2018 21st International Conference on Intelligent Transportation Systems (ITSC)
Maui, Hawaii, USA, November 4-7, 2018

Trajectory Prediction for Safety Critical Maneuvers in Automated Highway Driving

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Abstract— **Situation understanding and interpretation are one of the essential features for automated vehicles. To enable safe and comfortable driving, sensing the current situation is not sufficient, but accurately predicted trajectories of other traffic participants are required. The paper presents a novel trajectory prediction approach utilizing a combination of maneuver classification and probabilistic estimation of temporal properties with a model based trajectory representation. Probabilistic *time-to-lane-change* estimation is applied to gather information about the conditional distribution for the time of lane marking crossing. Lower tails of the distribution, which represent more critical lane change maneuvers, are utilized with a suitable prediction model to estimate appropriate trajectories. The three parts of the prediction framework are evaluated on the NGSIM data set. It shows, that based on a good performance of the maneuver prediction as well as the *time-to-lane-change* estimation, lane change trajectories with high accuracy can be predicted. In particular, the consideration of critical maneuver executions shows promising results and demonstrates its general applicability in real-world scenarios.**

I. INTRODUCTION

Safe and comfortable navigation through nowadays traffic is one of the critical challenges to realize the idea of automated driving. Before decisions about future maneuvers can be made and a trajectory can be planned a comprehensive understanding of the current traffic situation, its participants, and its prospective evolution is required. In this context, the future states of surrounding vehicles are key information for algorithms in the areas of decision making and trajectory planning. Only with reliable information an ego trajectory which fulfills all demands to safety and comfort can be planned. Since nowadays complete coverage with inter-vehicle communication technique cannot be guaranteed the prediction should entirely rest on information gathered by onboard perception.

According to [1] risky cut-in and overtaking maneuvers represent one of the leading causes of accidents on highways. Accurate prediction of future states especially during lane change maneuvers enables early adoption of the ego driving strategy to avoid critical situations and minimize the risk of collision. To achieve the former, the paper at hand presents a novel combination of a maneuver prediction approach and probabilistic *time-to-lane-change* information with a computationally efficient model based trajectory estimation approach. In the context of automated driving, not only the most probable future trajectory is of interest, but especially faster-executed maneuvers can induce strong deceleration and are thus of high risk for the ego vehicle. This risk is minimized considering lower quantiles of the estimated *time-to-lane-change* distribution in the trajectory prediction process (see Fig. 1).

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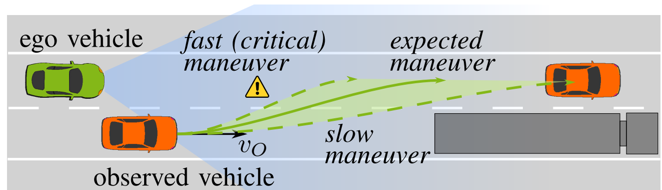


Fig. 1: Predicted safety critical trajectories with different quantiles of the conditional *time-to-lane-change* distribution.

II. STATE OF THE ART

Predicting upcoming maneuvers of nearby vehicles and their future trajectories in different traffic situations is a broad research topic in literature. Regarding maneuver prediction, the majority of available publications formulate the problem as a classification task, with a limited number of maneuvers in the considered scenario. Various machine learning techniques have been applied to address the problem of lane change prediction. Kumar et al. [2] propose a combination of a *Support-Vector-Machine* (SVM) and a *Bayesian Filter*. Another frequently investigated approach is the method of *Baysian Networks* [3], [4] as well as their dynamic extension [5]. Meyer-Delius et al. [6] apply *Hidden Markov Models* to the problem of lane change prediction and Krueger et al. [7] utilize neural networks. In the latter case, the problem is treated as time series analysis.

Following the overview in [8], the prediction of future trajectories for adjacent traffic participants can be divided into maneuver based and interaction based prediction approaches. The former first determines the most likely driving maneuver or intention and estimates a trajectory without considering the interaction with other vehicles. In [5] the authors combine *Dynamic Bayesian Networks* for behavior estimation with Bèzier curves as trajectory models. Schreier et al. [4] also utilize a *Bayesian Network* and couple it with individual trajectory distribution models for each maneuver. In [9] the authors propose a mixture of experts approach to combine *Gaussian Mixture Regression* with a *Random Decision Forest*. The *Decision Forest* is utilized to weight trajectory samples obtained from three regression models, which represent the classes lane change left, lane change right and lane keeping. In interaction based trajectory prediction the interplay between traffic participants is directly modeled. The authors of [10] combine a model-based interaction-aware intention estimation with a maneuver-based motion prediction on the basis of supervised learning to achieve better long-term prediction results. A slightly different approach is implemented by the authors of [11], where an over-approximation of future occupancy by other traffic participants is estimated. With such worst-case considerations safe driving space can be identified as non-occupied areas.

The novel approach presented in this paper implements a maneuver-based trajectory prediction with intention estimation. However, in contrast to approaches from literature additional temporal information of the maneuver is estimated, which enables more accurate prediction and due to the probabilistic formulation additionally allows reasoning about safety critical maneuver execution. Unlike worst-case considerations, possible driving maneuvers are weighted by their probability and the corresponding temporal properties are considered and dynamically updated. By adding the temporal component a straightforward and computationally efficient trajectory generation model can be utilized. Hence, it suits reasonably well for integration into production cars.

The remaining paper is structured as follows: In section III the framework for safety critical trajectory prediction is presented. After a general overview, the maneuver classification algorithm and the estimation of related temporal information are outlined. In III-D a model based trajectory prediction approach is shown, which directly benefits from the estimated quantities. Afterwards, all three parts are evaluated in section IV. Finally, a conclusion and outlook are given in section V.

III. SAFETY CRITICAL TRAJECTORY PREDICTION

In common automated driving architectures decision making and ego trajectory planning modules estimate the output based on fused sensor measurements and results of the situation analysis. Hereby the future motion of other traffic participants is represented by a predicted trajectory $\mathbf{x}(t{:}t{+}n)$ for n time steps or more general by its respective probability distribution $P(\mathbf{x}(t{:}t+n)|\mathbf{x}(t), \mathcal{O}(t), m(t), t_{LC}(t))$. In general, highways can be seen as a structured environment such that the lateral motion is mainly defined by a set of basic maneuvers $\mathcal{M}$. The maneuver $m(t)$ any vehicle performs at time t is given by

$$m(t) \in \mathcal{M}(t) \coloneqq \{\text{LCL, LK, LCR}\}, \tag{1}$$

where LCL corresponds to lane change to the left, LK to lane keeping and LCR to lane change right, respectively. In case of lane change the maneuver is temporally augmented with an estimated *time-to-lane-change* $t_{LC}(t)$. Furthermore, the modeled distribution depends on the current measured state $\mathbf{x}(t)$ and the environment $\mathcal{O}(t)$, i.e. lane boundary and road geometry. In a first step, a maneuver prediction is carried out. Due to the unobservable intentions of human drivers a probability is assigned to each maneuver class

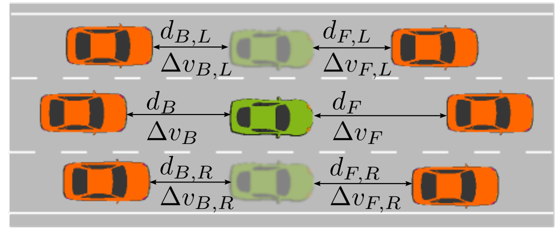


Fig. 2: Situation related features for the observed (middle) vehicle utilized for the maneuver prediction. For features on adjacent lanes the observed vehicle is projected onto the respective lane.

$P(m(t)|\mathcal{X}(t)) \in [0, 1]$, such that the trajectory distribution can be approximated by the Cartesian product

$$\begin{aligned}\mathbf{x}(t{:}t+n) \propto P(\mathbf{x}(t{:}t+n)|\mathbf{x}(t), \mathcal{O}(t), t_{LC}(t))\\ P(m(t)|\mathcal{X}(t)).\end{aligned} \tag{2}$$

For the same reason it is not sufficient to model the *time-to-lane-change* with a point estimate, but the conditional distribution $P(t_{LC}(t)|\mathcal{X}(t))$ has to be considered, where $\mathcal{X}(t)$ is a set of features. Including these maneuver information into the prediction, a computationally efficient model-based approach is chosen for trajectory representation. This has two major advantages, first the estimated *time-to-lane-change* can directly be incorporated into the model and second the execution time remains very low.

A. Feature Definition

As the maneuver classification as well as the probabilistic *time-to-lane-change* prediction utilize supervised learning techniques and provide information on lane change maneuvers, equal feature matrices $\mathcal{X}(t)$ are chosen. It consists of two feature groups: object-related features and traffic situation related features. The former are based on the state of the observed object and include the lateral distance of the object to the lane center d_t^{lat}, the lateral velocity $v^{lat}(t)$ and the longitudinal velocity $v^{lon}(t)$. All features are measured in a curvilinear coordinate system to ensure functionality for curved road geometries. The second group includes features dependent on the current traffic situation of the observed object and are depicted in Fig. 2. In general, the set includes distances and relative velocities to six surrounding vehicles. Distances to the following vehicles are denoted with d_B for the follower on the same lane and $d_{B,L}$ and $d_{B,R}$ for the left and right lane, respectively. For vehicles in front of the observed one the subscript $d_{F,*}$ is utilized. Relative velocities are calculated as $v_B = v_{Leader} - v_{Follower}$ and follow the same notation as the distances. All relative distance features at time stamp t are aggregated in $\mathbf{d}^{rel}(t)$ and relative velocities in $\mathbf{v}^{rel}(t)$, respectively. To account for the dynamics of a lane change maneuver, the object-based features are aggregated with the history of length t_H, which is chosen via cross-validation. All data samples are recorded with a frequency of $10\,\text{Hz}$, which is also the rate of the predictor. For a history of $t_H = 0.5\,\text{s}$ the length of the feature vector sums up to 27. The m-dimensional feature vector is defined as follows:

$$\mathcal{X}(t) = [\mathbf{d}^{lat}(t)\, \mathbf{v}^{lat}(t)\, \mathbf{v}^{lon}(t)\, \mathbf{d}^{rel}(t)\, \mathbf{v}^{rel}(t)]^{\mathrm{T}} \in \mathbb{R}^m, \quad (3)$$

where

$$\mathbf{d}^{lat}(t) = [d^{lat}(t - t_H)\, d^{lat}(t - (t_H - \Delta t)) \ldots d^{lat}(t)],$$
$$\mathbf{v}^{lat}(t) = [v^{lat}(t - t_H)\, v^{lat}(t - (t_H - \Delta t)) \ldots v^{lat}(t)],$$
$$\mathbf{v}^{lon}(t) = [v^{lon}(t - t_H)\, v^{lon}(t - (t_H - \Delta t)) \ldots v^{lon}(t)]$$

and Δt denotes the sampling time.

B. Maneuver Classification

Given the features $\mathcal{X}(t)$ a probabilistic maneuver classification is carried out to estimate the probability of $m(t) \in \mathcal{M}$. In general, any approach resulting in a class wise probability can be applied. The proposed approach utilizes a multi-class *Support Vector Machine* (SVM) similar to [12] which is trained in a *one-vs-one* fashion. To obtain probabilities for each class the resulting scores are mapped using a sigmoid function.

C. Time-To-Lane-Change Prediction

In addition to maneuver prediction temporal information of upcoming maneuvers are crucial to enable safe and comfortable driving. For lane change maneuvers the most important information is the time it takes for the observed vehicle to approach the target lane. Thus, the *time-to-lane-change* $\hat{t}_{LC}(t)$ is defined as the duration between the current timestamp and the time when the observed vehicle's center of gravity has crossed the lane marking. It is worth mentioning, that $\hat{t}_{LC}(t)$ is estimated independently of the predicted maneuver class.

For safety-critical applications and due to the unknown intention of a human driver, an estimation of the conditional mean is not sufficient, but further knowledge of the underlying probability distribution is required. Since this distribution is neither symmetric nor has a consistent shape, the approach in [13] formulates a probabilistic regression problem and applies *Quantile Regression Forests* to predict various conditional quantiles τ_i of the distribution

$$\hat{t}_{LC,\tau_i}(t) = \inf\{t_{LC}(t) | P(t_{LC}(t)|\mathcal{X}(t)) \geq \tau_i\}. \quad (4)$$

While the median $\tau = 0.5$ represents the most probable predicted *time-to-lane-change* (*ttlc*), other quantiles can be used depending on the context. In case of safety critical applications lower quantiles minimize the risk of reacting too late on an upcoming lane change. In the presented approach the 10% quantile of the conditional distribution $\hat{t}_{LC|\tau=0.1}(t)$ is utilized as lower bound of the predicted trajectory distribution.

D. Trajectory Prediction

Based on the predicted maneuver class and *ttlc* the future vehicle movement is described in time and space domain to be available for subsequent algorithms in automated driving, e.g. *Decision Making* or *Ego Trajectory Planning*. To keep the trajectory model as simple as possible without loosing

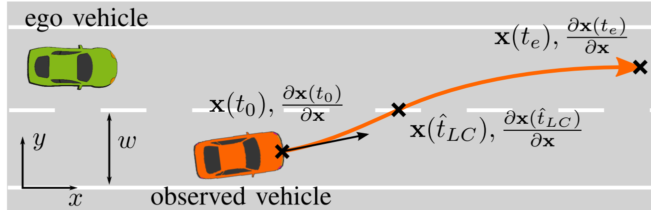


Fig. 3: Spline-based trajectory prediction.

information on the predicted *ttlc*, the distribution in (2) is approximated by single realizations of

$$\hat{\mathbf{x}}_{\tau=\tau_i}(t{:}t+n) = f(\mathbf{x}(t), \hat{t}_{LC|\tau=\tau_i}) \quad (5)$$

with a cubic spline based representation and for $\tau_i \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$.

A cubic spline $z(t)$ is defined by

$$z(t) = \begin{cases} \mathbf{s}_l(t) & t_l \leq t \leq t_{l+1} \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

If η is the number of control points and $t \in [t_l, t_{l+1}]$ the spline consists of $\eta - 1$ segments

$$z(t) = c_{3,l}(t - t_l)^3 + c_{2,l}(t - t_l)^2 + c_{1,l}(t - t_l) + c_{0,l}. \quad (7)$$

To obtain unique parameters $\{c_{0,l}, c_{1,l}, c_{2,l}, c_{3,l}\}$, start and end conditions $\{z_0, \dot{z}_0, z_l, \dot{z}_l\}$ have to be defined for $l = 1, 2, \ldots, \eta$.

In general, trajectories in a two dimensional plane are represented by the states $\mathbf{x}(t) = [x(t)\, y(t)]^{\mathrm{T}}$. Considering the state estimation uncertainties and that the human driver is still in the loop for observed vehicles, it is assumed that the motion on a highway can be described by a cubic polynomial with sufficient accuracy. For lane following maneuvers the estimated states $\hat{x}(t)$ and $\hat{y}(t)$ are modeled as a cubic spline with two control points ($\eta = 2$): the current state at $t = t_0$ and the goal state $t = t_e$. The corresponding boundary conditions are

$$\hat{x}(t_0) = x_0, \qquad \dot{\hat{x}}(t_0) = v_0 \sin(\psi) \quad (8)$$
$$\hat{y}(t_0) = y_0, \qquad \dot{\hat{y}}(t_0) = v_0 \cos(\psi) \quad (9)$$
$$\hat{x}(t_e) = x_0 + v_0 \sin(\psi) t_e, \qquad \dot{\hat{x}}(t_e) = v_0 \sin(\psi) \quad (10)$$
$$\hat{y}(t_e) = w/2, \qquad \dot{\hat{y}}(t_e) = 0, \quad (11)$$

where w denotes the lane width of the current lane and conditions (8) and (9) represent the start state. As no further information on the desired velocity of an observed vehicle is available and the acceleration is subject to measurement noise, constant velocity is assumed in equation (10). Furthermore, the driver is assumed to follow the road center without any significant lateral velocity with regard to the road curvature, which is expressed by equation (11).

In case of a lane change maneuver one additional control point ($\eta = 3$) is placed on the respective lane marking (see Fig. 3) at time $t = \hat{\mathbf{x}}_{\tau=\tau_i}$. The most probable trajectory is described by $\hat{\mathbf{x}}_{\tau=0.5}$, i.e. the median of the conditional *time-to-lane-change* distribution. To enable a higher level of safety and also to consider critical maneuvers in the prediction, lower quantiles of the distribution can be utilized in the trajectory estimation. In the paper at hand the 10% quantile $\hat{t}_{LC,\tau=0.1}$ is applied for critical maneuver prediction. As lane change maneuvers end on a different lane, the first part of condition (11) changes to $y(t_e) = \frac{3}{2}w$ and one additional boundary condition for the mid point is required

$$\begin{aligned} \hat{x}(\hat{t}_{LC|\tau=\tau_i}) &= x_0 + v_0 \sin(\psi)\hat{t}_{LC|\tau=\tau_i} \\ \hat{y}(\hat{t}_{LC|\tau=\tau_i}) &= w. \end{aligned} \tag{12}$$

With equation (12) and continuity conditions for $\dot{z}(t)$ and $\ddot{z}(t)$ all spline coefficients are uniquely defined.

At the last point the total prediction time t_e has to be determined. For lane following maneuvers a default prediction time $t^*_{LF} = 5\,\mathrm{s}$ is chosen which is sufficient for most planning algorithms (e.g. [14]). Regarding lane change maneuvers the predicted trajectory is split into one part, describing the trajectory from the current position until crossing the lane marking, and a second segment on the target lane. While the first fraction is described by condition (12), t_e has to be chosen suitable for lane change maneuvers. Since for ego-motion planning, the lane is blocked anyway as soon as the vehicle is partially on the lane, approaching the target lane is the more critical phase. The duration of the second half of the lane change is set to a default lane change time, which can be extracted from recorded vehicle trajectory data. It was found, that the lane change direction does not affect the maneuver duration as the median for right and left maneuvers do not differ much, i.e. less than $0.5\,\mathrm{s}$. The combined median is then set to $t_{LC,\text{default}} = 7.7\,\mathrm{s}$, which leads to

$$t_e = \hat{t}_{LC|\tau=\tau_i}(t) + t_{LC,\text{default}}/2 \tag{13}$$

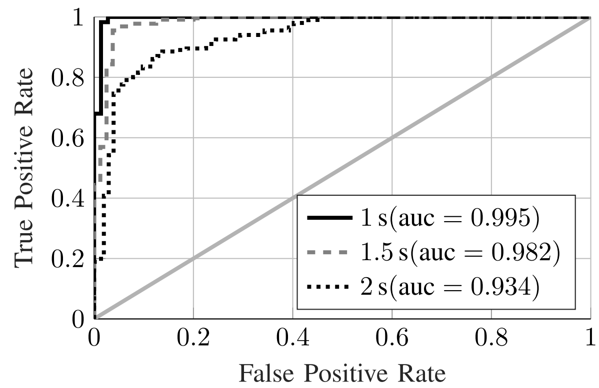
for lane change maneuvers.

IV. EVALUATION

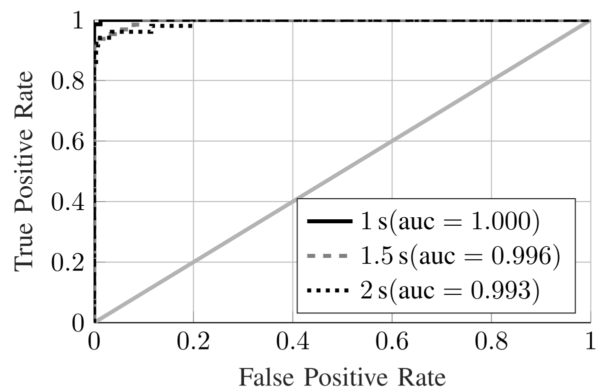
To evaluate the overall performance of the proposed trajectory prediction approach the each part of the framework has to be investigated. Since the trajectory prediction is based on the results of the maneuver estimation (Section III-B) and its temporal characteristics (Section III-C), the performance strongly depends on the accuracy of those. The two algorithms, on the other hand, can be evaluated completely independent.

A. Dataset

Evaluation is performed on the Next Generation Simulation (NGSIM) dataset for the Interstate 80. It contains three 15 minutes intervals of vehicle trajectory data, recorded by several video cameras, which track object positions on the highway at $10\,\mathrm{Hz}$ [15]. To cope with tracking noise as well as inconsistencies and extreme acceleration values, position measurements are filtered with a first-order Butterworth filter, as suggested in [16]. Furthermore, invalid tracks (i.e. with switching IDs) are removed completely. Each lane change track is labeled according to the start and end of the maneuver. For maneuver classification as well as for *time-to-lane-change* prediction the data is divided into training and test data by 70-30. To get a balanced training set, the number of sets for lane change left is reduced to match lane change right. For testing, however, no balancing is applied.



(a) ROC curves for lane change left $1\,\mathrm{s}$, $1.5\,\mathrm{s}$ and $2\,\mathrm{s}$ before the maneuver finishes.



(b) ROC curves for lane change right $1\,\mathrm{s}$, $1.5\,\mathrm{s}$ and $2\,\mathrm{s}$ before the maneuver finishes.

Fig. 4: ROC curves.

TABLE I: Maneuver classification performance for lane change left and lane change right.

	acc_S	Δt_{pred}
LCL	0.91	$2.26 \pm 0.72\,s$
LCR	0.98	$2.21 \pm 0.68\,s$
LK	0.90	-

B. Maneuver Detection Performance

In a first step solely the maneuver classification performance is evaluated. The overall goal is the detection of a beginning lane change maneuver as early as possible to enable most considerable available reaction times. At the same time a minimal number of false alerts should be achieved. After crossing the lane marking a vehicle is considered to keep the current lane, such that the data is labeled as lane change until the center of gravity reaches the target lane and as lane keeping afterward.

The performance of the maneuver classification is evaluated using the Receiver Operator Characteristics (ROC curve). The curve plots the *true positive rate* versus the *false positive rate* and is generated class wise. In general, a larger *area under the curve* (auc) means better classification performance. Furthermore, the sample wise accuracy is evaluated for each class. Finally, the temporal detection capabilities for lane change events are characterized by the average prediction time Δt_{pred}, which is defined as the duration between the first class prediction and the lane marking crossing.

Fig. 4a and 4b show the ROC curves at three time stamps prior to the lane change event for lane change left and right, respectively. Naturally, the detection capabilities improve with decreasing time to lane change, since the observed vehicle is approaching the target lane and exhibits a considerable lateral distance and velocity. This can also directly be observed by the increasing auc values. Furthermore, LCL shows slightly worse results compared to LCR. Maneuvers to the right-hand side are detected perfectly one second in advance and still very good two seconds ahead (auc $= 0.993$). The other evaluation metrics are presented in table I. Regarding maneuvers, LCR is again predicted with a good accuracy of 98% and hence, more reliable compared to 91% for LCL. For lane keeping an accuracy of 90% is reached. Regarding the prediction time LCL are detected earlier compared to LCR as it is shown by Δt_{pred}. Both maneuvers are detected on average more than two seconds before lane marking crossing.

In general, the maneuver classification shows convincing performance on the NGSIM data set, such that good results for the trajectory prediction can be expected.

C. Time-To-Lane-Change Prediction Performance

Similar to the maneuver classification the *ttlc* prediction is evaluated separately on the same data set. As a performance measure, the root-mean-square error ($RMSE$) is applied. It is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(t_{ref} - \hat{t}_{LC|\tau=0.5})^2}{N}}, \tag{14}$$

where t_{ref} denotes the difference between the current time and the next lane change. Since a probabilistic prediction is performed, the predicted uncertainty grants more information on the true *ttlc*. Similar to [13] an additional metric is defined, expressing the percentage of correct predictions (*cpr*). Therefore two intervals are defined representing different parts of the conditional distribution

$$IQR = t_{LC|\tau=0.75} - t_{LC|\tau=0.25}, \tag{15}$$

$$I_{80} = t_{LC|\tau=0.9} - t_{LC|\tau=0.1}. \tag{16}$$

In this context a prediction is considered correct, if t_{ref} lies in the predicted I_{80} interval.

Fig. 5 depicts the $RMSE$ for LCL and LCR maneuvers. On average the error for both maneuvers is very low. Even three seconds ahead, the error for a lane change to the left is just 0.55 s and decreases to 0.27 s for LCL and 0.19 s for LCR one second before a lane change. At the same time the prediction uncertainty, which is expressed by the two intervals I_{80} and IQR, decreases when approaching the target lane. This can again be explained by the growing lateral distance and velocity, which indicate an imminent lane change maneuver. In terms of prediction accuracy the applied Quantile Regression Forest achieves a *cpr* of 90% for LCR and 77% for LCL.

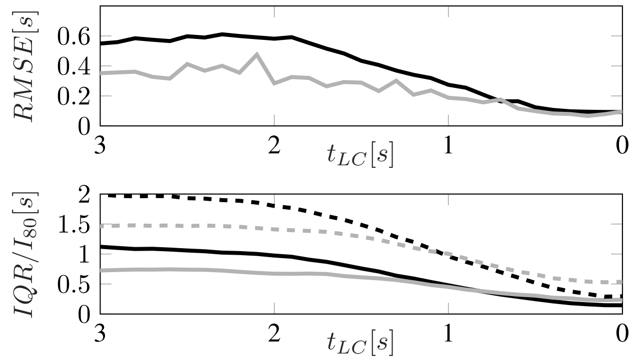


Fig. 5: Results of time-to-lane-change prediction for the NGSIM data set. Black lines denote LCL and gray LCR, respectively. The top figure shows the $RMSE$ and the bottom one the IQR (solid lines) interval and I_{80} (dashed lines) interval.

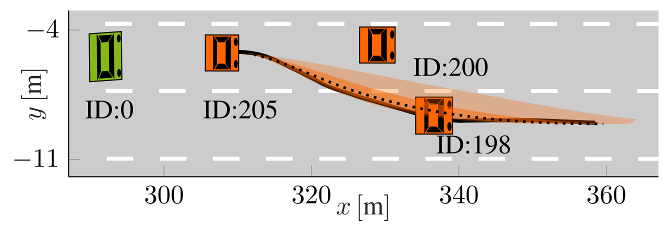


Fig. 6: Sample traffic situation for vehicle 205 and predicted trajectories in the local NGSIM coordinate system. The dotted black line denotes the most probable trajectory $\hat{\mathbf{x}}_{\tau=0.5}$ and the shaded ares the predicted intervals. The reference trajectory is represented by the solid black line.

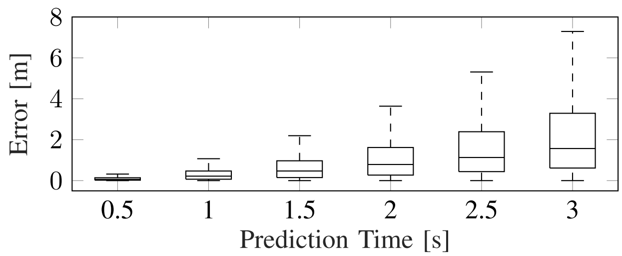
D. Trajectory Prediction Performance

For the predicted trajectories several quantities are evaluated. First the absolute longitudinal and lateral error of the trajectory, utilizing the median estimate of the *ttlc* prediction $\hat{\mathbf{x}}_{\tau=0.5}$, is estimated. As already pointed out, the most critical part of lane changing maneuvers is the approaching of the target lane. For save driving it is essential, that the vehicle does not reach the target lane earlier than expected. As a metric the percentage of trajectories crossing the lane marking later than $\hat{\mathbf{x}}_{\tau=\tau_i}$ is defined as

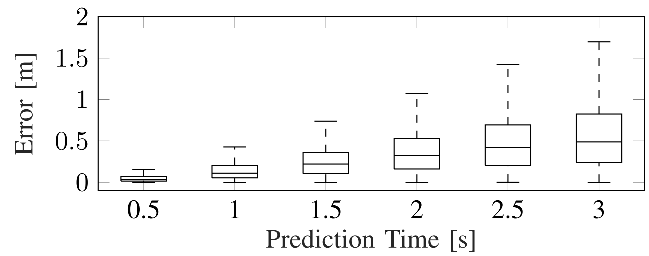
$$cr_{\tau=\tau_i} = \frac{1}{N_{LC}} \sum_{N_{LC}} \mathbb{I}_{\{\hat{x}_{\tau_i}(t_{LC}) \leq x_{ref}(t_{LC})\}}. \tag{17}$$

Fig. 6 shows an example of a predicted lane change trajectory including the I_{80} and IQR interval. The predicted median trajectory is shown as a dotted line in the center of the intervals and crosses the lane marking on the right slightly after the reference trajectory (solid black line). However, the reference is still included in the I_{80} as well as in the IQR interval and hence the maneuver is considered correctly. Furthermore, the rear tail of the predicted trajectories indicates a possible slower lane change, which results from the tailed *ttlc* distribution.

Fig. 7 visualizes the statistical properties of the absolute error in longitudinal and lateral direction for lane change



(a) Longitudinal error



(b) Lateral error

Fig. 7: Lateral and longitudinal error of predicted lane change trajectories. Whiskers denote the 99.3% interval, boxes the interval between the 25% and the 75% quantile and the vertical line represents the median.

TABLE II: Lane keeping trajectory prediction performance.

Prediction Time	0.5	1.0	1.5	2.0	2.5	3.0
Median	0.02	0.05	0.11	0.16	0.21	0.26

maneuvers. Since the primary focus of this work is the modeling of more critical maneuvers (i.e. lane changes), the error for lane keeping is considered separately and shown in table II. In general, the longitudinal error is rather high due to the simplified assumption of constant velocity during trajectory prediction. This could be improved by the introduction of more realistic assumptions as for example a driver model. The median of the lateral error, however, is sufficiently small for a lane width of approximately four meters. More than 99% of the errors are smaller than $1.5\,\mathrm{m}$ for a prediction time of three seconds, which is a good result considering an average maneuver prediction time of approximately two seconds. Trajectories based on false maneuver predictions are not included here and would result in higher errors due to a prediction onto the wrong lane. Considering the prediction of critical maneuvers the approach reaches a $cr_{\tau=0.1} = 0.96$ if the 10% quantiles is applied. This means that only in 4% of all samples the vehicle trajectory reaches the target lane faster than predicted. This results mainly from abrupt changes in driving direction.

V. CONCLUSION

The paper at hand presents a novel model-based approach for trajectory prediction approach resting on a combination of maneuver classification and probabilistic estimation of related temporal properties. The chosen model directly takes advantage of the temporal information to enhance the predicted trajectory and is kept computationally efficient to enable real-time compatibility. Furthermore, the probabilistic *time-to-lane-change* estimation allows the consideration of safety critical, faster lane change maneuvers without the requirement of a worst-case assumption. The performance of the prediction framework is evaluated on the NGSIM dataset and shows promising results on real-world trajectory data. In future work the application in a test vehicle is planned to evaluate the influence of limited sensor field of view as well as measurement and tracking noise.

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