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# Framework for risk aversive and efficient behavior planning under multiple situations with uncertainty

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# Risk-Aversive Behavior Planning under Multiple Situations with Uncertainty

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*Abstract*— **This paper addresses the problem of future behavior evaluation and planning for upcoming ADAS, especially for inner city traffic scenarios. Situations in inner city traffic scenarios are generally highly complex and of high uncertainty. The behavior in such complex scenarios differs strongly depending on the actually occurring situation. In general the current situation can only be determined with high uncertainty based on current and past sensory measurements of the ego entity and the other involved entities. Additionally a situation can change very quickly, e.g. if a traffic participant suddenly changes its behavior. Here we propose an approach how to plan safe, but still efficient future behavior under consideration of multiple possible situations with different occurrence probabilities. For each situation we predict prototypical future trajectories of all involved entities using a highly general, interaction aware model *Foresighted Driver Model* (FDM). Then, based on a continuous, probabilistic model for future risk, we build so-called predictive risk maps, one for each possible situation, and plan the own behavior while minimizing overall risk and utility. We show that our approach generates efficient behavior for situations with high probability, while generating a "plan b" to safely deal with improbable but risky situations.**

## I. Introduction

The target of future Advanced Driver Assistance Systems (ADAS) is to relief the strain on the driver, starting from simple warning and comfort functions such as parking assistance, up to partially or fully automated driving. We aim for a system that is generally able to securely support driving, especially in inner city scenarios with multiple behavior alternatives. Inner city scenes are highly complex, especially if more than a few traffic participant are involved. Current ADAS, targeting at inner-city scenarios, are either mainly reactive or designed to work under very narrowly defined conditions and therefore not applicable as a general approach for risk-based behavior control.

Risk in general can be understood as the expectation value of the cost related to a future critical event, e.g. a collision, and depends heavily on the possible behavior alternatives of all involved entities. In complex scenarios, it is unfeasible to evaluate all possible state evolution alternatives of the involved traffic participants. A way to reduce complexity is on one hand to group similar behavior alternatives of the acting entities by using situations, which represent prototypical behaviors, and on the other hand to restrict the behavior alternatives to those which are relevant for the ego entity's behavior.

Still, predictions of the "behaviorally relevant" future dynamics in certain situations/behavior alternatives of the regarded entity and of the other traffic participants, as well as their relations, are required. This then leads to an evaluation of the possible future behavior in terms of behavioral risk and utility for the entity in the context of the surrounding traffic participants.

The main problem is how to plan the best future behavior in multiple possible situations with uncertainty. Incorporating every possible behavior alternative of the involved entities, the system might end up foreseeing risk everywhere and no safe or only highly inefficient future behavior can be found. In contrast, by neglecting situations with high risk and low probability the system might end up in constellations leading to a crash. Thus we present an approach, where the general future behavior is planned mostly under consideration of highly probable situations, which provides us efficient behavior in those situations. Situations with lower probability are also incorporated in the behavior, but with less influence. Then we check the behavior on each possible situation for risky constellations and apply a safe Plan B to avoid such risky states in case those unlikely situations kick in.

Situation classification is a general approach to tackle and partition complex scenarios. It has received a lot of attention in the recent years, especially in combination with situation-dependent trajectory prediction and risk assessment [1], [2], [3], [4]. In [1] an approach for driver assistance systems is introduced, which predicts maneuver-based, long-term trajectories and assesses their risk. Risk is evaluated based on the maneuver-dependent, probabilistic sampling of trajectories by applying noise to the situation specific, hand designed prediction model. Due to the high computational effort, such an approach is restricted to quite simple prediction models (e.g. constant velocity), which would not be applicable to the general, interaction aware prediction model used over here. A similar approach is presented in [2] where the authors perform a longer-term risk assessment in structured highway environments. The trajectory prediction is based on the assumption that other traffic participants behave in a risk aversive manner, which is also taken into consideration in [3] and in the presented work. This allows a long term stable, realistic prediction of future behavior. In [3] a situation classification and risk evaluation system is proposed, which is mainly used to predict other traffic participants' future trajectory, but not directly used to plan the ego entity's own behavior. Additionally there is a large amount of work

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related to planning future behavior, such as [5], [6]. [7] uses continuous POMDPs to perform decision making under uncertainties in traffic scenarios. Since a discrete set of actions is required it is not straightforward how to perform full behavior planning.

In II we briefly introduce the probabilistic measure for predictive risk, which is then used to build predictive risk maps in III. After defining situations in IV we propose an approach for situation based risk evaluation and behavior planning in V, which is applied to an intersection scenario in VII. The focus of this paper lies within the safe future trajectory planning step in VI. Further contributions of this paper are an interaction aware trajectory prediction using the Foresighted Driver Model [8] and the evaluation of different behavior possibilities based on predictive risk maps using the general predictive risk measure [9].

## II. Predictive Risk Estimation

Risk is in general defined as the expectation value of the cost or benefit related to future critical events [10], [11]. As stated in [9] this can be expressed in a probabilistic way. Probabilistic risk includes a prediction of *future* critical events and the evaluation of the damage in case that a related event actually happens, in the time interval $[t, t+s]$.

$$risk \sim P(\text{damage}_{t+s}|\text{states}_t) \tag{1}$$

$$= P(\text{damage}_{t+s}|\text{states}_{t+s}, \text{event}_{t+s} = \text{true}) \tag{2}$$
$$P(\text{event}_{t+s} = \text{true}|\text{states}_t),$$

The first term in (2) represents the probability that a certain damage will occur, assuming that an event[1] occurs at future time $t+s$. The second term represents the probability that an event happens at time $t+s$, given the known states at the current time $t$. Thus we first have to model the prediction of future states using a proper prediction model, second the damage probability using a damage approximation model, and third the probability of a future event happening at time $t+s$, which can be done using a model for a stochastic process similar to a Poisson process, as explained in the following.

As shown in [9] the **future event probability** $P(\text{event}_{t+s} = \text{true}|\text{states}_t)$ can be modeled as in (3) using a so-called inhomogeneous **survival function** $S(s;t)$ in combination with a total event rate $\tau^{-1}(\text{states}(t+s'))$,

$$P_E(s;t,\delta t) = \{\tau^{-1}(\text{states}(t+s))\delta t\}S(s;t), \tag{3}$$

with
$$S(s;t) = \exp\{-\int_0^s \tau^{-1}(\text{states}(t+s'))\,ds'\}, \tag{4}$$

$$\tau^{-1}(\text{states}(t+s')) = \sum_i \tau_i^{-1}(\text{states}_i(t+s)). \tag{5}$$

Every single event rate $\tau_i^{-1}$ represents different types of risks and can be modeled using appropriate risk indicators as shown in the following on the example of car-2-car collision.

The survival probability is the probability that a certain entity "survives" during the time interval $[t, t+s]$ [9]. This probability decreases monotonically with time. Additionally if the total event rate increases, the survival probability decreases faster, because the probability that the entity gets involved in a risky event also increases. The survival probability has the effect that critical events that are predicted to occur further in the future are usually considered as less probable. This is a desired property which matches with the intuition that, with more distant time, the likelihood to escape a critical event increases because (i) the state prediction gets more inaccurate and (ii) a driver may have more time to start a reaction that leads to the avoidance of the event. The future predicted risks therefore get "discounted" by the survival function, which at the same time serves to incorporate uncertainties (explicit and implicit) in the prediction process. Assuming that critical events are usually triggered by a single cause (eg. a car collides *or* drifts out of the curve), different risk sources are superposed in the total event rate (5).

The car-2-car collision risk is modeled by an event rate that depends on the distance between two traffic participants,

$$\tau_d^{-1} = \tau_{d,0}^{-1} \exp\{-\beta_d(d - d_{min})\}, \tag{6}$$

where $d$ is the distance between the ego-car and another traffic participant and $d_{min}$ the minimally allowed distance corresponding to a physical overlap. The parameter $\tau_{d,0}$ defines the event rate at minimal distance and $\beta_d$ the steepness of the event rate. (6) describes a continuous, instantaneous event rate, whose parameters (esp. the steepness parameter) are used to describe uncertainties in the involved context variables. As shown in [9] further risk sources can be modeled in a similar way and superposed in the total event rate (5).

Starting now from (1), in the following we assume equidistributed $P(\text{states}) = \text{const}$. We set $t = 0$ at the actual / starting time for the risk estimation and $\delta t = \text{const}$ in (3). In addition, as shown in [6] we model the damage deterministically, assuming that if an event happens/does not happen, the damage occurs/does not occur. This leads to the risk model as a function of predicted time $s$,

$$risk(s) = \text{damage}(\text{states}(s))\, P_E(s;0,\delta t) \tag{7}$$

where $\text{damage}(s) = f(\text{states}(s))$ is an empirical damage model as a function of the predicted states at future time $s$, so that $\text{damage}(s)$ quantifies the severity of the occurring damage if the event (here: the accident) actually happens.

For the collision risk, as a simple approximation we consider a 2D inelastic collision model (more accurate damage models can be applied here in similar ways).

Since we focus on the future risk evaluation of the ego car along predicted spatio-temporal trajectories, instead of using a time-dependent risk function $risk(s)$, we can also calculate the risk as a function of the longitudinally traveled distance $x_e$ along the ego-car path (see [5]), so that we will exchangeably also write $\text{risk}(x_e)$ ($\text{risk}(s) := \text{risk}(x_e(s))$).

## III. Predictive Risk Maps

For each situation, we build a so-called "predictive risk map" to evaluate the ego car's future behavior in terms

[1] *An event* means, that any event of a set of possible event types occurs

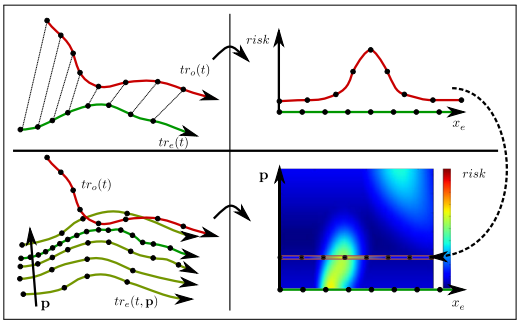



Fig. 1: Predictive Risk Map - Top: evaluation of risk (top right) based on predicted ego car (green) and other car (red) trajectories (top, left) - Bottom: Generation of predictive risk map (bottom, right) based on risk evaluation of a variation of ego car trajectories and other car trajectory (bottom, left).

of risk. Using the model for continuous predictive risk, explained in section II, and based on the situation-dependent predicted trajectories of the ego car and other involved entities, $\mathrm{tr}_e$ and $\mathrm{tr}_o$, as shown in Fig. 1 (top), we gather a continuous measure for future risk. Then we build a variation of trajectories using parameters $p$ (here the ego car velocity $p = v_e$) for the ego car, and evaluate the risk according to section II for each ego car trajectory alternative together with the predicted other car's trajectory. We then arrive at a predictive risk map $\mathrm{Risk}(p, x_e)$ (here $\mathrm{Risk}(v_e, x_e)$), as shown in Fig. 1, which indicates how risky a certain behavior/velocity profile will be in the future. Predictive risk maps can then be employed to plan future behavior/future velocity profiles, in a way that minimizes risk and maximizes utility.

In general the planned velocity profile varies only smoothly and thus does not differ strongly from the velocity profiles used to generate the risk map. In those cases the timing error and its resulting influence caused by the risk map is sufficiently small. Additionally predictive risk maps are highly beneficial to illustrate our approach, but can also be easily exchanged by any other risk evaluation scheme.

## IV. Situation Classification and Trajectory Prediction

Situation classification and trajectory planning are central aspects in our risk evaluation approach. Without going into too much detail we use a **situation classification** similar to [12], which uses the sensory input of the current scene to classify situations against a predefined set of situations and provides the most relevant situations and their occurrence probabilities (see Fig. 2).

A situation describes a prototypical behavior of a subset of involved scene entities, comprising the states of the ego-car and optionally other traffic participants parameters, the road structure and their relations. Different behavior alternatives of the other entities lead to different situations, resulting in a different risk evaluation and corresponding consequences of the ego-car behavior planning.

On one hand situations separate different discrete behavior alternatives of the other car resulting from the *road structure*, e.g. the type of intersection providing possible spatial paths.

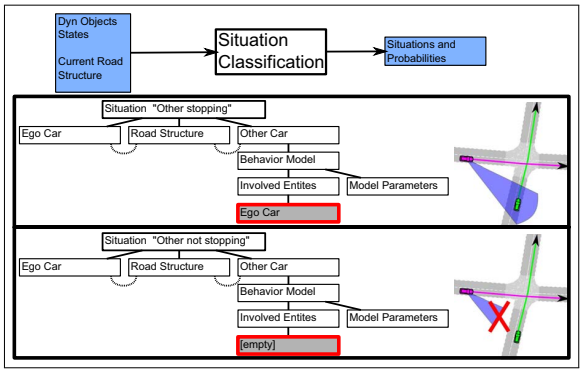



Fig. 2: Situation classification concept (top). Situation structures for "Other car stopping" (middle) representing the situation that the other car (purple) gives way to the ego car (green), and "Other car not stopping" (bottom) representing the situation that the other car overlooks the ego car and violates the left-yields-to-right rule. The only difference in the structural settings of the two situations is the presence/absence of the ego car in the set of entities taken into consideration by the other car's prediction model.

On the other hand a situation is defined by the other entity's *longitudinal behavior model* along a chosen spatial path, e.g. braking to stop at a stop line. The behavior of an entity is mainly influenced by the interaction with other traffic participants and structural elements, such as curves or traffic lights, as well as a certain parameter set (e.g. desired velocity, maximal possible acceleration or deceleration, etc).

As a result a situation's structural setting provides the corresponding **trajectory prediction** step with all information needed to generate a prototypical predicted trajectory for each involved entity, which also incorporates different types of interactions of the involved entities. It is quite common to use simple non-interaction aware models, such as [13], [5], for the trajectory prediction. But as interaction plays a central role in predicting the behavior of other entities, an interaction-aware prediction model is necessary to gather meaningful predicted spatio temporal trajectories. Here we use the Foresighted Driver Model (FDM) [8], which is a highly general, interaction-aware driver model, suitable to predict realistic, long term stable, spatio temporal trajectories in a wide range of traffic scenarios, such as intersections with multiple entities, highway driving, car following and curve driving. More technically spoken the FDM uses the situation-dependent spatial path, a set of interacting entities to predict the entity's future spatio temporal trajectory by performing a forward simulation of all involved entities and a predefined model parameter set. A precise, realistic, situation-dependent prediction of other traffic participants results in general in a much more accurate risk evaluation and allows thus a better planning of the ego car's future behavior.

## V. General approach for situation based risk evaluation and behavior planning

Our general target is to show that a situation classification is beneficial for behavior, in terms of risk and utility. In order to show that we use the following situation-based evaluation and behavior planning approach, which basically consists of the following 6 steps in the evaluation and planning phase,

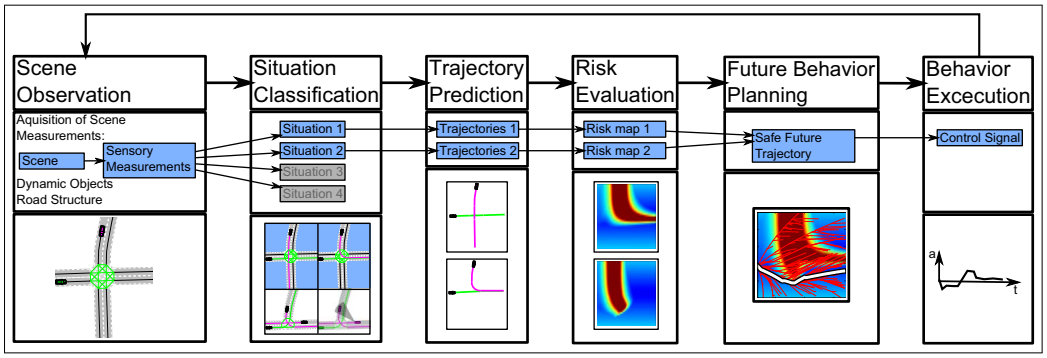



Fig. 3: General approach for situation based risk evaluation and behavior planning.

as shown in Fig. 3. The main contribution of this work lies within the "behavior planning" step.

a) In the **scene observation** step the system reads all sensor data to update the current state of the environment. This includes all states of dynamic objects, other cars, pedestrians and states relevant for the ego car as well as infrastructure related information, like parking cars, traffic signs and map data. Here the most important information are states of dynamic objects and the road structure delivered by map data.

b) In the **situation classification** step we use the updated state to classify and select, out of a set of predefined situations, those situations which are most relevant to determine the future ego car's behavior. As output we get a set of relevant situations and an occurrence probability for each situation.

c) As presented in section IV each situation describes a different behavior alternative of all involved scene entities. In the **trajectory prediction** step we predict one prototypical spatio temporal trajectory for each other entity in every selected situation.

d) Next in the **risk evaluation** step we build a variation of ego-car trajectories and evaluate the risk for each variation together with the predicted spatio temporal trajectories of the other entities. According to [5], [6] this provides us with one predictive risk map per situation / constellation of behavior alternatives, which indicates how risky a certain behavior alternative in a certain situation will be at certain point in future time.

e) After evaluating the situation-dependent risk for possible ego car behavior alternatives, the target in the **behavior planning** step is to find a future behavior for the ego car, which minimizes risk while maximizing utility, meaning that we want a future behavior that is of low risk, but still efficient in terms of e.g. travel time, comfort, etc.
As shown in [5], [6] for one situation this can be achieved in a straightforward way using a suitable planning algorithm, e.g. a sampling based approach, and finding a suited trajectory through the risk map.
But as we now consider multiple uncertain situation, we have to plan depending on the set of situations. We need to find a behavior which is of low risk in all possible situations but which is still efficient in the overall constellation of the scenario. In section VI we present an approach to plan such a future trajectory by combining risk maps for multiple situations, planning with regard to the situation occurrence probability and applying a "plan b" in case unlikely situations kick in.

f) Finally in the **behavior execution** step we take the safe future plan to generate control signals out of the safe future plan and apply them to the dynamical system. As we act in a dynamically changing environment, we have to reevaluate and replan from time to time, using a preset time interval $\Delta t$. Additionally we reevaluate and replan right before our system would perform the escape trajectory to verify that it really has to be executed. During the executing of the escape trajectory we reduce $\Delta t$ in order to allow leaving the escape trajectory as early as possible and get back to normal behavior. The escape trajectory is part of the future plan, which means that it would definitively be executed if the system does not reevaluate and replan.

## VI. Safe Trajectory Planning in Multiple Situations

In [6] and [5] only one situation/setting of behavior alternatives was used. Thus for risk evaluation and behavior planning only one prototypical future spatio-temporal trajectory for each traffic scene entity was taken into account.

Here we target the problem that each other traffic participant has several possibilities to behave, meaning that we have to cope with multiple uncertain situations.

As described above each situation results in one constellation of predicted trajectories, one for each involved traffic participant. Based on those predicted trajectories one predictive risk map is calculated for each situation according to section III. Additionally the situation classification step provides our system with an occurrence probability value for each situation.

The target is now to find a future trajectory, that is of low risk but still high utility for the finally occurring situation. The safest way would be a behavior, that minimizes risk in all possible situations, which could be understood as max-combining the risk maps of all possible situations without taking the situation occurrence probability value into account. By simply combining the risk maps our system might foresee risk everywhere and possibly no safe future trajectory can be found. If a future trajectory can be found

the resulting behavior would avoid all risky areas in all situations, also of unlikely situations, and is thus very safe and defensive, but in general also of low utility, as only one or at least a small subset of situations will actually occur.

The most efficient way would be only taking the most probable situation into account and plan the future trajectory only based on this risk map. If this situation actually becomes the finally occurring situation we get the most efficient future behavior. But in case another situation with lower probability kicks in we might end up in a state, where a crash is inevitable, as we didn't consider situations with lower probability, but possibly of high risk, in the planning of the future behavior.

Here, as shown in Fig. 4, we propose an approach that delivers us safe and efficient future trajectories taking all possible situations into account.

As described earlier the "situation selection and prediction" phase provides us with relevant situations, their probabilities and predicted spatio temporal trajectories.

The "risk evaluation" phase uses the predicted spatio temporal trajectories to generate one predictive risk map for each situation. The planning phase itself consists of the following steps.

a) First we calculate a **combined risk map** of all the situations, indexed by $i$, to find a desired future behavior. If we simply sum up the risk maps weighted by the corresponding probability $\sum_i Risk_i(v_e,x_e)\cdot P_i$ we encounter the problem that an increasing number of similarly probable situations results in a decrease of the situation occurrence probabilities. As the risk is weighted by the situation's occurrence probability the overall risk would be quite low, compared to the utility costs used during planning, but widely spread. This results in an unsuitable behavior, which would be mainly optimizing for utility and less for risk. In contrast, in such a case we would expect quite high overall risk as this indicates a highly uncertain situation classification.

Therefore we normalize the combined risk map by the maximal probability value of all involved situations. Normalizing the probabilities by the maximal probability has the desired effect, that the situation with highest probability is fully taken into account and in case of an uncertain situation classification we get an overall high risk.

$$Risk_{combined}(v_e,x_e) = \frac{\sum_i Risk_i(v_e,x_e)\cdot P_i}{\max_i(P_i)}$$

b) Then we use an RRT* based behavior planning approach, introduced in [6] to find a **future trajectory** through the risk map, that minimized risk and maximizes utility. The RRT* based behavior planning approach generates a future trajectory by globally minimizing a cost function (risk and utility), while taking the dynamical model of the entity and it's physical constraints into account.

c) As we plan the future trajectory by optimizing mainly for highly probable situations, the planned trajectory might be of high risk in improbable situations. In terms of utility it makes sense to consider situations with high probability more than situations with low probability. But in case a situation with low probability suddenly kicks in, the system might encounter inevitable high risks, e.g. collisions.

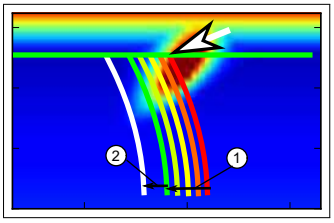



Fig. 5: Application of escape trajectory. Starting from the risk threshold violation (white arrow) we move back along the path (1), while checking if the execution of an escape trajectory is safe. Once a safe exceution point is found (green escape trajectory), we move an additional safety time gap $t_{safety}$ back (2) and apply the escape trajectory to the planned future path (white escape trajectory).

In order to solve this problem we **check the future trajectory on each risk map** without taking the situation occurrence probability into account. This means, that we check the planned future trajectory on each situation, assuming that this situation will kick in and check for states of high risk, which might occur.

In order to do that we define a maximal acceptable risk threshold. As shown in Fig. 5 we place the planned future trajectory on every situation-dependent risk map and check the trajectory for the earliest encounter of a threshold violation in each situation.

d) If such a risk threshold violation of the planned future trajectory is detected in a certain situation, an **escape trajectory is applied** to the originally planned future trajectory, such that the final trajectory is not violating the threshold for acceptable risk and such that the escape trajectory kicks in the latest possible along the planned trajectory. Here we use emergency brake trajectories as an emergency trajectory.

Therefore, as shown in Fig. 5, we start from the point of the first risk threshold violation, apply the escape trajectory and check if we still encounter a threshold violation. As long as there is still a threshold violation we move back in time along the planned trajectory, until the application of the escape trajectory is safe.

e) As a result we get a **safe future trajectory**, in which the first part consists of the planned future trajectory based on the combined risk map incorporating the situation probabilities, until the latest possible, but earliest necessary, state of performing the escape trajectory in order to avoid a risk threshold violation in any of the still possible situations. The second part consists of the escape trajectory.

## VII. Application of the Approach to an Intersection Scenario

To show the ability of our approach to produce efficient, but still safe trajectories we apply it to an intersection scenario as shown in Fig. 7a, where the ego car (green) and another car (purple) are approaching a crossing. Due to the left yields to right traffic rule, the other car has to give way to the ego car. But from time to time it might happen, that the other car overlooks the ego car and crosses the intersection without looking.

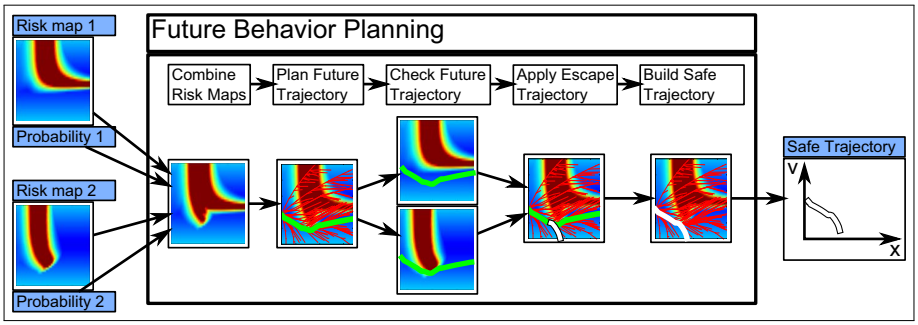



Fig. 4: Planning of safe and efficient future behavior: Scenario with 2 active situations with different probabilities, generating 2 risk maps. Both risk maps are then weighted with their situation occurrence probability and combined into one risk map, which is then used to plan the future behavior. The resulting future trajectory is then checked for risk threshold violations in each situation and escape trajectories are applied. As a result we get an efficient safe trajectory by using the planned future trajectory with the earliest necessary escape trajectory.

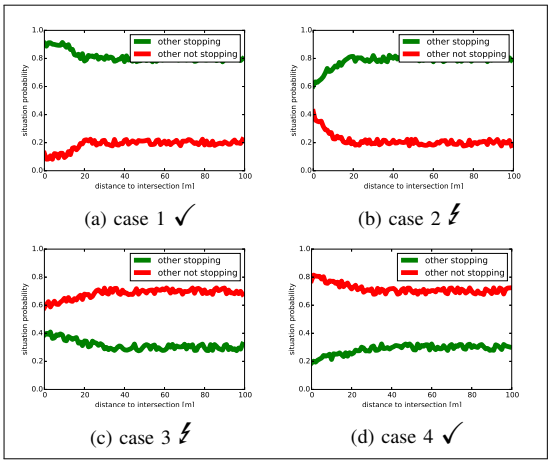



Fig. 6: Probability for each case for the situations "other car stopping" (green) and "other car not stopping" (red). (a) and (b) predict with high probability that the other car would stop, (c) and (d) predict that the other car is not stopping. For (a) and (d) the prediction is correct, whereas for (b) and (c) the prediction is wrong.

In this scenario we model two possible situations, a) the other car recognizes the ego car, lets it pass and crosses behind the ego car and b) the other car does not recognize the ego car and violates the left-yields-to-right-rule.

We evaluate the behavior for the following 4 cases to show how our system copes with a correct and a false situation classification, where ✓ / ↯ indicates a correct / false situation expectation:

| expected \ occurring | other stopping | other not stopping |
|---|---|---|
| other stopping | Case 1 ✓ | Case 2 ↯ |
| other not stopping | Case 3 ↯ | Case 4 ✓ |

As this paper does not target the probability evaluation of certain situations, we model a probability setting for each case as a function of the other car's distance to the intersection, as shown in Fig. 6.

*a) Case 1:* The first case (Fig. 7) represents the general case, where the other car actually follows the rules and gives way while the ego car expects the other car correctly to give way. In this case we start with a high probability for the situation "other stopping", which increases further when the other car comes closer to the intersection, as we gain certainty that the other car is definitively stopping. Whereas the situation that the other car overlooks the ego car and drives through is low and decreases further.

The risk map for the situation "other stopping" (Fig. 7d, top) is in general of low risk, whereas the risk map for "other not stopping" (Fig. 7d, bottom) is of high risk at a certain position on the ego car path and at certain ego car velocities.

The combined risk map is dominated by the risk map for the situation with high probability "other stopping", while the situation "other not stopping" is only marginally included. The resulting future velocity profile is at almost constant speed and no deceleration.

The planned trajectory is then checked on each single situation. At planning time $t = 0s$ a risk threshold violation in situation "other not stopping" is detected, which results in an application of an emergency braking to the originally planed trajectory to satisfy the risk conditions for this situation.

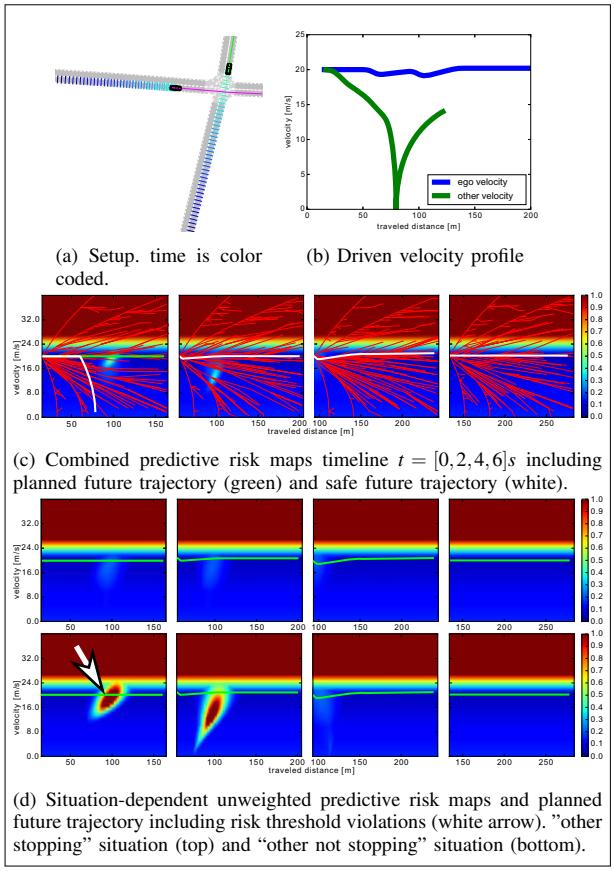
As the other car behaves as expected and brakes, the risk spot in situation "other not stopping" decreases and at planning times $t = [2,4,6]s$ keeping velocity constant is not violating any risk threshold anymore and the planned emergency braking is thus never executed.

*b) Case 2:* In this case (Fig. 8) the ego car expects again, here falsely, the other car to stop. But this time the other car violates the left-yields-to-right rule and drives on. The probability setting for this case shows high probability for the situation "other stopping" while the probability for this situation drops very late (too late to react).

The planned velocity profile shows only a slight deceleration, as the probability for "other not stopping" is low, but violates the risk threshold for this situation. Thus an emergency braking trajectory is applied. Even though the probability remains low for "other not stopping" the planned trajectory still violates the risk threshold.

It can be seen, that at a certain point in time even the situation "other stopping" becomes risky, since the prediction model for this situation predicts that the other car is not able to stop anymore, even if it would react to the ego car.

Once the point of executing emergency braking is reached, the situation "other not stopping" is still of high risk, even though with low probability, and emergency braking has to be executed in order to remain in an overall safe regime.




(a) Setup. time is color coded.

(b) Driven velocity profile

(c) Combined predictive risk maps timeline $t = [0,2,4,6]s$ including planned future trajectory (green) and safe future trajectory (white).

(d) Situation-dependent unweighted predictive risk maps and planned future trajectory including risk threshold violations (white arrow). "other stopping" situation (top) and "other not stopping" situation (bottom).

Fig. 7: Case 1. Expecting other car to stop and other car is stopping.

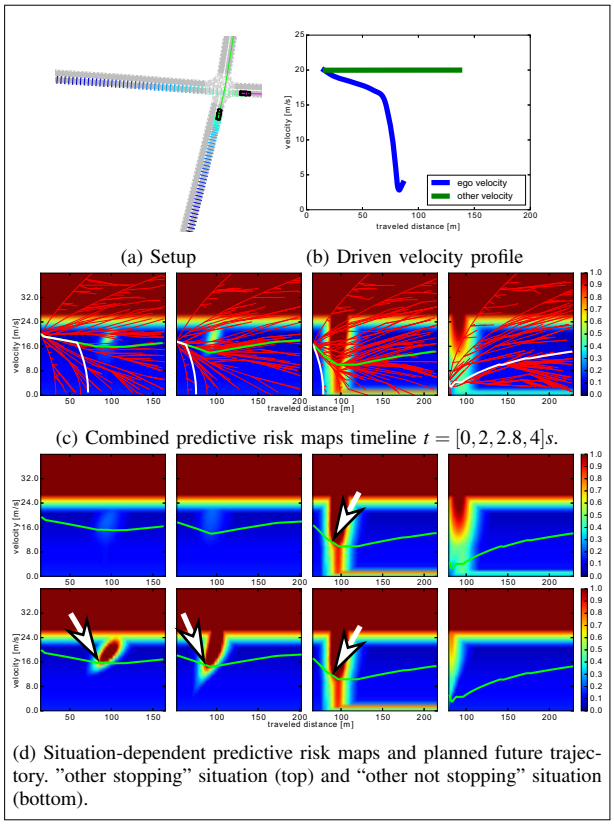
*c) Case 3:* Now we evaluate the case (Fig. 9) that the ego car expects the other to not stop, but in fact the other car stops.

It can be seen in the combined risk maps, that now the "other not stopping" situation dominates, which results in a planned future path adapting mainly to this situation. This means, that the ego car starts to brake in order to avoid an upcoming crash, in case this highly probable situation occurs.

While the ego car is braking, as it expects the other car not to brake, the other car is braking as well, which leads again to a further deceleration of the ego car. As this scenario (both cars brake) is of low risk, no emergency behavior is executed. Finally once the other car is quite slow, both situations "other stopping" and "other not stopping" are of low risk and the ego car accelerates again to pass the intersection.

*d) Case 4:* Here, the ego car expects the other car to not stop, as it overlooks the ego car (Fig. 10) . The expectation is correct and the other car finally violates the rules and drives through.

As the situation classification provides a high probability for the situation "other not stopping" this situation dominates in the combined risk maps and the planned trajectory adapts in that way. The ego car starts early to slow down to let the other car pass (even though the other car has to give right). At a certain point in time the situation "other car is stopping" becomes risky, as the other car could not brake anymore.




(a) Setup

(b) Driven velocity profile

(c) Combined predictive risk maps timeline $t = [0,2,2.8,4]s$.

(d) Situation-dependent predictive risk maps and planned future trajectory. "other stopping" situation (top) and "other not stopping" situation (bottom).

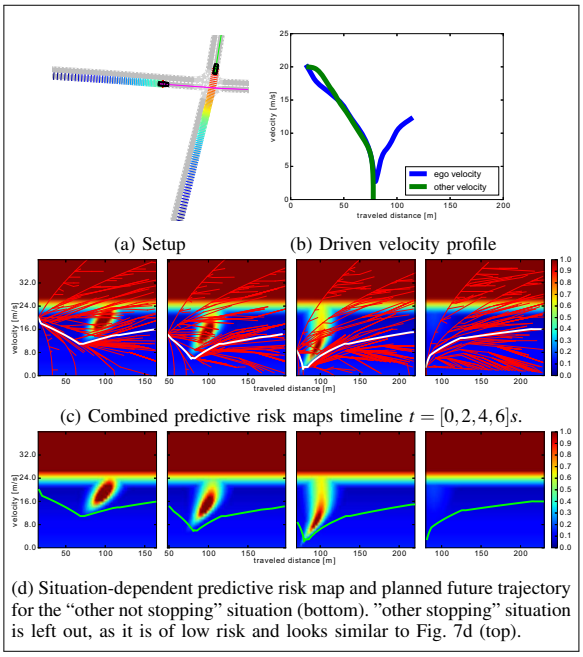
Fig. 8: Case 2. Expecting other car to stop but other car is not stopping.

The result is a velocity profile, where the ego car lets the other car pass and only brakes as much as needed and then accelerates again.

## VIII. Discussion

It could be shown, that our approach provides us with a safe behavior / velocity profile in all 4 cases. Even in cases 2 and 3, where the situation classification provides the system with a wrong situation hypothesis, the resulting behavior can be considered as safe.

Although we gather safe trajectories for all 4 cases, it can be seen easily from the comparison of the 4 velocity profiles in Fig. 11, that a correct situation classification is highly beneficial for the planned future behavior in terms of utility and comfort. For the cases with a correctly classified set of situations, the resulting behavior is highly efficient for the actually occurring situation, e.g. driving by without much braking, if the other car stops (case 1), or early braking, only to the extent to let the other car pass, if the other car does not stop (case 4). For the other two cases, where the situation classification is false, the resulting behavior is safe, but not efficient for the actually occurring situation, e.g. the ego car does not brake enough to let the other car pass, if the other car does not stop and is then performing an emergency braking as safe behavior (case 2), or even though the other car stops the ego car also brakes almost down to zero, until it is completely safe to continue driving (case 3).

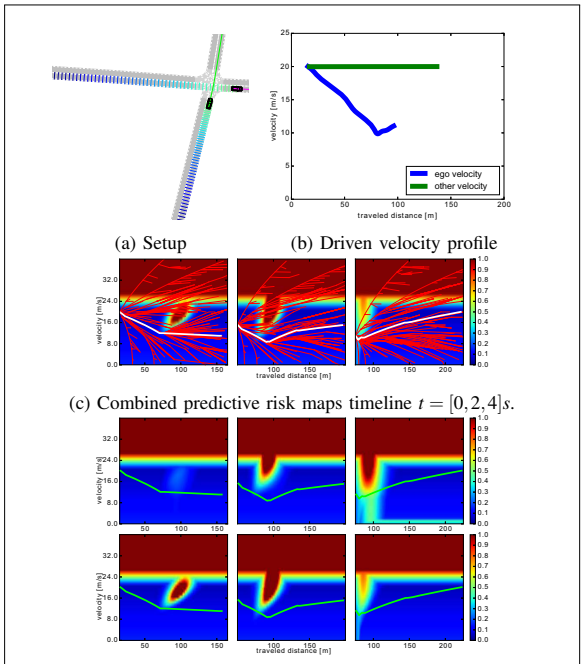



(a) Setup (b) Driven velocity profile

(c) Combined predictive risk maps timeline $t = [0, 2, 4, 6]s$.

(d) Situation-dependent predictive risk map and planned future trajectory for the "other not stopping" situation (bottom). "other stopping" situation is left out, as it is of low risk and looks similar to Fig. 7d (top).

Fig. 9: Case 3. Expecting other car to not stop but other car is stopping.




(a) Setup (b) Driven velocity profile

(c) Combined predictive risk maps timeline $t = [0, 2, 4]s$.

(d) Situation-dependent predictive risk maps and planned future trajectory. "other stopping" situation (top) and "other not stopping" situation (bottom).

Fig. 10: Case 4. Expecting other car to not stop and other car is not stopping.

## IX. Conclusion

In this work we introduced an approach to plan safe but still efficient future trajectories under consideration of multiple uncertain situations. Based on the outcome of a situation classification and selection step, our approach evaluates risk using situation-dependent predicted trajectories of other entities, evaluates future behavior alternatives of the ego car and represents them as predictive risk maps, one for each situation. By combining the risk maps for all possible situations, taking the situation probabilities into account, we plan an efficient trajectory, which adapts mainly to highly probable situations. In a further step we check this efficient future plan and apply a "plan B" in form of escape trajectories to provide a safe future behavior even if unlikely situations kick in. We evaluated our approach on an intersection scenario and could show that the resulting behavior is always safe, even for a wrong situation classification. This confirms that behavior strongly benefits from a good situation classification in terms of utility and comfort.

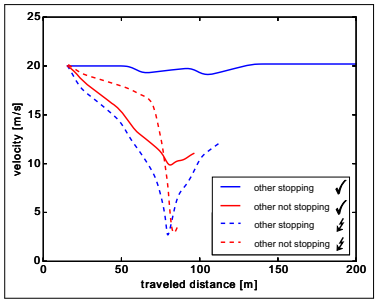



Fig. 11: Comparison of velocity profiles. Check indicating correction situation classification, flash indicating wrong situation classification

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