Constraint-based Context-Rule Representation and Risk Classification for Driver Assistance Systems

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ABSTRACT

Driving context, including oncoming and approaching vehicles, traffic signs, road conditions and legal traffic law, has major influence on the recommended behavior of a driver. For a driver assistance system these legal and environmental constraints must be available to produce useful behavior recommendations. Using a context-aware overtaking assistant as demonstrational, conceptual reasoning component we present an approach for representation of legal and environmental context rules, exploiting constraint-logic programming, where spatio-temporal influence factors are modeled as dynamic constraints. A-priory fuzzy risk-classification is done to point out potential risks. The probability of an accident is then obtained for the recommended maneuver, using information from the driver context.

Keywords

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

1. INTRODUCTION

Not only modern concept cars, but also upper-class serial models are nowadays equipped with sophisticated on-board sensing systems, e.g. intelligent cameras, lidar, radar etc. Furthermore, substantial progress has been made in the research areas of VANETs (Vehicular Ad-hoc Networks) and vehicle-to-infrastructure communication. It can be safely assumed that information about the surrounding is available to a driver assistance system (DAS), so the next step is to investigate how the information can be processed and exploited to improve the knowledge and capabilities of DAS that aim for driver support.

One especially difficult driving maneuver is the process of overtaking. Drivers often underestimate the duration of the maneuver and the speed and distance of oncoming traffic, thus causing dangerous situations and often enough, fatal accidents. In Austria alone, approximately 5 300 accidents were related to overtaking in 2007 and 200 of them have been fatal [1]. An overtake assistant can analyze the situation based on available context-information about other participants, traffic signs and environmental conditions and tell the driver whether overtaking is currently feasible and can be legally performed or not. On roads without oncoming traffic, like a highway, an overtaking assistant can optimize the maneuver, by measuring speed and distance to other participants and decide if overtaking would hinder other participants or not. It is important that the driver is provided an explanation why a certain decision has been reached. Thus, trust can be increased and the driver can additionally decide, if the assistant's decision is justified. The final decision whether to follow the recommendation or not is within the responsibility of the driver, as the current legislation demands.

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 a constraint-logic programming approach. Additionally, an a-priori risk assessment is conducted for every constraint using a linear fuzzy classification method, to provide a natural language risk result to the driver. Assuming that a driver follows this recommendation and based on an assessment of the driving skills, a probabilistic a-posteriori risk assessment can be provided that is based on simulation using the recommendation plus possible deviations due to lack of driving skills. We conclude with simulation results for the proposed approach that demonstrate the feasibility.

2. RELATED WORK

[2] presents an overview of possible application areas of intelligent DAS with respect to overtaking maneuvers. She also analyzed the overtaking behavior of drivers on roads with oncoming traffic [3] and built an overtaking assistant prototype that was used to test driver overtaking behavior in a traffic simulator. In [4] 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.

The authors of [5] present 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 to deduce driving behavior. The authors clearly demonstrate the appropriateness of qualitative scene representation for successful reasoning about spatio-temporal patterns of moving objects. In contrast to this work, our approach uses absolute speed and distance values to determine a feasible speed difference and time-frames for an overtaking maneuver. These are comparatively easy to obtain with on-board sensing

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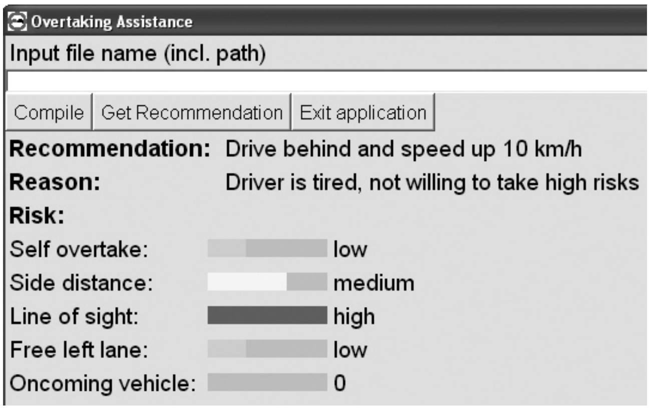

Figure 1: Graphical Frontend of Conceptual Overtake Assistant

systems or through collaborating vehicles and can thus be used for the reasoning process to obtain more accurate results.
Most of the other work in overtaking assistance focuses on vehicle blind-spot detection [6] and lane change assistance [7], without regarding the general overtaking maneuver.

3. A CONTEXT-AWARE OVERTAKING ASSISTANT

We developed a conceptual reasoning component for a context-aware overtaking assistant that gives the driver a recommendation whether overtaking is wise or not. Figure 1 shows the graphical frontend. The system takes a description of the driving situation with contextual information as input, analyzes it, and deduces a recommendation, together with a speed adjustment value and an explanation. For rules that depend on speed/distance combinations of participants and own-vehicle, a natural-language risk value is given. Giving the driver an explanation about the reason for a decision leads to increased trust, because the driver can always decide for her-/himself if the recommendation may be justified or not. There are of course better ways to present the information to the driver, but a discussion about cognitively suitable human-machine-interfaces is out of scope within this paper. In the example risk for a insufficient line of sight is high, meaning that it is exceptionally close but within the legal limit. In a spatial context without oncoming traffic (e.g. highway), it is not necessary to present a corresponding risk value in the result. The driver context is check before making the final decision and if its found that the driver is not in top form (e.g. tired, with a low risk willingness), the recommendation is adjusted.

4. CONSTRAINT-BASED DECISION PROCESS

The overtake assistant reasoning system integrates ontological context information with a logic based reasoning approach. Scene descriptions are given as class instances in OWL syntax and are then translated to the dynamic knowledge base of the reasoning component. For this purpose, an ontological context-model for traffic scene representation is used together with a set of transformation rules for creating the necessary static framework and the dynamic knowledge base. This work is described in [8]. Next to the driving scene information, traffic regulations are the vital part of the reasoning component. On close examination, the number of relevant objects involved into an overtaking maneuver is comparatively small: there are other participants with different relative distances, speeds and orientations to the subject vehicle; traffic signs and markings can influence the decision and of course the spatial context of the vehicle, as well as speed limits and environmental conditions. The difficulty in finding a decision arises from the high number of possible object combinations. A subarea of logic programming is concerned with this special kind of problems - constraint logic programming (CLP), which has been originally developed for production and planning systems.
A constraint satisfaction problem is stated as a triple $\langle X, D, C\rangle$ where X is a finite set of variables $X = \langle x_1, ..., x_n\rangle, D$ is a corresponding n-tuple of domains $D = \langle D_1, ..., D_n\rangle$ such that $x_i \in D_i$, meaning a variable x_i can be assigned values from its corresponding domain $D_i = \langle v_1, ..., v_n\rangle$. C is a finite set of constraints $C = \langle C_1, ..., C_n\rangle$. A constraint $c \in C$ involving variables $x_i, ..., x_j$ is a subset of the Cartesian Product $D_i \times ... \times D_j$ of compatible variable assignments. A constraint c is satisfied by a tuple of values $v = (v_i, ..., v_j)$ assigned to variables $x_i, ..., x_j$ 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. In a typical CSP the programmer defines the decision variables $x_i, ..., x_j$ and states the constraints as well as an (optional) optimization function. A constraint solver tries to find variable assignments for the decision variables, which satisfy all constraints, while at the same time minimizing (or maximizing) the objective function (*constraint optimization problem*). A sound introduction to constraint logic programming can be found in [9].
With regards to the stated 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 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 that satisfies all constraints, 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. Examples are absence of a double white line and that the necessary minimum speed difference is legally reachable. If one (or more) of the static constraints is violated, the reasoning process is stopped and the driver is told to stay behind the front vehicle and adjust the speed if necessary. The dynamic constraints for an overtaking maneuver all depend on the current speed/distance relations of participants and traffic objects to the subject vehicle.

4.1 Moving Participant Constraints

The most important constraint is the check for oncoming vehicles. Figure 2 shows the path-time diagram for an overtaking maneuver with oncoming traffic. The subject vehicle always starts at distance 0 and is represented by the solid line. At the start of overtaking, the front vehicle, represented by the dashed line, has a certain distance to the own vehicle, observable on the y-axis. The x-axis shows the time line for overtaking in units of 0.04 seconds. At the point where the two lines intersect, the vehicles are next to

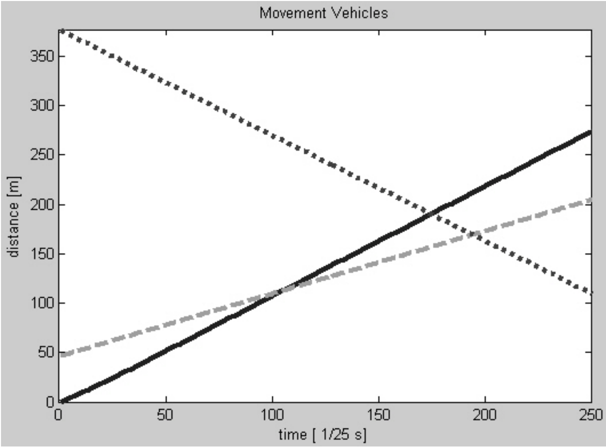

Figure 2: Path-time diagram of an overtaking maneuver with an oncoming vehicle

each other. Realigning is done with approx. one second safety distance with respect to the speed of the overtaken vehicle, e.g. for 100 km/h the safety distance is approx. 28 meters. The oncoming vehicle (dotted line) gradually approaches during overtaking. The point of contact between the oncoming and the subject vehicle is indicated by the intersection of the dotted with the solid line. For safety reasons this encounter should take place approximately one second after completing the overtaking maneuver. If the intersection occurs at an earlier point, a collision is imminent.

In the context information, speed and distance are represented numerically. They are used for obtaining the minimum and maximum overtake time. 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 speed limit. The two values confine the potential overtaking speed interval. Together with the speed and distance of the vehicle in front, we can determine the minimum time (with maximum speed difference) and maximum time (with minimum speed difference) needed for overtaking. When overtaking, the car is accelerated (or 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

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

where v_1 is the overtaking speed of the subject vehicle in m/s, v_0 is the present speed of the subject vehicle in m/s and a is the acceleration factor in m/s^2. We set v_1 to the minimum and maximum value of the overtaking speed interval respectively. For a the average acceleration for a standard middle class car is approximately $3m/s^2$. If the overtaking speed is slower than the current speed, the vehicle is decelerated with an average negative acceleration value of $-4m/s^2$ (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

$$t_{\text{u}} = \frac{\frac{a \cdot t_{\text{acc}}^2}{2} + t_{\text{acc}} \cdot (v_0 - v_f) - d_o}{v_f - v_1}$$

where t_{acc} is the time for accelerated motion as above, d_0 is the overtaking distance and v_f is the present speed of the front vehicle in m/s. d_o is calculated as

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

with d_f being the initial distance between front and subject vehicle, l_o being the length of the subject vehicle, l_f being the length of the front vehicle and d_s as the safety distance for realignment. If l_f is unknown, a length of 20 meters is assumed, which is approximately the maximum allowed length of the longest truck according to law. The complete time for the overtaking maneuver is then given by

$$t_o = t_{\text{acc}} + t_{\text{u}}$$

and used to check for fulfillment of dynamic overtaking constraints. In our example, to check if the oncoming vehicle reaches the own vehicle at some time during the overtaking maneuver, we first have to determine the time until the point of contact between the oncoming vehicle and the subject vehicle. This is done with

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

where d_{onc} is the distance between oncoming and own vehicle and v_{onc} is the present speed of the oncoming vehicle in m/s. To fulfill the dynamic constraint the condition must hold that $t_{\text{onc}} > 1 + t_o$ - the encounter with the oncoming vehicle must be at least one second after completion of the overtaking maneuver. Otherwise, a collision is likely and overtaking is not recommended.

Oncoming vehicles are without doubt the greatest hazard for an overtaking maneuver. However, other moving participants in the surrounding of the subject vehicle must also be considered. On highways, for example, fast vehicles approaching from behind should not be forced to slow down by inconsiderate overtaking maneuvers, because of the potential negative influence on the overall traffic flow stability. Neither is it optimal, if the subject vehicle is hindered by another participant in the overtaking lane, as shown in Figure 3, where the dotted line now is the approaching vehicle and the dot-dashed line the vehicle in the overtaking lane. For both vehicles we can calculate the time-of-contact and relate it to the overtake time. The time for the approaching vehicle to catch up with the subject

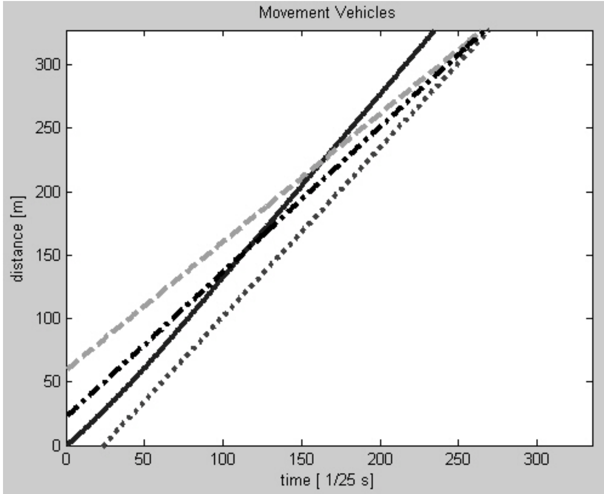

Figure 3: Path-time diagram of an overtaking maneuver with an approaching vehicle and a vehicle in the overtaking lane

vehicle is

$$t_{\text{app}} = t_{\text{acc}} + \frac{\frac{a \cdot t_{\text{acc}}^2}{2} + t_{\text{acc}} \cdot (v_o - v_{\text{app}}) + (d_{\text{app}} - \frac{v_{\text{app}}}{2})}{v_{\text{app}} - v_1}$$

with d_{app} being the distance between approaching and own vehicle and v_{app} being the present speed of the approaching vehicle in m/s. The constraint must hold that $t_{\text{app}} > t_o$ or $t_{\text{app}} < 0$, whereas the point of contact is assumed to be half a second behind the own vehicle for safety reasons. The constraint is automatically violated, if the necessary lane change for overtaking would lead to a safety distance violation between the approaching vehicle and the subject vehicle, even if it would not reach the subject vehicle 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 time needed for the subject vehicle to reach the vehicle in the overtaking lane is

$$t_{\text{fl}} = t_{\text{acc}} + \frac{\frac{a \cdot t_{\text{acc}}^2}{2} + t_{\text{acc}} \cdot (v_o - v_{\text{fl}}) - (d_{\text{fl}} - \frac{v_1}{2})}{v_{\text{fl}} - v_1}$$

with d_{fl} being the distance between the subject vehicle and the vehicle in the overtaking lane and v_{fl} being the present speed of the latter in m/s. The constraint must hold that $t_{\text{fl}} > t_o$ or $t_{\text{fl}} < 0$. The constraint is automatically violated if the lane change would bring the own vehicle within the safety distance to the vehicle in front. For both calculations, a very small value is added to the divisor to avoid a a division by zero, in case of equal v_{app} respectively v_{fl} and v_1.

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 interval's beginning can be obtained with e.g. on-board camera sensing systems, using distance [10] or time-to-contact measurements [11]. 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 traffic sign's validity interval start. To fulfill the constraint, the condition must hold that $t_{\text{start}} > t_o$, 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

There are additional constraints that depend on the overtaking speed. According to traffic law, the line of sight must be sufficient for overtaking. The subject vehicle's present line of sight is a context information from the dynamic knowledge base. For a context without oncoming vehicles, the line of sight equals the stopping distance for the overtaking speed and is given as

$$d_{stop} = v_1 \cdot 0.36 \cdot 3 + (v_1 \cdot 0.36)^2$$

The constraint must hold that d_{stop} must be smaller than the current line of sight. For contexts with oncoming traffic, the necessary line of sight is determined by the subject vehicle's and a potential oncoming vehicle's distance driven within the overtaking time t_o. An additional safety factor of two seconds is usually added to the subject vehicle's way. So we can calculate the necessary line of sight using the combined overtake time t_o of the accelerated motion t_{acc} and the uniform motion t_u with

$$l_n = t_{\text{acc}} \cdot (v_0 + v_l) + \frac{a \cdot t_{\text{acc}}^2}{2} + v_1 \cdot (t_u + 2) + v_l \cdot t_u$$

Table 1: Necessary side distance

Vehicle Type	$\leq 50km/h$	$> 50km/h$
multi wheel	1 m	0.5 m + 1 cm per km/h
single wheel	1.5 m	1 m + 1 cm per km/h

where v_l is the current speed limit. For line of sight estimation, the speed of a potential oncoming vehicle is set equal with the allowed speed limit of the spatial context. As above, the condition must hold that l_n must be smaller than the current line of sight.
Another speed dependent constraint, dictated by traffic law, is a sufficient side distance to the overtaken participant. To determine the necessary side distance, we have to distinguish between single- and multiwheel vehicles. Table 1 gives an overview for the legal regulations. If we overtake, for example, a motorbike with 130 km/h, the necessary side distance is determined by 100 cm + 130 cm = 230 cm. The available side distance is derived from the context information, using the lane width, the subject 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.

4.4 Influence of Environmental Conditions

Weather dependent road surface conditions greatly influence the recommended driving maneuver and speed. The acceleration factor a has to be adjusted to the varying conditions, which changes the duration of overtaking. For a full brake on dry road, the average maximal negative acceleration a is $-8m/s^2$ according to [12]. Additional constraints are modeled for an approximated deceleration value of 57% from the maximum deceleration (full brake) for adjustment to the current road conditions. Similar considerations are made for positive acceleration. When dry, the average maximum acceleration is $3m/s^2$. On a wet road, acceleration is done more carefully, so the value is adjusted to approximately 80%. On snow or ice an acceleration factor of 20% is used for overtaking (from experience). Additionally, the legal safety distance varies with bad weather. Standard values on a dry road depend on the current speed: for less than 50 km/h one second is sufficient, for higher speeds two seconds are the minimum. On a wet road and with difficult sight conditions the safety distance is increased by one second, on snow or ice by three seconds. The overtaking distance increases with a longer safety distance, meaning a longer overtaking time.
We conclude this section with the insight that a successful overtaking maneuver depends on more than just checking vehicles in the blind spot. Additional constraints, both dynamic and static, must hold before the driver can be told to overtake, an oncoming vehicle being only one of them. We have shown how to formulate overtaking regulations as constraints within a constraint satisfaction problem, in order to exploit the reasoning power of this approach. 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 of course further regulations for ban on passings, e.g. when approaching a zebra or level crossing. These constraints could be easily added in a similar way to the presented examples, based on the given context-information.

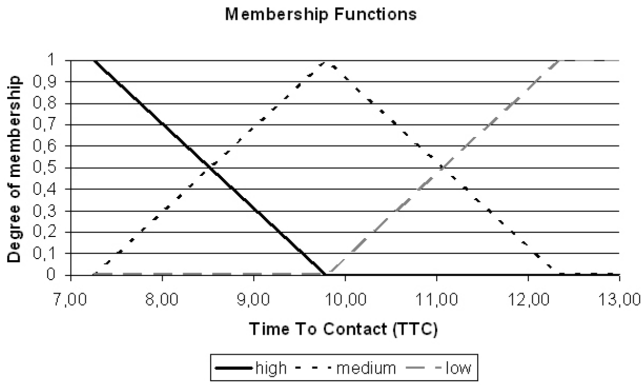

Figure 4: Linear membership functions for fuzzy risk classification with three classes

5. RISK CLASSIFICATION

5.1 A priori fuzzy risk classification

As demonstrated in the previous section, a feasible overtaking speed is determined from the speed interval given by the minimum necessary and maximum possible speed difference. The driver is always recommended the highest possible speed that fulfils all constraints. For dynamic constraints, which have a dependency to 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, meaning that we must have a look if the constraint is only just fulfilled or if it's far from violation.

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, as allowed by the speed limit, the overtake time can be minimized. For a given speed, we can calculate the exact time to contact (TTC) between the own vehicle and other participants resp. traffic objects for every dynamic constraint as demonstrated in the previous section, and see how it relates to the overtake time interval. If the time is near to the minimum overtake time, we can conclude that the risk is higher, because the maneuver is already done near the highest legal speed and we should not go faster. 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, because the overtaking maneuver can be safely completed. First we obtain a numerical risk value, using fuzzy classification with linear membership functions (see figure 4). 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 by $0.5 \cdot (t_o max - t_o min)$. If the difference between the $t_o max$ and $t_o min$ is smaller than one second or greater than five, a stepwidth of 1.5 seconds is used for risk classification to 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 of the corresponding class. The TTC cannot be smaller than $t_o min$, this would violate the constraint. If TTC is larger than $t_o max$, risk is always low. We now find the two risk classes for which the condition $c_i \leq TTC \leq c_{i+1}$ holds. The memberships μ_i and μ_{i+1} of TTC to the two classes are determined with

$$\begin{aligned}\mu_i &= Y_i + \frac{TTC - X_i}{s} \cdot (Y_{i+1} - Y_i) \\ \mu_{i+1} &= 1 - \mu_i\end{aligned}$$

where Y_i is the 1-upper boundary of the membership interval, Y_{i+1} is the 0-lower boundary of the membership interval, X_i is the lower boundary of the class interval c_i and s is the 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 and communicated to the driver. The risk values influence the final driving maneuver recommendation. If the driver is not in top-condition (e.g. tired or stressed), insufficiently experienced, is not willing to take high risks or is elderly, then 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 driving assistance system, we may employ collected information about her/his driving skills in order to provide a measure of safety for the maneuver. This once more utilizes the context as including the driver itself in the considerations of the system.

For the car following example depicted in figure 5, 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, let us 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 actual moves and comparing it to the recommendations). Our intention is to get a measure of safety being interpretable as the probability for an accident. For a simple construction, let us first focus our attention on only two possible outcomes of a decision, which are either *no accident* or *accident with possible injuries or damage to the vehicle*. Note that here, we do not explicitly treat differences between light injuries and severe injuries up to paralysis or death. Neither do we distinguish between damages like scratches in the lacquer or a crushed engine. We treat them all on an equal basis as giving zero utility, while avoiding an accident is assigned utility one. Let us define our utility as binary valued variable depending on a choice $s \in [a, b]$:

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

How can we arrive at a safety-measure that gives useful figures to be provided to a driver apart from either "do it" or "don't do it"? Clearly, a driver would prefer some continuous measure of risk or at least discrete measure with more than two extremes. Can we give the probability for an accident? Probability, although technically unfamiliar to many drivers, still has an intuitive understanding that is most valuable for a significant number of drivers. The idea is running simulations of several scenarios incorporating the random behavior of a driver. Exact decisions may be capable of preventing accidents, but impossibility of realizing a correct decision may still render an accident likely. Knowing about the uncertainty in behavior gives the chance to run simulations taking 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 instance, a driver may choose his speed according to a truncated Gaussian distribution on the interval that is recommended to her/him by the overtaking assistant. The relative frequency of accidents, collected from the set of tri-

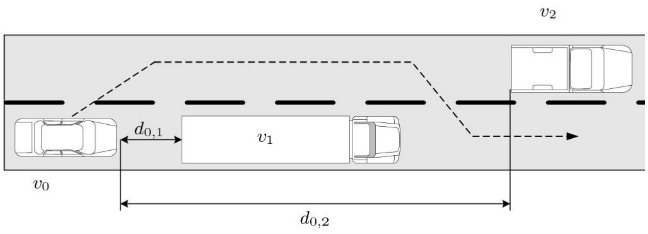

Figure 5: Overtaking scenario involving three vehicles

als, is then a measure for the probability of an accident and can be provided to the driver before taking the operative measures. Let us illustrate this with the example shown in figure 5. Vehicles are termed 0,1,2 (from left to right) and drive at the corresponding velocities v_0, v_1 and v_2. The distance $d_{0,2}$ is assumed 90m and the distance $d_{0,1}$ is 30m in our example. Initially, assume the velocities to be exactly known as $v_0 = 100km/h, v_1 = 130km/h$ and $v_2 = 130km/h$. Then a simple calculation shows that the overtaking maneuver can be done by accelerating to 130km/h without risk (i.e. utility comes to 1). Keeping the strategy s to be "accelerate to 130", on the other hand, if vehicle 2 goes only with 100km/h, then a crash will surely occur (utility is 0). Now, suppose that either from observation or from communication (cooperation), 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 optimal (expected) value of 120km/h), which makes 99.7% of the random choices lie within the interval $90 \leq v_2 \leq 150$. There is a small chance that the driver of vehicle 2 slows down and thus creates a dangerous situation if the overtaking maneuver is carried out with the recommended choice. 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 10000 trials gives 930 cases in which a crash occurs, which comes to a probability of 0.093 for a crash. The utility value $u = 1 - 0.093 = 0.907$ 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 graphical user interface, context model mapping and reasoning control. Approximately 120 scenarios from traffic videos and traffic school books were manually modeled using the context-model, to test a) the translation component and b) the general functionality of the overtaking assistant (for static and dynamic constraints). Since the most dangerous constraints involve other moving participants, these were separately simulated using MATLAB and the Virtual Reality toolbox. Different simulation programs were 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 b and c. Every situation was simulated 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 recommendation component and the decision compared with the simulation. If a collision occurs in the simulation, the overtake assistant must not recommend overtaking. If overtaking is recommended with a certain risk, there must not be a collision in the simulation. For verifying feasibility of the risk classification, five test persons were given positive samples (without collisions) from the simulation scenarios and had to estimate the risk of the overtaking 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 0.001 and 0.002 seconds (1 000 to 2 000 microseconds), thus achieving real-time capability, which is a critical factor for a DAS. We further found that the overtake assistant always forbids overtaking if a collision or hindrance would occur in 99.84% of all cases. In the remaining 0.16 % the overtake assistant forbid overtaking while the simulation showed no collision. This deviation is related to inaccuracies in the simulation and can occur in situations with extremely small time differences. A manual re-check of these conflicting situations proved the recommendations of the overtake-assistant to be correct. For the risk-classification in case of a positive recommendation, the risk results matched with the rating of the test persons 80%, with an tendency for the overtake assistant to be overcautious. For some cases, test persons admitted that they rated the risk lower than they would have done in reality, because of the simulated environment.

7. FUTURE WORK

Fine-tuning of the safety parameters and risk-classification intervals must be done to increase feasibility of the risk rating. Also, a larger group of test persons should be beneficial to the significance of test results.

Furthermore, the reasoning component 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 or not. With the ongoing progress in both accurate and reliable on-board sensing systems (camera, radar, lidar etc.) 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 is not able to deal with uncertain, ambiguous or incomplete information. 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.

8. CONCLUSIONS

With the ongoing progress in on-board sensing systems and collaboration between vehicles and infrastructures, comprehensive information about the driving environment will soon be available for intelligent DAS. In this paper, we demonstrated the use of constraint-based reasoning methods for DAS with an overtake assistant reasoning system. With dynamic constraints, the speed and distance dependent relationships between the subject vehicle and other participants can be smartly represented and tested for violation. A standard solver can be used to find a suitable speed for the recommended driving maneuver. 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, for example, intersection assistance.

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