A CONSTRAINT-BASED AND CONTEXT-AWARE OVERTAKING ASSISTANT WITH FUZZY-PROBABILISTIC RISK CLASSIFICATION

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ABSTRACT

Overtaking is one of the most dangerous driving maneuvers and thus a clear candidate for driving assistance. Many factors from the driving context, like oncoming and approaching vehicles, traffic signs and road conditions have influence on the behavior in an overtaking situation. In other words, a variety of legal and environmental constraints exist for the recommendation provided by a driving assistance system. In this paper, we present a logic-based approach for a context-aware overtaking assistance system, exploiting constraint satisfaction. Influence factors that depend on present speed and distance values of the involved vehicles are modeled as dynamic constraints and a solution is determined that fulfils all constraints. Before presenting the recommendation to the driver, a-priori fuzzy classification is performed for every dynamic constraint to estimate the risk for a potential overtaking maneuver. Assuming that a driver follows the recommendation of the assistance systems, we use driver context information, like skills or state, to provide a measure of safety for the maneuver, interpretable as the probability for an accident. Simulation results are discussed afterwards, together with future work.

KEYWORDS

Context-awareness, Constraint Programming, Fuzzy-probabilistic Risk Classification, Overtaking Assistance

1. INTRODUCTION

Over the last decade, substantial progress has been made for on-board vehicle sensing systems and also in the field of vehicle-to-vehicle/infrastructure collaboration. Now that it can be safely assumed that information about the surrounding is available to a driver assistance system (DAS), the next step is to investigate how the information can be exploited to improve the knowledge of DAS that aim for driver support. One especially difficult driving maneuver is overtaking. Drivers often underestimate the duration of the maneuver and speed and distance of oncoming traffic. An overtake assistant can analyze the situation based on available context-information and tell the driver whether overtaking is currently feasible and legal. However, an overtake assistant is not only interesting for oncoming traffic or checking ban on passings. On highways an overtake assistant can optimize the maneuver. Often, approaching participants are forced to slow down by inconsiderate overtaking by other drivers, thus negatively influencing the overall traffic flow. An overtake assistant could measure the speed and distance of other participants and decide if overtaking would hinder other participants or not. The driver is also given an explanation for a certain decision. Currently, the final decision always remains with the driver, for legal reasons. However, we can provide the driver with support and sensitize him/her to the speed/distance estimations of overtaking. A successful overtaking maneuver depends on a variety of constraints, both legal and environmental. Thus, a sophisticated reasoning method is necessary that analyzes the available information and derives a decision near real-time. We are going to demonstrate how overtaking constraints can be represented with constraint-logic programming. After finding a solution, an a-priori risk assessment is conducted using a linear fuzzy classification method. Assuming that a driver follows the recommendation, and based on an assessment of the driving skills, a probabilistic a-posteriori risk assessment is done, based on simulation using the recommendation and possible deviations due to lack of driving skills. We conclude with simulation results.

2. RELATED WORK

Hegeman (2006) presents an overview of possible application areas of DAS with respect to overtaking. She also analyzed the overtaking behavior of drivers on roads with oncoming traffic (Hegeman (2005)) and built a prototype that was used to test driver overtaking behavior in a simulator. In Hegeman (2007) the results of this study show that drivers performed overtaking with shorter gaps, when supported by the assistant. However, the usefulness score of the assistant was rated low by most test persons, because recommendations did not well match with driver's perception. Most of the other work in overtaking assistance focuses on vehicle blind-spot detection (Mota (2004)) and lane change assistance (Ruder (2002)), without regard to the general overtaking maneuver. Lattner (2005) presents a knowledge-based approach for modeling spatio-temporal driving situations using qualitative motion descriptions. Direction, speed and distance are mapped from quantitative data into qualitative classes for abstraction. A rule-base reasons on the qualitative scene descriptions. The authors demonstrate the appropriateness of qualitative scene representation for reasoning about spatiotemporal patterns of moving objects. In contrast to this work, our approach uses absolute speed and distance values. These are comparatively easy to obtain with on-board sensing systems or through collaborating vehicles and can thus be used for the reasoning process to obtain more accurate results.

3. A CONTEXT-AWARE OVERTAKING ASSISTANT

We developed a prototype for a context-aware overtaking assistant that gives a recommendation whether overtaking is wise or not. The system takes a description of the momentary driving situation with contextual information about other participants, traffic signs/markings, environmental and road conditions, the present state of the driver and so on. The scene information is analyzed and a recommendation is retrieved with a speed adjustment value and an explanation. Natural language risk values are presented for speed/distance dependent regulations. This feedback is important for gaining a driver’s trust. There are of course better ways to present the result to the driver, but the discussion about suitable HMIs is out of scope here. In the example, the risk for being self-overtaken and for another vehicle in the overtaking lane is low, whereas the line-of-sight risk is high (close to the legal limit). Assuming that we are currently on a highway, no risk must be determined for oncoming vehicles. The example recommends not to overtake and gives a reason: the driver is apparently tired (increased reaction times) and the driver’s risk willingness is low. The prototype works event-based: when intent to overtake is indicated, the scene description is analyzed and the reasoning process started. The next section describes the methods and techniques used for the reasoning process.

4. CONSTRAINT-BASED DECISION PROCESS

The prototype integrates ontological information representation with logic based reasoning. Scene descriptions are given as class instances in OWL syntax and are then transformed to the dynamic knowledge base of the reasoning component, using an ontological context-model for traffic scene representation and a set of transformation rules (Fuchs (2008)). Additionally, traffic regulations are the vital part of the reasoning component. We decided to use a logic based approach, to exploit the advantages of a powerful reasoning mechanism. On close examination, the number of relevant traffic objects involved into an overtaking maneuver is comparatively small: there are other participants with different relative distances, speeds and orientations to the own vehicle; traffic signs and markings can influence the overtaking decision and of course the current spatial context of the vehicle (highway vs. rural road). Speed limits and environmental conditions have further influence on the maneuver. The difficulty in finding a decision arises from the high number of possible object combinations. A subarea of logic programming is concerned with this specific kind of problems - constraint logic programming (CLP). CLP was originally developed for production and planning systems, however, we found the approach fit for the decision process of a tactical DAS.

A constraint satisfaction problem is stated as a triple $<X,D,C>$ where X is a finite set of variables $X = x_1,\ldots,x_n$, D is a corresponding n-tuple of domains $D = D_1,\ldots,D_n$ such that $x_i \in D_i$, meaning a variable x_i can be assigned values from its corresponding domain $D_i=v_1,\ldots,v_n$. C is a finite set of constraints $C=C_1,\ldots C_n$. A constraint $c \in C$ involving variables $x_i,\ldots,x_n$ is a subset of the Cartesian Product $D_i \times \ldots \times D_j$ of compatible variable assignments. A constraint c is satisfied by a tuple of values $v=(v_i,\ldots,v_j)$ assigned to variables $x_i,\ldots,x_j$ if $v \in c$. An assignment is complete if every variable is assigned a value. A complete assignment is a solution to a CSP if it satisfies all constraints in C. The programmer defines the decision variables $x_i,\ldots,x_n$, states the constraints and an (optional) optimization function. A constraint solver tries to find assignments for the decision variables, which satisfy all constraints, while at the same time minimizing/maximizing the objective function. A sound introduction to constraint logic programming can be found in Rossi (2006).

With the problem definition of a CLP we can now investigate how it can be used to express an overtaking maneuver on a tactical level. First of all, traffic regulations for overtaking represent the constraint base. With regard to the decisions variables, a *mixed constraint satisfaction problem* is at hand. The dynamic knowledge base containing the traffic scene description provides variables with pre-defined values from their given domains that cannot be influenced by the reasoning process, e.g. speed and distance of other participants. The decision variables we want to find a value for, are the desired speed and driving maneuver, assigned to a domain of possible values (an integer value interval for speed and a set of finite domain values for driving actions). The solver tries to find a solution for the decision variables that does not violate any given traffic regulations. If no solution is found, the violated regulations are given back. Traffic regulations are represented as a set of static and dynamic constraints that must be checked with regard to a certain spatial context. Static constraints for overtaking must not be violated under any circumstances: a) there is a lane on the left, available for overtaking; b) there is no double white line and c) the necessary minimum speed difference is legally reachable within the speed limit. If the static constraints are violated, the driver is told to stay behind and adjust the speed if necessary. With dynamic constraints the situation is more complicated. They all depend on the current speed/distance relations of participants and traffic objects to the own vehicle.

4.1 Moving Participant Constraints

The most important example is the check for oncoming vehicles. In the context information, speed and distance values are represented as numerical values. They are used for obtaining the minimum and maximum time needed to complete the overtaking process. We have to distinguish between the minimum legal speed difference (approx. 20 km/h in Austria) and the maximum possible speed difference, determined by the legal speed limit. These two values confine the potential overtaking speed interval. Together with speed and distance of the vehicle in front, we can determine the minimum time (with max. speed difference) and maximum time (with min. speed difference) needed for overtaking with path-time calculations. Figure 1 shows the path-time diagram for overtaking with oncoming traffic.

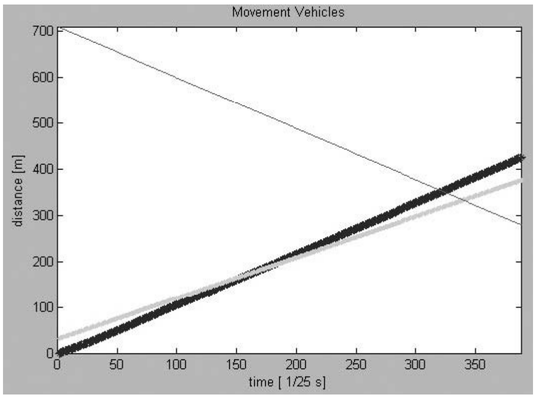

Figure 1 Path-time diagram of an overtaking maneuver with an oncoming vehicle

At the start, the front vehicle has a certain distance to the own vehicle. The thick grey line shows the path of the front vehicle over time, whereas the thick black line represents the own vehicle. At the intersection point the vehicles are next to each other. Realigning is done with approx. one second safety distance with respect to the speed of the overtaken vehicle (all safety measures are derived either from law or driving school material). The oncoming vehicle (thin grey line) starts with a far away distance and approaches during the maneuver. The point of contact with the thick grey line indicates the time the oncoming vehicle has reached the overtaking vehicle. For safety reasons this encounter should take place approx. one second after completing the overtaking maneuver. Given the speed and distance value of the front vehicle and the speed interval for overtaking, we can calculate the necessary overtaking time. When overtaking, the car is accelerated/decelerated until the desired overtaking speed is reached. The remainder of the maneuver is completed with the overtaking speed. Thus, the overtaking time consists of the time needed for the *accelerated motion* and the time needed for the *uniform motion*. The accelerated motion t_{acc} is determined as

$$t_{acc} = \frac{v_1 - v_0}{a}$$

v_1: overtaking speed of own vehicle in m/s
v_0: present speed of own vehicle in m/s
a: acceleration factor

We set v_1 to the minimum and maximum value of the overtaking speed interval respectively. For the variable a, the average acceleration for a standard middle class car is approx. 3 m/s². If the overtaking speed is slower than the current speed, the vehicle is decelerated with a negative acceleration value of -4 m/s² (normal braking behavior for optimal road surface condition). The remaining time t_u needed for completion of the overtaking maneuver with uniform motion at the desired overtaking speed is given with

$$t_u = \frac{0.5 * a * t_{acc}^2 + t_{acc} * (v_0 - v_f) - d_o}{v_f - v_1}$$

t_{acc}: time for accelerated motion as above
d_o: overtaking distance
v_f: present speed of the front vehicle in m/s

For this, the overtaking distance d_o is calculated as

$$d_o = d_f + l_o + l_f + d_s$$

d_f: distance between front and own vehicle
l_o: length of the own vehicle
l_f: length of the front vehicle
d_s: safety distance for realignment

The complete time for the overtaking maneuver is given by $t_o = t_{acc} + t_u$ and is used to check for fulfillment of dynamic overtaking constraints. Now, to check if the oncoming vehicle reaches the own vehicle during the overtaking maneuver, we first have to determine the time necessary for the oncoming vehicle to reach the own vehicle. This is done with a similar path-time calculation as

$$t_{onc} = t_{acc} + \frac{d_{onc} - 0.5 * a * t_{acc}^2 - t_{acc} * (v_o + v_{onc})}{v_f + v_{onc}}$$

d_{onc}: distance between oncoming and own vehicle
v_{onc}: present speed of the oncoming vehicle in m/s

To fulfill the constraint the condition $t_{onc} > 1 + t_o$ must hold - the encounter with the oncoming vehicle must be at least one second after completing the overtaking maneuver. If this is not the case, a collision is likely and overtaking is not recommended. The constraint is fulfilled if there is no oncoming vehicle.

Oncoming vehicles are the greatest hazard for overtaking, but there are other moving participants that have to be considered. For example, law forbids starting an overtaking maneuver while being overtaken oneself. On highways, fast vehicles approaching from behind should not be forced to slow down by inconsiderate overtaking, because of the potential negative influence on the overall traffic flow stability. The time an approaching vehicle needs to catch up with the own vehicle can be calculated as

$$t_{app} = t_{acc} + \frac{0.5 * a * t_{acc}^2 + t_{acc} * (v_0 - v_{app}) + d_{app}}{v_{app} - v_1}$$

d_{app}: distance between approaching and own vehicle
v_{app}: present speed of the approaching vehicle in m/s

The constraint must hold that $t_{onc} > t_o$, whereas the point of contact is assumed to be 5 m behind the own vehicle for safety reasons. If the condition is violated, overtaking is not recommended. The constraint is also violated, if the necessary lane change for the overtaking maneuver would lead to a safety distance violation with the approaching vehicle, even if it would not reach us while overtaking. This settles the case that the approaching vehicle is already near and driving at nearly the same speed as the own vehicle.

A similar constraint is created for checking if the overtaking lane is free and if not, if the vehicle in it is going to force us to slow down. The calculation is similar to the path-time calculations we have seen so far, with only slight differences. We leave it to the interested reader to derive the appropriate formula from the given speed/distance values of the vehicle in front.

4.2 Static Traffic Object Constraints

Constraints are also introduced for static traffic objects, e.g. ban-on-passing signs. The context information includes a validity time interval for static traffic objects. The beginning of the interval can be obtained with e.g. on-board camera sensing systems, using distance (Lamprecht (2008)) or time-to-contact measurements (Camus (1995)). The interval's end can be left open, meaning "valid until further notice" or closed. To check if the traffic sign becomes valid while overtaking, the time needed for overtaking is added to the current time and compared to the validity interval start. To fulfill the constraint, the condition $t_{start} > t_o$ must hold, meaning that the maneuver is completed before the sign becomes valid. The constraint is automatically violated if the present point in time is contained within the validity interval, meaning the sign is currently valid.

4.3 Other Speed Dependent Constraints

Besides other participants and traffic signs, there are additional constraints that depend on the overtaking speed. The line of sight (LoS) must be sufficient for overtaking. The present LoS is a context-information from the dynamic knowledge base. For a context without oncoming vehicles, the LoS equals the stopping distance for the overtaking speed and is given by the formula $d_{stop} = v_1 * 0.36 * 3 + (v_1 * 0.36)^2$. The constraint must hold that d_{stop} must be smaller than the current LoS. For context with oncoming traffic, the LoS is determined by our and a potential oncoming vehicle's distance driven within the overtaking time t_o. A safety factor of two seconds is added to the own vehicle's way. So we can calculate the necessary LoS using the combined overtake time t_o of the accelerated motion t_{acc} and the uniform motion t_u with

$$l_n = t_{acc} * (v_0 + v_1) + 0.5 * a * t_{acc}^2 + v_1 * (t_u + 2) + v_l * t_u$$

v_l: current speed limit

For LoS estimation, the speed of a potential oncoming vehicle is the allowed speed limit. The condition must hold that l_n must be smaller than the current LoS.

Another speed dependent constraint dictated by traffic law is a sufficient side distance to the overtaken participant, which varies with the participant type (single or multi wheel). If we overtake, for example, a motorbike with 130 km/h, the necessary side distance is determined by 1m (minimum distance), plus 130 cm (1cm per km/h). The available side distance is derived from the context information, using the lane width, the own vehicle's width and the available space on the left in the lane of the overtaken vehicle (if known). The constraint must hold that the available side distance is greater than the necessary side distance.

We conclude this section with the insight that a successful overtaking maneuver depends on more than just checking for oncoming vehicles and vehicles in the blind spot. Additional constraints, both dynamic and static, must hold. We have shown how to formulate overtaking regulations as constraints, in order to exploit the reasoning power of CLP. Standard problem solvers from the constraint logic community can be applied to find a solution or, in case that there is no solution, to give an explanation of the violated constraints. We presented only the most important regulations with regard to overtaking; there are further regulations that could be easily added.

5. RISK CLASSIFICATION

5.1 A Priori Fuzzy Risk Classification

As demonstrated, a feasible overtaking speed is determined from the speed interval given by the minimum necessary and maximum possible speed difference. The driver is recommended the highest possible speed that fulfils all constraints. For dynamic constraints with a dependency on the overtaking time, a risk value can be obtained. In principle, if a dynamic constraint is violated, overtaking is forbidden. For a fulfilled constraint, we have to investigate to which degree the condition holds. In theory, a driver could overtake with the minimum possible speed difference, thus increasing the necessary overtake time. When overtaking with maximum possible speed difference, the overtake time can be minimized. For a given speed, we can calculate the exact time to contact (TTC) between us and other participants resp. traffic objects for every dynamic constraint, and see how it relates to the overtake time interval. If the time is near to the minimum overtake time, the risk is higher because the maneuver is already done near the highest legal speed. The maneuver is going to be successful, but with a narrow margin. If the TTC is nearer to the maximum overtake time, the safety gap increases as the driver is always recommended the highest possible speed and thus, risk decreases. If the TTC is long after the maximum overtake time, risk is low. First we obtain a numerical risk value, using fuzzy classification with linear membership functions.

Three risk classes are introduced: *high, medium* and *low*. The mapping is done within the interval [$t_o$min, $t_o$max]. The stepwidth s between classes is determined as

$$s = \begin{cases} 0.5 * (t_o \max - t_o \min) & 1 < t_o \max - t_o \min < 5 \\ 1.5 & otherwise \end{cases}$$

These stepwidth adjustments achieve smoother results that better reflect reality. Membership to a risk class is taken from the interval [0, 1], where 1 means full membership and 0 means no membership. The TTC cannot be smaller than $t_o$min (constraint violation). If TTC is larger than $t_o$max, risk is low. For all other cases we find the two risk classes for which $c_i \leq TTC \leq c_{i+1}$ holds. The memberships μ_i and μ_{i+1} of TTC to the two classes are determined with

$$\mu_i = Y_i + \frac{TTC - X_i}{s} * (Y_{i+1} - Y_i), \quad \mu_{i+1} = 1 - \mu_i$$

Y_i: 1-upper boundary of the membership interval
Y_{i+1}: 0-lower boundary of the membership interval
X_i: lower boundary of the class interval c_i
s: stepwidth

If $\mu_i \geq \mu_{i+1}$, then TTC belongs to the risk class c_i, else to the risk class c_{i+1}. The risk is determined separately for every dynamic constraint. The risk values influence the final driving maneuver recommendation. If the driver is not in top-condition, insufficiently experienced, or not willing to take high risks overtaking is not recommended in case of a high risk for one or more dynamic constraints.

5.2 A Posteriori Probabilistic Risk Classification

Assuming that a driver follows the recommendation of the assistant, we may employ information about the driving skills in order to provide a safety measure for the maneuver. For the car following example in Figure 2, assume that there are five parameters, being the velocities v_1, v_2, v_3 and distances $d_{0,1}$, $d_{0,2}$ as depicted. For simplicity, we focus only on one parameter a driver chooses within the recommended interval [a, b], but still with a certain imprecision that is known from past experience through collection of historic data.

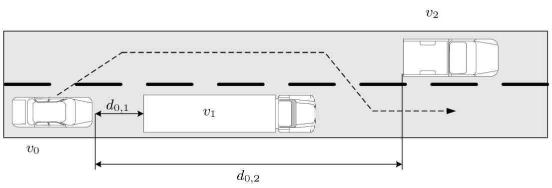

Figure 2 Overtaking scenario involving three vehicles

Our intention is to get a safety measure that is interpretable as the probability for an accident. Let us first focus on only two possible outcomes of a decision, which are either *no accident* or *accident with possible injuries or damage*. Note that we do not explicitly differ between light and severe injuries resp. damage. We treat them all equal as giving zero utility, while avoiding an accident is assigned utility one. Our utility is a binary valued variable depending on a choice s ∈ [a, b]:

$$u(s) = \begin{cases} 0 & \text{if } s \text{ leads to an accident} \\ 1 & \text{otherwise} \end{cases}$$

Clearly, a driver would prefer some continuous or discrete risk measure with more than the two extremes "do" or "don't do". For example, the probability measure of an accident, although technically unfamiliar to many drivers, still has an intuitive understanding that is valuable. The idea is running simulations of several scenarios incorporating the random behavior of a driver. Exact recommendations may be capable of preventing accidents, but impossible to realize, thus rendering an accident likely. Knowing the uncertainty in behavior gives the chance to run simulations with a large number of trials and collecting the frequencies of cases in which misbehavior leads to an accident. In each trial, the driving parameters are drawn from a random variable, which's specification is available in the internal context model. For example, a driver may choose the speed according to a truncated Gaussian distribution on the recommended interval. The relative frequency of accidents, collected from the set of trials, is then a measure for the accident probability and can be told to the driver. Let us illustrate this with the example shown in **Figure 2**.

Vehicles are termed 0,1,2 (from left to right) and drive at the velocities v_0, v_1 and v_2. The distance $d_{0,2}$ is assumed 90m and the distance $d_{0,1}$ is 30m. Initially, assume the velocities to be exactly known as v_0 = 100km/h, v_1 = 130km/h and v_2 = 130km/h. The calculation shows that the overtaking maneuver can be done by accelerating to 130km/h without risk (i.e. utility comes to 1). On the other hand, keeping the strategy s to be "accelerate to 130" if vehicle 2 drives with 100km/h, will surely lead to a crash (utility is 0). Now suppose that either from observation or from collaboration, we know that the driver of vehicle 2 maintains his speed with a variance of 10 (assuming a normal distribution of speed choice around the expected value of 120km/h), which makes 99.7% of the random choices lie within the interval $90 \leq v_2 \leq 150$. With a small chance the driver of vehicle 2 slows down and creates a dangerous situation for the recommended overtaking speed. Drawing random samples and re-calculating the scenario for a large number of cases then gives a relative frequency of times when the maneuver cannot be completed successfully. Running a simulation with 10 000 trials gives 930 cases in which a crash occurs, which comes to a probability of 0.093 for a crash. The utility value $u = 1 - 0.093 = 0.907 \approx 91\%$ is then presented to the driver as likelihood of successful completion of the maneuver if he does the overtaking.

6. SIMULATION RESULTS

We implemented the reasoning component within the open-source ECLiPSe constraint programming environment. ECLiPSe has interfaces to C++, Java and TCL/TK. We used the latter for the prototype's graphical user interface, context model mapping and reasoning control. Approximately 120 scenarios from traffic videos and driving school books where manually modeled using the context-model, to test a) the translation component and b) the general functionality of the overtaking assistan. Since the most dangerous constraints involve other moving participants, these were separately simulated using MATLAB and the Virtual Reality toolbox. Different simulation programs where created for overtaking with a) oncoming vehicle, b) vehicle approaching from behind, c) vehicle in the overtaking lane, driving in the same direction and d) both the latter two. Every situation was simulated approximately 3 000 times with random values for vehicles' speed and distances to each other. The path-time-diagram for every scenario and the occurrence of a collision were recorded. The same values were given to the reasoning component and the recommendation compared with the simulation. If a collision occurs in the simulation, the overtake assistant must not recommend overtaking. If overtaking is recommended, the result is checked against the path-time-diagram for plausibility. Additionally, seven test persons were given positive samples (no collisions) from the simulation scenarios and had to estimate their subjective risk of the maneuver according to their own experience. Results were compared with the overtake assistant's recommendations.

Simulation was done on a standard laptop PC with Windows XP, 2 GB memory and a 2 GHz Intel Pentium processor. The average time needed to derive a recommendation was between 1 000 and 2 000 microseconds, thus achieving real-time capability, which is a critical factor for a DAS. We also found that the overtake assistant always forbids overtaking if a collision or hindrance would occur. In case of a positive recommendation, the risk estimations matched with the risk rating of the test persons in 80% of all cases, with a tendency of the overtake assistance to be slightly over-cautious. Also, the test persons tended to rate the risk a little bit lower for the simulation than they would have done in real situations (with some of them freely admitting so).

7. FUTURE WORK AND CONCLUSIONS

Weather dependent road surface conditions greatly influence the recommended driving behavior, especially with regard to overtaking. Presently, this information is not fully considered by the overtaking assistant. Road surface conditions especially influence the acceleration/deceleration factor a. While on a dry road, a maximum negative acceleration of -8 m/s² (for a full brake) can be safely assumed for a middle class car, the value drops down to approx. -3 m/s² on snow (cf. Herman (2007)). The influence on the acceleration factor changes the duration of overtaking maneuvers and the necessary line of sight. Extension of the overtake assistant to cope with environmental information is one of the currently ongoing tasks.

Furthermore, the prototype currently assumes that all information needed for the reasoning process is available. If information is missing, the system does not recommend overtaking, because it cannot decide if problems would occur. With the ongoing progress in both accurate and reliable on-board sensing systems and vehicle/infrastructure collaboration, it can be safely assumed that availability of information is no longer a killing argument against intelligent DAS. However, it cannot be expected that the information is always 100% available and accurate. We respected this by including meta-information about the quality of an object into the context-model, but currently the meta-information is not evaluated during the reasoning process. This means that at present the system does not include uncertain, ambiguous or incomplete information during reasoning. The investigation of which types of uncertainty can occur and how to deal with them in the reasoning process, is one of the major future task to improve the overtake assistant.

Comprehensive information about the driving environment will soon be available for intelligent DAS. In this paper, we presented a prototype for an overtaking assistant that uses constraint-based reasoning methods for the decision component. With dynamic constraints, the speed and distance dependent relationships between the own vehicle and other participants can be smartly represented and tested for violation. A standard solver can be used to find a suitable speed for overtaking. In addition, risk assessment is done on two levels: For dynamic constraints, an a-priori fuzzy classification is provided to increase the driver's awareness for potential risks. If a driver chooses to follow the recommendation, a posterior probabilistic simulation-based risk measure is then given for convenience of the driver, in order to provide her/him with an additional likelihood for a successful completion of the maneuver. Simulation results show that the presented approach is feasible for use in intelligent DAS that aim for driver support on a tactical level. Besides overtaking, the approach is suitable for other driving maneuvers involving moving participants and traffic objects, e.g. intersection assistance.

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