Manuscript version
DOI original paper: 10.1109/TIV.2021.3065933

A Review of HMM-based Approaches of Driving Behaviors Recognition and Prediction

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***Abstract*—Current research and development in recognizing and predicting driving behaviors plays an important role in the development of Advanced Driver Assistance Systems (ADAS). For this reason, many machine learning approaches have been developed and applied. Hidden Markov Model (HMM) is a suitable algorithm due to its ability to handle time series data and state transition descriptions. Therefore, this contribution will focus on a review of HMM and its applications. The aim of this contribution is to analyze the current state of various driving behavior models and related HMM-based algorithms. By examining the current available approaches, a review is provided with respect to: i) influencing factors of driving behaviors corresponding to the research objectives of different driving models, ii) summarizing HMM related methods applied to driving behavior studies, and iii) discussing limitations, issues, and future potential works of the HMM-based algorithms. Conclusions with respect to the development of intelligent driving assistant system and vehicle dynamics control systems are given.**

***Index Terms*—Machine Learning Methods, Hidden Markov Model, Driving Behaviors Prediciton, State and Intent Recognition, and Advanced Driver Assistance Systems.**

I. Introduction

Many people die or are injured yearly due to traffic accidents. The World Health Organization (WHO) provided a global status report on road safety in 2015 and showed that more than 1.2 million people are killed each year on the roads [1]. Therefore much attention has been paid on driving safety over the years. Investigation conducted by the National Highway Traffic Safety Administration (NHTSA) in 2015 [2] assigns the most critical reason for traffic accidents to drivers accounting for 94 %. Individual driver factors in the driving process and road traffic accidents are mainly reflected in driver's own behavior. Therefore, the research of driving behavior is meaningful for traffic safety.

Nowadays many institutions have conducted research on driving behavior prediction. Different machine learning algorithms like Artificial Neural Networks (ANN) , Dynamic Bayesian Networks (DBN), Support Vector Machines (SVM), Fuzzy Logic (FL), Random Forest (RF), Convolutional neural network (CNN), and Hidden Markov Models (HMM) are applied for learning and modeling driver's decision. Some review papers summarized the driving behavior studies with focus on the driver behavior characteristics identification [3] [4], the tactical driving behavior prediction [5], the driver drowsiness and distraction detection [6], the driving style identification [7] [8], and the human behavior recognition through visual monitoring [9] or human emotional states [10]. However, these review papers only summarize and discuss specific aspects of driving behaviors, like driving styles, drowsiness, etc. In addition, the authors often summarize popular algorithms. The derivation of popular algorithms or other approaches developed are not discussed. In [11] a taxonomy of 200 models is constructed around different modeling tasks including state estimation, intention estimation, trait estimation, and motion prediction. However, specific information about model input, output, and explanation/discussion of algorithms are not presented in this survey [11].

Some related algorithms such as HMM, Neural Network (NN), Fuzzy rule-based classifier, and Gaussian Mixed Model (GMM) are compared in the review paper [3]. The authors listed the advantages and disadvantages of the four algorithms considered, and pointed out that the HMM algorithm demonstrate a high accuracy and a very good performance in real-time driving behavior prediction. Compared with other popular algorithms, the HMM and DBN are designed as a probabilistic graphical model. One advantage is that it is easier for a human to understand directly the probabilistic relationships between the nodes. However, the DBN is more complicated than HMM in terms of network definition. In addition, driver's driving behaviors are based on the driver's own experiences, habits, and the current traffic environment. During driving, driver's behaviors cannot be measured directly but can be inferred by analyzing measurable parameters described current driving situation. The upcoming behavior is stochastic and only depends on the present state. Therefore, driving behaviors can be described as a hidden Markov process [12]–[14]. The HMM algorithm has an advantage for handling time series data and stochastic signal process. For these reasons, the HMM algorithm is suitably applied for driving behavior or other human behavior studies [3]. In 2016, the authors of [15] reviewed machine-learning techniques for statistical analysis and modeling of driver behavior. The authors also pointed out that HMM has been successfully applied to model driver behavior using large amounts of driving data. Additionally, only a few HMM-based approaches are summarized in [15]. Nowadays, there are a large number of driving behavior researches developed by HMM-based approaches. In general, the design ideas of these HMM-based approaches are roughly divided into two categories: HMM-derived and HMM-combined. However, review papers focusing on introducing and surveying HMM and HMM-based methods in this field are not available yet. Therefore, this contribution aims to summarize popular HMM-based approaches applied in driving behavior studies in the past 6 years.

The following section will present the influencing factors

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as well as the main research objects of current researches. Moreover, this contribution summarizes popular HMM-based methods of recognizing and predicting driving behaviors. Finally, the discussion on the applications, advantages, and disadvantages of the mentioned methods, limitations, as well as the development trends of driving behavior models will be concluded.

II. Influencing factors of driving behaviors

In this contribution, the driving behavior is not only a real action or a specific behavior, but also includes the reactions when drivers realize driving tasks denoted as driver's driving patterns, driver's intentions, driving maneuvers, trajectories of the vehicle, etc. In this section, the main topics (common influencing factors) of driving behaviors are summarized and their current corresponding researches are introduced.

A. Driving styles

Due to the driver's character, psychological status and other factors, driving behaviors could be categorized into many driving styles. Sagberg et al. [16] state that driving style depends on the individual driver and it is a habitual driving way. The authors point out that in the existing literature labeling of driving styles are commonly defined by common sense. In current driving style contributions [16]–[18], aggressive driving is a very common term. Aggressive driving behaviors include driving without obeying the traffic rules, such as over speed limit driving, sudden accelerating, sudden braking, abrupt lane changing, or sharp turning. These driving behaviors will lead the driver/vehicle to risks or even accidents. Therefore, one of the purposes of driving style studies is to sort out these aggressive driving. It is helpful to develop ADAS, because when a dangerous driving behavior is recognized, the driver can be warned immediately. At the same time, the driver's behaviors will be guided to improve traffic safety. To detect aggressive driving behaviors, in many driving style analysis studies, normal (safe/defensive) driving is given as a referent [17]. As explained in [16], dangerous and safe driving styles can be divided into different levels. Several different terms are used to label global driving styles, like calm, careful, aggressive [16]. However, it still lacks an unified conceptual standard to clearly distinguish these styles. In the existing contributions, the levels, the terms, and the concepts of driving styles depend on author's own definitions.

Aggressive driving can be classified based on physiological signals, biometric information, or vehicle driving state like vehicle velocity, acceleration, etc. In [18] a FL-based model is developed to classify driving styles into below normal (BN), normal (N), aggressive (A), and very aggressive (VA). Longitudinal / lateral acceleration and velocity are selected as inputs and collected from a 2-axis accelerometer. Based on fuzzy rules the output of the system is used to classify the individual driving behaviors into the different driving styles. In [17] aggressive driving style is classified using 3-axis (lateral, vertical, longitudinal) accelerometer data. The authors compare using one acceleration signal alone or combining two or three of them to recognize driving styles. The results are shown that using longitudinal acceleration signal the aggressive and safe driving style can be more effectively classified.

In addition to judging aggressive driving, driving style analysis is also used for reducing fuel consumption. In [19] Bao et al. proposed a method for predicting the driving style to search a personalized eco-friendly style. The drivers were divided into three classes including calm, normal, and aggressive driving based on Learning Vector Quantization (LVQ) neural network. Based on the predicted driving style, current traffic (congestion and average speed of each road), time, and road type, the fuel-consumption-minimizing route could be determined. In [20] Derbel et al. summarize existing driving style studies with HMM and propose an approach for calculation of car insurance fee through estimating the driver aggressiveness.

From these researches it can be concluded that the study of driving styles/patterns cannot only be used for warning drivers to avoid dangerous driving and related problems, but also for calculating car insurance fees, improving fuel economy, and other aspects. The information about driving styles is obviously helpful to develop driving assistant systems. Based on different types of drivers these systems can give drivers suitable suggestions to fit their driving habits.

B. Fatigue driving

Fatigue driving is another important driving style leading to traffic accidents. The drivers inattentiveness, tiredness, drowsiness, or sleeping during the driving process refer to fatigue driving. The National Highway Traffic Safety Administration [21] reported that about 90000 accidents involved fatigue driving in 2015. Driver fatigue detection research can be divided into two main categories: based on driver behavior and on vehicle behavior.

Based on driver behavior means selecting driver's own characteristics or patterns as inputs, such as physiological parameters or biometric information. The driver's physiological parameters include electroencephalogram (EEG), electroencephalogram (EOG), electrocardiogram (ECG), etc., which can indicate driver's mental fatigue and psychical fatigue. Therefore, in some researches these parameters are used to determine whether drivers are fatigue. In [22] the authors propose a feature-extraction method to extract drowsiness-related features from the EEG, EOG, and ECG signals. These features are used to classify the drivers fatigue into different levels. In addition, the authors compare the differences between using only one signal or using a combination of different signals. The conclusion of the research shows that the ideal results cannot be obtained with ECG or EOG alone. However, a high classification accuracy can be achieved using only EEG, or using a combination of EEG+ECG, or EEG+EOG.

The other measures of driver's characteristics are through the analysis of eyelid blinking, eye movement, eye closure, head pose, etc. to detect fatigue driving. In [23] Qin et al. focus on the analysis of eye closure of the driver. The authors extract two-dimensional Discrete Cosine Transform (2D-DCT) feature of each eye images. Two HMMs are trained based on eye opening and closure images, respectively. The states of the two HMMs are calculated at the same time. The recognition result with the highest likelihood is used to determine the fatigue statues of the driver. Lee and Chung [24] use a dynamic Bayesian network framework to evaluate the driver fatigue. Two sensors are used to collect data including eye movement and photoplethysmograph (PPG) signal. If the calculated driver fatigue reaches a defined threshold, the drivers will be warned.

In addition to the aforementioned researches based on studying the driver's own characteristics, analyzing the vehicle situation is also used to detect driving fatigue. The driver's maneuvers could be estimated to determine whether there is fatigue driving. Generally this method is using the current vehicle status including the distances between the vehicle and other vehicles, deviations from lane position, steering wheel angle, velocity, acceleration, as well as other controller-area-network (CAN) signals. For example, in [25] an approach is given for detecting driver fatigue based on HMM. Signals are processed according to three independent modules including vision, audio, and other-signals module. The inputs of vision and audio modules are video and voice respectively. The module namely 'other-signals' use heart rate, steering wheel position, gas, brake, and clutch pedal positions as inputs to detect driving fatigue. The three modules are independent from each other and final results are fused using the output of each module.

As shown in the mentioned researches, the fatigue driving behaviors can be determined from analysis of the driver and the vehicle states. Physiological parameters or biometric information are often used for fatigue driving detection. However, drivers are required to wear an appropriate equipment like helmet to collect data. It is impractical for drivers in real driving. To avoid this, possible solutions are through analyzing the state of the human eyes and the state of vehicle. In this case, drivers are not required to wear equipment, the data can be collected by eye trackers, camera, or the vehicle CAN bus. This can be achieved in driving assistance systems.

C. Drunk driving

The National Highway Traffic Safety Administration (NHTSA) reported that in 2014 the accidents due to drunk driving accounted for 31% of the total accidents in the United States [26]. Obviously, drunken driving is one of the major causes of traffic accidents.

In [27], a drunk driving recognition model is developed by analyzing the driver's state. The integrating multi-physiological variables such as blood alcohol concentration, eye movement, and head movement are selected as inputs, which are collected by drunken breath analyzer and image capture devices. The authors propose a simple graphical model integrating all the informations to recognize the abnormal driving behaviors. The results show that the fatigue and drunk driving behavior can be detected in a simulated environment. In addition to the driver state, the vehicle state is also often used to determine drunk driving. In [28] the authors select CAN bus data such as GPS, torque, engine RPM, vehicle speed, acceleration, etc. to detect drunk driving patterns. Using machine learning algorithm (Logistic Regression) the drunk driving patterns can be classified with an accuracy of 82 %. Dai et al. [29] propose a system for detecting drunk driving only using a smart phone. Using smart phone the orientation angles and accelerations of the mobile phone are collected to determine the lateral and longitudinal acceleration of the vehicle. Through the both accelerations two behavioral clues including lane changing (drifting, swerving, etc.) and speed changing (suddenly accelerating and braking) can be detected. Finally, by considering these two information the model based on pattern matching techniques can judge whether the driver is a drunk driver. In [30] the authors propose a context-aware driver behavior system for detection of different behaviors, which include normal, drunk, reckless, and fatigue driving. By collecting contextual information about the driving environment, the abnormal behavior can be detected, in the meanwhile other vehicles on the road will be warned to avoid traffic accidents.

The recognition of drunk driving is similar to fatigue driving, which can be analyzed through the driver's and vehicle's state. The difference is that physiological parameters of drunk driving recognition is based on blood alcohol concentration instead of using EEG, EOG, etc.

D. Driving skill

In general, driving skills can be defined as the drivers actions that are independent on the drivers conscious attention [31]. Driving skills are reflected by human drivers manually controlling vehicles to achieve specific driving tasks, such as speed changing, steering, gear shifting, etc. However, each driver has his own individual driving skills. To realize intelligent driving and improve driver assistance systems, it seems to be helpful to analyze these individual characteristics of driver. The main idea of driving skill prediction is that by learning a driver's historical driving behavior, to determine and to predict the behavior of the driver in the future for different driving situations. Before the driver is making decisions, advice will be given or the driver will be warned early enough before a risky action is taken.

Deng et al. [32] propose to use HMM in determining driver intention for vehicle maneuvers including keep lane and change lane left/right on the highway. The authors in other studies focus on the prediction of the ego vehicle velocity [13] [14], lane-changing trajectory [33] [34], driver intention to stop the vehicle at an intersection [35] [36], or other driving maneuvers like stop/non-stop, change lane left/right, and turn left/right [37].

The goal of driving skill researches in this section is mainly to predict the driver's next actions and also to avoid misoperations of the driver or give suggestions for the next step. However, the main purpose of driving styles/patterns, fatigue driving, and drunk driving researches is to identify whether the drive is abnormal or not. Thus, the driver will be suggested to change the driving style or to stop driving.

E. Traffic environment

Another important factor affecting driver behavior is related to different driving scenes, such as highway and inner-city scenarios. For different driving environments, driving behaviors are also different. There are relevant studies of driving behaviors for some typical traffic environment. The main cause of accidents in highway are speed and lane changes. The authors of [36], [38], [39] focus on lane-change or speed-change [13], [14], [34] prediction in highway scenarios. Another highway scenario discussed is at highway lane drops, such as in [40] [41]. The authors studied driving behaviors entering a highway. The driving behaviors in this scenarios are mainly considered whether the driver need to change lane, i.e. merge and non-merge behaviors. Other studies like [42]–[44] discuss the behaviors at an inner-city intersection. The driving behaviors in the inner-city are complex, they mainly include acceleration, deceleration stopping, turning, driving through the intersections with or without traffic signals.

III. Existing HMM-based approaches

In this section existing HMM-based approaches evaluating and classifying driving behaviors will be discussed and summarized.

A. HMM and HMM-derived approach

Hidden Markov Model (HMM) is applied for estimation of unmeasured states, therefore, it is widely applied in fields of driving behavior estimation.

1) HMM: According to [45] an HMM describes the relationship between two stochastic processes which consists of a set of unobserved (hidden) states and a set of observable states respectively. The hidden state and observation symbol at time t are defined as S_t and O_t respectively. Thus a hidden state sequence is $S = \{S_1, S_2, ...S_T\}$ and an observation sequence is $O = \{O_1, O_2, ...O_T\}$, where T is the length of the sequence. To train HMM the Baum-Welch algorithm [45] is used to estimate the maximum likelihood model parameters.So from a given observation sequence O and its corresponding hidden state sequence S, the parameters of the HMM can be computed and adjusted to best fit the both sequences. Based on the saved HMM, the most probable sequence of driver's behaviors which has the highest probability, can be calculated by using Viterbi algorithm.

In [37], the authors propose to use HMM in determining driver intention for a variety of vehicle maneuvers including stop/non-stop, change lane left/right and turn left/right. To predict a trajectory of a lane changing, Liu et al. [34] establish two HMMs including normal lane change model and dangerous change model, which are trained based on normal sample data and crash data respectively. In [32], the HMM algorithm is applied for driving behaviors prediction, where a prefilter is used to process and combine signals to form features for the HMM recognition process. Three different driving intentions namely: lane change left, lane change right, and lane keeping are modeled as hidden states for the HMM. The results show that the evaluation metrics including all accuracy (ACC), detection rate (DR), and one minus false alarm rate (1-FAR) values are larger than 80 %.

2) Hierarchical HMM: The hierarchical HMM (HHMM) is a multi-level HMM derived from HMM [46]. Like HMM, the HHMM algorithm contains a set of hidden states and a set of observations. The difference from HMM is that the states of HHMM contains three different kinds including root states, internal states, and the production states. Root and production states indicate states of the highest and lowest levels HMM respectively. Only production states contain an observation probability distribution matrix, i.e. observations are generated directly from production states. Each state of high-level HMMs (root and internal states) can be considered as a low-level HMM, that means each root and internal state serves as a probabilistic model [46]. Therefore, HHMM can be used to describe the relationships between each HMMs.

In [47] the authors propose a system for estimation and prediction of driver/vehicle behaviors in autonomous vehicles. Four different HMMs are trained according to four different scenarios, which include turning left/right, going straight, and stopping at an intersection. The results show that using this method driver behaviors can be successfully predicted. The authors present an extension through using HHMM for prediction process. The driver states are the low-level HMMs, so the relationship between them can be estimated by the high-level HMMs. In [48] an HHMM approach is used to develop a rollover warning system of heavy duty vehicle. The authors point out that using lateral acceleration and roll angle the lateral slip and rollover behaviors of heavy duty vehicle can successfully be detected with a high accuracy of 99.7 %.

Unlike common HHMM, in [49] a Multi-Layer (3-layer) HMM approach is proposed and developed for predicting lane changing behaviors. The approach is based on situation-specific HMMs combined with thresholds, for which related parameters are adapted during a training phase. The first layer is considered to predict the driving behaviors using only one signal as input. The inferential results from the first layer are given to the second layer, and the second layer only considers some selected information, such as all velocities, all distances, etc. Only the third layer considers all information. All sub HMMs of each layer are calculated in parallel and all of them can be used to predict driving behaviors. The results show that the accuracies of lane changing to right and lane changing to left are more than 90 %.

3) Bayesian Nonparametric HMM: Hierarchical Dirichlet Process (HDP)-HMM: One main issue in HMM is that the number of assortment of hidden states must be set before training, so each hidden state must be defined before modeling. If the assortment of hidden states increases, the model complexity also increases. If any of the assortments of the hidden states has not been defined during the training phase, consequently the whole model is incomplete and incorrect. To solve this problem, Hierarchical Dirichlet Process (HDP)-HMM was proposed by [50] [51]. As a Bayesian non-parametric alternative for standard HMM, it is used without fixing the number of assortments of hidden states. In 2007 Fox et al. [52] proposed a Sticky HDP-HMM, which is an extension of HDP-HMM. It's frequency of transition between hidden states is reduced compared to the HDP-HMM model.

In [53] [54] [55] [56] the authors assume that contextual information of driving behavior has a double articulation structure, which is similar to language, i.e., the driving behavior is a sequence of "driving words". A "driving word" is a sequence of "driving letters". In [56] steering angle, brake pressure, and accelerator signals are selected as input. Different segments of input signals are generated as "driving letters", which are considered as short-term behavior unit. A long meaningful behavior unit is named as a "driving word", such as "start", "turning right", "following a leading vehicle", etc. Here, the sticky HDP-HMM is used to find meaningful segmentations ("driving letters") from driving behavior. Nested Pitman-Yor language model (NPYLM) [57] is used to combine and sequence meaningful chunks ("driving word"). Based on these chunks the driver's intention can be estimated. It is worth to mention that sticky HDP-HMM with NPYLM is a development of an unsupervised learning method, i.e. "driving letters" and "driving words" are unknown before training. Therefore, the evaluation method is different from common methods that use accuracy or detection rate to evaluate the prediction performance. In [56] three experiments are used to verify the model performance. The results of the first experiment indicate that more than two next "driving letters" are correctly predicted using a developed NPYLM with sticky HDP-HMM method. The results of the second and third experiments show that the averaged prediction time are 17 s and 8.9 s respectively. The sticky HDP-HMM approach is also used to develop a general framework to learn and recognize lane-change interactions of the ego vehicle with its surrounding vehicles on highways [58].

In [59] a new framework for driving style analysis is developed by combining Hierarchical Dirichlet Process and Hidden Semi-Markov Model (HDP-HSMM) derived from HDP-HMM. After comparing with HDP-HMM and sticky HDP-HMM, the authors in [59] state that HDP-HSMM is able to segment driving patterns as expected, but HDP-HMM cannot learn driving patterns as expected. Furthermore, the sticky HDP-HMM method is denoted as sensitive to data fluctuation. According to [59], HDP-HSMM performs best among them.

4) Auto-Regressive HMM (AR-HMM) and Beta Process Autoregressive (BP-AR)-HMM: As illustrated in Fig. 1, Auto-Regressive HMM (AR-HMM) is similar to standard HMM, but it has one more weight matrix W which consists of probabilities of moving from one observation to another. Abe et al. [60] applied AR-HMM for modeling and predicting driving trajectory behaviors. Different driving behavior models can be switched by analyzing gas pedal stroke and brake pedal stroke.

Similar to an HMM, the AR-HMM needs to determine the number of choosing hidden states (driving behaviors), i.e. the number of classes. To avoid this problem, Fox et al. [61] propose the Beta Process AR-HMM (BP-AR-HMM), which combines the nonparametric Bayesian technique and AR-HMM. Therefore, this BP-AR-HMM model can produce infinite state. The total number of states can be determined in theory, but cannot be defined before training. In [62] the author apply BP-AR-HMM to predict the driving behavior, historical driving behaviors will be segmented into discrete states,

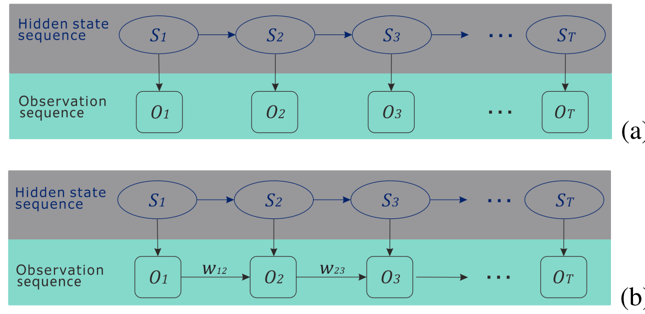

Fig. 1: Compare the HMM and the AR-HMM
(a) Sequence of standard HMM
(b) Sequence of AR-HMM

which are produced by BP-AR-HMM. Each discrete state corresponds to an AR model. The observations in [62] consider accelerator opening rate, brake pressure, and the steering angle signals. Using the BP-AR-HMM, driving behaviors including brake pressure and steering angle are predicted. The results show that, compared with HMM, AR-HMM, and HDP-HMM, the BP-AR-HMM has the smallest mean absolute error (MAE) which is about 0.05-0.2 MPa between the measured and predicted brake pressure values.

5) Summary: It can be concluded that, the approaches derived from HMM are based on similar ideas, the HMM's characteristic of time series is mainly considered and used in these algorithms. Driving behaviors will be decomposed into multiple layers tasks. The lowest level task is to recognize each specific operation, such as acceleration, deceleration, and steering wheel signals. Obtained results of the lowest level will be given as inputs to higher level to identify driving behaviors like go straight, turn left/right. It is worth pointing out that these methods are proven to be effective in predicting driving behaviors. One possible reason is that signals and driving behaviors change always over time, and the current driving behavior is always affected by the previous one.

B. HMM-combined approach

Except for using HMM-derived approaches, HMM is often combined with other algorithms to improve the performance. Usually in this case, HMM and other algorithms are used to complete different tasks respectively.

1) Artificial neural network (ANN)-HMM: In addition, HMM is often combined with other algorithms. Different from HMM's derivative algorithm, in combination methods, HMM and other algorithms are used to complete different tasks respectively. For example in [63] Boyraz et al. propose a method to determine a driving maneuver in an urban road scenario. An ANN is used to recognize and classify driving maneuvers based on different signals, such as steering wheel angle and speed. These labels are classified by ANN and then use to train the HMM. In the final phase, driving maneuvers of Right Turn, Left Turn, U-Turn, Roundabout, Emergency Brake, and Reversing can be predicted based on HMM. In addition driver performance is also classified from 1 (best) to 8 (worst) using HMM. In [13] [14], a prediction method of vehicle speed is presented. By using neural network (NN) models the average traffic speeds can be predicted, afterwards the estimated traffic speeds are given as inputs to predict individual vehicle speeds based on HMM. Zhang et al. [64] propose a deep neural networks (DNN)-HMM approach. Acceleration data are collected as inputs. The DNN approach is used to extract features from the row sensor data, by solving the observation probability distribution of HMM can be modeled automatically. This solves a disadvantage of HMM that HMM usually needs to manually define observations (features of inputs) relying on the experience of the researchers. In [65] an approach combining HMM and ANN is constructed to identify driving intention and to predict maneuvering behaviors on cornering, where HMM is used to predict three driving behaviors including emergency steering, normal cornering, and straight line driving. Then HMM prediction results are used as a guideline to train ANN, so specific steering angle is obtained by ANN. This solves a disadvantage of ANN which needs a lot of training samples. The results show that the steering angle can be successfully predicted, where the result has a low absolute deviation of real and predicted steering angles.

2) Support Vector Machine (SVM)-HMM: As a two-class classifier, a SVM is a supervised machine learning method. As known the approach is transforming data into a suitable space divided by hyperplanes. It's pattern classification is based on current observations, but not on context. If the current analyzed observations are interference signals, wrong results will be obtained. In addition, driving behaviors are dynamic, the decisions of the drivers at each time point will be affected by driving behaviors at the last time point. The HMM approach has an advantage of being able to analyze dynamic data and the temporal evolution of states. Due to the driving behaviors in different driving styles are not the same, in the same driving environment the drivers make different decisions. Using one HMM it is difficult to classify these driving behaviors of different drivers. Also here HMM results are depending on which hidden state has the largest output probability, i.e. the maximum log-likelihood. However, when the input features are not obvious, it may lead to small differences between the log-likelihoods. Therefore, it is difficult to distinguish some easily confused driving behaviors using HMM. To avoid this problem, a SVM-HMM approach is proposed in current researches. For example in [66], the SVM is used to distinguish different driving behavior styles like normal and fatigue driving styles. For each driving style a corresponding HMM is used representing the upcoming driving behaviors.

The SVM-HMM based model is usually applied to predict or recognize the driving behavior of different driving types/patterns. The general flowchart of the system based on SVM-HMM is shown in Fig. 2. Here a SVM is used to distinguish different driving patterns. For each driving pattern a corresponding HMM is trained with respective observation sequences (i.e. training samples). The whole model including SVM and all HMMs is trained and saved in training phase. In test/application phase, the SVM can determine which driving pattern a test data set belongs to, and then switch to the corresponding HMM.

In [66] the authors choose SVM-HMM for detection of driver drowsiness. Here two different HMMs are trained for

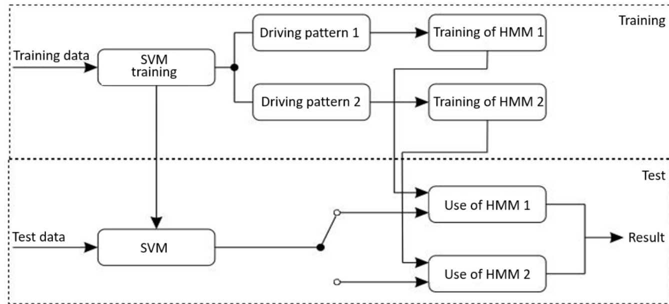

Fig. 2: Flowchart using SVM-HMM

drowsy or non-drowsy. The SVM is used for determining which HMM should be used. Similarly, Aoude [67] apply SVM-HMM for estimating driver behavior at intersections. The drivers are classified into compliant or violating type. In [68] the authors propose a framework to predict accident of vehicle collision on a straight two-lane highway. The SVM is used to classify a Leaving Lane scene (LL) and a Remaining in Lane scene (RL) based on the vehicle's trajectory. The HMMs are trained for each lane scene respectively and predicting whether the driver will have an accident.

3) Fuzzy logic (FL)-HMM: Fuzzy logic (FL) is an extension of Boolean logic (classical logic), in which the degrees of truth may be any real number between zero and one defined by related membership functions labeled and denoted with linguistic variables. The approach is used to present vague estimations and verbal descriptions, based on experiences. For this reason, in [69] Ding et al. introduce a lane-change intention recognition method based on FL and HMM. Here a Comprehensive Decision Index (CDI) is designed using FL to represent the driver's estimations about the current surrounding traffic. The CDI is calculated through three parameters, which include the ratio of the average traffic speed of original lane and target lane, Enhanced-Time-to-Collision, and the ratio of the real as well as the ideal distance from the ego-vehicle to the vehicle in front. Afterward, estimated CDI values can be used as input to train HMM. Finally, driver's intention including lane keeping, transition state, and lane change can be recognized through the trained HMM. By analyzing the test data sets including 69 lane change intention, in total 65 intentions are correctly identified with a short delay gap about 1.67 s. The authors in [70] proposed a newly developed approach Fuzzy Logic-based Hidden Markov Models (FL-HMM). The FL approach is used for additional distinction of driving scenes into very safe, safe, and dangerous driving scenarios. Afterwards, a corresponding HMM is trained for each driving scenes respectively and predicting the driving behaviors. Three different driving behaviors including left/right lane change and lane keeping are modeled as hidden states for these HMMs. High accuracies of 93 % and 91 % for lane changing to right and lane changing to left are observed respectively.

4) Gaussian Mixture Model (GMM)-HMM: In [71] a Gaussian mixture model (GMM) combined with HMM (GMM-HMM) is proposed to predict drivers braking behaviors. The GMM is used to model stochastic relationships between driving situations and braking actions. After learning the GMM parameters, HMM is applied to estimate drivers braking behaviors based on the mixture components of GMM. The obtained results show that the accuracy, sensitivity, and specificity reach 89.41 %, 83.42 %, and 97.41 % respectively. Lefevre et al. [72] develop a driver model based on GMM-HMM and its two application examples. One is used to predict lane departures on the highway and the other is to predict acceleration while lane keeping. The obtained results show that the proposed driver model can successfully predict and therefore avoid all 65 lane departure instances. In addition, the acceleration are also estimated correctly. By comparing the results of predicted acceleration, the author pointed out that the performance of a personalized/individualized model is always better than an average/general model. Similarly, in [73] Gaussian mixture regression (GMR)-HMM is applied to develop a lane-departure warning system. For each driver, an individualized model is established to predict the upcoming lateral vehicle trajectory. The authors also discussed some influencing factors, some of them depend on the design of the system and can be tuned according to different design requirements. Other factors like vehicle dynamics, road curvature, and driver state depend on the design of experiments and the states of vehicles/drivers, which do not affect the algorithm/system. Based on [73], the authors further propose a new Bounded Generalized GMM-HMM method derived from GMM-HMM [74], which performs better than GMM-HMM. However, due to its structural complexity, it has more computational costs than GMM-HMM.

5) Summary: The modeling ideas of HMM combined with other algorithms can be concluded using three common forms. First, the classification result of HMM (/other algorithms) can be used as input of other algorithms (/HMM), such as in [65] results of HMM are guiding to train ANN, and in [69] results of FL are given as inputs to HMM. Second, parameters like observation probability distribution of HMM can be modeled by other algorithm [64] [72]. Third, other algorithms are used to distinguish different driving styles/patterns/scenarios, then HMMs are trained and used to recognize driving behaviors for different situations [68]. Using the combined approaches, it is able to utilize both of the advantages of HMM and the respective other algorithms. It was proven that, the HMM combined with other algorithms have better performance than a common HMM or a conventional algorithm used alone [64] [70].

IV. Discussion

In this contribution different types of driving behavioral researches and related typical research objects are introduced. In existing studies, the various algorithms were proposed to recognize and predict human driving behaviors.

Each algorithm has it's characteristics and therefore advantages and disadvantages. They may perform well in different domains or different data sets. In this section, a brief comparison between different algorithms is given to explain which algorithm is suitable in which context.

A. Application

Related features as well as the application fields and a brief comparison of the data collection approaches are summarized in table I. According to the summary in this table, conventional machine learning algorithms like ANN, SVM, FL, RF, CNN, HMM, and HMM-based approaches are used in recent years for research related to driving behavior recognition and prediction. As the most popular method for deep learning, the CNN algorithm is not commonly used for this field because in most of the cases the inputs for CNN are images. It's worth to mention that DBN and HMM are capable to handle temporal data. In comparison to HMM, DBN requires complex definition of the network, and perform poorly on high dimensional inputs. However HMM is not able to utilize raw data directly and requires data processing upfront. The detailed strength and weakness of all algorithms are discussed in the below subsection.

B. Advantages and disadvantages

In comparison to other algorithms like ANN, SVM, CNN, RF, etc., an HMM is designed as a probabilistic graphical model. One advantage of HMM is that the probabilistic relationships between the nodes can be easily interpreted. Based on the principle of HMM, the current state also depends on the state at the previous moment [3]. Therefore, another advantage of HMM is that it has the ability to handle dynamic data and temporal pattern recognition. Using HMM the class label is determined by the calculated probability, rather than obvious boundaries. In addition, through the summarization and comparison of various researches, the authors in [3] conclude that the HMM algorithm has a high accuracy and a very good performance in real-time driving behavior prediction. It was also proven in other researches, eg. in [37] that high accuracies between 82-90 % can be achieved when predicting lane changing, turning, and stopping behaviors.

The major limitation of HMM is that the number of assortment of hidden states must be known before training, therefore this algorithm is not suitable for long-term forecasting systems [3]. However, some researches have shown that HMM-derived algorithms could effectively solve these problems, such as Sticky HDP-HMM [52] [56] and BP-AR-HMM [61]. Other algorithms [13] [14] [66] [68] [69] based on a combination with HMM were proposed to improve the performance of driving behavior model, such as NN-HMM, SVM-HMM, FL-HMM, and other similar algorithms.

C. Open problems and future outlook

Although a variety of HMM-related approaches can be used to establish driving behavior model, there are still some problems that need further research to resolve.

- The HMM is commonly combined with other algorithms or derived into new approaches to improve and to achieve the desired performance of the driving behavior model. However, it would cause an increased complexity and computational cost of the model. Therefore, the reduction of model complexity need to be considered before the design.

TABLE I: Comparision of the different approaches

Algorithm	Popular algorithms							HMM-derived methods					HMM-combined methods			
	ANN	DBN	SVM	RF	FL	CNN	HMM	HHMM	HDP-HMM	AR-HMM	BP-AR-HMM	ML-HMM	ANN-HMM	SVM-HMM	GMM-HMM	FL-HMM
Sample references	[13], [14], [19], [33], [41], [75]–[77]	[24], [27], [30], [35], [43], [78], [79]	[41], [80]–[83]	[17], [39], [84], [85]	[18], [20], [86]	[39], [87], [88]	[13], [14], [23], [25], [32], [34], [40], [42]	[47]–[49]	[53]–[56], [58], [59], [62]	[61], [62]	[62]	[47]–[49]	[13], [14], [63]–[65]	[66]–[68]	[71]–[74]	[69], [70]
Typical application field																
Driving styles/patterns	yes	yes	yes	yes	yes	-	yes	-	-	-	-	-	yes	yes	-	yes
Fatigue driving	yes	yes	yes	yes	yes	-	yes	-	-	-	-	-	yes	yes	-	yes
Drunk driving	yes	yes	yes	yes	yes	-	yes	-	-	-	-	-	yes	yes	-	yes
Driving behavior and intention	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Data used																
Physiological variables (recorded by Bio-sensor)	yes	yes	yes	yes	yes	-	yes	-	-	-	-	-	-	-	-	-
Images (recorded by camera or eye tracker)	yes	yes	yes	yes	yes	yes	yes	-	-	-	-	-	-	-	-	-
Vehicle operation signals (recorded by CAN-Bus, driving simulator, or other sensors)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Vehicle movement (recorded by smart-phone, driving simulator, or other sensors)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Traffic information (recorded by GPS, driving simulator, or other sensors)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Traffic environment																
Highway with traffic	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Inner-city / urban with																
- traffic	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	-
- signalized intersection	yes	yes	-	-	-	yes	yes	-	yes	-	-	-	-	yes	yes	-
- unsignalized intersection	yes	yes	-	yes	-	yes	yes	yes	yes	yes	yes	-	-	-	yes	-
Other ability																
Temporal pattern recognition	-	yes	-	-	-	-	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Results	ACC: 73 % - 95 %	DR: 83 % - 95 %	ACC: 84 % - 91 %	ACC: 89 % - 95 %	ACC: 83 %	ACC: 82 % - 86 %	ACC: 82 % - 90 %	ACC: 99.7 %	MAE of brake pressure: 0.5-0.8 MPa	MAE of brake pressure: 0.1-0.5 MPa	MAE of brake pressure: 0.1-0.2 MPa	ACC: > 90 %	RMSE of speed: < 4 % MAPE of speed: < 5 %	ACC: 85 % FAR: 3.8 %	ACC: 90 % DR: 84 % TNR: 97 %	ACC: 85 % - 95 % DR: > 82 % FAR: < 10 %
Results based on real / experimental driving	real	real	real	exp.	exp.	real	exp.	exp.	real	real	real	exp.	real	real	exp.	exp.
Online / Offline test	Offline	Online	Offline	Online	Offline	Offline	Offline	Online	Offline	Offline	Offline	Offline	Offline	Online	Offline	Offline
Related reference	[89]	[24]	[41]	[39]	[90]	[87]	[37]	[48]	[62]	[62]	[62]	[49]	[14]	[68]	[71]	[70]

yes: available
-: not available yet
ACC: Accuracy
DR: Detection rate
FAR: False alarm rate
TNR: Specificity
MAE: Mean absolute error
RMSE: Root mean square error
MAPE: Mean absolute percentage errors

- Driving behavior model established using all mentioned HMM-related approaches can only be trained offline through the learning of historical experience, which limits their adaptive capabilities. To accommodate new problems during the driving, the solutions of online learning need to be addressed in the future.
- Each driver has his own individual characteristics, the development of the driving behavior model for unique driver is helpful for the vehicle to become more human friendly. However, datasets performed by different driver require models with different predefined parameters (design parameters). Setting these parameters values with better performance manually will be very tedious. Therefore, it is necessary to find an effective way to determine these design parameters.
- Hyperparameters defined the structure of HMM-based model need to be preset, e.g. the number of hidden states of conventional HMM, the number of hidden layers of HHMM, etc. In addition, for Bayesian Nonparametric HMM, the number of assortment of hidden states depends on the size of the training data. How to adjust these parameters can be discussed in further research.
- In addition to the prediction of ego vehicle behavior (a single driver behavior), the prediction and recognition of multi-vehicle interaction is also an important topic of current researches. Reliable predicting the movement of surrounding vehicles plays an important role in the development of autonomous vehicles. This contribution does not detail this point which can be considered as an important influencing factor in future work.

V. Summary and Conclusions

Due to the importance of driving safety and efficiency, the research of human driving behaviors prediction is being focused in recent years. In this contribution, the most commonly used HMM-related algorithms in this field are introduced and summarized.

The HMM algorithm is widely used in temporal pattern recognition and therefore, appropriate for human behavior/intention recognition and prediction. However, review papers focusing on introducing and comparing the various HMM-based methods in this field are not available. Therefore, this contribution emphasizes on the researches for conventional HMM, methods derived from HMM, and combination methods based on HMM for the driving behavior recognition. The modeling ideas of the combination methods are also summarized in this contribution to facilitate future researches in this field.

To effectively and comprehensively compare the relevant researches in this field, the applications (objectives) are grouped into different categories in this contribution. The objectives are mainly referring to the driving styles or the personal state of the drivers, for instance, normal/aggressive driving, fatigue, drunk, driving skills / maneuvers / intentions of ego-vehicle, etc. Thus, for future researches in this field with similar objectives, the researchers can easily find and apply the most appropriate approaches summarized in this contribution. In this contribution actual HMM approaches are briefly illustrated and compared using an example representation to compare typical tasks of human driver's behavior recognition and prediction. For the first time a complete comparison of HMM-related human driving behavior researches obtained from a representative scenario is done, clearly pointing out the differences, advantages and disadvantages of the different HMM-derived and HMM-combined approaches. As outcome of the contribution the reader can now immediately choose a suitable HMM-related approach or develop new approaches based on existing methods and design ideas to solve the corresponding driving behavior recognition and prediction problems. Furthermore, this contribution is also used to inspire new ideas to improve the performance of HMM-based models. Therefore, this contribution will be used to guide the direction of the driving behavior research and support the development of intelligent driving assistant systems as well as vehicle dynamics control systems.

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