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Prediction of human driver behaviors based on an improved HMM approach

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Abstract— **Research and development of predicting driving behaviors play an important role in the development of Advanced Driver Assistance Systems (ADAS) for assisting drivers. In this contribution, an approach is developed based on Hidden Markov Model (HMM) for predicting human driving behaviors. Three different driving maneuvers including left/right lane change and lane keeping are modeled as hidden states for the HMM. Based on observations (training), the HMM approach is able to calculate the most possible driving behaviors using observed sequences. Furthermore, the observed sequences are also used for training of HMM in the 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.**

In this contribution the definition of a suitable prefilter will be discussed and finally optimized. The approach focuses on the definition of optimal prefilters. Here optimality is defined as the optimal segments describing a quantized prefilter mapping the vehicle's environment to quantized states. In combination with related HMM-based results in terms of accuracy, detection, and false alarm rates an optimal parameter set of the prefilter can be determined. Using experimental data from real human driving behaviors (taken from driving simulator) it can be concluded that the optimal definition of the prefilter can increase the detection rate and accuracy, and in the meanwhile decrease the false alarm rate. The effectiveness of driving behaviors prediction has been successfully proved by comparison with other methods in this contribution.

I. INTRODUCTION

Driver Assistance Systems are systems developed to assist the human driver and therefore to make driving safer and better. Typical assistance systems focus on avoiding traffic accidents using warnings with respect to detect dangerous scenes. The predictions of these assistance systems are calculated based on physical variables such as distances and vehicle speed, etc. These physical variables describe the vehicle state and the driving environment. Although the vehicle state and the driving environment are relevant for current driving safety assessments, the most common cause of accidents is related to human behavior. Therefore, an assistance system should help the driver to detect possibly improper behaviors. However following general driving rules, drivers will usually choose the most appropriate operations based on their own driving experiences and habits. Driver's driving behaviors are assumed as individual. Therefore, the driving assistance systems should be adjusted based on the analysis of individual driving behaviors to improve traffic safety as well as realize intelligent driving. The individual driving behaviors depend on many factors including current environment conditions, individual driving characteristics, and so on. Thus, the driver's intention and the next driving action cannot be easily and directly measured by physical variables.

To establish a model of driving behaviors, some approaches have been proposed. For example, neural network (NN) models have been used in predicting the acceleration distributions for vehicle following on highways [1]. In [2] dynamic Bayesian networks (DBN) are used for estimation and prediction of acceleration as well as turn-rate for car-following and lane-change in a 4-way-intersection. In [3] a fully probabilistic model is presented by using feature function to evaluate the situational context to predict the next state of a traffic participant. The authors of [4] used a fuzzy logic (FL) model, which is established from drivers empirically observed behavior at high-speed signalized intersections.

In this contribution, the driving behaviors are predicted using Hidden Markov Model (HMM) approach, which is applied for estimation of unobservable states. The unobservable states can be inferred through the observation states based on the expectation maximization (EM) and maximum likelihood estimation (MLE), which are standard methods to estimate the HMM parameters and the most possible hidden states respectively [5][6]. For modeling performance improvement, suitable segments of the observation states have to be defined. Experimental results are shown, using those suitable observation segment ranges which improve the quality of the driving behaviors prediction model.

II. DRIVING BEHAVIORS PREDICTION BASED ON HMM

Hidden Markov Models (HMM) are successfully applied in fields such as speech recognition and synthesis [7], DNA profiles recognition in biology [8], and human behaviors recognition from video [9]. Nowadays applications of HMM have been extended to more and more research areas, such as driving behaviors recognition and prediction. In [10], the authors propose to use HMM in determining driver intention for a variety of vehicle maneuvers. In addition, HMM is often used with other algorithms. In [11], the authors proposed a Hybrid-State System (HSS)-HMM framework for the estimation of driver behaviors at intersections. The driver behaviors and vehicle dynamics are modeled as a HSS. The HSSs provide the system architecture, and HMMs define the relationship between system components. A detailed definition of HMM and related basic algorithms are described in [5].

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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. Thus a hidden state sequence is $Q = \{Q_1, Q_2, ...Q_T\}$ and an observation sequence is $O = \{O_1, O_2, ...O_T\}$, where T is the length of the sequence. Using HMM parameters the sequence of the unobserved state can be determined by analyzing the sequence of the observation.

In this contribution, the driving behaviors mainly consider lane changing. The driving maneuvers performed are the hidden states. They include 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. 1. The driving behaviors are denoted as S_i, and the

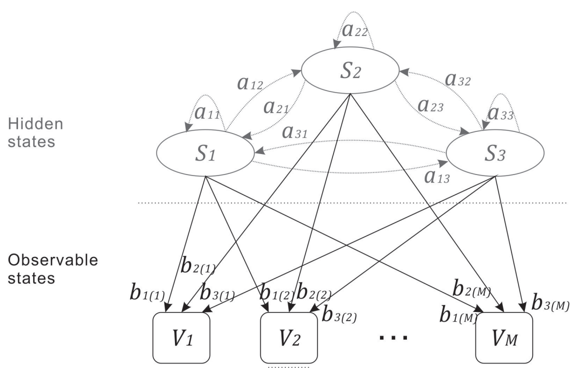

Fig. 1. HMM model with 3 states

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 with a state transition probability $a_{ij} = P(Q_t = S_j \mid Q_{t-1} = S_i)$, $i,\ j \in [1, N]$, which means the probability of moving from state S_i to state S_j. All transition probabilities a_{ij} can constitute a state transition probability matrix

$$A = \{a_{ij}\},\ i,\ j \in [1, N]. \tag{1}$$

An observation probability $b_{j(k)}$ defines the probability of an observation V_k being generated from a state S_j at time t, that means $b_{j(k)} = P(O_t = V_k \mid Q_t = S_j)$. The corresponding observation probability distribution matrix is denoted as

$$B = \{b_{j(k)}\},\ j \in [1, N] \text{ and } k \in [1, M]. \tag{2}$$

To describe an HMM it is necessary to use an initial probability distribution, which indicates the probability of starting in state S_i, where

$$\pi_i = P(Q_1 = S_i), i \in [1, N]. \tag{3}$$

Using above definitions, a complete HMM can be defined as $\lambda = (A, B, \pi)$.

To achieve HMM-based driving behaviors prediction the process has to be divided into two parts: first training of the model and second estimating the most probable hidden state sequence. To train HMM the Baum-Welch algorithm (also called expectation maximization) will be used to estimate the maximum likelihood model parameters $\lambda = (A, B, \pi)$. In a given observation sequence O and its corresponding hidden state sequence Q, the parameters of the HMM λ are computed and adjusted to best fit both sequences. Based on the saved HMM λ, the most probable sequence of driving behaviors, which has the highest probability, is calculated by using Viterbi algorithm.

As previously described, the sequence of hidden states will be determined by the sequence of observations. Therefore, the selection of parameters describing the current situation composed to an observing state, is very important. These parameters must take the feasibility of data collection into consideration, and also equip the ability to achieve the purpose of the identification of the model. When a driver is driving on the highway, the relationships between the ego vehicle and other surrounding vehicles are the main factors to affect the driver making a decision. In this contribution, the relative velocity with the vehicle in front, the distance between the ego vehicle, and the surrounding vehicle are selected as observation variables, i.e. an observation vector at time t is defined as

$$O_t = V_k = [\Delta v_t, d_{ft}, d_{flt}, d_{frt}, d_{blt}, d_{brt}],$$

where $k \in [1, M]$, and M is the number of observation choices. Details of the parameters are given in Table I. In this contribution, a driving simulator is used to collect data of each parameter. In the real world, these parameters will be taken from different sensors, such as camera, radar, lidar, and ultrasonics [12].

TABLE I
DESCRIPTION OF OBSERVATION SEGMENT RANGES

Symbol	Definition	Thresholds left	right
Δv	Deviation of the velocity between ego vehicle and vehicle in front	$a_{\Delta v}$	$b_{\Delta v}$
d_f	Distance to vehicle in front	a_d	b_d
d_{fl}	Distance to vehicle in left-front	a_{dfl}	b_{dfl}
d_{fr}	Distance to vehicle in right-front	a_{dfr}	b_{dfr}
d_{bl}	Distance to vehicle left-behind	a_{dbl}	b_{dbl}
d_{br}	Distance to vehicle right-behind	a_{dbr}	b_{dbr}

During driving, all observation parameters are assumed as measurable. Signals are dynamic and change with time. The change of each parameter will lead to changes of the observation vector. Here a quantized signal realized by prefilter is assumed, which is typical within the automotive field using related electronic equipment with limited accuracy. On the output side of the prefilter a quantized signal featuring the feature vector is derived. By using the feature vector, different driving situations should be distinguished. Based on the prefilter the signal data of each observation parameter will be divided into segments. Each segment represents a corresponding observation. Thus, the ranges of segments are important and will be defined to describe observations. Using these segment ranges the signals can be processed and combined to form features for the HMM prediction process. To simplify the modeling process, in this contribution a prefilter is defined, which uses only two different range values, and divides each observation parameter into three segments. The left and right thresholds (i.e. the two range values) for each observation parameter are shown in Table I. Obviously, the values of the observation segment ranges are very important, because they define implicitly the observation sequence for HMM training and finally affect the accuracy.

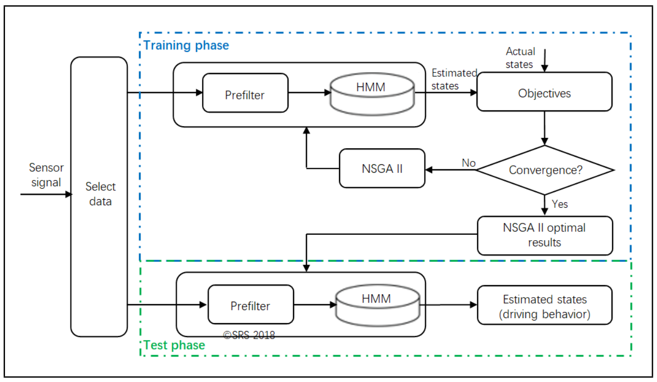

Fig. 2. Illustration of optimal prefilter definition

A simple approach is to choose a general prefilter by the general driving rules, e.g. in Germany 50 m is the corresponding distance between two guide posts on the highway. Therefore, the segment range values of the distance can be defined as 50 m and 100 m, and the interval on the speedometer can be used to represent the range values of the relative velocity, such as 10 km/h and 20 km/h.

The core of prediction process is realized by an HMM. Using a given hidden state sequence and its corresponding observation sequence, HMM could be trained. Therefore, the feature vectors input to the HMM could be extracted by using a general prefilter, which is helpful to determine an optimal HMM and improve the prediction performance. For this reason for each driver the HMM with individualized optimal prefilter can be generated.

In Fig. 2 the process of generating an optimal prefilter is illustrated. To define optimal prefilter parameters Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used. The NSGA-II was derived from the NSGA and used to solve Multi-objective Optimization problems (MOPs)[16]. By using NSGA-II the HMM are repeatedly trained using different range values. Considering all possible range values, each range changes from the minimum to the maximum value of this parameter. The optimal thresholds for each observation parameter (optimal prefilter) are determined to minimize the objective functions.

Accuracy (ACC), detection rate (DR), and false alarm rate (FAR) are widely used for evaluating classifiers [13][14]. They are calculated based on True Positive (TP), False Positives (FP), True Negative (TN), as well as False Negative (FN) numbers. For explanation a confusion matrix is illustrated (Fig. 3) as example to describe the parameters for changing lane to the right. True Positive (TP) denotes

Is changing to the right lane the estimated state?		Is changing to the right lane the actual state? Yes	No
	Yes	Ture Positive (TP)	False Positive (FP)
	No	False Negative (FN)	Ture Negative (TN)

Fig. 3. Explanation of confusion matrix [Lane changing to right]

the number of the events when the estimated maneuver is positive (changing lane to the right) and the actual one is also positive, contrastively False Positive (FP) denotes the number of the events when the estimated maneuver is positive and the actual value not, similarly for True and False Negatives (TN/FN). The ACC, DR, and FAR are defined by [14]

$$ACC = \frac{TP+TN}{TP+TN+FP+FN}, \tag{4}$$

$$DR = \frac{TP}{TP+FN}, \text{ and} \tag{5}$$

$$FAR = \frac{FP}{TN+FP}. \tag{6}$$

As previously discussed, the left/right thresholds for each observation parameter (prefilter) are the critical values that determine the observation sequence for HMM training, and thus affect the estimated states. The values of TP, FP, TN, and FN will be defined by the estimated states and finally affect the ACC, DR, and FAR values. In this contribution the optimal prefilter will be selected with respect to the improvement of the aforementioned ACC, DR, and FAR parameters. Therefore, the objective function is defined as

$$f = (1-ACC)+(1-DR)+FAR \tag{7}$$

for the three driving behaviors.

III. Experimental Results

The experimental setup and obtained results of HMM-based lane changing maneuver prediction is introduced in this section. Using the proposed model, driver's lane changing behaviors have been predicted based on the measured distances and velocities. To improve the prediction performance, optimal prefilters (feature parameters) have to be defined.

A. Design of the experiment

A professional driving simulator SCANeR^{TM}studio as shown in Fig. 4 is applied to collect the driving data, which are used for the training and test of the proposed approach. The simulator is equipped with five monitors with 180 degree field of view, 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. The data acquiring frequency of the driving simulator is 20 Hz.

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

The driving scenario is based on a highway driving scenario 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 9 participants with age ranged from 25 to 38 years were recruited. They all held valid driving license. Each participant performed a drive about 25 minutes.

1) Data processing phase: To label the data as the hidden state sequence as well as the 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 center point. Therefore, by comparing the value of lane i at different times, the lane changing of the vehicle can be determined. Lane keeping is defined when the value of the current lane i_t is as the same at last moment i_{t-1}. Lane changing to the left is defined when this value is increased, and lane changing to the right is defined when it's decreased. In the experiment, the time at which the drivers decided to change the lane (turned light) was already between 2 and 3 seconds before the lane change. The average value is 2.5 s. Thus, the lane changing as the driving behavior will be considered occurring 2.5 s before the action. However, it could be a problem that, if the ego vehicle overlaps the white line by driving, it could generate some data of lane changing, and these data do not reflect the true behaviors of the driver. For this reason, it is necessary to remove those interference data to get accurate experimental data. The symbol as well as its specific description of each hidden state are given in Table II.

TABLE II
DEFINITION OF HIDDEN STATES

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

The observation vectors can be classified and processed into sequences by a prefilter. As described in section II, an optimal prefilter will be determined with the maximum ACC, the maximum DR as well as the minimum FAR. Therefore, it should be used to improve the performance of driving behaviors prediction. To prove this, two different prefilters were used to classify the observation vectors. One prefilter is using these optimal segments. The other is using a set of general segment ranges for comparison, which are given by comparing the experimental data, such as average value, minimum safe distance, etc.

2) Training phase: In this experiment, each experimental data set is divided into 10 subsets, 7 of these 10 subsets are considered as training data set, and the others are considered as test data set. The location of each training data set is different, and not repeated, e.g. the first training data set is selected from the first to the seventh subsets, the second is from second to eighth subsets, and so on. Each training and test data set must contain different lane changing maneuvers.

A training data set can be used to estimate the HMM parameters. With this HMM parameters the hidden state could be calculated. In the next step, the hidden state sequence from the training data, and the hidden state sequence which is calculated by HMM model will be compared to check the correspondence and to calculate ACC, DR, and FAR. Afterwards, the objective functions (7) are calculated. Then the prefilter values are defined by optimization regarding the aforementioned objective functions. This prefilter and its corresponding HMM model will be used in test phase.

3) Test phase: Each driver specific test data set must be related to the data, which are used in training phase. Therefore, the optimal prefilter, and the corresponding HMM model for each test data set are already calculated in the training phase. The most possible driving behaviors will be determined by using the corresponding HMM. Through the comparison between the calculated and the actual driving behaviors, the accuracy could be evaluated.

B. EVALUATION

To evaluate the presented approach, an HMM will be learned by using the same training data set, and different prefilters. After the optimal prefilter is selected, the approach is compared using a general prefilter against the optimal prefilter.

The calculated and the actual driving behaviors will be compared to evaluate the similarity. The results of test phase for data set #5 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 II. The green, blue, and red lines denote the original states,

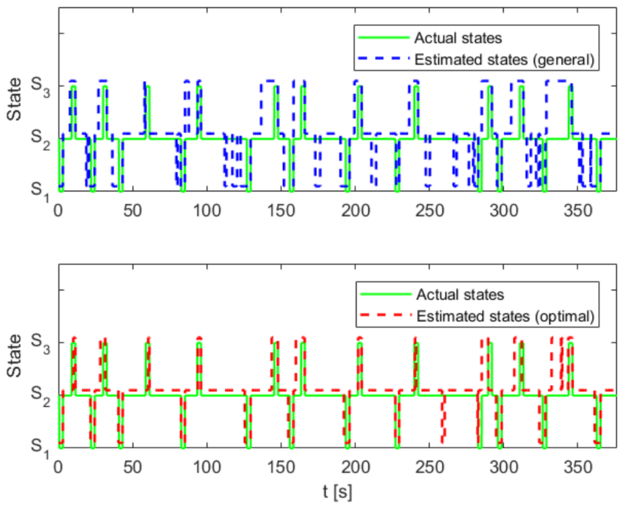

Fig. 5. Result of HMM validation [Test data set #5]

the calculated hidden states using general prefilter, and the calculated hidden states using optimal prefilter respectively. The results show that the states predicted by the optimized prefilter-based HMM fit best to the original states. The number of wrong calculated hidden states of blue line is more than the red one.

The percentage of ACC, DR, and FAR by selection of general as well as optimal prefilter for data set #5 are shown in Table III. From the obtained results it becomes clear that, using the optimal prefilter the overall ACC is increased from 73.4% (Training) and 68.8 % (Test) to 91.9% and 87.5 % respectively. Similarly, using the optimal prefilter the DR is higher than using the general prefilter.

TABLE III
PREDICTION RESULTS USING GENERAL/OPTIMAL PREFILTERS FOR DATA SET #5

Data set #5		General prefilter Training	General prefilter Test	Optimal prefilter Training	Optimal prefilter Test
Overall	ACC %	73.4	68.8	91.9	87.5
S_1	ACC %	84.7	83.5	98.2	96.0
	DR %	96.4	88.7	99.4	90.3
	FAR %	15.9	16.9	1.9	3.5
S_2	ACC %	73.4	68.8	92.0	87.5
	DR %	70.5	65.3	91.0	89.2
	FAR %	1.7	11.8	0.2	22
S_3	ACC %	88.7	85.5	93.7	91.5
	DR %	100	87.6	100	64.6
	FAR %	11.9	14.9	6.6	6.4

Among the FARs of three different maneuvers, the FARs of training and test phases for lane changing to the right are 15.9% and 16.9% respectively. After optimization the FARs are reduced to 1.9% and 3.5%. The value of FAR can be defined by equations (6). It can be seen that, the higher FAR value results from a higher value of numerator FP (False Positive) defined in Fig. 3. For the maneuver lane changing to the right, the FP is the number of the events when the true actual state is not, but the estimated state is lane changing to the right. These results can also be detected from Fig. 5. Here S_1 defines the lane change to the right. It can be observed that, in several cases the estimated states are incorrectly calculated as S_1. The above descriptive issue occurs more often in the blue line (using general prefilter) than the red line (using optimal prefilter). It can be concluded that the prediction result can be improved using suitable prefilter. Even through, some exceptions can still be found during the experiment, for example, the optimized FAR value of lane keeping (test) is worse than the presetting value (about 10% higher). However, the overall result considering all situations are improved due to the optimization of the prefilter.

To verify the effectiveness of the model in terms of driving behaviors prediction, other algorithms are used for comparison. Typical algorithms like Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are used to establish driving behavioral models. In [17] the authors established three models including ANN, SVM, combined ANN and SVM (ANN-SVM) to estimate the lane changing behaviors at highway lane drops. An advantage of the both algorithms are that they do not require data processing. To evaluate these methods, the actual driving behaviors are compared to the estimated driving behaviors for all data sets. Then, the ACC, DR, and FAR of each driving behavior are calculated. The respective rates for each group are shown in Fig. 6. From the results (Fig. 6) it can be stated that, after the optimal selection of the prefilter all ACC, DR, as well as (1-FAR) values are larger than 80%. Although some exceptions can still be found, for example some ACC of ANN-SVM (conservative) are higher than optimal HMM, but the values of DR are decreased. To further evaluate the performance of driving behaviors prediction, the Receiver Operating Characteristic (ROC) graph is given in Fig. 7. From the results it can be stated that, using the optimal HMM the DR is highest and the FAR is lowest among all the approaches. Thus, the optimal HMM has the best performance in all models.

IV. SUMMARY AND CONCLUSION

In this contribution, a driving behaviors prediction model was developed based on Hidden Markov Model (HMM). Three different driving maneuvers including left/right lane change and lane keeping are modelled as hidden states for the HMM, and simulated on a highway scene using driving simulator. Based on HMM the unobservable states can be inferred through the observation states. The considered approach is based on the assumption that relevant physical variables are discretized into segments to consider typical sensors properties. The prediction performance of HMM by finding the optimal prefilter, rather than by optimizing HMM model was considered and improved. In this approach, based on data achieved from 9 different test drivers, the method is verified. For each time, subsets of different positions are selected for training and test purpose. With the same experimental data set the HMM models using general (presetted) and final (optimized) values of observation segment ranges are

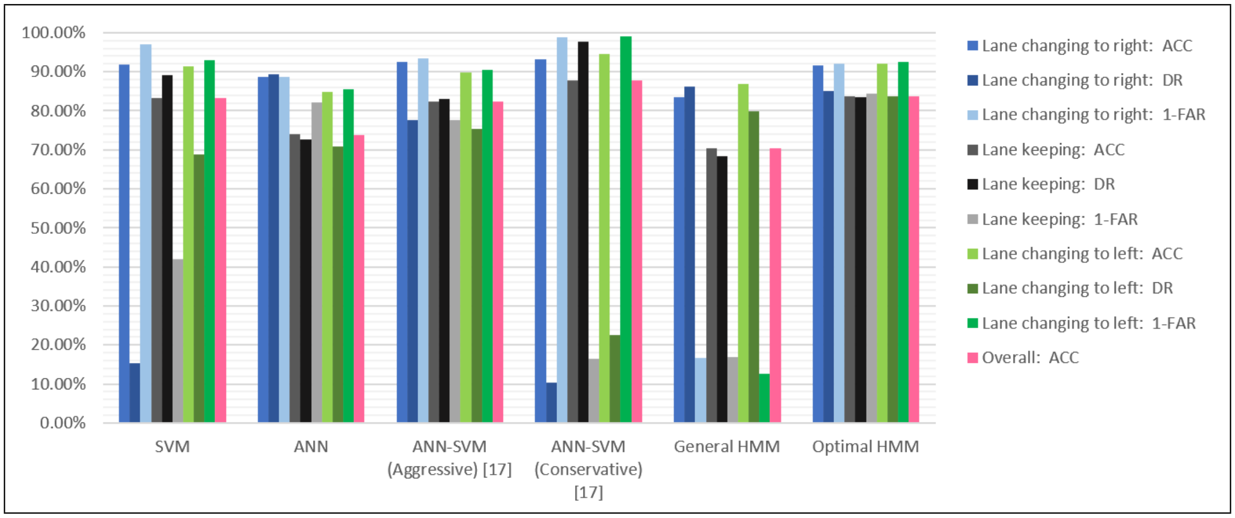

Fig. 6. Average ACC, DR, and FAR achieved by different models for 9 test data sets

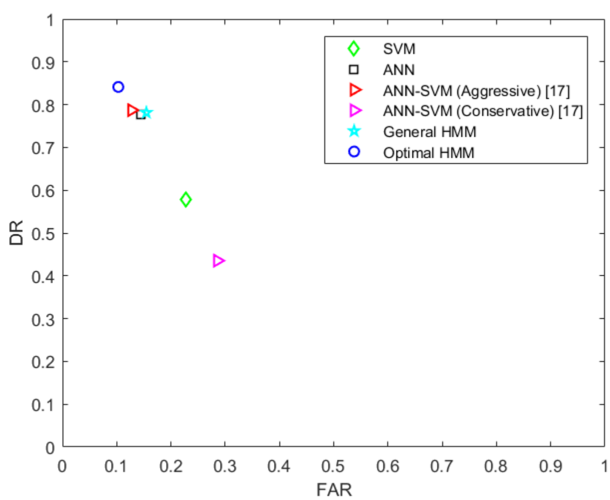

Fig. 7. ROC graph for different models

compared. The finally obtained results show a significantly improved ability of the HMM to identify driver behaviors. The results show that beside the classifier (here: HMM) the combined presetting and adaption strategy has a significant impact on the statistic properties of the approach. The HMM model using optimal parameters increases detection rate and accuracy as well as decreases false alarm rate. The prediction performance could be improved through selecting optimal prefilter parameters, which has been successfully proved in this contribution.

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