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Improved driving behaviors prediction based on Fuzzy Logic-Hidden Markov Model (FL-HMM)

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***Abstract*— Research and development of human driving behaviors play an important role in the development of assistance systems. In this contribution, a driving behaviors prediction model is based on a newly developed approach combining different Hidden Markov Models (HMM) cooperatively combined by Fuzzy Logic (FL). Due to variations of individual human drivers decision behavior the task to classify related behaviors based on individually trained models is difficult. The FL approach will be used for additional distinction of driving scenes into very safe, safe, and dangerous driving scenarios. For each scenario corresponding HMMs will be trained. Three different driving behaviors including left/right lane change and lane keeping are modelled as hidden states for the HMM. Based on observations, the algorithm calculates the most possible driving behaviors through the observation sequences. Furthermore, the observed sequences are also used for training of HMM during modeling process. To improve the prediction performance of the model, a prefilter is proposed to quantize the collected signals into observed sequences with specific features.**

To optimize the model performance NSGA-II was used to define the optimal thresholds of FL and the optimal prefilters of HMMs. Using experimental data from real human driving behaviors (taken from driving simulator) it can be concluded that selecting optimal thresholds will increase the performance of driving behaviors prediction. The effectiveness of the suggested fuzzy-based HMM has been successfully proved based on experiments.

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) are systems developed to assist the human driver and therefore to make driving safer. A statistic of traffic accidents show that most accidents are caused by driver misoperations [1]. Therefore, prediction of driving behaviors play an important role in the development of ADAS. An important idea in this field and also in this contribution is to establish a model by learning from the given driving behaviors to predict the decisions and behaviors of the driver in different driving environments. Before the driver taking the decision, advices can be given or the driver will be warned early before a dangerous situation appears.

Establishing driving behavioral models, several approaches have been applied in recent researches. Typical kinds of machine learning algorithms like Artificial Neural Networks (ANN) [2], Dynamic Bayesian Networks (DBN) [3], Support Vector Machines (SVM) [4], Fuzzy Logic (FL) [5], and Hidden Markov Models (HMM) are used to establish driving behavioral models. The HMM approach has a significant advantage in dynamic data analysis and the temporal pattern recognition. It is suitable for human behaviors prediction. In [6], 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. However, the results of driving behavior recognition are not always good by using the standard HMM. To improve the performance of driving behaviors prediction based on HMM, many approaches have been proposed.

In general, there are two common approaches. One is estimating different HMMs according to different scenarios or different inputs. For example, Liu et al. [8] established two HMMs including normal lane change model and dangerous change model to predict a trajectory of a lane changing, the two HMMs were trained based on normal sample data and crash data respectively. The other is combining HMM with other algorithms like using Neural Network (NN), SVM, etc. In [9] SVM was used to classify a leaving lane scene and a remaining in lane scene based on the vehicle‘s trajectory. Then the HMMs were trained for each scenario respectively and predicting whether the driver will have a risk of collision.

In fact, current researches propose new methods to realize and improve driving behaviors prediction. However, only a few articles concern the optimization of an established prediction model to improve the recognition efficiency. Therefore, one of the objectives of this contribution is to propose a method to improve driving behaviors prediction model with respect to the increase of detection rate (DR), accuracy (ACC), and the decrease of false alarm rate (FAR). To accomplish this task, a Fuzzy Logic-based Hidden Markov Model (FL-HMM) approach is been developed.

The contribution is organized as follows: in Section II an overview of HMM and FL is given. The driving behaviors prediction model based on FL-HMM is presented in Section III. The task how to define and improve this proposed model is also described in this section. The experiment and experimental results are given in Section IV. Finally, a conclusion is provided in Section V.

II. METHODOLOGY

The aim of this contribution is to establish a reliable method for human driver behaviors prediction. The main aim is the prediction performance with respect to improve prediction (accuracy (ACC), detection rate (DR), and false alarm rate (FAR)). However, in different driving scenes, the driver's behaviors are different. For example, the drivers need to take a long/short time to change lanes in relatively safe/dangerous driving scenes. Therefore, a FL approach

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will be used for additional distinction of driving scenes into very safe, safe, and dangerous driving scenarios. Afterwards, a corresponding HMM will be trained for the different scenarios.

A. Fuzzy Logic

Fuzzy Logic (FL) is a popular approach used for modeling vagueness introducing many-valued logic. Based on this a classification task can also be realized. It does not require to model all classifications mathematically. The structure of FL is easy to interpret by using IF-THEN rules. The logic of FL-based model can be easy implemented. The FL approach is considered as an extension of Boolean logic, it is based on fuzzy sets and allows to model the truth of statements continuously between true (one) and false (zero) using membership functions [10]. Common fuzzy sets are based on triangular, trapezoidal, or Gaussian membership functions [11]. In this contribution, trapezoidal membership function will be used to describe different driving situations.

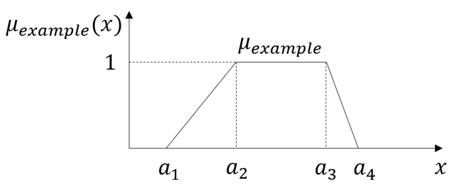

Fig. 1. Trapezoidal membership function

As shown in Fig. 1, x as input variable so $\mu_{example}(x)$ denotes the degree of membership. A trapezoidal membership function can be described by four parameters a_1, a_2, a_3, and a_4 as

$$\mu_{example}(x) = \begin{cases} 0, & x < a_1 \\ (x-a_1)/(a_2-a_1), & a_1 \le x < a_2 \\ 1, & a_2 \le x < a_3 \\ (a_4-x)/(a_4-a_3), & a_3 \le x < a_4 \\ 0, & x \ge a_4. \end{cases} \quad (1)$$

Obviously these parameters a_1, a_2, a_3, and a_4 are four threshold values for the input variable.

In driving far, middle, and close distance respectively indicate very safe, safe, as well as dangerous scenes for lane change. In addition a Time to Collision (TTC) statement first suggested by Hayward in 1972 [12] is used to determine the safety of lane changes. The value of TTC refers to the time for two vehicles to collide on the same path. Lower TTC values correspond to higher dangerous levels. In the design of Driver Assistance Systems, the use of TTC values for classifying the safety of lane changing maneuvers strongly depend on the speed of the vehicle. In [13] TTC values were computed to prevent forward collisions and reduce the damage caused by the crash. It shows that when the speed is around 130 km/h, the drivers will be warned if the TTC value is less than 3 s, and the drivers need to fully brake if the value under 2 s. However, in reality the drivers often successfully change lanes with low TTC values. In [14], the authors analyzed the TTC values for lane change based on data from the "100-Car naturalistic driving study" collected by Virginia Tech Transportation Institute (VTTI). The results show that the minimum TTC values for lane change are between 2.1-2.7 s, when the speeds are ranged from 70-90 mph (i.e. 113-145 km/h). A smaller TTC value denotes that the drivers are in a dangerous scene and need change lanes as soon as possible if they want to overtake. Therefore, these two variables including the TTC and distance to vehicle in front will be considered as inputs for classification of driving scenes.

In this contribution, two variables will be considered as inputs for classification of driving scenes. The first input is the distance to vehicle in front. The corresponding fuzzy values are close, middle, and far. Similarly, the value of TTC to the vehicle in front will be considered as a second input, and the corresponding fuzzy values are low, middle, and high. Finally the output of the fuzzy model are three different driving evaluations denoted as Very Safe (VS), Safe (S), and Dangerous (D). The fuzzy rules are summarized in table 1. In very safe scenes, the drivers possibly take a long time for changing lanes. However, in dangerous scenes the drivers will change lane in a short time or hard brake. Safe scenes contains the largest uncertainty.

TABLE I

FUZZY RULES USED IN DRIVING SITUATION RECOGNITION

Distance \ TTC	Low	Middle	High
Close	D	D	S
Middle	D	S	VS
Far	S	VS	VS

B. Hidden Markov Model

An HMM describes the relationship between two stochastic processes: one consists of a set of unobserved (hidden) states $S = \{S_1, S_2, ...S_N\}$, with N as the number of hidden state which cannot be measured directly. The other stochastic process is denoted by a set of M observable symbols $V = \{V_1, V_2, ...V_M\}$. The hidden state and observation symbol at time t are defined as Q_t and O_t respectively. The hidden state sequence can be inferred through the observation state sequence based on the expectation maximization (EM) and maximum likelihood estimation (MLE), which are the standard methods of estimating the parameters of HMM and the most possible hidden states respectively [7].

In this contribution, the driving behaviors mainly considers lane changing. The driving maneuvers performed are the hidden states including left/right lane change and normal lane keeping, so $N = 3$. The driving behaviors prediction model can be regarded as a standard HMM, as shown in Fig. 2. The driving behaviors are denoted as S_i, and the observations V_k are designated by subscript k. This model can be defined as a system in which a driving behavior is switched to another. A complete HMM is defined as $\lambda = (A, B, \pi)$, where $A = \{a_{ij}\},\ i,\ j \in [1,N]$ denotes the probability of moving from state S_i to state S_j, and $B = \{b_{j(k)}\},\ i,\ j \in [1,N]$ defines

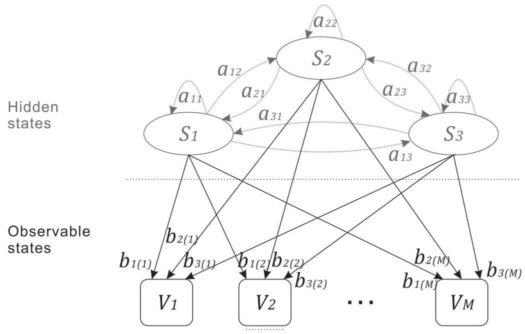

Fig. 2. HMM model with 3 states (S_1, S_2, S_3)

the probability of an observation V_k being generated from a state S_j at time t, that means $b_{j(k)} = P(O_t = V_k \mid Q_t = S_j)$. In addition, it is necessary to use an initial probability distribution $\pi_i = P(Q_1 = S_i)$, which indicates the probability of starting in state S_i.

To apply HMM-based situation recognition first the model has to be defined by training, using the model then the most probable state sequence can be estimated. To train HMM the Baum-Welch algorithm (also called expectation maximization) will be used to estimate the maximum likelihood model parameters $\lambda = (A, B, \pi)$. That means in a given the observation sequence O and its corresponding hidden state sequence Q, the parameters of the HMM λ can be computed and adjusted to best fit the both sequences. Based on the saved HMM λ, the most probable sequence of driving behaviors, which has the highest probability, can be calculated by using Viterbi algorithm.

III. DRIVING BEHAVIORS PREDICTION BASED ON FL-HMM

The driving behaviors prediction model based on FL-HMM is shown in Fig. 3. It consists of two important processes including driving behaviors prediction and parameter definition, which are described in the following sub-sections.

A. Driving behaviors prediction

As previously described, the individual driving behaviors depends on the current environment conditions and the individual driving characteristics.

The driving behaviors prediction model and related training are shown in Fig. 3. It is realized in three steps.

1) FL-HMM based on driving scenes: Driving on the highway, the relationships between the ego vehicle and the other surrounding vehicles are the main influences effecting the driver making decisions. In this step, the current driving situation will be mainly discussed.

Assuming three categories of driving scenes, FL is used for modeling and therefore to distinguish VS, S, and D scenes. For each scenario a corresponding HMM (HMM VS, HMM S,or HMM D (in Fig. 3)) will be used representing the upcoming driving behaviors. The driving behaviors (i.e. the sequence of hidden states) will be determined by the sequence of observations. Therefore, the selection of parameters describing the current situation is important.

The TTC values contain the information of relative velocities and the distance between the ego vehicle and the surrounding vehicles. Therefore, the TTCs are selected as observation variables, the symbols and the corresponding descriptions are given in Table II.

During driving, all observation variables are measured. The change of each parameter will lead to changes of the observation vector. For modeling convenience, a prefilter will be applied. The signal data of each observation variable will be divided by this prefilter into segments containing certain information. Each segment represents a corresponding observation. Thus, the segment ranges are important and has also to be defined to describe observations. To simplify the modeling process, in this contribution a prefilter using five different thresholds is defined. Each observation variable is divided into six segments.

2) HMM based on driver's operation: Normal driving behaviors can be predicted through the driving environment. However, sometimes the drivers may make exceptional decisions like changing lanes with sudden acceleration or keeping lane during deceleration. As a supplement to the model based on the driving environment, another HMM will be established based on the driver's operation signals to predict these exceptional driving behaviors. In [15], driver's acceleration and deceleration behaviors were effectively predicted by using the driver's operation signals such as accelerator pedal stroke, brake pedal stroke, etc.

Therefore, the indicator signal, the steering wheel angle, the accelerator pedal position, and the brake pedal pressure are selected as observation variables of HMM-operation (in Fig. 3). Similarly, the corresponding prefilter of this HMM is defined by using two different thresholds for each observation variable.

3) Fusion: As previously mentioned both methods are combined in this work, one model considers the relationships with other vehicles (driving scene), and the other considers the driver's operation. As shown in Fig. 3, using the two models the probabilities of the next driving behaviors are calculated separately. The final probabilities are fused using the weight w, expressed as

$$P = w * P_{scene} + (1 - w) * P_{operation}, w \in [0, 1]. \tag{2}$$

Finally, the hidden state with the highest probability is predicted as next driving behaviors.

B. Optimization

The last part of the modeling is related to the definition of parameters, here connected with optimization. As previously described, the thresholds of FL, the prefilters of HMMs and w are affecting the prediction capability:

- FL thresholds definition (prediction of driving scene, selecting HMM and prefilter)
- Prefilter tresholds (defining observation sequence)
- w (affecting driving scene prediction)

Therefore, the optimization of all parameters is important to improve the performance of driving behaviors prediction. To optimize the model performance, Non-dominated Sorting

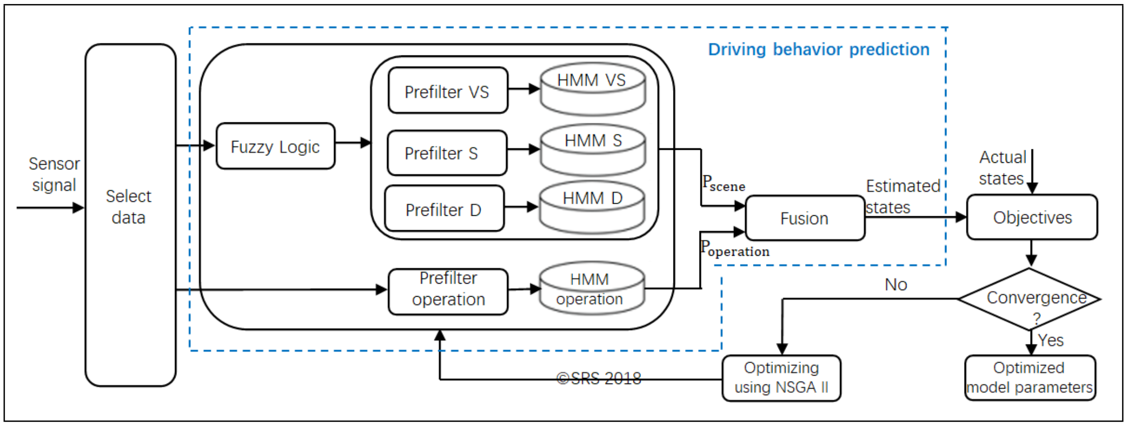

Fig. 3. The FL-HMM-based driving behaviors prediction model

TABLE II
DESCRIPTIONS OF NSGA-II DESIGN PARAMETERS

Approach	Input	Definition	Design parameters
FL	d_f TTC_f	Distance to vehicle in front TTC to vehicle in front	$[x_{df1}...x_{df4}]$ $[x_{ttc1}...x_{ttc4}]$
HMM (scene)	TTC_f TTC_{fl} TTC_{fr} TTC_{bl} TTC_{br} TTC_b	TTC to vehicle in front TTC to vehicle in left-front TTC to vehicle in right-front TTC to vehicle left-behind TTC to vehicle right-behind TTC to vehicle behind	$[ttc_{f1}...ttc_{f5}]$ $[ttc_{fl1}...ttc_{fl5}]$ $[ttc_{fr1}...ttc_{fr5}]$ $[ttc_{bl1}...ttc_{bl5}]$ $[ttc_{br1}...ttc_{br5}]$ $[ttc_{b1}...ttc_{b5}]$
HMM (operation)	I I P_a P_b	Indicator Steering wheel angle Accelerator pedal position Brake pedal pressure	$[I_1...I_3]$ $[S_1...S_3]$ $[P_{a1}...P_{a3}]$ $[P_{b1}...P_{b3}]$
Fusion	w	Weight	$[w]$

Genetic Algorithm II (NSGA-II) was used. The NSGA-II was derived from the NSGA and used to solve Multi-objective Optimization problems (MOPs) [16]. By using NSGA-II the design parameters will be determined to minimize the objective functions which describe the targets of the optimization.

Therefore, the thresholds of FL, the prefilter for each HMM, as well as the weight w of the FL-HMM are defined as design parameters of NSGA-II. The details of the design parameters are given in Table II. Accuracy (ACC), detection rate (DR), and false alarm rate (FAR) are widely used to evaluate classifiers [18]. Ideal thresholds for each input variable (design parameters) can be achieved synthetically the maximal ACC , maximal DR, and minimal FAR. To define the best fitting model parameters during the optimization process, suitable objective functions has to be chosen. From this point of view the optimization process using NSGA II defining optimal FL and HMM parameters serves as training process. The objective functions in this contribution are expressed by

$$f_{1-3} = (1-ACC)+(1-DR)+FAR, \text{ and} \tag{3}$$

$$f_4 = abs(estimated\ maneuvers - actual\ maneuvers), \tag{4}$$

where f_{1-3} represent using the same equation (3) for different behaviors including left/right lane change and lane keeping. By comparing the degree of coincidence between the actual state and the estimated state at each moment, the values of ACC, DR, and FAR can be calculated for the complete driving sequence applying the well-known formulas (cf. [18]).

IV. APPLICATION OF THE NEW APPROACH

In this section the FL-HMM-based behaviors prediction of lane changing maneuvers is realized. In the following the experiment setup is described. Training and test as well as the suitable NSGA-II design parameters are used to develop this model. Finally experimental results will be presented.

A. Design of the experiment

A driving simulator SCANeR^{TM}studio (Fig. 4) is applied to perform the driving simulation. The simulator is equipped with five monitors, base-fixed driver seat, steering wheel, and pedals. The three rear mirrors, which are essential to decide to change lane, are displayed on the corresponding positions of the monitors.

Fig. 4. Driving simulator, Chair Dynamics and Control, U DuE

The driving scenario is a highway with four lanes of two directions and simulated traffic environment. During driving, the participant could perform overtaking maneuver when the preceding vehicle drives slowly. After overtaking the participant could also drive back to the initial lane. The time points of changing lane to left and right were decided by the participant. Following the traffic rules in Germany, it is only allowed to overtake from left lane. Totally 7 participants with age ranged from 25 to 38 years were recruited. They all held valid driving licenses. The training dataset is related to each participant performed a drive about 40 minutes. Data from another 10 minutes drive are used for test.

1) Data processing phase: To label the data as hidden state sequence as well as observation sequence, the signal data need to be classified and processed. The hidden states in this contribution consider only lane changing. In the driving simulation, the current lane i can be determined through the position of the vehicle's canter point. Therefore, the lane changing behavior at time t_{lane} can be recognized when the value of lane i is changed. The starting time of the lane changing behavior can be determined by detecting the last significant change of steering wheel angle at time t_{angle}. The time interval in between t_{angle} and t_{lane} is defined as lane changing. The symbol as well as its specific description of each hidden state are given in Table III.

TABLE III
DEFINITION OF 3 HIDDEN STATES

Symbol	Description
S_1	Lane changing to the right
S_2	Lane keeping
S_3	Lane changing to the left

2) Training phase: During training the model is trained by the following steps.

(a) According to the principle of NSGA-II methodology, first a set of design parameters (thresholds of FL, HMM-prefilters, w) is generated randomly by NSGA-II.
(b) Based on the selected parameter set, the fuzzy model and the prefilters of each HMMs are defined.
(c) A training data set is distributed by the fuzzy model to the respective HMM and its prefilter. Then the processed training data set can be used to estimate each HMM parameter, with these HMMs the hidden state could be calculated.
(d) The actual hidden state sequence and the hidden state sequence calculated by the proposed model will be compared. Afterwards, the objective functions (3) and (4) could be calculated.
(e) Process is repeated from (a) to (d) until convergence.
(f) Through the comparison of the objective functions results for each model, multiple Pareto-optimal solutions are found.

3) Test phase: The proposed model (based on driver-specific parameters) is applied for driver behaviors prediction. The predicted behaviors and the real behaviors can be compared for evaluation.

B. Evaluation

The estimated and the realized driving behaviors will be compared to evaluate the similarity. The results of test phase for dataset #2 are shown in Fig. 5. Here the hidden states (driving behaviors) are given as a function of simulated time. The symbols of hidden states are shown in Table III. Here the actual (green) and the estimated ones (blue) are illustrated as a function of time. It could be stated that, these two sets of hidden states are basically consistent, and the driving behaviors can be predicted before the actual lane change. The average prediction time for dataset #2 is about $1.8 \pm 0.7s$ before the t_{angle} and $3.9 \pm 0.8s$ before t_{lane}.

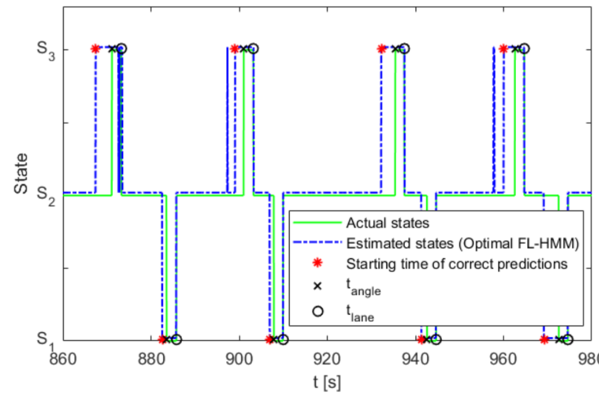

Fig. 5. Prediction result of the optimal FL-HMM [Test dataset #2]

For comparison alternative advanced classification algorithms (ANN, SMV combined ANN and SVM (ANN-SVM) [17]) are applied. In contrast to HMM, the algorithms ANN and SVM do not need data processing. A general HMM is also used as reference, which use all the observation variables mentioned in table II. Here related parameters [14] are used.

To verify the effectiveness of the models in terms of driving behaviors prediction, the actual driving behaviors are compared to the estimated driving behaviors for all data sets. The percentage of the ACC, DR, and FAR for each group is calculated. Finally, the average values of the ACC and FAR by using different models are shown in Fig. 6. It can be stated that using optimal thresholds (FL-HMM) all ACC, DR, and (1-FAR) values are larger than 80%, i.e. a high ACC and DR in combination with a very low FAR can be achieved.

To further evaluate the performance of driving behaviors prediction, the Receiver Operating Characteristic (ROC) graph is calculated (in Fig. 7). From the obtained results it is clear that, using the optimal FL-HMM the DR is improved to 82%. The FL-HMM generates the lowest FAR in comparison to other approaches applied to identical driving data. Thus, the optimal FL-HMM shows the best prediction performance in terms of ACC and FAR of all models.

V. CONCLUSIONS

In this contribution, a new driving behaviors prediction model was proposed denoted as FL-HMM. The new approach is based on situation-specific HMMs combined with thresholds and a fuzzy approach, for which related parameters are adapted during a training phase. The FL approach will be used for additional distinction of driving scenes into very safe, safe, and dangerous driving scenarios. Afterwards, a corresponding HMM will be trained for each driving scenes respectively and predicting the driving behaviors. Three different driving behaviors including left/right lane

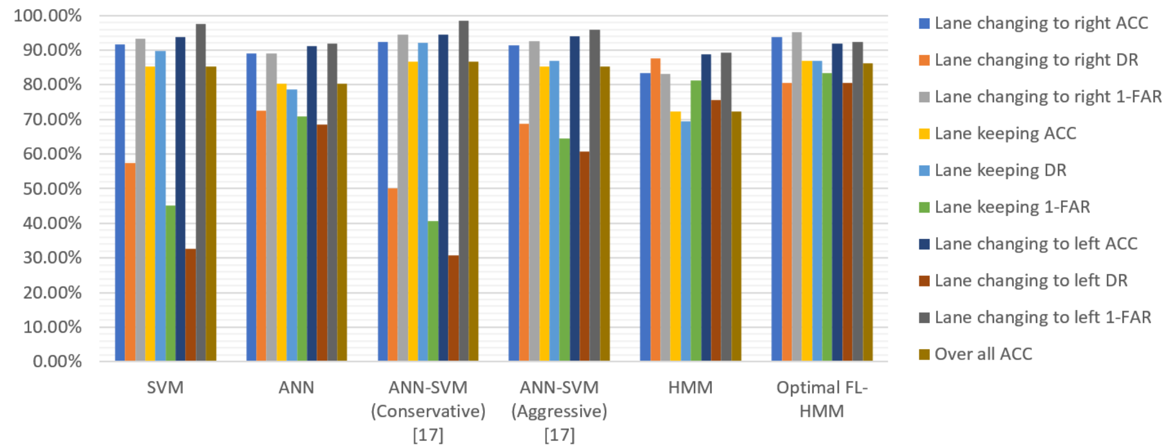

Fig. 6. Average ACC, DR, and FAR achieved by different models for 7 test datasets

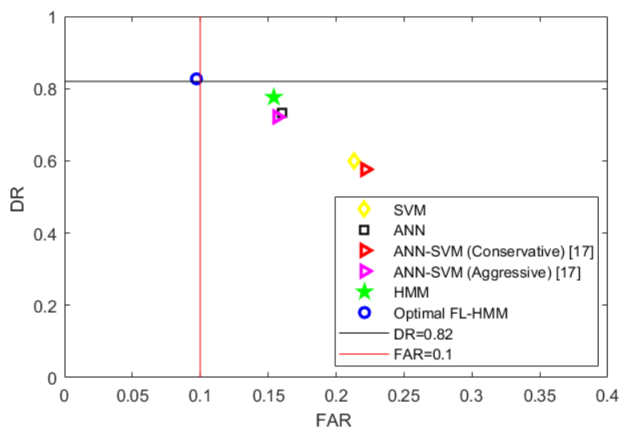

Fig. 7. ROC graph for different models

change and lane keeping are modelled as hidden states for these HMMs. In this contribution, based on data achieved from 7 different test drivers the method is validated. The finally obtained results show a significant improvement of the proposed method to identify the driver behaviors, and the driving behaviors can be well predicted. In comparison to other algorithms, through the proposed approach in this contribution, a prediction model can be established and furthermore optimized. In combination with NSGA-II, the targets of the optimization can be realized through objective functions to improve the recognition performance. In practical application, the objective functions can be adjusted according to actual situations.

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