Review Article

Driver Behavior Modeling: Developments and Future Directions

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The advances in wireless communication schemes, mobile cloud and fog computing, and context-aware services boost a growing interest in the design, development, and deployment of driver behavior models for emerging applications. Despite the progressive advancements in various aspects of driver behavior modeling (DBM), only limited work can be found that reviews the growing body of literature, which only targets a subset of DBM processes. Thus a more general review of the diverse aspects of DBM, with an emphasis on the most recent developments, is needed. In this paper, we provide an overview of advances of in-vehicle and smartphone sensing capabilities and communication and recent applications and services of DBM and emphasize research challenges and key future directions.

1. Introduction

Modeling driver behavior is a complex task that has garnered significant research attention throughout the past decades. This interest is fueled by the constant growth of cities as indicated by the recent statistics that the *urban* population has grown from 746 million in 1950 to 3.9 billion in 2014 (54% of the current world population) [1]. As more people migrate to cities, the transportation infrastructure is faced with significant challenges leading to more accidents, deaths, congestion, and environmental pollution. Studies have indicated that there are over 30,000 deaths and 1.2 million injuries annually on roadways in the United States, 80% of which are due to driver inattention or as a result of unintended maneuvers [2, 3]. Human error is therefore the primary cause of such tragedies.

Driver behavior modeling (DBM) has primarily emerged to predict driving maneuvers, driver intent, vehicle and driver state, and environmental factors, to improve transportation safety and the driving experience as a whole. These models are then typically incorporated into Advanced Driver Assistance System (ADAS) in the vehicles. For instance, by coupling sensing information with accurate lane changing prediction models, an ADAS can prevent accidents by warning the driver ahead of time of potential danger. In addition to modeling the vehicle behavior, determining the drivers' state such as their attention level and driving competence can play a crucial role in the success of ADASs. At another level, gaining insight on the drivers' objectives such as destination and road preferences opens the door to novel travel assistance systems and services.

Despite the progressive advancements in various aspects of DBM, only a limited number of surveys can be found that review the growing body of literature. Among those, lane changing models have been reviewed in [4, 5], while Doshi and Trivedi [2] survey developments in driver *intent* prediction with emphasis on forecasting the trajectory of the vehicle in real time. Works covering driver skill and different approaches to driver models have recently been reviewed in [6]. A review of the cognitive components of driver behavior can also be found in [7] where the author addresses the situational factors and motives that influence driving. The surveys mentioned above only target a subset of DBM processes and thus a more general review of the diverse aspects of DBM with an emphasis on the most recent developments is needed. In particular, advances in vehicle sensing capabilities (as well as smartphones), vehicle-to-vehicle (V2V) communication, and cloud-based services are facilitating an unprecedented era of data collection that is enabling researchers to develop more sophisticated DBM.
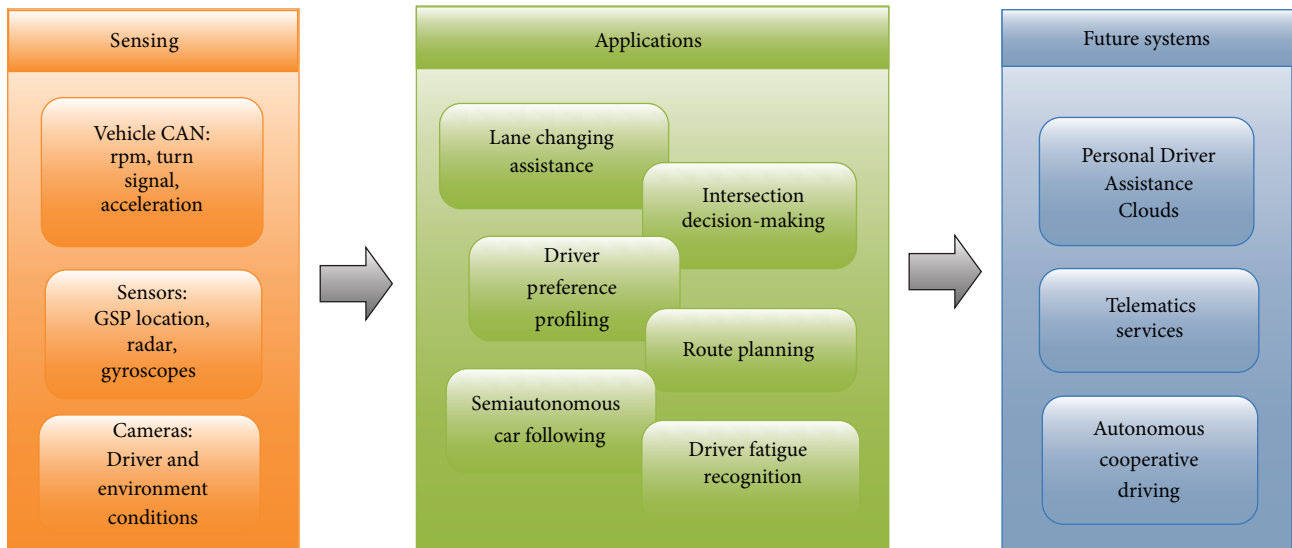
FIGURE 1: Driver behavior modeling (DBM): sensing, applications, and future systems.

The contemporary emergence of "big data" storage and processing solutions is another technological development that is anticipated also to drive new avenues of research and exploration in DBM. As such, the objective of this survey is to provide a review of the recent applications and research areas in DBM and emphasize key future directions. We believe such a state-of-the-art work is needed to assist those interested in embarking in this evolving field. To accomplish this we organize the survey into the following sections:

(i) Section 2 first provides an introduction to the components and stages involved in driver behavior modeling, the various forms of input, and the primary modeling approaches.

(ii) Section 3 discusses the typical applications and uses of DBM with emphasis on ADASs and the emerging autonomous vehicles.

(iii) In Section 4 we review fundamental modeling objectives in detail. The objectives are the specific research components that enable the development of the applications mentioned earlier. This includes topics such as predicting behavior at intersections, lane changes, and route choice.

(iv) Simulation-based and data-driven evaluation techniques are highlighted in Section 5. References to datasets for specific DBM objectives and applications are provided.

(v) Finally, Section 6 discusses several open research issues and directions such as collaborative DBM and Driver Assistance Clouds (DACs).

2. Overview and Preliminaries

2.1. Modeling Frameworks.
As mentioned in Section 1, modeling driver behavior includes the driver intent, state, and vehicle dynamics. It is therefore difficult to develop a single modeling framework for the complete driving task. However, traditionally a typical modeling framework includes inputs from various sensors and vehicle controllers, preprocessing algorithms to filter the data if necessary, the core predictive models for particular tasks (these can follow the various levels discussed below), and feedback. An overview of various models that capture the dynamics between the driver, the vehicle, and the environment is presented in [6, 8]. More generically, DBM can be considered to involve (1) a sensing phase, (2) a reasoning phase, and (3) an application layer, as illustrated in Figure 1. The sensing phase involves various forms of data collection from the vehicle, driver, and the environment. This is then typically fed into a reasoning engine with some application in mind. Although current research in individual applications has not yet matured, the ultimate goal is to develop assistance systems that integrate multiple personalized services for the driver as shown in Figure 1. This requires a high level of data abstraction and processing from multiple resources.

2.2. Inputs for Driver Behavior Modeling.
Inputs to the DBM include vehicle data from the Controller Area Network (CAN), sensors, and more recently input from smartphones.

2.2.1. CAN.
The CAN provides accurate information of several in-vehicle parameters such as the pedal positions, steering wheel angle, RPM acceleration, and turn signal state [2]. Data collected using the CAN is typically more accurate than that from mobile sensors as it is directly connected to the vehicle. Several adapters can be used for data acquisition from the CAN such as the OBD-II (On-Board Diagnostics) Bluetooth adapter with the Torque Pro Application [9].

2.2.2. Sensors.
Several sensor systems can be used in DBM such as radars, lane position sensors, Global Positioning System (GPS), accelerometers, and gyroscopes. The use of

sensors embedded in smartphones is currently being investigated as an alternative/complementary input to the CAN, and the outcomes of several projects have been reported recently [10–14]. This is particularly useful for older vehicles and in developing countries where smartphones are popular and may facilitate simpler integration into crowd sensing and cloud-based services. However, sensor calibration is required and the accuracy may vary from device to device which is a topic of current investigation.

2.2.3. Cameras. While cameras can be considered to be one type of sensor, they are particularly useful in several aspects of DBM. For instance, cameras focused on the driver can be used to predict the driver's state and fatigue levels. They can also be used to improve maneuver recognition by incorporating cues of the drivers eye gaze, hand position, and foot hovering. Examples of such maneuvers include intent to change lanes, brake, and turn that can be inferred earlier with the use of cameras as drivers check their blind spots and grip the steering wheel prior to taking action.

2.3. Modeling Levels. In driver behavior literature, several models have been proposed; examples of these models are the hierarchical control model, the GADGET-Matrix model, and the DRIVABILITY model. The hierarchical control model is based on Michon's theory. It has commonly been categorized as operational, tactical, and strategic based on the timescales through which they operate [2, 7].

2.3.1. Operational Level. Modeling operational maneuvers involves actions performed over less than a second primarily in order to remain safe or abide by traffic regulations. *Sudden* braking and turning are examples of this modeling domain, which operate at the shortest timescale of human interaction. Such models can be used to improve vehicle design, human-vehicle interaction, and emergency assistance systems. An overview of such modeling techniques can be found in [15, 16].

2.3.2. Tactical Level. Tactical maneuvers can be defined as a coherent set of operational maneuvers intended to achieve a short-term goal such as lane changes, turns, and stops. These operations typically last for several seconds, thereby enabling predictive modeling and inference. Modeling and predicting tactical maneuvers have significant potential to improve ADASs since there is time to prevent unsafe driving behaviors if the drivers are unaware of the danger of their actions. As such, models that enable early prediction of driver intent prior to a tactical maneuver are of particular interest. An interesting survey of tactical maneuvers with emphasis on modeling driver intent can be found in [2].

2.3.3. Strategic Level. At the strategic level, actions are triggered by the long-term goals of the driver. For instance, destination and route calculation is an example of strategic actions where the timescale extends to minutes or hours [17–19]. Driver preferences can also be considered within

this modeling domain since they impact strategic maneuvers. Understanding strategic maneuvers provides additional context and preliminary input to tactical and operational maneuvers by modeling the underlying driver preferences and long-term goals of the trip. In this regard, a lane change can be modeled at the tactical level based on the strategic input of the drivers route and behavioral information.

Hatakka et al. [20, 21] have debated that the hierarchical control model would need to capture and include the driver's general goals for life and skills for living and hence extended the three hierarchical levels into four by adding the behavioral level on top of the three hierarchical control levels, introducing the GADGET-Matrix model. The hierarchical levels of the GADGET-Matrix model consist of the Vehicle Maneuvering level mapped to the operational level in Michon's model. It mainly accounts for the drivers capability of operating the vehicle such as controlling of speed, the vehicle's direction, and braking. The mastering traffic situations level (mapped to the tactical level) is mainly related to the drivers' thinking skills, which allow drivers to adapt to the current traffic situation. The third level is the goals and context of driving level (mapped to the strategic level), which includes the tools that evaluate the purpose and the environment of driving, that is, driving rules and where and when to drive. The top level considers the importance of driving for the driver that motives and allows describing behaviors which are "less congruent with the norms of the society" [21].

The DRIVABILITY model [22] is different from the aforementioned models by mainly focusing on the strategic model. The model describes driving behavior as a result to five permanent and temporary contributors, which simultaneously affect a driver's decisions:

> *Individual Resources.* They are physical, social, psychological, and mental conditions of a driver.
>
> *Knowledge and Skills.* They are the driver's training, education, experience, and knowledge not only related to driving skills but in general, since these factors greatly influence motivation and behavior of the driver.
>
> *Environmental Factors.* They include the vehicle status, the existence of traffic hazards, the weather, and road and traffic conditions.
>
> *Workload and Risk Awareness.* They are the main two key elements that tie the drivers' resources to their environmental status to facilitate understanding and analyzing driving performance.

2.4. Reactive and Predictive Models. DBM can be classified as either reactive or predictive models. *Reactive* models learn the observed behavior or driving maneuver *after* the action has been conducted. For instance, driver coaching applications can employ reactive models that identify dangerous driving maneuvers performed by the trainee during the training session. On the other hand, *predictive* models are required to identify the driver action on the onset of the behavior in *real time*. This is needed in ADAS where precautionary action should be performed immediately. The success of predictive

models is contingent on how early they can predict the driver behavior, and they are therefore typically more difficult to develop than reactive models.

2.5. Algorithms and Approaches. Algorithms and approaches for DBM encompass a broad range of statistical, machine learning, and pattern recognition techniques, among others. We highlight some of the most commonly used approaches below.

2.5.1. Basic Statistical Classification. Statistical models can be used to study the behavior of drivers based on collected data. Simple trends in the data can be used to gain insight on the anticipated driver maneuvers and classification criteria can be identified. Model fitting and regression techniques are some common examples of such methods. While statistical classification approaches are generally intuitive, they may be limited in their ability to classify complex multidimensional data [23].

2.5.2. Discriminative Approaches. Discriminative approaches such as Support Vector Machines (SVMs) are generally used to overcome some of the limitations of basic classification schemes. SVMs can be used to efficiently model driver behaviors where binary classification is involved such as determining driver compliance to traffic rules or deciding whether a driver will make a particular maneuver. Two particular advantages of SVMs are as follows: (1) they solve an optimization of a convex function, and thus the derived solution is a global optimum, and (2) the upper bound on the generalization error does not depend on the problem dimension [23, 24].

2.5.3. Generative Models. Generative approaches are another primary modeling technique in DBM. Here, the underlying patterns in the collected driver data are investigated and the probability of observing a set of outputs for a given model is determined. Hidden Markov Models (HMMs) are one example where the relationship between the observations and the hidden states that generate these observations can be identified [25]. Here, the states of the HMMs define different behaviors and the transitions between these states capture the evolution of the driver model.

3. Applications

Modeling driver behaviors enables a plethora of applications facilitated by the constant advances in sensing and computational capabilities. We discuss the recent developments and applications in this section and summarize our discussion in Table 1.

3.1. Driver Training and Self-Coaching. Many of the driver models are developed aiming at facilitating better driver training models. The idea is to monitor driver actions either in a simulator or in a real environment and assess the driver safety and competence levels based on models for ideal driving. There has been particular interest in developing such

systems for novice drivers and to retrain elderly drivers by understanding their deficiencies at different levels [8, 26].

3.2. Driver Assistance Systems. As mentioned in the Introduction, the majority of the driver fatalities and injuries are caused due to driver inattention and unintended maneuvers. ADASs are thus being developed by industry and academic projects in an effort to reduce or eliminate at best these casualties. The primary object of ADASs is to forecast the trajectory and behavior of a vehicle in real time and then compensate for dangerous circumstances or events. To do so, it is essential for the ADASs to be capable of differentiating between potentially dangerous situations and regular driving behavior. Accurately modeling deceleration behavior is one element of such systems [27]. A primary challenge however is to develop such systems without annoying the driver with irrelevant recommendations and precautions or misinterpreting the state of the driver or the surrounding vehicles. Research in ADASs that involves multiple vehicles can lead to models that capture right-of-way rules and general road scene-awareness. Eventually Driver Assistance Systems may evolve to *driver-less* systems for either semiautonomous or fully autonomous vehicles [28].

3.3. Energy Efficiency. Driver behavior models can also be applied towards improving vehicle energy efficiency by monitoring the pedal actuation and fuel usage. Reports and recommendations can then be provided to the driver. Additionally, optimizing electric vehicle sharing has been recently proposed in the literature [29].

3.4. Crowdsourced Sensing for Road Conditions. Traditional research in DBM has focused on input from a single driver. The current direction of crowdsourced sensing and big data analysis can be coupled with driver behavior models to gain insight on the current road conditions. This includes traffic jams, road types, and speed limits, as well as predicting the weather conditions and degree of slipperiness [30].

4. Modeling Objectives

While the applications discussed in the previous section demonstrate the desired uses of DBM, they are typically achieved by individual modeling objectives which we review in this section. The objectives discussed herein are not meant to be comprehensive but rather representative of the major classes of DBM objectives.

4.1. Lane Changing. Lane changing models describe the drivers' lane changing behaviors under various traffic conditions. The primary goal is to determine whether or not it is safe for a driver to make a lane change given the vehicle's speed and the surrounding traffic. The *gap acceptance measure* is a traditional approach used in lane changing models. A driver will only make a lane change if both the lead and lag gaps in the target lane are above the safety threshold. There are several challenges however that make lane changing models complicated such as the variance of

TABLE 1: Summary of reviewed DBM approaches and challenges.

	Modeling Approaches	Challenges and Directions
Lane changing	(i) Lane changing literature reviews and classification [4, 5]. (ii) Rule-based approaches using Gipps Model with the lane changing process as a decision tree with a series of fixed conditions [31]. Other rule-based schemes include Cellular automata [32] and game theory based models [33]. (iii) Discrete-choice models based on probabilities include [34, 35]. (iv) Fuzzy-logic and artificial neural networks have been used in [4, 36, 37], to account for uncertainty and facilitate unsupervised training on real data. (v) Incentive-based models that incorporate factors such as the desire to follow a route, gain speed, and keep right [39] and politeness factors [38].	(i) Incorporating personal driving incentives and preferences, with contextual factors such as weather and lighting, is needed to develop more personalized lane changing models. (ii) Works addressing more the less common and complex driving tasks such as ramp merging and multiple lane changing.
Intersection decision-making	(i) Identifying the degree of stopping violations at intersections based on Speed Distance Regression (SDR) classification [52]. Field-test based characterization of driver stopping decisions for different age groups and genders [53]. (ii) Driver behavior classification at intersections based on SVMs and HMMs. Validation performed on a large naturalistic dataset [23]. (iii) Recognizing other behaviors at intersections, for example, turning and stopping [42, 43] and left turns at signaled intersections [44]. (iv) Predicting multiple situations using case-based reasoning [45]. Modeling the evolution of an intersection using situation assessment and behavior prediction [46].	(i) Developing cooperative models that leverage information from multiple vehicles to enable collective behavior at intersections. (ii) Coupling intervehicular communications with driver behavior modeling. (iii) Developing unified standard datasets to evaluate different intersection behaviors. This will offer a platform for researchers to compare and evaluate their modeling techniques.
Driver profiling	(i) Detecting aggressive driver behavior and competence using probabilistic ARX models [54]. (ii) Measuring in-vehicle acceleration using smartphone sensors to count events of sudden acceleration, braking, and sharp turning [10]. (iii) Fuzzy-logic based scoring mechanisms to profile driver aggressiveness [11]. (iv) Using an onboard diagnostic reader and an inertial measurement unit along with a Bayes classifier to model aggressiveness [12].	(i) Trading off accuracy versus cost for use of traditional cell-phone sensors versus advanced in-vehicle sensors and OBD. (ii) Differentiating between aggressive behaviors and skilled maneuvers that include acceleration.
Router choice modeling	(i) Survey on the current literature on route choice models with the focus on using fuzzy-logic and genetic algorithms [55]. (ii) Classification of literature according to the considered user preferences, for example, travel time, the number of intersections, traffic lights, and roadside aesthetics [56]. (iii) Incorporating feedback to learn user preferences [58] and exploring the evolution of driver route choices with time [57].	(i) Building distributed end-to-end travel assistance systems that incorporate real-time sensing of traffic, weather, and road conditions. (ii) Developing more sophisticated personalized navigation and travel systems that learn and model user preferences.

the gap acceptance behavior under different traffic conditions and the dependence on the capabilities and types of the vehicles.

There is a very large body of research on lane changing models—a few literature surveys [4, 5] have been conducted to classify the different approaches. According to Rahman et al. [4] there are four categories of models: rule-based models, discrete-choice probabilistic models, artificial-intelligence models, and incentive-based models. The Gipps Model [31] is among the most notable *rule-based* models. It models the lane changing process as a decision tree with a series of fixed conditions that are typically found on the roadways and the output is a binary choice that indicates the lane changing decision. Gipps Model incorporates a number of logical and practical reasons into lane changing tree such as intent of turning, presence of heavy vehicles, existence of the safety gap, and speed advantage and has been used in several microscopic traffic simulation tools. However, Gipps Model does not include mechanisms to deal with different traffic conditions. For instance, during congestion drivers may cooperate to allow other drivers to change lanes, or on the other hand drivers may be aggressive and force lane change in theoretically an unsafe way. Cellular automata [32] and game theory based models [33] have also been developed as rule-based models. The work in [33] tackles cooperative and forced lane changes using game theory with driver experience as a parameter.

Discrete-choice models based on probabilities have also received considerable attention in the literature. Ahmed [34] developed a generic lane changing model that captures both mandatory and discretionary lane changes in a simple mathematical formulation. Toledo et al. [35] also propose a probabilistic model where the trade-offs between forced and discretionary maneuvers are combined in a single utility and tuned using maximum-likelihood estimation approaches. Extensive tests on microscopic vehicle trajectory data collected in Arlington, USA, have confirmed the effectiveness of Toledo's models.

Several lane changing models based on fuzzy-logic and artificial neural networks have also been developed, although their adoption remains limited [4]. The advantage of fuzzy-logic is that the uncertainty in lane changing can be modeled and a number of abstract IF-THEN rules can be used to represent the complex decision-making. Among the more recent works is that of Moridpour et al. [36] which focuses on lane change behavior of heavy vehicles. Neural networks have demonstrated high accuracy in modeling lane changing decisions on field collected data [37]. Inputs such as the vehicle's direction, speed, distance from surrounding vehicles, and preferred speed have been used to train the network using the backpropagation algorithm with promising results. The primary disadvantage of artificial-intelligence based approaches is the dependence on field collected data for different traffic situations in order to calibrate and develop the models satisfactorily.

Incentive-based models have been more recently considered in modeling lane changing behavior. In essence, the incentive criterion models the attractiveness of a lane based on its utility to the driver, and a safety criterion captures the risk associated with the lane change [38]. Modeling the incentives can include a variety of factors such as the desire to follow a route, gain speed, and keep right [39], in addition to politeness factors [38] that can be tuned to account for different driver personalities. While incentive-based approaches capture the human element of maximizing personal benefits and driving preferences they lack more detailed physical modeling that may limit applicability to different traffic situations such as congestion.

As discussed, several types of lane changing models have been proposed in the literature. However, novel models that combine the personal driving aspect (incentives and preferences), road congestion, and geometric considerations, as well as contextual factors such as weather and lighting, are needed to develop generic lane changing models. Works addressing specific lane changing maneuvers such as ramp merging [40, 41] and multiple lane changing are another open area of research.

In addition to determining stopping, estimating the general driver behavior at intersections is of significant importance. Various works have addressed specific goals such as recognizing turning and stopping maneuvers [42, 43] and left turns at signaled intersections [44]. In [45] Vacek et al. consider the more challenging problem of predicting multiple situations using case-based reasoning. Modeling the evolution of an intersection situation is also investigated in [46] where the authors propose a multiple stage approach that combines situation assessment with behavior prediction. In the first stage, the current intersection situation is classified by decomposing it into more manageable sets of related road users to prevent a combinatorial explosion of variables. The interactions between the entities are used to determine the configuration; for example, a vehicle has to slow down to keep a safe distance or stop at a traffic light. Subsequently, in the second stage the velocity profile of each vehicle is predicted taking advantage of the previously estimated situation using random forest regressors [47]. More recently, a two-layer framework for estimating driver decisions at intersections has been proposed [48]. As opposed to the top-down approach of estimating the intersection situation and then using the underlying continuous model to determine the vehicle dynamics (as in [46]), the authors propose bottom-up architecture. Their reasoning is that it is easier to observe the lower level states such as vehicle position, velocity, orientation, and yaw. These continuous observations are modeled as Gaussian Mixture Models (GMMs), and the higher level discrete state system is modeled using HMMs corresponding to the potential driver decisions.

4.2. Intersection Decision-Making. Reports indicate that an estimated 45% of injury crashes and 22% of roadway fatalities were intersection related in the United States [49]. Such statistics have driven several international research projects that specifically target intersection decision collision avoidance systems [44, 50, 51].

A primary objective in signalized intersection decision-making is to predict whether the driver will stop safely before the stop bar if the signal turns red. This classification is then integrated into ADASs to warn drivers of the own

violations and may also be used to warn other drivers via V2V and Vehicle-to-Infrastructure (V2I) communication. The observations typically needed are the vehicles position, speed, and acceleration and the traffic signal phase that are monitored over a time window [23]. Time Transmission Interval (TTI), Time-to-Collision (TTC), and Required Deceleration Parameter (RDP) are also commonly used in intersection safety systems. The vehicles TTI $= r/v$, where v is the vehicle's current speed and r is its distance to the intersection. The TTI is computed on the onset of braking and compared to the required time for a safe stop. In a similar approach, RDP denotes the required deceleration for the vehicle to stop safely given its current distance and speed and a comparison is made to RDP threshold to determine if the required deceleration is larger than that permissible. A slightly more involved classification based on SDR has been presented in [52]. Here, instead of making independent observations, a regression curve is generated from a set of speed and distance measurements of compliant vehicles. Measurements are then compared to the compliant SDR curves to identify the degree of violations and issue warnings. In [53] field tests are conducted to characterize the driver stopping decisions for different age groups and genders. More sophisticated models based on SVMs and HMMs have also been developed for higher classification accuracy [23].

In summary, modeling driver behavior at intersections is indeed a very complex task, and a lot of further research is needed before the goal of fully autonomous driving can be achieved.

4.3. Driver Profiling and Characterization. The objective of driver profiling is not to model specific maneuvers but general driver characterization. Examples include detecting aggressive driver behavior [54] and the level of driver competence by assessing behavior in difficult situations/maneuvers such as driving on ice and avoiding accidents. Driver profiling can be integrated into ADASs for vehicles with multiple drivers to tailor the assistance recommendations to each driver.

A large body of literature is available on driving behavior analysis to determine aggressive behaviors and provide safety recommendations in Driver Assistance Systems [10–12, 14]. For instance, the work in [10] measures in-vehicle acceleration using smartphone sensors to count events of sudden acceleration, braking, and sharp turning. The authors emphasize the need for dynamic calibration algorithms when using phone sensors. More recent efforts have also been conducted in [11] where a fuzzy-logic based scoring mechanism is introduced to profile driver aggressiveness on a scale of [0, 100]. In addition to using smartphone sensors, an onboard diagnostic reader and an inertial measurement unit were used in [12] along with a Bayes classifier to model aggressive driving behaviors.

4.4. Route Choice Profiling and Travel Assistance. Navigation systems and online maps have garnered increasing user adoption over recent years, with statistics indicating that 55% of smartphone holders use mapping services on a regular basis. These services typically provide one or more alternative routes primarily based on the shortest distance between the source and destination. However, in reality there are several other factors that influence the preferred route for a user. For instance, different drivers may have varying comfort levels with driving along highways, making multiple lane changes, or left turns at traffic lights. This is important for novice drivers and the older population who are in particular need of using mapping services. In addition to the driver competence level, personal preferences can also play a significant role in route selection. This includes the number of controlled intersections, stop signs, or routes with frequent public transportation stops and school buses. Thus, while mapping services have revolutionized the user navigation experience today, much research and development are needed towards personalized travel information and Driver Assistance Systems.

A recent survey of the current literature on route choice models in transportation networks has been covered in [55]. According to the survey, several fuzzy-logic and reasoning approaches have been adopted due to their simplicity in dealing with uncertainty and qualitative variables. Genetic algorithms and ant colonization were also considered in several applications of route-finding problems in transportation networks. Another interesting literature review is available in [56] where Ramaekers et al. classify the works according to the factors considered in the models such as travel time, number of intersections, traffic lights, roadside aesthetics, and several other factors. This study also investigates the relationship between the purpose of the trip and the road categories used. A major limitation of previous studies is the assumptions of perfect knowledge due to lack of information about the transport network. Thus, incorporating real-time information from a cloud-sourced sensing platform is one open area of research. Learning user preferences is another relevant area of research where Tawfik et al. [57] explore the evolution of driver route choices with time. The authors conclude that while some drivers maintain their choice, others are keen to continuously evaluate alternative routes. A detailed analysis is made where factors such as ethnicity, education, driving experience, and gender are included. These results dictate that personalized travel information systems are needed to cope with such differences. In such systems, collecting user feedback is elemental and is concluded in the work of Park et al. [58].

5. Evaluation Methodologies

In this section we discuss the common evaluation techniques of DBM that include real datasets and driving simulators, as well as some of the typical metrics.

5.1. Microscopic Datasets. Datasets of driver behavior are typically generated by collecting vehicle and sensor data of multiple subjects as they drive. The collected datasets are further classified as naturalistic and instructed. In naturalistic data collected, the subjects are told to drive as they normally would where only the route may be specified but the goals of

the study are not. This enables the most *natural* form of data for use in ADASs. On the other hand, instructed data collection typically involves informing the subjects to perform specific driving tasks or scenarios and monitoring the output. This allows more focus and emphasis on collecting data of particular maneuvers but potentially modifies the driving behavior since the subjects are consciously repeating certain tasks. Specific datasets are typically created for different driving tasks/objectives. For instance, references to datasets for driver behavior at intersections can be found in [50, 59], while several lane changing datasets are discussed in [4].

5.2. Simulators. Several DBM studies have been based on simulator studies as well. The advantages of driving simulators are that several variables such as distractions, traffic conditions, and weather can be controlled accurately without compromising safety. Simulator-based studies are also easily repeatable and facilitate large data collection. However, simulator-based models may not accurately reflect the on-road performance and therefore validation with real data is needed.

5.3. Metrics. True and false positive rates are common metrics for evaluation in DBM where a specific task is to be predicted. True positive rates represent the percentage of correctly predicted events while false positive rates denote the percentage of events that were incorrectly predicted as true. While these statistics provide an overview of the model's success, it is important to consider the details of the testing and learning environment of each study in order to objectively compare performances objectively. The *timeliness* of the prediction is another important parameter used in DBM that indicates the proactive capabilities of the different models. Naturally, as the time gets closer to the maneuver, the performance increases.

6. Open Research Challenges and Future Directions

Driver behavior modeling is currently receiving increasing interest from industry and academia due to several contemporary factors, including the challenges of increasing global urbanization and demand for smart infrastructure solutions, the emergence of enabling technologies such as advanced sensing and data analytics, and the demand for futuristic applications such as autonomous vehicles. In this section we first summarize some of the current open research challenges and then highlight two emerging directions of future research in Driver Assistance Systems (DASs).

6.1. Research Challenges

(i) Novel DBM that incorporates personal driving incentives and preferences, with contextual factors such as weather and lighting, is needed to develop more personalized and generic models.

(ii) Works addressing more the less common and complex driving tasks are needed to complement the current literature. This includes but is not limited to ramp merging, multiple lane changing, cooperative intersection behavior, and driver intention modeling.

(iii) Although there are several available datasets for DBM evaluation, more work is needed towards a unified standard dataset for different applications. This will offer a platform for researchers to compare and evaluate their modeling techniques. Thus, more representative data from field tests for drivers of different genders and age groups is without a doubt also required.

(iv) Personalized navigation and travel systems that learn and model user preferences are another challenging area of research. Previous works in this direction have primarily assumed perfect knowledge of the road network and environment, which is not realistic. Therefore, incorporating real-time information from a cloud-sourced sensing platform will foster greater readiness for practical implementation.

(v) Personalized driver monitoring and state recognition that can capture drivers' state dynamically and online. Previous proposals make use of vehicle or/and smartphone sensors and the driver profile to detect drivers' abnormal states such as drowsiness. Most drowsiness detection schemes assume that the driver is always facing the camera or ignore the level of illumination, which directly affects the correctness of the collected data for image processing, which render these proposals impractical. Other methods such as context-aware schemes could be explored to recognize the driver state by detecting abnormal actions such as zigzag pattern driving and random and risky acceleration and lane changes. In addition, simpler and dynamic image processing methods are required to detect the driver's states online.

6.2. Emerging Directions

6.2.1. Cooperative Modeling Approaches for Collective Scene Modeling and Sensing. Most of the current literature on driver behavior modeling has focused on a single vehicle making inferences based on sensed measurement of the driver, the vehicle, and its environment. Today, advances in vehicle-to-vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications can facilitate novel approaches to driver behavior modeling. In particular, cooperative models can be developed that leverage information from multiple vehicles to develop more global behavioral models. This can enable driving-scenario or situation modeling for diverse applications and scenarios such as collective behavior at intersections [60]. For instance, coupling intervehicular communications with driver behavior modeling can facilitate the following advancements in DBM.

Signaling Warnings. In addition to alerting the driver to dangerous situations, these can be communicated to surrounding vehicles. Previous efforts in ADAS have primarily focused on alerting the driver and not the surrounding vehicles. Some
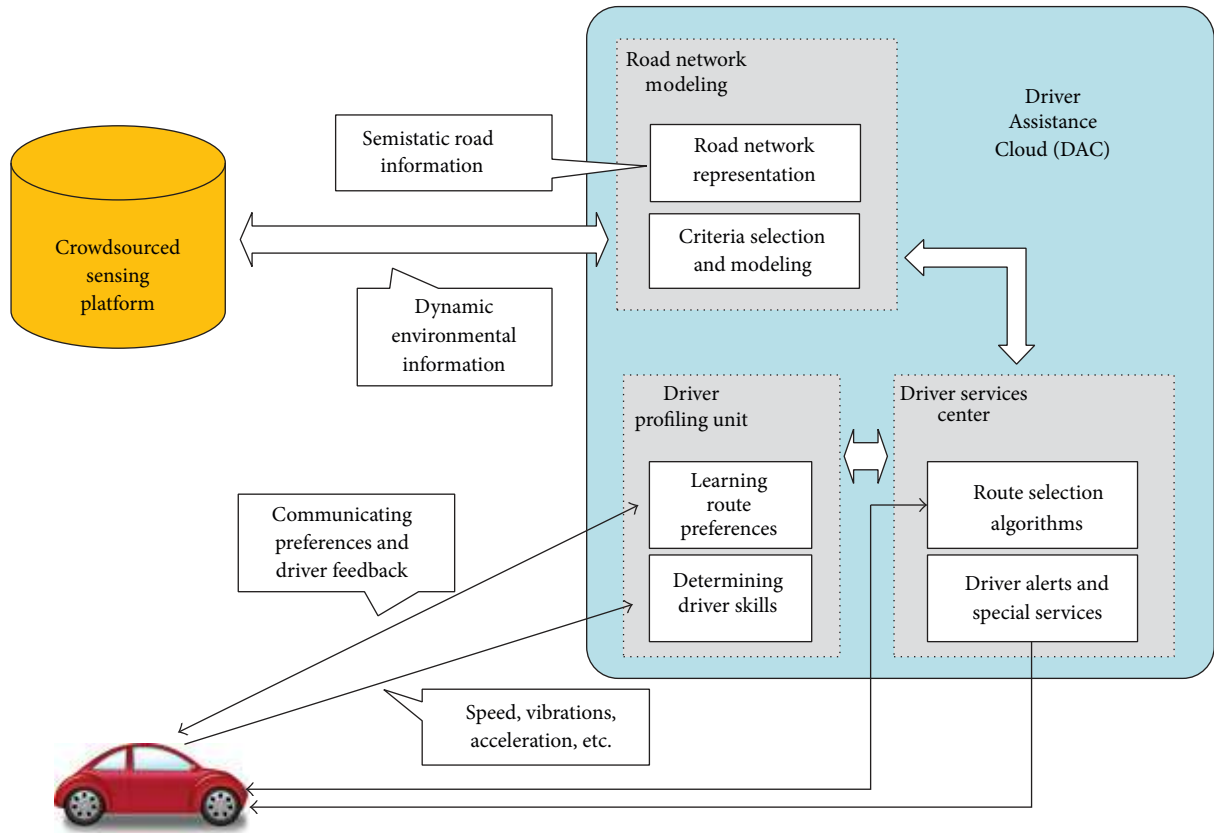
FIGURE 2: Overview of a personalized Driver Assistance Cloud (DAC).

recent works that investigate the use of V2V communication to signal warnings include [23, 61].

Scene Modeling by Information Exchange. In essence, road driving is a collaborative action. The behavior of one driver will impact the behavior of others. Thus, building models that simultaneously incorporate inputs from multiple drivers can generate a model that can more accurately predict the collective behavior. With intervehicular communications such models can be derived, and we refer to this as scene or road situation modeling.

Early Model Building. The sensors used to model driver behavior for Driver Assistance Systems typically have a range of a couple of hundred meters. Vehicle-to-vehicle communication can expand the sensing range further and enable models that can predict driver behavior early on.

Collaborative Objectives. Applications such as adaptive cruise control can benefit significantly from intervehicular communications where long-term planning based on the positions of several vehicles can be beneficial. In such cases, fuel efficiency can be improved by optimizing the speed over a time horizon.

In order to develop cooperative driver behavior models we need to answer the following research questions:

(i) What information is relevant for intervehicular communication? Different applications will have different

needs, and it is necessary to identify the beneficial information exchange.

(ii) How can multiagent models be developed that aggregate the information from multiple sources? As single driver behavior modeling is already a difficult task that involves several parameters, simple multidriver modeling approaches should be developed first.

(iii) How can feedback be effectively incorporated to model the scene evolution as time progresses?

6.2.2. Personalized Driver Assistance Clouds. While several developments have independently been made in features for in-vehicle ADAS, there is limited work towards a framework that integrates the current sensing capabilities, driver behavior models, and communication to the cloud. Such a system, which we refer to as a Driver Assistance Cloud, can provide novel personalized driver services, applications, and safety, as illustrated in Figure 2.

In order to develop such systems a road traffic information repository can be created to integrate environmental and road attributes such as weather conditions, construction, prevalence of pedestrians, bus stops, and potholes. These attributes can be incorporated from diverse sensing sources after intricate calibration and pruning. DBM that provides insight on the driver skill level for different maneuvers will then be needed. For instance, acceleration profiles can be

analyzed to determine lane changing and ramp merging competence. A particular feature of DACs may be designing efficient route selection algorithms based on driver profiles. This includes first learning route preferences based on monitoring both the routes taken by drivers and their competence levels on different road types. Then, multicriteria decision-making techniques can be applied to determine the routes most suited to different drivers.

6.2.3. DBM for Level 3 Automated Driving. Level 3 automated driving [62] refers to vehicles that are automatically equipped to control all driving functions with little to no attention of the driver for specific periods. In level 3 automated driving human intervention is expected at any moment at the human's discretion. This is a new area of research with several nontrivial DBM challenges:

(i) Rapid onboarding: modeling of the driver behavior of reestablishing the driving context when switching from automated driving to human driving

(ii) Complexity: the fact that fully automated vehicle results in increased complexity of the vehicle functionality and communication. Fully automated vehicles are expected to utilize VANET communication, which is too fast for human to monitor. Consequently, careful DBM design and analysis are needed especially on the event of automated system error when the human intervention is needed in short time.

(iii) Cooperative DBM between level 3 automated driving and levels 2 and 1 automated driving

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.
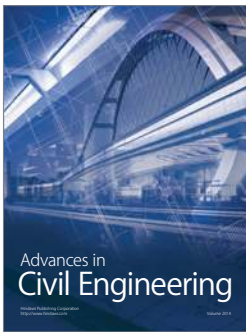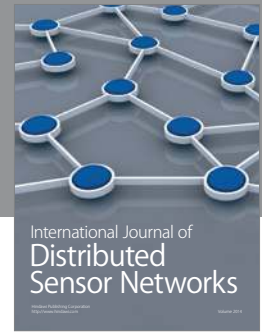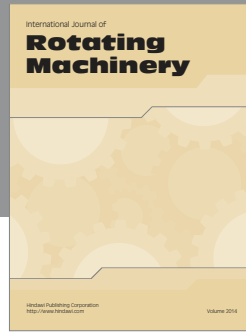
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