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Knowledge-based Risk Assessment for Intelligent Vehicles

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Abstract— *In order to set up assistance systems in intelligent vehicles or to control an autonomous vehicle a number of cognitive functions has to be realized in an integrated architecture. In this paper we propose a knowledge-based risk assessment procedure in order to identify objects which might be dangerous for the own vehicle. Having an advanced vision system with gaze control in mind a knowledge-based risk assessment can determine where to concentrate the attention. The approach is evaluated by simulating different traffic scenes.*

1. Introduction

Recent developments in the field of intelligent vehicles have shown that nowadays it is possible to provide the driver with useful assistance systems like, e.g., lane departure warning, lane change assistants, adaptive cruise control, or even letting a car drive autonomously over long distances on highways [4], [7].

In order to set up assistance systems in intelligent vehicles or to control an autonomous vehicle a number of cognitive functions has to be realized in an integrated architecture (Fig. 1). As processing tasks for perception, situation assessment, behavior decision and actual control of the vehicle have tight time constraints, it is necessary to focus on relevant objects in the environment. We propose a knowledge-based risk assessment in order to identify objects which might be dangerous for the own vehicle. Having an advanced vision system with gaze control in mind as proposed by Dickmanns [8] a knowledge-based risk assessment can determine where to concentrate the attention.

Risk assessment as scientific topic is basically known from management science, finance, and health care. Therefore a number of methodologies for organizational risk identification and management can be found in the literature [9], [17].

Risk identification is described as the ongoing risk management task of identifying the significant risks to the success of an endeavor. The proposed techniques are of organizational nature, i.e., checklists of risks and their factors, brainstorming of risks and their factors, cross functional teams, interviews with stakeholders and domain experts, etc. In the recent literature much attention is paid to software engineering risk management [13], [14], [26] which tends to adapt existing methodologies to the special needs of software development projects.

In sociology and ethology a great deal of research is done on human risk handling [17], [21], [25], [29] which also includes the ways human perceive and communicate risk. Risk sensitive professions like aircraft pilots — to give just one prominent example — are subject to specialized studies which aim on identifying the influence of liability on coping with risk [10]. Work focusing on the cognitive models of risk and risk perception can lead a way towards better understanding how knowledge influences the identification of risks.

An upcoming field is the development of computer-based tools to assist in the risk management process. Zoysa and Russel [30] give an exhaustive overview on „computerized knowledge-based methodologies [...] to capture and reuse risk-related knowledge“. An additional interesting approach which fits in this category is proposed by Kim [12].

Knowledge-based risk identification based on sensory data (in contrast to specific software-guided user input), i.e., a fully automated knowledge-based risk management system has not yet been proposed to the best of our knowledge. This paper simplifies the rather manifold notion of risk sketched above as it sees risk mainly as the approaching of environmental situations which might endanger the intelligent vehicle and its passengers or other traffic participants.

In the field of intelligent vehicles most of the approaches to identify critical situations are rather specialized to the application domain. Different systems address functions like adaptive cruise control (ACC), lane change detection, intersection assistance, and lane change assistance [3], [5], [6], [20], [22], [27]. In these approaches usually sensory information is more or less used directly on a quantitative level in order to identify critical situations. The approach presented here addresses risk identification qualitatively and thus allows for integrating background knowledge and describing complex situations in

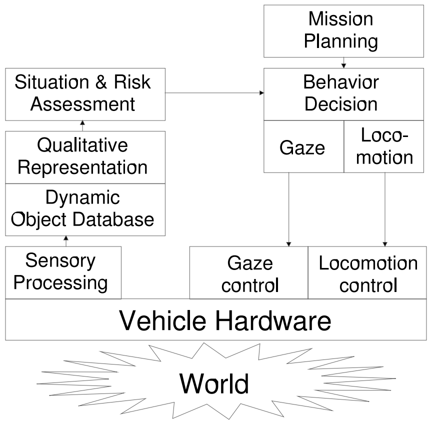

Figure 1. Architecture adapted from Dickmanns

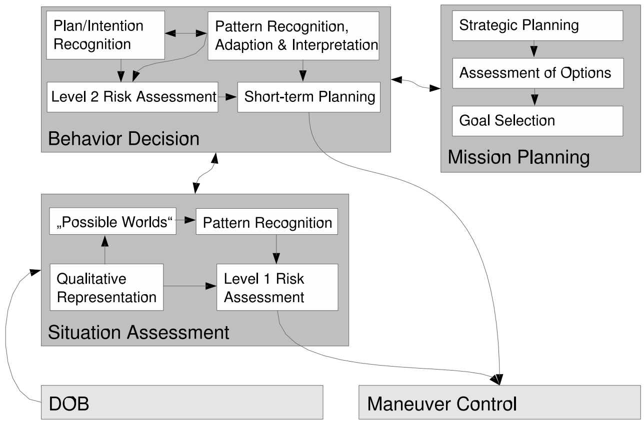

Figure 2. Higher-level components

a comprehensible way.

The paper is organized as follows: Section 2 gives an overview of the overall architecture. The qualitative scene representation is described in Section 3. Section 4 introduces our approach to knowledge-based risk assessment. The paper closes with some experimental evaluation and conclusions in sections 5 and 6.

2. Architecture

The architecture presented here is a refinement of Dickmanns' architecture ([8], see Fig. 1). Dickmanns' architecture consists of different components in order to realize various cognitive functions in an intelligent vehicle. Fig. 2 shows a refinement of the higher-level components: situation assessment, behavior decision, and mission planning. These three components have different characteristics w.r.t. time criticality. While mission planning can be done in rather long cycles, situation assessment must be able to identify risks quickly.

The situation assessment analyzes the situation perceived by the sensory information and recognizes situation patterns. Some decisions have to be made already at this level based on the current situation if they need a fast intervention to the maneuver control. The central component here is the qualitative representation of the information perceived by the sensors, which is mapped into a qualitative abstraction (see Section 3). The current situation can be evaluated by considering matching situation and behavior patterns. If a dangerous situation is identified a direct interaction with the vehicle control might be necessary in order to avoid a collision with some obstacle. Having formalized the current situation and possible actions of traffic participants future world states can be computed ("possible worlds"). This allows for identifying risks in the near future.

The main task of the behavior decision is to create a short-term plan about the next actions of the vehicle. Here, the next mission goal (from the mission planning component) and the current situation must be taken into account. This also includes the plans of other traffic participants which might interfere with the own plan. The risk assessment on this level evaluates possible conflicts in the plan.

Mission planning is on the most abstract and least critical (w.r.t. time) level. Here, decisions are made on a very high level, e.g., for basic strategies (e.g., economic vs. time-saving driving) or route planning. The selected goals are passed to the behavior decision component where planning is performed on a more detailed level.

3. Qualitative Scene Representation

We propose a symbolic representation of the world within the higher layers of the architecture. The quantitative data originating from the sensors is mapped onto a qualitative abstraction. This builds the basis for higher level tasks like situation assessment, planning, and behavior control. In order to create such a representation, time series of different measures are divided into intervals by monotonicity-based or threshold-based segmentation algorithms [18]. This leads to time intervals for different properties of objects or object pairs, e.g., intervals where the distance between two objects decreases monotonically, or intervals where the velocity of an object can be described by a qualitative class (e.g., "high speed"). Using such an abstraction spatiotemporal patterns can be described in a human comprehensible way, e.g., "A approaches B" if the distance between those two objects decreases monotonically. The temporal dimension is represented by time intervals. This representation can be easily mapped to a qualitative representation like Allen's interval logic [1].

In order to create such a qualitative scene representation qualitative mapping modules have to observe different quantitative time series or have to obtain information from other sources (e.g., object classification modules). The qualitative mapping is done cyclically. During each cycle an update of the knowledge base (KB) is performed, i.e., new facts are inserted into the KB or existing intervals are extended (if a relation is still valid). The performance of the mapping cycles is crucial as it must be fast enough to provide information to the higher level components in order to allow the intelligent vehicle to act in time.

Our knowledge base allows for storing relevant information for describing traffic situations, e.g.:

- Object classes: This includes classes (e.g., truck), class properties (like capabilities or special traffic rules for a class), class hierarchy, and the assignment of instances to classes.
- Topological information: In order to represent the position of dynamic objects in relation to the ground regions RCC-5 is used in this approach [2]. With these relations it can be represented whether an object region is disconnected, overlapping, inside, part of, or (spatially) equal to a ground region.
- Spatial relations: It is useful to use other spatial representation in order to represent relations between objects, e.g., before/behind relations from an egocentric point of view.
- Speed information: Information about speed and acceleration of single objects (e.g., high speed, decelerating). In this domain lateral speed, acceleration and position (w.r.t. to a lane) are also important.
- Distance information: Distance classes and the development of distances between object pairs (e.g., close, approaching; cf. [19]).
- Road network: Information about roads, lanes, junctions, lane regions and their connectivity. This is needed in order to know which region transfers are possible and allowed.
- Traffic situation: Different information about signals, signs and traffic rules (possibly assigned to lanes and thus to vehicles on these lanes).
- Background knowledge: Here, different rules can be set up in order to allow for deriving information from atomic facts, e.g., the definition of a one-way street (if all neighboring lanes just allow for driving in the same direction).

4. Knowledge-Based Risk Assessment

This section introduces our approach to knowledge-based risk assessment. In the following subsections the representation of risk patterns, the use of an inference engine for pattern matching, and gaze control as application are presented.

Risk Patterns

We define a risk pattern as an abstract description of a situation where certain objects are dangerous for the own vehicle or some other traffic participant. The patterns are based on the qualitative representation in the knowledge base. Complex patterns can be composed of the different basic predicates. Allen's temporal relations between these predicates can be used for a more concise definition of risk patterns. Risk patterns extend the pattern description described in [15] by the definition of risk variables and corresponding risk values.

In the patterns "a child approaches the lane where the car is driving" or "an unknown object is moving fast at a close or medium distance" risk values would be assigned to the objects "child" and "unknown object".

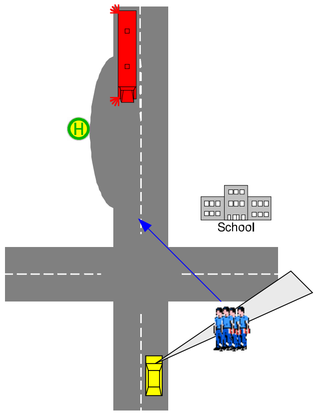

Figure 3. Illustration for gaze control to dangerous objects (children approaching bus)

A risk pattern for a child that approaches at a high speed a bus stop where also a bus is approaching (see Fig. 3) can be represented by[1]:

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approaching(child, busstop),
speed(child, fast),
approaching(bus, busstop).
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Pattern Matching

A pattern matching module observes the KB and notifies the risk assessment if certain patterns are detected. In each risk assessment cycle all risk patterns are evaluated and all valid assignments are derived by an inference engine. An assignment maps constants (i.e., objects) to variables. The inference engine just returns valid assignments w.r.t. the defined pattern and its temporal interrelations.

For all objects which are identified as risky by at least one pattern, a risk value is assigned. If more than one pattern matches for an object, the risk value is computed by taking into account all values of the matching risk patterns. Right now we use a simple risk function by assigning the maximum risk of all matched risk patterns for a single object, i.e., if an object is risky due to more than one pattern the highest risk value is assigned.

The risk assessment component continuously analyses the KB triggering further action on every risk pattern found. The result of the risk assessment is a list of dangerous objects with their respective risk values (Fig. 4). This list of risky objects is available for the behavior decision for gaze control.

Gaze Control

More attention should be paid to objects with high risk values, e.g., if their class membership is not recognized, if they constitute a very high danger, or if their behavior is known to be highly unpredictable. It is crucial to get further, more

[1] This is a simplified representation for a better understanding.

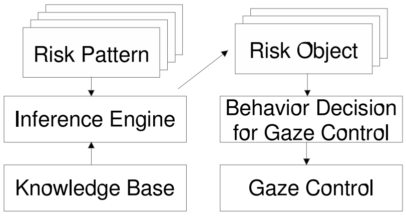

Figure 4. Knowledge-based risk assessment and gaze control

detailed information about such objects, thus they should be especially considered during perception of the environment. Advanced vision systems as proposed by Dickmanns [8] enable intelligent vehicles to control gaze and pay attention to certain important regions of the environment.

The approach presented here identifies possibly dangerous objects which should be focused by the vision system. Based on the risk values it can be decided in what order and to which extent objects are to be examined. This leads to knowledge-based behavior decisions for gaze control (Fig. 4).

The behavior decision for gaze control selects which object should be focused in the next gaze control cycle. We propose a simple scheduling where the most risky object is focused (if it was not examined in the cycle before). In order to prevent objects with low risk values from being ignored forever due to other objects with higher risk values the risk value of all non-examined objects is increased by a constant in each cycle. Achieving optimal scheduling was not the main focus of this work. Scheduling algorithms are well-investigated, e.g., in the field of operating systems.

5. Experimental Evaluation

For the evaluation of our approach a prototype was developed. The ASKOF demonstrator allows for setting up traffic situations with different regions (like roads, lanes, crossings) and dynamic objects (traffic participants). The movements in the simulation are mapped onto the qualitative representation which is shown in Section 3. For the qualitative mapping different mapping modules were realized, e.g.:

- **SpeedMapper**: Creates intervals with different speed classes (e.g., high speed) and the development of the speed (e.g., acceleration).
- **DistanceMapper**: Creates intervals with different distance classes (e.g., far distance) and the development of the distance (e.g., approaching).
- **ClassMapper**: Assigns the recognized class(es) to objects in the dynamic scene.
- **TopologyMapper**: Creates the topological information between objects and ground regions.
- **RelativeDirectionMapper**: Assigns egocentric direction information relative to the direction of an object (e.g., before/behind).
- **LateralPositionMapper**: Creates intervals with different lateral positions within a lane (e.g., left, center, right) and the lateral movement (e.g., moving left, moving right).

The different mapping modules create and update facts representing the belief about the world and assert them to the KB. For the ASKOF prototype we decided to use F-Logic as representation language because of its representational power [11]. As implementation we used Flora-2 [16], [28] which is based on XSB [23], [24]).

Different sample risk patterns have been defined. In Table 1 the different patterns and their corresponding queries and risk values are shown. S and E represent the start and end values of an interval where this pattern is valid. The KB is queried with the risk patterns, all results are collected, and corresponding risk values are assigned to the risky objects.

Table 1. Risk pattern examples and their risk values

Risk pattern	Formalization	Risk value
Dynamic object in medium distance	maxDistHolds(medium_distance, Actor, iv, S, E), relationHolds(ahead, Actor, iv, S, E),isMemberOfClass(Actor, dynamic_object)	0.1
Unidentified object	isDirectMemberOfClass(U, object)	0.5
Child ahead in close distance, low speed	dynamicObjectPropertyHolds(iv, speed, slow, S, E), maxDistHolds(far, Actor, iv, S, E), relationHolds(ahead, Actor, iv, S, E), isDirectMemberOfClass(Actor, child)	0.6
Child ahead in close distance, medium speed	dynamicObjectPropertyHolds(iv, speed, medium_speed, S, E), maxDistHolds(close, Actor, iv, S, E), relationHolds(ahead, Actor, iv, S, E), isDirectMemberOfClass(Actor, child)	0.75
Child ahead in close distance, high speed	dynamicObjectPropertyHolds(iv, speed, fast, S, E), maxDistHolds(close, Actor, iv, S, E), relationHolds(ahead, Actor, iv, S, E), isDirectMemberOfClass(Actor, child)	0.9

For an evaluation the approach was tested on different scenarios. In the basic setting of the scenarios there are four dynamic objects in the scene: the own vehicle, a bus, and two children. In the simulation the own vehicle has a camera attached to the car body which can be directed to focus different objects. The experiments show that risky objects are identified correctly and that the gaze control is directed towards these objects. The gaze control scheduling algorithm mentioned above causes the camera to look at different objects at each gaze control cycle. Fig. 5 shows a screenshot of the ASKOF prototype. On the right three tables give information about gaze control, risk assessment, and pattern matching. The table at the top shows the objects which currently have been identified as risky. The object presently observed is marked with a red box. The table in the middle shows the history of the risk objects. The table at the bottom shows all patterns that have matched so far.

6. Conclusion

In this paper we presented an approach to knowledge-based risk assessment. This approach presumes a qualitative scene representation which has to be created by a qualitative map-

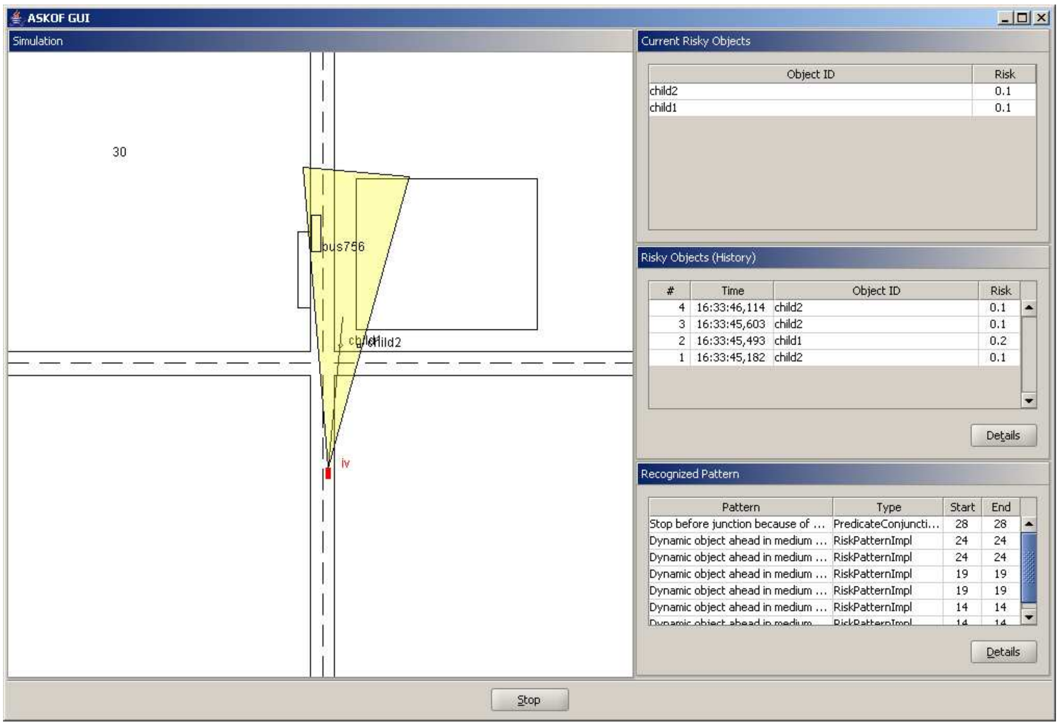

Figure 5. Screenshot of the ASKOF prototype

ping. Risk patterns are defined by combining different predicates from the KB and possibly setting them into temporal interrelations. Relevant information about the scenes are stored in a KB. The KB is queried in order to identify dangerous objects. The different objects identified by the risk assessment are focused by gaze control.

Existing approaches for recognizing or avoiding dangerous situations are usually not generic and do not allow for integrating background knowledge, i.e., very often these approaches are specialized in performing one single task (e.g., warning the driver that a lane change might be dangerous). Some situations demand background knowledge to be taken into account in order to accurately assess a risk value. For non-standard or complex traffic situations (e.g., in cities) it is usually hard to formulate all possible aspects relevant for risk assessment. A knowledge-based approach allows for realizing abstract rules and background knowledge and to use an inference engine in order to evaluate a situation.

Future work will address the learning of behavior patterns and their application in order to create adaptive intelligent agents. It has to be investigated to what degree the performance of agents can be increased by learning and applying such patterns.

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