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Driving Situation Analysis in Automotive Environment

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Abstract— **In this paper, we show the concept of an automotive situation analysis (ASA) to determine the current driving situation in a given traffic scenario. To fulfill these we propose a consistent and extendable description of a driving situation, a situation model and a situation analysis. In the situation model, information of in-car sensors is used to build up a representation of the environment around the ego vehicle. On top of the situation model, a situation analysis is established to detect the current driving situation according to the given description of driving situation.**

Furthermore, we briefly discuss two applications that are using the proposed situation analysis to enhance safety and comfort in next generation automotive applications.

I. Introduction

Comfort and safety applications rely on the knowledge of the car's environment and therefore environmental sensing plays a fundamental role in this field [1]. For Advanced Driver Assistance Systems (ADASs) this holds true not only for detecting the environment but also for getting additional information about the current situation the vehicle is in. Hence, situation awareness is a core part of future ADASs. For example, Adaptive Cruise Control (ACC) systems [2] already account for risky situations like cutting-in vehicles [3] and other useful criteria such as driver behavior [4].

As mentioned in [5] efficient collision prevention relies on knowledge about the environment and other traffic participants. So not only tracking of obstacles is the challenge but also obtaining detailed information about the current traffic scenario including the actions of the own vehicle (in the following referred to as ego vehicle) and the interactions with other traffic participants. To meet these requirements we propose an Automotive Situation Analysis (ASA) approach that essentially consists of a situation model, mapping and a situation analysis. The situation model takes care of the integration of internal and external representations of a situation while mapping is used to map surrounding objects relatively to the position of the ego vehicle. Situation analysis uses the gained information to determine the actions of the ego vehicle and the interactions with other traffic participants. The proposed ASA includes all four levels of the traditional JDL (Joint Directors of Laboratories) model [6]. The focus of this paper is on the levels two and three of this model. Especially the situation model and the situation analysis will be core parts of this discussion.

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The remainder of the paper is organized as follows. The relevant uncertainty definitions for this paper are introduced in section II. The possible maneuvers are described and ordered into two maneuver groups for the description of the whole situation in section III. The core part follows with the section IV for the situation model and the proposed flexible mapping method. The situation analysis based on this map is described in section V. Two applications using the proposed situation model and situation analysis are briefly introduced in section VI. The paper will be concluded in section VII.

II. Uncertainty

In order to define a finite set of relevant situations it is important to identify the inherent uncertainty. In [7], two general meanings of uncertainty are proposed.

1) Uncertainty as a state of mind
2) Uncertainty as a physical property of information

In the proposed model, the uncertainty in the available data (meaning 1 and 2) and in the model itself (meaning 1) have to be managed. The uncertainty in the acquired targets of the vehicle environment is vagueness (meaning 1) in the sense of "Is the target a real object?" which makes it unclear whether the concerned element should be in the set of considerable elements. The imperfect information about the element itself like the imprecise knowledge about the position, speed or other attributes of the physical object is uncertainty as categorized by meaning 2 in [7].

The state of mind of the proposed model produces uncertainty because the computed situation used for the situation awareness cannot be determined exactly. Therefore, as a simplification, the most probable situation is taken into account. This is artificial uncertainty due to the simplification which has to be made in order to make the model feasible for the automotive environment.

III. Situations

The first step for ASA is to develop a conceptional representation of a traffic situation. In [8] Tölle describes possible actions and interactions for an artificial copilot. The actions differ from interactions because they can be accomplished without another traffic participant. [8] identifies the following nine maneuvers (MRs):

MR1 running up	**MR4** pass	**MR7** turning off
MR2 follow	**MR5** cross	**MR8** backwards
MR3 approach	**MR6** lane change	**MR9** parking

Note that Tölle originally identifies **MR 8** as *turning back* which is a useful action for autonomous driving but not for situations awareness. In case of situation awareness we changed **MR 8** to *driving backwards* to get a representation for the traffic situation when the ego vehicle drives backwards. The original maneuver *turning back* can now be described by a sequence of the maneuvers *turning off* and *follow*.

The nine identified maneuvers can be split up in two maneuver groups. This maneuver groups (MG) and the associated actions (MG I) and interactions (MG II) from [8] are listed in figure 1. As the table shows, MR 2 and MR 9 are assigned to both groups. MR 2 can be interpreted as "follow the current lane" or "follow a leading vehicle". The former makes MR 2 an action and the latter an interaction. In the case of MR 9 the detection of other vehicles can lead to an interaction like "parking between vehicles".

	MR 1	MR 2	MR 3	MR 4	MR 5	MR 6	MR 7	MR 8	MR 9
MG I	X	X			X	X	X	X	X
MG II		X	X	X					X

Fig. 1. association of maneuvers to maneuver groups [8]

Interactions (MG II) have the property $0 \leq |S_t^i| \leq |W_t|$ with S_t^i as the set of interactions i (MG II) and W_t as the set of vehicles in the environment at time t. The set of actions a (MG I) at time t has to fulfill $|S_t^a| \leq 1$. Hence MR 2 and MR 9 could violate the latter equation due to the duality which was made as a simplification in [8] to reduce the number of maneuvers. To define an accurate set of actions and interactions the definitions of MR 2 and MR 9 have to be adapted for the situation scope. For MR 2 Tölle introduces a virtual traffic object that would lead along the lane. Hence, he does not differentiate between a lane and a normal traffic participant. Therefore, the MR 2 has to be broken up again in two maneuvers **MR 21** *follow lane* and **MR 22** *follow vehicle*. The former can now be categorized as an action and the latter as an interaction. For MR 9 the interpretation as an interaction can be avoided by considering that a car can be parked while additionally interacting with other traffic participants. This leads to two distinct maneuver groups, which can be used in the situation model.

Aside from actions and interactions, the behavior of the driver depends on the current traffic regulations for inner and outer city and on highways. In order to get a more accurate situational representation this has to be taken into account. As the vehicle can only be in one (composite) regulation at a given time t, $|S_t^r| = 1$ holds with S_t^r being the regulation S^r active at time t. This leads to an additional criterion. Altogether, there are three different aspects of a situation in an automotive environment from the driver's point of view. These are *Actions*, *Interactions* and *Regulations*. Hence for the current situation S_t a tuple of sets $S_t = < S_t^a, S_t^i, S_t^r >$ is a feasible description, where S_t^i may be composed of more than one interaction (see above).

The mentioned situation representation is a modular concept that can be extended easily. If we assume an object oriented implementation of the ASA approach, further actions, interactions and regulations can be added without interfering existing applications. This is a key feature to deal with the alternating system configurations in automotive environment.

IV. Situation Model

The situation analysis process relies on the integration of internal and external representations of the situation. Internal representations stand for the awareness of the process about itself, while external representations cope with awareness about the environment [7]. According to [9] a complete situation model must take into account the following tasks:

1) *Situation perception*
2) *Situation comprehension*
3) *Situation projection*

The situation element acquisition implies all the object tracking and data fusion procedures to acquire objects in the environment. To optimize decision-making, the situation model should be as precise as possible (*situation perception*). The situation model should present a fused representation of the data (*situation comprehension*) and provide support for the projection needs (*situation projection*) in order to facilitate the applications goals. This is no trivial task but essential for the situation analysis process.

In figure 2 the association with the representation levels of ASA, the JDL levels [6], and Roy's situation model definition [9] is shown. Note that the last level of ASA will implement the situation analysis itself and the whole information processing will be situation aware. The situation awareness of the situation analysis process is needed because of stringent hardware limitations in automotive environment. So parts of the situation analysis will be activated/deactivated in consideration of the current driving situation. Assuming no hardware limitations, this part could be omitted to reduce implementation complexity.

Level	Description	JDL 0	1	2	3	4	Roy 1	2	3
0	Sensor Data	x					x		
1	Ego Track	x					x		
2	Multi Target Tracking	x					x		
3	Track Fusion	x					x		
4	Classification		x	x			x		
5	Mapping				x			x	x
6	Strategics				x	x			

Fig. 2. representation levels and association with JDL levels [6] and Roy [9] situation model definition

One of the most important levels in our representation is level 5 (Mapping). [10] divides maps into the four classes grid based [1], feature based, topological [11] and sequential monte carlo methods. The map described in the following fits best into the category *topological* as it considers the logic links between the different map elements.

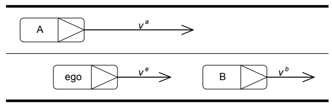


Fig. 3. ego vehicle with two interactions

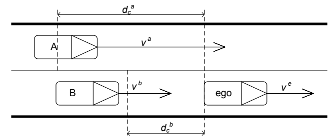


Fig. 4. scheme with critical distances

To support the situation analysis process, the map has to represent the elements with logic and spatial scope. In order to minimize the computational need of the mapping algorithm only the minimal assignment essential for the situation analysis will be computed. This means for example that only interactions with the ego vehicle as a participant will be considered. In this way, the algorithm only has the computational complexity of $O(n)$ instead of $O(n^2)$ for n traffic participants. In addition, it is very difficult to predict simultaneously the behavior of all vehicles, and it is impossible to know the durations of their maneuvers [12].

Figure 3 shows a simplified overview of a traffic configuration at time t with an ego vehicle with velocity v^e, and vehicles *A* and *B* with velocities v^a and v^b. So $|W_t| = 3$ with $W_t = \{ego, A, B\}$. The vehicles are arranged in such a way that A is passing the ego vehicle and will pass B within a few seconds which means $v^a > v^e$ and $v^a > v^b$. Since an interaction requires two interacting participants, the elements of the interactive situation subset S_t^i are triples $< s^i, w^1, w^2 >$ with

- $s^i \in S^i = \{$ *follow vehicle, approach, pass* $\}$
- $w^1, w^2 \in W$ and $w^1 \neq w^2$.

The triples for the example in figure 3 are $<$ $"pass", A, ego >$ and $< "approach", ego, B >$. Note that a possible third triple like $< "pass", A, B >$ will not be considered as the *ego* vehicle is not part of this interaction.

For a reduction of complexity there is at most one $s_t^i \in S_t^i$ that has the property $\pi(s_t^i) = w$ for each $w \neq ego \in W$, with $\pi(\cdot)$ being a function that returns the interaction participant $w' \neq ego$. The problem with this statement is that the definition of the possible interaction types in S^i cannot take place exactly. This uncertainty has to be taken into account. Hence, the definition of an interaction has to be extended to represent this additional information of uncertainty. An interaction $s_t^i \in S_t^i$ is a 4-tuple with $< s^i, w^1, w^2, p >$ with p the probability $prob(s_t^i)$. Since there should be only be one s_t^i with $\pi(s_t^i) = w$, $\sum_{\{s_t^i | \pi(s_t^i) = w\}} prob(s_t^i) \leq 1$ holds. If an implicit interaction of type "no interaction" is considered and the interaction set S^i is extended to $\{S^{i\ old}, none\}$ the inequation results in an equation. For a given example, a state graph of possible interaction types a single participant can attend, can be build. Generally, for $n = |W_t|$ there are n state graphs. The exact current state and interaction respectively of a vehicle for such a state graph is uncertain.

Before determining the probabilities for the different interaction types, the other participants (q.v. situation analysis in section V) are assigned to the lanes of the road relative to the ego vehicle. The current lane is l_0. Lanes to the left/right get a higher/lower index, respectively. In the configuration of figure 3 the vehicle set of l_0 is $L_t^0 = \{ego, B\}$ and for l_1 it is $L_t^1 = \{A\}$. If the configuration is not as clear as in figure 3 and a vehicle is between two lanes the lane sets do not have to be distinct and the association function $a(L_t^x, w)$ for the association value of w to L_t^x can be inside $[0...1]$. These fuzzy lane sets have the additional property that $\sum_{L_t^x} a(L_t^x, w) = 1$ so a vehicle w cannot be over-associated. After the fuzzy lane sets are complete, an additional ordering is made depending on the position in the lane itself. The mapping algorithm proposed here will cut the lanes into three parts around the ego vehicle with the sets ${}^xP_t^b, {}^xP_t^c$ and ${}^xP_t^f$ for the backward, center, and forward parts of lane x. The elements in the set for the center section are "too near" vehicles. This property "too near" can be calculated from the vehicle positions and their current derivation(s) in time. A classic attribute is the Time-To-Collision (TTC) or some recent approach like the Time-To-Break (TTB) [5]. Hence, here the association to the set for the center section has not only the distance as a parameter but also additional information like the velocities and accelerations of the ego vehicle and the other participant.

Figure 4 shows another scenario with three participants driving at different velocities. The sets for the lane parts with more than zero elements are ${}^1P_t^c = \{A\}$ and ${}^0P_t^b = \{B\}$. Since A is faster than B the minimum distance for the center section is bigger than referring to B. Hence participant A is in the set ${}^1P_t^c$ despite its bigger distance to the ego vehicle in comparison to participant B. The association to a section set is also fuzzy like the association to the lane set with an analog constraint: $\sum_{{}^kP_t^e} a({}^kP_t^e, w) = a(L_t^k, w)$ with $e \in \{b, c, f\}$ and k as the lane number. Additionally the speed of the vehicles is taken into account. Like in the description with a natural language the vehicles are ordered in three sets V_t^-, V_t^+ and V_t^0 for slower, faster and equally fast vehicles. Again, the sum of all association probabilities for a single vehicle is 1.

Summarizing, the map M_t is a set of lanes L_t^k which consists of sets of parts ${}^kP_t^e$. The elements (traffic participants) can belong more or less probably (fuzzily) to one of these sets and the sum of all associations for one element is 1.

V. Situation Analysis

Situation analysis is used to establish relationships (not necessarily hierarchical) and associations among entities in the situation model, it should anticipate with a priori knowledge in order to rapidly gather, assess, interpret and predict what these relationships might be. Furthermore, it should plan, predict, anticipate again with updated knowledge, adaptively learn, and control the fusion processes for optimum knowledge capture and decision-making [9]. To achieve this goals the proposed situation analysis uses the situation model and the proposed mapping algorithm from section IV. Using the set M_t as the situation model the probabilities of the interactions for each participant can be computed. Instead of Bayesian Networks [13] a computationally more feasible approach will be described in the following. The probability of each interaction s_t^i with $\pi(s_t^i) = w$ obeys a rule for each type contained in S^i. For the elements of S^i the rules are:

- *"follow vehicle:"*
  $follow(w) = a(L_t^0, w) \wedge a(V_t^0, w) \wedge a({}^0P_t^b, w)$;
  (is vehicle w following the ego vehicle?)
- *"approach:"*
  $approach(w) = a(L_t^0, w) \wedge a(V_t^+, w) \wedge a({}^0P_t^b, w)$;
  (is vehicle w approaching the ego vehicle?)
- *"pass:"*
  $pass(w) = (1 - a(L_t^0, w)) \wedge a(V_t^+, w) \wedge a({}^0P_t^c, w)$;
  (is vehicle w passing the ego vehicle?)
- *"none:"*
  $none(w) = 1 - [follow(w) + approach(w) + pass(w)]$;
  (w is not in a defined interaction with the ego vehicle)

These rules exclude each other in a way that the constraints $follow(w) + approach(w) + pass(w) + none(w) = 1$ and $follow(w) + approach(w) + pass(w) \leq 1$ hold. The first constraint is obviously always fulfilled because of the definition of $none(w)$. The second constraint can be explained with a decision tree (Figure 5). If the sum of all edges to the child nodes is 1 and the traversal from a parent to a child node means a conjunction of the possibilities the sum of all possible leaves in the tree is 1. If the rules above are interpreted as traversals in such a tree, and if they do not include each other and are not identical, then the sum of the possibilities is less than or equal to 1.

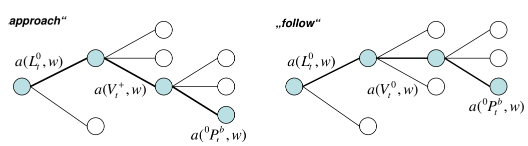


Fig. 5. decision trees for "approach" and "follow"

It is not feasible to support ambiguous situations in automotive environment. Safety applications cannot deal with multiple possible situations because hard real-time requirements have to be met and so processing several situations is not possible. Thus the most probable interaction will enter the situation set S_t^i except for the artificial "$none$" interaction. As all the observed targets are modeled with physical parameters, the probabilities of the interactions cannot change from one extreme to another. To avoid continuous situation switching between nearly even possible situations a threshold for switching to another situation is introduced. This threshold is highly application dependent and have to be tuned during implementation of a specific application.

The current action S_t^a can be determined according to similar rules based on actuator information. Therefore, the following variables specify actuator states and physical values of the ego vehicle.

• **"running up"** $vel = 0 \wedge acc > 0$ (is the ego vehicle running up?)
• **"lane change"** $(ts\_on \wedge sl(right) \wedge L_{-1}) \vee (ts\_on \wedge sl(left) \wedge L_1)$ (is the ego vehicle changing lanes?)
• **"turning off"** $(ts\_on \wedge sl(right) \wedge !(L_{-1}) \wedge S_t^a(cross)) \vee$ $(ts\_on \wedge sl(left) \wedge !(L_1) \wedge S_t^a(cross))$ (is the ego vehicle turning off the current road?)
• **"driving backwards"** $rg \wedge vel > 0$ (is the ego vehicle moving backwards?)
• **"parking"** $S_t^r(inner\ city) \wedge ts\_on \wedge !(back\ up)$ (is the ego vehicle parking?)
• **"follow lane"** $!(running\ up) \wedge !(cross) \wedge !(lane\ change) \wedge$ $!(turning\ off) \wedge !(back\ up) \wedge !(parking)$ (is the ego vehicle following the current lane?)

TABLE I

CONSTRAINTS DESCRIBING THE START OF ACTIONS IN ASA

- *vel* as the Velocity
- *acc* as the Acceleration
- *ts_on/ts_off* as turn signal on/off
- *rg* as to go into reverse
- *sl(right)/sl(left)* for steering lock to right/left

The introduced linguistic variables have to be adjusted to a specific use case. For example the steering lock to identify a lane change or a turn off is a highly car dependent value. Therefore, it has to be trained for every target environment.

Using these linguistic variables in combination with the knowledge of the situation model the specified actions of section III can be described on a high abstraction level the following way.

The given constraints in table I model the beginning of a the respective actions. To determine the end of an action two solutions are possible. First we can assume that an actions ends when the next actions starts. This holds only if we introduce an artificial action to model the idle case after an action was performed. In our approach this idle case is modeled by the non-artificial *follow lane* action, because we assume that when no other actions are performed the ego vehicle just follow the current lane. Nevertheless, it is necessary to determine the end of an action. So the second possible solution is to model an action a as a set of states $A_a = (s_0, s_1, \ldots, s_n)$ with the starting state s_0 already defined by the constraints given in table I. So for example the action *lane change* is described by the states shown in table II. By doing so the duration of an action a is covered by the set of states A_a. So an action ends when the final state of the action is reached.

Modeling driving maneuvers by a set of states was already introduced by Nigro and Rombaut in the IDRES approach [12]. The main difference between the IDRES solution and our approach is the start of a driving maneuver. IDRES does not differ between actions and interactions and it is also not

s_0 : $ts\_on \wedge sl(left) \wedge L_1$
s_1 : left dashed line crossed
s_2 : ego vehicle is in new driving lane
s_3 : ts_off
s_4 : End of lane change

TABLE II

STATES OF THE ACTION *lane change*. FOR REASONS OF CLEARNESS ONLY A LEFT LANE CHANGE IS CONSIDERED HERE.

planned to predict the most likely next driving situation. So IDRES can keep the first states of an driving maneuver more generic and decide on later states which driving maneuver is performed at the moment. In ASA the states are used to determine the duration and the end of an *action*. The beginning of an *action* is recognized by the constraints in table I and by using situation model information (see section IV).

The *cross* action is not modeled through linguistic variables because of an upcoming cross can be obtained more easily and more precisely through a road map concept. This road map concept is considered in the following and is primary used to gain information about traffic regulations.

To reduce the computational needs for the detection of the current action transitions between certain actions can be omitted. For example when *cross* is the current action, which means that the ego vehicle drives towards a cross, it is impossible that a transition to the action *parking* occurs. So these edges are not included in the state graph representing the action transitions in ASA. Figure 6 shows the possible transitions for the actions specified in section III. The conditions for the arcs are given by the rules shown above, e.g. for every ingoing arc to state *driving backwards* the condition is specified via the rule $rg \wedge vel > 0$. Note that some actions also can be succeed by themselves, e.g. on a highway with three driving lanes it is possible that the action *lane change* occurs twice in a row.

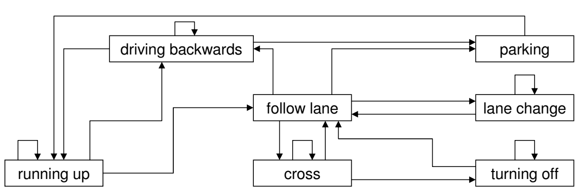
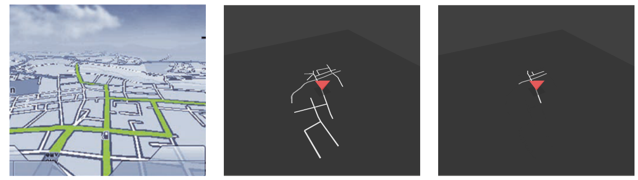


Fig. 6. state graph for actions of the ego vehicle

After given rules to determine the current interaction and action of a vehicle the third part of ASA situation representation, the specific traffic regulations of an area, still have to be covered. In our situation representation, we differ between inner city, outer city and highway specific traffic regulations (see section III). So for regulation aspect of the current situation S_t^r knowing the road type the ego vehicle drives on is usually sufficient. Common navigation systems contain information about the road type but also graphical representations, route planning algorithms and information about service businesses like gas stations (see figure 7(a)). All this information is necessary for navigation issue but not important to determine the type of the road the ego vehicle drives on it. Due to the stringent hardware, limitations in automotive environment a reduction of the non-necessary features of the navigation map have to take place.



(a) Common navigation map (b) Navigation map reduced to roads (c) Compressed road map

Fig. 7. Compression of a navigation map to determine current road type

As shown in figure 7(b) the navigation map can be stripped-down to a basic representation of the roads. Thereby the memory usage of the map could be reduced significant without loosing information for the use case of traffic regulation determination. To decrease the computational needs only the roads, which can be reached by the ego vehicle in less than 30s, will taken into account from the self-localization algorithm (compare the figure 7(c)). The self-localization algorithm use GPS signal to assign the ego vehicle to one of the roads in the road map. Note that having an imprecise GPS signal can influence the quality of the self-localization and can cause a wrong assignment of the ego vehicle to one of the possible roads. In many cases this did not provoke problems because of roads in the near surrounding of the current road are usually of the same type. So a short-time failure did not affect the quality of traffic regulation determination. However, there are scenarios, which have to be covered by the algorithm to prevent dangerous situations. We identify two different possible problem cases as are:

- determine the switch from one road type to another
- crossover or underbridge roads of different type

In these cases, the self-localization algorithm can use information of the situation model and situation analysis to determine which road type hit the spot. The first problem case can be resolved be adding additional information of the environmental sensing, e.g. a town sign was detected or the ego vehicle significant reduce/increase velocity.

The second problem case can also be worked out by using situation analysis information. In case of a crossover or underbridge the ego vehicle can only turn left, turn right or go ahead. In case off turning off the situation analysis will recognize a change of S_t^a form *cross* to *turning off*. Based on this knowledge of a situation change it is straightforward to determine on which road the ego vehicle drive on.

In the case of an upcoming cross situation, the self-localization algorithm can enhance the situation analysis too. As described above the roads that can be reached by the ego vehicle within 30s are covered through the road map representation. Therefore, an upcoming cross situation can be determined much earlier as through common automotive sensors. Also the end of a cross situation can be detected through the road map. Therefore, in the case of an upcoming or ending cross situation the information of the road map and self-localization is used to enhance the situation analysis.

VI. Applications

The proposed driving situation analysis concept is used in the Distributed Environment Model to determine the current driving situation in real life traffic scenarios. In [14] we showed how to use the information of the current driving situation to establish a situation dependent data distribution. By using, a situation dependent data distribution the bus-load in a vehicle can be reduced significant. Furthermore, the non-trivial task of environmental sensing is merged in the situation model and situation analysis. So the developers of driver assistance systems can focus on their key algorithmic. These reduce the complexity of the software and facilitate the reuse of ADAS source code. Furthermore, we showed the possibility of a proactive data distribution. Considering the concept of situation analysis an upcoming driving situation change will result in a shift of the confidence in the current driving situation. So if the confidence in current driving situation decreases and the confidence in another driving situation rise than a driving situation change will most likely happen. This information is used to distribute data to hosts, on which it is needed in the upcoming driving situation, in the cycles before the situation change will happen. In [15] we gave an evaluation of the situation analysis in a common road scenario on a german highway. We achieved recognition rates of about 89% of the driving situations in this scenario and by using the current driving situation for data distribution the bus-load could be reduced by about 17%.

Also in [15] we showed that a proactive sensor system [16] can benefit from the gained information about the current driving situation. If the ego vehicle is located in an urban environment, it is useful to assign a higher utility to detecting pedestrians and bicyclists, whereas if the road map indicates a highway traffic environment, the search for pedestrians might well be substituted with an intensive search for cars and lorries. Therefore, by considering the current driving situation it is possible to adapt the algorithms of the proactive sensor system to the current needs. Thereby salient regions in a traffic scenario can be determined. These salient regions can be analyzed by using a high-resolution sensor, e.g. laser scanner, to get detailed information about possible threats for the ego vehicle. By not scanning a whole traffic scenario with a high-resolution sensor, the hard real time requirements in automotive environment can be achieved. The focus on salient regions in a traffic scene reduces the amount of raw sensor data to 4% of the original high-resolution data [16].

VII. Conclusion

In this paper, an Automotive Situation Analysis concept was introduced. It includes a description of a driving situation as a tuple of sets of actions, interactions and traffic regulations. This representation is used to build up a situation model with a detailed mapping method at a feasible computational complexity for the automotive scope. The description of interactions and actions is given through fuzzy set and constraints. Furthermore, a method to detect location specific traffic regulations was described. This method uses a compressed navigation map to determine the current road type and GPS information to localize the ego vehicle in the resulting road map. We briefly showed two applications using the proposed framework to get information about the current driving situation. Both applications achieve promising results in enhance safety and comfort applications in automotive environment.

Future work will focus on the predication of upcoming driving situation changes. Because of the fuzzy nature of the situation analysis, an upcoming driving situation change will result in a reduction of the confidence for the current driving situation. Furthermore, the confidence in another driving situation rises. So when this shift in confidence of driving situations can be recognized it is possible to predict an upcoming driving situation change. Using this technique will give applications the opportunity to prepare for the upcoming situation before the situation change actually happens. Hence, the predication of an upcoming driving situation can help to meet real-time requirements in high dynamic road scenes.

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