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Complex Lane Change Behavior in the Foresighted Driver Model

Julian Eggert[1,†] and Florian Damerow[2,†]

***Abstract*— This paper presents a general model for lane-change decision and dynamic lane-change behavior based on the Foresighted Driver Model. Differently to previous models, it does not rely on indirect features like gap lengths, TTC or decelerations, but it models the lane-change process by explicitly calculating the involved risks and benefits of the different trajectory alternatives. The lane-change decision occurs by searching a tradeoff between the anticipated risks and the utility of the maneuver for the driver. In such a way, the model generalizes to a large variability of lane-change situations with varying number of involved traffic participants, since their states are incorporated into the risk estimation. We show that with our model, regular lane-change processes can be reliably captured. We also show, how in complex constellations, the model reacts in plausible ways which are not covered by previous models. This is the case e.g. when an emergency lane-change is forced by a fast rear-end approach, or when a lane-change occurs in anticipation to an expected merge-in at an entrance.**

I. Introduction

General lane changing behavior is a major influencing factor of risky situations as well as traffic perturbations. It has a direct effect on a drivers safety (e.g. when other traffic participants enter the intended driving path) and efficiency (e.g. when forcing a driver to brake down from the targeted cruising velocity or when forcing him to plan alternative maneuvers). Therefore, reliable lane changing models are crucial for the advancement of future advanced driver assistant systems (ADAS). Their application potential ranges from anticipatory warning functions when lane-changes of other vehicles cutting-in are predicted up to the planning and control of autonomously executed lane-change maneuvers.

In this paper, we concentrate on the operational stage [1] (as opposed to strategic and tactic stages) of lane-change maneuvers, where it is determined if a lane-change is both safe and desirable according to the environment constellation, and the lane-change is then executed with the appropriate speed and trajectory.

Lane-change decisions are typically modeled using gap-acceptance models. In this case, the available gaps between lead and lag vehicles in the target lane are compared to some acceptable critical gap, which depends on the relative speeds of the involved vehicles (the ego vehicle and the lead and lag vehicles in the target lane) [1], [2], [3].

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A model which does not take critical gaps explicitly into account, but which considers the difference in the accelerations / decelerations before and after the assumed lane-change, is proposed in [4]. Their model MOBIL (minimizing overall braking induced by lane-change) combines a safety check which depends on the deceleration in the target lane with an incentive criterion which depends on the assumed accelerations/decelerations in the current vs. the new lane, where the accelerations/decelerations are calculated according to standard longitudinal car-following models such as the IDM (Intelligent Driver Model, [5]). Advantage and disadvantage of the lane-change are expressed in terms of the single-lane accelerations/decelerations, so that e.g. a slow leader in the current lane might incentivate a lane-change, however a slow leader in the target lane might result in a necessary braking, making a lane-change unattractive.

Several previous approaches have concentrated on the *r*ecognition of lane-changes. Oliver and Pentland [6] use Hidden Markov Models with different features for the classification of lane-keeping and lane-changing behaviors. Other authors use support vector machines for similar purposes [7], [8]. Some also model the lane-change process itself, such as [9] who predict the drivers subsequent actions, and [10], who generates detailed dynamic lane-change trajectories.

In this paper we propose to address the problem of lane-change maneuver decisions and control based on the involved risks and benefits / utility along the future driving trajectories, instead of relying on indirect measures like gap lengths, time-to-x collision features or required longitudinal decelerations. The influencing factors are formulated explicitly, making them easily generalizable to incorporate different types of risk and varying complexity of the situations. The lane-change decision is then a result of the tradeoff between the advantages and disadvantages imposed by the risks and the utility. The lane changing model is based on an extension of the Foresighted Driver Model (FDM) [11] towards non-longitudinal behavior. The main considered risks are based on predicted collision events with all lead and lag traffic participants in the current and the targeted lanes, however, by construction, other risks such as imposed by road structures and road geometry (e.g. the influence of road curvature as in [12]), can also be incorporated. We see one of the main applications of the FDM to provide an interaction aware yet sufficiently simple model for the prediction of the behavior of the other traffic participants for ADAS applications.

In the following, in section II, we first recapitulate the FDM, concentrating on the components that we extend afterwards for the implementation of the lane changing behavior. In section III, we explain the details of the lane-change

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model. In section IV we show results of the lane-change behavior for different scenarios.

II. The **F**oresighted **D**river **M**odel (**FDM**)

The **F**oresighted **D**river **M**odel (**FDM**) simulates a driver's behavior by assuming that he/she tries to minimize expected future risks, searching a tradeoff between driving utility (given e.g. by general driving goals such as a desired time to reach a target) and criticality along the intended driving path. It is fundamentally different from other driver models in that the risks and utility, which constitute the main driving force, are modeled explicitly, and not implicitly in terms of e.g. velocity differences, braking decelerations or Time-To-Contact (TTC).

Since the FDM tries to capture the main causes for a drivers' behavior (especially under critical conditions), it generalizes to a large variety of different situations, such as curve driving, intersection approaches, and highway driving. For other scenarios, the FDM can be applied similarly without changes. For increasingly complex situations, the main task is rather to increase the accuracy of the modeled risks and the number of involved traffic participants, while the approach and the fundamental structure of the model remains unchanged.

In short, we assume that a driver is aware of the risks of different possible upcoming situations, which he/she is able to foresee by a prediction of the others' behavior, and that he/she compares them with the benefits he/she will obtain when following a particular driving behavior.

The FDM comprises the following steps:

- Coarsely predict the time course of the driving scene sorroundings including the most important behavioral alternatives of the traffic participants. This involves a prediction of the main possible trajectories of e.g. the own car and other cars as well as maneuver alternatives such as braking or accelerating and driving alternatives such as turning left, right or following straight.
- By comparing the own driving trajectory in relation to the temporal evolution of the other traffic participants and road structures, estimate state and time of future points where the probability that a risky event happens is maximal. This has to be done for all involved entities that should be considered (e.g. all sorrounding cars that have a chance to interact with the own car within a limited time horizon).
- Estimate the expected risk at the current time, by calculating the combination of the occurrence probability and the severity of the future, predicted critical events. The expected risk will then be a function of the current driving parameters such as the own velocity, since it largely influences the own predicted trajectory.
- Combine with a utility term which quantifies the benefit of the own driving behavior along the predicted trajectory. This is usually a combination between target settings (e.g. a desired driving speed) and timing considerations (since it is desirable to reach a target in a limited amount of time). The combination of risk and utility results in a general cost function.
- Find the own parameter variation related to a possible behavior of the own vehicle (e.g. velocity change) which decreases the cost function (e.g. which decreases the expected future risk and increases the utility).

In the FDM, prediction of behavior alternatives should not be understood as in sampling approaches, instead only a very limited subset of the main behavioral alternatives is considered. There is however a relationship to sampling approaches in that the subset should reflect the major risks, so that it can be seen as the outcome of a sampling-based evaluation of the overall future risk. In [12], such an approach is presented by deriving a drivers' behavior plan from so-called *risk maps*, and the FDM can be understood as a averaging approximation to risk-based behavior planning.

A. Trajectory Prediction

The first step of the FDM comprises the trajectory prediction of the other traffic participants and the ego vehicle. If the route of a vehicle is unknown, the main possible trajectory alternatives are taken into account. This amounts to the consideration of a discrete set of spatial paths, e.g. at an x-intersection corresponding to the driving straight, turning left and turning right alternatives (for the FDM, we consider that the vehicles continue driving longitudinally along the possible paths predetermined by the road geometry). In the simulations, we processed OpenStreetMap (OSM) data to calculate road geometry and intersection connectors, and extracted the paths from the centerline of lanes and intersection lane connectors. We assume that for ADAS applications, map data at a similar level of detail is available.

Within the discrete set of alternative spatial paths, we additionally consider different possible behaviors of the ego-driver and the other traffic participants. By analyzing the FDM simulation results, we found that concentrating on a small set of behaviors, namely keeping constant velocity and braking hard as in emergency situations, either for the ego car or the lag/leading car, suffices to capture the major risks, as usually addressed with TTC measures. We therefore calculate two different spatiotemporal trajectories for each spatial path as a lowest-order prediction of the future development of the scene. The particular collision risk can then be calculated by relating all possible spatiotemporal trajectories between the ego-car and each other traffic participant.

As an example, for the ego car driving in the same lane with another car, we consider 3 ego-behavior constellations for the FDM trajectory predictions:

1) Both ego car and other car keep constant velocities.
2) Ego car keeps constant velocity, other car brakes hard.
3) Ego car brakes hard and other car continues driving at constant velocity.

The trajectory from 1) captures standard TTC risks given by velocity differences, whereas trajectories 2) and 3) serve to capture front and rear approach collision risks if one of the involved drivers suddenly stops. The priors for the

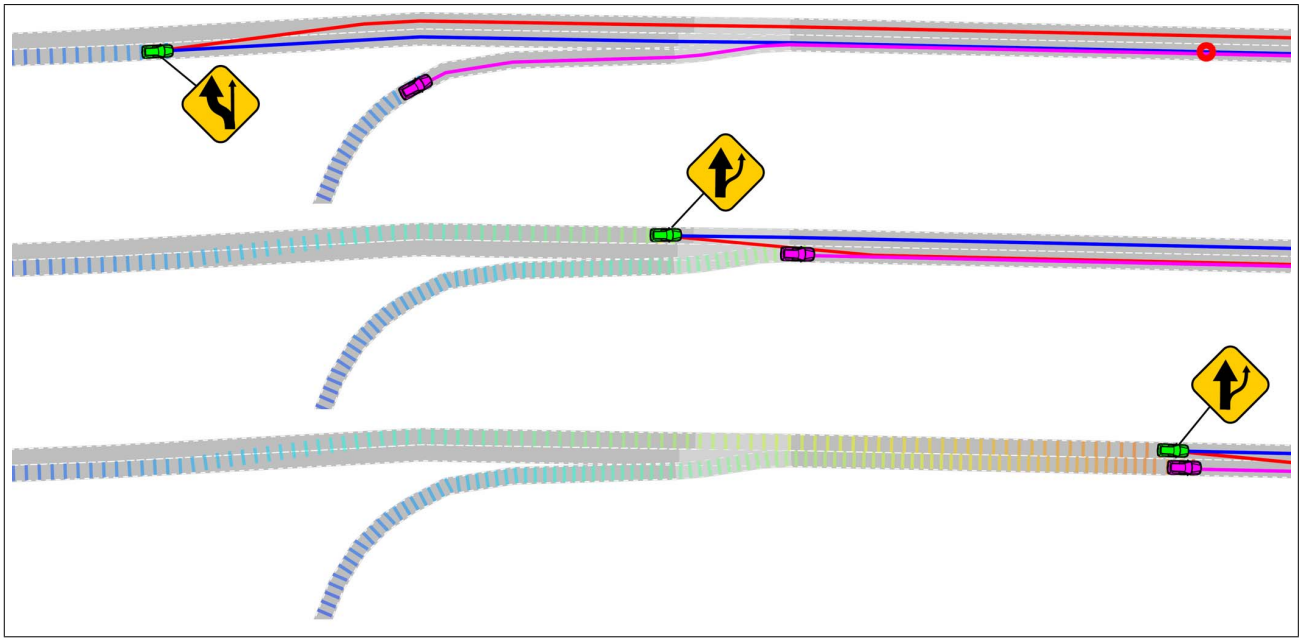


Fig. 1: Scenario with lane-change due to expected merge-in at a freeway entrance. Driving constellations at different moments in time (from top to bottom $t = [4, 8, 12]s$). The ego-car (green) drives with an initial and cruising velocity $v^{0,l} = 27m/s$ towards an entrance with a merging car (pink), driving at $v_o^{0,l} = 20m/s$. Indicated are the ego-car's current path (blue lines), the alternative path (red lines) after a lane-change, the other car's predicted future path (pink lines), current upcoming risk which mainly influences the driving behavior (red circle on top row, predicted collision point) and yellow signs indicating the current lane current decision. Horizontal small bars density along the trajectories indicate velocities, with color coded time. The ego-car starts to brake early to let the other car merge in, however (because the merging car is slow) it cannot reduce the risk and utility costs sufficiently and so decides to change lane.

different behaviors are set to $2:1:1$ (constant velocity case more likely than braking) in case that the critical event is imminent; if the critical event is exprected further in the future the ratio of constant velocity driving vs. braking gets larger as determined by (3).

B. Collision Risks

The second step of the FDM comprises the evaluation of trajectory constellations for a simple estimation of an occurrence probability of the most risky upcoming events. For this purpose we compare pairs of trajectories (each pair comprising one possible ego-car trajectory and one trajectory from another traffic participant) and extract estimated points of maximal risk in time and space. As a simplification, for collision risks we compute the **P**oint of **C**losest **E**ncounter **PCE** between the two trajectories (using standard geometrical tools and libraries) and the corresponding **T**ime **T**o **C**losest **E**ncounter (**TTCE**) and the **D**istance of **C**losest **E**ncounter (**DCE**) as parameters that quantify the event probability. For other types of risk, similar points and parameters can be calculated, refer e.g. to [11] for a more detailed explanation.

For a longitudinal driver model, DCE$= 0$ for a collision that will actually occur. However, using PCE, TTCE and DCE we assume that the risk is proportional to a collision probability that increases monotonously with decreasing TTCE and DCE, reaching 1 for $t \rightarrow$TTCE and small DCE. Such a formalization allows to capture uncertainties in the time and position of the involved cars. In addition, is can be used for a generalization to lateral collision risks, which are necessary for a risk-based treatment of lane-change behavior targeted in this paper.

The FDM then calculates the expected risk at time t according to (this and eqns. 2,3,4 and 5 taken from [11])

$$\begin{aligned}\text{risk}(t) = \sum_n \sum_{\text{Events } i} \text{sev}_n^{\text{co}}(P_{n,i}^{\text{co}})\,\text{prob}_n^{\text{co}}(P_{n,i}^{\text{co}}, t_{n,i}^{\text{co}}|t) \\ + \text{other risk types} \quad .\end{aligned} \tag{1}$$

Here n denotes the different trajectory pairs (one trajectories from the ego car and one from another traffic participant), $t_{n,i}^{\text{co}}$ are the critical collision event times, i.e., the times of the points of maximal risk / PCE for a trajectory pair, and $P_{n,i}^{\text{co}}$ are the parameters at the points of maximal risk like TTCE and DCE. The collision event probability is given by $\text{prob}_n^{\text{co}}$ whereas the severity sev_n^{co} quantifies the actual damage that would occur if the collision happens with the predicted parameters.

The severity factor is included to capture the qualitative dependencies of the damage from the involved parameters at the moment of collision, like the velocities and the angles at the moment of impact. In practice, this could be estimated from measured and predicted states of the ego-car and other traffic participants. Here we use a simple physical partially inelastic 3D collision model according to

$$\text{sev}^{\text{co}}(P_{n,i}^{\text{co}}) = S_n^{\text{co},0}[1 + \alpha_n^{\text{co}} \frac{M M_n}{2(M+M_n)} (\Delta\bar{v}_{n,i})^2 (1-k_n^2)] \tag{2}$$

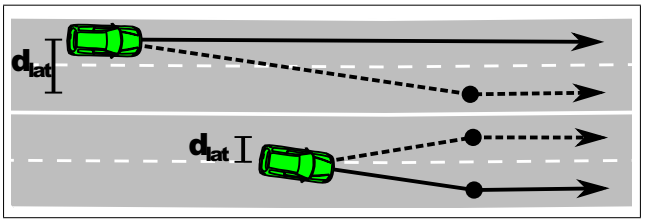


Fig. 2: Predicted trajectories for the calculation of risk and utility costs of a lane-change. For a 2-lane road, a trajectory along the current driving path is predicted (solid line), and a trajectory that leads to the other lane (dotted line). Top: Regular trajectory for the intended lane-change (dotted). Bottom: Predicted trajectories if the car is already performing the lane-change maneuver. The lane-change is assumed to be completed in approx. constant time. See Section III for an explanation.

with restitution factor k_n and ego-car and other traffic participant masses M, M_n (more detailed models can be used here, however, we found this one to be sufficient for capturing the main risk parameter dependencies like influence of velocities at impact, etc.). $\Delta\bar{v}_{n,i}$ denotes the velocity difference at the moment of collision (in 2D calculated using the velocity components parallel to the predicted impact direction).

The collision event probability is qualitatively approximated by a function

$$\text{prob}_n^{\text{co}}(P_{n,i}^{\text{co}}, t_i^{\text{co}}|t) \sim e^{-\frac{\max(\text{DCE}_{n,i}-\text{d}_n^0,0)}{\sigma_n^{\text{d}}}} e^{-\frac{|\text{TTCE}_{n,i}|^2}{2(\sigma_n^{\text{co}})^2}} \tag{3}$$

which depends on the **T**ime-**T**o-**C**losest-**E**ncounter (**TTCE**, time until the distance to the other traffic participant gets minimal) and the predicted **D**istance-of-**C**losest-**E**ncounter (**DCE**), accounting for uncertainties in time and space. It depends on the closest distance that is predicted to occur, discounted by a temporal decay term which indicates that a collision gets less likely if it is predicted to occur further in the future, and gets maximal when DCE$\to d_n^0$ and TTCE$\to 0$. It is $\text{TTCE}_{n,i} := t_{n,i}^{\text{co}} - t$, and $\text{DCE}_{n,i} :=\text{DCE}(t_{n,i}^{\text{co}})$. The parameter dependency was motivated by the "survival function" approach according to [13], quantifying the future accumulated event probability starting at t if we assume that e.g. a collision event would happen at t_i^{co} with parameters $P_{n,i}^{\text{co}}$.

Several traffic participants are considered each by its own predicted trajectory and its own risk term contribution. For complex scenarios, in this way we incorporate the interactions pairwise between the ego-car and all other cars in the vicinity, in the sum of (1). This allows to scale the approach to scenarios with arbitrarily many traffic participants. This can be seen in Fig. 5, where the ego-car is taking several cars into account, including cars approaching from the rear.

C. Risk and Utility Aware Driving Behavior

Additionally to the predicted risk, a utility term is added to describe the targeted driving benefits. For free driving, we use a utility term which leads to a continuous approach towards a cruising velocity v^0 for the ego-car:

$$\frac{\text{d}v^{\text{free}}}{\text{d}t} = a\left[1-\left(\frac{v}{v^0}\right)^{\beta}\right] \tag{4}$$

This is of the same form as in the IDM, and throughout the simulations we used $a = 1.25m/s^2$, a typical value for the maximal acceleration to cruising speed in IDM simulations.

The desired driving behavior is then gained by a tradeoff between avoiding future risks and satisfying the utility target. The predicted risk is minimized by a gradient descent in the risk landscape, so that by the combination with the utility term (4) we get

$$\frac{\text{d}v}{\text{d}t} = \frac{\text{d}v^{\text{free}}}{\text{d}t} - \gamma\frac{\text{d}\,\text{risk}(t,v)}{\text{d}v} \tag{5}$$

as the central equation for the FDM driving dynamics.

Eq. (5) can be seen as a general gradient descent using a cost function which combines utility and predictive risk aspects.

$$\text{Cost}(v) := \text{Cost}^{\text{utility}}(v) + \text{Cost}^{\text{risk}}(v) \tag{6}$$

From (5) and (6) we see that stationary states with $\text{d}v/\text{d}t = 0$ always demand a tradeoff between the utility cost and a residual risk. Only for vanishing risk is the cruising velocity v^0 reached. While the risk term determines critical behavior, the utility term can be adjusted to different utility targets, like desired speed, lane and comfort.

Integrating (6) over v, we get, together with the condition that $\text{Cost}^{\text{utility}}(v^{\text{free}}) = 0$,

$$\text{Cost}(v) := a\left(v - \frac{v(\frac{v}{v^0})^{\beta} + \beta v^0}{\beta+1}\right) + \gamma\,\text{risk}(t,v) \tag{7}$$

as the velocity-dependent overall cost function (parameter a is from eq. 4). This function can now be used to compare different behavior alternatives, choosing the one with the lowest overall cost.

III. Modeling Lane-Change Behavior

In [11], the FDM has been formulated largely in terms of longitudinal behavior limited to a single driving path, for the sake of simplicity. Nevertheless, the model has already been applied to a highway entrance (on-ramp) scenario. It lends itself naturally to multilane scenarios in the sense that all the steps from section II, including the behavior selection guided by a minimization of a cost function involving predicted risk and utility, can be directly applied. What has to be done, though, is to include predictions of the own cars' trajectories that include the multilane options.

In the trajectory prediction step of the FDM we therefore use different spatial paths for the ego-car, one for each lane that can be travelled (a generalization to a smooth lateral behavior by introducing a larger number of paths is straightforward, however, for the sake of simplicity we will stick to one per lane in the following).

Considering a typical 2-lane road, we generate two paths, one which continues longitudinally along the current ego car traveling lane, and another one which describes a lateral movement which leads to a lane-change in a fixed amount of time and then continues longitudinally on the next lane. Fig. 2 shows the two paths in two cases, in the first case

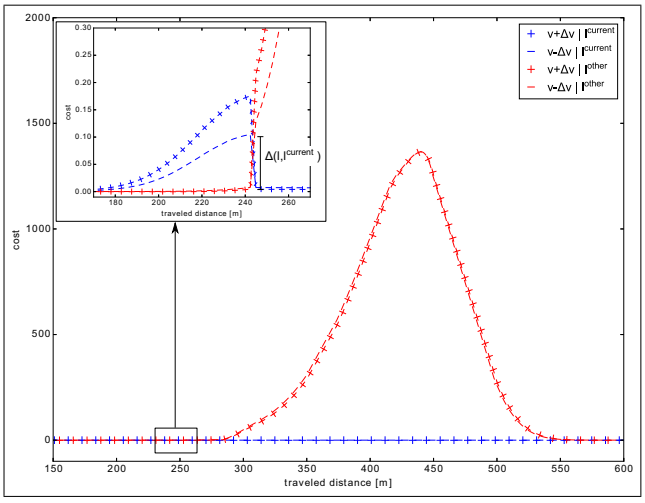


Fig. 3: Decision cost function (8), calculated during regular time intervals along the traveled path for the merging-in scenario from Fig. 1. The cost function is calculated and plotted for 4 different behavior alternatives, corresponding to the future path on the current (blue) and on the other (red) lane, i.e., without and with lane-change, and for a slight acceleration (+) and deceleration (-) of the current velocity. The inset shows the costs for the behavior alternatives during the lane-change of the ego-car.

$\text{Cost}(v,l)$	l^{current}	l^{other}
$v+\Delta v$	0.7	0.1
$v-\Delta v$	0.3	0.2

TABLE I: Exemplary risk and utility costs for driving decision on a 2-lane road. Depending on the trajectory predictions on the current ($l = l^{\text{current}}$) and the other lane ($l = l^{\text{other}}$) and increased ($v+\Delta v$) or decreased ($v-\Delta v$) velocity, the cost landscape is calculated and the behavior decision for l against a lane-change is taken by searching for the minimal cost. In this particular case, risk and utility are minimal for $v+\Delta v$ and $l = l^{\text{other}}$, so that a lane-change is favored. For our tests, we used $\Delta v = 0.1$ m/s.

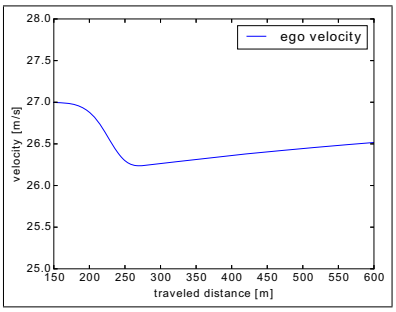


Fig. 4: Longitudinal velocity profile of the ego car along the traveled distance for the scenario from figure 1

before a lane-change and in the second case when a car is already in the midst of a lane-change maneuver.

For both paths, risk and utility cost terms as introduced in (7) are calculated. We then get a new cost function which depends on the target lane l, since different lanes imply different predicted trajectories and therefore also different expected risk costs. We then get that

$$\begin{aligned}\text{Cost}(v,l) \quad &:= \quad \Delta(l,l^{\text{current}}) + a\left(v - \frac{v(\frac{v}{v^{0,l}})^{\beta} + \beta v^{0,l}}{\beta+1}\right) \\ &\quad +\gamma\,\text{risk}(t,v,l) \quad . \end{aligned} \tag{8}$$

Here a utility cost threshold $\Delta(l,l^{\text{current}})$ is added for the lane-change option to prevent unnecessarily frequent lane changes. In addition, different desired cruising velocities $v^{0,l}$ can be introduced for each lane, as it is e.g. the case on German highways. We define l^{current} as the current driving lane before a hypothetical lane-change, and l^{other} as the lane after a lane-change has been performed. It is $\Delta(l,l^{\text{current}}) = 0$ for $l = l^{\text{current}}$ and $\Delta(l,l^{\text{current}}) > 0$ for $l \neq l^{\text{current}}$.

Thinking of l as the continuous lateral position, the behavior would again be chosen by a minimization of the overall cost function (8) using gradient descent on v and l,

$$\frac{\mathrm{d}(v,l)}{\mathrm{d}t} \sim -\nabla_{(v,l)}\,\text{Cost}(v,l) \tag{9}$$

For a discrete 2-lane road lane-change, we chose a more direct way, calculating the utility and risk cost for a small 2x2 cost landscape composed by velocities $\{v+\Delta v, v-\Delta v\}$ and lanes $\{l^{\text{current}}, l^{\text{other}}\}$ [1]. We then get 4 cost values, from which we choose the one with the minimal cost to decide for a behavior. An example is given in table I, which shows the costs for a typical lane-change decision. In this case, the lowest cost is associated with an increased velocity $v+\Delta v$ and lane-change with $l = l^{\text{other}}$, so that a lane-change process is started and the velocity is increased.

Once a decision for or against a lane-change has been taken by choosing the minimum driving cost according to eq. (8), the predicted trajectories are restricted to the favored driving path and the normal FDM is applied to adjust the velocities. Since the decision is calculated based on the conservative assumption of low ($\pm\Delta v$) acceleration/deceleration, if the circumstances do not change, the lane-change will be possible given the dynamics of the car. If other risks appear during the lane-change maneuver, the model will accelerate/decelerate according to (5) up to the point where a lane-change gets again more beneficial in terms of costs.

The lane-change decision check occurs at regular time intervals. If a lane-change has been initiated and the ego car is e.g. in the middle between two lanes, the two possible paths are calculated as the continuing path to the new lane and a return path to the original lane, respectively, so that a lane-change decision can be revoqued dynamically at any time depending on changes in the environment and the corresponding consequences for risk and utility. Fig. 2 shows the alternative paths for the risk and utility cost calculations before and in midst of a lane-change maneuver. The predicted lane-change trajectories have been modeled in the simplest possible way as straight lines, since we are interested in the involved risk and utility. More realistic paths (sigmoidal, polynomial) can be used, however the impact on predicted risk and utility turned out to be negligible.

The result is a model for a lane-change decision based on utility and risk considerations and which takes all involved

[1] Pre-post lane-change acceleration/deceleration $\pm\Delta v$ as well as the predicted lane-change time and path are chosen to be within the dynamical limits of the modeled car.

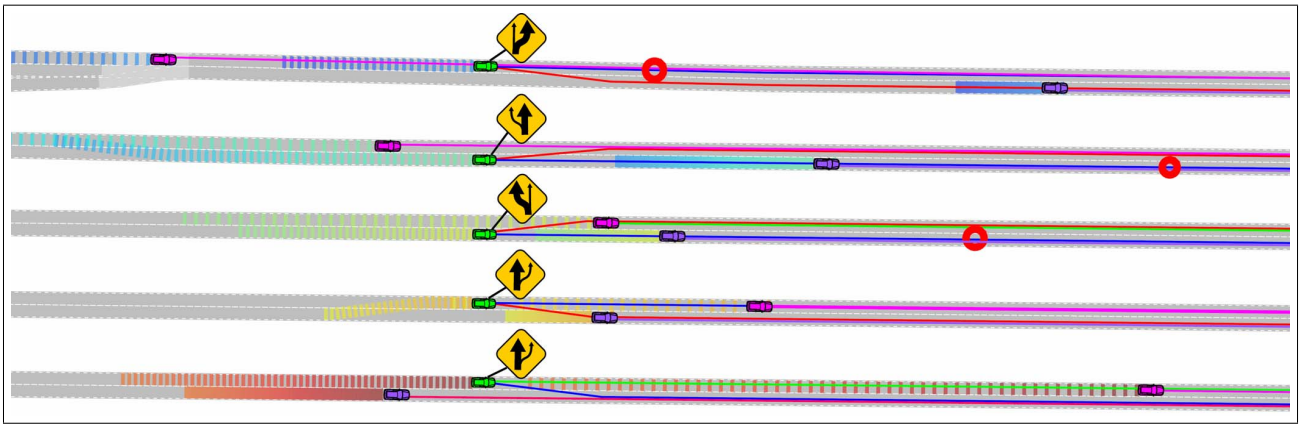


Fig. 5: Scenario with forced lane-change due to a fast rear approach, camera centered on the ego-car (green). Driving constellations at different moments in time (from top to bottom $t = [8, 14, 19, 2230]s$). The ego-car drives with an initial velocity $v_e^{0,l} = 20m/s$ between 2 other cars (pink) driving with cruising velocities $v_1^{0,l} = 30m/s$ (rear), $v_2^{0,l} = 10m/s$ (front). Indicated are the eg-car's current path (blue lines), the alternative path (red lines) after a lane-change, the other cars' future paths (pink lines), current upcoming risk which mainly influences the driving behavior (red circles on top 3 rows, predicted collision points) and yellow signs indicating the current lane current decision. Horizontal small bars density along the trajectories indicate velocities, with color coded time. The ego-car's lane-change decision is caused by the risk of the approaching car from behind; after the car passes the ego-car retakes the left lane to pass the slow car in front.

traffic into account. By construction, traffic participants in the same lane as well as in the other lane are considered and inspected for their risk and utility implications. lane-changes with more lane options (e.g. left and right) can be treated with little less effort in the same way. Similarly, the lane-change model can be used for lanes runnning parallel, but also for lanes with opposing traffic. Traffic obstructing the route of the ego car is evaluated as well as traffic approaching from behind or from the front. At any time, lane-change decisions are based on explicit risk and utility criteria, and lane-change decisions will be revoked as soon as conditions change, allowing a smooth transition between lane-change maneuver initiation and aborting.

IV. Results on Different Scenarios

A. Expected Merge-In at a Freeway Entrance

First we applied our approach to scenarios of forced lane chanes at freeway entrances. One setup is shown in Fig. 1, where the ego car drives on the right lane of a two-lane highway, while another car plans to access the highway and merge onto the right lane. Fig. 1 (top) shows an upcoming collision risk spot (red circle) for the case that both cars keep their current behavior. At this particular point, the ego-car (blue trajectory) would collide with the merging car (pink trajectory). The expected future risk on the ego-car, calculated according to eq. (8) for ongoing trajectories, increases as the cars approach each other.

Fig. 3 shows the details of the costs during the temporal evolution of the scenario. Evaluated are the 4 behavior options: Staying on the current lane (blue lines) or changing lane (red lines), and accelerating (+) or decelerating (-). Staying on the current lane, the best option for the ego-car is to brake (inset, blue "-" line from left), however the cost continues to increase due to the collision risk with the merging car. Once the lane-change cost threshold has been reached, the maneuver is executed, reducing the cost to almost zero (right part of blue line in inset), since both cars are not on collision course any more. At the moment of lane-change the current and other lane switch and thus also the corresponding lines in the diagram. After the lane-change, a further lane-change option involves high risks (steep increasing red curves in inset and large red peak) because the adjacent lane is occupied by the merged car. The cost maximum for the other lane is approximately slightly before both cars drive next to each other.

From Fig. 4, it can be clearly seen that the car has to slow down if it tries to stay on the current lane, however at a certain point it decides to change lane since the benefits in terms of risk and utility dominate, allowing it to continue driving with the desired velocity on the new target lane. The ego car then adapts its velocity back to the desired travel velocity $v^{0,l}$ on the new current (left) lane, as there is low risk and utility can be optimized by accelerating towards the desired travel velocity.

By construction, since the cost incorporates the expected future risk for upcoming critical events, the lane-change is anticipative, so that the ego car prepares and executes a lane-change well before the critical situations kick in.

B. Fast Rear Approach

As a second scenario, we investigated the case of a forced lane-change by a fast rear approach with a further blocking car in front. The setup and the time course of the model behavior is shown in Fig. 5. The ego car is driving on the left lane, while a fast car approaches from behind. At the same time there is a slower car ahead of the ego car on the right lane. The ego car has to find a proper safe driving behavior in this constellation and has to choose a suitable lane.

It can be seen from Fig. 6 (top left inset), that the cost/risk on the current path rises (blue lines), while the other car is

approaching from behind. The risk for decelerating (-) rises faster than the risk for accelerating (+), as a deceleration would more likely result in a collision. Thus the initial behavior adaptation of the ego car, resulting from the longitudinal FDM, is an acceleration in order to reduce risk on the current lane, as shown in Fig. 7.

Once the difference between minimal costs while staying on the current lane (here accelerating) and minimal costs for a hypothetical lane-change (here decelerating) exceeds the cost threshold for a lane-change, the lane-change to the right lane is executed to let the fast approaching car pass.

While the fast other car is passing the ego car the costs on the other (left) lane heavily rise. In addition, the cost on the current path start to rise due to the collision risk with the other car driving slowly in front. Now the costs for accelerating get higher than for decelerating, as accelerating would result in a higher collision risk. As there is very high risk on the other (left) lane, the ego car decides to stay on the current lane and brakes in order to stay behind the leading car (this can be seen in the ego-car velocity profile from Fig. 7)

Once the fast other car passed by the ego car the costs for the other lane decrease sharply. When the costs on the other lane drop below the minimal costs of the current path including the lane-change cost threshold the ego car decides for a second lane-change, as shown in the top right inset of Fig. 6. It can be seen that the costs for accelerating are now lower, since accelerating would optimize the utility costs. Thus the ego car now accelerates to reach its desired cruising velocity.

During our tests, we used a variety of complex and normal lane-change situations in a simulator environment, while other cars were either following a fixed route, modeled using standard driver dynamics. The street geometry of the scenarios, including Figs. 1 and 5 was generated from OpenStreetMap data expanded by lane information. The parameters for the simulation $S^{\mathrm{co},0}_{1,2,3} = 1.0$, $\alpha^{\mathrm{co}}_{1,2,3} = 10^{-6}$, $\sigma^{\mathrm{co}}_{1} = 2\,s$, $\sigma^{\mathrm{co}}_{2,3} = 1\,s$, $d^{0}_{1,2,3} = 0$, $\sigma^{d}_{1,2,3} = 2\,m$, $M, M_n = 1000kg$, $k = 0$ and $S^{\mathrm{co},0} = 1$ (the subindices $\{1,2,3\}$ refer to the 3 different collision risk terms of the FDM introduced in Sec. II-A for both cars driving at constant speed, the other car braking hard or the ego car braking hard). Furthermore, we set $\gamma = 100\,m^2/s^3$, $\beta = 1.0$ and $\Delta(l, l^{\mathrm{current}}) = 0.1$. The time constant for the lane-change duration of the predicted lane-change trajectories was set to $4\,s$. This value is targeted as a mean duration, however it does not mean that the lane-change always takes this time, since other cars in the original or the target lanes influence the velocity of the lane-change by their overall risk and utility considerations according to eq. 5.

For the simulations, we used an own environment written in Python. It uses augmented OSM data and cars as agents that either drive according to the FDM or according to other models like the IDM. In videos we show (at 2.5x speed) several simulated lane-changes in complex situations, including predicted trajectories and risk points on a highway setting.

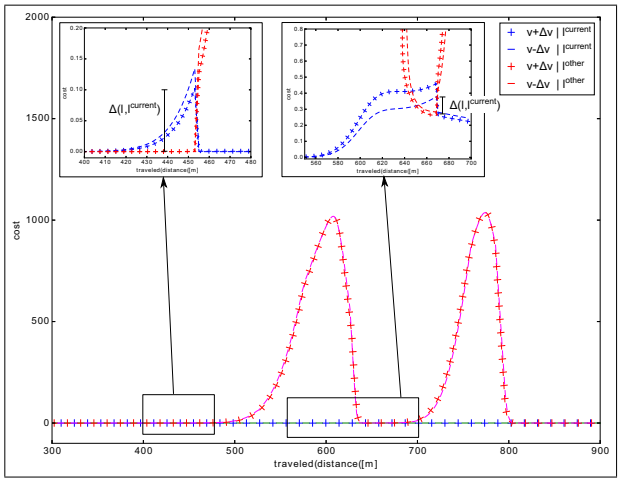


Fig. 6: Decision cost function (8), calculated during regular time intervals along the traveled path for the merging-in scenario from Fig. 5. The cost function is calculated and plotted for 4 different behavior alternatives, corresponding to the future path on the current (blue) and on the other (red) lane, i.e., without and with lane-change, and for a slight acceleration (+) and deceleration (-) of the current velocity. The 2 insets show the costs for the behavior alternatives during the lane-change of the ego-car.

V. Discussion

In this paper, we have introduced extensions to the Foresighted Driver Model which enable to capture typical risks as encountered during lane-change maneuvers and which allow to decide whether a lane-change is beneficial or not in terms of driver risk and utility. The introduced model lends itself naturally to model situations with several involved traffic participants and complex behavior. By construction, the model anticipatively evaluates behavior options together with their involved costs.

We have applied our model to several driving scenarios and showed (i) that it reacts in a foresighted way to upcoming risks, (ii) that the risks and utility costs are transparently and explicitly evaluated to retrieve the lane-change decisions choosing the lowest-cost trajectories and (iii) that the early anticipation of risks results in smoothly adjusted velocity profiles in the current driving context.

It remains to be evaluated, however, to which extent such "complex" scenarios actually occur in real driving situations. Reliable data related to lane-change statistics is scarse ([14], [15]) and data related to the simulated complex lane-change cases does (to our knowledge) not exist. It could be argued that for averaged traffic statistics, these cases may be rare so that it may not be necessary to include such a complexity in a driver model. On the other hand, we are mainly interested in naturalistic single-case driving prediction for ADAS functions, where such cases would be of relevance since they have a large impact on the risk landscape of the driving situation. In addition, the simulated scenarios cover situations which are commonly encountered in settings with largely variable velocities at different lanes, as they

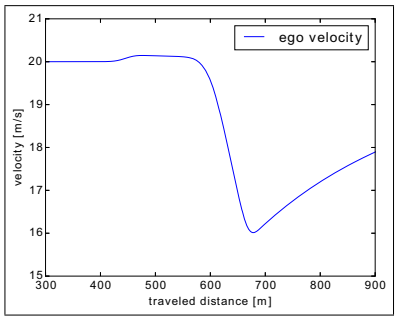


Fig. 7: Longitudinal velocity profile of the ego car along the traveled distance for the scenario from figure 5.

occur e.g. on German highways. We see the benefits of the lane-change FDM particularly in dynamic environments; in quasistationary traffic flow with very slow lane-changes, gap-acceptance models with conservative parameterization could suffice, even if risk and utility are not treated explicitly.

An interesting direction would be a customization of the proposed model to different driver characteristics by modification of the main risk and utility parameters. The propensity of a driver to take risks and use critical maneuvers can be directly controlled by the parameter γ from eq. 5. In the lane-change model from [4], a "politeness" factor was proposed which controlled how much a driver would also take disadvantages imposed on other drivers, approaching from behind, into account. A similar effect can be achieved in the proposed model if we neglect the risk of rear-end approaches by giving these a lower risk weight. In addition, for real-world driving statistics the (currently fixed) predicted lane-change duration time would have a larger variability across drivers.

Straightforward extensions of the presented model are given by an inclusion of further specific risks, like e.g. the risk of curve geometry, so that curve velocity considerations would be evaluated in parallel to the lane-change risks. Furthermore, with lane- and geometry- specific lane-change cost thresholds, we can model also assymmetric lane-change and passing rules, as they exist in most European countries. The model also allows for a more fine-grained lateral control according to eq. 9, at the cost of generating and evaluating a larger number of predicted trajectories with lateral offsets.

Currently, as described by (4), one of the driving forces for a lane-change is the desire to maintain or adjust the speed towards the cruising velocity. Alternative utility factors could be incorporated to formulate prefrences in terms of the targeted traveling lane, e.g. if a route demands a particular lane for turning. Such preferences would have the form of lower utility costs for the favored lanes in relation to non-favored ones.

Finally, since the lane-change process was modeled based on a decision about a certain future path out of a set of predefined future paths, the model could be extended further in a straightforward way by taking more complex trajectories into account. On one side trajectories could be used which return to the original lane, to capture overtaking processes, and evaluate them in the same way in terms of risk and utility. On the other side in situations where a threat is imminent, emergency trajectories could be evaluated for their benefit, as shown in Fig. 8. The different trajectories would be analyzed as before for their respective risk and utility, and the most appropriate trajectory would be proposed and an avoidance maneuver would be triggered or supported.

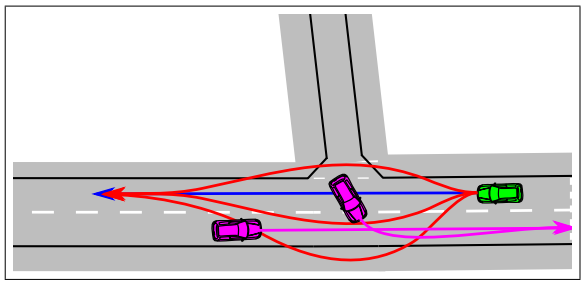


Fig. 8: Extension of the risk and utility based evaluation approach for emergency situations. Similar to the FDM approach used in the lane-change evaluation, by constructing different predicted paths (e.g. alternative braking trajectories shown in pink) the best behavioral option in an emergency case can be found by comparing the overall costs.

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