Evaluating the Utility of Driving: Toward Automated Decision Making Under Uncertainty

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***Abstract*—The complexity of advanced driver-assistance systems (ADASs) is steadily increasing. While the first applications were based on mere warnings, current systems actively intervene in the driving process. Due to this development, such systems have to automatically choose between different action alternatives. From an algorithmic point of view, this requires automatic decision making on the basis of uncertain data. In this paper, the application of decision networks for this problem is proposed. It is demonstrated how this approach facilitates automatic maneuver decisions in a prototypical lane change assistance system. Furthermore, relevant research questions and unsolved problems related to this topic are identified.**

***Index Terms*—Decision network, decision support system, intelligent vehicles, lane change assistant.**

I. Introduction

One of the main research goals in the domain of intelligent transportation systems is to make traveling safer, more efficient, and more sustainable. Concerning road traffic, advanced driver assistance systems (ADASs), which perceive the environment of a vehicle using an application-dependent set of sensors, are a promising development toward this aim. It has been shown that such systems are indeed having a positive influence on road safety [1].

Over the past few years, a significant increase in complexity could be observed in the domain of ADASs. While early systems (e.g., blind spot monitoring [2]) restricted themselves to the provision of warnings, later developments are actively executing certain maneuvers, such as braking [3]. Current research projects are working on even more sophisticated concepts such as highly automated driving [4] or autonomous vehicles [5].

A common requirement for all these systems is that, at the end of the data-processing chain, a *decision* needs to be taken. In the simplest case, this decision can be binary (e.g., display a warning or not), and the procedure for its derivation may be based on a simple threshold comparison of a certain situation parameter, such as the time to collision. However, there are several reasons the process of automatically taking a decision is becoming significantly more complex for current and, in particular, future systems.

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First, the number of action alternatives is increasing. While the simplest warning-based systems have to choose from only two possibilities, intervention-based functions have, for instance, to decide if they need to warn the driver, execute a partial or a full braking maneuver, or are not required to do anything. Highly automated or autonomous vehicles even have to select the optimal maneuver from a set of given possibilities such as changing the lane, overtaking another vehicle, and stopping. In addition to these discrete decision alternatives, future vehicles can also be expected to decide on continuous quantities, e.g., which deceleration to apply to avoid a collision.

Furthermore, the number of decision criteria is also increasing. Instead of relying on a single quantity such as the time to collision, maneuver decisions have to be based on different aspects such as road safety, passenger comfort, traffic rules, and (in case of cooperative systems) maybe the actions of other traffic participants as well. Another reason for the increasing complexity is the severity of possible consequences, which may arise from inappropriate decisions. Automatically executing a braking or lane-changing maneuver carries the risk of serious injuries or even deadly incidents. Thus, the validation of decision-taking procedures must be further refined.

The probably most critical issue for decision systems is, however, the presence of uncertainty. Due to the limited sensor performance, a vehicle will never have unequivocal knowledge about its surrounding. Even if such knowledge were available, the limited predictability of the traffic situation would still introduce significant ambiguities. This uncertainty is increasing with the earliness of a decision: On the one hand, this is because the distance to detected entities is larger, which, in the common case of angular sensor errors, results in a more uncertain lateral position; on the other hand, this results because the time interval for predicting the traffic scene is increasing.

Due to these reasons, future intelligent vehicles require reliable systems for automatically taking decisions that are capable of taking into account several alternatives and multiple criteria in the presence of significant uncertainties. This paper attempts to propose a potential path toward this aim.

In Section II, a brief summary of current algorithms for decision taking is given to motivate the work described thereafter. Section III introduces decision networks (DNs) as an algorithmic Bayesian framework, which, in theory, complies with all of the aforementioned requirements. A prototypical implementation of DNs on the example of a lane change assistant (LCA) is described in Section IV. The aim of this prototype is to determine a lane-change maneuver recommendation, which is provided to the driver via a human–machine interface (HMI).

It will be shown how DNs can be applied as an integral part of a Bayesian data-processing and data fusion scheme.

In Section V, empirical results of the presented prototype are presented. In particular, the influence of sensor uncertainties on the ambiguity of the maneuver decision will be demonstrated. This paper concludes with an analysis of unsolved questions and further research issues.

II. Previous Work on Decision Algorithms

As an important aspect for decision algorithms is the existence of appropriate interfaces to previous data-processing steps, the following overview will be embedded in the context of the JDL data fusion model:[1] This generic model for data fusion is (after having undergone several revision) one of the most widely used schemas for structuring data-fusion-related functions. In this work, the revised model presented in [6] is applied. The fusion levels 0 (subobject assessment) and 4 (process refinement) are not described, as they are not the focus of this paper. It appears important to emphasize that these levels do not specify a process model, that is, they do not necessarily have to be successively performed.

A. Object Assessment

JDL data fusion level 1 is defined as the "estimation and prediction of entity states on the basis of inference from observations" [6]. In most ADAS applications, this means to estimate the existence, position, and kinematic parameters of different traffic participants, as well as the parameters of other relevant entities such as lanes. For that, *Bayesian filtering* algorithms are predominant. The main tasks when implementing an ADAS are to choose an appropriate implementation of Bayes' filter and to design statistical models for the system dynamics, sensors, clutter, etc. If the data fusion levels are separately implemented, the output of the object assessment stage is often a set of probability density functions (PDFs) over the relevant entity states [7].

B. Situation Assessment

JDL level 2 refers to the "estimation and prediction of entity states on the basis of inferred relations among entities" [6]. The difference to level 1 is that, instead of separately analyzing different entities, the relations among them are investigated to derive a model of the current *situation*. For ADASs, this may mean to associate vehicles to certain lanes or to evaluate relations between vehicles and pedestrians.

Compared to object assessment, the algorithmic variety at this level is higher. One common approach (particularly for systems with a high computational complexity or low computing resources) is to use the expectation values of the PDFs provided by the previous stage to calculate certain situation parameters such as the time to collision [3].

As an alternative, fuzzy-based algorithms are proposed by some authors to model uncertainty [8], [9]. A situation assessment can then be performed by applying fuzzy rules. One of the main drawbacks of this approach is the unavailability of interfaces to Bayesian object assessment techniques.

Bayesian techniques for situation assessment are, for instance, proposed in [10]. Furthermore, the author proposed a unified Bayesian approach for object and situation assessment, which includes a generic interface between Bayes' filters and Bayesian networks (BNs), as well as an algorithm for exploiting situational knowledge at the object assessment stage [11].

C. Impact Assessment

The third level of the JDL data fusion model contains the "estimation and prediction of effects on situations of planned or estimated/predicted actions by the participants" [6]. This stage can be seen from two perspectives: On the one hand, it includes an explicit prediction of maneuvers that are expected to be performed by the host vehicle or other traffic participants. Although this is an important research questions, it is not the scope of this paper. (Further information and references can, for instance, be found in [12].)

On the other hand, this stage includes the planning of actions to be executed by the host vehicle. In the context of ADASs, there are two main perspectives on this topic: If actions are planned on a kinematic level, the term *motion planning* is usually used. As this concept is well known in robotics, there is a considerable number of approaches (see [13] for a thorough introduction on this topic). An application of motion planning to autonomous driving in the context of the DARPA Urban Challenge is, for instance, given in [14]. The main characteristics of this approach are the optimization of an optimality criterion (in this example, the time for following the planned path is used) taken into account various restricting constraints.

An alternative perspective is focusing on the high-level behavior of the host vehicle. From this point of view (which is taken throughout this paper), impact assessment can be interpreted as taking maneuver decisions. From an algorithmic perspective, it is (apart from reliability aspects) not relevant if the selected maneuver is recommended to the driver or automatically executed using a subsequent path-planning module. The rationale of planning on maneuver level is to reduce complexity, as motion planning can be specifically designed for particular maneuvers.

In the domain of autonomous driving, such an approach has, for instance, been chosen by different participants of the DARPA Urban Challenge. In [15], which illustrates the relationship to different design paradigms from robotics, this approach is called *behavioral programming*. In this work and in [16], decisions are taken using a hierarchical finite-state machine, whereas the state transitions are based on the underlying decision rules and the perception results. A similar approach is proposed in [17] in the context of the German project Stadtpilot for autonomous driving in urban areas. All these works have in common that uncertainties are mainly accounted for on the object and situation assessment level but not for the decision process itself. In a recent paper about autonomous driving, a multiple-criteria decision-making approach is presented [5]. The authors proposed to divide the decision process into two

[1]The name of this model is derived from the U.S. Joint Directors of Laboratories Data Fusion Group, which proposed it in 1985.

stages: while the first one determines feasible maneuvers based on Petri nets, the second selects the most appropriate maneuver using a multivariate utility function. While this approach complies with the requirements of having different decision alternatives and multiple criteria, uncertainties are not explicitly considered.

In addition to these methods, there is a variety of algorithmic paradigms for decision taking: Some authors propose to take decisions based on a set of rules while accounting for uncertainties by means of fuzzy theory. Such an approach for taking maneuver decisions is, for instance, proposed in [18] and [19]. Alternatively, sensor uncertainties are modeled by intervals to influence the decision [20]. In [21], a human-centered decision approach is proposed. The authors argue that decisions that are based on one optimality criterion are not suitable for applications that involve technical systems and humans. Compared with the argumentation in Section I, the requirement to have a tradeoff between safety and comfort aspects can be interpreted as decision taking based on multiple criteria.

A statistical approach for decision making is presented in [22]. This approach is based on an acceleration-based metric and models the binary decision process as a hypothesis test. This problem is solved using Monte Carlo integration, which appears interesting due to the natural interface toward Monte Carlo techniques for object assessment.

It turns out that decision algorithms that can handle an arbitrary number of alternatives and multiple decision criteria in the presence of uncertainty and facilitate a natural connection to the object and situation assessment stage are rarely available, although numerous sophisticated systems that focus on a subset of these requirements have been proposed.

From a Bayesian point of view, it appears natural to apply DNs to this problem. As it will be shown in the following section, this framework complies with the defined requirements, although there are nevertheless several practical issues to solve. The application of DNs to a prototypical ADAS application is described in the remainder of this paper. However, there are also authors that propose alternative representations of uncertainty. A proposal of an evidential network based on belief theory is, for instance, presented in [23]. This work does not attempt to compare Bayesian and non-Bayesian approaches. The decision for a Bayesian approach has been mainly taken due to the predominant usage of Bayesian techniques at the object assessment level, which implies that, by also using the Bayesian paradigm for situation and impact assessment, a unified approach for handling uncertainties can be expected.

Due to the complexity of the illustrated system, this work builds on two previous publications: In [24], the prototypical implementation of an ADAS for lane change assistance is presented, including detailed information about the object assessment stage (e.g., tracking and filtering techniques, as well as process and sensor models). The content of [11] is more related to the situation assessment stage. In particular, a bidirectional interface between object and situation assessment is investigated.

The focus of this work is to both complete the previous publications in terms of impact assessment and present the topic of decision taking under uncertainty in a more general context due to its relevance for future ADASs. A unified and significantly more detailed presentation of these topics can be found in [25].

III. Decision Networks

DNs, which are also known as influence diagrams [26], are an extension of BNs for deriving decisions under uncertainty. In the following material, which is based on [11], BNs will be introduced, followed by a description of the necessary extensions for DNs.

A. Bayesian Networks

BNs are a graph-theoretic concept for representing uncertain and incomplete knowledge using Bayesian statistics. A BN can be formally defined as a *directed acyclic graph* (DAG) $\mathcal{G} = \{\mathcal{X}, \mathcal{E}\}$, which contains a set of n_X nodes $\mathcal{X} = \{X_1, \ldots, X_{n_X}\}$ and a set of directed edges $\mathcal{E} = \{X_i \rightarrow X_j | X_i, X_j \in \mathcal{X}, i \neq j\}$ pointing from a *parent node* to a *child node*. The set of all parent nodes of X_i is denoted by $\mathrm{Pa}(X_i)$. All nodes X_k for which a *path* exists from X_i to X_k, that is, there is a sequence of nodes $[X_i, \ldots, X_k]$ such that $(X_{j-1} \rightarrow X_j) \in \mathcal{E}\ \forall j \in [i+1, \ldots, k]$, are called *descendants* of X_i. Likewise, all nodes X_k for which a path exists from X_k to X_i are referred to as *ancestors* of X_i [27].

Each node in a BN represents a random variable that can either be discrete or continuous. Each edge denotes a direct *conditional dependence* relationship between two nodes, which is quantified by a conditional probability table (CPT) representing the conditional probability distribution $P(X_i|\mathrm{Pa}(X_i))$. Usually, the direction of the edge represents a causal relationship; that is, edges are drawn from *cause* nodes to *effect* nodes.

A BN can be interpreted as a factorized representation of a joint probability distribution. In fact, each joint distribution can be written in an alternative form using the *chain rule*, which can be derived from the definition of conditional probability

$$P(X_1, \ldots, X_{n_X}) = \prod_{i=1}^{n_X} P(X_i|X_{i-1}, \ldots, X_1). \qquad (1)$$

For $i = 1$, the factor is the unconditional probability $P(X_1)$.

It follows from this identity that the DAG $\mathcal{G}$ previously defined is a BN if and only if the joint probability distribution of the random variables represented by $\mathcal{X}$ can be factorized as follows:

$$P(X_1, \ldots, X_{n_X}) = \prod_{i=1}^{n_X} P\left(X_i|\mathrm{Pa}(X_i)\right). \qquad (2)$$

This definition implies that, for each random variable in the network

$$P(X_i|X_{i-1}, \ldots, X_1) = P\left(X_i|\mathrm{Pa}(X_i)\right) \qquad (3)$$

holds, that is, each variable is conditionally independent from its nondescendants, given the values of its parent variables. This is sometimes also called the *local Markov property*.

The main advantage of BNs, compared with other representations of joint probability distributions, is the possibility to model conditional independence, which drastically decreases the number of necessary conditional probabilities. Furthermore, graphical modeling makes it easier for a human designer to adapt the model to his or her perception of the system characteristics. At the same time, the concept of BNs is formalized enough to allow efficient computational evaluation.

The most important task for BNs is the ability to perform *probabilistic reasoning*. That is, knowledge about the state of certain nodes (which is generally called *evidence*) can be incorporated into the network for the purpose of calculating the joint probability distribution $p(X_1, \ldots, X_{n_X}|e)$ of the other nodes under the condition of the entered evidence e. While, for small networks, the reasoning can be done in a simple way using enumeration, efficient algorithms exist to allow real-time operations for larger models (see, for instance, [28]).

B. Decision and Utility Nodes

DNs are extending the syntax of BNs by introducing two additional types of nodes. To avoid ambiguities, the nodes that have been used in the previous section (representing random variables) are henceforward called *chance nodes*. The other types are decision nodes and utility nodes.

1) *Decision nodes* represent occasions where the decision maker has to choose between a set of discrete alternatives. Each alternative is reflected by one particular state of the node. Edges pointing from decision nodes to chance nodes indicate a direct dependency between the decision and those variables. Conversely, the interpretation is slightly different: Edges pointing to decision nodes are called *information links* and indicate that the state of the parent is known prior to the decision [26].
2) *Utility nodes* represent the utility function of the decision maker. A *utility function* can be defined as a mapping from the state space to real numbers [27]—given that the decisions are part of the state space. Usually, normalized utilities, which assess the best possible outcome by unity and the worst state by zero, are used. The parents of a utility node comprise all chance and decision nodes that directly affect the utility. The utility function itself is often represented by a conditional utility table (CUT) in similarity to the CPTs.

According to [26], a DN is a DAG consisting of chance nodes, decision nodes, and utility nodes with the following properties.

1) There is a directed path comprising all decision nodes.
2) Utility nodes do not have children or states.
3) Decision nodes have a finite set of mutually exclusive states, which represent decision alternatives.
4) A conditional probability distribution $P(X_i|\mathrm{Pa}(X_i))$ (encoded in a CPT) is associated to each chance node X_i.
5) A real-valued function $U(U_i|\mathrm{Pa}(U_i))$ is associated to each utility node U_i.

DNs can be solved by applying the *maximum expected utility (EU)* principle, that is, the decision alternative with the highest EU is chosen. To determine the EU values, the posterior probability distribution for the parents of the utility node needs to be calculated for each possible decision alternative—conditioned on every available piece of evidence. If the decision node is set to one particular state, it behaves like a chance node that received hard evidence; that is, any inference algorithm for BNs can be applied. The required EU can then be calculated using

$$\mathrm{EU}(X^d|e) = \sum_{x \in Pa(U)} P(x|X^d, e)U(x) \tag{4}$$

where X^d denotes the decision node, x represents all possible state permutations of $\mathrm{Pa}(U)$, and $U(x)$ is the utility value for a certain instantiation of U's parent nodes.

C. Advantages and Limitations

DNs are based on a *sound theoretical foundation;* that is, all operations in these networks are derived from the three axioms of probability. In addition, the design of DNs can be decomposed into a *structural* and a *quantitative* part. The structure mainly captures causal and independence relationships, which are considered easier to construct than full probabilistic models. The necessity of deriving numerous CPTs is occasionally criticized in literature (e.g., in [29]). However, provided that a sufficient amount of data is available, these parameters can also be automatically learned [26].

Due to the exploitation of conditional independence relationships, BNs are computationally tractable for many practical applications. Limitations exist for complex hybrid models and dynamic DNs. Furthermore, there is a close similarity between DNs and the Bayes' filter, which is prevailingly used for tracking purposes. As it is demonstrated in [11], this facilitates close interactions between tracking, situation, and impact assessment.

Compared with the requirements derived in Section I, it turns out that DNs are capable of dealing with numerous decision alternatives. This can be achieved by having an arbitrary number of states within one decision node or even by modeling several decision nodes. The latter approach also facilitates *decision sequences*.

DNs can naturally handle uncertainties, which may arise from both uncertain evidence or the situational model itself. If the *adaptive likelihood nodes* proposed in [11] are used, sensor uncertainties can directly influence the final decision.

In addition, multiple decision criteria can theoretically be incorporated into a DN. One possibility is to use several utility nodes, which results in the inference algorithm maximizing the sum of all EUs. Another possibility is to use multiple decision criteria but still blend them into one utility function. However, as the next section is going to demonstrate, the availability of practical guidelines for constructing such utility functions is currently not satisfying, which can be considered as the main limitation of DNs at the moment.

Another limitation for DNs is the disability to efficiently handle arbitrary continuous distributions. Even if Gaussian representations are applied, many exact inference techniques cannot be applied.

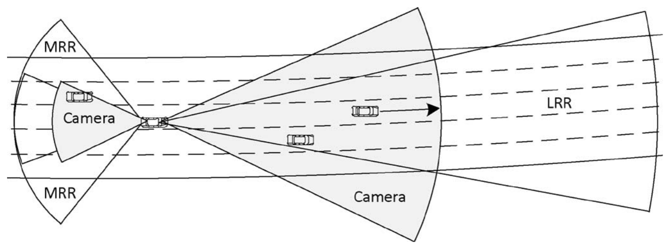

Fig. 1. Sensor configuration of the maneuver recommendation system.

IV. Implementation in a Lane-Change Assistant

The algorithms proposed in this paper are illustrated on the example of a system that is capable of assessing the current traffic situation on highways to give lateral maneuver recommendations to the driver. The recommendation may advice the driver to stay on the current lane or to perform a lane-change maneuver (either left or right). In the following, the system architecture and the algorithmic principles of the object and situation assessment stages will be presented based on two previous publications by the author [11], [24]. After that, the applied DN will be described.

A. System Architecture

Fig. 1 shows the sensor configuration of the system. A 77-GHz long-range radar in the driving direction and two 24-GHz medium-range radars in the opposite direction are detecting vehicles in the environment of the ego vehicle. This perception task is supported by two grayscale cameras (one in each direction), which are also used for detecting lane markings on the road surface. Additionally, ego motion data from the ego vehicle controller-area-network bus are used.[2]

The modular functional structure of the system is shown in Fig. 2. Each lane estimation module provides a Gaussian PDF over the state-variable curvature, distortion, lateral offset, and lane width. In addition to those geometric properties, the lane estimation modules also perform a discrimination analysis of the lane borders into the classes *continuous*, *noncontinuous*, and *noise*. This analysis is based on the frequency power spectrum of the lane detections [30]. As dashed- or solid-lane borders in many countries represent a permission or a prohibition of lane-change maneuvers, respectively, this information is used as an input for determining the maneuver recommendation.

The two vehicle-tracking modules are estimating the existence, position, and dynamic parameters of all detected objects using unscented Kalman filters [31]. The motion of the vehicles is modeled using a *Constant Turn Rate & Acceleration* motion model [32]. The output of the modules is a Gaussian PDF over the state-variable position, heading, velocity, yaw rate, and acceleration for each object whose existence probability exceeds a predefined threshold.

[2]It can be noted that the sensor configuration of the prototype contains a significant blind spot area, which makes it impossible to detect vehicles beside the host vehicle. While this is obviously critical for an end-user implementation, this restriction could (under controlled test conditions) be compensated by predicting vehicles that have been previously detected by the sensors while they are located in the blind spot zone. More details about this approach can be found in [24].

B. Probabilistic Situation Assessment

To derive a lateral maneuver recommendation, different situation variables need to be determined from the perception results. In the proposed system, those situation variables are represented by chance nodes of a DN, which are described in the following.

1) *BorderLeft/BorderRight:* These two nodes denote the lane border type, which can be either `Continuous` or `Noncontinuous`.
2) *EgoLane/LaneLeft/LaneRight:* These three variables describe the status of the lane under consideration with respect to its *occupancy*. The possible states are `Free` (that is, there are no vehicles within a relevant distance), `Occupied` (the closest vehicle in the lane is within a relevant distance but outside a critical distance), and `Dangerous` (the closest vehicle is inside the safety margin).
3) *LaneChangeLeft/LaneChangeRight:* These nodes describe the feasibility of a lane change maneuver to the left or to the right. State `Impossible` indicates that such a maneuver is by no means to be performed because it is either not safe or not allowed. In contrast, state `Safe` declares that the maneuver is allowed and that there is no relevant vehicle in the target lane. However, a high probability of this state does not necessarily mean that the maneuver is recommended—this is evaluated in a separate *decision node*. The third state `Possible` represents situations in which a lane change is allowed, but there is a vehicle present in the target lane at a noncritical distance.

The interface between the DN and the unscented Kalman filters used at the object assessment stage is based on the concept of *adaptive likelihood nodes* proposed in [11]. In this approach, particular likelihood functions are designed for the three nodes, which represent the occupancy of the lane. These likelihood functions implicitly cover the aspects of associating vehicles to lanes and determining if a vehicle is within a critical safety margin.

The DN does not contain any temporal interdependencies, that is, the situations and decisions are not *directly* dependent on previous situations or decision, respectively. The rationale behind this approach is that temporal dependencies are excessively applied at the object assessment level. Adding additional temporal relationships would decrease the modularity of the system and increase the required resources for validation.

C. Deriving Maneuver Decisions

The ultimate goal of the DN described in the previous section is to derive lane-change maneuver decisions. As previously described, this can be achieved by adding decision and utility nodes. For the LCA, there are three possible maneuvers that are represented by the decision node *LateralManeuver* (`LM`): The host vehicle may stay on the current lane (state $\mathtt{KL} = KeepLane$) and perform a lane change maneuver to the left (`CL`) or right (`CR`).

To derive a decision, each alternative needs to be evaluated with respect to a utility value, where a high utility represents

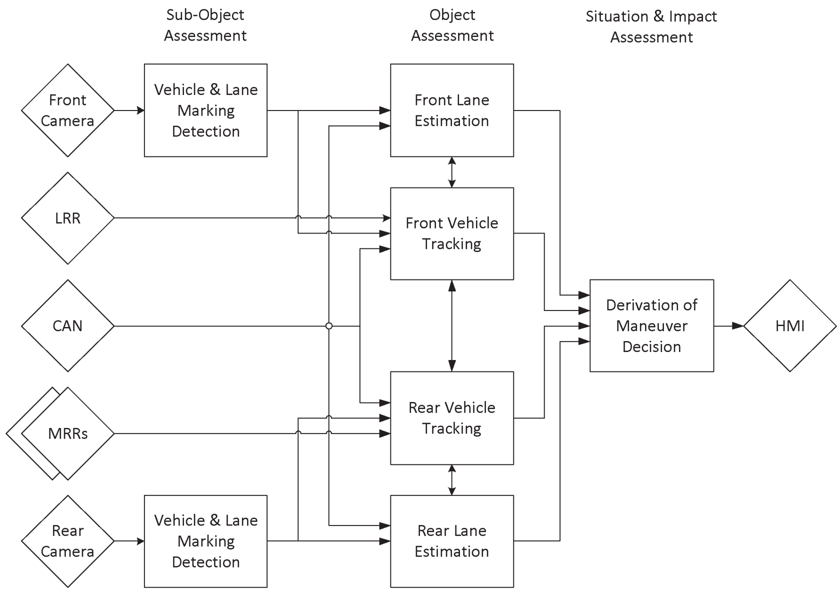

Fig. 2. Functional structure of the maneuver recommendation system.

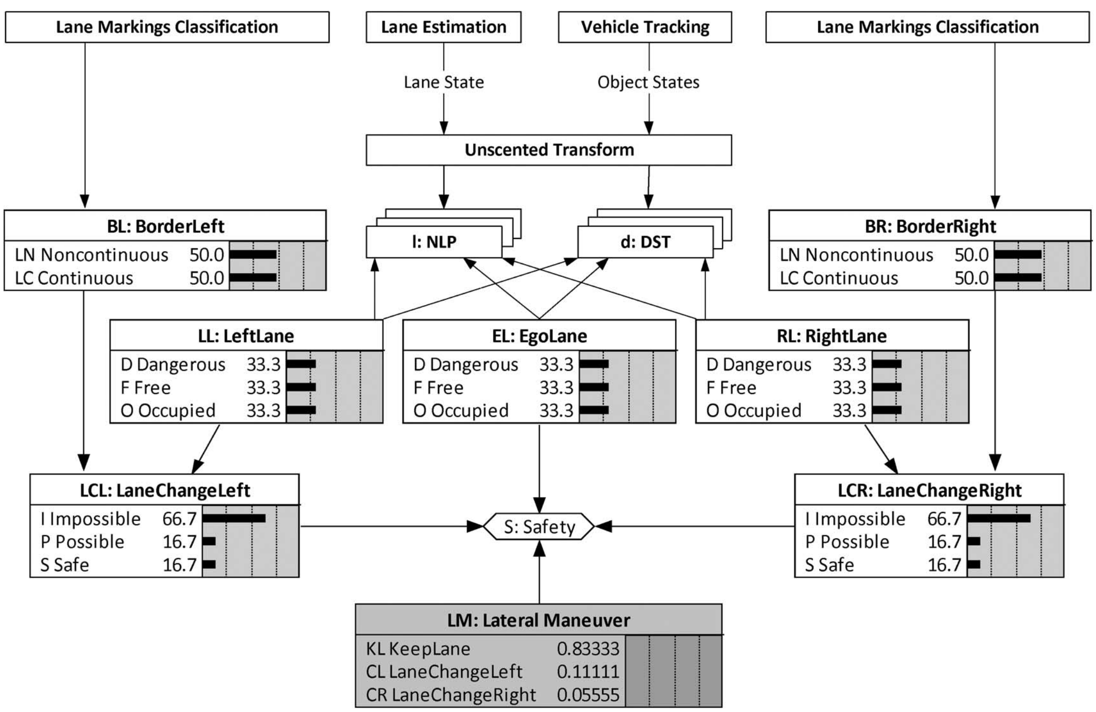

Fig. 3. DN for deriving lane change maneuver decision. In contrast to a BN, this graph also contains utility node S and decision node LM. If no evidence is available, the illustrated prior probability distribution leads to the recommendation of the maneuver *KeepLane*. The EUs for CL and CR are not symmetrical as a lane change to the left is recommended in more situations than one to the right. The interface between the lane occupancy nodes and the object assessment stage is implemented by calculating PDFs for two situation variables called *normalized lateral position* and DST for each vehicle and combining them using a combinatorial relation [11]. For determining probability distributions over these quantities, the PDFs of the lane and the vehicles are used as inputs for the Unscented transform.

a more desirable situation than a lower one. For the LCA, the main requirement is that, regardless of the chosen maneuver, the host vehicle remains safe. Thus, the utility node in this system is called *Safety* ($\mathtt{S}$). The complete network is shown in Fig. 3.

The main effort in designing a DN is to define the CUT. This table must contain a utility for each possible combination of the situation variables and the decision alternatives; that is, $U(\mathtt{S}|\mathtt{LM},\mathtt{LCL},\mathtt{LCR},\mathtt{EL})$.[3] In other words, the utility depends on the current situation and the decision, which is also represented by the fact that all edges point toward S. The complete list of conditional utilities is given in Table I.

[3]This motivates the introduction of nodes LCL and LCR, which are not necessary from a functional point of view. However, these nodes reduce the size of the CUT from $2^2 \cdot 3^4 = 324$ to $3^4 = 81$.

TABLE I
CUT FOR NODE S, WHICH REPRESENTS A QUANTIFICATION OF THE UTILITY FOR EACH POSSIBLE COMBINATION OF SITUATION AND DECISION

LM	LCL	LCR	EL	*U*	LM	LCL	LCR	EL	*U*	LM	LCL	LCR	EL	*U*
KL	I	I	D	1	CL	I	I	D	0	CR	I	I	D	0
KL	I	I	F	1	CL	I	I	F	0	CR	I	I	F	0
KL	I	I	O	1	CL	I	I	O	0	CR	I	I	O	0
KL	I	P	D	1	CL	I	P	D	0	CR	I	P	D	0
KL	I	P	F	1	CL	I	P	F	0	CR	I	P	F	0
KL	I	P	O	1	CL	I	P	O	0	CR	I	P	O	0
KL	I	S	D	1	CL	I	S	D	0	CR	I	S	D	0
KL	I	S	F	0	CL	I	S	F	0	CR	I	S	F	1
KL	I	S	O	1	CL	I	S	O	0	CR	I	S	O	0
KL	P	I	D	1	CL	P	I	D	0	CR	P	I	D	0
KL	P	I	F	1	CL	P	I	F	0	CR	P	I	F	0
KL	P	I	O	1	CL	P	I	O	0	CR	P	I	O	0
KL	P	P	D	1	CL	P	P	D	0	CR	P	P	D	0
KL	P	P	F	1	CL	P	P	F	0	CR	P	P	F	0
KL	P	P	O	1	CL	P	P	O	0	CR	P	P	O	0
KL	P	S	D	1	CL	P	S	D	0	CR	P	S	D	0
KL	P	S	F	0	CL	P	S	F	0	CR	P	S	F	1
KL	P	S	O	1	CL	P	S	O	0	CR	P	S	O	0
KL	S	I	D	0	CL	S	I	D	1	CR	S	I	D	0
KL	S	I	F	1	CL	S	I	F	0	CR	S	I	F	0
KL	S	I	O	0	CL	S	I	O	1	CR	S	I	O	0
KL	S	P	D	0	CL	S	P	D	1	CR	S	P	D	0
KL	S	P	F	1	CL	S	P	F	0	CR	S	P	F	0
KL	S	P	O	0	CL	S	P	O	1	CR	S	P	O	0
KL	S	S	D	0	CL	S	S	D	1	CR	S	S	D	0
KL	S	S	F	0	CL	S	S	F	0	CR	S	S	F	1
KL	S	S	O	0	CL	S	S	O	1	CR	S	S	O	0

It does not appear reasonable to give a detailed explanation of each row in the table. Instead, particular properties and selected situations shall be explained in the following.

As a first observation, it may be noted that the utilities are either zero or unity. In other words, a maneuver is regarded as either safe or unsafe, without intermediate values. Furthermore, there is only one unity entry in each row of the table, which implies that, for each situation, there is exactly one nominal maneuver. These properties are no general requirements for utility values. For the LCA, they have been chosen to avoid a continuous quantification of the parameter *Safety*. In fact, this parameter determines if a maneuver possibly leads to an accident, which may cause severe injuries or even loss of lives. For this reason, a rather rigorous interpretation of the safety value has been applied, instead of defining which situations are "slightly safer" than others.

A particular tribute to the German traffic regulations is represented by the three unity values for the maneuver CR. On German roads outside towns with several lanes per direction, there is an obligation to use the rightmost lane, unless the vehicle is overtaking another traffic participant. Furthermore, another vehicle may only be overtaken on its left side. This is implemented in a rather restricted way by the LCA. Only if a lane change maneuver to the right is considered safe and there is no relevant vehicle on the ego lane is this maneuver recommended. The motivation behind this design decision is that, if the ego lane is occupied, there is a significant probability that the host vehicle is going to overtake the vehicle ahead.

As a lane change maneuver is potentially dangerous, the number of situations where it is recommended is kept to a minimum. This is reflected by the fact that there are only six entries in Table I that recommend a lane change maneuver to the left. In fact, such a maneuver is only recommended if $\mathtt{LCL} = \mathtt{S}$ (that is, if the maneuver is considered as safe) and if the ego lane is not free. This design is also due to the primacy of safety. In reality, lane change maneuvers are often performed if the neighbor lane is occupied, provided that the vehicle ahead is outside the safety margin. However, for the LCA, a conservative implementation has been chosen, which recommends keeping the lane unless the left neighbor lane is indeed completely free.

The proposed CUT has been designed for a lane-change assistant, which is considered to be a comfort system. Thus, lane changes are not recommended to avoid collisions. In fact, it has been assumed during the design that additional longitudinal control takes place (by either the driver or, for instance, an additional adaptive cruise control system). This is the reason why, in Table I, it is not distinguished between the states *Occupied* and *Dangerous* of the ego lane. However, the definition of these two states facilitates the extension of the decision module to lateral and longitudinal maneuvers.

D. Maximum EU Decision and Ambiguity Measure

Taking a decision means to calculate the expectation value of the utility for each decision alternative, i.e., the EU, conditioned on the available evidence. Thus, the final decision is given by

$$\mathtt{LM}^* = \max_{\mathtt{m} \in \mathrm{LM}} \mathrm{EU}(\mathtt{m}). \tag{5}$$

To obtain an ambiguity measure of the decision, the author proposes to calculate a value that is similar to the normalized

Fig. 4. Images of the (top row) front camera and (bottom row) rear camera during the field test scenario. The result of the lane recognition module is illustrated by the yellow curves. The four columns correspond to the times $t = 4.7$ s, $t = 9$ s, $t = 18.5$ s, and $t = 20.7$ s.

entropy for probability distributions, i.e.,

$$H = -\sum_{\mathrm{m} \in \mathrm{LM}} \mathrm{EU}(\mathtt{m}) \frac{\log_2 \mathrm{EU}(\mathtt{m})}{\log_2 |\mathtt{LM}|} \tag{6}$$

where $|\mathtt{LM}|$ denotes the number of decision alternatives. In accordance with the standard properties of entropy, the definition

$$\lim_{\mathrm{EU}(\mathrm{m}) \to 0} \mathrm{EU}(\mathtt{m}) \log_2 \mathrm{EU}(\mathtt{m}) = 0 \tag{7}$$

holds to allow a calculation, even if one EU is zero.

If $H = 1$, the EUs are uniformly distributed, and the ambiguity of the obtained decision is high. On the other hand, if $H = 0$, one decision alternative yields an EU of unity, whereas the others yield zero. In this case, the decision can be accepted with high confidence. Thus, the quantity H may serve as an ambiguity measure for the derived decision, and each application may define a threshold that has to be exceeded to accept a decision. It appears relevant to emphasize that the calculation of H does, by no means, increase the amount of available information; however, it may serve as a useful quantity for application designers who have a preference for an uncertainty measure encoded in one single number.

V. Empirical Results

For the evaluation, a scenario was selected from recorded test data, which contains an exemplary overtaking maneuver. The scene has a duration of approximately 22.5 s and is shown in Fig. 4.

During the scene, the host vehicle is traveling on a part of a two-lane highway, on which lane-change maneuvers are allowed by traffic regulations. The environment of the host vehicle consists of one additional vehicle, which is traveling on the right lane of the highway in front of the host vehicle at the beginning of the scene. As the host vehicle approaches the object, it performs a lane change maneuver to the left, passes the vehicle, and returns to the right lane. The lane changes take place at $t = 4.6$ s and $t = 20.6$ s.

A particularity of the prototype is the existence of a blind spot area that is not covered by any sensor. In the evaluated scenario, the tracked object is outside the sensors' fields of view (FOVs) between $t = 5.5$ s and $t = 15.5$ s. To demonstrate the consequences of this limitation, the uncertainty of the object's longitudinal position ${}^{o}x$ is also shown in Fig. 5(a) by means of a 3σ-confidence interval. It can be observed that, during the blind spot period, this uncertainty is significantly increasing.

Fig. 4 also shows the results of the subobject and object assessment stages: The yellow curves visualize the estimated lane parameters. In addition, the front images also show the discrimination analysis of the lane markings, which correctly marks the center line as noncontinuous and the road border markings as continuous. Objects whose existence probabilities exceed a certain threshold are denoted by elliptic overlays in the camera images of Fig. 4. The colors of these overlays correspond to the result of the individual threat assessment: Green and yellow ellipses represent the states *Free* and *Occupied*, whereas red indicates that the object is evaluated as being *Dangerous*.

Fig. 5(b) shows the EU of each decision alternative: At the beginning of the scene (until $t < 4.6$ s), the EU for $\mathtt{KL}$ is decreasing, whereas the EU of state $\mathtt{CL}$ is increasing. This results from the shrinking distance to the tracked object, which leads to the ego lane's occupancy slowly changing from *Free* to *Occupied*. A particularity occurs at $t = 4.6$ s: As the host vehicle is crossing the lane border, the left lane, which was previously considered to be a neighbor lane, is now interpreted as the ego lane. Conversely, the lane that was regarded as being the ego lane before the lane change is considered as the right neighbor lane afterward. As a consequence, the EU for a lane change to the left is dropping due to the continuous road border, whereas the EU for $\mathtt{KL}$ is increasing.

While the object is located in the host vehicle's blind spot zone (between $t = 5.5$ s and $t = 15.5$ s), the ambiguity of the EU distribution is significantly increasing. This reflects the direct influence of the uncertainties, which result from the object assessment stage on the maneuver decision.

At $t = 19.4$ s, the host vehicle is leaving the safety margin of the object. In accordance to German traffic regulations, a lane change maneuver to the right is immediately becoming the maneuver with the highest EU. Finally, as the host vehicle is

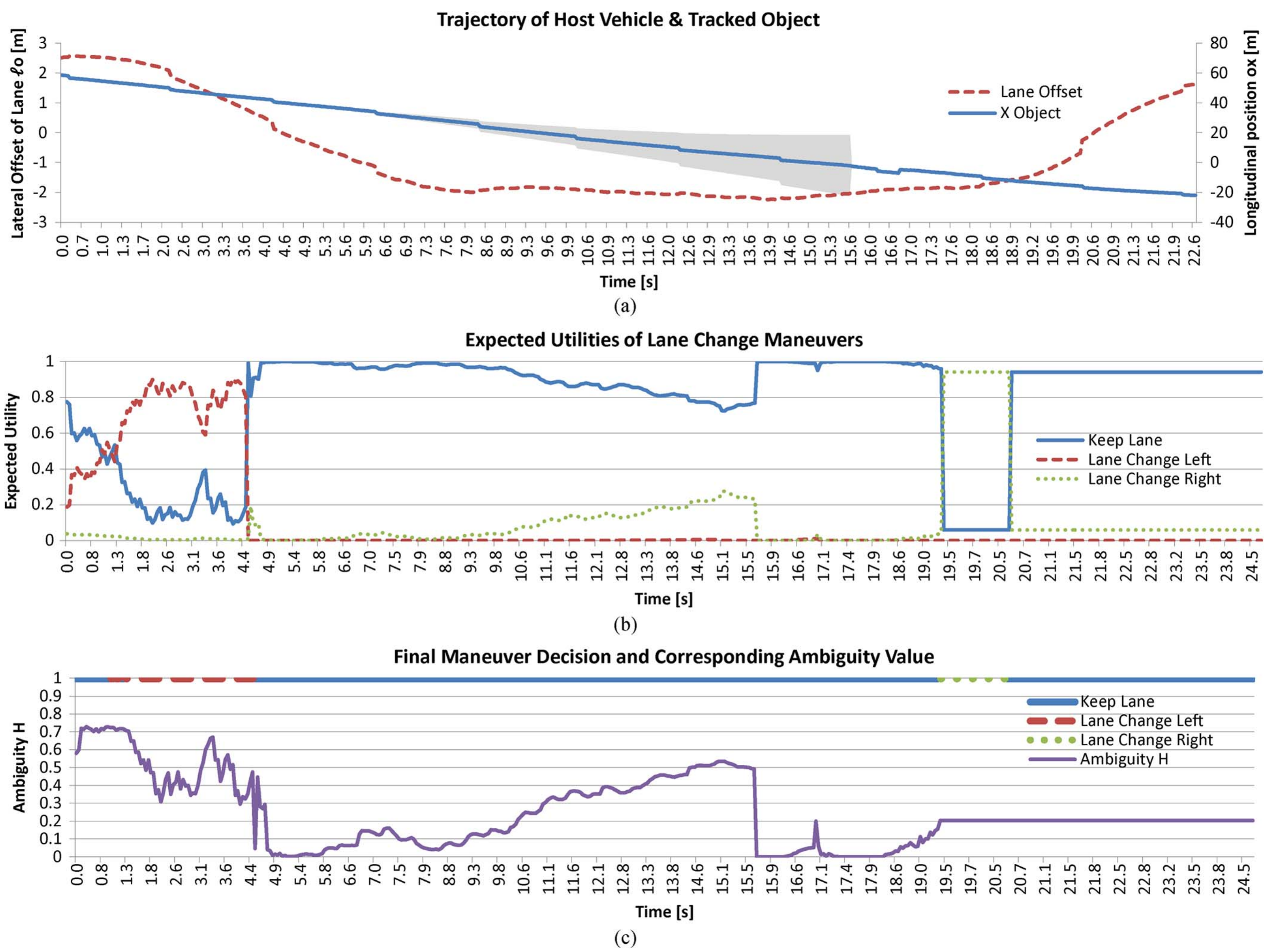

Fig. 5. Results of LCA during the exemplary overtaking scene illustrated in Fig. 4. (a) The offset of the lane border (dashed/red) and the longitudinal distance to the tracked object (solid/blue) are shown. The gray area denotes the 3σ-confidence interval for ${}^{o}x$, which is increasing due to the blind spot zone. (b) The expected maneuver utilities for the field test scenario are changing while the host vehicle is approaching. At $t = 4.6$ s and $t = 20.6$ s, the expected utilities are swapping due to the lane changes of the host vehicle. (c) The final maneuver decision and the normalized ambiguity of the maneuver utility distribution. The ambiguity is steadily increasing during the blind spot period, which reflects the growing object assessment uncertainties.

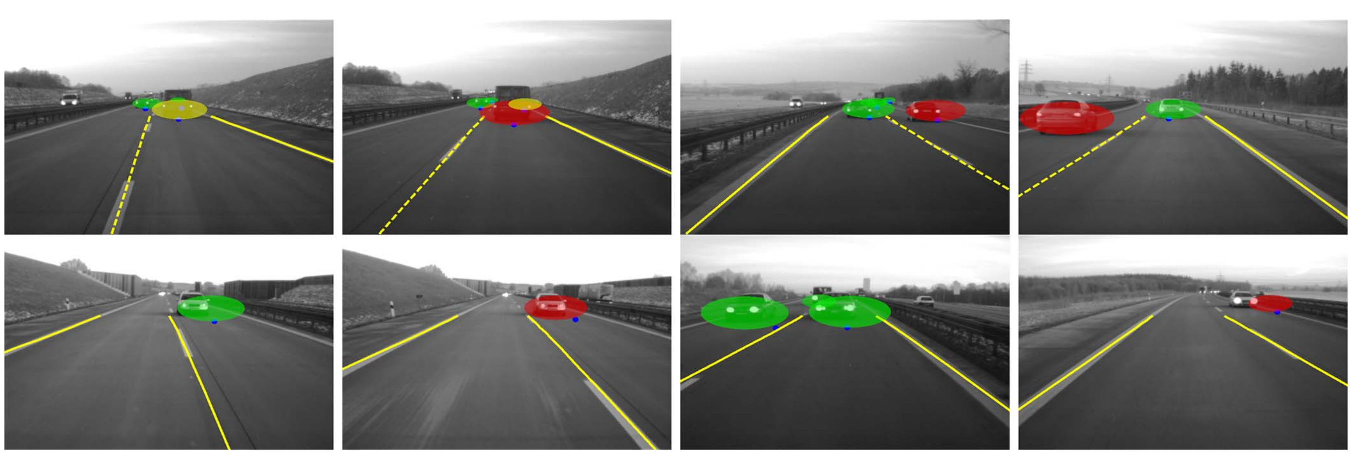

Fig. 6. Images of the (top) front camera and (bottom) rear camera during selected scenes of the field test scenario.

crossing the lane border at $t = 20.6$ s, the roles of the lanes are changing again.

The colored bar at the top of Fig. 5(c) shows the final maneuver decision, which is obtained according to (5). In addition, the proposed ambiguity value is shown. It can be observed that this quantity can indeed be interpreted as an uncertainty measure, as it is particularly high in periods where the EU distribution is comparably ambiguous. Furthermore, the effect of the blind spot period is clearly reflected by the steady increase in H between $t = 5.5$ s and $t = 15.5$ s.

TABLE II
RESULTS OF THE SITUATION ASSESSMENT FOR SELECTED SCENES. EACH COLUMN OF THE TABLE CORRESPONDS TO A COLUMN IN FIG. 6

$P(\cdot)$	Scene 1	Scene 2	Scene 3	Scene 4
EL=D	0.053	1.000	0.000	0.000
EL=F	0.000	0.000	1.000	1.000
EL=O	0.947	0.000	0.000	0.000
LCL=I	0.059	0.549	0.941	1.000
LCL=P	0.019	0.000	0.000	0.000
LCL=S	0.922	0.451	0.059	0.000
LCR=I	0.941	0.941	1.000	0.941
LCR=P	0.018	0.012	0.000	0.000
LCR=S	0.041	0.047	0.000	0.059
LM=KL	0.078	0.549	1.000	0.941
LM=CL	0.922	0.451	0.000	0.000
LM=CR	0.000	0.000	0.000	0.059
Ambiguity H	0.395	0.993	0.000	0.323

Further to the overtaking scenario, additional selected scenes of the field test trials are shown in Fig. 6. Each row of this figure represents a separate scene. The columns of Table II contain all relevant results of the situation assessment for each of these scenes.

In the first scene, the ego lane is occupied by an object in front of the host vehicle. The left lane, however, is evaluated as *Free* due to the fact that the object behind the host vehicle is traveling slower than the host vehicle and the safety time margin is not violated. Thus, it is recommended to perform a lane change maneuver to the left. The second column of Fig. 6 shows the same scene 4 s later. Due to a deceleration of the host vehicle, it is now traveling slower than the rear object. As a result, the *deceleration to safety time* (DST) is no longer zero, which, in turn, changes the evaluation of the left lane to *Dangerous*. Due to this change, the maneuver recommendation changes to *Keep Lane*; however, there is a significant uncertainty for this recommendation, which is reflected by the ambiguity value. This behavior illustrates the influence of the relative velocity on the situation assessment result.

The third column shows a rather complex scene with four objects in front of the host vehicle and three objects behind it. However, the probability distributions reveal that, despite this high number of objects, the situation is much less ambiguous than the previous situations. In fact, the clear evaluation of the right neighbor lane as *Dangerous* results in an unequivocal recommendation to keep the current lane. This recommendation is supported by an ambiguity of zero.

The last column of Fig. 6 shows that the prediction of objects in the blind spot area is also possible if the host vehicle is overtaken, instead of performing an overtaking maneuver itself. In this scene, the object on the left lane in front of the host vehicle is not within the FOV of the front radar yet.

VI. UNSOLVED ISSUES AND FUTURE RESEARCH

Although the results presented in the previous section demonstrate the potential of DNs for deriving maneuver decisions under uncertainty, this proof of concept is, by no means, capable of giving answers to all related questions. Thus, a discussion about limitations of the presented approach and open research questions will be given in the following.

A first observation is that the DN approach rigorously transforms uncertainties that are associated to object states into ambiguities of the maneuver decision. Using the proposed normalized ambiguity measure, a threshold may be defined to act only if the confidence is within an acceptable range. As a consequence, there will be periods in which the system is not capable of producing a result at all. While this may appear as a limitation from a superficial point of view, the author prefers to consider this behavior as a strength of the approach, as it appears beneficial to obtain an “honest” error message from the system instead of a potentially unreliable result. In fact, pretending a reliability that cannot be justified due to the ambiguity of the current situation appears potentially safety critical.

However, this does not solve the problem of uncertainty but only shifts it to another part of the data processing. It needs to be defined what an intelligent vehicle has to do if it discovers that it is not capable of providing a clear result, i.e., some kind of *fallback action* that minimizes the risk of having an accident on the majority of situations is necessary.

The requirement of having an arbitrary number of decision alternatives can be easily achieved by adding more states to the decision node. If the problem can be divided into several decisions that can be sequentially taken, a set of separate decision nodes can be applied.

Taking into account several decision criteria can theoretically be achieved by using several utility nodes, each of which models a particular aspect of the decision process (e.g., safety, traffic regulations, and comfort). A weighting of the criteria could be achieved by using different codomains for each utility scale. However, it is difficult to prevent several less-important criteria from overriding a particularly important one. An alternative may be to use only one utility node whose CUT has been obtained by *multiplying* the utilities of different decision criteria. For instance, it appears reasonable to evaluate the aspects of safety and compliance to traffic regulations using binary utilities, i.e., zero or unity. On the other hand, criteria such as comfort can possibly be defined on a continuous scale. If these three utilities are multiplied, unsafe or prohibited alternatives receive a utility of zero, whereas all others are evaluated with respect to the driver's comfort. This discussion illustrates that there are numerous open questions related to the construction of appropriate utility functions.

In other domains, approaches such as *Pareto optimization* are applied to multiobjective decision [33]. Even though such approaches do not necessarily produce one clear result for each possible situation, their application to the ADAS domain may prove useful to reduce complexity.

Another issue is the complexity of the design process. Even for the relatively simple decision problem presented in this paper (which assumes that the utility of the decision is influenced by only three situation variables with only three states each) $3^4 = 81$ utility values need to be specified. This number significantly increases if the situational model becomes more complex.

An alternative design strategy that is proposed in [5] is to separately evaluate each situation variable, instead of considering each permutation. While this drastically reduces the design effort, it may introduce problems in the validation of the decision system.

Finally, the validation of a probabilistic decision system may also prove difficult. On the one hand, it needs to be verified that the correct decisions are taken (while *correct* may be interpreted in a technical but also in a subjective human-centric way). On the other hand, the validation would have to determine if the confidence value is correct, i.e., if decisions are provided only if they are certain enough.

Despite these issues, the application of DNs in the ADAS domain appears natural, as they facilitate a unified Bayesian view on the data-processing chain from the sensor to the decision stage. Furthermore, all requirements that have been discussed in the introduction of this paper can be met, whereas the computational complexity is comparably low. Thus, further research on this topic appears both necessary and promising to continue the development toward safer and more comfortable vehicles.

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