Rule-Based Highway Maneuver Intention Recognition

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***Abstract*— Future advanced driver assistance systems or fully automated driving systems require an increased ability to classify and interpret traffic situations in order to appropriately account for, and react to, the behavior of surroundings vehicles. When driving on a highway, humans are able to recognize the maneuver intentions of surrounding vehicles by observing lateral and longitudinal motion cues. The main idea presented in this paper is to adapt this ability to technical systems by formulating simple logic rules for intention recognition of highway maneuvers. As such, the presented algorithm is able to recognize the intention of left and right lane change maneuvers with an accuracy of approximately 89 % while maintaining the false positive rate low at approximately 3 %. Further, due to the algorithm's low computational complexity, flexibility, and straight-forward design based on easily comprehensible logic rules, the proposed method fulfills the requirements of future advanced driver assistance systems or fully automated driving systems.**

I. INTRODUCTION

Within the automotive industry, the area of active safety has quickly evolved during the last decades. In many vehicles, Advanced Driver Assistance Systems (ADAS) such as Adaptive Cruise Control (ACC), Lane Keeping Aid (LKA), and parking assistance systems are now standard. These systems aid the driver in difficult and tedious tasks in order to increase traffic safety and personal comfort. Since a substantial percentage of traffic accidents and fatalities on highways is related to human errors, it is expected that the introduction of ADAS or fully automated driving systems, which are capable of assisting the driver in highway maneuvers or even autonomously perform highway driving, will further increase traffic safety by reducing the impact of human errors [1]-[2].

In order to further develop ADAS functionality and eventually progress to fully automated driving systems, it is crucial that the intelligent vehicle system has the ability of scene understanding and interpretation. Or in other words, the intelligent vehicle system must posses the capability of predicting the behavior intention of surrounding vehicles. In highway driving, a challenge within scene interpretation is the intention recognition of principal driving behaviors such as stay in the current lane and change lane either to the left or to the right. The considered maneuver intention recognition problem can thus be formulated as follows: *given that a vehicle drives on a highway, determine whether the vehicle intends to stay in the current lane or change lane to either the left or to the right.* The recognition of these maneuver intentions could for instance increase the ability of ACC systems since it creates the possibility of early detection of cut-in vehicles. Further, it can be utilized by other ADAS to assess the risk of the current traffic situation, or as an input to an intelligent vehicle system for automated highway driving in order to allow the system to account for, and adapt to, the surrounding vehicles when planning its behavior.

In the literature, the term intention prediction can have several interpretations and different terminologies such as behavior prediction/recognition/identification, situation assessment/prediction, intention prediction/estimation have been used to qualify the same type of problem for which various research have been presented [3]-[5]. Common methods include, but are not limited to, Support Vector Machines (SVM) [6], Artificial Neural Networks (ANN) [7]-[8], Bayesian Networks (BN) [9], Bayes Classifier (BC) [10]-[11], and Case-Based Reasoning (CBR) [12]-[13].

The above approaches have been shown to predict lane change maneuvers on highways approximately 2 s prior to their occurrence. For instance, in [3] the proposed solution is able to predict lane change maneuvers 2 s in advance. In [6], the presented result demonstrates the ability of the proposed approach to recognize lane change intention on average 1.3 s in advance, with a maximum prediction horizon of 3.29 s. In [7], it is reported that the proposed system solution can predict lane change maneuvers up to 1.5 s prior to their occurrence in experimental test drives. In [8], test results using driving simulator data show that the proposed solution has the ability to predict lane change maneuvers at a 1-2 s prediction horizon. In [12], a prediction accuracy of 79 % is reported for the detection of vehicles on adjacent lanes cutting into the lane of the host vehicle in average 2.3 s before the situation terminates, i.e. when the cut-in vehicle is positioned within the host vehicle's lane. In [13] experiments regarding lane change prediction in different highway scenarios show that the proposed solution can predict lane change maneuvers 2 s in advance.

The National Highway Traffic Safety Administration (NHTSA) reports that it takes on average 1.5 s from the initiation of a lane change maneuver until the vehicle has crossed the lane markings and entered into the adjacent lane [14]. Hence, it is very advantageous if a system for lane change intention recognition identifies the intention of a vehicle to change lane at least 1.5 s prior to the maneuver occurrence. Although the above mentioned approaches meet this requirement and have the ability to predict lane change maneuvers on highways approximately 2 s prior to their

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978-1-4673-6596-3/15 $31.00 © 2015 IEEE
DOI 10.1109/ITSC.2015.159

occurrence, many of the proposed approaches rely on training data for feature recognition, on-line learning, or suffer from high computationally complexity, rendering them difficult to verify or inappropriate for real-time implementation on a vehicle platform.

To reduce the need of training data and computational resources, in this paper the problem of maneuver intention recognition is considered by a simple rule-based system. Rule-based systems have the advantage of traceability and ease of implementation, and provide a clear overview and understanding of the system model. A rule-based system also provides a natural representation of highway driving behavior since highways are structured environments with relatively simple and easily maintainable traffic rules. As such, the rule-based system takes into consideration both lateral and longitudinal motion cues for maneuver intention recognition. The lateral motion cues include the lateral velocity and position in relation to the road, i.e. distance to the left and right lane boundaries, while the longitudinal motion cues are related to the preceding vehicle in the current lane expressed by the relative velocity, time gap (TG), and time-to-collision (TTC).

The remainder of the paper is organized as follows: in Section II the proposed maneuver intention recognition algorithm is presented, while Section III presents the traffic data simulator which is used to obtain the simulation results presented in Section IV. Finally, conclusions are stated in Section V.

II. MANEUVER INTENTION RECOGNITION

When driving on a highway e.g. as illustrated in Fig. 1, at each time instance a driver must determine whether he/she should stay in the current lane, or change lane either to the left or to the right. Depending on which maneuver the driver decides to execute, he/she adapts his/hers driving behavior to the surrounding vehicles in different ways. For instance, if the driver decides to stay in the current lane, he/she should adapt the vehicle's velocity to the velocity of the preceding vehicle and maintain a lateral course which will keep the vehicle in the lane. If the driver decides to change lane to the left or to the right, he/she should adapt the vehicle's velocity to both the velocity of the preceding vehicle in the current lane and the velocity of the vehicles in the adjacent lane, while performing a lateral movement into the adjacent lane. As such, which maneuver the driver intends to perform can be recognized by observing cues in both the lateral and longitudinal vehicle motion.

A. Lateral intention cues

In order to change lane, the driver must perform a lateral movement into the adjacent target lane. As such, lateral motion cues for lane change intention recognition include the lateral velocity, and the lateral position relative to the lane boundaries. For a left lane change, the lateral motion cues can thereby be expressed as

$$LCL_{vqy} = v_y \geq \alpha, \tag{1a}$$
$$LCL_{pqy} = y \geq y_L - \beta w, \tag{1b}$$

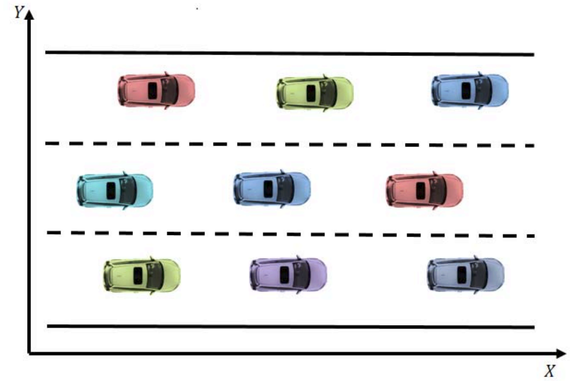

Fig. 1: Vehicles driving on a three lane highway.

where LCL_{vqy} and LCL_{pqy} respectively denotes a lateral velocity and position cue for a left lane change, v_y and y respectively denotes the lateral velocity and position of the vehicle, y_L and w respectively denotes the left lane boundary and width of the current lane, and α and β are positive scaling parameters.

Similarly, for a right lane change, the lateral motion cues can be expressed as

$$LCR_{vqy} = v_y \leq -\alpha, \tag{2a}$$
$$LCR_{pqy} = y \leq y_R + \beta w, \tag{2b}$$

where LCR_{vqy} and LCR_{pqy} respectively denotes a lateral velocity and position cue for a right lane change, and y_R denotes the right lane boundary of the current lane.

B. Longitudinal intention cues

In right-hand traffic, vehicles normally drive at a higher velocity in the left lanes. Hence, if a driver decides to change lane to the left, he/she could be expected to drive at a higher velocity than if he/she would have decided to stay in the current lane. As such, the relative velocity, TG, and TTC (7) to the preceding vehicle in the current lane are motion cues for left lane change maneuver intention. For a left lane change, the longitudinal motion cues can thereby be expressed as

$$LCL_{aqx} = a_x \geq \kappa, \tag{3a}$$
$$LCL_{vqx} = v_{x_{\text{rel}}} \leq \gamma, \tag{3b}$$
$$LCL_{TTCqx} = (TTC \leq \varsigma) \wedge (v_{x_{\text{rel}}} < 0), \tag{3c}$$
$$LCL_{TGqx} = TG \leq \xi, \tag{3d}$$

where $\wedge$ is the logic AND operator, LCL_{aqx} and LCL_{vqx} respectively denotes a longitudinal acceleration and velocity cue for a left lane change, LCL_{TTCqx} and LCL_{TGqx} respectively denotes a TTC and TG cue for a left lane change, TTC, TG, and $v_{x_{\text{rel}}}$ respectively denotes the time-to-collision, time gap, and relative longitudinal velocity to the vehicle's preceding vehicle in the current lane, a_x denotes the vehicle's longitudinal acceleration, and κ, γ, ς and ξ are scaling parameters.

TABLE I: Summary statistics of the Interstate 80 data set.

Traffic state	Time period	Traffic flow [vph]	Average velocity [m/s]
Transition	4.00 - 4.15 P.M.	8144	9.92
Congestion	5.00 - 5.15 P.M.	7288	8.34
Congestion	5.15 - 5.30 P.M.	7048	7.78

C. *Rule-based maneuver intention recognition algorithm*

Utilizing the lateral and longitudinal motion cues presented in Section II-A-II-B, a rule-based maneuver intention recognition algorithm can determine whether a vehicle is likely to either stay in the current lane or change lane to either the left or to the right depending on whether the vehicle exhibits the lateral and longitudinal motion cues which corresponds to each maneuver. In order to intuitively model the ability to predict a left lane change maneuver by distinguishing the corresponding motion cues, a left lane change maneuver intention can be recognized as

$$\begin{aligned} LCL_I =& (LCL_{vqy} \wedge LCL_{pqy}) \vee \\ & (LCL_{qx} \wedge (LCL_{pqy} \vee LCL_{vqy})), \end{aligned} \tag{4}$$

where $\vee$ is the logic OR operator, and LCL_{qx} is the longitudinal motion cues for a left lane change combined as

$$\begin{aligned} LCL_{qx} =& LCL_{TTCqx} \vee \\ & (LCL_{aqx} \wedge (LCL_{vqx} \vee LCL_{TGqx})). \end{aligned} \tag{5}$$

Similarly, a right lane change intention can be recognized as

$$LCR_I = LCR_{vqy} \wedge LCR_{pqy}. \tag{6}$$

Finally, if neither a left nor a right lane change intention is recognized, the vehicle is expected to stay in the current lane.

Remark 1: In the maneuver intention recognition algorithm (4), (6), it is assumed that the lane boundaries, lane width, lateral position and velocity, longitudinal acceleration, relative longitudinal velocity, TG, and TTC are estimated from a sensor system e.g. [15]. Hence, the more accurate information from the assumed sensor system the more accurate maneuver intention recognition.

III. TRAFFIC DATA SIMULATOR

As a realistic traffic simulator, the NGSIM Interstate 80 data set provided by the Federal Highway Administration's NGSIM project is used [16]. The NGSIM Interstate 80 data set is an open-source data set collected from a segment of Interstate 80 in San Francisco, California, USA, which includes vehicle trajectories e.g. lane ID, the longitudinal and lateral position coordinates, longitudinal velocity and acceleration, and space and time headway, at a resolution of 10 frames/s. As shown in Fig. 2 the study segment of Interstate 80 is 502.92 m in length and consists of five highway lanes, one auxiliary lane, and one on-ramp. The data set contains a total of 45 minutes observed traffic, divided into three data subsets collected from 4.00 P.M. to 4.15 P.M., from 5.00 P.M. to 5.15 P.M., and from 5.15 P.M. to 5.30 P.M.

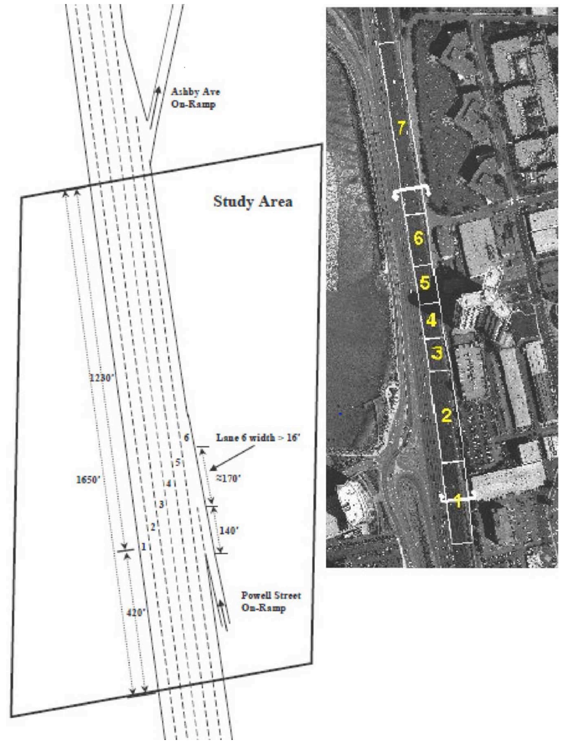

Fig. 2: The NGSIM Interstate 80 study segment [16].

on April 13, 2005. The data set thereby represent two traffic states, namely a transition period when traffic congestion is building up, i.e. 4.00 P.M. to 4.15 P.M, and two congested periods when traffic is congested, i.e. 5.00 P.M. to 5.30 P.M. In Table I, the aggregated mean velocity and traffic flow are shown for each data subset.

A. *Algorithm input variables*

As described in Section II, the maneuver intention recognition algorithm is based on lateral and longitudinal motion cues. In order to obtain these cues, the lane boundaries, lane width, lateral velocity, relative longitudinal velocity, and TTC must be estimated from the Interstate 80 data set, while the lateral position, longitudinal velocity and acceleration, and time and space headway can be obtained directly from the considered data set.

The lane boundaries are estimated as the mean of the lateral position interval over which the assigned lane ID is altered when the vehicles change lane. The estimated lane boundaries are further used to estimate each lane width. The lateral velocity is estimated from the lateral position coordinate as the mean deviation in lateral position over an observed time interval e.g. 1 s. Similarly, the relative longitudinal velocity is estimated as the mean deviation in the space headway over an observed time interval e.g. 1 s. The estimated relative longitudinal velocity is further used to estimate the TTC as

$$TTC = \frac{h_x}{|v_{x_{\text{rel}}}|}, \tag{7}$$

where h_x denotes the space headway.

TABLE II: General confusion matrix.

		Actual	
		Presence	Absence
Predicted	Presence	a	b
	Absence	c	d

TABLE III: Confusion matrix parameters for the left lane change maneuver.

	1 s	2 s	3 s	4 s	5 s
LCL_a	1057	454	145	75	50
LCL_b	2599	3147	3400	3431	3423
LCL_c	126	709	983	1033	1025
LCL_d	99543	97571	96045	94870	93776

TABLE IV: Confusion matrix parameters for the right lane change maneuver.

	1 s	2 s	3 s	4 s	5 s
LCR_a	317	144	52	33	23
LCR_b	565	719	798	803	799
LCR_c	73	235	324	334	334
LCR_d	100283	97881	96138	94912	93803

TABLE V: Confusion matrix parameters for the stay in the current lane maneuver.

	1 s	2 s	3 s	4 s	5 s
SIL_a	99226	97427	95993	94837	93753
SIL_b	196	925	1284	1349	1336
SIL_c	3161	3847	4175	4216	4199
SIL_d	1374	598	197	108	73

IV. SIMULATION RESULTS

To evaluate the capability of the maneuver intention recognition algorithm, it is applied to the NGSIM Interstate 80 data set traffic simulator described in Section III. Table II shows a general confusion matrix which is used to summarize the performance of the maneuver intention recognition algorithm by crosstabulate the observed and predicted presence/absence patterns for each of the considered maneuvers. Maneuver presence means that the maneuver is either predicted to occur or actually occurred. Maneuver absence means that the maneuver is neither predicted to occur nor actually occurred. For instance, predicted absence of a left lane change maneuver means that the vehicle is predicted to either stay in the current lane or change lane to the right.

In Tables III-V the confusion matrix parameter values, i.e. a, b, c, and d of the maneuver intention recognition algorithm for the three considered maneuvers, i.e. left lane change, right lane change, and stay in the current lane are given. Note that all the data values are given as counts and not percentages. The vehicle data is identified from the NGSIM Interstate 80 data set in 1 s intervals, i.e. at every 1 s the data is sampled and the maneuver intention recognition algorithm is applied to determine if the vehicle intends to stay in the current lane or perform a lane change maneuver either to the left or to the right. To investigate the ability of the algorithm to correctly recognize the maneuver intentions prior to their occurrence, at each sample instance the lane ID of each vehicle is checked over a future time horizon of 1 s, 2 s, 3 s, 4 s, and 5 s respectively, in order to observe which maneuver each vehicle actually will perform. If the lane ID changes within the considered time horizon, a lane change maneuver is considered to occur, else the vehicle is considered to stay in the current lane.

From the confusion matrix, a variety of error and accuracy measures can be calculated [17]. For the purpose of illustrating the ability of the maneuver intention recognition algorithm to recognize the left lane change, right lane change, and stay in the current lane maneuvers, two interesting measures are the sensitivity and the false positive rate. Sensitivity is the conditional probability that maneuver M is correctly classified, i.e. $p(M_{\text{predicted}}|M_{\text{actual}})$. Utilizing the confusion matrix, the sensitivity is thus calculated as

$$\text{sensitivity} = \frac{a}{a+c}. \tag{8}$$

The false positive rate is the probability that maneuver M is wrongly predicted, i.e. that maneuver M is predicted to occur although it does not actually occur. It is calculated from the confusion matrix as

$$\text{false positive rate} = \frac{b}{b+d}. \tag{9}$$

Figs. 3-5 respectively shows the sensitivity and the false positive rate for the left lane change, right lane change, and stay in the current lane maneuvers. In Fig. 3 it can be seen that the maneuver intention recognition algorithm is able to recognize a left lane change maneuver 1 s prior to its occurrence with an accuracy of 89 %. For intention recognition 2 s prior to the maneuver occurrence, the accuracy decreases to 39 %, and it continues to decrease as the prediction horizon increase. Fig. 3 also shows that the false positive rate is quite low. Starting at 2.5 % 1 s prior to the left lane change maneuver occurrence, it only increases slightly to 3.5 % for a 5 s prediction horizon.

Regarding right lane change maneuvers, in Fig. 4 it can be seen that the maneuver intention recognition algorithm is able to recognize a right lane change maneuver 1 s prior to its occurrence with an accuracy of 81 %. For intention recognition 2 s prior to the maneuver occurrence, the accuracy decreases to 38 %, and it continues to decrease as the prediction horizon increase. As in the case of left lane change maneuvers, Fig. 4 also shows that the false positive rate is low. Starting at 0.6 % 1 s prior to the occurrence of the right lane change maneuver, it only increases slightly to 0.8 % for a 5 s prediction horizon.

When a vehicle is neither predicted to change lane to the left nor to the right, it is predicted to stay in the current lane. From Fig. 5 it can be seen that the maneuver intention recognition algorithm is able to recognize the intention to stay in the current lane with high accuracy for the entire prediction horizon. At 1 s prior to the maneuver occurrence the accuracy of the maneuver intention recognition algorithm is 97 % which only decreases slightly to 96 % 5 s prior to

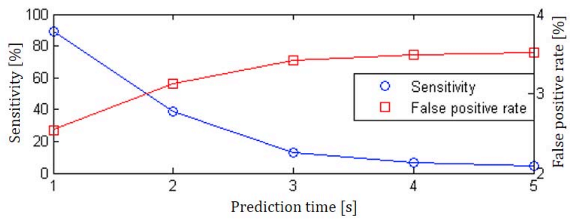

Fig. 3: The sensitivity and the false positive rate for the left lane change maneuver.

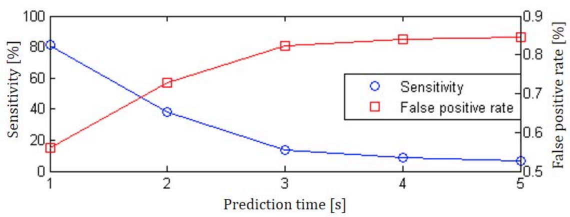

Fig. 4: The sensitivity and the false positive rate for the right lane change maneuver.

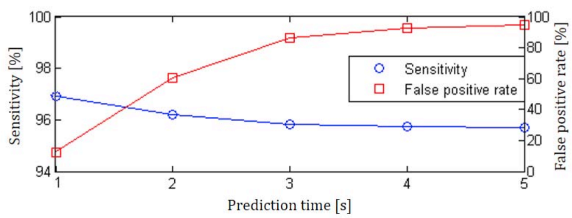

Fig. 5: The sensitivity and the false positive rate for the stay in the current lane maneuver.

the maneuver occurrence. In difference to the left and right lane change maneuvers, Fig. 5 shows that the false positive rate is high. Starting at 12 % 1 s prior to the maneuver occurrence, it increases to 95 % for a 5 s prediction horizon. This result corresponds with the low sensitivity value for accurately recognize left and right lane change maneuvers long before their occurrence.

In the results presented in Tables III-V and Figs. 3-5, the on-ramp vehicles have been excluded from the NGSIM Interstate 80 data set. Since vehicles driving on the on-ramp must perform a left lane change maneuver in order to reach the auxiliary lane, their maneuver intention is quite clear. Hence, if it is known that a vehicle is driving on an on-ramp it can be assumed to reach the auxiliary lane. However, if it is unknown that certain vehicles are driving on an on-ramp their maneuver intention needs to be recognized.

Table VI show the confusion matrix parameter values of the maneuver intention recognition algorithm for the left lane change maneuver when the on-ramp vehicles are included. The confusion matrix parameter values are only shown for the left lane change maneuver since the on-ramp vehicles primarily affect the intention recognition of this particular maneuver. In Fig. 6 the sensitivity and the false positive rate for the left lane change maneuver when the on-ramp vehicles are included are shown. Similarly to the case when the on-ramp vehicles are not included as shown in Fig. 3, it can

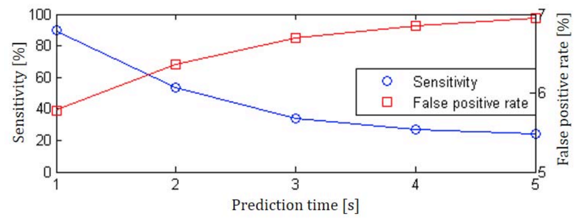

Fig. 6: The sensitivity and the false positive rate for the left lane change maneuver when the on-ramp vehicles are included.

TABLE VI: Confusion matrix parameters for the left lane change maneuver when the on-ramp vehicles are included.

	1 s	2 s	3 s	4 s	5 s
LCL_a	1987	1175	727	573	515
LCL_b	8513	9240	9607	9703	9711
LCL_c	230	1022	1435	1567	1591
LCL_d	138728	135962	133711	131856	130135

be seen that the maneuver intention recognition algorithm is able to recognize a left lane change maneuver 1 s prior to its occurrence with an accuracy of 89 %. However, when comparing the accuracy of intention recognition 2-5 s prior to the maneuver occurrence, it can be seen that the accuracy is higher when the on-ramp vehicles are included. For 2 s prior to the maneuver occurrence, the intention recognition accuracy is 53 % in contrast to the 39 % accuracy in the case when the on-ramp vehicles are not included. As the prediction horizon increases to 5 s the intention recognition accuracy decreases to 24 % when the on-ramp vehicles are included in comparison to 5 % when they are not included. When comparing the false positive rate, it can be seen that it is slightly higher when the on-ramp vehicles are included. However, as shown in Fig. 6 it is still quite low, starting at 6 % 1 s prior to the occurrence of the left lane change maneuver, it only increases slightly to 7 % for a 5 s prediction horizon.

In addition to the data input mentioned in Remark 1, the performance of the maneuver intention recognition algorithm is affected by the parameter values for the lateral and longitudinal motion cues (1)-(3) given in Table VII. These values are selected through tuning in order to get high sensitivity and low false positive rate for the maneuver intention recognition. However, different sets of parameters will result in different performance rates. For the considered data set consisting of traffic conditions when congestion is building up and congestion, the lateral motion cues have a stronger impact on the algorithm's performance than the longitudinal motion cues. Hence, the algorithm's performance is mostly affected by changes in the design parameters concerning the lateral motion cues, i.e. α and β. To illustrate, in Table VIII the sensitivity and the false positive rate for the left lane change maneuver when the on-ramp vehicles are not included, are shown for three different sets of values on α and β including the values in Table VII. The maximal value of β is set to $1/2$ since this values corresponds to the vehicle being

TABLE VII: Parameter values for the lateral and longitudinal motion cues.

$\alpha = 0.03$ m/s	$\beta = 1/3$	$w = 3.5$ m	$\kappa = 0$ m/s^2
$\gamma = -2$ m/s	$\varsigma = 5$ s	$\xi = 0.5$ s	

TABLE VIII: The sensitivity and the false positive rate for the left lane change maneuver for three different sets of values on α and β. The sensitivity and the false positive rate values are respectively shown for a prediction horizon of [1, 2, 3, 4, 5] s.

Parameters	Sensitivity [%]	False positive rate [%]
$\alpha_1 = 0.05$ m/s $\beta_1 = 1/7$	[59, 8, 3, 2, 1]	[0.3, 0.9, 1, 1, 1]
$\alpha_2 = 0.03$ m/s $\beta_2 = 1/3$	[89, 39, 13, 7, 5]	[3, 3, 3, 3, 4]
$\alpha_3 = 0$ m/s $\beta_3 = 1/2$	[96, 85, 64, 52, 43]	[35, 35, 35, 36, 36]

positioned in the lane center, while the minimal value of β is set to $1/7$ which corresponds to the vehicle being positioned approximately 0.5 m from the lane boundary. The maximal and minimal values of α have been identified by analyzing the observed lateral velocities in the considered data set.

V. CONCLUSIONS

This paper presents a rule-based maneuver intention recognition algorithm which is able to determine whether a vehicle driving on a highway is likely to either stay in the current lane or change lane to the left or to the right. The publicly available NGSIM vehicle trajectory data set which consist of traffic conditions approaching congestion and congested traffic conditions is used for simulation testing. It is shown that the algorithm is able to recognize the intention of a left lane change maneuver 1 s prior to its occurrence with an accuracy of 89 %, and 2 s prior to the maneuver occurrence with an accuracy of 39 % while maintaining a low false positive rate of approximately 3 %. For the right lane change maneuver, the algorithm is able to recognize the maneuver intention with an accuracy of 81 % 1 s prior to its occurrence, and 2 s prior to the maneuver occurrence with an accuracy of 38 % while maintaining a low false positive rate of approximately 0.7 %.

Since the maneuver intention recognition algorithm relies on lateral and longitudinal motion cues, including the lateral velocity and position in relation to the road, i.e. distance to the left and right lane boundaries, and the relation to the preceding vehicle in the current lane, i.e. the relative velocity, time gap, and time-to-collision, the algorithm can not predict which maneuver a vehicle will perform until the vehicle indicates its maneuver intention by its motion. Hence, there is a trade-off between early detection and the false positive rate. Which performance that is preferable depends on the application, i.e. the advanced driver assistance system or fully automated driving system, that will utilize the prediction. Irrespective, the capability of the simple rule-based algorithm to recognize maneuver intentions is comparable to the state-of-the art, while the algorithm's low computational complexity, flexibility, and straight-forward design based on easily comprehensible logic rules, allows it to meet the requirement of future advanced driver assistance systems or fully automated driving systems.

In order to further increase the ability of the proposed maneuver intention recognition algorithm, future work includes incorporating rules for anticipatory behavior such as changing lane to allow highway entry and passing of faster moving vehicles, as well as lane change intention recognition based on adjustment to the velocity and nearby traffic gaps in the adjacent lanes. Further, efforts should be made towards a real-time vehicle implementation to evaluate the algorithm in real-world traffic scenarios.

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