A context-aware overtaking assistance system with fuzzy-probabilistic risk classification

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Summary

Driving context, including oncoming and approaching vehicles, traffic signs, road and environmental conditions as well as traffic regulations, has substantial influence on the recommended driving behaviour. For a driver assistance system all these constraints must be considered to produce useful behaviour recommendations. Using a context-aware overtaking assistance for demonstration purposes, we present an approach for representation of legal and environmental context rules, exploiting constraint-logic programming, where contextual influence factors are modelled as static and dynamic constraints. A-priory fuzzy risk classification is performed to point out potential risks for dynamic constraints. Afterwards the probability of an accident is obtained for the recommended manoeuvre, using additional information from the driver context.

1. INTRODUCTION

With the ongoing progress of on-board sensing systems and vehicle-infrastructure collaboration, information about the surrounding is becoming available to driver assistance systems, thus increasing their abilities. Since overtaking is one of the most dangerous manoeuvres in road traffic, it is a clear candidate for assistance. Overtaking heavily depends on contextual factors like other vehicles, traffic signs and driving regulations. Also hazardous road conditions have substantial influence on the recommended behavior. On a slippery road, acceleration factors change, increasing stopping and safety distances, making speed adjustments necessary. We present a prototype for a context-aware overtaking assistant that reasons on the available abstract contextual information and gives a recommendation to the driver. The prototype uses a logic-based reasoning approach, where restrictions on an overtaking manoeuvre are modeled as constraints. For a positive decision, a speed value must be determined that does not lead to constraint violations. Before presenting the result to the driver, a fuzzy a-priori risk classification is done, in combination with a probabilistic a-posteriori risk classification for the overall overtaking recommendation. Simulation results demonstrate the feasibility of the proposed approach.

2. RELATED WORK

The authors of [3] present an overview of possible application areas of overtaking assistants. They analyzed the overtaking behavior of drivers on roads with oncoming traffic [4] and built an overtaking assistant prototype for testing driver's overtaking behavior in a traffic simulator. The results show that drivers performed overtaking with shorter gaps, when supported by the assistant [2]. However, the assistant's usefulness was rated low by most test persons, because recommendations did not well match with driver's perception. Other work in overtaking assistance focuses on vehicle blind-spot detection [8] and lane change assistance [10]. [7] presents a knowledge-based approach for modeling spatio-temporal driving situations using qualitative motion descriptions. Direction, speed and distance are mapped into qualitative classes. A rule base reasons on the qualitative descriptions to deduce driving behavior. The authors clearly demonstrate the appropriateness of qualitative scene representation for successful reasoning about spatiotemporal patterns of moving objects. In contrast, our approach uses absolute speed and distance values to determine a feasible speed. These are comparatively easy to obtain with on-board sensing systems or through collaboration and can be used for the reasoning process to obtain more accurate results.

3. A CONTEXT-AWARE OVERTAKING ASSISTANT

To demonstrate the feasibility of our approach, we developed a prototype for an overtaking assistant that gives a recommendation about whether overtaking is wise or not and points out the potential risks. Figure 1 shows the graphical frontend of the prototype.

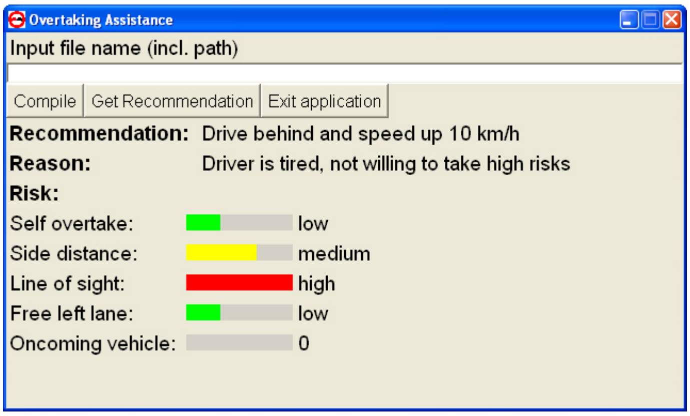

Figure 1 Prototype of Overtake Assistant

The contextual information about the current situation is the input, which is analyzed. The retrieved recommendation and an explanation are presented to the driver. For speed/distance dependent factors, a risk value is obtained. In the example, the risk for being self-overtaken and for another vehicle occupying the overtaking lane is low, whereas the line of sight risk is high (very close to the legal limit). If the current road type is a highway, no risk must be determined for oncoming vehicles.

4. CONSTRAINT-BASED DECISION PROCESS

On close examination, the number of relevant traffic objects involved into an overtaking maneuver is small: there are other participants with different speed and relative distances and orientations to the own vehicle; environmental conditions, speed limits and the spatial context (highway vs rural road) influence the overtaking decision. The difficulty in finding a decision arises from the high number of possible object combinations. A subarea of logic programming, concerned with this specific problem kind, is constraint logic programming (CLP) [9]. 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 $x_1,\ldots,x_n$, D is a corresponding n-tuple of domains $D_1,\ldots,D_n$ such that $x_i \in D_i$, meaning a variable x_i can be assigned values $v_1,\ldots,v_n$ from its domain. C is a finite set of constraints $C_1,\ldots C_n$. A constraint $c \in C$ involving variables $x_i,\ldots,x_n$ is a subset $D_i \times \ldots \times D_j$ 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 in X and states the constraints. A standard solver tries to find variable assignments that satisfy all constraints.

In our approach, traffic rules represent the necessary constraints that must be checked within a spatial context. Some conditions, named static constraints, must not be violated under any circumstances, e.g. legal reachability of the minimum speed difference. Others, named dynamic constraints, depend on current speed/distance values of involved participants and traffic objects and can be gradually fulfilled with a certain risk until they become violated. We want to find the desired driving maneuver and speed so that no traffic regulations are violated. If no solution satisfies all constraints, overtaking is not recommended and the violated regulations are given as explanation.

4.1 Moving Participant and Static Traffic Object Constraints

Participants' speed and distance are given as numerical values. For the duration of overtaking, we have to obtain the minimum necessary (> 20 km/h) and maximum possible speed limit. From these two values we derive the minimum and maximum time for overtaking and use them as boundaries for the potential speed interval. The vehicle is first accelerated (or decelerated) until the desired overtaking speed is reached; the remaining maneuver is completed with the overtaking speed. The complete overtaking time consists of the *accelerated motion* and the *uniform motion:* $t_o = t_{acc} + t_u$. Here, t_{acc} is determined as $t_{acc} = \frac{v_1 - v_0}{a}$, where v_1 is the overtaking speed in m/s, v_0 is the present speed in m/s and a is the acceleration factor. For a, the average acceleration for a middle class car is approximately 3 m/s². If the overtaking speed is slower than the current speed, the vehicle is decelerated with an average value of -4 m/s² (normal braking behavior for dry road). The remaining time t_u is given with $t_u = \frac{0.5 * a * t_{acc}{}^2 + t_{acc} * (v_0 - v_f) - d_o}{v_f - v_1}$, where t_{acc} is the accelerated motion as above, d_o is the overtaking distance and v_f is the 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 distance between front and own vehicle, l_o being the length of the own vehicle, l_f the length of the front vehicle and d_s as the safety distance for realignment. The complete time t_o is then used to check for violation of dynamic overtaking constraints.

For example, to check if an oncoming vehicle reaches us during overtaking, we first determine the time t_{onc} needed by the oncoming vehicle to reach the own vehicle, as $t_{onc} = t_{acc} + \frac{d_{onc} - 0.5 * a * t_{acc}{}^2 - t_{acc} * (v_o + v_{onc})}{v_1 + v_{onc}}$, where d_{onc} is the distance between oncoming and own vehicle and v_{onc} is the speed of the oncoming vehicle in m/s. For a positive overtaking recommendation the condition must hold that $t_{onc} > 1 + t_o$, meaning the encounter must be at least one second after completing the overtaking. Figure 2 shows the graphical representation of the presented calculations, where the solid line represents the own vehicle, the dashed line the front vehicle and the dotted line the oncoming vehicle. At the intersection of two lines, the vehicles are next to each other.

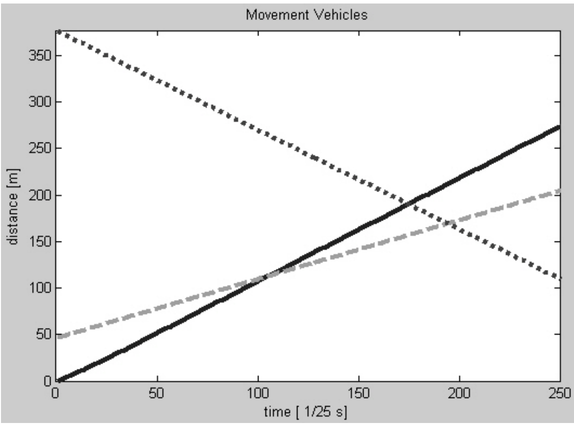

Figure 2 Path-time diagram of an overtaking maneuver with an oncoming vehicle

Similar constraints are modeled for approaching vehicles and vehicles blocking the overtaking lane. We leave it to the reader to derive the appropriate formulae for checking the time/distance relations against the overtaking time. Additional constraints are needed to check if a traffic sign (e.g. ban-on-passing) or other static object is reached while overtaking. The distance to the sign is either derived from a time-to-contact measurement [1] or directly obtained using distance measurements [6]. To complete the overtaking maneuver successfully, the constraint must hold that the time needed to reach the sign with the accelerated/uniform motion is larger than the overtaking time t_o. The constraint is automatically violated if the sign is already valid.

4.2 Influence of environmental conditions

Weather dependent road surface conditions are included in the context information. They greatly influence the recommended driving maneuver and speed and especially the acceleration factor a, which in turn changes the duration of overtaking. For a full brake on a dry road, the average max. negative acceleration is -8 m/s². On a wet road, the value decreases to -6 m/s² and on ice/snow, it drops further down to -0.5 to -2 m/s² [5]. Constraints are modeled for an approximated deceleration value of 57% from the maximum deceleration (full brake) for the overtaking maneuver and for adjustment to the current road conditions. Similar considerations are made for positive acceleration. When dry, the average maximum acceleration is 3 m/s². On a wet road, drivers usually accelerate more carefully, so the value is adjusted to approx. 80%. On snow/ice, we use an acceleration factor of approx. 20% for overtaking (from experience). Also, 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 for multi-wheel vehicles. On a wet road or with bad sight, the safety distance must be increased by one second, on snow/ice by three seconds. The safety distance influences the overtaking distance, and the larger the safety distance the longer the necessary overtaking time. Additional constraints are added to the knowledge base to account for this.

5. TWO-PHASE RISK CLASSIFICATION

5.1 A priori fuzzy risk classification

The highest possible speed that fulfils all constraints is recommended. For a fulfilled constraint, we have to investigate to which degree it holds. In theory, a driver could overtake with the minimum speed difference, thus increasing the overtake time. With maximum speed difference as allowed by the speed limit, the overtake time can be minimized. The recommended speed lies in between and for it we can calculate the exact time to contact (TTC) between the own vehicle and other participants or traffic objects and see how it relates to the overtake time interval. Three risk classes are introduced: *high, medium* and *low*. The risk mapping is done within the interval [$t_o$min, $t_o$max]. The stepwidth s between classes is given by 0.5*($t_o$max-$t_o$min). If the difference between the $t_o$max and $t_o$min is < 1 second or > 5 seconds, a stepwidth of 1.5 is used to achieve smoother, more realistic results. Membership to a risk class is from the interval [0, 1], where 1 means full membership and 0 means no membership of the corresponding class. TTC < $t_o$min means constraint violation. If TTC > $t_o$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} are determined with $\mu_i = Y_i + \frac{TTC - X_i}{s} * (Y_{i+1} - Y_i), \quad \mu_{i+1} = 1 - \mu_i$, where Y_i is the upper and Y_{i+1} the 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 c_{i+1}.

5.2 A posteriori probabilistic risk classification

Assuming that a driver follows the recommendation of the driving assistance system, we use contextual information about the driving skills to provide a safety-measure for the maneuver. For the example depicted in Figure 3, there are five parameters: the velocities v_1, v_2, v_3 and distances $d_{0,1}$, $d_{0,2}$. For simplicity, we focus only on one parameter a driver chooses within the recommended interval [a, b], with a certain imprecision that is known from past experience.

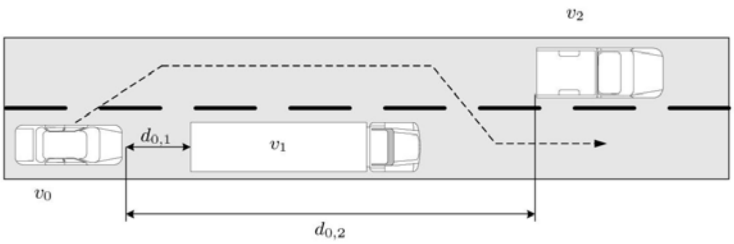

Figure 3 Overtaking scenario involving three vehicles

We want to get a safety-measure as the probability for an accident and first focus on only two possible outcomes of a decision: *no accident* or *accident with possible injuries or damage*. All injuries and damages (light or severe) are treated equally as giving zero utility, while avoiding an accident is assigned utility one. The utility is then a binary variable depending on a choice $s \in [a, b]$:

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

We want to give the probability for an accident, because has an intuitive understanding that is valuable for the majority of drivers. While exact decisions are capable of preventing accidents, the impossibility of realizing an exact decision may still render an accident likely. Knowing about uncertainty in driver behavior gives us the chance to run simulations with large number of trials and to collect 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 context model. For example, a driver may choose his speed according to a truncated Gaussian distribution on the interval that is recommended by the overtaking assistant. The relative frequency of accidents is then a measure for its probability and can be provided to the driver with the recommendation.
We illustrate this with the example shown in Figure 3. Vehicles drive at velocities v_0, v_1 and v_2. The distance $d_{0,2}$ is 90m and the distance $d_{0,1}$ is 30m. Initially, the velocities are exactly known as v_0 = 100km/h, v_1 = 130km/h and v_2 = 130km/h. The overtaking maneuver can be done by accelerating to 130km/h without risk (u = 1). However, keeping the strategy s at "accelerate to 130" if vehicle 2 goes only with 100km/h will lead to a crash (u = 0). Now, suppose that 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 vehicle 2 slows down and creates a dangerous situation for overtaking 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 $u = 1 - 0.093 = 0.907 \approx 91\%$ is then presented to the driver as likelihood of successful completion of the maneuver.

6. SIMULATION RESULTS

Approximately 120 traffic scenarios were modeled to test the general functionality of the overtaking assistant. Situations with moving participants were separately simulated using MATLAB and the VR toolbox. Different simulations 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 of the latter two. Every situation was simulated approximately 3000 times with random values for vehicles' speed and distances taken from a given interval. The occurrence of a collision was recorded.

Every scenario was given to the reasoning component and the recommendation was compared with the simulation. Also, seven test persons were given positive samples (without collisions) from the simulation scenarios and had to estimate their subjective risk of the maneuver. Results were compared with the overtake assistant's risk assessments. On a standard laptop with 2 GB memory and a 2 GHz processor, the average time needed to derive a recommendation is between 1 and 2 milliseconds, thus achieving real-time capability. The overtake assistant forbids overtaking if a collision or hindrance occurs in the simulations in 99.98 %. The discrepancy of 0.02% is due to inaccuracies in the simulation. In case of a positive recommendation, the risk values matched with the test persons' subjective risk ratings in 70-80 % of all cases, with the overtake assistant tending to be slightly overcautious.

7. 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 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 is used to find a suitable speed for overtaking. In addition, risk assessment is done on two levels: 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 in order to provide the driver 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.

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