Manuscript version
DOI original paper: 10.1109/CogSIMA49017.2020.9216115

Online intention recognition applied to real simulated driving maneuvers

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***Abstract*—Advanced Driver Assistance Systems (ADAS) are systems developed to assist the human driver and therefore to make driving safer. Research and development of human driving intention recognition (behavior prediction) plays an important role in the development of ADAS, because the estimated driving intention can be used to supervise the drivers intended actions and to avoid dangerous situations. In this contribution, an approach is developed based on fuzzy-Random Forest (fuzzy-RF) for recognizing human driving intentions in real time. Three different driving maneuvers including left/right lane change (LCL/LCR) and lane keeping (LK) are modeled as classes. Driving simulations are generated for highway scenes using a driving simulator.**

To improve the recognition performance of the proposed approach, membership functions are applied to quantify input signal data into fuzzy sets for RF training. The design parameters of membership functions can be generated automatically by a fuzzy density clustering method. Using experimental data from real human driving, driver intentions are predicted. The results show accuracy values of off-line training phase and on-line test phase are larger than 98 % and 91 % respectively. The effectiveness of driving intention recognition has been successfully proved in this contribution.

***Index Terms*—Advanced Driver Assistance Systems, Lane Change Prediction, Driver Attention Estimation, and Machine Learning Methods.**

I. Introduction

A cognitive system represents a set of human cognitive processes, which are applied to model human intelligence, such as perceiving, understanding, planning, deciding, analyzing, and problem solving [1].

Drivers intention recognition is related to human behavior recognition and prediction in cognitive systems, which plays an important role in the development of Advanced Driver Assistance Systems (ADAS) [2]. According to a report from European Commission [3], even though the trend of accidents in Europe has decreased, many people still lost their lives in traffic accidents. In 2017, the number was about 49 road fatalities per one million. Statistic [4] of traffic accidents show that most accidents are caused by driver misoperations. Therefore, prediction of driving behaviors is importance of traffic safety. Recognized driver intention can be used as input to evaluate whether driver's intended action is safe in each context. If situations may become unsafe a corresponding maneuver suggestion or even a warning can be given to enable safe actions as illustrated in Fig. 1. This is applicable to assisted [5] and conditionally automated [6] driving modes as defined by the SAE [7]. In each mode, variations in the suggestions could be adapted to driver's needs. This can also be used to determine when to provide maneuver action assistance that optimizes driving maneuver action such as lateral steer-by-wire control and longitudinal brake-by-wire control systems [8].

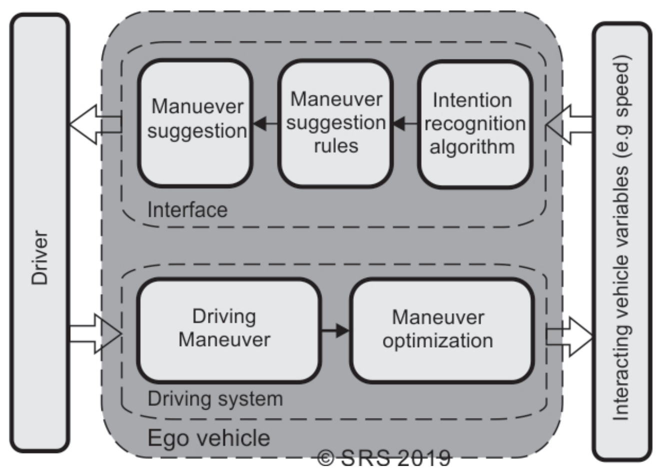


Fig. 1. Driver vehicle interation with online assistance

Driver behaviors are dynamic and changing over time, they are detectable and can be measured through trajectories of ego-vehicle. However, driver intentions are based on inner mental states of human (understand as cognitive states) which are not measured. To predict driving behaviors (i.e. driving intentions recognition), machine learning algorithms like Artificial Neural Networks (ANN) [9], Dynamic Bayesian Networks (DBN) [10], Support Vector Machines (SVM) [11], Fuzzy Logic (FL) [12], Hidden Markov Models (HMM) [14], and Random Forest (RF) [13] can be applied for learning and modeling driver behaviors.

In the previous work [15], a driving intention recognition system is established based on different machine learning approaches like HMM, SVM, Convolutional Neural Networks (CNN), and RF. The results show that for this task the performance of RF algorithm is the best. Especially combining environmental and eye-tracking data the RF algorithm achieved the best results with an accuracy of more than 99 %. However, it was pointed out that depending on the selected algorithm, the integration of eye-tracking data will not necessarily improve the recognition performance. For example using HMM, CNN, and RF, the performance can be marginally improved in comparison to the results using environmental data. Using SVM in combination with eye tracking data leads to worse results in comparison using only environmental data. According to the results of the previous work [15], RF algorithm and environmental data are considered to establish driving intention recognition model in this contribution. One of the methods to improve model performance is to define suitable input features. In the previous study [14], a prefilter was applied to process and combine signals to form features for recognition process. It was proven that by using formed input features the ability of the HMM to predict driver behaviors can be significantly improved. Therefore, the definitions of the input features are important to affect the performance of recognition model.

In this contribution a new fuzzy Random Forest (fuzzy-RF) approach is proposed to implement an on-line driving intention recognition model. Membership functions are applied to quantify input signal data into fuzzy sets for RF training.

This contribution is organized as follows: in Section II the driving intention prediction model based on fuzzy-RF is presented. An overview of the methodology used is also described in this section. Description of driving scenarios and data collection is introduced in section III. In Section IV the experiment and experimental results are given. Finally, a conclusion is provided in Section V.

II. Driving intention recognition based on fuzzy-RF approach

To establish a recognition model it is necessary to define the output and input of the model. Lane changing, as a usual driving behavior, will be used as representative for driving behavior prediction in this contribution. The study of lane changing behavior can help drivers to safely and efficiently achieve lane changing or overtaking. Three different driving maneuvers including Lane Keeping (LK), Lane Changing to Left (LCL), and Lane Changing to Right (LCR) are modeled as output of the model. As inputs, 24 variables affecting drivers decisions are considered. In general, the states of the ego-vehicle (position, speed, acceleration, steering wheel angle, etc.), information about surrounding vehicles, traffic signals, and traffic information are used as input.

A. Methodology

1) Fuzzy Logic: Fuzzy Logic (FL) is a popular approach used for modeling vagueness introducing many-valued logic. 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 [20]. Common fuzzy sets are based on triangular, trapezoidal, or Gaussian membership functions [21]. In this contribution, trapezoidal membership function is used to convert the signal data to membership degrees, the output of FL is a vector which contain all membership degrees of signals.

As shown in Fig. 2 core and support parameters of each membership function (MF) are unknown and defined as design parameters, which can be determined through a fuzzy density clustering method [16] [17] called "Fuzzy Neighborhood density-based spatial clustering of applications with noise (FN-DBSCAN)". Therefore, the membership functions for each variable of data set can be generated automatically.

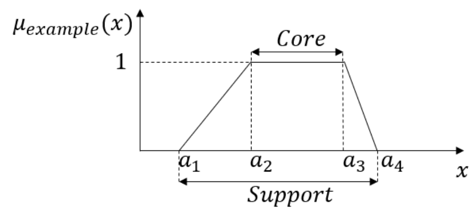


Fig. 2. Trapezoidal membership function defined by core (a_2, a_3) and support (a_1, a_4) parameters

2) Random Forest: Random Forest (RF) was firstly proposed by Breiman [18]. As an extension of decision tree method it is used to solve classification or regression problems. A decision tree poses a series of selection problems, and each final answer to these questions is represented by leaves. The structure of a decision tree is divided into several stages. Each non-leaf node represents a question that needs to be answered by making a decision between two or more selections. After each selection, the question of the next node becomes more specific. This process is considered as feature extraction, which are evaluated by each node and passed to one branch until finally the level is reached and thus a classification is determined. In this contribution, the driving intentions mainly consider lane changing. Decision trees have only three types of 'leaves' including LK, LCL, and LCR.

The algorithm RF contains a set of randomized decision trees, all the decision trees are independent from others. Each decision tree is trained by a randomly selected Bootstrap sample [19], which is generated from the training data set with replacement. After these decision trees are generated, the output result of the RF is obtained through the voting results of all relevant decision trees.

B. Fuzzy-RF approach

The driving intention recognition model based on fuzzy-RF is shown in Fig. 3. It consists of two important processes: off-line training phase and on-line test phase, which are described in the following sub-sections.

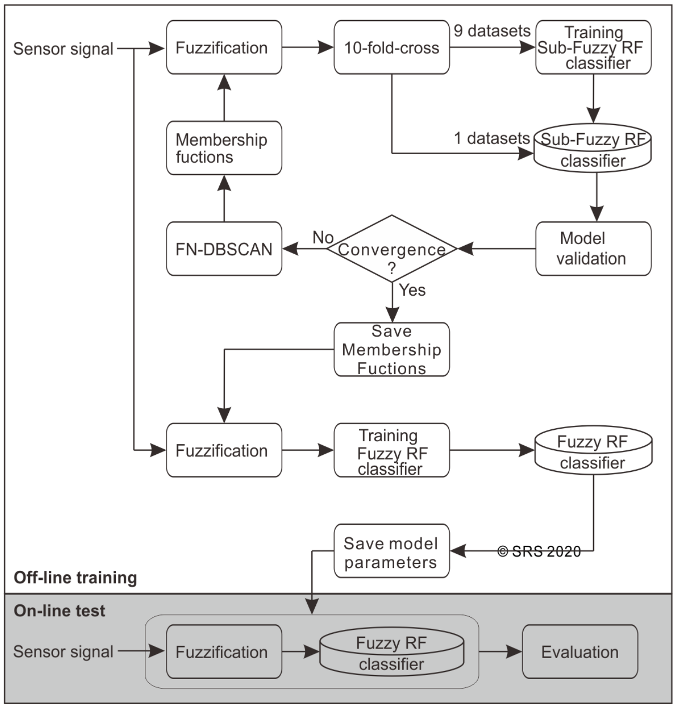


Fig. 3. Flow chart of off-line training and on-line test of fuzzy-RF model

1) Off-line training: The main goal of this part is to establish a driving intention recognition model based on fuzzy-RF approach. As shown in Fig. 3, the first step to train the model is to generate suitable membership functions. Then signal data measured from driving simulator can be fuzzified based on optimal membership functions. After fuzzification process a fuzzy-RF classifier can be trained using fuzzy data.

As previously stated, membership functions of fuzzy logic are generated by FN-DBSCAN method. Afterwards, signal data are fuzzified to train a RF classifier. To verify membership functions and fuzzy RF classifier, data used for training and for validation should be different and both datasets must contain different lane changing intentions. Therefore, the 10-fold-Cross-Validation [22] technique is applied. This method divides a dataset into 10 sub-datasets. For each time one sub-dataset will be selected for validation, and other sub-datasets for sub-model training. This process will be repeated 10 times until all the sub-dataset have been selected for validation.

Membership functions are saved if fuzzy RF models is sufficient to recognize driving intentions. Otherwise, process of generating membership functions and data fuzzification should be repeated. Finally fuzzy-RF models are trained with the whole training data and the selected membership functions and saved for driving intention recognition in real time.

2) On-line test: During the on-line test phase, the most possible driving intentions will be calculated and saved in real time. Through the comparison between the calculated driving intentions and the actual driving behaviors, the veracity of the prediction could be evaluated.

III. Description of Scenarios and Data Collected

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, Germany

The scenario used in this study is a two-way highway, each consisting of three lanes. Normal daytime weather (without rain, snow, storm etc) condition is implemented in the scenario. Besides ego vehicle driver, other interacting vehicles are introduced intermittently such that ego vehicle driver would accelerate, decelerate, maintain relative speed, and change lanes to left or right as determined by driving rules in Germany. This requires driving on right lane unless overtaking or having approximately the same pace as other vehicles present in other lanes. In addition, while on right lane, when ego-vehicle speed is higher than a lead vehicle driver can change lanes to left, overtake and return to right lane. In the case the driver intends to turn right and exit highway, the driver can only stay behind lead vehicle on the right lane and maintain current speed.

Data describing ego vehicle dynamics (e.g. speed, steering angles etc.) and surrounding interacting vehicles status (e.g. time to collision (TTC), speed) relative to ego vehicle are collected to predict ego-vehicle intention. The presented intention recognition algorithm uses the collected data to predict driver intentions continually online.

IV. Application of the New Approach

The purpose of the proposed approach is to recognize the driving intentions in real time. In the training phase, not only the related models are established, the correctness and the performance of the models are evaluated in the meantime. Totally 8 participants were recruited, they all held valid driving licenses and were asked to drive about 25 minutes for off-line training phase.

A. Input selection

Driver's driving behaviors depend on the current environment conditions and the individual driver's characteristics. On the highway, the relationships between the ego vehicle and other surrounding vehicles are the main factors effecting the decision making of the driver. In this contribution, the feasibility of data collection must be considered while defining input parameters. As shown in Table I, in total 24 variables are selected as inputs. It can be found that some input types are integers, e.g. values of current lane number denote the codes of lane in the simulation. Indicator values describe the indicators states, the values 0/1/2 stand for none/left/right indicator blinking respectively. Gearbox signal thresholds indicate the engaged gear. Other remaining inputs are real values and need to consider fuzzification. Inputs with the same nature are categorized into a category, such as distances to other vehicles, velocity of other vehicles, and time to collision (TTC) to other vehicles. Therefore, selected inputs are divided into 6 general types of categories: velocity of ego-vehicle, velocity of other vehicles, distance to other vehicles, TTC to other vehicles, ego-vehicle angle, and steering wheel angle. For each category a set of membership functions will be generated in the training phase.

B. Labeling

To label the data as intentions, the signal data need to be classified and processed. The intentions 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, the lane changing behavior at time t_{lane} can be recognized when the value of lane i is changed. The variable t_{lane} denotes the end time of the lane changing.

In the previous work [15], the starting time of lane changing maneuver was determined by the moment of turning on lights indicates $t_{indicator}$. The interval between the beginning of lane changing $t_{indicator}$ to the completion of lane changing t_{lane} is the total required time for the lane changing intention defined as t_{change}. When the drivers change the lane without turning signals, the average value of all t_{change} will be used to determine the lane changing behavior. To analyze the impact on the intention recognition, different values like 2 s, 2.5 s, and 3 s are selected as the preset t_{change}. The results show that the earliest lane changing can be predicted by using 3 s as the preset t_{change}, and considering 2.5 s as t_{change} the obtained results are closest to the actual labels. Therefore, a fix time of 2.5 s is considered as a reference to study lane changing intentions. In this contribution, a novel parameter of "difference between road angle and heading angle of ego-vehicle" is applied to define the starting time of lane changing. Relative angle between road and ego-vehicle has a significant deviation during the lane changing process. The values of relative angle will be decreased or increased to its minimum or maximum values, when the drivers change the lanes to left or right. By analyzing the values of this parameter at the time of lane changing, three values like 0.05 °, 0.2 °, and 0.5 ° are set as relative angle thresholds to train the model and then to analyze the impact on the intention recognition. Therefore, the four mentioned definitions of class label are implemented to establish four models (three models based on relative angle and one model based on 2.5 s of t_{change}) in the experiment, details are shown in Table II. Afterward, results of four models for each driver are evaluate and finally established models are applied for on-line phase.

TABLE I
DESCRIPTIONS OF SELECTED INPUTS

Input	Definition	Range	Unit	Data type
Category #1				
v_{ego}	Velocity of ego vehicle	[0 220]	km/h	Real
Category #2				
v_f	Velocity of vehicle in front	[0 220]	km/h	Real
v_{fl}	Velocity of vehicle in left-front	[0 220]	km/h	Real
v_{fr}	Velocity of vehicle in right-front	[0 220]	km/h	Real
v_{bl}	Velocity of vehicle left-behind	[0 220]	km/h	Real
v_{br}	Velocity of vehicle right-behind	[0 220]	km/h	Real
v_b	Velocity of vehicle behind	[0 220]	km/h	Real
Category #3				
d_f	Distance to vehicle in front	[0 250]	m	Real
d_{fl}	Distance to vehicle in left-front	[0 250]	m	Real
d_{fr}	Distance to vehicle in right-front	[0 250]	m	Real
d_{bl}	Distance to vehicle left-behind	[0 250]	m	Real
d_{br}	Distance to vehicle right-behind	[0 250]	m	Real
d_b	Distance to vehicle behind	[0 250]	m	Real
Category #4				
TTC_f	TTC to vehicle in front	[0 12]	s	Real
TTC_{fl}	TTC to vehicle in left-front	[0 12]	s	Real
TTC_{fr}	TTC to vehicle in right-front	[0 12]	s	Real
TTC_{bl}	TTC to vehicle left-behind	[0 12]	s	Real
TTC_{br}	TTC to vehicle right-behind	[0 12]	s	Real
TTC_b	TTC to vehicle behind	[0 12]	s	Real
Category #5				
α	Heading angle of ego-vehicle	[-3.14 3.14]	rad	Real
Category #6				
S	Steering wheel angle	[-3.14 3.14]	rad	Real
Category #7: Fuzzification is not necessary				
Ln	Current lane number	[1, 2]	-	Integer
I	Indicator	[0, 1, 2]	-	Integer
G	Gearbox	[1, ...5]	-	Integer

TABLE II
DRIVING INTENTION RECOGNITION MODELS

Model number	Parameter	Threshold
M1	Classifier labeled with relative angle	0.05 °
M2		0.2 °
M3		0.5 °
M4	Classifier labeled with t_{change}	2.5 s

C. Validation (off-line)

To verify the effectiveness of the obtained models, evaluation measures such as accuracy (ACC), detection rate (DR, i.e. sensitivity), and false-alarm rates (FAR) are selected to evaluate the efficiency of the fuzzy-approach. By comparing the degree of coincidence between the actual and the estimated driving intention at each moment, the values of ACC, DR, and FAR can be calculated through the well-known formulas (cf. [23]).

The aim of off-line training is to generate suitable membership functions according to data density. As shown in Table III, differences between drivers experiences are represented through the different number of membership functions. Using these automatically generated membership functions, four types of fuzzy-RF models are implemented to discuss the influences of the labeling design. By comparing the actual and estimated driving intentions, the percentages of the ACC, DR, and FAR of each group are calculated.

TABLE III
NUMBER OF AUTOMATICALLY GENERATED MEMBERSHIP FUNCTIONS

Driver \ Category	#1	#2	#3	#4	#5	#6
D1	7	7	22	5	4	9
D2	2	15	37	1	4	7
D3	1	80	227	2	30	6
D4	1	34	143	6	32	6
D5	1	34	33	11	42	10
D6	1	6	2	1	55	7
D7	2	5	70	1	45	10
D8	1	5	43	6	49	6

The 10-fold-cross validation result can be observed from the boxplot of ACC, DR, and FAR based on four classifiers for 8 drivers (Fig. 5), each box represents a distribution of metrics for 8 drivers. The values of ACC and DR for all models are above 98 % and 92 % respectively. The FAR values are smaller than 4 %. In addition, the worst results (ACC: 98.4 %, DR: 92.5 %, FAR: 3.9 %) are for driver 2 with classifier labeled with threshold 0.05 °, which are plotted as individual points. Therefore, it can be concluded that the generated membership functions are suitable for fuzzification process. As shown the Fig. 5, the results from the proposed definition is matching the results of the reference definition (model M4) from the previous study [15]. In next step, two models are selected for the on-line test phase. In this contribution. the new definition is the focus of discussion, therefore the maximum and minimum thresholds of angle difference are selected for on-line test phase.

D. Evaluation (on-line)

The proposed fuzzy-RF approach is based on individualized trained models. According to off-line results, two models based on labeling with thresholds of 0.05 ° and 0.5 ° are selected to establish on-line intention recognition models. Suitable membership functions and the corresponding fuzzy-RF models for each test driver are already calculated in the training phase. Based on these models, the driving intentions in the upcoming driving processes could be determined.

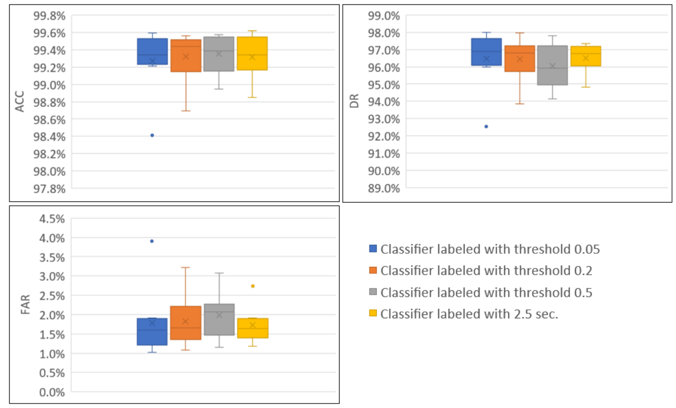


Fig. 5. 10-fold-Cross-Validation - Boxplot of ACC, DR, and FAR for 8 drivers

After training data collection and model training, the drivers were required to drive twice for each on-line model separately, each time is about 10 minutes and was realized in different driving scenarios. The estimated intentions will be calculated on-line and saved for evaluation.

TABLE IV
ONLINE TEST - AVERAGE ACC, DR, AND FAR FOR 8 TEST DRIVERS

Driver	ACC %		DR %		FAR %	
	M1	M3	M1	M3	M1	M3
D1	92.9	**93.6**	**73.9**	71.2	**13.7**	15.0
D2	97.2	97.2	81.0	81.0	9.8	9.8
D3	94.9	94.9	68.2	68.2	16.5	16.5
D4	91.8	**94.6**	73.0	**73.8**	14.1	**13.5**
D5	**99.5**	99.3	97.6	**98.8**	1.2	**0.8**
D6	97.2	**97.3**	77.6	**87.2**	15.7	**7.6**
D7	91.3	**93.6**	60.3	**66.6**	19.8	**17.1**
D8	95.5	**96.2**	**70.8**	67.7	**14.7**	16.4
Average	95.0	**95.8**	75.3	**76.8**	13.2	**12.1**

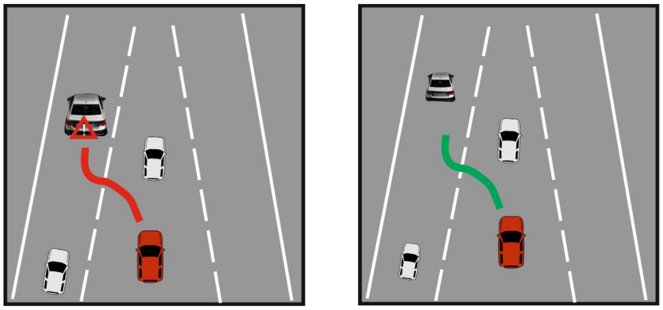
The measured and estimated driving intentions are compared to check the correspondence. The average values of the evaluation measures (ACC, DR, FAR) of the both models for 8 drivers are shown in Table IV, bold values indicate better results.

For all drivers, the average ACC for model M1 (labeled with 0.05 °) and model M3 (labeled with 0.5 °) are above 91 % and 93 % respectively. Except for two cases including driver 1 and driver 8, the performance of the model M3 for other drivers are better than the model M1. It can be stated that driving intentions can be recognized successfully based on the proposed fuzzy-RF approach and the new definition of class label.

In addition, it can also be found that the percentages of DR and FAR of on-line test are worse in comparison to off-line validation. This can be possibly explained by individual habits and mental conditions of drivers in relation to different driving scenarios.

E. Application samples in driving simulator

The estimated intentions could be used in the next step of this research as input to generate suggestions for drivers. For



(a) Warning: lane change to left (b) Suggestion: lane change to left

Fig. 6. Visual warning and suggestion on controlpad

example if estimated intention is lane change left and the left-front and left-behind vehicles are within critical proximity (e.g. TTC $< 3\ s$), then the driver would be warned not to change lane as illustrated in Fig. 6(a). Otherwise if intended lane change is safe, then driver should be encouraged to do so as illustrated in Fig. 6(b).

V. SUMMARY AND OUTLOOK

In this contribution, a driving intention recognition model was developed based on a new fuzzy-RF approach. Three different driving maneuvers including left/right lane change (LCL/LCR) and lane keeping (LK) are modeled for classification, and simulated on a highway scene using driving simulator.

To improve the recognition performance of the proposed approach, membership functions are applied to quantify input signal data into fuzzy sets for RF training. The design parameters of membership functions can be generated automatically by a fuzzy density clustering method. Unlike the previous works, a novel parameter of "difference between road angle and heading angle of ego-vehicle" is applied to redefine lane changing intentions. Three fix values ($0.05\ °$, $0.2\ °$, and $0.5\ °$) are used as different angle thresholds to label the classification. Their impacts on the intention recognition are discussed. A classification model labeled with $t_{change} = 2.5$ is trained as reference. Based on data achieved from 8 different drivers the proposed approach is validated. From the obtained results it can be stated that all ACC values of off-line training phase are larger than 98 %. The new labeling definition shows a very close performance to the reference definition. Finally, the angle thresholds ($0.05\ °$ and $0.5\ °$) are selected for on-line test, and the ACC of the both models are larger than 91 % and 93 % respectively. The effectiveness of driving intention recognition has been successfully proved in this contribution. The online examination will be related to warnings or more detailed to suggestions regarding lane changes. This can be realized by using a suitably defined interface.

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