Situation Assessment in Tactical Lane Change Behavior Planning for Automated Vehicles

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Abstract— Automated driving *within* a lane is a fascinating experience already. However, more exiting but also technically more challenging is to dare the next step of automating tactical behavior decisions for lane changes, as well. In this paper, we present our approach for situation assessment in tactical behavior planning for lane changes, whether lane changes are *beneficial* and/or *possible*. We present a way to tackle perception uncertainties and how to monitor the system's abilities and current skills. This is achieved by a dynamic Bayesian network and an unscented variance transform. Our approach is evaluated not only in a simulation, but also in real traffic. Our implementation has recently been demonstrated to the public in the *Audi A7 piloted driving concept* vehicle, driving 550 miles from Stanford to Las Vegas to the Consumer Electronics Show (CES) 2015.

I. INTRODUCTION

Driver assistance systems like an adaptive cruise control or lane keeping system are able to take over some stabilization level related tasks, already. Among the key challenges toward automated driving is to automate behavior on a tactical level, too. For this, it is necessary to have a situation assessment for tactical behavior planning. This situation assessment transforms various factors of the current driving situation into abstract, aggregated state estimates for particular situation aspects. Such a situation assessment needs to consider information about dynamic objects, the scenery as well as information from a self-representation all along with transient and permanent goals and values of the system.

In Ulbrich & Maurer [1], we presented our general framework for tactical lane change behavior planning. This paper focuses on which aspects need to be considered for a lane change situation assessment. It provides details about the situation assessment for the dynamic traffic situation. We extend previous works by performing not only a situation assessment, whether a lane change is *possible* but also if the lane change is *beneficial* at all.

For that purpose, this paper is structured as follows: In section II we pinpoint situation assessment in the overall system architecture of an automated vehicle, review existing literature on situation assessment and provide a theoretic foundation of dynamic Bayesian networks. Section III presents our implementation of a dynamic Bayesian network for lane change behavior planning. This is followed by an evaluation in a simulation environment as well as in real traffic in section IV. Last of all, section V finalizes this paper with conclusions and a research outlook.

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II. BACKGROUND

Donges [2] distinguished different levels of driving tasks. He introduced the classification into navigation tasks (strategic level), guidance tasks (tactical level) and stabilization tasks (operational level). The focus of this paper are guidance tasks, which entail any tactical behavior planning for an automated vehicle. Figure 1 illustrates situation assessment for tactical behavior planning as a part of the overall architecture of an automated vehicle.
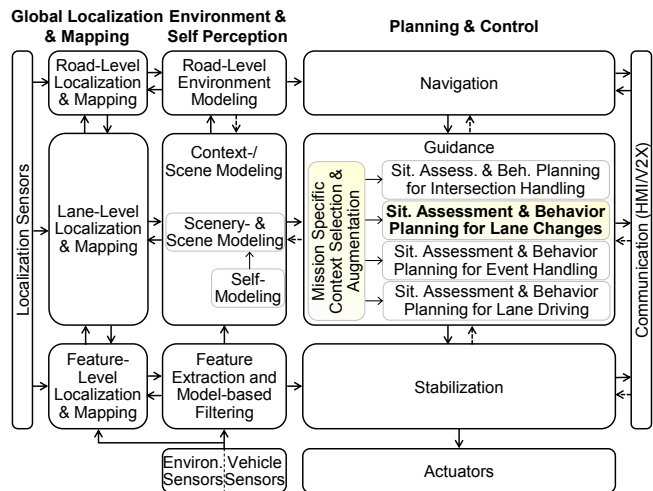

Fig. 1. Tactical behavior planning for lane changes as a part of the overall functional system architecture of an automated vehicle (cf. [3], [4], [5]).

A. Related work

A review of relevant literature has been presented in Ulbrich & Maurer [6] already. Therefore, the focus is limited to some particular aspects of the situation assessment itself.

Pellkofer [7] and Naranjo [8] use a fuzzy logic for modeling lane change decision making problems. The advantage of such a fuzzy logic approach is its simplicity and computational efficiency.

Schubert et al. [9] use a Bayesian network for situation assessment and decision making for lane changes. Deceleration to safety time (DST) is used as a central criterion for lane change situation assessment. In [10], Schubert et al. illustrate how to transform value-continuous (measured) state variables into discrete state variables by a discretization of so called *situation parameters*. In [11], he does a more in depth practical evaluation of the proposed Bayesian network. He picks some sample sequences of highway driving and illustrates how situation assessments' expected utilities for

doing lane changes vary over time. Moreover, he illustrates the consequences of uncertainties on the ambiguity of the situation over time.

Reichel et al. [12] present an approach for situation aspect modeling and situation assessment for merging situations. It is used it to analyze if the ego vehicle is part of a convoy merging maneuver or if a convoy is about to merge to the ego lane.

Ardelt et al. [13], [14] present BMW's lane change situation assessment approaches in its *ConnectedDrive*-project, focused on highly automated driving on highways. They use a decision tree to assess the current feasibility of maneuvers, depending on the driving goal and a situation interpretation.

Also in the field of driver assistance systems for lane change assistance, Chen [15] and Habenicht [16] provide an approach for situation assessment based on the point mass motion equations of an object. In his implementation, Chen focuses on an assessment based on time gap and time-to-collision. However, in his theory part, he derives necessary motion equations for objects. By solving these equations for the necessary acceleration/deceleration to safety he provided the framework for the metric being used in this paper.

B. Dynamic Bayesian Networks

Bayesian networks allow probabilistic reasoning based on the idea of conditional probability. Bayesian networks graphically represent relationships between random variables. Every node in Bayesian network stands for a random variable and directed edges among nodes encode information about the conditional dependence of the random variables. A Bayesian Network is a *directed acyclic graph* $\mathcal{G} = \{\mathcal{X}, \mathcal{E}\}$ with a set of n_X nodes $\mathcal{X} = \{X_1, ..., X_{n_X}\}$ and a set of directed edges $\mathcal{E} = \{X_i \rightarrow X_j | X_i, X_j \in \mathcal{X}, i \neq j\}$. All nodes on which a node X_i conditionally depends on are called $Dep(X_i)$[1]. Hence, a Bayesian Network can be written by: $P(X_1, ..., X_{n_X}) = \prod_{i=1}^{n_X} P(X_i | Dep(X_i))$

Evidence, or *measurements*, can be incorporated by a joint probability distribution $p(X_1, ..., X_{n_X} | m)$.

Typically, Bayesian networks assume discrete random variables for their nodes. However, they can also be used to handle continuous random variables. A continuous random variable has an infinite number of possible values. Hence, it is not possible to explicitly state conditional probability tables for the set of edges $\mathcal{E}$. There are two ways to address this issue: On the one hand a continuous random variable can be discretized, on the other hand a random variable can be described in terms of a particular probability density function, which can be represented by a finite set of parameters (cf. Russel & Norvig [17, p. 520]). In this paper, a transformation between value continuous node (e.g. *lane traffic flow velocity*) and a value discrete node (e.g.,

lane change beneficial due to velocity gain) is performed with a sigmoid function. We use the cumulative distribution function of a normal distribution for this purpose.

A dynamic Bayesian network extends a regular Bayesian network by the temporal dependency among nodes. Special cases of this general framework are Kalman filters or hidden Markov models. In these, a random variable not only depends on its set $Dep(X_i)$ within a time slice, but also on earlier time slices (cf. figure 2). We assume the Markov property to hold. That is, a system state only depends on current measurement updates and a *finite* history of previous states. In our case a first-order Markov process only depending on current measurement updates and the *last* state $P(X_t | X_{t-1}, m_t)$ is used.
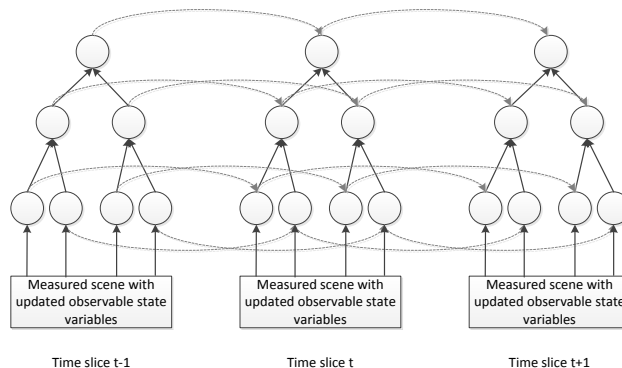

Fig. 2. Measurement update for hidden state variables (circles) in dynamic Bayesian network for lane change planning based on observable measurements (rectangular).

III. SITUATION ASSESSMENT FOR LANE CHANGES

This section presents our implementation of a dynamic Bayesian network for lane change situation assessment. This is part of a so called measurement model in a novel framework for tactical behavior planning in uncertain, mixed-integer state spaces presented in Ulbrich & Maurer [1].

This paper focuses on the measurement model and in particular the situation assessment.

The measurement model translates current measurement information about the driving situation into an aggregated belief of the system's state. Measured information may partially be value-discrete (e.g., number of lanes) and partially be value-continuous (e.g., distance to a front vehicle). Some aspects of the system state are directly observable (e.g., how long the indicator has been switched on already) or at least no better state estimate can be obtained by modeling them as hidden (e.g., object velocities). For other aspects it may be possible to obtain *better* or *at least some* state estimates by modeling them as hidden. Hidden state variables may contain information, whether a lane change seems possible or beneficial in the current situation, which gap is the best to head to, etc.

Figure 3 shows different stages within the measurement model. The leftmost part of the image shows a visualization of the information in the context model as an abstract scene

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[1]This set is often called the set of parent nodes $Pa(X_i)$. Given the hierarchical structure of abstraction in our Bayesian network in figure 2 and figure 3, we see a chance for misunderstandings that a more abstract node like *Lane change possible left* is indeed a dependent child node to, e.g. *Lane change possible left due to infrastructure situation*. Hence we suggest to call this set $Dep(X_i)$.
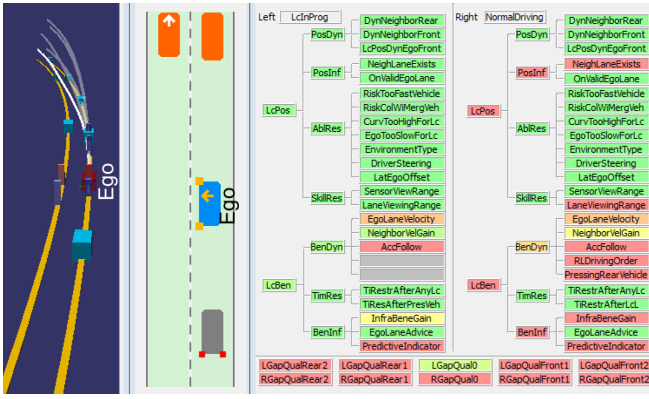
Fig. 3. Estimation of situation aspects by a Bayesian network. Left: scene, center: situation, right: visualization of dynamic Bayesian network.

description of the vehicle itself and its environment. The center part of figure 3 illustrates a situation abstraction of the lane change relevant information. Here, a situation where the automated vehicle performs a lane change to the left to overtake a slower front vehicle is depicted. For obtaining beliefs for the distributions of hidden state variables, a dynamic Bayesian network is used. The rightmost part of that figure illustrates the dynamic Bayesian network used to estimate distributions for the hidden state variables. Every node in that dynamic Bayesian network is considered a hidden state random variable.

Figure 2 illustrates the belief update in the dynamic Bayesian network. Every round node is a hidden state variable in the dynamic Bayesian network. A new belief estimate at time slice t is derived from the latest values of observable state variables like distances or velocities of objects and -with a certain weight- the old belief of that particular state variable at the previous time slice.

The four high-level hidden state variables for planning lane changes are, whether a lane change is *possible* to the *left* or *right* and whether it is *beneficial* to the *left* or *right*. To obtain state estimates for those hidden state random variables, several other random variables need to be estimated.

A. Lane Change Possible Estimation

For the estimation if a lane change is possible, it is necessary to consider if it is possible due to the dynamic traffic situation, due to the infrastructure, due to ability induced skill restrictions, as well as due to the system's current skill-level induced skill restrictions.

1) Lane Change Possible due to the Dynamic Traffic Situation: Maybe the most obvious aspect for situation assessment is the consideration of dynamic objects in the automated vehicle's environment.

To evaluate if a lane change is possible due to the dynamic traffic situation, the automated vehicle's environment is split into different regions of interest. Figure 4 illustrates three different regions of interest for deciding a lane change to the left. In purple, the region of interest "front ego" (FE), in yellow "front left" (FL) and in orange "rear left" (RL). Accordingly, "front ego" (FE), "front right" (FR) and "rear right" (RR) will be considered for a lane change to the right.
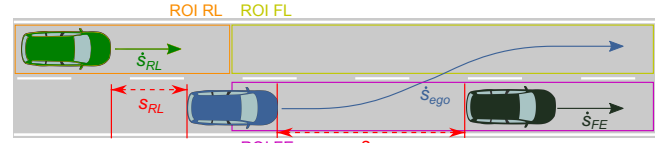

Fig. 4. Typical scenario for lane change situation assessment with three dynamic objects and three regions of interest rear left (RL), front left (FL) and front ego (FE).

To calculate, whether other vehicles allow to change lanes, we use the motion equations of a point of mass similar as in Chen [15] and express the distance between the ego vehicle and a vehicle in the rear left neighbor lane by a difference of $s_{ego}(t) - s_{RL}(t)$. For the sake of analytic solvability, we assume that the driver of the green vehicle will brake with a constant (negative) acceleration a_{RL} and that he would like to maintain a time gap of $T_{RL} = 0.8\,s$ and has a reaction time of $T_R = 1\,s$. With $\Delta v = \dot{s}_{ego} - \dot{s}_{RL}$. The acceleration we enforce on the green vehicle to avoid collisions can be calculated[2] by:[3]

$$a_{RL} = \frac{\Delta v^2}{2 \cdot (s_{RL} - \Delta v \cdot T_R + \dot{s}_{ego} \cdot T_{RL})} \quad (1)$$

Based on measurement data from real traffic, we assume that an averagely altruistic driver will let us merge as long as he does not have to decelerate with more than $a_{RL,begin} = -1\,m/s$. Thus, if the calculated necessary deceleration for a_{RL} is below this threshold, a lane change is considered possible. Vice versa, if a lane change has been initiated already and a rear left vehicle has to brake more than $a_{RL,abort} = -3.5\,m/s$, we consider a lane change no longer possible and will abort it.

If the relative velocity $-\Delta v < 3\,m/s$, vehicles will accept a lot smaller time gaps as the situation is easier to manage. Thus, we allow T_{RL} to decrease to $0.3\,s$ or $0.2\,s$ depending on the urgency of a lane change. This is necessary to enable lane changes in traffic jam situations.

To consider uncertainties, all distances, velocities and accelerations are conservatively estimated by not just using the mean but rather $\mu \pm 1.0 \cdot \sigma$.

Similar calculations can be done for approaching a slower vehicle in the "front left" (FL) and "front ego" (FE) region of interest.

2) Lane Change Possible due to the Infrastructure Situation: For deciding, whether a lane change is possible it is necessary to consider the infrastructure, as well. On the one hand it is necessary to consider if the automated vehicle is currently driving on a valid lane and if a neighbor lane exists and is valid, as well. Moreover, it is necessary to evaluate if lane markings, traffic signs and traffic rules allow to do a lane change.

3) Ability Induced Skill Restrictions: Ability induced skill restrictions rule a lane change impossible due to general limitations of the automated vehicle. For a discussion of a theoretical framework, see Reschka et al. [18].

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[2]Part of the mathematical derivations have been done together with my colleague Patrick Pascheka.

[3]We assume $s_{RL} < 0\,m$ for a vehicle behind the ego vehicle.

a) Risk of too fast vehicles: Doing a lane change to a left neighbor lane on a highway stretch without a speed limit may not be a safe maneuver, because objects might approach the automated vehicle with high velocities from behind. Given a limited ability of the environment perception modules to track objects far behind and a minimal time necessary to finish a lane change, it may happen that a fast vehicle from behind is forced to initiate a strong emergency braking maneuver in order to prevent a collision with an automated vehicle pursuing a lane change. However, a lane change to the left on a highway without a speed limit will be possible if the environment perception modules see a slow vehicle on the neighbor lane, because a fast vehicle from behind will have to adapt its velocity to those vehicles anyway.

b) Collision avoidance with merging vehicles: A lane change to the rightmost lane of a highway may result in a hard to resolve situation if it is performed right next to a highway on-ramp and another vehicle is entering the highway from such an on-ramp. In particular, heavy trucks merging to a highway expect some cooperative behavior of regular vehicles on the highway while they merge. As lane and object perception modules do not always detect those merging objects reliably two lanes to the right of the ego lane, lane changes are currently avoided in those situations.

c) Ego vehicle too slow: A lane change may also be impossible, if the automated vehicle is driving too slow. Because in those situations a lane change might take longer to be completed than a reliable prediction of the environment changes being possible.

d) Environment domain type: Last of all, the environment domain type may impose ability induced skill restrictions for lane changes. For instance, currently our implementation of the automated vehicle is not able to offer safe overtaking maneuvers on rural or urban roads, where it is necessary to change lanes to lanes with oncoming traffic. Other examples for lane change domain ability restrictions are areas with road works on highways.

4) Skill Restrictions: Skill restrictions rule lane changes impossible due to a temporary decreased skill level. Among them are in our model restrictions in the sensor viewing range to perceive objects, to perceive lanes and the monitoring of the correct execution of all components necessary for the operation of the automated vehicle. Once again, a theoretical framework is presented in Reschka et al. [18].

a) Sensor object viewing ranges: To calculate sensor viewing ranges for perceiving objects, a simple form of the incept theorem is used. Given another vehicle is driving directly behind an automated vehicle, it obstructs the view to the neighbor lanes, as well. It may cause occlusions due to the fact that our main sensor for covering the rear and the front area are mounted in the middle of the automated vehicle's bumpers.

b) Lane viewing ranges: To calculate lane viewing ranges for perceiving lanes, the ego lane segment and its neighbor lane segments perceived by the lane tracking algorithms are traversed to their front and rear ends.

B. Lane Change Beneficial Estimation

To estimate whether a lane change is beneficial, it is necessary to evaluate the dynamic traffic situation for relative velocity gains in different regions of interest (ROIs) around the ego vehicle and if a lane change is beneficial due to infrastructure related information. A third aspect for lane change beneficial situation assessment are timing restrictions to reflect disadvantages of immediate behavior changes.

1) Lane Change Beneficial due to Dynamic Situation: In this paper, any kind of benefit considerations for doing a lane change regarding the dynamic situation are based on estimated lane specific traffic flow velocities and resulting velocity gains.[4]

2) Lane Change Beneficial due to Infrastructure Situation: Apart from dynamic traffic situation based reasons for are lane change, the predominant source for lane changes will be infrastructure related factors. For instance, if the navigation layer necessitates a right turn to another road, the tactical layer should take care to reach the turning point on the rightmost lane. To accomplish this, every lane segment is attributed with a cost to reach the destination.[5]
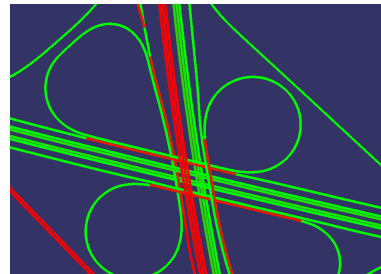

Fig. 5. Lane advice from the navigation layer. Red denotes, in comparison, bad lane choices to reach the navigation goal, green indicates favorable lanes to reach the destination.

3) Lane Change Beneficial due to Timing Restrictions: In some situations, it might be possible but still not beneficial to perform a lane change due to timing restrictions. One example of these are some timing restrictions to enabling a re-centering to a lane between finishing one lane change and starting a next one.

C. Gap Quality Assessment

In dense traffic, it is necessary to adjust the automated vehicle towards a cost-optimal gap. Therefore, it is necessary to determine the most appropriate gap for a lane change. This is done by calculating the relative distances and velocities to each gap around the automated vehicle. Space constraints do not allow an extensive discussion of relevant aspects and their implementation. Details will be provided in another paper.

D. Calculating and Propagating Uncertainties

Among the key challenges for tactical lane change behavior planning is the inherent uncertainty from any kind of

environment perception modules. The higher the abstraction level of the perception gets, the bigger the uncertainty about state estimates will be.
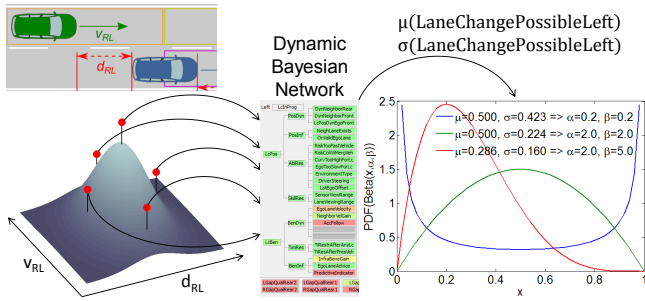

Fig. 6. Sigma point variance propagation of uncertainty prone state dimensions through a non-linear dynamic Bayesian network.

As illustrated in figure 2, every hidden state variable of the dynamic Bayesian network will be estimated based on old state information and current measurement updates. Every of these measurement updates will come along with an uncertainty. As the expected values μ of specific measurement updates propagate to some hidden state variable estimates, so will their variances do according to the measurement update model outlined above. A challenge are the inter-dependencies between state variables causing a non-linear propagation of those variances through the dynamic Bayesian network to represent beliefs about the driving situation. An approach to address this is to use an unscented transform with a minimal set of sigma points in the same way it is used in an Unscented Kalman filter [19, p. 65].

The unscented transform, as illustrated in figure 6, is a method to calculate the statistics of random variables through a non-linear transformation function like the dynamic Bayesian network. We use eleven sigma points to transform positions and velocities of the immediate next objects in the regions of interest named in section III-A.1 and the automated vehicle's ego velocity. The authors preferred an unscented transform over a more generic but slower particle filter approach, to keep evaluation times of the situation assessment low, as the situation assessment is performed several times per update cycle, for the current plus several predicted future scenes as detailed in Ulbrich & Maurer [1].
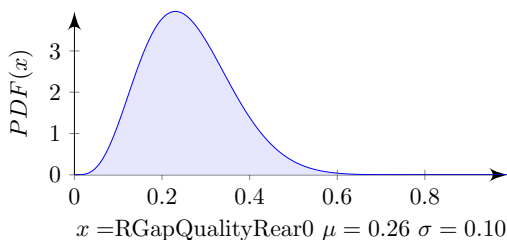

Fig. 7. Example of a hidden state variable as an estimate for a gap quality. The variance is derived from measured variances of object positions, velocities and accelerations.

Figure 7 illustrates an estimated mean and variance for a beta distributed random variable to represent the probability that a gap is suitable for making a lane change.

IV. EVALUATION

In this section we present our evaluation. After evaluating the general feasibility of the proposed algorithms in a simulation environment, we present an evaluation in real traffic.

A. Evaluation in a Simulation

A simulation environment is a crucial during the development process and for validation of the algorithms. We use *Virtual Test Drive (VTD)*[6] and *Automotive Data and Time-triggered Framework (ADTF)*[7] as a tool chain to test the presented algorithms. Figure 8 shows the situation assessment for a lane change during an overtaking scenario.
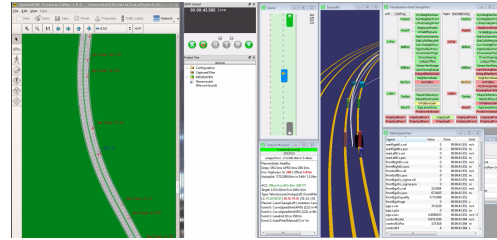

Fig. 8. Screenshot of a scenario-based closed loop testing in Virtual Test Drive.

B. Evaluation in Real Traffic

To prove the feasibility of a concept, it is best to evaluate it in real traffic. Our algorithms have been tweaked and tested in the *Audi piloted driving concept* vehicles for about 60.000 km in public traffic. The lane changing behavior has recently been presented to the public in the 550 miles drive from Stanford to Las Vegas to the Consumer Electronics Show 2015[8] and on a German highway[9]. Our focus has been on highways, but it has also been tested on (sub-)urban multilane streets.

In figure 10, the first two plots depict driving a 20 km stretch of the A9 from Ingolstadt, Germany northbound. The longitudinal ego velocity of the automated vehicle is visualized by the first diagram. There is no speed limit on this stretch of a 3+3 lane highway. The target velocity is set to $40 \, m/s$. Occasionally, traffic in front of the automated vehicle slows it down, if it is not able to perform a lane change due to traffic on the neighbor lanes.

The lateral offset of the automated vehicle to the center of the ego lane is shown in the second and third diagram of figure 10. Each time a lane change is executed, the ego lane jumps to another lane and the lateral offset jumps from negative to positive (lane change right) or positive to negative (lane change left). The third till eighths plot of figure 10 illustrate the situation assessment before and during a lane change to the left.

The maneuver is visualized by a sequence of images from the lane tracking camera and a situation visualization widget

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[6]http://www.vires.com

[7]https://automotive.elektrobit.com/products/eb-assist/adtf/

[8]https://audimedia.tv/en/vid/550-miles-piloted-drive-the-last-stage-2

[9]http://www.stern.de/auto/news/jack-das-selbstfahrende-auto-von-audi-erstmals-auf-einer-deutschen-autobahn-2174446.html
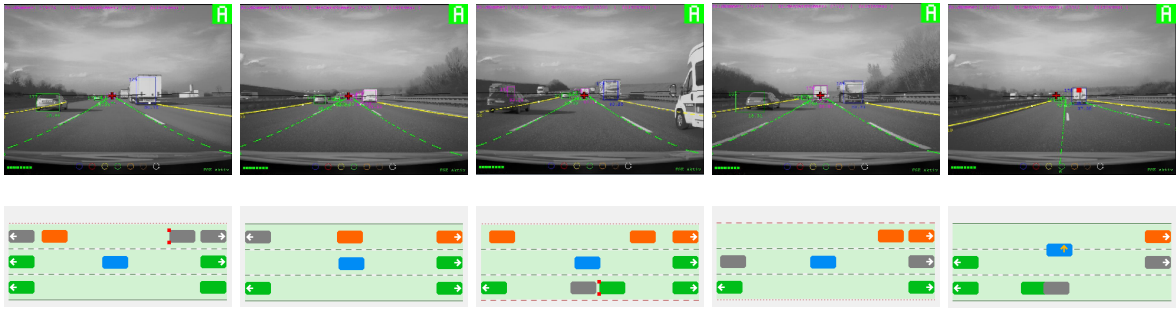
Fig. 9.   Video and situation visualization for lane change situation assessment. Blue=ego vehicle; white arrows indicate squeezed vehicle distances.
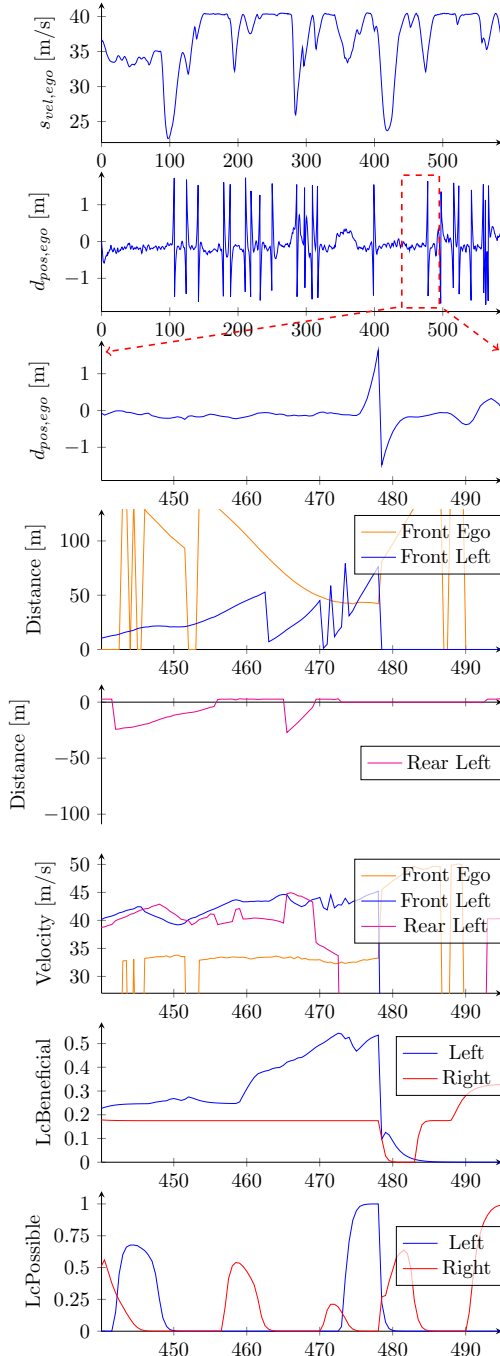

Fig. 10.   State variables during an overtaking scenario.

in figure 9. Initially, the automated vehicle drives on the middle lane of a three lane highway. In front of it appears a slow truck (green). As overtaking on a highway in Germany is only allowed on the left, a situation assessment for a lane change to the left is evaluated. The forth till sixth plot in figure 9 illustrate the distances and velocities of the immediate next vehicles on the left neighbor lane and on the ego lane in front. Starting from $t = 442\,s$ a slower vehicle with a velocity of about $33\,m/s$ is detected $150\,m$ in front. The first few seconds, a lane change to the left is still to some extent considered possible at the current time step (cf. *Lane change possible left*) in the eighths plot. However, due to the planning ahead into the future and due to a still relatively low disadvantage of staying behind a vehicle being $150\,m$ away, no lane change gets executed. Till $t = 463\,s$ the rear left neighbor lane's vehicle approaches the automated vehicle from behind until it is next to the automated vehicle. Here, the blindspot radar sensors do not allow an accurate position estimation but only an object existance estimation. At $t = 463\,s$ the same object is seen again by the front laser scanners and the distance towards this object increases, again.

A second vehicle approaching the automated vehicle on the left neighbor lane is detected $-30\,m$ behind with a velocity of $44\,m/s$ at $t = 465\,s$. This has passed the automated vehicle at $t = 470\,s$. Behind this fast vehicle, no other vehicle follows. Hence a gap opens up to the left. In the mean time, the automated vehicle has approached the slow vehicle in front of it on the ego lane to a relative distance of $42\,m$. To avoid a collision, the automated vehicle decreased its speed to $33\,m/s$. Hence, it obtains a high dynamic benefit of performing a lane change to the left to reach its target velocity of $40\,m/s$, again (cf. *Lane change beneficial left* in the seventh plot). The lane change decision making module decides to activate the indicator and perform a lane change to the left. This can be seen by the lateral offset to the center of the ego lane $d_{pos,ego}$ to increase until the lane markings have been passed and the automated vehicle re-centers to the left neighbor lane.

C. Runtime

The algorithm runs in real time on an Intel i7 4800MQ CPU sharing resources with trajectory planning, situation modeling and visualization modules. Typical peak loads for

any of the cores are below 20%. Per cycle, the situation assessment is executed several thousand times. This is because according to Ulbrich & Maurer [1] a tree of future situations is predicted. Observable state variables are predicted according to a car following model for each vehicle and a recalculation of hidden situation aspect estimates is performed by the dynamic Bayesian network. On average a resulting tree of actions and future situations has about 100 situation nodes. An unscented transform with 11+1 sigma points is executed for every situation to estimate resulting variances in the dynamic Bayesian network. Scene updates from the perception modules are obtained with a rate of $25\,Hz$. Therefore, the dynamic Bayesian network is executed on average $100 \cdot 12 \cdot 25 = 30,000$ times per second. As there are no big *for*-loops in the dynamic Bayesian network implementation, most evaluation time is used for floating point operations and some if conditions.

V. Conclusions

In this paper, the authors present an approach for situation assessment in tactical lane change behavior planning for automated vehicles. It provides estimates for hidden state variables in uncertain, high-dimensional, mixed-integer state spaces in real-time. A dynamic Bayesian network provides temporal consistency. An unscented transform allows the propagation of uncertainties within the situation assessment. An ability and skill monitoring facilitates not only the consideration of the scenery and dynamic objects but also the consideration of an automated vehicle's self-representation.

The paper evaluates the algorithms' performance in a simulation environment and online in real traffic.

Despite demonstrating a solid performance already, several areas of improvement exist. So far, many random variables and their relationships within the situation assessment are hard coded by rules and impact weights. While this provides simplicity and application specific fine tuning options, it involves significant engineering efforts. It would be interesting to learn these models or parameters for those. Except for this, the handling of uncertainties leaves room for improvements. So far, the existence of objects is assumed to be binary. However, once stable object existence probabilities are estimated on the perception side, those could be used for a more accurate situation assessment, too. The gap quality estimation is still limited, mainly by the persistent detection of objects and gaps.

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