INTENTION OF MANOEUVRE AND MOTION PREDICTION OF OTHER ROAD USERS: A HYBRID APPROACH

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ABSTRACT

Automated driving is gaining more and more interest in the recent years. In order to drive safely, automated vehicles reconstruct the environment using mainly the information coming from the in-car sensors. By using this reconstruction a prediction of the future states of the surrounding vehicles can be computed, which in turn is used to decide which manoeuvre and accompanying path to accomplish. This problem is known as motion prediction. Whilst physics-based models perform well on a short horizon, machine learning has the potential to predict a more accurate motion on a longer horizon, especially if the manoeuvre of the other road user is known in advance (manoeuvre-based prediction).

In this paper a hybrid approach is proposed that consists of an intention of manoeuvre predictor, a physics-based motion predictor and a manoeuvre-based motion predictor.

The vehicles around the host vehicle are continuously tracked. The intention of manoeuvre predictor, based on Support vector machines (SVM), computes the probability for each surrounding vehicle of changing lane or of staying in lane. In addition, a kinematical model which assumes a constant turn rate and velocity (CTRV) is used to predict the trajectories. Once the intention of manoeuvre is known, the manoeuvre-based motion model, based on machine learning algorithms as Gaussian Processes and SVR, predicts the lane change or lane following trajectories. The models are trained using a collection of cut-ins manoeuvres from 60 hours of naturalistic driving. In the end, the physics-based and the manoeuvre-based motion predictions are merged together by a weighting function.

The models were validated with cross-validation and the performance and the integration between sub-modules was tested in a Hardware In the Loop (HIL) environment. The models are capable of detecting the intention of a surrounding vehicle of changing lane with a positive predictive value of 82% 1.2 second before it crosses the lane marker. The combination of SVR and CTRV is capable of predicting well for shorter and longer horizons, keeping the advantages of both methods. The combined model predicts the longitudinal distance and the lateral distance with an error that is 50% lower than the one using the physics-based model, after 4s and an even better performance on shorter horizons in comparison with SVR.

The presented approach is capable of predicting the motion of the other road users in a standard situation. In order to handle more sophisticated scenarios, the road information should be used for training. The training set needs to be extended for better results and the models need to be validated on safety-critical scenarios.

A hybrid approach for predicting the motion of vehicles from a host vehicle perspective is presented in this work. A combination of machine learning and physics-based models is used to enhance the accuracy of the prediction in shorter and longer horizons. The information coming from the prediction module can be used path planning of (partly) automated vehicles.

The results and the integration in the HIL environment show great potential to allow autonomous driving to go to higher levels of automation.

INTRODUCTION

Automated driving is gaining more and more interest in the recent years. In order to ensure more safety on the road, higher levels of automation are needed. The automated vehicle must be able to reconstruct the environment using the information coming from the in-car sensor. The current state of the environment and traffic around is not enough to make safe decisions on which path to follow: prediction of the future states of road participants around the automated vehicle is required.

Another important use case in which the prediction of other road users is needed is truck platooning, when two or three trucks drive with short inter-vehicle distance to reduce fuel consumption and improve traffic efficiency [1]. Early prediction of the behaviour of the car performing the cut-in will help to increase operational safety, because the controllers can use this additional information to anticipate the behaviour of the car, which is especially important in case the Vehicle-To-Vehicle communication fails.

The prediction of road participants can be separated in two phases: intention of manoeuvre and motion prediction. The intention of manoeuvre prediction gives as output the most likely manoeuvre that the road participant will accomplish, before the manoeuvre has clearly started. Typical manoeuvres are lane change, lane following, accelerating, braking, turning. The intention can be predicted using e.g. logistic regression [5] or Support Vector Machine [6].

The motion prediction gives as output the most likely trajectory that the road participant will follow in the future. Machine learning is broadly used to accomplish this task, for example using Gaussian Processes [7], Gaussian Mixture Models [8], Bayesian Networks [9], Neural Networks [6], Support Vector regression [4].

Based on [3], there are 3 main families of motion prediction algorithms:

1. Physics-based models: kinematics or vehicle dynamics is used to predict the motion in the future.

2. Manoeuvre-based models: the intended manoeuvre is known and based on this, the motion is predicted.

3. Interaction-aware models: the motion is modelled taking into account the interaction with the other road users

Interaction-aware models will be not considered in this paper, because they require a big amount of data in order to be trained. The focus of this work is predicting the intention and the motion of other road users on the highway, where the complexity is still limited and interactions can be ignored up to a certain extent. In this case, manoeuvre-based approaches can achieve a good performance ([10], [12]), if the intention of manoeuvre is known in advance.

Whilst physics-based models perform well on a short horizon, machine learning has the potential to predict a more accurate motion on a longer horizon, especially if trained on a manoeuvre-specific training set. In order to get the best out of both methods, physics-based prediction and machine learning can be combined. For example in [11] Dynamic Bayesian Network and Constant Turn Rate and Acceleration (CTRA) are used to predict lane change motion.

In this paper a hybrid approach is proposed that consists of an intention of manoeuvre prediction, a physics-based motion predictor and a manoeuvre-based motion predictor.

The models are then integrated in a Hardware In the Loop (HIL) environment and are suitable for online deployment in an automated vehicle.

METHOD

The objective is to increase safety of automated vehicle by making predictions of the future states of road users on the highway, catching the intention before the manoeuvre actually started, from the point of view of the instrumented vehicle (host vehicle).

In order to predict the motion of other road users, we segmented our solution into the following modules:

- Intention of manoeuvre predictor
- Physics-based motion predictor
- Manoeuvre-based motion predictor
- Combination of the physics-based and manoeuvre-based models

The general architecture of the abovementioned modules is depicted in Figure 1. The intention of manoeuvre predictor computes the probability for each surrounding vehicle of cutting in or of staying in lane. In addition, a kinematical model is used to predict the trajectories (short term). Once the intention of manoeuvre is known, a manoeuvre-based motion model, predicts the cut-in trajectories (long term). In the end, the physics-based and the manoeuvre-based motion predictions are merged together by a weighting function.

In the next subsections, the different modules will be explained in detail.

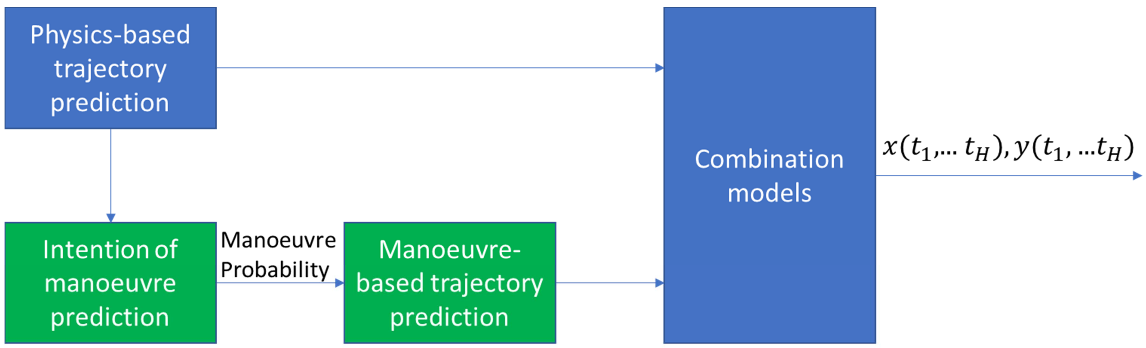

Figure 1 High-level architecture of the prediction models. The green modules are data-driven, based on machine learning. The blue modules are based on physical laws and rules.

Intention of manoeuvre prediction
The manoeuvre intention predictor, based on Support vector machines (SVM), computes the probability for each surrounding vehicle of cutting in or of staying in lane. The vehicles around the host vehicle are continuously tracked. To achieve the most accurate input for the cut in manoeuvre intention prediction algorithm, tests are performed with a high accuracy measurement system (OxTS) together with the vehicle sensors (radar and MobilEye camera). In total 80 cut-ins are performed in a highway setting. The data of all these cut-ins are synchronized at the moment of lane crossing. The start of the cut-in is defined as the last time when it a velocity towards the lane marker (looking back from the moment of lane crossing). As a control, lane keeping data is gathered from naturalistic driving. From all this data relevant parameters are extracted:

- Lateral distance/velocity and acceleration (to vehicle and lane)
- Longitudinal distance, velocity
- Yaw angle, rate and acceleration

These parameters are used in a SVM machine learning algorithm to classify an upcoming cut-in. The final chosen parameters are based on a performance check based on cross validation and a sequential forward selection method where additional parameters need to contribute at least 5% to the performance score to be included. Furthermore a simple computation provides the time it will take to this cut-in to provide an indication of the algorithms usefulness. Finally a validation is performed on said naturalistic driving data to provide an insight in the algorithms accuracy. In this validation a cut-in is predicted when the probability is higher than 0.95 for at least 0.1s to prevent unstable predictions.

Kinematic motion prediction model
For the kinematic model a constant turn rate (w) and velocity (v) algorithm is used (CTRV) [2]. This algorithm computes the longitudinal (x) and lateral (y) position and yaw angle(α) over a certain prediction horizon vector (T) as shown in the equation below:

$$x(T) = \frac{v}{w}\, sin(wT)$$

$$y(T) = \frac{v}{w}\, [cos(wT) + 1]$$

$$\alpha(T) = wT$$

where $T = [t_1, t_2 .. t_H]$.

Manoeuvre-based motion prediction model
Once the intention of manoeuvre is known, the manoeuvre-based motion model, based on machine learning algorithms, predicts the cut-in trajectories.

The machine learning models used are Gaussian Processes and Support Vector Regression. In general Support vector Machines and Gaussian Processes are capable of predicting only one value in the future. To make them predict a complete trajectory, an architecture called Direct Recurrent was used, as explained in our previous work [7]. This allows to avoid the propagation of error typical of recurrent architectures but to keep the relationship between consequent timesteps. The two models will be called DR-SVR and DR-GPR from now on.

The resulting predicted trajectory will be a couple of positions over time, with a horizon t_H up to 4 seconds:

$$(x(T), y(T)) = ((x(t_1), y(t_1)), (x(t_2), y(t_2)), \dots (x(t_H), y(t_H))$$

with $t_H = 4s$.

The prediction algorithms were developed by training on vehicle-kinematics data of cut-ins. The selected features are:

- Host vehicle: speed and acceleration.
- Other road user (to be predicted): longitudinal speed and acceleration, longitudinal and lateral distance with respect to host vehicle.

The training set was extracted from naturalistic driving data, that is part of the TNO Streetwise scenario database [13]. The vehicle used was the a passenger car with a radar and Mobileye system for lane detection**.**

Combination-hybrid model
Based on the crossvalidation results, a weighting function was designed to combine the outputs of the two models (see Figure 2). The physics-based model is used for a horizon up to 1.6s, afterwards only the manoeuvre-based is used. In the first interval of time a combination of the two is output, starting with 100% of physics-based output going to 100% of manoeuvre-based output after 1.6s. The cut-off value 1.6s is the horizon at which the manoeuvre-based model starts to perform better than the physics-based one when predicting the longitudinal distance, as it will be presented later in the Result section.

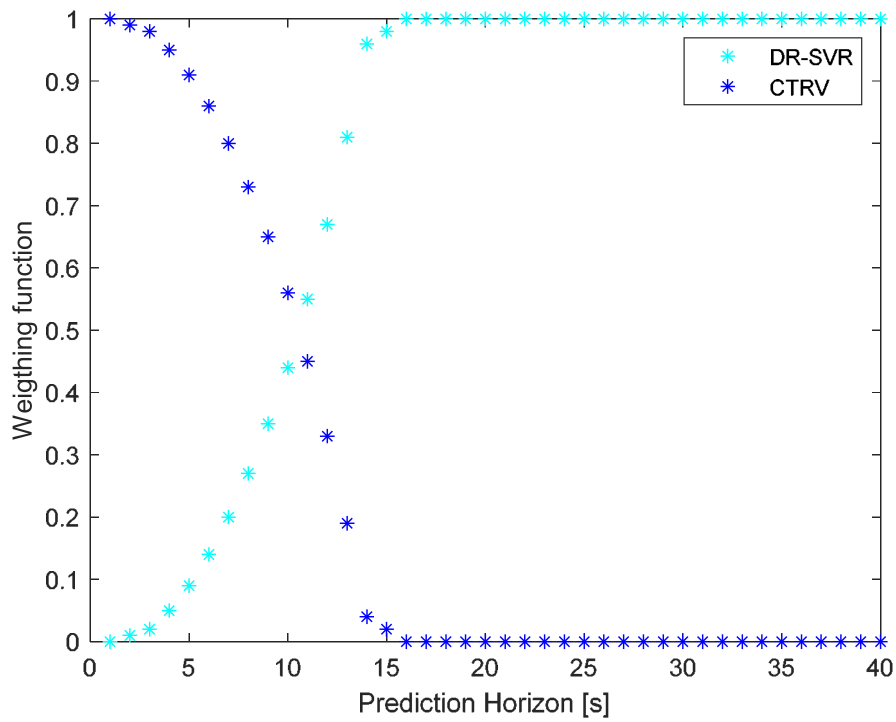

Figure 2 Weighting function used to combine the physics-based model (CTRV), in blue, and the manoeuvre-based model (DR-SVR).

RESULTS

Intention of manoeuvre prediction

For the intention of manoeuvre prediction algorithm the distance to the lane marker had the highest predictive score. Adding the velocity towards the lane made the prediction even better. Adding the best parameter in the third round (longitudinal distance) only added ~2% in prediction score. For that reason this and all following parameters are not included. Figure 3 shows the data used for the cut-in prediction with the cut-in (blue) and going straight events (black) with respect to the selected parameters. It can be seen that cut-ins can be identified by a small distance and substantial negative velocity to the lane marker. The outcome of the SVM machine learning algorithm can be seen in Figure 4. From this result a probability of an cut-in can be computed by using the current values of the 2 selected parameters.

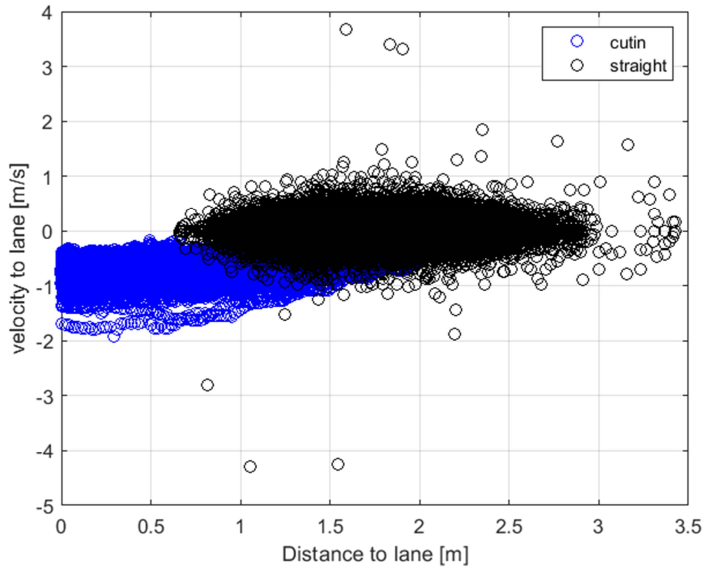

Figure 3 Data used to make the prediction algorihm with the selected parameters on the x- and y axis. Blue is cutin data and black is lane keeping data.

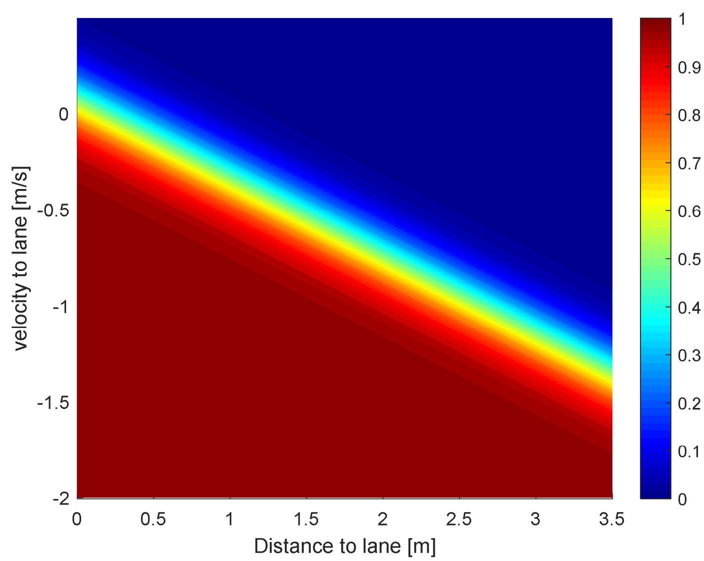

Figure 4 The cut-in prediction algorithm based on distance and velocity to the lane marker. Red area is high chance on a cut-in, while blue are is low chance

The validation showed a positive predictive value of 82%, meaning that 82% of a positive detection are cut-ins. At the moment of detection the average time to lane crossing for these cut-ins is 1.18s (0.27 STD).

Manoeuvre-based prediction

For the manoeuvre-based prediction, two models were considered: DR-SVR and DR-GPR models, as explained in the section Method. The models were validated with cross-validation and the root mean square error for the longitudinal distance and lateral distance are depicted in Figure 5 and Figure 6 respectively. For DR-GPR, the lateral distance RMSE does not exceed 0.5m, while the longitudinal distance RMSE is within the 1.6m limit after 4s. After 1s, 2s, 3s, 4s, DR-SVR has a RMSE of:

- 0.08m, 0.28m, 0,64m and 1,15m for the longitudinal distance

- 0.22m, 0.28m, 0.30m and 0.30m for the lateral distance.

DR-SVR suffers less from the small size of the training set, showing lower errors for both distances. For this reason, we will use this as baseline for the combination with the physics-based prediction result, described in next subsection.

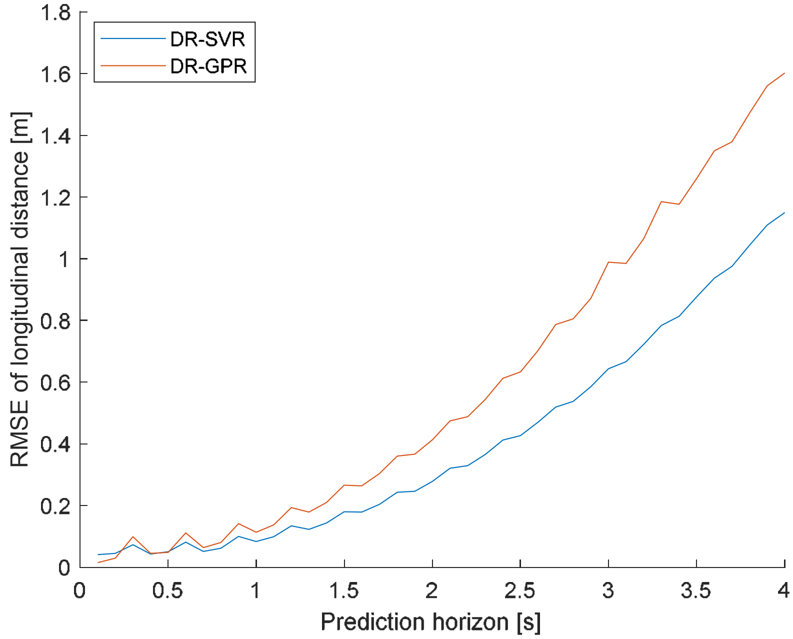

Figure 5 RMSE over time of longitudinal distance: the blue line and red line correspond respectively to DR-SVR and DR-GPR.

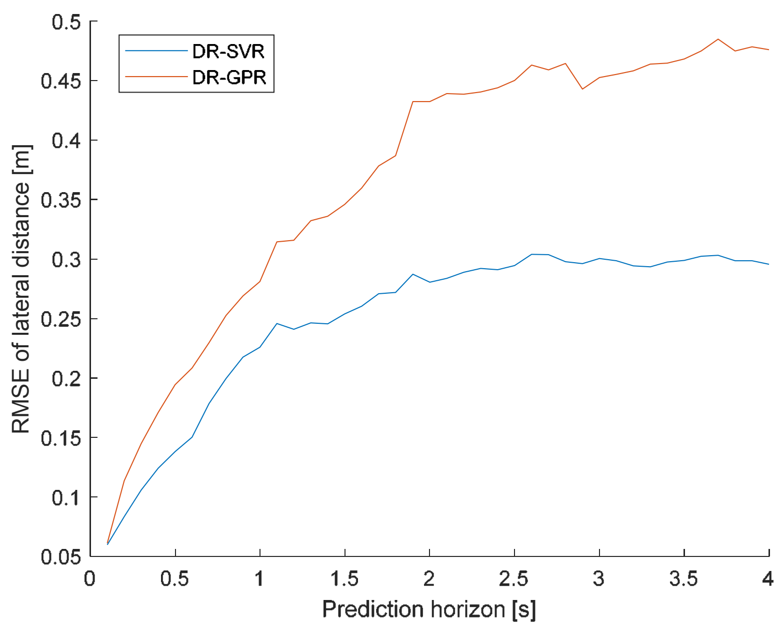

Figure 6 RMSE over time of lateral distance: the blue line and red line correspond respectively to DR-SVR and DR-GPR.

Comparison of physics-based and manoeuvre-based trajectory prediction

The manoeuvre based models (DR-SVR and DR-GPR) were compared with the physics-based (CTVR). Based on the results, the combination of DR-SVR and CTVR was based on the weighting function depicted in Figure 2.

As the CTRV requires more input signals than DR-SVR and DR-GPR in order to perform well, a new validation set was chosen to compare the performance of the different models. We selected the same set used for training the maneuver intention predictor, as explained in Method section. In Figure 10, the profiles of lateral distances of cut-ins are depicted; as it can be seen, both right and left cut-ins are included in the set.

In Figure 8 and Figure 9, the RMSE of the longitudinal distance and the lateral distance are showed. The physics-based model, CTRV, outperforms the manoeuvre based models up to $1.6s$ for the longitudinal distance and $2s$ for the lateral distance. The results show that the manoeuvre-based approach outperforms the physics-based approach for longer horizons, especially DR-SVR for longitudinal distance and DR-GPR for lateral distance. The combination of DR-SVR and CTRV is capable of predicting well for shorter and longer horizons, keeping the advantages of both methods. The combined model predicts the longitudinal distance and the lateral distance with an error that is 50% lower than the one using the physics-based model, after 4s. Looking at short horizons, the combined model is characterized by a RMSE that is one sixth of the RMSE of DR-SVR after 0.5s for the longitudinal distance and a RMSE 62% lower than DR-SVR for the lateral distance. Some examples of prediction are depicted in Figure 7.

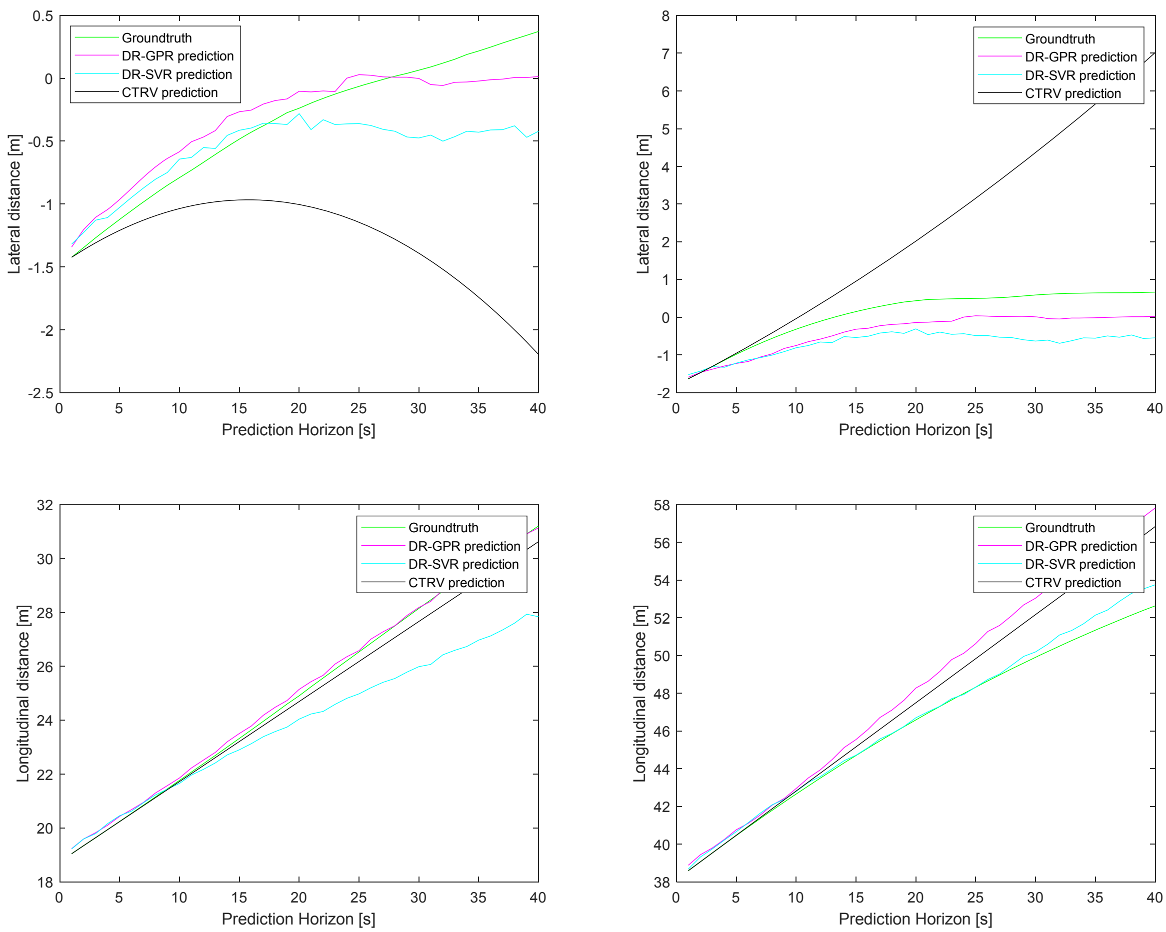

Figure 7 Examples of predictions using the different models. The groundtruth is represented in green, DR-GPR in magenta, DR-SVR in cyan and the CTRV in blue.

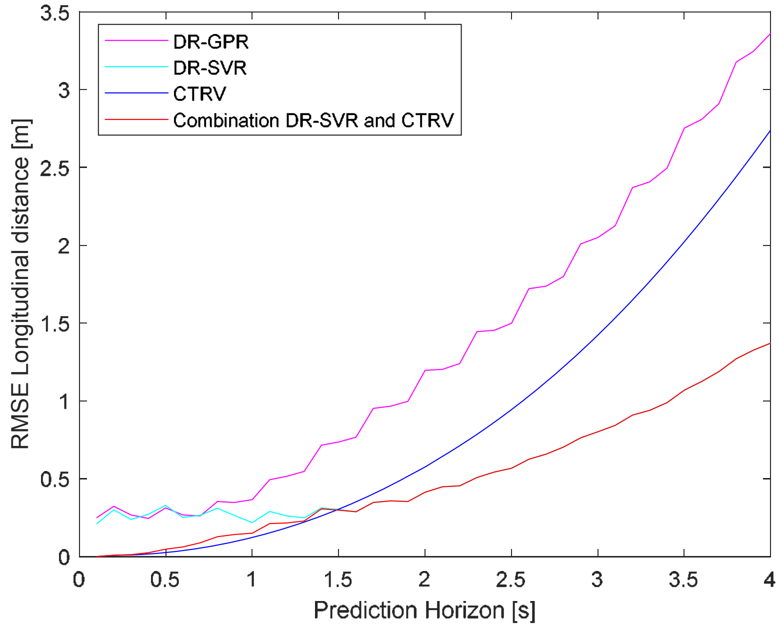

Figure 8 RMSE of longitudinal distance, based on the validation set, for the following models: DR-GPR (magenta), DR-SVR (cyan), CTRV (blue) and the combination of DR-SVR and CTRV (red).

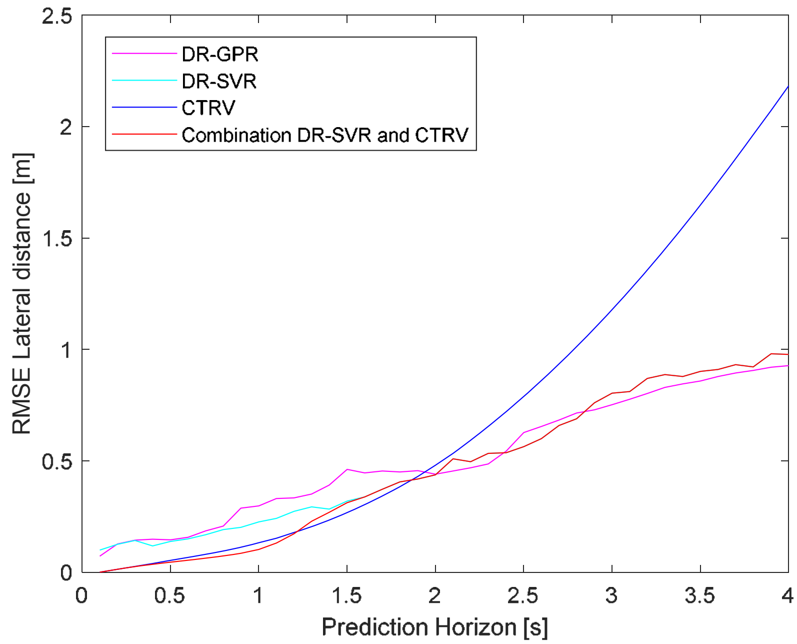

Figure 9 RMSE of lateral distance, based on the validation set, for the following models: DR-GPR (magenta), DR-SVR (cyan), CTRV (blue) and the combination of DR-SVR and CTRV (red).

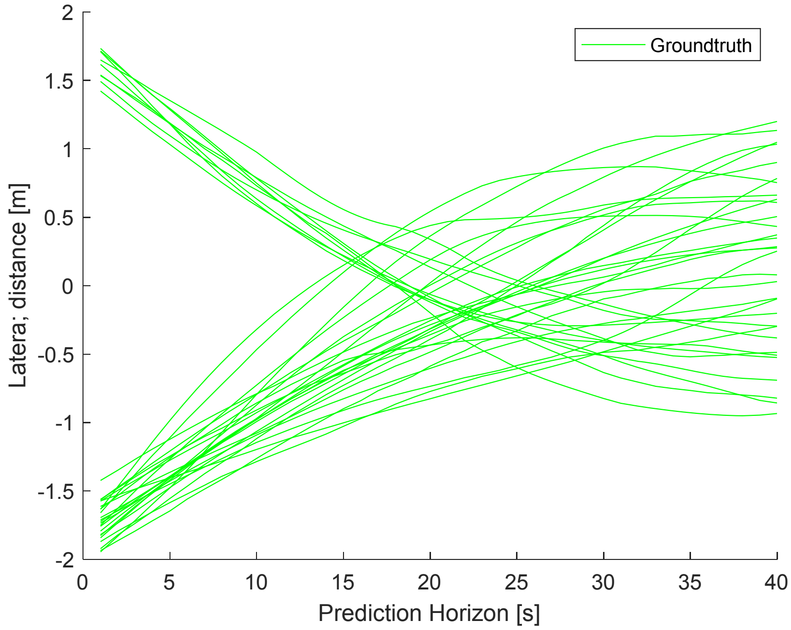

Figure 10 Validation set: the lateral distance over time of all cut-ins used for validation.

HIL setup

The prediction models are meant to be used to enhance automated driving functions. Knowing the future states of dynamic objects, as other vehicles, enables highly automated driving and increases safety. These models are often tested only via Software simulations, which can assess the accuracy of the models but doesn't ensure that these models can be integrated with the controllers and that they can infer in real-time using the data perceived by sensors such as radars or cameras. The Hardware-in-the-loop environment allows to test the functionality of the abovementioned model as if they were integrated in a real automated vehicle, testing the integration of them software and controllers with actual hardware components usually present in an automated vehicle, to give more realistic feedback. The models run in real-time and work correctly with the other components. The interfaces were facilitated by creating a ROS node of our model.

In Figure 11, three important moments from a demo video are depicted. The blue vehicle is the host vehicle, which is instrumented and it is going to predict the trajectory of the red vehicle. In the first moment, the red vehicle is not in the field of view of the blue vehicle yet. For this reason, the probability of cut-in and the time to cut-in are not measured yet. In the second snapshot, the cut-in is predicted with a probability of 98% and with a predicted time to lane crossing of 1.16s. The red continuous line is the physics-based prediction, based on CTVR. The third moment shows that the cut-in is already happening, therefore also the manoeuvre-based mode can be used, and it is the magenta line in the figure. As it can be seen, the manoeuvre-based prediction is far more accurate than the physics-based prediction.

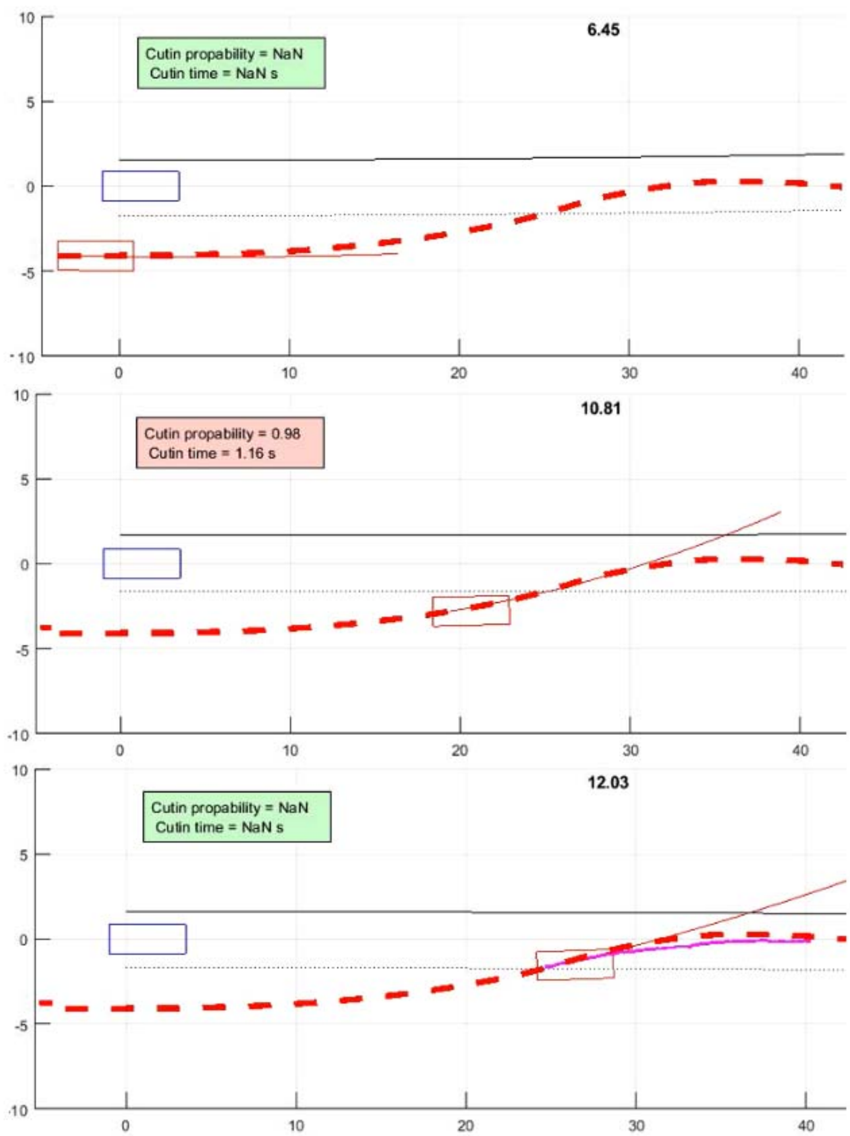

Figure 11 Three snapshots from a video where the models are functioning at the same time. The blue vehicle is the automated vehicle, which is instrumented and it is going to predict the trajectory of the red vehicle.

DISCUSSION

Validation of the cut-in prediction algorithm showed that the algorithm had problems with merging scenarios. This makes sense since the lane marker seen by the MobilEye is not the lane marker relevant for the target vehicle in merging situations. This induces large velocities towards the lane marker providing false positives. When removing these scenarios (which can be done online with the use of GPS and map data). the positive predictive value of 82% can become substantially higher when the lane detection on the Mobileye is improved. In almost all of the false positives, it is the erratic detection of the lane that triggers the cut-in prediction. For the computation of the average time to lane crossing a small portion of the detections is omitted. In this small portions the detections occur immediately when the object comes into view of the sensors, which induces a unrepresentative small time to lane crossing. In this research the Constant Turn Rate and Velocity (CTRV) kinematic model is chosen to be used for short prediction. There are other models, e.g. Constant Turn Rate and Acceleration (CTRA), Constant Steering

Angle and Velocity (CSAV) or Constant Curvature and Acceleration (CCA), which may or may not provide better results in the presented cut-in scenario.

The manoeuvre-based models have been trained also for predicting lane following trajectories and for predicting the orientation α over time. In both cases the models were not successful: the lane following set was too small to train appropriately the models, showing overfitting and therefore it was decided to use CTRV that shows quite good results for this kind of linear behaviour. Future work will focus on training machine learning models capable of predicting trajectories for lane following as well. The orientation is very difficult to predict, as it can't be accurately measured by current sensor sets and therefore the available training sets are not good enough to ensure a valid training of the models.

In the results, the Gaussian Processes model (DR-GPR) underperform compared to the support vector regression (DR-SVR), because DR-GPR suffers more of the incompleteness in the range of the feature space. However, we will keep investigating DR-GPR because of its potential. For example, it can also output the confidence of the predicted trajectory. This information is very valuable, as in case the prediction is not reliable, the automated vehicle might decide to ignore it and assume (for example) the worst case in order to ensure safety, or a set of prediction models can be used and the one with the highest confidence can be selected while driving on the road. In addition to this, gaussian processes are very good with handling noisy data, which is exactly the case for data sensed by current automotive sensor sets.

The presented approach is capable of predicting the motion of the other road users in a standard situation. In order to handle more sophisticated scenarios, the road information should be used for training. The training set needs to be extended for better results, and the validity of the models needs to be checked for safety critical scenarios. This can be done in the HIL, where critical scenarios can be simulated and therefore the models can be tested on them.

CONCLUSIONS

A hybrid approach for predicting the motion of vehicles from a host vehicle perspective is presented in this work. A combination of manoeuvre-based and physics-based models is used to enhance the accuracy of the prediction in shorter and longer horizons. The combined model predicts the longitudinal distance and the lateral distance with an error that is 50% lower than the one using the physics-based model. In addition to this, the combined model is characterized by a RMSE that is one sixth of the RMSE of SVR after 0.5s for the longitudinal distance and a RMSE 62% lower than SVR for the lateral distance. The information coming from the prediction module can be used path planning of (partly) automated vehicles. The integration in the HIL environment shows great potential to allow autonomous driving to go to higher levels of automation. Future work will focus on a broader use of machine learning for prediction and on the validation on safety-critical scenarios using the HIL environment.

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