Object-Oriented Bayesian Networks for Detection of Lane Change Maneuvers

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Abstract— **In this paper we introduce a novel approach towards the recognition of typical driving maneuvers in structured highway scenarios and identify some of the key benefits of traffic scene modeling with object-oriented Bayesian networks (OOBNs). The approach exploits the advantages of an introduced lane-related coordinate system together with individual occupancy grids for all vehicles. This combination allows for an efficient classification of the existing vehicle-lane and vehicle-vehicle relations in a traffic scene and thus substantially improves the understanding of complex traffic scenes. We systematically propagate probabilities and variances within our network which results in probabilistic sets of the modeled driving maneuvers. Using this generic approach, we are able to classify a total of 27 driving maneuvers including merging and object following.**

I. INTRODUCTION

The interpretation and classification of traffic scenarios are important key elements of modern driver assistance systems. The challenges for these issues are incomplete knowledge, scene complexity and sensor uncertainties. Thus the recognition of driving maneuvers requires reasoning under uncertainties. A number of approaches can be found in the literature that address this field of research, namely Dempster-Shafer-Theory, hidden Markov models, or Bayesian networks.

The recognition of driving maneuvers (e.g. lane change, object follow, overtake) and the degree of driver's attention have been studied by use of the Dempster-Shafer-Theory [1], [2]. Similar problems (incl. driver intentions, vigilance, turn maneuver, etc.) have been treated with hidden Markov models [3], [4], [5]. Bayesian networks have been utilized for the recognition of driving maneuvers like lane change, overtaking or left turn maneuvers [6], [7]. They have also been used to recognize turning maneuvers as well as cross over at red traffic light [8], [9]. Other applications of Bayesian networks involve cut-in maneuvers [13] and emergency braking [10], or the prediction of driver behavior (e.g. driver intention, driver stress) [11], [12].

Our pursued approach for the recognition of driving maneuvers profits from the advantages of OOBNs to deal with interrelated objects [15]. They offer a natural framework to handle vehicle-lane and/or vehicle-vehicle relations. These advantages are additionally boosted due to the exploitation of the left/right symmetry of a lane-change-course. The causal probabilistic treatment of situation features allows exploiting heterogeneous sources of information and the quantitative incorporation of uncertainties in the measured signals. Furthermore, they provide a framework for systematically structured "a priory" knowledge representation of the problem domain. And finally, the object-orientated modeling is efficient for exploring repetitive structure patterns. This allows reusability through the building of model libraries containing generic fragments of object-oriented Bayesian networks (OOBN-classes).

In this paper we focus on the theoretical background of our approach as well as its application for the modeling and the recognition of driving maneuvers in longitudinal traffic scenarios. Section II is dealing with the properties of object-oriented Bayesian networks (OOBNs). In section III we outline the features of a driving situation for the modeling of lane change maneuvers and our approach to handle uncertainties. In addition, we describe the developed OOBN for the recognition of driving maneuvers. The corresponding results and outlook for future work are summarized and discussed in section IV.

II. OBJECT-ORIENTED BAYESIAN NETWORKS (OOBNS)

Bayesian networks (BN) are utilized for the representation of non-observable events, inference on possible conclusions, and represent specific characteristics of probabilistic models. The advantage of such a probabilistic approach lies in the capability to handle all uncertainties implicitly. Uncertainties can originate from measurement noise in the sensor data as well as from incomplete knowledge of complex dependencies in real world situations. For example, due to complexity reasons, not all maneuver variants can be modeled. Moreover changes in the driving- and environmental conditions can lead to uncertainties in the models.

A Bayesian network represents a directed, acyclic graph, consisting of nodes and links, which connect the nodes. The nodes represent discrete random variables X with n states $x_1,...,x_n$, together with their conditional probability distributions (CPD). The links induce a set of conditional in/dependence relations between the nodes. Thus the CPD expresses the strength of the (causal) dependency relations between the nodes in this model. These relations change when the states of a subset of the nodes are known or observed events (evidence). Evidence on a variable provides information on its states and its conditional probability distribution.

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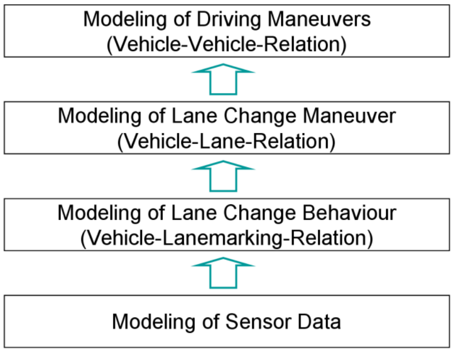

Fig. 1. Hierarchical OOBN-layers for the recognition of driving maneuvers

Although the graphical structure of a BN expresses the knowledge on causal in/dependencies between the variables, it requires expert knowledge to build the network. This has the advantage that a-priory knowledge of the problem domain can be taken into account. The explicit exploitation of causality allows a compact representation of the joint probability for all the variables involved in the model.

The OOBNs possess the advantages of classic Bayesian networks [14]. An object-oriented Bayesian network contains instance nodes in addition to the usual nodes. An instance node is an abstraction of a network fragment into a single unit (network class) [15]. Therefore instance nodes can be used to represent different network classes within other nets, and they transmit all properties of the net fragment (encapsulation). Thus an object-oriented network can be viewed as a hierarchical description/model of a problem domain. Every layer in this hierarchy expresses another level of abstraction in the OOBN model. This simplifies the modeling since the BN-fragments at different levels of abstraction are easier to discuss and to review.

III. Modeling and Recognition of Driving Maneuvers by the use of OOBNs

In our approach we model driving maneuvers as object-to-object relations, such as vehicle-lane relations and vehicle-vehicle relations. These relations are modeled on four different hierarchical levels of abstraction (Fig. 1). The first level promotes to model the properties of sensor measurements and delivers the evidence input data for the developed Bayesian net. On the second level the vehicle-lane-marking relations represent the likelihood that a vehicle crosses a specific lane marking. These vehicle-lane relations are modeled by exploiting the natural left/right symmetry of lane change maneuvers. The next level takes all vehicle-lane relations into account and evaluates potential lane-change maneuvers. The combination of vehicle-lane-relations for any two neighbor vehicles leads to 9 movement classes at this level of abstraction. They represent the pairwise relative movement of any two vehicles with respect to their associated lanes.

All existing vehicle-vehicle relations are considered within the fourth level. These vehicle-vehicle relations are used to assess potential hazards and thus they represent all possible relative positions between the considered vehicle pairs: to the left, to the right or in front of it. This results in 27 feasible driving maneuvers, which are recognizable by our OOBN. The "cut-in maneuver" is just one from these 27 elementary maneuvers.

The hierarchical structure allows a structured overview and is an easily extendable design for the recognition of the considered driving maneuvers. In the following section, we will describe the four levels of abstraction in more details.

A. *Modeling of sensor data*

At the first level of our OOBN model we are using a generic network class for the handling of uncertainties in the sensor data. This data is used partly as direct evidence in the OOBN model and partly as soft evidence for our defined situation features, which are estimated by physical models.

In general, the measured signal $s_{measured}$ is composed of its real value under measurement $s_{expected}$ and its disturbance (sensor noise) s_{err} around the real value, i.e. $s_{measured} = s_{expected} + s_{err}$. In many practical applications (and in this work), the sensor noise is modeled as a zero-mean Gaussian random process. In that case, the disturbance is fully described by the variance $s_{err} = s_{\sigma^2}$. Thus the measured signal is conditionally dependent on the random changes in these two variables:

$$p(s_{measured}|s_{expected}, s_{\sigma^2}) = N(s_{expected}, s_{\sigma^2})$$

where $N(s_{expected}, s_{\sigma^2})$ denotes the Gaussian distribution. Fig. 2 shows the structure of our network class for handling of uncertainties due to measurement noise within a sensor device.

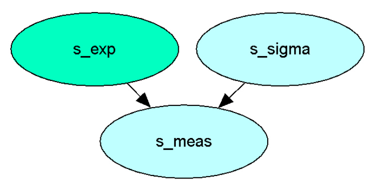

Fig. 2. Model for handling of uncertainties in measured data

To deal with the uncertainties in the sensor signals and to be able to distinguish between the states of deduced features, the measured signals are discretized in predefined partitions. Through the observation (evidence) of the variables $s_{measured}$ and their variances s_{σ^2}, one obtains here the probability distribution of their real values $s_{expected}$.

B. *Modeling of the driving behavior during a lane change maneuver*

This section constitutes the background, which prepares the BN model to mimic the human reasoning for maneuver recognition. It starts with the observation and evaluation of characteristic features, which are used to build the vehicle-lane and/or vehicle-vehicle relations at the higher levels of the OOBN. A model simplification is achieved due to the observation, that a lane change towards the right or left is

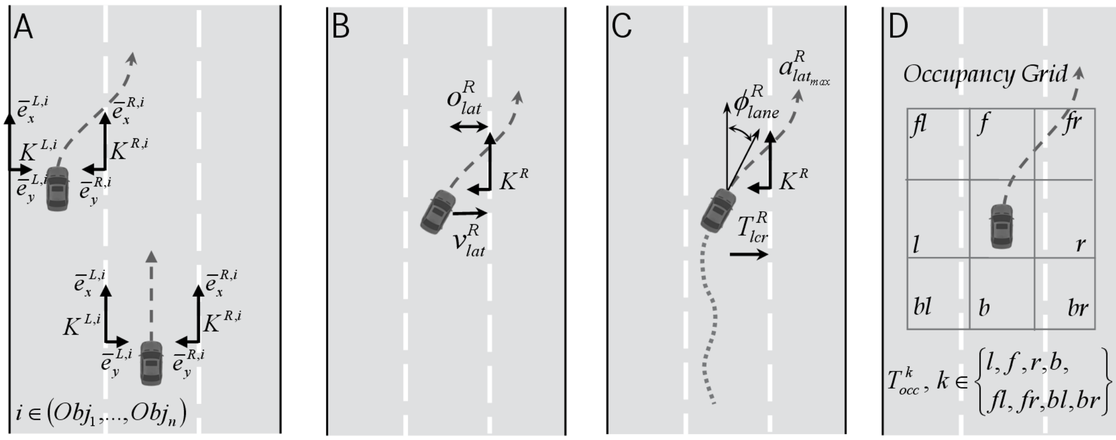

Fig. 3. A: Symmetric lane-coordinate-system for each vehicle; B,C,D: Situation features for a lane change maneuver, in the right coordinate system (B: Lateral Evidence, C: Trajectory and D: Occupancy Grid)

symmetric from the point of view of a vehicle positioned in the middle of its associated lane. To incorporate the symmetry into the model, we have introduced for all n observable vehicles $\{veh_1,\ldots,veh_n\}$ the corresponding coordinate systems:

$$K_{s,i}, \quad s \in \{L,R\}, \quad i \in \{veh_1,\ldots,veh_n\}$$

which are attached to the left/right (L/R) lane marking (or road boundaries) (Fig. 3A).

Some suitable characteristic features were published earlier [13]. Our approach represents a certain extension of this work. The extension includes

- modeling and computation of the features for both left and right lane-coordinate-system, (Fig. 3A)
- the new introduction of occupancy grids around a vehicle, taking into account the occupancy time of other objects in the grid,
- and consideration of the relative position of its neighbor objects.

These are performed for all observable vehicles, recognized lane markings or road boundaries.

In our approach, we use the following situation features:

- the lateral offset between a vehicle and a lane marking $o_{lat}^s, \quad s \in \{L,R\}$ and the lateral speed v_{lat}^s (Fig. 3B),
- the time to lane marking crossing T_{lcr}^s, the lateral acceleration $a_{lat_{max}}^s$ as well as the head angle relative to the lane course ϕ_{lane}^s (Fig. 3C),
- the occupancy time spent by neighbor objects in a cell of the occupancy grid $T_{occ}^k, \quad k \in \{l,f,r,b,fl,fr,bl,br\}$ (Fig. 3D) and the relative position of neighboring vehicles $Pos^p, \quad p \in \{left, right, infront\}$.

Thus we obtain the following novel definition for the feature vector F of a traffic situation:

$$F_{s,i,k,p} \quad = \quad \left(o_{lat}^{s,i}, \quad v_{lat}^{s,i}, \quad T_{lcr}^{s,i}, \quad a_{lat_{max}}^{s,i}, \quad \phi_{lane}^{s,i}, \quad T_{occ}^{i,k}, \quad Pos^{i,p}\right),$$

where the indices $s \in \{L,R\}$ denote the left and right lane-coordinate-system, $i \in \{vehicle_1,\ldots,vehicle_n\}$ the considered vehicle, $k \in \{l,f,r,b,fl,fr,bl,br\}$ the position of the occupancy cells around the vehicle, and $p \in \{left, right, infront\}$ the position of a neighbor object. Thus the feature vector of the entire observable traffic situation has the dimension $n \cdot 21$.

We base our computation on two different models representing the vehicles behavior: a lane follow model and a lane change model. The lateral velocity of the vehicle v_{lat}^s within the lane and the distance to the left/right lane marking o_{lat}^s are calculated according to the lane follow model [16]. The maximum lateral acceleration of the vehicle $a_{lat_{max}}^s$ is estimated from the lane change model introduced in [17]. The latter is achieved by computing a non-linear fit of a lane change trajectory in the points of the vehicles trajectory history using Levenberg−Marquardt optimization. The above mentioned values T_{lcr}^s and ϕ_{lane}^s (Fig. 3C) are derived from the characteristics of the matched lane change trajectory. Here it is assumed that the driving states of all observable vehicles as well as the lane course are detected by the on-board sensors and consequently can be considered as known.

The listed situation features are used to model the lane change behavior as a relation between the considered vehicle and its associated left (or right) lane marking. They are combined into the three nodes: *Trajectory*, *Lateral Evidence* and *Occupancy Grid*. We associate the same weights to these basis hypotheses (to achieve more robustness if one sensor fails). Their combination is expressing the probability for the hypothesis *Lane Marking Crossing* (Fig. 4).

The node *Lateral Evidence* describes the driving state of the vehicle in the lane (Fig. 4). The node *Trajectory* collects situation features, estimated from the trajectory's history. The node *Occupancy Grid* describes the occupancy of the cells in the grid around other objects during a certain time horizon. If a cell is free for a predefined time, the vehicle can move unobstructed towards this cell. To recognize a lane change maneuver, one has to parametrize the nodes expressing the above mentioned basic hypotheses. The parametrization of these nodes is shown in Fig. 4 on the example of the node *Lateral Evidence*. The parametrization of the conditional probabilities for the other nodes is done by analogy.

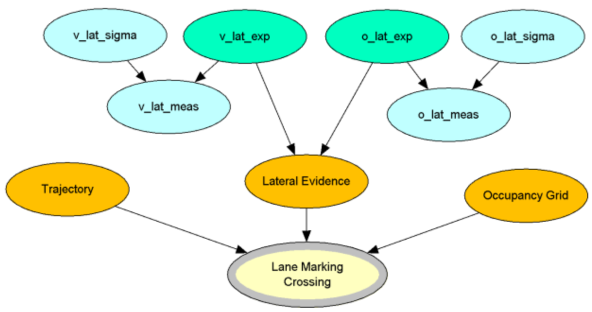

Fig. 4. OOBN instance modeling the hypothesis *Lane Marking Crossing*

The lateral velocity of a vehicle in its associated lane $v_{lat\,expected}$ and its lateral offset to the lane marking $o_{lat\,expected}$ are estimated by the above represented model for handling of sensor uncertainties (Fig. 2, Fig. 4). They collect the discretized input data of the node *Lateral Evidence*.

The conditional probability of the node *Lateral Evidence* $P(LE|v_{lat\,expected}, o_{lat\,expected})$ is modeled as product of the two independent conditional probabilities $P(LE|v_{lat\,expected})$ and $P(LE|o_{lat\,expected})$. The last are sigmoid functions with scaling parameters $a_{vlat}, b_{vlat}, a_{olat}, b_{olat}$, which are defined as follows:

$$
\begin{aligned}
P(LE|v_{lat\,expected}) &= \eta \cdot \frac{1}{a_{vlat} + exp(b_{vlat} \cdot v_{lat\,expected})} \\
\forall\ v_{lat\,expected} &\in \{-1.5, -1.25, ..., 0.25, 0.5\} \\
\text{and}\quad P(LE|o_{lat\,expected}) &= \eta \cdot \frac{1}{a_{olat} + exp(b_{olat} \cdot o_{lat\,expected})} \\
\forall\ o_{lat\,expected} &\in \{-1.5, -1.125, ..., 1.125, 1.5\}
\end{aligned}
$$

For simplification the indices s, i, k, p were omitted. Fig. 5 shows the shape of the modeled conditional probabilities $P(LE|v_{lat\,expected})$, $P(LE|o_{lat\,expected})$, and $P(LE|v_{lat\,expected}, o_{lat\,expected})$.

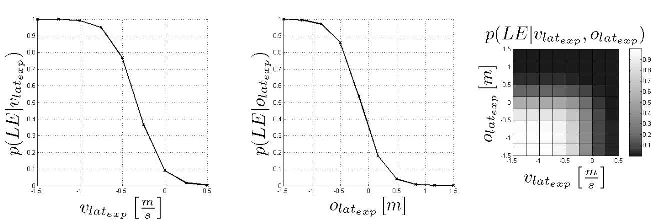

Fig. 5. Conditional Probabilities of the node *Lateral Evidence*

C. Modeling of Lane Change Maneuvers

For the recognition of lane change maneuvers, the hypothesis *Lane Marking Crossing* (*LMC*) towards right or left are modeled as vehicle-lane relations. These are shown by the two instance nodes in the BN fragment. Instance nodes are represented as rounded squares, while the output-interface-nodes are represented as ellipses with shaded line borders (Fig. 6).

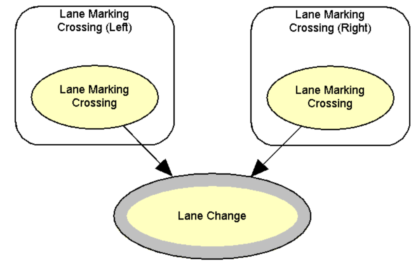

Fig. 6. OOBN fragment for the modeling of lane change maneuvers

To model lane change maneuvers, we consider elementary actions, which a vehicle can perform. It can follow the lane (f), leave the lane towards the left (l) or towards the right (r). Since the hypothesis *LMC* is used for both left and right lane marking crossing, one can identify three movement classes (l, r, f) of a vehicle, which are logically combined in a node *Lane Change*. In the case of lane change towards the right, the logical parametrization of the node *Lane Change* reads:

$$LC = r \quad \Longleftrightarrow \quad (LMC_{left} = false \wedge LMC_{right} = true)$$

Besides the single states (l, r, f) of the node *LMC*, their combination $(LMC_{left} = true \wedge LMC_{right} = true)$ is also possible and has to be also taken into acount. In that case, the states of *Lane Change* are characterized by a uniform probability distribution.

D. Modeling of Driving Maneuvers

For the recognition of driving maneuvers one has to consider also vehicle-vehicle relations $R = (vehicle_i, vehicle_j)$, $i, j \in \{1, ..., n\}, i \neq j$. These are expressed by elementary driving maneuvers, as outlined below.

For the purpose of modeling the elementary driving maneuvers, we introduce the two nodes *Movement-* and *Position classes* (Fig. 7). The node *Movement classes* is classifying

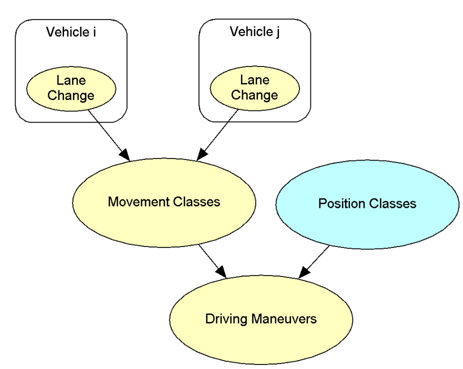

Fig. 7. OOBN for modeling of elementary driving maneuvers. It contains the hypothesis *Lane Change* as instance and the movement-, position classes.

the relative movement of a pair of vehicles towards their associated lanes. The combination of all states given by the nodes *Movement-* and *Position classes* results in 27 possible elementary driving maneuvers, which two vehicles

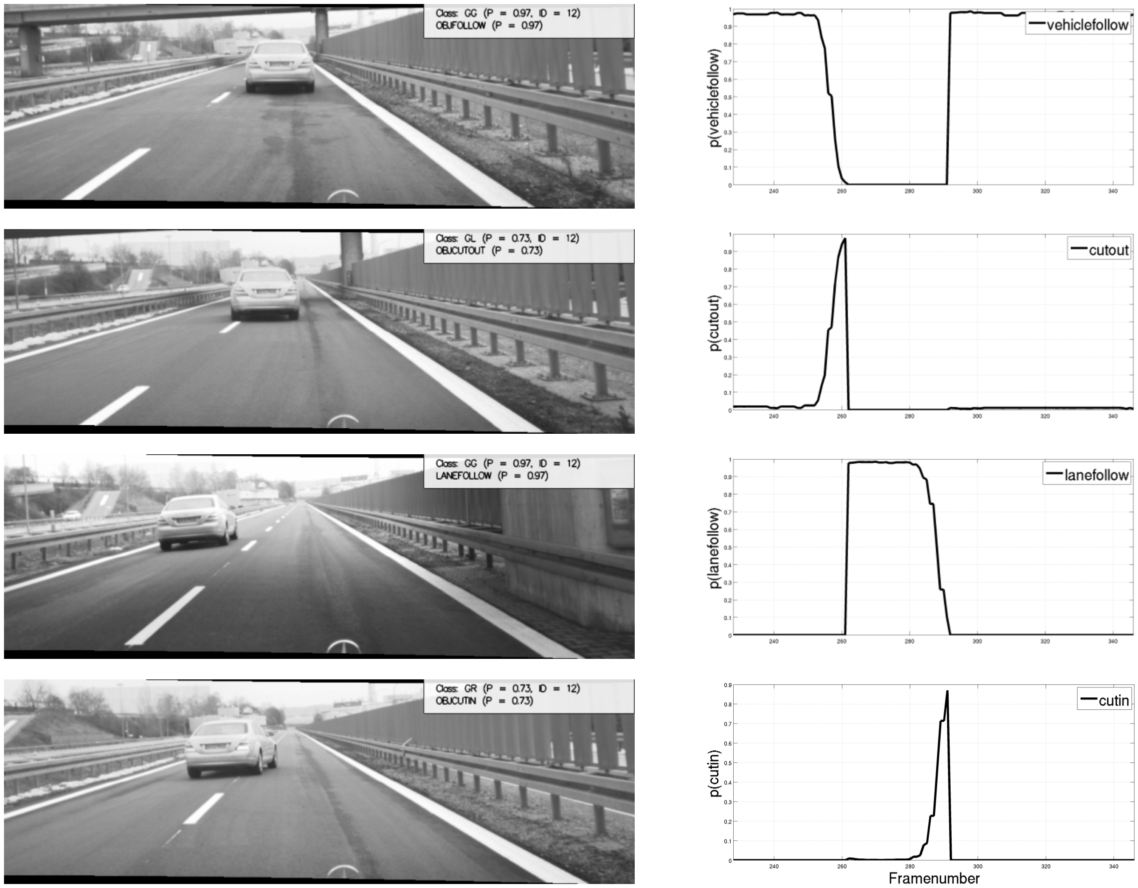

Fig. 8. Showcases of a vehicle-vehicle relation $vehicle_1 - vehicle_2$ ($vehiclefollow_{vehicle_{1,2}}$, $cutout_{vehicle_2}$, $lanefollow_{vehicle_{1,2}}$, $cutin_{vehicle_2}$).

can perform, as explained in section III. In this framework, a cut-in maneuver is just one case out of the 27 possibilities. It is defined as follows: The preceding neighbor vehicle is moving to the considered vehicle's current lane from the left or right side i.e. cutting in. From here, one can deduce the logical parametrization for the recognition of selected driving maneuvers. In the following we list, as an example, the cut-in and cut-out maneuvers for the considered $vehicle_i$ and its neighbor $vehicle_j$

$$\begin{aligned}
cutin_{veh_2} &\iff (LC_{veh1} = f \wedge LC_{veh2} = r \wedge Pos_{veh2} = left) \\
cutin_{veh_1} &\iff (LC_{veh1} = r \wedge LC_{veh2} = f \wedge Pos_{veh2} = right) \\
cutout_{veh_2} &\iff (LC_{veh1} = f \wedge LC_{veh2} = r \wedge Pos_{veh2} = infront) \\
cutout_{veh_1} &\iff (LC_{veh1} = r \wedge LC_{veh2} = f \wedge Pos_{veh2} = infront)
\end{aligned}$$

Figure 8 demonstrates possible traffic scenarios considering the feasible measurements between a pair of vehicles from the perspective of the ego vehicle. These maneuvers are $vehiclefollow_{veh_{1,2}}$, $cutout_{veh_2}$, $lanefollow_{veh_{1,2}}$, $cutin_{veh_2}$. The probabilities, which were deduced as results for the recognition of the driving maneuver, are depicted in the second column of Fig. 8 for the four showcases.

IV. Summary, Results and Outlook

In this paper, we have represented an object-oriented approach for the recognition of driving maneuvers with OOBNs. The modularity and reusability of Bayesian networks fragments were simplified through the consideration of two model properties: symmetric lane-coordinate-system for each vehicle and pairwise defined object-object relations. The hierarchical modeling allows the building of various model libraries with generic OOBN-fragments. This leads to models with good overview and easily extendable design. Our approach allows to handle uncertainties in the model and in the measurements. The probability distribution of certain maneuvers between two vehicles can be read out from node *Driving Maneuver*.

Future work will focus on the analysis of the performance for the developed network and on possible improvements. In order to detect lane change maneuvers at an earlier stage, one needs situation features, such as *blinker* or *shoulder check*, for earlier maneuver indication. These features can then contribute to the Bayesian network and help to recognize lane change maneuvers with a high reliability at an earlier stage. Moreover one can adjust online the network parameters depending on approaching either the lane marking or the solid road boundaries. The last could be recognized earlier in order to prevent crashing into the solid boarders. However, there will still be a trade-off between an earlier detection and the false positive rate of our algorithm.

Moreover, we will study if the performance can be boosted by the extension of the static network to a dynamic OOBN. Since the parametrization of the network is time consuming, learning algorithms can be employed. In addition, the recognition of the criticality of an observed situation or maneuver can be extended by physical models exploiting the relative states (distance, speed, acceleration) between the vehicles.

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