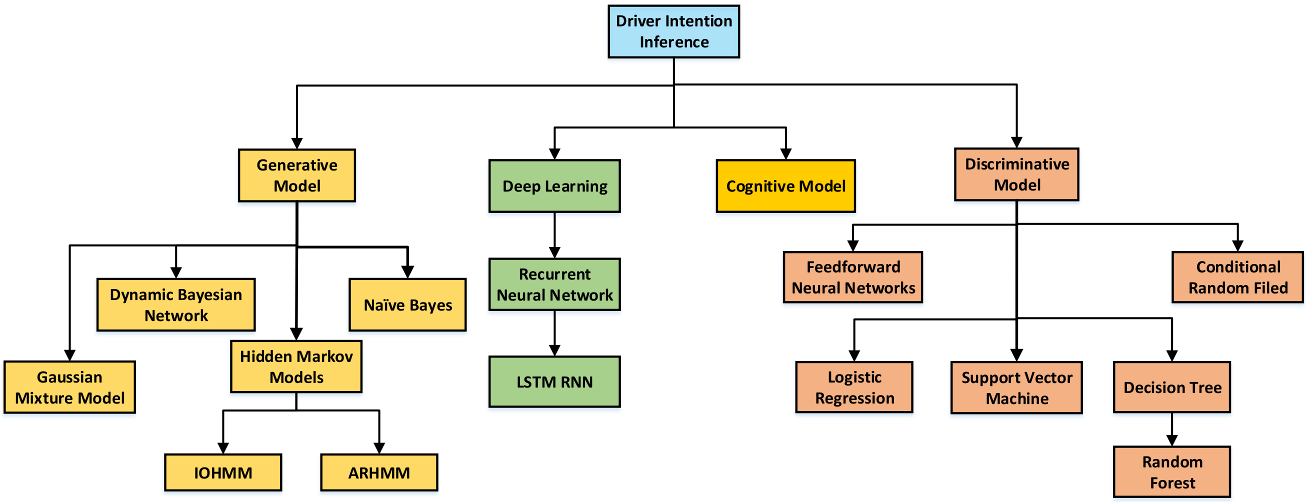

Fig. 5. Taxonomy of intention inference algorithms.

identification and can help to recognize the intent at an early stage after the intended maneuver has been initiated.

3) Driver Behaviors: Unlike the vehicle dynamic data, driver behavioral signals such as the head and eye movement give an early clue about the driver intention. Many studies have evaluated the impact of head/eye movement on the intention prediction [59]–[64]. Typically driver eye movement can be classified into intention-oriented and non-intention-oriented. Intention oriented eye movement means that the eye fixation or saccades is in purpose, while non-intention-based eye movement is cause by surrounding distractions. Driver visual fixation will no longer follow the attention when the driver is distracted. In this case, eye movement can neither reflect driver mental purpose nor the predicted intention being trusted [61]. Regarding the intention-oriented eye tracking, it can be viewed as a cognitive progress of information gathering, which provides an early indication of driver mental states. Besides, the driver intention at the information gathering stage is less likely to change compared than that at the action execution stage [62].

Although head/eye movement can be caused by distraction, most of the time, the driver will shift the eye gaze in purpose, which makes the eye movement an important signal for the intention decoding and inference [63]–[65]. It has been proved that the eye movement information improves the intention prediction accuracy and help to decrease the false alarm rate [66], [67]. A significant challenge to the eye information gathering is the eye tracking task. Dues to the physical characteristics of the eye (small scale and occlusion, etc.), it is not easy to detect the eye and track the pupil robustly. Moreover, the glass, lightness, and even hairs can influence eye tracking performance. According to these challenges, some robust algorithms for eye movement detection have been proposed [68]–[70]. Lethaus *et al.* [71] evaluated how early and how much data can be used to predict driver intention on a driving simulator. They concluded that a ten seconds window of the eye gaze data is large enough for intention prediction, and a five seconds window gives a better performance since less noise was carried.

Similarly, head motion also reflects the cognitive process of information gathering. It was regarded as the most critical factor for intention prediction [66]. Head movement was widely adopted in DII systems [72], [76]. In [66], the authors claimed that both eye and head movement are useful data for the detection of driver distraction, attention, and mental state inference. However, head moves earlier than the eye when the driver is executing a goal-oriented task. On the other hand, when an outside stimulus occurs, and the driver is facing a non-goal-oriented task, she/he will shift her/his eye before rotating the head [66]. This is an interesting conclusion since it offers a way to determine whether the ongoing driver behavior is goal-oriented or stimuli-based. In [50], the authors evaluated the impact of LDW, ACC, SWA, and head tracking on intention detection. It was found that head tracking is most relevant to the intention recognition and the ACC and SWA systems have limited influence on the lane change intention prediction task.

In addition to the eye gaze and head movement, some other behavioral signals like EEG, foot gesture, hand, and body gesture were also involved in literature [77]–[80]. EEG is an essential sensor for BCI design. EEG is sensitive to the small changes in the electrical activities, which is suitable to detect human mental state. Since EEG measures the brain activities, it can reflect the intention faster than the human muscle reaction. It was found that by using EEG, the braking intention can be detected 130 milliseconds faster than that only consider the brake pedal position [83], [84]. The drawbacks of EEG are the large signal noise, hard to acquire the signal, and getting weak if sampled with poor quality [81]. This is because brain electric current is under the brain layers, skull, and scalp and detected with the non-invasive method [82]. Despite the less robustness in the real-world application, EEG devices are widely accepted on the driving simulators and laboratory environment.

C. Algorithms for Driver Intention Inference

In [49], the proposed intelligent vehicle carries more than 200 kinds of sensory signals from the LDW, ACC, SWA, and head tracking system. At this moment, machine learning

TABLE II
SUMMARIZE OF VARIOUS PREVIOUS LANE CHANGE INTENTION INFERENCE SYSTEMS

Paper	Signals	Algorithm	No. Subjects	Environment	Performance	Predict Horizon
[58]	Steering angle, steering force, velocity	CHMM	10	Simulator	100%	0.5-0.7s after steering
[67]	Lane position, CAN bus, Eye and Head	RVM	8	On-road	88.51%	3s before the lane change
[102]	Lane, CAN, and Head	Sparse Bayesian Learning	3	On-road	90%	3s before maneuver
[66]	Eye movement	Finish Questionnaire	17	Simulator	77%	–
[103]	Eye movement	SVM	24 Samples	On-road	73.13%±1.25%	–
[52]	CAN, Digital map	HMM	50 LCL, 50 LCR	On-road	71%L, 74%R	–
[90]	CAN, Distance	HMM	20	On-road	80%-90%	–
[51]	CAN, LDW, ACC, Head,	RVM	15	On-road	91%	1s prior to maneuver
[44]	CAN, Head, Eye	HMM	70	On-road	12.5%LR,17.6LL	1s prior the maneuver
[41]	CAN, Lane style and position, Head, Eye	Relevance vector machine	108 Lane changes	On-road	79.20%	–
[86]	Steering angle	Queuing network model	14	Simulator	LCN 98.61% LCE 91.67%,	–
[104]	CAN, Eye movement	State Transition Diagram	20 (8576 lane changes)	Simulator	80%	–
[50]	CAN, ACC, SWA, LDW, Head	RVM	15 (500 samples)	On-road	80%	3s before the lane change
[105]	CAN, GPS, Eye	Finish Questionnaire	22	On-road	–	–
[42]	Steering angle and relative lane position	SVM and Bayesian Filtering	2 (139 Samples)	On-road	80%	1.3s before the lane change
[59]	CAN, Eye	ANN	10	Simulator	95%(L), 85%(R)	–
[106]	CAN, Lidar, Radar, Hand, Head, Foot	Latent Dynamic Conditional Random Field (LDCRF)	1000 samples	On-road	90%	2s prior the lane change
[107]	CAN	SVM and Bayesian Network	4	Simulator	95%(LK), 80%(LC)	–
[34]	CAN, eye movement	Computational model based on ACT-R	11	Simulator	90%	1s after steering
[89]	CAN bus	CHMM and Bayesian Filtering	188LCL, 212LCR, 242 LK	On-road	93.5%(L), 90.3%(R)	0.5-0.7s after steering
[97]	GPS, digital map, head, CAN bus	LSTM-RNN	Ten drivers, 1180 miles	On-road	90.5%	3.5s prior the lane change

algorithms are becoming the most suitable tool for data fusion and model construction. As discussed in [31], discriminative models lead to a better result on the single target detection than the generative models, while the generative models are more suitable for the multi-target problems. Despite these two typical methods, driver intention can also be modeled based on the cognitive models and the deep learning models. A taxonomy of the algorithms for intention inference is shown in Fig. 5. In Table II, the comparison between different LCII systems are illustrated. In Table II, signals and algorithm represent the model inputs and algorithms used to construct the inference model. The on-road environment means the data are collected in real-world while simulator means the experiment does not have naturalist on-road data and all the data are collected with a driving simulator. The number of subject measures how many subjects or how many data are involved in the experiment. The performance and prediction horizon are two different evaluation metrics that will be further discussed in the next part.

1) Generative Model: Generative models like HMM are widely used in existing LCII studies [51], [55]–[60], [85], [86]. In [67], the authors used three different algorithms, which were ANN, Bayesian network (BN), and Naive Bayesian. In [87], a new feature named comprehensive decision index (CDI) was introduced. Fuzzy logic was applied to represent the surrounding environment and driver lane change willingness. Li. *et al.* proposed an integrated intention inference algorithm based on HMM and Bayesian Filtering (BF) technique [88]. A preliminary output from the HMM was further filtered using the BF method to make the final decision. The HMM-BF framework achieved 93.5% and 90.3% recognition accuracy for the right and left lane change, respectively. In [56], the authors proposed a driver lane change/keep intention inference method based on a dynamic Bayesian network (DBN). A four-step framework for the DII was developed, and the auto-regression (AR) was combined with the HMM to take the previous driver behaviors into consideration.

In [89], the classification performance did not show a significant increase with additional traffic context information. However, the authors showed that the additional context information leads to a high false positive and the system performance was worse than the system with vehicle state information only. One possible explanation is that the HMM has limited ability to capture the context information during the lane change process.

Therefore, a more powerful algorithm such as double layered HMM and input-output HMM should be used [96]. In [90], a lane change detection method based on the object-oriented BN was proposed. The system was designed acco rding to the modularity and reusability of the BN, which makes the system easier to be extended according to different requirements.

2) Discriminative Model: Discriminative models such as SVM and ANN are widely used in the past dues to the rich background theories and the successful application experiences [49]–[54], [87]–[92]. In [49] and [50], a Bayesian extension to the support vector machine algorithm, namely, the relevance vector machine (RVM) was used to classify the driver lane change (right and left), and lane keeping intention. The classifier achieved 80% accuracy with a relatively low false alarm rate. The authors in [58] proposed a driver intention recognition method based on artificial neural networks. The detection accuracy for left lane change achieved better detection accuracy than the right lane change. The results indicated that the head rotation had consistent gains between 1.5s to 2.5s before the lane change maneuver. In [54], a multiclass classifier was constructed by combining the SVM and BF. Results showed that the proposed algorithm can realize an average of 1.3s prediction in advance and can achieve a maximum prediction horizon of 3.29s. It was concluded that one of the crucial tasks for intention inference is to improve the performance of the lane tracking system and reduce the false alarm rate.

3) Deep Learning Methods: Recently, tremendous achievements have been made in the deep learning area dues to the development of deep learning theories, parallel computation hardware, and large-scale annotated datasets, etc. The deep Convolutional Neural Networks (CNN) have achieved state-of-art performance on many computer vision tasks, such as the image classification, segmentation, and object detection domains [93], [95]. Meanwhile, the Recurrent Neural Network (RNN) has achieved significant performance on time-series problems such as natural language processing and image captioning [73], [96]. RNN can be used to process the temporal dependence between the dataset as it allows the weighted connection between previous hidden-layers and the current layer. A long short-term memory (LSTM) scheme was proposed to increase the long-term dependency property and overcome the gradient descent [97]. As aforementioned, DII usually need to take previous driver behaviors and traffic context into consideration. The conventional HMM method has limited ability to capture long-term dependency. While the RNN can provide a better prediction of the driver intention. In [98], an LSTM-RNN model was developed to infer the driver intention when the vehicle enters an interaction. The RNN outperforms the quadratic discriminate analysis model. Similar, a series of studies have been proposed in [96]. The authors compared the LCII performance of the LSTM-based RNN with multiple HMMs. The lane change intent can be detected 3.5 seconds earlier before the vehicle come into another lane. The LSTM-RNN achieved one of the state-of-art results with the precision and recall of 90.5% and 87.4%.

4) Cognitive Model: Despite the machine learning algorithms, human cognitive models were also adopted in the past. Salvucci *et al*. introduced a real-time LCII system based on mind tracking architecture [32], [33]. The mind tracking computational model continuously infers the driver's unobserved intention from the observed actions, which was built based on the Adaptive Control of Thought-Rational (ACT-R) framework. The system achieved 85% accuracy and 4% false alarm rate for the lane change intention detection. In [85], the authors constructed a queuing network cognitive architecture to model driver behavior during normal and emergency lane change. The differences between the outputs of the model and the measured data were compared. The proposed method achieved a high accuracy (above 90%) and low false alarm rate (29.4%). Comparing with the inference methods based on the eye gaze and head moment, this method can be easily extended into real-world application. However, since the algorithm was based on the steering wheel angle only, it cannot infer the driver intention before the maneuver happens or at a very early stage.

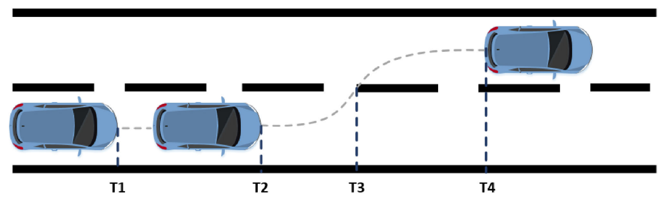

Fig. 6. Illustration of a typical lane change progress with critical moments.

D. Evaluation of Driver Intention Inference System

Evaluating the performance of the DII system is essential and lead to a clear understanding of how the system works in the real world. DII system can be evaluated from two aspects, which are the detection accuracy and prediction horizon.

1) Detection Accuracy: In [92], To evaluate the classification performance, four evaluation criteria were introduced, which were the mean value of prediction horizon, the number of the correctly recognized lane change, the number of not recognizing the lane change, and the number of false alarms. Among these, the true positive rate (TPR) and false positive rate (FPR) are two critical factors to indicate the performance of the classifier. TPR measures how many times the classifier detects the intent successfully, while the FPR describes how many times the classifier miss-classify the intention into the wrong category. Sometimes, FPR is more critical than the TPR since the driver does not want to be disrupted by the assistance system frequently. If a classifier pursues a TPR at the price of high FPR, this system can be hardly accepted by the users. However, if a system has a slightly lower TPR and a lower FPR, it is still helpful in some situations. Therefore, the primary objective is to increase the TPR and decrease the FPR as much as possible [99].

2) Prediction Horizon: Prediction horizon is another critical factor. Some of the studies reported the TPR and FPR without giving a clear prediction horizon, which was unfair. As shown in Fig. 6, there are four critical moments for a lane change process. T1 represents the moment when the driver generates the lane change intention. T2 is when the driver finishes traffic context checking and begin to change the lane. T3 represents the moment that the vehicle starts to cross the lane. Finally, the driver completes the lane change task at T4. Because there is no precise driver mental model can be used to explain when exactly the driver generates an intention, T1 is hard to be precisely determined. Hence, most of the studies use T2 and T3 as the time criteria to evaluate the prediction horizon. The earlier the prediction is made, the more difficult the task will be.

After the driver has taken some actions such as steering the wheel and accelerate/brake, it is straightforward to recognize their intent. However, if the intelligent vehicles try to recognize the driver's intent before the actions are taken, the task will be much more difficult since only limited and uncertain information can be used. As shown in Table II, some of the studies achieved 90% prediction accuracy with 2-3s prediction horizon [96], [101], [105]. It was reported that the lane change intention can be recognized with a high accuracy (100% and 93.5%) in [57], [88]. However, these results are made after the lane change maneuver has been initiated. The earlier the prediction is made, the higher FPR will be. Therefore, a trade-off between the FPR and the prediction horizon exists, which need to be carefully evaluated [50]. It was found that the data collected 3s before the maneuver was enough to present the lane change intention. The prediction horizon in the simulation environment is usually better than that in real-world testing. This is mainly due to the large noise and distraction exist in the real-world environment. However, the real-world results indicate a more natural performance, and benefit the analysis of driver mental-physical collaboration.

IV. Challenges and Future Works

In this section, challenges and part of the future works are highlighted. Four primary works to enhance the DII system are discussed, which are the design of next-generation ADAS, driver situation awareness and interaction aware modeling, autonomous driving, and parallel DII, respectively.

A. Design Next-Generation ADAS

Next-generation ADAS require further advances in driver understanding from outer behaviors, mental status, and sophisticated environment perception. As aforementioned, current ADAS are only equipped with isolated driver status recognition system, which fails to exploit the relationship between different functions. Meanwhile, a holistic traffic context perception system is required according to the fast development of sensors and an onboard computing device. These concerns give rise to the following discussion.

1) Integration of Driver Monitoring Systems: The studies of driver behavior-oriented assistance systems can be partially summarized into the following aspects, driver attention, driver intention, driver workload, driver style, and driver distraction, etc. For each research area, a vast amount of studies have been proposed. However, there are still no explicit connections between these systems. It is believed that driver behavior under the distracted condition, and the non-distracted state is different [107], [108]. Also, if the driver is overloaded after a long drive, the physical behaviors are also different [109]. In terms of the DII system, how to correctly infer driver intention with different mental status need to be studied. Therefore, the construction of a robust DII, which can adapt to different driver status is expected. Also, by considering driver monitoring systems has a whole, the control conflicts between the driver and the vehicle can be reduced.

2) The Need for Comprehensive Environment Model: Sensing efficiently and precisely is another emerging requirement for the context perception module. A holistic approach is needed in the future to construct a comprehensive environment model from both sensors' view as well as the drivers' view. The driver-oriented context perception must process the context data sequence and analysis the potential driving solutions for the human driver. This can be treated as active guidance that can influence the driver intention generation process rather than only provide the fused context data to the driver and infer the intention afterward. Dynamic analysis of the potential driving behaviors concerning the current context will significantly increase the intention prediction horizon and accuracy. However, real-time estimation leads to a more stringent requirement to onboard perception and computing hardware.

3) Design Cognitive Model for Driver Intention: A more challenge work is to exploit a comprehensive understanding of the intention generation process according to the traffic context and human behaviors. Currently, driver attention and workload can be mathematically modeled, which provide a better explanation for the driver cognitive attention and workload behaviors [111], [112]. However, there are still limited studies on the explicit modeling of driver intention. Describing the intention generation process with more precise cognitive language and a mathematical model would be one of the core studies in the future.

B. Situation Awareness and Interaction Aware

The prediction of driver maneuver and the vehicle trajectory needs to be made according to the driver situation awareness and interaction behaviors. In [113], three kinds of vehicle motion modeling methods were proposed, which were the physics-based motion model, maneuver-based motion model, and interaction-aware motion model. The maneuver-based motion model predicts the vehicle trajectory based on the early recognition of the driver intended maneuvers, which is like the intention inference task described in this study. However, most of the maneuver-based models assume the surrounding vehicles move independently without interacting with each other, which can be unreasonable in some complicated situations such as in the roundabout or urban area. Therefore, the interaction-aware modeling methods with respect to the driver situation awareness should be further studied in the future. This part will discuss this problem from two points, which are driver situation awareness modeling and interaction-awareness modeling.

1) Situation Awareness Modeling: Driver situation awareness (SA) can be viewed as the knowledge that learned and updated from the driving tasks to handle the multifaced situation and guide the driver to make decisions when engaged in real-time multitasking [114]. The perceptual and cognitive process of maintaining the SA also can be divided into three categories, which are automatic (usually unconscious and require no cognitive resources), recognition-primed process (few demands on cognitive resources), and conscious controlled process which requires heavy cognitive resources [114]. Driver SA model carries the habit, knowledge, and attitude towards the specific driving tasks and closely related to the DII since the SA knowledge direct how to understand the driver correctly. For example, a driver intention-oriented situation awareness system at the intersection has been discussed in [26]. Four significant contributions of the situation awareness system are summarized as avoidance of unnecessary warnings, detection of occluded traffic participants, enhancement of driver intent inference, and helps to predict future trajectories of other entities.

Regarding the lane change maneuvers, the four factors are also important since situation awareness model enables the analysis of surrounding traffic flow and provide guidance to the DII system. In [115], driver lane change maneuver was classified into five categories based on the different interaction style with surrounding vehicles. With the analysis of 1000 naturalistic highway lane change data, it was found that 72% of the lane change was self-motivated and had no significant interaction with the surrounding vehicles. However, without the proper SA, drivers may be unable to finish the intended maneuver smoothly when encountering a complex interaction. For example, a low-speed vehicle is in front of the ego-lane and a rear vehicle is fast approaching in the overtaking lane. In this case, the driver may wish to overtake the front vehicle and must control the vehicle according to the SA and the motion prediction of the rear vehicle. If the driver may postpone his lane change maneuver and let rear vehicle pass first, a conflict will be generated between the desired intention and the actual maneuver.

Most of the driver intention studies in the past do not provide enough analysis of this conflict because the driver intention is unable to be predicted and labeled precisely, especially in such a complex condition. Further, as mentioned in [115], most of the naturalistic lane change maneuvers have no significant interaction with other vehicles. The complex interaction scenarios are hard to be repeated in the real world so that not enough data can be used to analyze the conflict situations. However, the situation assessment and understanding can be used to predict the dangerous maneuver at the intersections so that conflict between the actual intention and the expected intention can be clarified [116]. Specifically, the intended stop/go maneuver and the expected maneuver of the driver when approaching an intersection was compared to gain a risk assessment of the dangerous maneuver. In [117], the context information and the corresponding traffic rules were applied with the DBN so that the expected maneuver of the driver can be estimated. The future motion of the traffic participants is the combination of the tactical intentions and their corresponding risk assessment to perform the maneuver [118]. Therefore, it is believed that driver situation awareness and risk assessment can contribute to a better prediction of driver intention.

In sum, traffic situation awareness concerning the assessment of the traffic contexts, traffic rules, road layout, and driver behaviors, etc. are critical to the correct prediction to the driver intention. A driver may generate a series of checking behaviors and perform the maneuver after the intention. However, the intended maneuver may be postponed or aborted dues to the inappropriate situation. Hence, a comprehensive situation awareness model is needed to fully understand the driver behavior, cognitive process, perception, and interaction habit so that a precise prediction of the driver intention can be achieved.

2) Interaction-Aware Modeling: The interaction-aware motion prediction assumed traffic entities influence each other and provide a longer-term motion prediction of other road users as the mutual dependencies between the drivers' decisions are considered. Regarding the lane change maneuver, a suddenly cut-in maneuver in front of the ego-vehicle can cause a lane change decision to the ego-driver to avoid collision [119]. At this moment, the DII algorithms may become less powerful than with the interaction-aware algorithms in the prevention of collision as DII is mainly designed for the prediction of active intention. Here we roughly define the active intention as a goal-oriented intention while the passive intention is mainly caused by other road entities and the host driver must finish a specific maneuver in a short period. In [120], an integrated interaction-aware motion prediction model was proposed based on the combination of model-based intention estimation for surrounding entities and learning-based lateral motion prediction. The proposed method provides a reliable estimation of the future planning of the surrounding vehicles and the average prediction time before the lane change maneuvers can be extended by more than 60%.

In [121], a unified framework for maneuver classification, trajectory prediction, and interaction-aware motion prediction was proposed. It was shown that the predicted surrounding vehicle motion should be determined according to the comprehensive analysis of the potential maneuver and the probability of the future trajectory. In [122], a generic probabilistic interactive situation aware model is proposed based on a two-layer HMM framework (TLHMM). The TLHMM modeled the real-world interaction behaviors in the highway entrance, roundabout, and T-intersections by computing the joint maneuver distribution of the multiple interactive agents. However, the model has a limitation in the long-term prediction since the TLHMM cannot precisely remember the long-term dependency and temporal patterns. With interaction-aware prediction model, the long-term motion and intention of surrounding entities can be estimated and used for host driver intention inference. This will lead to a holistic understanding of current traffic context and enhance the DII system with an even earlier prediction. Moreover, the interaction-aware motion prediction enables the inference of suddenly lane change intention (passive intention) as discussed in the cut-in scenario. However, one of the disadvantages of the interaction-aware model is the computational complexity grows exponentially with the increasing number of vehicles [120]. The interaction-aware method relies on a comprehensive perception of the local traffic context, which increases the overall system cost.

Another interesting point is to predict the driver intention and interaction behaviors based on transfer learning. In [122], the second layer of the TLHMM was trained with virtual data and high-level meta-features instead of traffic context information, which can be quickly applied to the real-world target. The complex interaction behaviors and scenarios are hard to be recorded and duplicated in the real-world while it can be carefully designed and sufficiently tested in the simulation environment. Hence, if the knowledge learned from the simulation can be properly transferred into the real-world scenario, the real-world interaction-aware model can be more precise and robust. This is also a major concern of parallel driving and parallel driver, which will be discussed later.

Despite sensing traffic context with onboard multi-sensor fusion, the interaction-aware prediction model can also be constructed based on the vehicle-to-vehicle (V2V) techniques [123]. The V2V communication does not rely on high-cost sensors but can provide efficient interactive communication and situation awareness for the local area vehicles. The intention inference for the host driver and surrounding drivers can be detected and shared even earlier with the V2V techniques. The impact of the interaction-aware motion prediction and the V2V technique to the host driver intention inference have not been adequately studied in the past. Future works are expected in this area so that a risk-free and highly interactive traffic framework can be built.

C. Autonomous Driving

The automated driving technology was divided into different levels based on the SAE standard J3016. With Level three or higher intelligence, the autonomous vehicle is responsible for the environment perception, decision making, motion planning, and vehicle control. The automotive industry wishes to replace human drivers with autonomous cars so that human mistakes can be avoided. However, it does not mean that driver modeling is not needed in the future.

DII systems require a comprehensive understanding of the driving environment as well as the driver behavioral pattern. The process of intention generation and execution reflects the driver SA regarding the traffic context. Current decision-making algorithms for autonomous vehicles are mainly based on optimization, probabilistic models, and reinforcement learning. Neither of the algorithms takes the driver experience into the loop. The autonomous vehicle makes lane change mainly based on the pre-defined rule base or the probabilistic model like Markov chain. These algorithms usually fail to consider the acceptance of the human passenger. The DII system will provide important guidance to the autonomous vehicle so that the autonomous vehicle can learn how human drivers make lane change as well as when and where to execute the lane change. Meanwhile, combining DII with driving styles is also considerable [124]. Different drivers have different driving styles, and the intention inference system cannot work uniformly. For some situation, gentle drivers prefer to wait before changing the lane while aggressive driver likes the challenge tasks. If the autonomous vehicle takes the different intention pattern from different driver styles, the autonomous vehicle can minimize the uncomfortable driving experience for the passengers.

Another emerging topic for DII towards autonomous decision making and motion planning is to estimate when and where the driver is going to drive [125]. Most of the existing driver intention inference algorithms do not pay attention to the intended position. The position should be estimated with the comprehensive environment perception and driver behaviors in the past few seconds. Current intention inference algorithms enable the intention prediction before the maneuver. However, the intended position estimation is still a difficult task. The positioning pattern learned from the driver can be transferred to the autonomous vehicle more straightforward. The path planning model can take the estimated short-term destination into calculation so that a more reasonable and human-like path can be generated. Therefore, transferring the DII knowledge to the autonomous vehicle will bring more naturalistic human-like behaviors in both decision-making and motion planning stage.

D. Parallel Driver Intention Inference System

As aforementioned, the driver intention inference system suffers from hardware and algorithm limitation. Also, there is still no explicit model to describe the real mental intention process. One of the emerging challenges is short of data for model training and model evaluation. It is hard to collect plenty of real-world data to increase the data diversity since it dramatically increases the temporal and financial cost. Therefore, a novel approach is required to sufficiently train and evaluate the intention inference system, and it would be better to have a self-learning ability to exploit the unseen pattern and principles that are behind the driver intention nature. Fei-Yue Wang first developed the parallel theory in 2004 [126]. The construction of a parallel system requires the ACP approach as the background knowledge, which is the combination of Artificial society, Computational experiments, and Parallel execution [127].

The physical system in the real world can be viewed as a Newton machine, whereas the software defined-artificial world is a Merton machine [128]. In [129], the parallel system is described in the Cyber-Physical-Social space (CPSS), which extend the conventional Cyber-Physical space (CPS) by integrating an additional dimension of human and social characteristics. Based on the ACP approach, a parallel driver intention inference system is proposed in Fig. 7.

In the artificial society, a virtual driving environment will be developed based on the modeling of traffic context as well as the driver behaviors such as head, facial, and body features [130]. There are plenty of simulation software that can build the 3D driving context, such as the *CarSim* or *PanoSim*. The virtual facial images and videos can be generated based on the high-resolution 3D scans as used in [131]. The driver facial dynamic model can be trained according to the real driver patterns using deep learning approaches such as the generative adversarial networks (GAN) [132]. Then, a generative adversarial imitation learning method can be used to train the virtual driver model [133]. The virtual driver will be sufficiently evaluated with the data from both the artificial world and the real world. Finally, the learned driver behavior knowledge concerning the current traffic context can be used for the training and testing of the driver intention inference model. If the virtual model gives better inference accuracy, it will guide the real-world model to deal with challenge tasks and update the real-world model with online

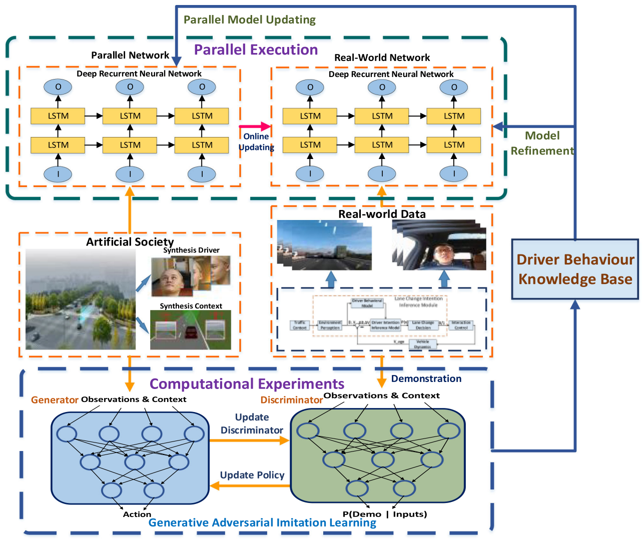

Fig. 7. Architecture of ACP-based parallel driver intention inference system.

learning methods. With the parallel driver intention inference system, the intention inference model can be trained and evaluated with much more scenarios so that a more robust intention inference model is generated.

V. Conclusion

Based on this review, driver intention inference is believed an important function for ADAS and intelligent vehicles, which is able to reduce the conflicts between the driver and the intelligent vehicle. Understanding of human intention also enables a better design of the decision-making algorithms for automated vehicles. In this study, the relationship between tactical and control level intention is clarified. Based on the DII framework, the traffic context is viewed as the stimuli for the intention, while the driver behavioral information and vehicle dynamics are the response to the stimuli. A comprehensive evaluation method for the intention inference should consider from the aspect of accuracy and prediction horizon. Future works for driver intention inference should concentrate on the precise modeling of the intention generation process, situation and interaction awareness, and autonomous vehicles. Meanwhile, it is believed that a parallel DII framework will dramatically increase the performance of the DII systems.

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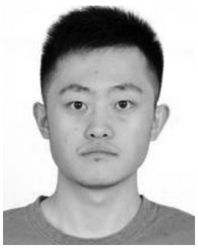

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