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A novel approach to driver behavior prediction using scene context and physical evidence for intelligent Adaptive Cruise Control (i-ACC)

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Abstract: Conventional driver assistance systems suffer from relatively late reaction timing. Adaptive Cruise Control (ACC) systems, for example, react to vehicles cutting-in from neighboring lanes once these vehicles are at least partly driving on the host vehicle's lane. The improvement by state of the art prediction approaches is limited, because the reliable approaches base on features, which are characteristic for the phenomenological effect of a behavior change. That means they are capable of predicting a behavior once it started. The Honda i-ACC overcomes the above mentioned limitation of delayed reaction by using a novel approach of behavior prediction. This approach combines two prediction methods: A context-based prediction (CBP) and a physical prediction (PP). The CBP evaluates the situational context of a predicted vehicle and does not use any phenomenological feature. It is thus capable of long-term prediction. In contrast, the PP evaluates phenomenological features by accumulating the predicted vehicle's history of recent positions and comparing them to a set of trajectories, which allows for an accurate short-term prediction. In an evaluation on 15000km of driving in Europe we will show that the new prediction approach achieves both, reliable and long-term prediction.

Keywords: Intelligent Adaptive Cruise Control, Prediction, Predictive Driver Assistance System, Prediction Methods, Situation Understanding.

1. INTRODUCTION

Conventional driver assistance systems react to another traffic participant's behavior as soon as it becomes apparent. In other words, they react as soon as the host vehicle's sensors detect the start of another vehicle's change of behavior. ACC systems, for example, react to a vehicle cutting-in from a neighboring lane when the sensors measure a significant lateral motion or displacement. However, a change of behavior is usually the effect of adapting to the current driving situation, i.e. a driver will change lane to overtake a slower vehicle driving ahead of him if the current traffic situation permits. By analyzing the driving situation of other vehicles, attentive drivers are well capable of foreseeing or predicting their behavior before this behavior actually starts. To bridge this gap between technical systems and human capabilities, future active safety technology should therefore base upon prediction to offer what we call assistance beyond sensing. The Honda intelligent Adaptive Cruise Control (i-ACC) is the first implementation of such a predictive system. This system, commercially available in the 2015 model year CR-V behaves like a conventional ACC for free-ride or follow- situations. However in cut-in situations it can predict cutting-in maneuvers of vehicles on the adjacent lane and react even before these vehicles start moving laterally, see Fig. 1. In this contribution, we will focus on prediction technology behind this function. A companion

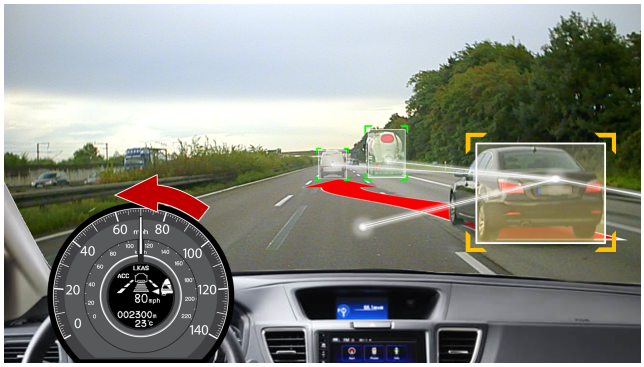


Fig. 1. Visualization of i-ACC function: The host vehicle predicts a cut-in of the vehicle on the neighboring lane and reacts even before the cutting-in vehicle started moving laterally.

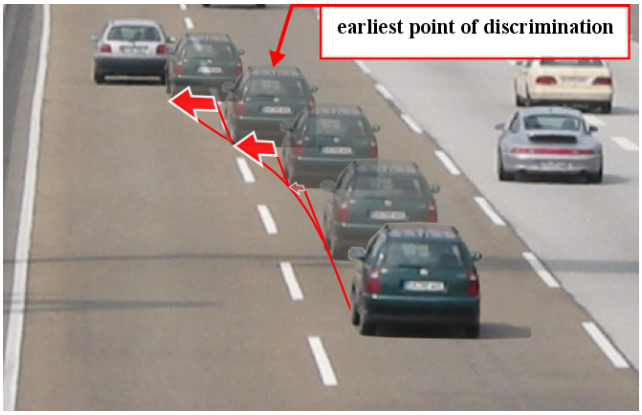


Fig. 2. Earliest point of discrimination: Systems relying on phenomenological features reliably predict a lane change when it has already started.

contribution by Kleinehagenbrock et al. (2015) will detail the system integration and provide a subjective user test.

2. STATE OF THE ART

Various methods for behavior prediction exist. For convenience we will focus here on the prediction of lane changes. A more thorough overview is given by Bonnin et al. (2014). On highway scenarios Bayesian methods are commonly used to estimate the probability of a lane change given a set features, e.g. by Dagli et al. (2004); Kasper et al. (2012); Schlechtriemen et al. (2014). This is usually achieved by estimating models for different behavior classes, consisting of conditional probability distributions over a set of features. Other approaches consider lanes changes as a Markov process, i.e. a future state is considered to depend on one or more previous states. For example Gindele et al. (2010) model such temporal dependency in a Bayesian Network and use if for estimation of future states given one or more recent states and a suited set of discriminative features.

In reasoning based approaches the current situation is compared to a database of known cases in order to determine the future behavior, as reported by Graf et al. (2013).

Behavior prediction can also be understood as classification problem. Similar to the Bayesian approaches the recognition of a situation based on discriminative features can be used to infer how this situation will develop in the future. This idea has been addressed e.g. by Reichel et al. (2010), who use Random Forrest Trees for classification or by Garcia Ortiz et al. (2012) who use Locally-Weighted Projection Regression. In general, model based approaches exhibit a high predictive power especially for long prediction time horizons, however they suffer from a limited application scope. A method to overcome this dilemma by efficiently combining various models is reported by Bonnin et al. (2014, 2013); Graf et al. (2013).

Some of the above approaches use multiple models or decision stages. However, they use a singular prediction method resulting in one singular prediction result. Those approaches achieving reliable results include features that are characteristic for the phenomenological appearance of a lane change, like the lateral velocity or the lateral displacement. Consequently, these approaches can only predict lane changes accurately once these lane changes started, which is much later than an attentive driver can do, see Fig. 2. Thus, these approaches are not suited to bridge the gap between the capabilities of an attentive driver and an ADAS. Other approaches, which do not use such phenomenological features, do not yet reach the quality required for commercial ADAS.

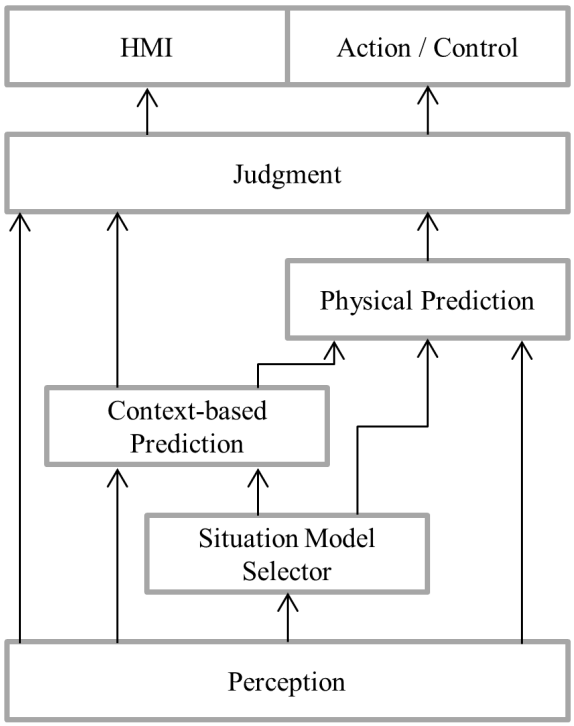


Fig. 3. System Graph: Please refer to the text below for a detailed explanation.

3. APPROACH

To overcome the dilemma of choosing between low prediction quality or low prediction horizon, this contribution presents a novel approach for the prediction of other vehicles' behaviors. This approach combines two prediction methods: First, a prediction based on the contextual situation of the predicted vehicle, which we call context-based prediction. Second, a prediction based on physical evidence of the predicted vehicle's movement. The context-based prediction evaluates relations between vehicles and the infrastructure, but it does not use any phenomenological features. This makes it capable of early behavior prediction, before the behavior actually starts. This method will be further detailed in section 3.1. The physical prediction, which will be explained in section 3.2 combines the results of the context-based prediction with observations of recent vehicle positions. These positions are compared with typical trajectories to predict behaviors. This prediction is highly accurate, but only capable of predicting behaviors once they started. To benefit from both, early and reliable prediction, a special system design is used, see Fig. 3:

The system, receives information about the environment and the host vehicle via the perception module. The resulting vehicles and lanes are passed to all following modules. The Situation Model Selector infers one or more fitting situation models for the current traffic situation and passes

them to the context-based and to the physical prediction. Both prediction modules use these situation modules to estimate the future behavior of various traffic participants. The key of this integration is to pass both prediction results to the judgement module, which determines the best fitting action based on the current traffic situation and based on the evidence provided by the prediction methods. This system design allows the judgement module to determine a proper action based on the individual prediction evidence as well as on the combined evidence.
In the current implementation, a high evidence for a cut-in by one of the prediction methods authorizes a mild deceleration, while high evidence from both prediction methods authorizes a strong deceleration.
In the following, we will describe the two prediction methods in more detail.

3.1 Context-based Prediction

The context-based approach considers prediction as a classification problem: The current traffic situation as represented by the perception module is matched against a set of known situation models. Each of these situation models contains information of how this situation will evolve in the future. Thus, a correctly recognized situation model results in a correct prediction. Literally speaking, the context-based prediction answers the question: *Is a vehicle in a situation in which it will change lane to the left?*
This leads to two principal problems: First, how to represent situation models in an efficient way, such that the number of situation models is minimized and at the same time the coverage of situations is maximized? Second, which discriminative features allow for a reliable classification of these situation models?
The problem of efficient situation model representation is handled by so called local relations. The underlying assumption is that driver behavior, especially on European highways, does not primarily require a holistic analysis of the whole scene, but is usually influenced by the traffic participants in the driver's direct vicinity. Which of the neighboring vehicles is relevant obviously depends on the behavior options of the driver – for a lane change left the vehicles on the left are usually more relevant than the vehicles on the right. Consequently the vehicles represented for a lane-change-left-behavior differ from those represented for a lane-change-right-behavior. Fig. 4 visualizes the situation models for both behaviors. The representation of the lane-change-left model contains the vehicle to be predicted, its predecessor on the own lane, as well as the predecessor and successor on its left lane. Equivalently, the lane change-right-model for left-hand driving contains the vehicle to be predicted, its predecessor, as well as the predecessor and successor on its right lane. The situation models are applied separately for each vehicle and each behavior to be predicted.
The second problem, the identification of discriminative features for a correct classification a represented scene, is usually handled by including phenomenological features, such as lateral velocity or lateral offset of the predicted vehicle in its lane. Obviously such features are highly discriminative, but only once the maneuver has already started. A classifier trained with these features would learn to rely on them and consequently only provide high confidence values once the predicted vehicle started its

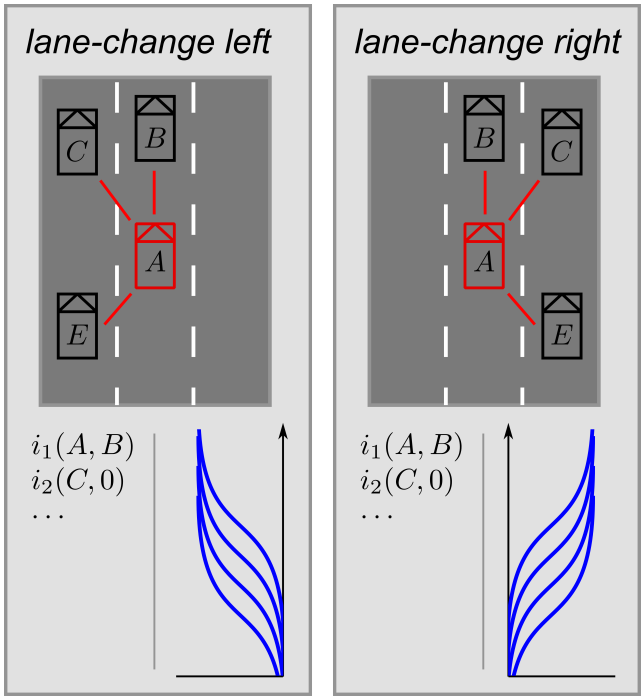


Fig. 4. Situation Models: Two situation models for lane change left and lane change right of vehicle A are shown. Each model consists of set of relevant vehicles (top), a set of indicators i and a set of physical trajectories.

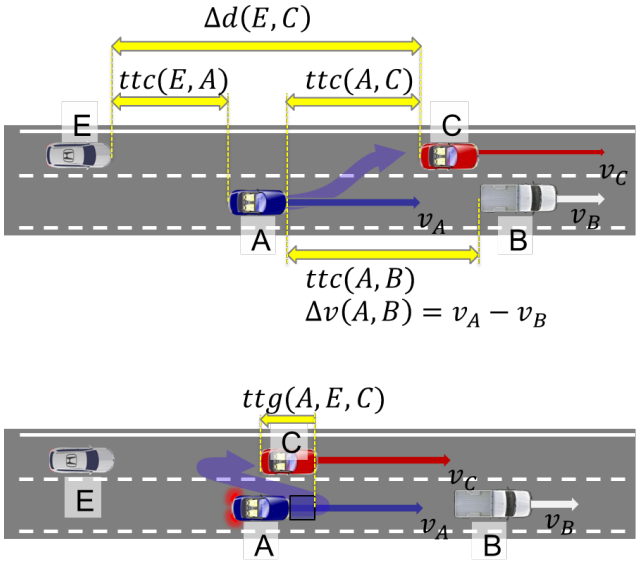


Fig. 5. Features used for context-based prediction: TTC between two vehicles, distances, relative velocities (top) as well as TTG (bottom). For all features only the longitudinal aspect is evaluated, otherwise e.g. the TTC between two vehicles on neighboring lanes would be infinite.

displacement in the lane. Therefore the context-based prediction explicitly excludes any of these phenomenological features.
However, especially in Europe a vehicle typically changes lane if it wants to overtake a slower predecessor and if there

is a fitting gap on the neighboring lane. Thus the context-based prediction evaluates longitudinal aspects of the local relations between vehicles in the situation models. This works in two steps: First the local relations are evaluated to compute features such as the time-to-collision (TTC), the relative velocity and relative acceleration, the distance, the absolute acceleration and the time-to-gap (TTG). TTC is computed by dividing the distance between two vehicles by the relative velocity, whereas TTG is computed by dividing the distance between a vehicle and the next gap by the relative speed between the vehicle and the gap. Compare Fig. 5 for visualization. After computing these feature values, they are recombined to so-called indicators. These indicators are functions which parameterize and combine the features such, that their output values are in [0,1], where 0 indicates that the current scene does not fit to the evaluated situation model and 1 means that it fits perfectly to the situation model. Describing all used indicators in detail would go beyond the scope of this contribution. Therefore we will exemplarily present two of the indicators used to explain the concept. A more thorough list can be found in Schmuedderich and Rebhan (2011); Rebhan (2013); Schmuedderich (2014):

- Approaching and Fitting Left Gap for Situation S_A of vehicle A and its local relations as computed by formula (1):

$$\varphi_a(S_A) = \begin{array}{ll} f(\text{TTC} & (A,B),\Theta_1,\Theta_2)\cdot \\ f(\Delta v & (A,B),\Theta_5,\Theta_6)\cdot \\ f(\text{TTC} & (E,A),\Theta_3,\Theta_4)\cdot \\ f(\Delta d & (E,C),\Theta_7,\Theta_8)\cdot \\ f(\text{TTG} & (A,E,C),\Theta_9,\Theta_{10}) \end{array} \quad (1)$$

  where $\Delta v(A,B)$ is the difference of velocity between two vehicles A and B, $\Delta d(E,C)$ is the distance between two vehicles E and C, $f(.)$ is a non-linear function and Θ_i are parameters to scale the functions output to $[0,1]$ such, that it produces high values ≈ 1.0 if A is approaching B, there is a fitting gap for A between E and C and this gap is soon available.
- Approaching and Accelerate to Gap for Situation S_A of vehicle A and its local relations as computed by formula (2):

$$\varphi_b(S_A) = \begin{array}{ll} f(\text{TTC} & (A,B),\Theta_{11},\Theta_{12})\cdot \\ f(\Delta a & (A,E),\Theta_{13},\Theta_{14})\cdot \\ f(\text{TTC} & (E,A),\Theta_{15},\Theta_{16})\cdot \\ f(\Delta d & (E,C),\Theta_{17},\Theta_{18})\cdot \\ f(\text{TTG} & (A,E,C),\Theta_{19},\Theta_{20})\cdot \\ f(a_A, & \Theta_{21},\Theta_{22}) \end{array} \quad (2)$$

  This function is scaled such, that it produces high values if A is approaching B, if A is accelerating, and if A's acceleration is suited to fit in the gap between E and C.

The parameters Θ_i are estimated by using a CMA-ES algorithm as described by Hansen (2006), an evolutionary optimization algorithm which considers the prediction algorithm as black box and finds the optimal parameters iteratively. The final classification confidence c_i for one situation model M_i for a vehicle A in situation S_A is obtained by maximizing over all indicator values of this classification model by formula (3):

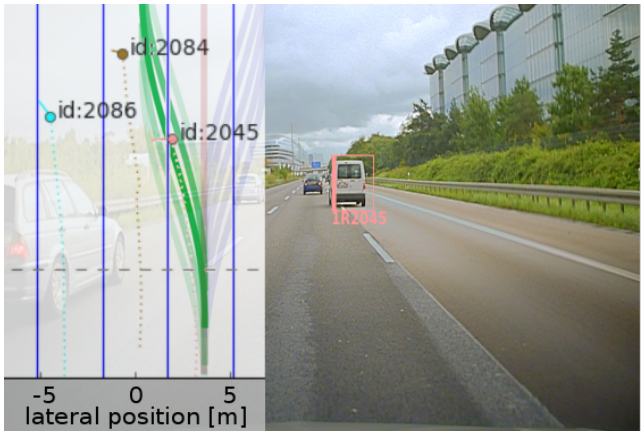


Fig. 6. Physical Prediction: Left side: Accumulated, curve-corrected positions as colored dots, and trajectories fitted for the vehicle on the right lane, where the trajectories' color opacity visualizes the trajectories likelihood fitting. Right: Corresponding scene.

$$c_i(S_A) = \max_{j \in M_i} \varphi_j(S_A) \ . \quad (3)$$

3.2 Physical Prediction

The detection of the scene context poses an additional challenge for the sensor system. Furthermore, with increasing prediction horizons the inherent uncertainty of predictions increases. This is due to the fact that, proportionally to the time to a cut-in, the number of options available to the driver of a potential cut-in vehicle increases.
To achieve a reliable estimate of future behaviors in all cases, an additional physical prediction approach is used. This physical prediction compares the history of recently measured vehicle positions to a set of trajectory models, each representative for a set of different behaviors, see Fig. 6. By doing so, the prediction horizon of this type of prediction is inherently limited to a point in time where the cut-in of a vehicle becomes observable.
The physical prediction proposed here uses a pointwise comparison resulting in a likelihood estimate for each possible behavior given the observed positions. In combination with the situation priors determined by the context-based prediction, finally a posterior belief is estimated for the different behavior options. To calculate the physical prediction, the history of positions is compared to a set of trajectory models. For the current system there exist models for 'stay on lane', 'lane change left' and 'lane change right'. A common problem of model-based approaches is to deal with the diversity of the input data. In our case sources for this diversity are:

- sensor noise in the perceived vehicle positions,
- differences in lane change shapes due to driver preferences such as doing a very smooth or very sudden lane change,
- differences in road shape like curved or straight roads.

Whereas the senor noise can be explicitly covered in the model, different models would be required for different lane change shapes (e.g. very smooth or very steep transitions). However, our analyses of real-world lane change data suggest that the majority of lane changes follow one average model, while minimal variations are covered

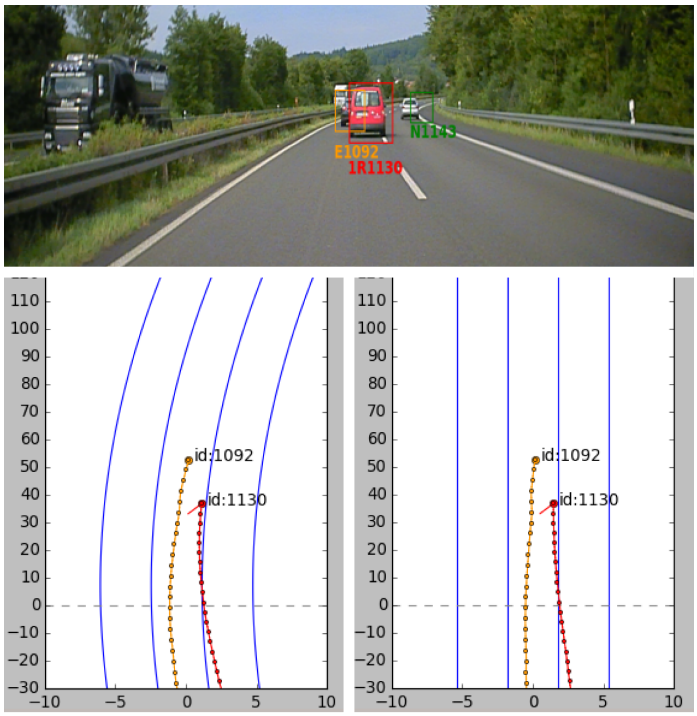


Fig. 7. Position rectification: Left bottom shows perceived history of raw positions for two vehicles, which are a superposition of their trajectory maneuvers and the road curvature. Right bottom shows rectified postions, in which the effect of the road curvature is cancled. Top image shows corresponding scene.

explicitly within this model. These minimal variations are within the range of sensor noise and thus can be handled by the same mechanism. However, the differences in road shapes introduce a large variety when comparing the raw position history with the set of models. This is due to the fact that the observed position history is a superposition of the actual lane change motion and the motion to follow the (curved) road. To eliminate the influence of the road-follow motion, we rectify the history of vehicle positions with respect to the road shape before performing the likelihood calculation minimizing the variance of observed behaviors.

Fig. 7 shows the effect of the road-shape rectification. The position history of a vehicle accumulated over time is projected onto the current estimation of the road shape. Thus the position history is transformed such as if it were observed on a straight road. As a consequence, the influence of the road shape on the position history is eliminated and the diversity of behavior models is minimized with respect to the road shape. In a first step, we calculate the Euclidian distance of each position to the closest point of the host-vehicle's lane center. These distances then correspond to the positions that would result from the motion of the vehicle on a straight road. To transform the position history, we simply use the resulting distances as new lateral and the longitudinal values of the closest points as new longitudinal component of the vehicle position history. As a result of using the proposed rectification, only one model for each behavior 'stay on lane', 'lane change left' and 'lane change right' is required.



Fig. 8. Ground-truth reference point: Manually annotated point in time for a cut-in, when the right tire touches the lane marking, see red arrow.

3.3 Judgment, Action, and HMI

The judgement module receives the result of both predictions as well as the current perception data. If any of the prediction methods predicts a lane change for the current situation, the judgment module determines the most relevant vehicle to control on based upon TTC and time gap.

To maximize the effect of an early context-based prediction and a reliable physical prediction, the strength of the control is based on the prediction evidence: If one of the prediction methods predicts a lane change with a confidence higher than a method-specific threshold, the judgment module authorizes a mild-deceleration maneuver. If both prediction methods provide a confidence higher than their respective threshold, a strong deceleration with up to 0.4g is authorized.

It has to be noted, that the judgment module only determines the maximum allowed deceleration force. The actual deceleration force is determined in accordance with the current situation. That means, even if both prediction methods predict a cut-in and thus a strong deceleration is authorized, the vehicle will only brake mildly if the cutting-in vehicle has a high TTC and time gap to the host vehicle.

Whenever the host vehicle brakes for a cutting-in vehicle, a symbol is shown in the meter, as shown in the left corner of Fig. 1.

4. EVALUATION

For a quantitative evaluation of the proposed prediction method, we extracted 15.000km from our recordings of driving with a prototype vehicle equipped with i-ACC on European highways. This subset is a representative sample in terms of varying traffic density from mild to dense traffic, weather conditions from sunny to rainy, day and night, as well as driving style. The prototype vehicle is equipped with the Honda Sensing technology which feeds the system with data of lane markings and vehicles perceived by a sensor fusion of a 74Ghz electric scanning radar and a camera. The longitudinal control was done by the i-ACC system.

For evaluating the Honda intelligent ACC system we use an event-based evaluation as explained by Bonnin et al.

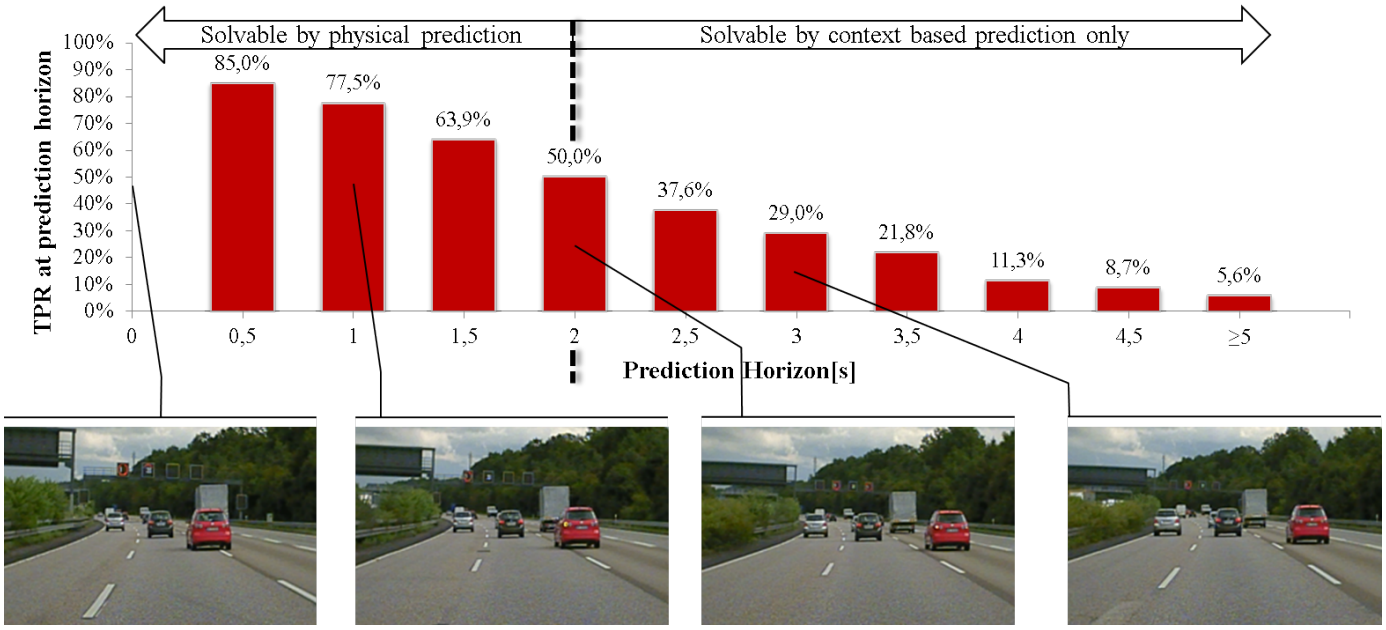


Fig. 9. Prediction Horizon and TPR: Plot of TPR of targeted situations for a given prediction time horizon. For example, 85% of targeted cut-ins are predicted 0.5s before the cut-in and 50% are already predicted 2s before the cut-in (top). For four points in time, the typical corresponding position of a cutting-in vehicle is shown (bottom). As the plot shows, the cutting-in vehicle starts moving laterally at about 2s before the referene point. This is the earliest point in time, where a conventional prediction algorithm can earliest detect a lane-change. With our proposed approach, already 50% of cut-ins are already detected at or before this point.

(2014). This type of evaluation groups successive timesteps of positive prediction to one event, which is especially suited to estimate the effect of a prediction algorithm on an ADAS function. To generate the required ground-truth all targeted cut-in situations are marked: A sitution in which vehicle A cuts-in in front of ego vehicle E is marked as target situation if the following condition is true:

$$\begin{aligned} &(\mathrm{TTC}(E,A) && \leq && 10[\mathrm{s}] && (4)\\ &\vee \Delta d(E,A)/v_E && \leq && 2[\mathrm{s}]) && (5)\\ &\wedge \Delta v(B,A) && \geq && 2.5[\mathrm{m/s}]\ , && (6) \end{aligned}$$

where v_E is the velocity of the ego vehicle E, $\Delta d(\cdot,\cdot)$ and $\Delta v(\cdot,\cdot)$ are the relative distance and relative velocity respectively. By this definition a cut-in situation is only marked as relevant, if the ego vehicle has to react to the cut-in, either to avoid a collision (4) or to adjust its time gap (5). Additionally the reason for B's cut-in must be a detected slower vehicle A, expressed by a difference speed of at least 2.5m/s (6). The latter restriction is used to limit the system to cases which are also predictable by the driver.

For each of the target cut-in situations a point in time when the cut-in happens is defined. This reference point is shown in Fig. 8. We have chosen the point where the right rear tire first touches the lane marking as reference because at this time conventional ACC systems will take control over the host vehicle. Together with the reference time, the ID of the cutting-in vehicle is stored as ground-truth.

Knowing the manually annotated ground-truth reference, we can classify the predictions of our systems into False-Positives (FP), False-Negatives (FN) and True-Positives (TP). To do so, we apply a threshold to each prediction for each vehicle in the scene individually, where a prediction output above or equal to the threshold will indicate a reaction of our system and a threshold below the threshold will indicate no reaction by our system. A reaction means that our system will take control to adapt the host vehicles velocity and distance to the predicted cut-in vehicle. Contrary to frame-based evaluations, we do not evaluate the TP, FN and FPs for each frame individually, but group successive frames of activation (output above threshold) to one reaction event (see Bonnin et al. (2014) for more details).

A true-positive in our case is defined as at least one frame of activation within 10 seconds before the annotated reference point for the annotated vehicle ID. A false-negative is defined at no frame of activation within 10 seconds before the annotated reference point for the annotated vehicle ID. Finally, a false-positive is defined as one or more successive frames of activation outside a window of 10 seconds before and 4.5 seconds after any annotated cut-in. Please note that the evaluation is vehicle specific, thus both a FP and FN is counted in case our system predicts a cut-in (output above threshold) for one vehicle (FP), but the cut-in is actually performed by another vehicle (FN). Finally, the prediction horizon is defined for TP events as the first frame of activation within the group of successively activated frames.

When discussing the results of our evaluation we use the true-positive rate (TPR) defined by (7)

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (7)$$

and the false positives per hour (FP/h) driving time.

To evaluate the prediction accuracy two separate thresholds were chosen, one for the context-based and one for

the physical prediction. If the confidence of the respective prediction method exceeds the corresponding threshold a cut-in is predicted, otherwise no cut-in is predicted. Both thresholds result from a Receiver-Operating-Characteristics (ROC) analysis as introduced by Spackman (1989) and were chosen to optimize the trade-off between true positives and false-positives. In this setting a TPR of 85% of all targeted situations is achieved at 1one false-positive in 10hours. It has to be noted, that all false-positive cases were caused by one of the two prediction algorithms and thus only led to mild braking. No case of simultaneous false-positive prediction by both methods can be found in the data.

Figure 9 visualizes the dependence of TPR and prediction horizon by plotting the TPR of targeted situations for a given prediction time horizon. For example, 85% of targeted cut-ins are predicted 0.5s before the cut-in and 50% are already predicted 2s before the cut-in (the graph does not show the prediction horizon for 0s, because cut-ins which are not predicted *before* this point are considered as FNs). The TPR slowly drops with increasing prediction horizon, however still 5.6% of cut-ins are predicted 5s before the cut-in or earlier.

The reason for the decreasing TPR with inreasing prediction horizon is threefold: First, in general the number of behavioral options dramatically increases with increasing prediction horizon. For example, the driver of a vehicle with a TTC of 10s to its predecessor can choose between braking or changing lane, freely choosing between mild and strong deceleration, shallow or steep lane-change, chaning lane now or later. In contrast, at 1s TTC, the driver can only choose to evade to another lane with a steep emergency trajectory. So in general, prediction with a high prediction horizon is more challenging because there are more alternatives to consider. The second reason for the decrease of TPR with increasing prediction horizon is caused by the physical prediction, because it provides a high confidence for a cut-in maneuver, if the cut-in trajectory significantly differs from the going-straight trajectory - which is at a late state during the cut-in maneuver. Finally, also the confidence of the context-based prediction raises with decreasing prediction horizon, because of the TTC based features used for prediction. These features rise for low TTC values which occur when a vehicle comes close to its predecessor.

Figure 9 additionally shows the typical corresponding position of a cutting-in vehicle at four points in time. At 0s, the vehicle is at the annoted reference point. At 1s, the blinker is activated, the car is in transition of a lane-change and the left tire touches the lane marking. 2s before the cut-in, the vehicle's blinker is active, but only a minimal lateral displacement is observable, whereas at 3s before the cut-in, the vehicle does not show any sign of the upcoming cut-in. Even with highly accurate sensing a conventional prediction algorithm that bases on phenomenological features is not capable of predicting behaviors more than 2s before they happen - simply because they are not yet observable. However, at this point in time, our proposed approach already predicted 50% of the cutting-in vehicles. In other words, context-based prediction is *required* for predicting lane changes more than 2s before they occure, whereas the combination with physical prediction is required to increase the performance in the interval from $[0, 2[$s.

5. CONCLUSION

This contribution presents a novel approach for predicting other vehicles' behavior by combining a context-based prediction with a physical prediction. In contrast to existing approaches, the context-based prediction evaluates relations between vehicles and does not use any features that are phenomenological for a cut-in. The evaluation shows that the proposed combination of context-based and physical prediction achieves a high accuracy and a high prediction horizon: The context-based prediction is required for predicting maneuvers *before* they become observeable, whereas the physical prediction is required to achieve a high accuracy *once* the behavior becomes observable. The technology has been integrated in to the Honda i-ACC, which is now commercially available in the 2015 Honda CR-V. A companion paper by Kleinehagenbrock et al. (2015) details the system embedding and presents a subjective user test.

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