Improved Information Processing for Cooperative Vehicle Safety Applications

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Abstract

Current Vehicle-to-Vehicle and Vehicle-to-Roadside communication based on IEEE 802.11 cannot guarantee a reliable dissemination of situational information which is required for Situation-Aware Driver Assistance Systems. By using a local Knowledge Base which manages the situational information, the drawbacks of the absence of congruous situational information for the hazard detection can be mitigated. Our work identifies four requirements which have to be fulfilled by this Knowledge Base.

The objective of this paper is to show the potentials and benefits of using Bayesian Networks for the processing of uncertain and missing information. Bayesian Networks provide an optimal solution for the management of situational information in local Knowledge Bases and thus we suggest to use Bayesian Networks for the early and reliable hazard detection in Situation-Aware Driver Assistance Systems.

1 Introduction

Every year about 40,000 people die on European roads [1]. They are fatalities as a result of more than 1.4 M accidents [1]. Countermeasures distinguish between *Active* and *Passive Safety Applications*. Passive Safety Applications react on the incidence of an accident or the definite indication of an accident and thus reduce the number of fatalities but not the number of accidents. In contrast to this an Active Safety Application is any application that tries to prevent accidents. Active Safety Applications intervene at the first indication of a potential accident situation (in the remainder also called hazardous situation) and thus act proactively trying to prevent the accident.

To detect these hazardous situations applications have to collect situational information and draw conclusions using this situational information. Currently, such applications merely use a small subset of the available information and therefore are very restricted to the detection of a small number of hazardous situations. Extending the applications with broader knowledge about their environment (e.g. overall traffic situation, pavement conditions, etc.) will enhance their capability of recognizing hazardous situations earlier, more reliably and with a higher precision.

Up to now the basis for gathering situational information is the in-vehicle sensor system. Using only this local information limits the detection of hazardous situations to a restricted perspective. A challenge is the exploitation of the sensors of other vehicles in the surrounding as well, resulting in an extended situational awareness. To achieve this extended situational awareness, information produced by remote sensors has to be disseminated to the surrounding vehicles (see fig. 1). Analyses [2] have shown that a suitable wireless communication technology for the information dissemination is given by IEEE 802.11 [3]. For coordination of multiple nodes joining one and the same *Independent Basic Service Set (IBSS)* IEEE 802.11 uses *Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA)* [4]. Although CSMA/CA works well under some circumstances, it cannot guarantee a reliable dissemination of situational information in all cases. This fact poses a challenge for the detection of hazardous situations in Active Safety Applications.

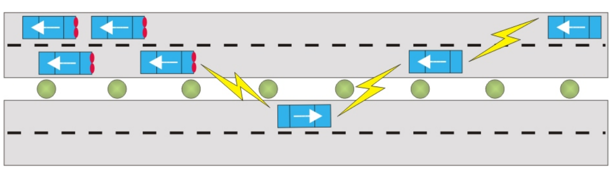

Figure 1: Traffic Jam Warning

The remainder of this paper is structured as follows. Section 2 illustrates the problem of CSMA/CA causing the unreliable knowledge dissemination. Section 3 shows the requirements for solving the problem in a smart knowledge base. The following section 4 presents a suitable solution to manage uncertain information in the Knowledge Base. The paper ends with a conclusion and outlook in section 5.

2 Unreliable Knowledge Dissemination

To enable the cooperative awareness of Situation-Aware Driver Assistance Systems [5], situational information has to be disseminated between vehicles by means of wireless networks. Basic information that may be relevant for the surrounding vehicles are for example the position, direction and motion parameters, as well as vehicle characteristics such as height and weight. But there is also other relevant information produced by measurements of several other sensors such as wheel, rain or brightness sensors or the state of the indicator signal or the steering wheel.

Packaging all this information into a message leads to messages with a size up to a few hundred bytes which have to be disseminated several times per second [6]. Torrent-Moreno et al. [7] simulated the message dissemination based on IEEE 802.11 and found that the probability of message reception in a distance of 100 meters from the sender may fall below 20 % under certain conditions.

The message loss is based on the concurrent medium access of different terminals and thus collision and destruction of the exchanged messages. This is caused by two or more terminals randomly performing the medium access at the same time or two or more terminals (not in inference/carrier sense range) using the medium simultaneously in order to exchange a messages with one or more terminals inside the intersection of their interference and transmission range (see fig. 2). The latter is known as the Hidden-Terminal-Problem [8]. In conventional IEEE 802.11 networks mainly using unicast messaging a Request-To-Send/Clear-To-Send (RTS/CTS) approach is used to apply a

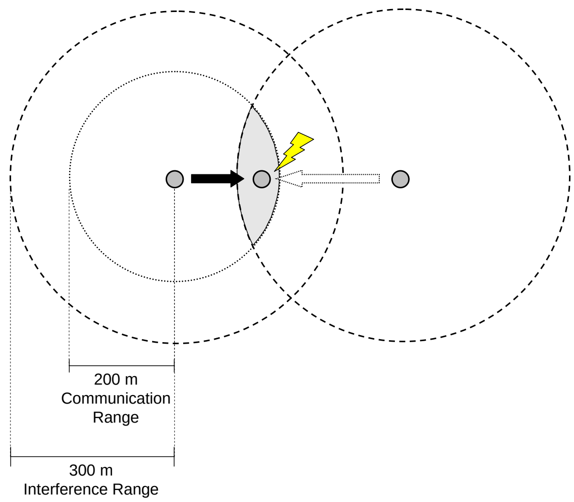

Figure 2: Hidden-Terminal-Problem

virtual reservation of the medium [3].

For the dissemination of situational information mainly broadcast messaging is applied because it needs less bandwidth compared to iterative unicast messaging. Furthermore the feasibility of using unicast messaging for situational information dissemination is limited because of the anonymity in the highly dynamic environment. Since in IEEE 802.11 there is no RTS/CTS mechanism for broadcast messaging, [9, 10, 11, 12] present solutions to use the RTS/CTS approach in broadcast environments as well. Unfortunately all of these solutions increase the number of medium accesses and are not feasible for highly dynamic networks with anonymous terminals [13]. Furthermore, the RTS/CTS approach cannot prevent message collisions completely and hence the risk of unrecognized message loss persists [14].

Summarizing, it has to be said that currently there is no possibility to guarantee a reliable information dissemination because of the above mentioned reasons. But this problem can be addressed by actively approaching the problem on upper layers. Therefore, we propose a local information management which does not rely on periodic reliable information exchange. This knowledge base is to a certain extent autonomous and permits the hazard detection with uncertain information.

3 Local Knowledge Bases

For the early detection of hazardous situations every vehicle equipped with the Situation-Aware Driver Assistance System has an integrated local Knowledge Base. The Knowledge Base contains situational information. On the one hand this situational information is obtained by the own vehicle (e.g. measured by the local sensor system) and on the other hand originates from other vehicles in the vicinity. Additionally, situational information may be gathered from an infrastructure system. Such infrastructure-based sources of information are for instance roadside units, satellites, local broadcast transmitters (using e.g. DMB, DAB) or cellular networks (e.g. GSM/UMTS).

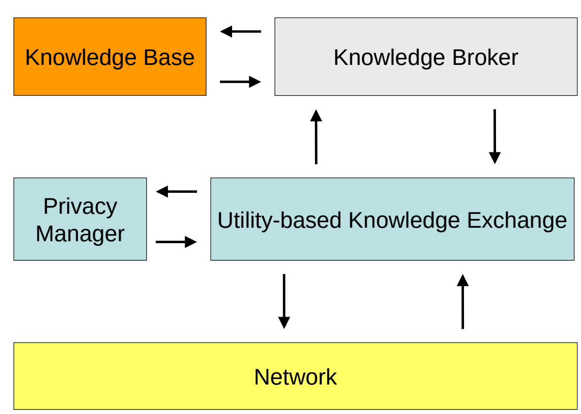

Figure 3: Knowledge Exchange [5]

The Knowledge Base interacts with other architectural components via the Knowledge Broker (see fig. 3). The Knowledge Broker provides a standardized interface for retrieving and integrating situational information into the Knowledge Base. The dissemination or request of situational information is triggered by the Utility-based Knowledge Exchange module [5] which has access to the situational information via the Knowledge Broker and may send and receive situational information over the wireless network interface. To preserve privacy constraints a module called Privacy Manager controls the knowledge exchange with regard to predefined or user-defined privacy issues.

For the hazardous situation detection a reasoner retrieves the necessary situational information from the Knowledge Broker and draws conclusions using this situational information. The situational information has to fulfil the following properties: it has to be up-to-date, pertain to the appropriate position, the appropriate driver, the appropriate vehicle, etc. In other words situational information has to correspond to the target context. If the context matches its target context, we call the situational information *congruous*.

Context that is relevant for the friction coefficient is for example:

- time
- location
- vehicle characteristics (e.g. tread depth)
- pavement condition

Currently, if the hazard detection algorithm has no access to congruous situational information, the algorithm has to use incongruous situational information or the algorithm fails. According to this, conventional reasoning processes provide no appropriate result or they provide no result at all. Hence hazardous situations may not be detected.

Therefore, we identified four requirements that have to be fulfilled by the Knowledge Base in order to enable a continuous and reliable hazard detection:

1. Provisioning of congruous situational information to current context:

A central requirement of the Knowledge Base is the continuous capability to provide congruous situational information even if only incongruous or even no information updates are available. Hence the detection of hazardous situations which is based on availability of congruous situational information depends not on constant updates of situational information. The lack of updates may for instance be the result of the unreliable wireless information dissemination, especially the Hidden-Terminal-Problem mentioned before. But it may also be the effect of the malfunctioning of sensor systems or privacy issues, if for example situational information must not be disseminated due to privacy constraints.

A priori knowledge about situational information, especially its interrelation and behaviour due to changing context, has to be used to predict congruous situational information without appropriate updates. Of course it is not possible to predict a situational information accurately in every case but in almost every case there is the possibility to determine a certain belief in the state of the situational information. Thus by observing the change in context (e.g. elapsed time) the belief of the state transition concerning the situational information can be determined.

2. Provisioning of situational information to future context:

A second requirement of the Knowledge Base is the prediction of future states of situational information. This feature refers to the same functionality as for the first requirement because there is, in general, no sensor data concerning future states available and thus no appropriate updates for situational information lying ahead. By exploiting the knowledge about the state change behaviour of the situational information the belief in future states can be determined.

3. Integration of situational information:
Furthermore, the Knowledge Base needs the capability to integrate updates of situational information. These updates concern congruous as well as incongruous situational information. While congruous situational information refers to regular updates of the Situation-aware Driver Assistance System, incongruous situational information is information that refers to different context. Updates of incongruous situational information occur if the situational information is generated in different context. This may be for instance a friction coefficient determination a certain time ago and/or a certain distance away and/or concerning a different vehicle. The Knowledge Base needs the functionality to integrate such incongruous situational information as well.

4. Maintaining consistency:
Last the Knowledge Base has to maintain a consistent state concerning the whole set of situational information. Therefore, the system has to verify consistency, every time new or updated situational information is integrated into the Knowledge Base.

As mentioned in the introduction the overall objective of Active Safety Applications is to prevent accidents. There is various situational information indicating hazardous situations. This interrelation between situational information and hazardous situations is not based on implication but indication. There is no stringent dependency. The dependency relies on probabilistic indication. This indication can be used to express that a set of situational information increases the probability of the occurrence of a hazardous situation. There is a probabilistic causal relationship between the occurrence of a hazardous situation and a set of situational information. These relations can be modeled in a complex system consisting of situational information and their causal dependencies. An appropriate way for the description are probabilistic graphical models.

4 Bayesian Networks

Probabilistic graphical models are an implement to understand and work with complex systems and uncertainty by exploiting the findings of graph theory and probability theory [15, 16]. Probabilistic graphical models with directed edges are called Bayesian Networks or Belief networks (BNs).

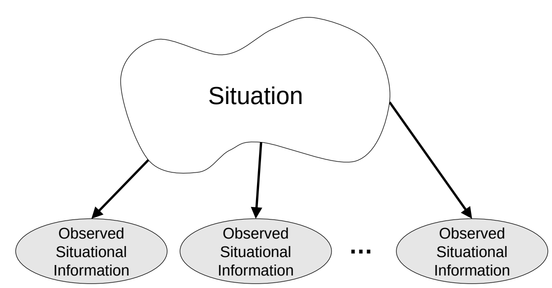

Figure 4: Situation observation

A Bayesian Network consists of a set of nodes which represent random variables and directed edges representing conditional dependencies. Every node has an associated conditional probability distribution (CPD) (or prior distribution if there are no parent nodes) specified in a Conditional Probability Table (CPT) if the node represents a discrete random variable or a conditional Probability Density Function (PDF) if the random variable is continuous.

The conditional dependencies depicted as directed edges may be seen as causal relationships, whereby the strength of causal relationships is encoded in the CPT or PDF [17]. A conditional probability associated with an edge from A to B can be regarded as the probability that A causes B. Thus, the probability of B given its Markovian parents $A_1, ..., A_n$ is the conditional probability $P(B|A_1, ..., A_n)$ [18].

A simple model structure of situational information for Active Safety Applications consists of one or more nodes directly observed by the sensor system being in a causal relation to the node indicating the hazardous situation (see fig. 4). Here, it has to be stressed that the information indicating the hazardous situation influences the situational information observed by the sensor system and not vice versa.

In contrast to observable nodes, nodes that can not be observed, e.g. by the sensor system, are sometimes called hidden nodes [19]. A hidden node indicates for instance the state of the hazardous situation. The state of the hazardous situation influences a set of states observed by the sensor system. By providing evidence to the observable nodes, conclusions on the hazardous situation can be drawn using the conditional dependency in reverse direction. This is sometimes called diagnostic reasoning because conclusions are drawn from a given effect in order to determine the underlying reason. In this sense the reason corresponds to the hazardous situation and the effect refers to the data provided by the sensor system.

Figure 5 shows a Bayesian Network that additionally takes into account different perspectives on the complex situation. A situational information is assigned to one perspective. Each situational information can be observed by $n \geq 0$ sensors. So every sensor state depends on a situational information and the situational information has a causal influence on the hazardous situation. According to the example, the situational information *Rain* has a causal influence on the observable nodes *Wiper Settings* (here the manual switching of the wiper is meant) and *Rain Sensor*. The observations of the *Rain Sensor* and the *Wiper Settings* are effects of the situational information *Rain* and thus conclusions can be drawn to assess the probability of *Rain* given the observations. The belief in the situational information *Rain* influences the probability of a *Hazardous Situation*. The introduction of further perspectives on the situation may combine situational information such as *Temperature* and *Rain* (among others) to assess the friction coefficient which has a causal influence on the *Hazardous situation*.

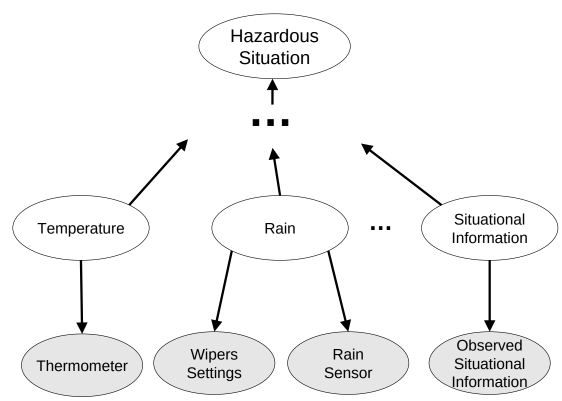

Figure 5: Hazard detection

In order to draw conclusions for the estimation of the hazardous situation, congruous situational information observed by the sensor system has to be available. If all situational information is congruous, that means all required situational information is available and observed in the required context, the diagnostic inference provides a realistic situation assessment. If some situational information is not congruous, but there is already some situational information with varying context available, a belief in the congruous situational information can be obtained by probabilistic inference. This inference is based on the state change behaviour of the situational information due to varying context. The behaviour is either gathered by Bayesian learning mechanisms or given by domain experts [17]. The state change behaviour is expressed by a CPD. Fig. 6 shows an extract of a Bayesian Network illustrating the state change behaviour due to varying temporal context of a specific situational information.

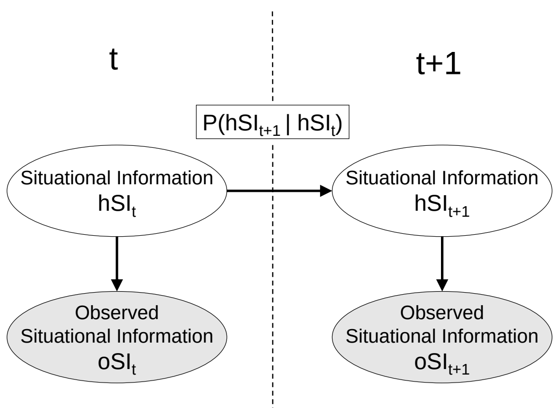

Figure 6: State change behaviour

This type of Bayesian network is also called dynamic Bayesian Network. Dynamic Bayesian Networks represent time-discrete stochastic processes [19]. They consist of collections of random variables partitioned into input, hidden and output variables. The random variables are separated into different time slices.

Dynamic Bayesian Networks may also be used to express the dynamic of other contextual aspects. Instead of specifying different slices separated by point in time, the slices may also be separated by their position, type of vehicle or characteristics of driver.

The usage of dynamic Bayesian Networks is not limited to the case when incongruous situational information is available. By exploiting prior knowledge given by Bayesian learning mechanism or domain experts, probabilistic inference will deliver a situation assessment even if no situational information is available. Thus conclusions can be drawn even without updates of situational information.

This functionality also enables the prediction of future states of situational information which is required for an early detection of hazardous situations (see second requirement of the Knowledge Base).

Otherwise, if updates of situational information are received, this information has to be integrated into the Bayesian Network. This can be done by bringing evidence into the Bayesian Network. The new evidence propagates its updated information through the network. Like that it is irrelevant whether the situational information is congruous or incongruous regarding the target context because the situational information received by the update always provides evidence to the appropriate observed node. That means the evidence observed under certain context is integrated into the observed node concerning exactly this context. If for example an update of situational information observed in time slot t is received at $t+1$, the evidence is integrated into the appropriate observed node oSI_t at time slot $t+1$ (see fig. 6).

By using Bayesian Networks inconsistencies generated by new or updated situational information can be prevented. The propagation of evidence assigns an implausible or impossible occurrence probability to inconsistent states. To achieve this, inconsistencies have to be identified and integrated into the CPD. This can be expressed for instance by assigning a low probability to the occurrence of *Rain* in combination with a *Temperature* of `-20` degree Celsius.

Summarizing, Bayesian Networks are a suitable mechanism satisfying the requirements of local Knowledge Bases (see sec. 3). They provide the possibility to determine situational information without appropriate updates, to predict future states, to integrate updates of situational information and to maintain consistency.

5 Conclusions

This paper has identified a serious problem of Vehicle-to-Vehicle and Vehicle-to-Roadside communication, namely the unreliable information dissemination. Among others this is caused by the Hidden-Terminal-Problem. Using a Knowledge Base that manages congruous as well as incongruous situational information without necessity of regular updates improves the operation of a Situation-Aware Driver Assistance System. This enables the hazard detection in environments exposed to unreliable communication. Furthermore, the Knowledge Base has to provide the capability to predict situational information concerning future states, to integrate updates of situational information and to maintain consistency.

We found that these requirements can be realised by Bayesian Networks. The exploitation of the probabilistic causal dependencies of Bayesian Networks facilitates the transition of incongruous to congruous situational information. Reasoning on the Bayesian Network hence remains operational and permits an assessment of the situation. This improves reliability of the Situation-Aware Driver Assistance System, although the situational information dissemination is exposed to the unreliable information exchange.

Our next steps are to implement such Bayesian networks and analyse their performance in a simulation of communications network behaviour and real traffic situations.

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