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Courtesy Behavior for Highly Automated Vehicles on Highway Interchanges

Cristina Menéndez-Romero[1], Mustafa Sezer[1], Franz Winkler[1], Christian Dornhege[2] and Wolfram Burgard[2]

***Abstract*— On the highway, human drivers continuously make decisions adapting their driving behavior. In some of these, for example near highway ramp-entrances, they adjust intuitively their own behavior in order to facilitate the merging of the incoming vehicles. On highly automated vehicles, this decision should be taken by the system. In such situations, not only the own goal should be optimized but also the comfort of the surrounding traffic. The ability to plan adequate courtesy behaviors improves public acceptance of autonomous systems and the comfort of the surrounding vehicles without considerably decreasing the own comfort. We present a novel method that automatically adapts the driving behavior, integrating the merging intention of other vehicles. In contrast to other systems, robustness is achieved by considering not only the most likely evolution, but also the expected value of the possible outcomes in real time. The flexibility of this method allows us to integrate it within different planning systems. We are therefore able to offer courtesy behaviors to other vehicles, thereby improving the collective comfort and also safety of the situation. We evaluate the method in simulation and in real world experiments with our test vehicle. Results show an improvement of the aggregate traffic comfort and in addition a reduction of critical situations, as a result of applying our courtesy behavior to different planning strategies.**

Fig. 1: On a merging scenario, incoming vehicles should select the appropriate gap to merge and vehicles in the main flow can cooperate to facilitate the maneuver.

I. INTRODUCTION

Vehicles of different automated levels are already operating on the streets and interacting with purely manually human-driven vehicles. One challenge lies in situations that a human driver solves in an intuitive way and that are still non-trivial for the machine.

Particularly interesting are those situations that arise from the politeness of the traffic participants. For many merging situation as presented in Figure 1, human drivers anticipate the merging intention of other vehicles driving on the neighbor lane and select a cooperative behavior. Drivers also expect such cooperative behavior from automated vehicles. In dense traffic situations, the vehicle should be able to adapt its strategy in such situations where a light decrease of the own comfort considerably improves the collective one. For example if a merging vehicle is reaching the end of lane or approaching a slower vehicle, the ego vehicle could decide to open a gap by decelerating or changing the lane.

This paper focuses on such cooperative behaviors. After the identification of a conflicting situation for a potential merging vehicle, our vehicle assesses the options between behaving cooperatively or following its own interest. The challenge is to optimize safety and comfort over the evolution of several possible scenes without the explosion of computational costs.

Many works address the prediction of other traffic participants behavior. However, this behavior is only partially predictable and only accurate for a short time horizon. Classical planning systems consider only the most likely evolution of the situation, neglecting less likely actions that could result in more dangerous situations. On the other extreme, some approaches include all possible scene evolutions resulting in too conservative systems or too high computational load to be used for real-world applications.

The decision-making should deal with the uncertainties derived from the behavior of other traffic participants in an efficient way. This means that the trade-off between computational load, comfort and safety should be optimized. The focus of this work concerns the integration of the intention of the merging vehicles within the decision-making process.

In this paper we present a courtesy behavior method that enhances several existing planning approaches. This method allows to assess the adequacy for the ego vehicle to adapt its own strategy in order to facilitate the merging maneuver of a potential merging vehicle. As the main contribution the improvement of two already existing planning approaches using our method is presented. The limits between a good

[1]C.Menéndez-Romero, M.Sezer and F.Winkler are with BMW Group, Munich, Germany cristina.menendez@bmw.de

[2]C.Dornhege and W.Burgard are with Autonomous Intelligent Systems, University of Freiburg, D-79110 Freiburg, Germany

intention and planning algorithm and the re-planning ability of the system are also analyzed.

II. RELATED WORK

Human drivers analyze and anticipate the traffic situation. In a similar manner, autonomous vehicles should integrate a prediction of the behavior of other participants into their driving task.

The problem of robots interacting on populated human environments is not only focus of autonomous driving but also point of interest of other robotic fields. Bennewitz *et al.* [1] presented a method to predict the trajectories of persons and improve the navigation behavior of a mobile robot. Kuderer [2] and Kretzschmar [3] present a cooperative navigation model for mobile robots interacting with pedestrians. Nevertheless, when navigating on freeways and highways, the topology is more structured and the velocities of the traffic participants are higher, which requires consideration of specific solutions.

In a near future, as presented by Hobert [4], the intercommunication between vehicles and infrastructure (V2X) will allow to acquire a precise information about the intentions of the traffic participants and the evolution of the situations. The authors of [5] proposed an on-ramp merging system which assessed the road traffic conditions and transmit the instructions to the vehicles on the surrounding area. The system performs well but relies on an advanced infrastructure. V2X technology presents encouraging results but the technology is still not mature enough.

Thourought the last years several prediction methods for traffic participants have been intensively studied in the literature. Different motion models like physic-based models, maneuver-based models or interaction-aware based models can be used for the prediction [6]. The integration of prediction and intention information within the decision-making process plays a crucial role in the system performance.

In [7] the authors compute the complete set of the collision-free start and end points of trajectories for each vehicle. This kind of intensive computations provide accurate results in detriment of the online capability of the system. Other strategies take the current most likely prediction and rely on a continuous update of the available information and fast re-planning system, as the multilevel planning system presented by Menéndez-Romero *et al.* [8]. Carvalho *et al.* [9] integrate the most likely cut-in prediction information to improve the autonomous cruise control. The combination of the most likely prediction with a fast re-planing works for most of the situations quite well, but still does not consider other possible interactions between the agents involved.

Iterative planning strategies combine the planning and prediction tasks. Wei *et al.* [10] propose an intention prediction based strategy generation. In [11] the authors suggest a game theoretic approach which can model the re-planning capabilities of the drivers. In [12] the decision-making is based on Partially Observable Markov Decision Process (POMDP). The multi-policy decision-making presented by Cunningham *et al.* [13] also simulates the scene evolution using the most likely evolution of the other agents involved in order to reason about the policies. The problem with such iterative planning approaches is that they only consider the most likely evolution of the other traffic participants. Especially in longer prediction horizons the model predictions can become inaccurate and overlook some critical situations.

One step further, our proposed system not only anticipates the behavior of other traffic participants to improve their own safety but also plans a cooperative behavior to improve the aggregate traffic comfort.

III. APPROACH

The objective of this work is to provide our system with a courtesy behavior, which identifies the intention of other traffic participants and assesses the cost of adapting the own ego strategy. We achieve this by integrating an intention prediction algorithm into the decision-making. Thereby we gain a better foresight of the scene evolution by including all possible outcomes to provide our system with robustness over false predictions. Decisions are made based on maximizing the expected utility of the involved traffic participants.

A. Problem and Task Description

We semantically determine the possible actions for the ego and the conflicting vehicle as shown in Tables I and II. All possible ego actions are clustered as *No Cooperative* (NC) and *Cooperative* (CO). Thus, the action space of the ego vehicle is defined as $\mathbf{A}_{ego} := \{NC, CO\}$. For the conflicting vehicle normal, courtesy and forced merge actions are combined into the *No Yield* actions (NY), corresponding to merging in front of the ego vehicle, and the *Yield* actions (Y). Thus, the action space of the conflicting vehicle is defined as $\mathbf{A}_{cv} := \{Y, NY\}$. The Cartesian product $\mathbf{A} = \mathbf{A}_{ego} \times \mathbf{A}_{cv}$ defines the joint action space.

Our goal is to choose an action for the ego vehicle so that the combined expected utility ($\mathcal{U}(a)$) is maximized, i.e.,

$$\begin{aligned} a^*_{ego} &= \underset{a \in \mathbf{A}_{ego}}{\operatorname{argmax}} \mathbf{E}(\mathcal{U}(a)) \\ &= \underset{a \in \mathbf{A}_{ego}}{\operatorname{argmax}} \sum_{a_{cv} \in \mathbf{A}_{cv}} p(a_{cv} \mid a_{ego}) \cdot \mathcal{U}(a_{ego}, a_{cv}). \end{aligned} \tag{1}$$

This makes necessary to predict the intention of the merging vehicle $p(a_{cv} \mid a_{ego})$, which is presented in the next section. The description of the expected utilities is given in Section III-C.

B. Prediction Module

In the state-of-the-art methods, the costs of actions are computed for the most likely actions of other traffic participants. But these approaches lack the robustness against false predictions. Our aim, on the other hand, is to predict the probability of unlikely behavior of other traffic participants, specifically the misprediction probability for the conflicting vehicle. Using this probability we can compute the expected utility of an ego action considering two possible decisions of the conflicting vehicle.

In order to predict the probability of unlikely outcomes, we use an ensemble learning based Gentle Boost classifier [14].

TABLE I: Ego Vehicle Actions.

NC		Follow solely the ego objectives
CO	CKL	Cooperation by deceleration when keeping lane
	CCL	Cooperation by changing lane

TABLE II: Conflicting Vehicle Actions.

Y		Yield the right-of-way to the ego vehicle and merge after it
NY	NM	Normal merge into available space in front of the ego vehicle
	CM	Courtesy merge - ego vehicle provides space for merging
	FM	Forced merge - no available space, ego vehicle has to react

The classifier's feature vector $\vec{x}$ consists of the Time-to-Lane-End (TTL) of the merging vehicle, the time headway ($THW_{\text{ego-cv}}$) between the ego and the conflicting vehicle, the velocities and positions of both vehicles relative to the ending lane ($\vec{x} = [TTL, THW_{\text{ego-cv}}, v_{ego}, v_{cv}, x_{ego}, x_{cv}]$). Its output is the merging decision, thus either Y or NY.

In order to learn the classification tree, we generate a scene with the ego and the conflicting vehicle at 300135 different initial configurations. We simulate it in the model predictive control framework of [11] to label the data. For the simulation, we used a conflicted vehicle model based on the merging models proposed by [15]. Then the classification tree is trained using a Gentle Boost classifier with 40 learners (classification trees) and 20 maximum splits with 20-fold cross validation. The output of the classifier is either Y or NY, thus not probabilistic. In order to compute how certain the prediction is, we use Monte Carlo sampling with Gaussian distributions around x_0^{ego}, x_0^{cv}, v_0^{ego} and v_0^{cv} with $N = 400$ samples. The votes for each class are counted within the sampling region and the ratio is computed to get the probability of each class.

The Monte Carlo sampling approach has three advantages. First, it provides the probability of an action of the conflicting vehicle, which is required for computing the expected utility in Section III-C. Second, it is robust to measurement errors, since we generate samples around the current measurement values. And third, it is robust to false classifications, because the 2-class classification is not binary but probabilistic.

This prediction provides us an accurate prediction of the intentions, but its computational load is too high. For this reason we also implemented a second prediction module, a Multinomial Regression Classifier.

We obtained an accuracy of 99.2% for the Gentle Boost Classifier and an accuracy of 97.3% for the Multinomial Regression Classifier. The Multinomial Regression Classifier fits directly a probability value, for the classification we accepted as positive probabilities over 0.5. The accuracy is computed as $\frac{TP+TN}{TP+TN+FN+FP}$ where TP are the true positives, TN the true negatives, FN the false negatives and FP the false positives. Table III shows the recall $\frac{TP}{TP+FN}$ and precision values $\frac{TP}{TP+FP}$ resulting for both classifiers.

The accuracy and precision values are better for the Gentle Boost classifier, but the experiments presented in Section IV show that a good performance can also be achieved with the regression classifier.

TABLE III: Values for different classifiers.

	Gentle Boost Classifier		Multinomial Regression Classifier	
	Precision	Recall	Precision	Recall
Y	92.85%	94.78%	82.22%	74.67%
NY	99.64%	99.50%	98.25%	98.87%

C. Decision Making

The goal of our approach is to deal with the uncertainties derived from the behavior of other traffic participants and provide a cooperative behavior if necessary. For this purpose, we enhance the planning strategy with the information coming from the prediction, providing a *courtesy strategy*.

The selection of the strategy is based on an utility function. The utility for an individual vehicle $\tilde{\mathcal{U}}(a_x)$, where $x \in \{ego, cv\}$, is defined as the inverse of the total cost, which is a combination of a safety and a comfort therm. The comfort cost is defined as the accumulated acceleration over the time. The safety cost, is the accumulated maximal risk defined on [16].

For each of the ego strategies the scene is forward simulated, firstly for the most likely predicted merging decision and once again for the opposite merging action. The common expected utility of an action combination $\mathcal{U}(a_{ego}, a_{cv})$ is defined as the combination of the individual utilities, i.e.,

$$\mathcal{U}(a_{ego}, a_{cv}) = \tilde{\mathcal{U}}_{a_{ego}}(a_{cv}) + \lambda \cdot \tilde{\mathcal{U}}_{a_{cv}}(a_{ego}) \quad (2)$$

The parameter λ in Equation 2 is the *cooperation coefficient*, from $\lambda = 0$ for purely egoistic up to $\lambda = 1$ for highly cooperative behavior.

Our goal is to choose the ego action which has the maximum expected utility. Hence, we marginalize out the action a_{cv} of the conflicting vehicle from the common expected utility Equation 1. Since in the proposed framework we analyze the behavior of the conflicting vehicle for a fixed ego strategy, the probability of the given ego action is assumed to be equal to 1 for each of the NC and CO actions. Using the Kolmogorov's conditional probability axiom we have $p(a_{cv}|a_{ego}) = p(a_{ego}, a_{cv})$. Thus, conditional probability can be used instead of joint probability in order to evaluate unlikely actions weighted by their probability. The conditional probability is provided by the prediction classifier.

This way, the Maneuver Planner Module is able to integrate and assess different scene evolutions with their associated probabilities of occurrence and select the ego action with the highest expected utility.

IV. Experiments

This work presents a method to enhance the decision-making strategy with cooperative behavior avoiding the infinite branching factor of all possible trajectory evolutions over the time. To evaluate it we used the same system configurations described below, modifying only the parts corresponding to the decision-making.

A. System configuration

Figure 2 presents the work-flow of our system. Firstly, the vehicle receives information about the environment through the different sensors and backend. This information is processed by the Environment Model. The other traffic participants behavior is predicted by the Prediction Module. Then, the Maneuver Planner Module selects the best policy for the current situation and provides a drivable and collision-free trajectory. This trajectory is tracked and the vehicle controller controls the actors, closing the control loop.

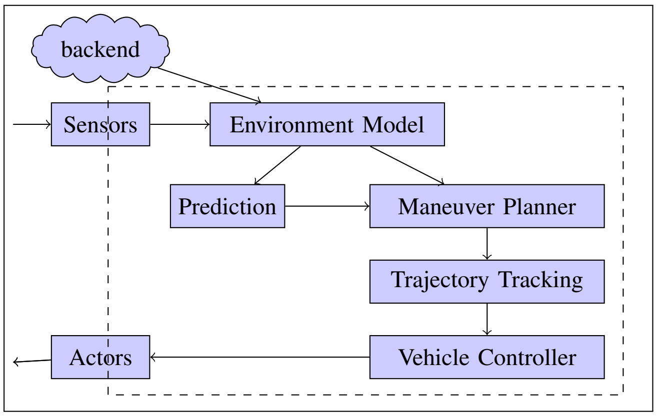


Fig. 2: Environment and vehicle control loop.

The Maneuver Planner Module consists of a decision-making module and a trajectory planning module. For our experiments we integrated two different non-cooperative decision-making implementations. The first one corresponds to a graph search over the discretized space, denoted as Driving Strategy (DS) [11]. The second planning strategy, Maneuver Planning (MPL) [8], searches over the space of actions induced by the available gaps. Both strategies present a Non-Cooperative (NC) behaviour as they follow solely the ego vehicle objectives. We enhanced both planning strategies with the presented courtesy behavior (CO) approach and generated the planning strategies DS-CO and MPL-CO. The trajectory planning and trajectory tracking are for both systems based on the approach described by Rathgeber [17].

The simulation runs in a Co-Simulation of MATLAB/Simulink® and the traffic simulator Pelops [18]. Pelops provides a realistic driver behavior for the other traffic participants. The real-world tests were performed on our test vehicle. There the information is obtained by the sensors and an environment model module sends the agents, objects and topology information to our system, which runs on the real time platform Autobox®.

B. Evaluation Metrics

The setup consists for both the real-world and simulated experiments of a merging ramp scenario, where a merging vehicle has to perform a mandatory lane change into the ego lane. In order to evaluate the performance of our proposed method, different safety and comfort metrics are evaluated:

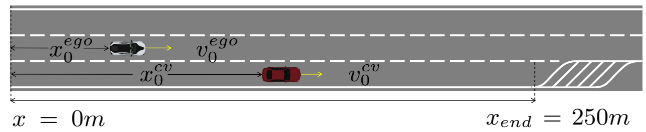


Fig. 3: Initial configuration for simulated experiments

Safety Evaluation:

- $maxTTC^{-1}$: Maximum inverse Time to Collision (TTC) over time. Note that TTC^{-1} is considered instead of TTC to also average the cases when TTC is infinite.

Comfort Evaluation:

- $maxDecEgo$: maximal longitudinal deceleration of the ego vehicle.

Conflict Resolution Efficiency:

- $tMerging$: The conflict resolution efficiency of the proposed approach is evaluated using the merging time.

C. Simulated experiments

The performance of the courtesy behavior strategy was evaluated working with different planning strategies. For this test, we used the Gentle Boost Classifier presented in Section III-B for the merging prediction and DS and MPL strategies with the courtesy and no courtesy configurations as described in IV-A. Both strategies are computed on 200 ms task time.

We have generated random initial configurations of the scene shown in Figure 3. During the experiments, the entrance ramp's length was 250 m and x_0^{ego}, x_0^{cv}, v_0^{ego} and v_0^{cv} were varied randomly between 0 to 200 m and 60 to 130 km/h respectively. The vehicles start with a constant velocity at the center of their lanes.

TABLE IV: Simulation Results for different strategies. Metrics were averaged over 469 cases.

Approach	maxTTC^{-1}	maxDecEgo	Merging Time	Computation Time
DS-NC	0.080 s^{-1}	-1.22 m/s^2	5.910 s	0.195 s
DS-CO	0.068 s^{-1}	-1.03 m/s^2	5.440 s	1.545 s
MPL-NC	0.049 s^{-1}	-1.04 m/s^2	7.576 s	6.667e-06 s
MPL-CO	0.023 s^{-1}	-1.67 m/s^2	5.206 s	1.350 s

Table IV shows the metrics for the different configurations and the computational time corresponding to the prediction and the decision-making modules. The enhancement of the DS with a cooperative module allows to improve all the considered metrics. A reduction of the $maxTTC^{-1}$ indicates that on average, the most critical time point becomes safer. The lower deceleration values also indicate that the ego reaction has a better foresight for the planning. Similarly, the merging times are improved by the cooperative strategy. With the non cooperative approach for the MPL (MPL-NC), the ego vehicle optimizes only its own utility and it does not decelerate. Therefore, the merging vehicle selects a conservative behavior yielding the right-of-way to the ego vehicle and merging after it. In this case, the ego vehicles

TABLE V: Simulation Results depending on the rate time. Metrics were averaged over 469 cases.

Approach	Computation Time	Task Rate	maxTTC^{-1}	maxDecEgo	Merging Time
MPL-NC	6.667e-06 s	200 ms	0.049 s^{-1}	-1.04 m/s^2	7.576 s
MPL-NC	6.667e-06 s	40 ms	0.048 s^{-1}	-1.14 m/s^2	5.400 s
MPL-CO GB (N = 400)	1.350 s	200 ms	0.023 s^{-1}	-1.67 m/s^2	5.206 s
MPL-CO GB (N = 35)	0.145 s	200 ms	0.051 s^{-1}	-1.03 m/s^2	5.242 s
MPL-CO MR	4.427e-05 s	200 ms	0.039 s^{-1}	-1.09 m/s^2	5.502 s

pursues a merely egoistic approach and the average merging time increases considerably. The enhancement of the MPL approach with a courtesy behavior, reduces the merging time and the values of $maxTTC^{-1}$, by increasing the average deceleration values. It provides a safer and faster conflict resolution by braking. However, the results including prediction (DS-CO and MPL-CO) present too high computational times, making it unsuitable for real time applications.

For this reason we integrated the intention prediction with the Multinomial Regression Classifier explained in Section III-B. From here on, we focus the study on the MPL strategy because it offered more computational reserves. We also evaluated different task times of the decision-making strategy according their online capabilities.

Table V shows the results. The MPL-NC presents results of the reactive strategy, without prediction for two different task times, in order to study the influence of faster updates. MPL-CO GB presents the courtesy strategy with the Gentle Boost Classifier for the prediction information presented in Section III-B. We variate the number of samples to obtain a online-capable computational time. The MPL-CO MR integrates the courtesy strategy with the Multinomial Regression Classifier. The non cooperative strategy improves the merging time by computing in a faster task rate, it becomes more reactive and increases the braking rate. Nevertheless, the $maxTTC^{-1}$ metrics remain similar. An improvement on the $maxTTC^{-1}$ values is obtained by the MPL-CO GB (400 samples) over the non cooperative strategy, whereas with an online capable number of samples samples (35) it remains similar. The use of Multinomial Regression for the predictions allows to find a balance between the computational time and the metrics improvement over a merely reactive approach. Hence, the MPL-CO with Multinomial Regression Classifier was selected for our real-time experiments.

D. Real-world experiments

The courtesy strategy was also evaluated on our test vehicle. The experiments should be reproducible to compare the results and therefore they were carried out in the controllable environment of a test track. To perform these experiments we placed a virtual end of lane in front of the merging vehicle, which we activated based on the relative distance between both vehicles.

We aimed to compare the enhancement of our strategy with and without using the courtesy behavior. The merging vehicle was instructed to perform the lane change independent of the ego vehicle. This situation represents the use case when the merging vehicle overlooks the vehicles driving on the merging lane or underestimates the danger of the situation. We drive a set of 14 configurations with different initial velocities (v_{ego}: $65-100km/h$, v_{cv}: $60-80km/h$). We took several repetitions for each measurement and in order to provide a more accurate overview we also simulate the scene with our traces.

Figure 4 presents the resulting metrics for the different configurations. The decrease of $maxTTC^{-1}$ values indicates that the experiments are less critical for our courtesy setup. In addition, for these experiments the deceleration values are lightly lower. The simulation with traces also provides a reference between the quality of simulations results and real-world experiments. Their similarity indicates that simulated results are also representative of real-world behavior.

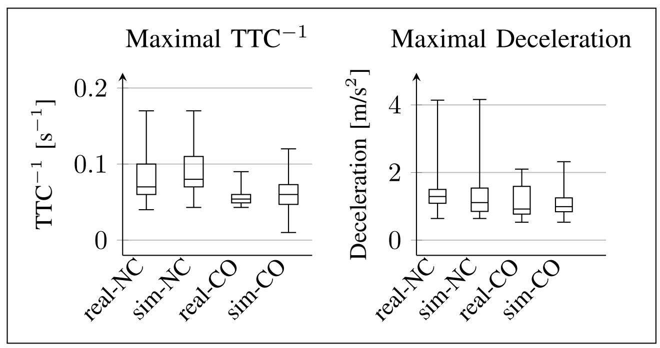
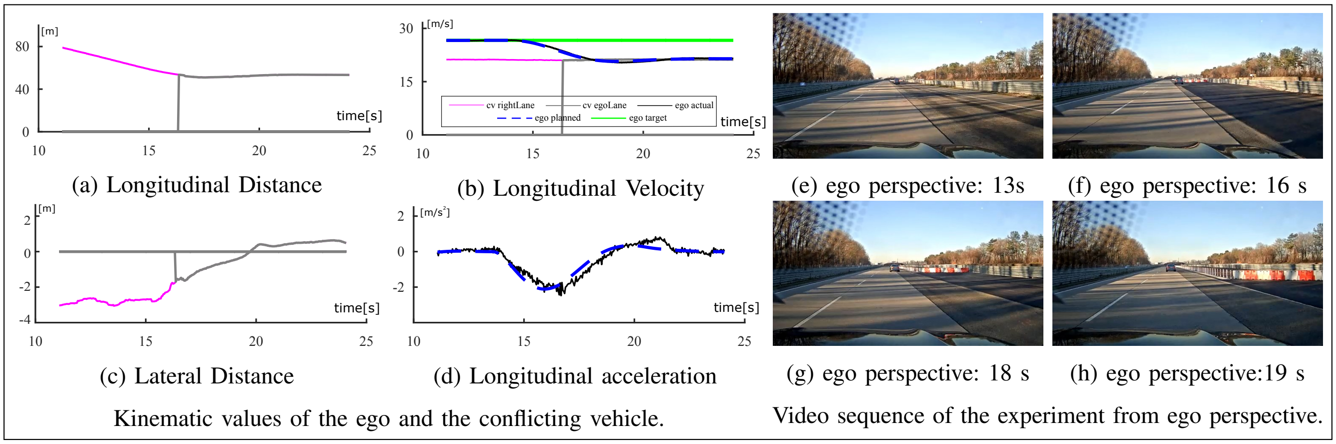


Fig. 4: Metrics for real-world experiments with and without the courtesy behavior strategy.

Figure 5 shows the velocities and positions of a real-world measurement with our MPL-CO strategy active, as well as the scene evolution (Figures 5e to 5h). Plots 5a and 5c show the longitudinal and lateral distance between the ego vehicle and the conflicting vehicle from the ego perspective. Plot 5b presents the velocity of the ego vehicle and the velocity of the merging vehicle differentiating between the classification on the right lane and on the ego lane. Plot 5d presents the longitudinal acceleration planned and measured of the ego vehicle. We observe that the longitudinal reaction of the ego vehicle begins about two seconds before the conflicting vehicle is classified at the ego lane.

E. Discussion

Simulation results show how the enhancement of a driving strategy with courtesy behavior improves the comfort of the merging vehicle, reducing its merging time. In addition, the safety metrics (TTC^{-1}) for the ego vehicle are also improved due to the foresight planning. Advantages of a foresight planning over a fast re-planning are particularly



(a) Longitudinal Distance (b) Longitudinal Velocity (e) ego perspective: 13s (f) ego perspective: 16 s

(c) Lateral Distance (d) Longitudinal acceleration (g) ego perspective: 18 s (h) ego perspective:19 s

Kinematic values of the ego and the conflicting vehicle. Video sequence of the experiment from ego perspective.

Fig. 5: Experiments results in the real-world, for an active courtesy strategy.

illustrated in the measurements of the real-world experiments. For critical situations, where the merging vehicle overlooks the ego vehicle, the selection of a cooperative strategy allows the ego vehicle to adapt itself in a comfortable way, outperforming the no-cooperative strategy.

For the prediction in our cooperative strategies we used the methods presented in Section III-B, however other prediction methods could provide more accurate information and optimize the computation time. We focused on merging lanes, but the situation is similar to other use cases like merging vehicles which overtake slower vehicles. The challenge is to estimate correctly the intention of potential merging vehicles, but the assessment of a courtesy behavior could be also applied in those situations. The real-world experiments were driven on a supervised environment.

V. CONCLUSIONS

We presented an approach that provides an automated vehicle with courtesy behaviors. During conflicting situations we assess different possible scene evolutions. It takes into account not only the most likely behavior of the other traffic participants, but also the opposite one to cooperate with them. We presented how this method can complement several decision-making strategies based on a generic prediction algorithm. The simulation results show that this courtesy behavior improves the results of already existing decision-making strategies. We show that our approach can be adapted to the computational requirements and therefore be online capable. Finally, experiments with our test vehicle illustrate the usability for real applications. An important future step is to test the system intensively in public environments.

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