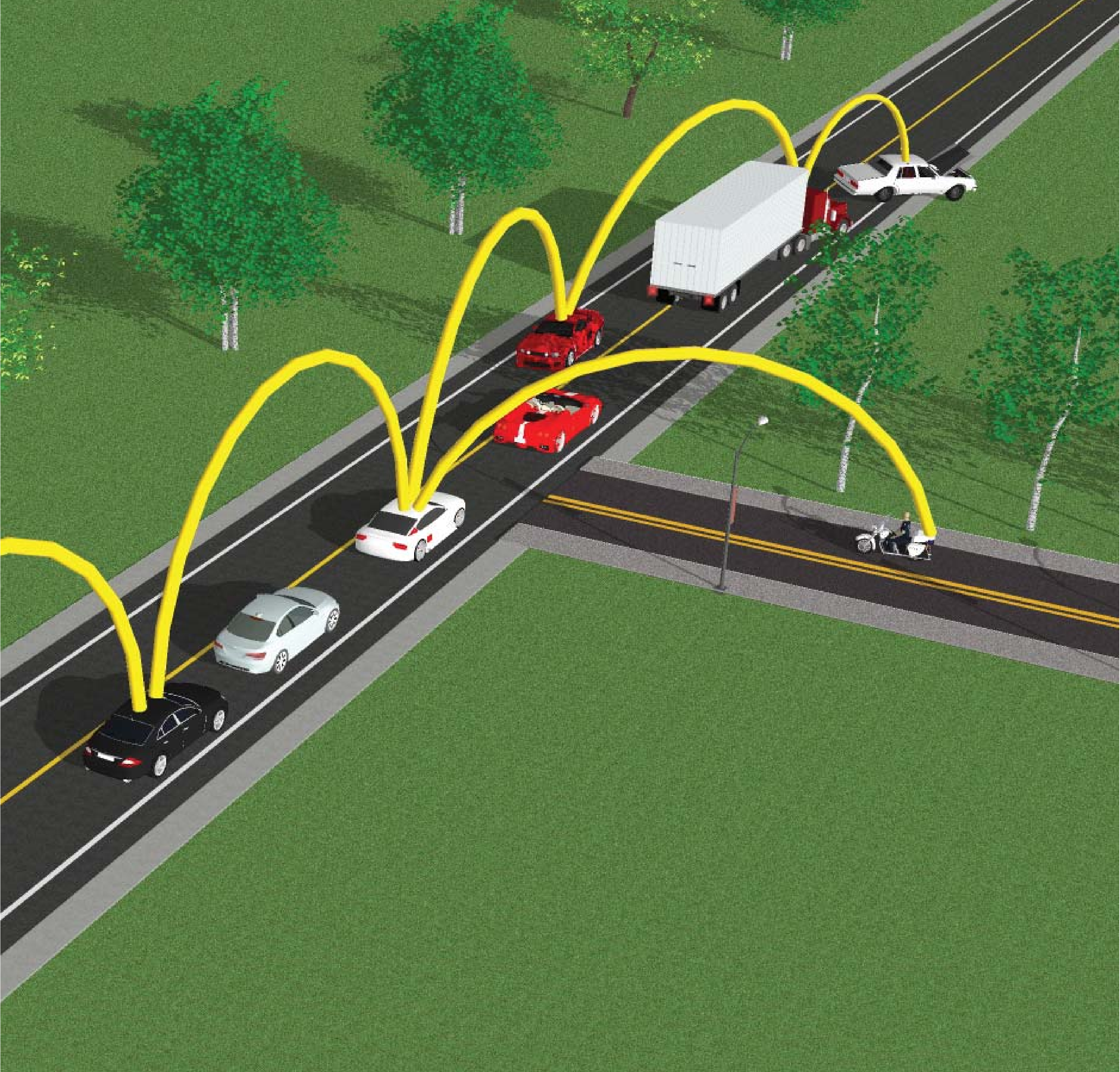

Cooperative Situation Awareness in Transportation

Integration of Information and Communications in Intelligent Transportation Systems

Matthias Röckl

COOPERATIVE SITUATION AWARENESS IN TRANSPORTATION

Integration of Information and Communications in Intelligent Transportation Systems

Dissertation
by

Matthias Röckl
born in Munich, Germany

submitted to the Faculty of Mathematics, Computer Science and Physics of the Leopold-Franzens-University of Innsbruck

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Supervisors: Prof. Dr. Thomas Strang
(Leopold-Franzens-University of Innsbruck, Austria)
Prof. Dr. Javier Manuel Gozálvez Sempere
(University Miguel Hernández of Elche, Spain)

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Abstract

Intelligent Transportation Systems (ITS) became a fast moving field of research in the last decades, in particular in the context of continuously growing mobility and a high employment of resources starting from energy and material consumption to travel time and finally the human life. As it has already been experienced in other application areas, the introduction of communications technology is able to bring a revolutionary change in structures and behaviors long-believed to be carved in stone.

The main idea behind this thesis is the usage of information not as a mere placeholder, e.g. a field in a static message, but actively utilizing its content and dependencies. This requires an estimation of the actual worth of a single piece of information for the entity itself and the entities which are in communication range. This worth has to be the essential driver for the cooperative situation estimation. The active utilization of information and its cooperative dissemination provides the entities the opportunity to become situation aware and detect hazardous or inefficient situations early in advance.

Since information always has a degree of uncertainty which is inherent to information in the real-world problem domain, as we are confronted with in ITS, probabilistic methods will be applied to model situation-relevant information. Conditional probability distributions in state transition models make for the evolvement of the situational information with the progress of time and handle causal dependencies between situational information. Together with a utility-based decision-making process *dynamic probabilistic causal decision networks* provide the functionality to select optimal actions given sequences of inaccurate and incomplete evidences.

This thesis provides concepts and strategies that push forward the exploitation of information in a cooperative way within a probabilistic framework that allows to make various kinds of decisions with maximum utility. For the evaluation of the proposed concepts, the exemplary application *Cooperative Adaptive Cruise Control (CACC)* has been implemented on the basis of a particle filter which is used for the situation estimation. Initial simulations provided promising results and hence constitute a solid basis for future work in the field of *Cooperative Situation Awareness in Transportation.*

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1 Introduction

Measured in time of transport and communication, the whole round globe is now smaller than a small European country was a hundred years ago.

John Boyd Orr (1880-1971)

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1.1 Intelligent Transportation Systems

Human life in these days is decisively influenced by mobility. In 2006 a European citizen travelled 12838 km in average by motorized means of transport [73]. This amounts to 35 km per day and a mean velocity of more than 2 km/h during the hours awake. The total travel distance constantly increased over the last decades with a growth of about 1.8% per year [73, 16, 40] (see figure 1.1). The total amount of passengers transport is made up of different modes of transport: passenger cars, buses and coaches, airplanes, railway, powered two-wheelers, tram and metro as well as ships. With 72.7 % (2006) passenger cars can be considered as the lion's share [73]. The second largest share is assumed by air transport with 8.6% which finally superseded buses and coaches from 2005 to 2006 (8.3%). If the modal split is analysed over travel time instead of travel distance (with mean velocities from [232]), the mode made up of buses and coaches still has longer periods of use with 17.2% in contrast to air transport with 0.6%. Passenger cars again have the largest share (see figure 1.1).

Besides passenger transport, the transportation of goods is also dominated by road transport with a share of 45.6% in contrast to 37.5% for maritime transport and 10.5% for rail transport [73]. The total amount of freight kilometers amounts to more than 4100 billion kilometers per year (2006) and is subject to constant increase of around 2.8% per annum [73] (see figure 1.2).

Independent of the mode and type of transport it can be said that mobility has been embedded to our modern life as nothing of the sort. Its continuous increase (see figure 1.1 and 1.2) which could be observed over the last decades in industrialized nations shows its exceptional significance. Mobility and transportation is often considered as one of the major cornerstones of industrialization and in this sense can even serve as an indicator for economic wealth [232] as figure 1.2 illustrates.

The rapid growth in mobility which took place over the last decades also entails severe problems. An increasing traffic density, vehicles moving with high speeds and larger travel distances cause a static increase in transportation costs, traffic fatalities and environmental pollution [40]. All of these factors have to be considered for all modes of transport.

Whereas the evolution of transportation of the last two centuries was mainly driven by the development of suitable drive and material technology, there is significant evidence [72, 17, 20, 42] that the upcoming development in transportation will be influenced to a large extent by **information and communications technology (ICT)**. Therefore, *"one is obliged to question whether this new era, with information and knowledge as important resources and with the world-wide introduction of ICT, will alter the 'rules' of the 'transportation age'"* [51]. Whereas in the past, vehicles primarily were seen as autonomous entities sharing merely the same infrastructure network, in the future vehicles are expected to share also information and knowledge. Thus, questions regarding a distributed information network become relevant and have to be solved. Certainly, one of the most fundamental questions is how to organize information within the distributed network of vehicles maybe also including intelligent infrastructure or even pedestrians which get involved by crossing the vehicle infrastructure.

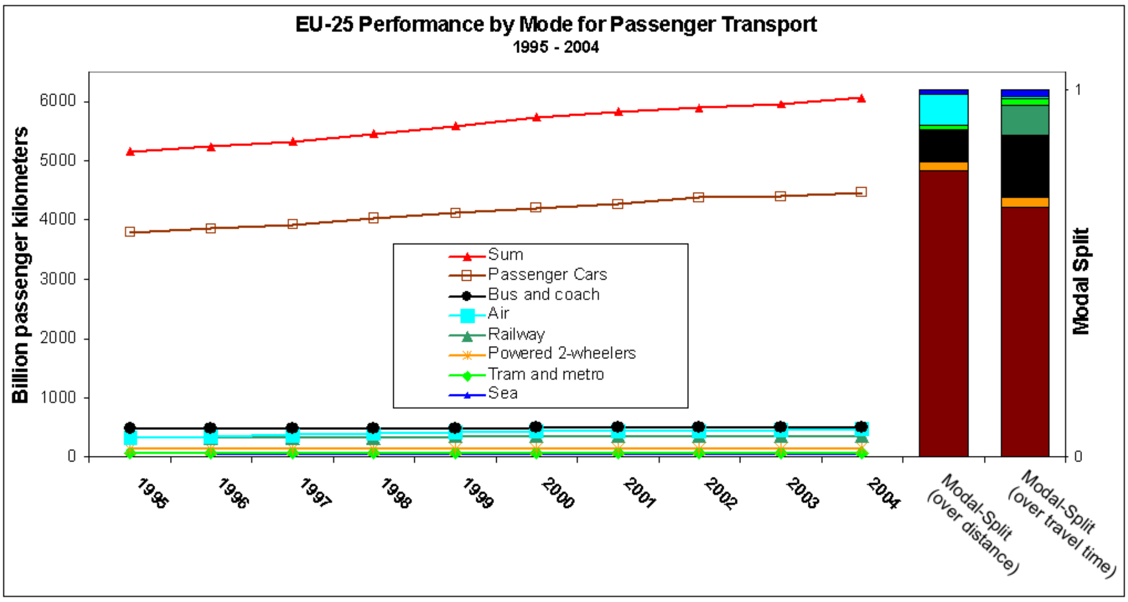


Figure 1.1: Passenger travel distance by mode of transport and modal split over distance and travel time (1995-2004) (based on EC Statistical Pocketbook [16])

There are two fundamental concepts in this expectation of future transport which are **information** and **communications**. The application of these concepts constitutes the future vision of transportation which often is referred to as **Intelligent Transportation Systems (ITS)** . According to [1] *"ITS is the integration of* ***information and communications*** *technology with transport infrastructure, vehicles and users"*, thereby *"ITS improves transportation safety and mobility and enhances productivity through the use of advanced* ***information and communications*** *technologies"* [7]. In this sense ITS brings together and fundamentally dovetails the two research areas of information theory and communications theory in the context of transportation.

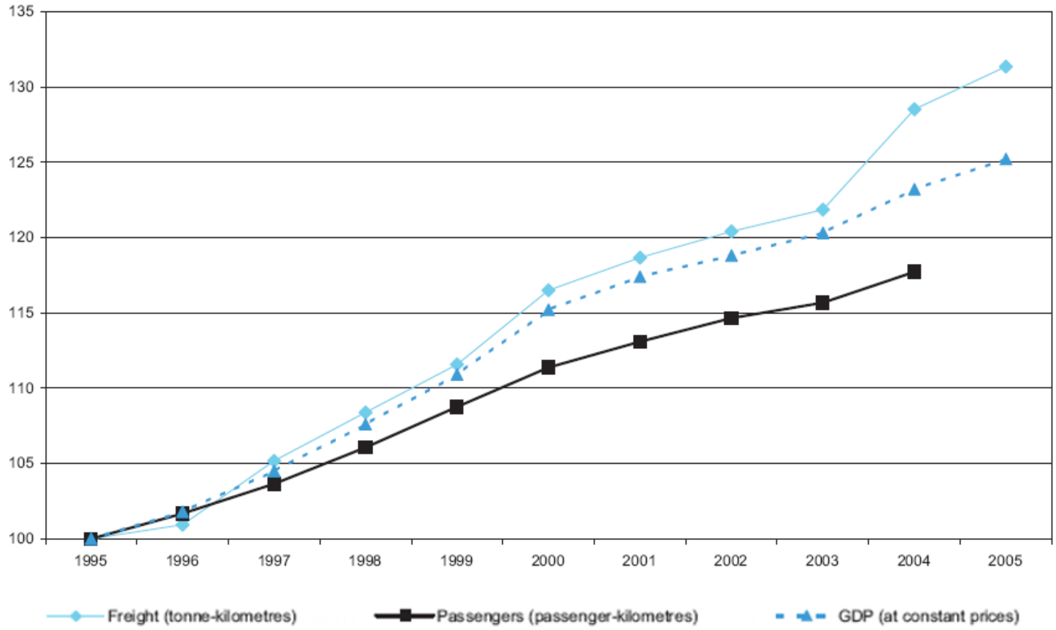


Figure 1.2: Variation of freight and passenger transport compared with Gross Domestic Product in the European Union (1995-2005) (source: EC Panorama of Transport [40])

1.2 Cooperative Situation Awareness in Road Transport

Between all modes of transport since decades road transport has the highest growth rates in the industry nations (more than 6% for road freight transport in Europe in 2007 [187] and more than 4% in passenger transport in Europe in 2006 [73]). The modal split assigns more than 55% in freight transport and more than 80% in passenger transport to road transportation [73]. In the emerging nations the road transport mode is expected to have an even higher growth rate, relative as well as absolute, forecast for the upcoming years [232]. Thus, road transport will be one of the major modes of transportation all around the world for the next decades although a softening of the modal borders and an increased relevance of inter-modality of transportation is to be anticipated [232].

Dedicated improvements of road infrastructure by the integration of information and communications technology to specific use cases has already taken place. Examples are the deployment of induction loops, Variable Message Signs (VMS) and centralized Traffic Management Centers (TMCs), all inter-connected by fast wired communication networks [192, 71, 126]. This enables that information of the current traffic density gathered by induction loops is communicated to TMCs and further to VMSs in order to optimize traffic efficiency from the infrastructure perspective.

This first step of incorporating information and communications technology to transportation infrastructure has the advantage that all communicating nodes are static and known a priori, network design is dedicated to the specific fields of application and central control instances can easily be deployed. All this is not the case for the deployment of information and communications technology to moving vehicles which is a further promising point of action for ITS. The communication network topology of communicating road vehicles is a priori unknown, subject to continuous and fast changes and ubiquitous control infrastructure is complicated to deploy and cost-intensive. Thus, new concepts to tackle these problems are strongly required.

The integration of information and communications technology into the vehicles in form of improved driver assistance systems is often referred to as *Advanced Driver Assistance Systems (ADASs)*. In contrast to conventional driver assistance systems (e.g. cruise control or the Anti-lock Braking System (ABS)) which merely take vehicle-internal information such as speed or wheel slip into account, ADASs have the objective to support the driver in her/his task of leading the vehicle taking into account an extended sensing horizon including additional information of the current surrounding [235, 260, 213]. Thus, information is gathered and communicated beyond the borders of the individual vehicle and utilized in a decentralized way in order to optimize application utilities.

Extending a system for distributed information opens a completely new field of transportation research related to the concepts of shared understanding [246] and exploiting the real **worth of information**[1]. The omnipresent focus of the system on this worth of information is one of the major contributions of this work and requires a general rethinking of present approaches. The information per se is worthless if its meaning and implications are unknown. The information always has to be contextualized to the situation of concern. The contextualization can then be used as an enabler to estimate the actual worth of the information. The concept of utilizing distributed information and treating the information with its actual worth for all entities in the cooperation is denoted as **Cooperative Situation Awareness**. A driver assistance system which uses this concept can be termed as *Cooperative Situation-Aware Driver Assistance System*.

> Cooperative Situation Awareness exploits distributed information beyond the borders of single entities and actively treat information with its worth according to the situation of concern [2]

The main concept which makes up this work hence is the usage of information not merely as a placeholder for one of many measurement values or data fields in a message but with all its implications involved and the worth it has for the entity and all other entities in the cooperation. Thereby, *"the use of information is influenced by the degree of uncertainty in the available knowledge and by the communication flows between knowledge producers and users"* [51]. Consequently, uncertainty has to be actively taken

[1]The term "worth of information" will accompany the reader throughout this whole work and will occur at various locations. The term is used as a general expression for the actual usefulness of a piece of information comparable to the importance or relevance of a piece of information in a specific situation. It shall not be mixed with the terms "mutual information" (see chapter 4.1), "value of information" (see chapter 4.2) or "weight of evidence" (see chapter 2.3.3 and 4.3) which describe concrete algorithms to determine the worth of information

[2]In the remainder of this work we will use such a "blue-box" notation for summarizing statements that have a high worth of information for the reader

into account for a proper situation estimation and if efficient communication is required; in particular, if the communication is not dedicated to a specific field of application and has to be flexible and extendible by design. It has to be operable in situations with sparse traffic and dense traffic as well as in situations with low penetration rates and high penetration rates. Communication has to be feasible for safety-critical applications as well as efficiency or comfort related applications, with high or low external disturbances, and many more factors that might completely change the communication characteristics. This implies that the communication has to adapt itself according to the current bandwidth, latency, reliability, etc. of the communication channel by distributing information with respect to its worth. As an example, an information with high worth, e.g. a collision warning, shall not be cut back due to information with low worth for the receivers, e.g. position information with high uncertainty or a traffic jam warning which has already been repeated dozens of times.

In this case the traffic jam warning which in general is of high importance was contextualized to the situation where already several identical message have been sent. This significantly reduces the importance of a further traffic jam warning. Throughout this thesis it will be seen that information which initially is considered as worthless becomes of high importance and on the other hand information which is considered as highly important becomes irrelevant. This results from the contextualization of the information to the current situation which can be totally different for different entities or different instants of time. The worth of the information therefore has to be one of the major drivers for data-distribution and decision-making with utility maximization.

With these concepts this work contributes to the fields of:

- Uncertainty Management (chapter 2): How to model and work with inaccuracy and incompleteness of information?

- Information Management (chapter 3): How to use, how to organize, how to incorporate information in a dynamic system environment?

- Utility Management (chapter 3): How to deliberate and optimize utilities which are gained by the selection of proper actions?

- Information Exchange and Radio Resource Management (chapter 4): How to identify information with high worth? How to exchange information taking into account its worth? How to optimize the radio resource usage considering the worth of information?

The concepts which are presented in this thesis have a generic character and shall serve as an enabler for various kinds of applications for future ITS. These include for instance cooperative collision avoidance, cooperative black spot warning, cooperative traffic jam detection and many more [55, 19]. It is important to note that this work will not focus on a concrete application but will show the benefit of information and communications theory applied to the transportation domain with the actual worth of information taking into account inherent uncertainty. An application which has been identified as one of the most potential is *Cooperative Adaptive Cruise Control (CACC)* [211, 258, 257] and thus is used in many sections of this work to motivate and exemplify the developed concepts and algorithms. CACC combines the usage of information from in-vehicle target tracking sensors, i.e. radar, lidar or camera, and position information, e.g. from GPS or Galileo, which is wirelessly communicated from the target vehicle. From a technological perspective this combination is perfectly suited to evaluate and characterize the worth of information which depends on the sensor measurements from both kinds of sensing technologies. Thus, CACC has been chosen as the application to evaluate the theoretical concepts on a concrete problem domain.

1.3 Outline

This thesis is structured in 7 chapters. The structure has been designed with the objective for each chapter to be mostly self-contained. Thus, each chapter can be read more or less independently of the other chapters. Required cross-references are marked explicitly. Since no comparable comprehensive work in this field has been done so far, state of the art analyses are broken down to specific sub-problems and are contained in the respective sections. Each chapter starts with a short introduction and ends with concluding remarks and evaluations. A short outline of each chapter is given in the following.

In order to work with information and its implications, a model to express knowledge and explicate its uncertainty has to be developed. Chapter 2 introduces concepts to model situations using probabilistic causal networks. The fundamentals of inference are shown and state of the art in situation modelling will be compared with probabilistic causal networks.

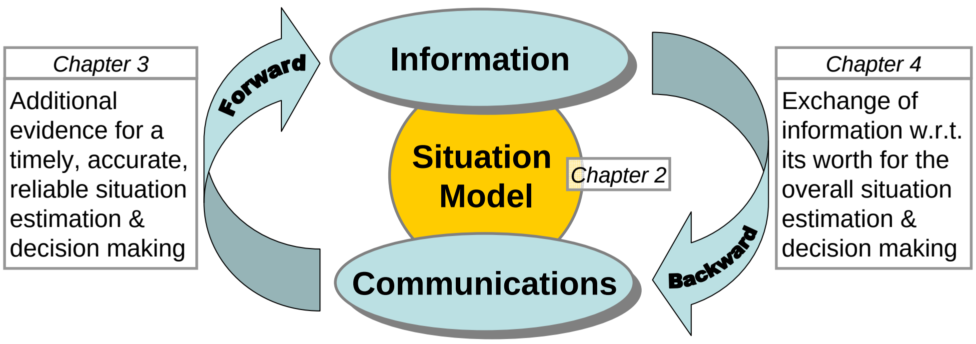


Figure 1.3: Circular integration of information and communications

Chapter 3 is named *Forward Integration: From Evidence to Decisions* and describes the path to reach an optimal decision given a set of evidences from in-vehicle sensors and/or via communications, thereby taking into account the diverse sources of uncertainty (see figure 1.3). Therefore, concepts such as sensor fusion, dynamic system algorithms and decision-making based on probabilistic causal models will be introduced and their application to the problem domain elaborated. Descriptive examples from different kind of ITS applications are used to illustrate the concepts.

Chapter 4 named *Backward Integration: Decisions for optimized evidence exchange* presents diverse approaches to reach an optimized exchange of evidence based on the actual knowledge within the situation model. The identification of the worth of information which an entity possesses or would like to possess is the main driver to optimize the communication of evidence between the distributed nodes (see figure 1.3). Different strategies to calculate the worth of information are introduced and their application to message prioritization, congestion control and opportunistic routing are elaborated.

After the introduction of the theoretical work, the developed concepts will be presented as parts of a prototype implementation of CACC. Chapter 5 will provide an introduction, requirements analysis and detailed system description for CACC which incorporates the concepts introduced in the previous chapters.

A performance analysis of the proposed algorithms will be presented in chapter 6. The chapter begins with a description of the used simulation environment, the models and parameter settings. Subsequently, a detailed comparison of algorithms in different reference scenarios will be given and the performance of the proposed algorithms evaluated. Some of the analyses are specific to the CACC application, in particular if a closed simulation loop is required to assess the whole system performance.

The final conclusions and an outlook to future work will be given in chapter 7.

2 Situation Modelling

The theory of probabilities is at bottom only common sense reduced to calculus; it makes us appreciate with exactitude that which exact minds feel by a sort of instinct without being able oftentimes to give a reason for it. It leaves no arbitrariness in the choice of opinions and sides to be taken; [...] Thereby it supplements most happily the ignorance and weakness of the human mind.

Pierre Simon, Marquis de Laplace (1749 -1827)

2

The main objective of a driver assistance system is to support the driver in her/his task of driving a vehicle. In order to achieve this in an optimal way, the driver assistance system needs to perceive and assess the environment, inform or warn the driver or perform certain actions on the environment at least as good as the driver in the adopted functions. For instance, a longitudinal control function which has to decide on the optimal acceleration of the vehicle needs to be aware of the headway character of the vehicle:

- Is there another vehicle in front?
- What is the safe following distance?
- What is the maximum speed limit on this road?
- Are there any other hazards such as icy pavements or blind bends?
- ...

Figure 2.1 shows an extract of relevant parameters which have an influence on the decision for longitudinal acceleration. Taking all these parameters into account will result in a quite complex system which is not located within an insulated “sandbox” but has to act in an environment with lots of peculiarities. The following listing shows how a driver assistance system relates to its environment according to the classification proposed by Russel and Norvig in [226]:

Fully Observable vs. Partially Observable

If every piece of information is given in the required accuracy and completeness which is relevant to perform the tasks and achieve the envisaged objectives, the environment is called *fully observable*. An example for a fully observable environment is a chess game where every player is able to fully observe the positions of all pawns on the board. If this is not the case the environment can be categorized as being merely *partially observable*. Tasks of transportation such as longitudinal control often are only partially observable due to information which cannot be sensed (e.g. nearby vehicle which are not within line of sight) or can only be sensed with an insufficient level of detail (e.g. nearby emergency vehicle

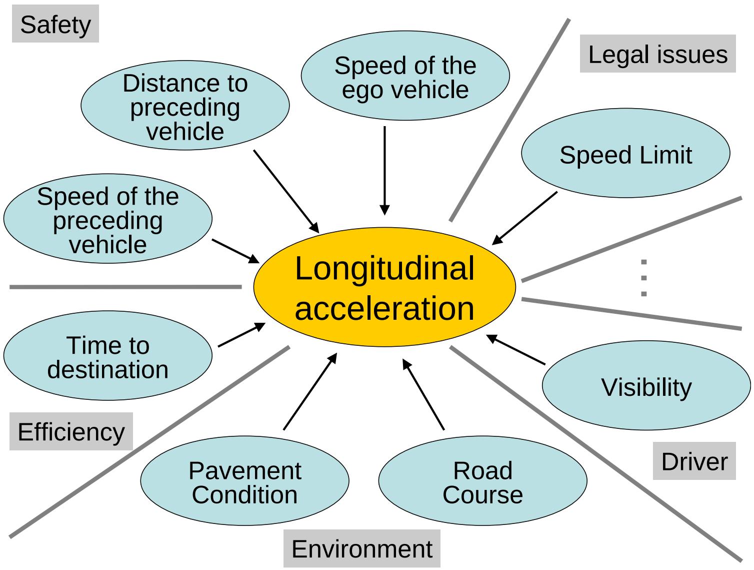


Figure 2.1: Influencing parameters for longitudinal acceleration

can only be heard but is not within line of sight). Therefore, this information has to be refurbished or has to be inferred from afferent information, i.e. information that has some influencing relation (e.g. pavement condition derived from weather information).

Static vs. Dynamic

During the runtime of the system, the environment can be subject to change. If the environment changes even without any interaction of the system, the environment is called *dynamic*. If on the other hand the environment only changes upon an action performed by the system, then the environment is called *static*. Systems in transportation normally have to cope with dynamic environments which will change due to actions of other entities, e.g. other vehicles, or due to natural physical variances, e.g. changing weather conditions or daylight intensity, which are totally independent of any short-term interactions of entities.

Deterministic vs. Stochastic

If in a changing environment the subsequent state of the environment is a deterministic function of the current state plus some additional fully observable input parameters, then the environment can be characterised as *deterministic*, otherwise it is *stochastic*. Tasks in transportation often are stochastic problems. Subsequent states are strongly influenced by the behavior of other entities which cannot be fully observed, such as the intention of the driver of the preceding vehicle or pedestrians unanticipatedly crossing the street.

Discrete vs. Continuous

A description of the environment can be *discrete* or *continuous*. Whereas the former describes the environment in quantized stages, the latter allows a continuous description without any quantization. The distinction can be met for various scales such as time, occurrence probability, intensity, etc. Tasks in transportation often require continuous descriptions or at least a discretization with extremely small quanta in order to cope with small changes and adequate actions respectively. In particular, continuous or at least short consecutive episodes in time are often required.

Episodic vs. Sequential

A further classification is the timely awareness range. If the system takes only the situation in the current episode into account neither looking backward on previous situations nor looking forward to upcoming situations, this is called *episodic*. In episodic environments the action performed in each episode depends merely on the episode itself. Otherwise it is called *sequential*. Tasks in transportation normally have to be regarded as sequential due to protracted process behavior, especially in maneuvering (e.g. an overtaking maneuver) and navigation (e.g. optimal wayfinding). In this examples single-shot actions will probably not succeed because they have to be coordinated over a duration of more than one episode.

Single Agent vs. Multi-Agent

In contrast to a *single agent* environment, a *multi-agent* environment is influenced by more than one agent. In this context an agent is a system that acts based on observations and performs actions on the environment. Among each other, agents can act in a competitive way or cooperatively. Whereas in the former an agent tries to optimize its own objectives without taking into account objectives of other agents, cooperative agents try to optimize global objectives which are valid for all or at least a subset of all agents. Systems in transportation normally have to act in a multi-agent environment with lots of other agents in their vicinity. Their coordination can be competitive or cooperative. Competitive objectives are for instance the acquisition of a parking lot. Safety-related objectives are normally regarded in a cooperative way.

Thus, systems in transportation normally have to cope with partially observable, dynamic, stochastic, continuous, sequential, multi-agent environments. The systems themselves are part of this environment and have to interact with it accordingly. Such kind of systems are often characterized by *acting intelligent* or *being intelligent*. *"**Intelligence** may be defined as the ability to adapt behavior to meet goals in a range of environments"* [81]. Hence, an *"intelligent system adapts to its environment [which may only be partially observable] by predicting future events, controlling its actions in light of those predictions, and revising its bases for making predictions in light of feed-back on the degree to which it is achieving its goals"* [81]. *"Intelligence is concerned mainly with rational action"* [226] in uncertain environments. *"A system is rational if it does the 'right thing,' given what it knows"*, or *"takes the best possible action in a situation"* [226] according to what it perceived from the environment.

Based on the above environment description, the remainder of this chapter provides the general system concept which serves as a basis for the consecutive chapters. First, an analysis and evaluation of different system design concepts will be given. Based on the evaluation, a suitable situation model will be elaborated. After that, alternative approaches will be shown and their specific deficiencies with the above given environment characteristics will be studied.

2.1 System Design

As a first step of a driver assistance system relevant information has to be observed, explored or acquired. This step is called **observation** or **perception** [213]. The information can be updated automatically or can be polled otherwise. That strongly depends on the technology and the control flow used in the acquisition and processing step in the source of information. Generally, a **source of information** is any device which is capable of generating a piece of information which characterizes one or more aspects of the environment. Among others, sensors are one of the most important sources of information in the ITS context but also a map data base or a user specifying its preferences can be considered as a source of information.

The output of an information source is either used directly as raw measurements or to infer higher-level information. If used as raw measurement, the measurement value may serve as an input for hard-coded decision-making as it is done in lots of "simple systems" such as powering on the light by pressing the light switch or adjusting the frequency of the windshield wipers according to the output of a rain sensor. In the context of artificial intelligence or cognitive systems [110, 264, 83] these systems are called **simple reflex systems** [226], *stimuli-response systems* or *event-response systems*. They behave according to a simple *if-then*-rule used for instance in procedural programming or *Event-Condition-Action (ECA)*-rules used in active data base management systems [61] or in event-driven architectures:

`if` *something happens* `then` *perform a certain action*

A rule set for longitudinal acceleration processed by a simple reflex system may be for instance:

- "`if` *car-in-front-is-braking* `then` *initiate-braking*" and
- "`if` *car-in-front-is-accelerating* `then` *initiate-acceleration*"

Simple reflex systems react on relevant external events, so called triggers, which allow these systems to be used in dynamic environments which change and generate events even without any direct interaction of the system.

This kind of system design has the big advantage that it is simple, traceable and less resource-consumptive. It performs well in simple environments but using simple reflex systems in complex environments will lead to a plethora of rules with complex conditions consuming lots of resources in terms of memory and processing power. Furthermore, it may lead to unwanted actions in stochastic (e.g. what is the best action if the vehicle in front is accelerating but the road surface is icy and the impact of an acceleration is unclear?) or partially observable situations (e.g. what is the best action if it is not clear whether the preceding car is on the same or on an adjacent lane?).

The reason for making inappropriate decisions hence is the fact that the environment is only partially observable and has stochastic dynamics. In this case sensor measurements cannot serve as a direct trigger for decision-making in complex systems without further considerations. In general, for most applications in the context of ITS raw sensor measurements do not directly provide the information which is required to fulfill the objectives. Accordingly, a thermometer measures the thermodynamic state, i.e. the average kinematic energy per degree of freedom of particles, at the location of the sensor. Although such a sensor output provide useful information in heat-sensitive systems, driver assistance systems will not directly profit from such information in most cases. For the longitudinal control function the relevant temperature information is required for the headway in order to estimate the braking distance and not at the location where the thermometer is mounted. And it is not the temperature that is relevant but the pavement condition in order to determine the friction coefficient which is required for the calculation of the safe following distance. Of course, the temperature at the location of measurement and the location of interest is highly correlated but the assumption that it is equal may cause wrong situation estimations and fundamental fallacies.

In most cases the raw sensor measurement can therefore merely serve as an indicator for the estimation of relevant parameters. Thus, questions have to be answered such as "If a thermometer shows 0 centigrades, what is the temperature of the road surface in a distance of 50 m?" or "what is the most likely pavement condition?" or even "what is the probability of an increased wheel slip?". An improvement of simple reflex systems can thus be achieved by the integration of additional ontological knowledge which reproduces the coherence of given input and required output parameters in order to get a better picture of the situation which caused the observation, the so called *causative situation* [216]. The coherence relations are specified within a **situation model** or *world model* [161]. Decision-making systems that use such a model are called **model-based systems** [226] or **knowledge-based systems** [29].

By using the situation model the system is able to initiate appropriate actions also in stochastic and partially observable environments. Based on this situation model the system is also able to infer what the effect of a certain action on the environment will be, thus being able to infer consequences of actions (see figure 2.2). This is especially important because intelligent systems in transportation *"do not only form an image of reality through observation, they can act on reality and change it through their activity because [they] [...] are part of the material world"* [85].

To act on the reality requires prediction capabilities of anticipated situations lying in the future and also requires taking into account previous situations and decisions made in the past. This can be used in sequential environment analysis to plan actions or action sequences over a longer period of time pursuing a certain goal. Such systems are called **goal-based systems** [226]. Goal-based systems are required for driver assistance for maneuvering or navigation where it is required to perform a sequence of actions. An overtaking maneuver for instance requires to change the lane, accelerate and return to the original lane. Systems that do not take into account goals might estimate the situation as too risky after changing the lane hence returning immediately back to the original lane without finishing the overtaking maneuver.

Goal-based systems may be effective in reaching intended goals but often they are not capable of making efficient decisions because their decisions are not based on an optimization criterion. In order to be efficient an agent needs to specify a performance metric that allows to order the set of alternative actions. A performance metric is for instance the *utility* which is a measure of the achievement of the envisaged objectives. Different actions contribute more or less to the achievement of the objectives. Systems that try to optimize this utility are called **utility-based systems**. A common scale to relate different alternatives is money (e.g. in Dollars \$ or Euros €) because utility-based systems are often used in economical evaluations. Alternatively, the amount of time needed to reach the destination, the amount of CO_2 emissions generated or the number of unnecessary decelerations can be used as performance metric. A further advantage of using utilities is the possibility of pursuing several objectives in parallel which might be contradicting, as for instance safety and efficiency. The most safe state will be in most cases to stop the vehicle but this also will be the most inefficient action in terms of time-to-destination because the destination will never be reached. This is of particular importance in multi-agent cooperative environments where goals of multiple agents have to be coordinated cooperatively in order to reach a global optimal utility. Pursuing the utility of a single agent (e.g. fastest time to destination) will probably only reach a local maximum if inspected in the whole set of agents (e.g. all other vehicles have to slow down in order to clear the way).

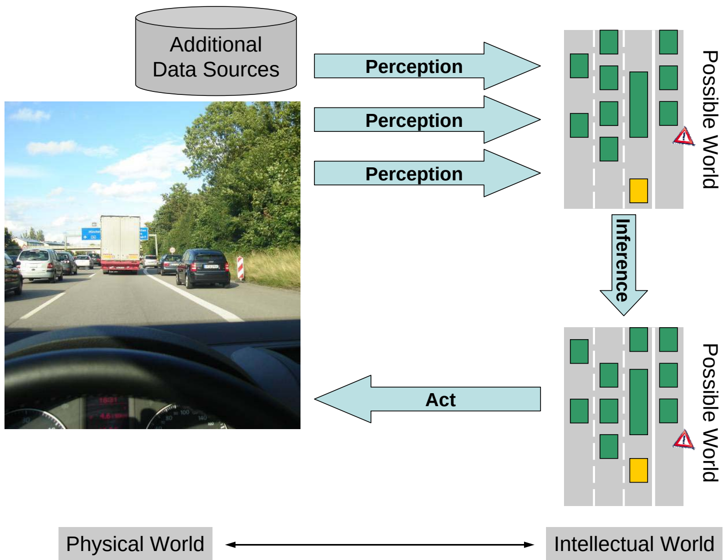


Figure 2.2: Model-based agents perceive their environment by various sources of information, infer possible situations and act appropriately

Especially systems that have to interact with the environment, i.e. that observe their environment and change the environment by their actions, have to take into account more than just what is perceived. They have to cope with observation errors, fallacies in observation, and they have to predict what their actions will entail because after they performed their action there is no way to turn back time and undo the performed action. Actions have an irrevocable bearing on the environment and have to be carefully chosen, especially in safety critical systems.

As a consequence, the intelligent system cannot be implemented as a simple reflex system. Instead it has to use a model of the situation which enables a detailed estimation of the environment, thereby avoiding observation fallacies, and taking into account the consequences of actions with regard to the targeted objectives. The following section will thus introduce the fundamental concepts to model situations which are required for a model-based system for future ITS. Further extensions for dynamic and flexible incorporation of various sources of information and decision-making will be provided in the next chapter.

2.2 Situation Model

When modelling a real-world situation, we have to distinguish between two *universes*: the **intellectual universe** (or **intellectual world**) and the **physical universe** (or **physical world**) [59]. Whereas the intellectual universe is a purely intellectual construct of the intelligent system, *"the physical universe, on the other hand, just does its own thing, entirely ignorant of, and careless of, any of our intellectual theories"* [59]. The objective of an intellectual universe which is modelled within the intelligent system is to represent the physical universe in the relevant aspects. The relevance of an aspect arises from the application domain which renders aspects of the physical world more or less relevant. For a more detailed inspection of aspect and relevance the reader is referred to [246]. The intellectual world hence merely reflects a subset of the physical world appropriate to the application domain. This is the so called **intellectual universe of discourse**. The only links between both universes are the observations which can be gathered from the physical world. These links can be used to inject evidence to the intellectual world which then, based on these evidences, attempts to get a clear picture of the physical world.

Whereas the physical world is unique and unambiguous given, the intellectual world does not need to be unambiguous - and in most cases it actually is not - and thus includes a certain amount of uncertainty. This uncertainty in the intellectual universe can be expressed by a distribution over **possible worlds** [194, 226] (see figure 2.3). The possible worlds semantic is borrowed from logical systems theory. There, a possible world is a world where a logical sentence is fulfilled. This can be generalized to the statement:

> The intellectual universe contains every possible world in accordance with the satisfaction of evidence gathered from observation of the physical universe

According to Russell and Norvig [226], the expression "possible worlds" can be substituted with **"model"** and the uncertainty in the possible worlds can be expressed by a suitable uncertainty measure. According to Endsley [68] a *"model may incorporate not only the value of different system parameters (e.g. the level of the fuel gauge, and the speed of the motor), but also includes an understanding of the dynamics of the system (e.g. rate of change and system vectors) developed from the changes in the situation model over time"*. As a consequence, to cope with the dynamic nature of

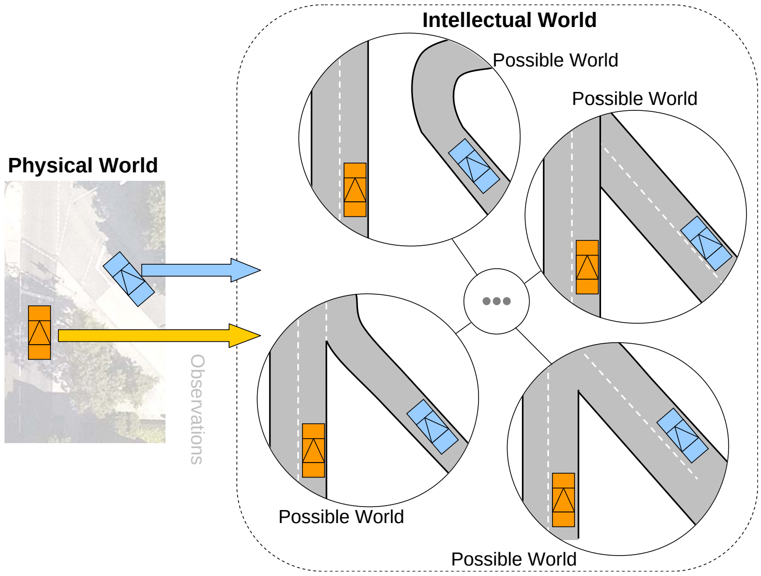


Figure 2.3: Ambiguous inter-connection of physical world and intellectual world by observation

the environment in ITS, a suitable situation model has to be capable of expressing the situation dynamics. According to Craik [54] an intelligent system by using a *"model of external reality and of its own possible actions [...], it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilise the knowledge of past events in dealing with the present and future, and in every way react to it in a much fuller, safer and more competent manner to emergencies which face it"*. Thus, an episodic modelling of the situation is inadequate for the ITS environment. Sequential modelling is required to learn from the past, estimate the present and predict the consequences of actions.

A suitable situation model has to represent all details that are required to evaluate the action space and make proper founded decisions relevant to solve the problem. But on the other hand, it should not take into account more than the required level of detail. Additional information which is irrelevant for a proper decision-making shall therefore not be taken into consideration. Although a sound inference process will not change its outcome according to irrelevant information, the consideration of irrelevant information makes the problem complexer than it is. This is based on the principle of Occam's razor stating: *"Thou shalt not seek an explanation based on more complex mechanisms, until you are satisfied that simpler mechanisms will not do!"* In model learning theory this is an aspect of over-fitting or over-parameterization of the model which is in effect, if the level of detail is inappropriately high. Model parameters shall be taken into account because they are decisive for the problem solution and not because they are simply there. On the contrary, as will be shown later, information which is not available can be inferred from others, if the parameter space is sufficiently broad. Thus, the design of a suitable model is based on a trade-off between minimality and redundancy and therefore is one of the major difficulties which determines success or failure of the whole system.

Based on a proper model of the situation and its coherences, intelligent systems can estimate the situation they are currently confronted with and predict its evolvement. This concept is referred to as **situation awareness**. Endsley defines situation awareness as: *"Being aware of what is happening around you and understanding what the information means to you now and in the future"* [69]. "Understanding" in this sense means that a system knows how to work with the information (what means temperature?), what is the "relevant" information which is embedded (e.g. what is the current temperature at my position given a measurement in a distance of 1000 meters 10 minutes ago?) and what is the worth of the information for other entities (is this temperature measurement also of interest for others?). The latter is of particular importance if cooperative systems are focused. **Cooperativeness** additionally extends situation awareness by the process of situation modelling in a multi-agent environment with cooperative observation and actions taking into account all relevant entities within the cooperation.

2.2.1 State Representation

A situation representation can be considered as a set of information items $\{S_1, \ldots, S_n\}= S$ whereas S_i represents an aspect of the intellectual universe which can be distinguished from other aspects of the universe, e.g. temperature, distance, speed or rain, in the following called **situational information**[1] [213]. Examples of situational information are for instance:

- `Temperature T` $= [-273.15; \infty)$ in centigrades (°C)
- `Distance D` $= \mathbb{N}_0^+$ in millimeters (mm)
- `Velocity V` $= \mathbb{R}$ in meters per second (m/s)
- `Pavement Condition PC` $= \{dry, wet, icy\}$ as discrete state values
- `Rain R` $= \{true, false\}$ as boolean value

The states of the situational information S_i are mutually exclusive and exhaustive.

A situational information is generated by a source of information, for instance a thermometer, a GNSS receiver or a rain sensor. Each source of information provides an output in the respective value domain if it is working properly. Normally this is a definite instance of the value domain as for example an instance of the temperature `T`, e.g. $T = 18.7$°C or a position of $(lat, lon) = (48.06°, 11.35°)$ in WGS-84 datum or a rainy weather `R` $= true$.

In order to evaluate the real worth of the sensor measurement and its implication for the situational information of interest, one has to critically analyse the source of information with respect to inaccuracy and incompleteness. **Inaccuracy** refers to the concept of error. The fact that every sensor is *"always fraught with error"* [158], is a major impact for inaccuracy of measurements and thus has to be actively

[1] In the remainder of this work situational information is written with a capital letter and with a monospaced font

taken into account in order not to be put off the scent by erroneous measurements. **Incompleteness** refers to the lack of information. If for instance a relative position information which consists of a direction and a distance value is of interest, e.g. for the blue vehicle in figure 2.3, but only a distance measurement appliance mounted in the orange vehicle provides evidence (e.g. by signal runtime or signal strength measurements [224]), the measurement is incomplete for the situational information of interest which does not mean that it is irrelevant. Indeed, as will be seen in the next chapters, the distance measurement can be of high worth even if it is not sufficient to provide the complete information.

Both inaccuracy and incompleteness provide uncertainty to situational information and this uncertainty has to be somehow explicated in the situation model. If this is not done and uncertainty is neglected, undesired effects often are indispensable. This becomes clear if the relative position information which was measured by a distance measurement appliance has to be denoted. Due to the missing direction measurement, no information regarding the direction of the blue vehicle is known. As a consequence the relative position will be located somewhere on a ring around the distance measurement appliance (see figure 2.4). If the relative position is specified as a "hard state", without explicitly expressing uncertainty about the direction of the other vehicle, the relative position can be reduced to the position which minimizes the mean squared error which would be the center point of the ring in figure 2.4. This point has a constant error in the order of the ring radius. On the other hand a random point on the ring can be selected which reduces the minimum error but increases the maximum error to twice the radius if the real position is exactly antipodal.

In contrast to a hard position representation Angermann et al. hence introduced in [25] the soft location concept. The soft location is specified by a probability distribution which can be used to explicate the uncertainty in the position specification. In this work, we adopt the concept of soft location and extend it to the general concept of **soft situational information** which uses a probabilistic measure for the explication of uncertainty.

Generally, for a situational information two different kinds of representations can be distinguished:

- **hard situational information** with its state represented by a single domain value $s_i \in S_i$, and [2]
- **soft situational information** with its state represented by a probability distribution P over the whole state space S_i. P can be specified by a *probability table* or a *probability mass function (PMF)* for discrete values or, in case of continuous values, by a *probability density function (PDF)*. Thus, the state of the situational information S_i is represented by the probability distribution $P(S_i)$.

An example of a PDF for the soft location is shown in figure 2.4. Although the relative position cannot be determined unambiguously due to the incompleteness of the measurement, the area of the possible location tends to the yellow-red circle due

[2] In the remainder of this work a state s_i refers to the situational information S_i and is written with a small letter and in a slanted font

to the given distance measurement. The blue area is considered as almost improbable. The red area shows the location with the highest probability for the location. Due to the inaccuracy of the measurement the area is not bounded by sharp edges but shows a gradient distribution. Thus, although the measurement is incomplete and inaccurate, the area of all possible locations is strongly constricted and may already be sufficient to make appropriate decisions.

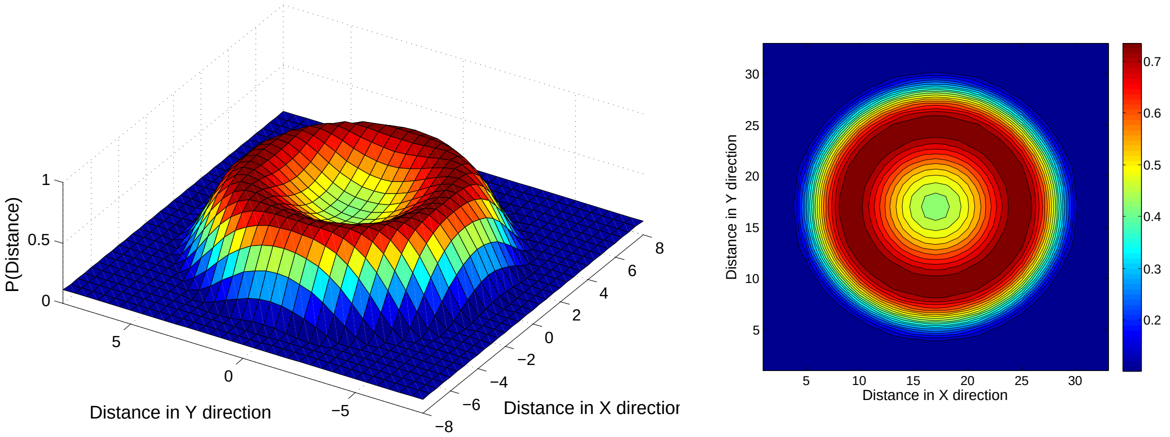


Figure 2.4: Soft Location measured with distance measurement appliance located at (0,0))

The predominance of the soft situational information concept emerges due to the explication of state-inherent uncertainty. Whereas a hard situational information disposes the inherent uncertainty and focuses on a single certain value (for instance the most probable state), therefore suppressing important information, soft situational information provide much more detailed information on the state, its distribution and uncertainty.

Of course in simple system environments it may be reasonable to use hard situational information for complexity reduction. But this fact does not invalidate the predominance of soft situational information because a hard situational information can always be formalized by a probability distribution with a single state value s_i with probability $P(x = s_i) = 1$ or by the equivalent Dirac delta function $\delta_{s_i}(x) = \begin{cases} 1, & x - s_i = 0 \\ 0, & x - s_i \neq 0 \end{cases}$.

Thus, it is sufficient to use only the concept of soft situational information throughout this work as hard situational information is only a specific occurrence of soft situational information.

In the soft situation model introduced by $S = \{S_1, \ldots, S_n\}$ and the respective probability distribution P_S every single situational information S_i with $i \in \{1, \ldots, n\}$ can be considered as an aspect of the intellectual universe described by a random variable with an associated probability distribution P_{S_i}. The probability of the situational information S_i being in state s_i hence is $P_{S_i}(x = s_i)$ with x being the outcome of interest of S_i and $s_i \in S_i$. In the remainder $P_{S_i}(x = s_i)$ will also be used by the abbreviated version as $P_{S_i}(s_i)$ or simply $P(s_i)$.

2.4 Comparison to alternative situation models

In order to embed probabilistic causal networks in the state of the art of intelligent system theory, this chapter will provide an overview of alternative methods for situation modelling and inference and will show their applicability in the context of ITS.

2.4.1 Formal Logics

One of the oldest forms of knowledge representation and reasoning is formal logics. Formal logics can be traced back to the Ancient Greeks, particularly Plato, Aristotle and Pythagoras. Aristotle's logical syllogism is one of the major achievement in logical inference which persists to modern times as basis for most inference methods. A typical syllogism is:

(1) If it rains, the road will get wet. (Major Premise)

(2) It is currently raining. (Minor Premise)

(3) The road will get wet. (Conclusion)

Every sentence is structured in the form *If* $\boldsymbol{A}$ *then* $\boldsymbol{C}$ with A being the *antecedent* and C the *consequence* or as a simple declarative sentence, e.g. "It is currently raining". The type of inference which is used to infer the third sentence using the first and the second sentence belongs to the so called *deduction* which concludes a consequence if the premises are true.

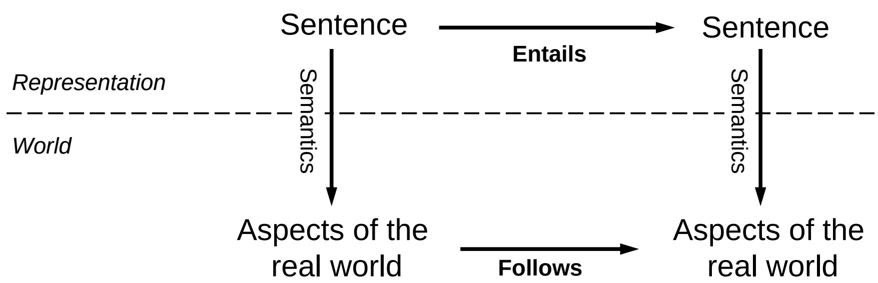


Figure 2.20: Logical entailment in the real-world and its representation (source: Russell and Norvig [226])

Major premises, such as 'if it is raining, the road will get wet', are the basis for reasoning in formal logics. They are valid in every intelligent system and thus belong to the commonsense propositions. Logical systems keep such propositions in a commonsense knowledge base. The knowledge base KB and observations such as "it is currently raining" serve as a basis to infer conclusions such as "the road will get wet" which can be written in the following form:

$$KB, o \models \alpha$$

$\models$ refers to the operator of *logical entailment* and means that in every possible world in which KB, the knowledge base, and o, the observation, are true, the conclusion α is true. For a real-world problem, this means that by observing o under the assumption *"KB is true in the real-world, then any sentence α derived from KB by a sound inference procedure is also true in the real-world"* [226] (see figure 2.20).

2.4.1.1 Propositional Logic

Logical entailment strongly depends on the logical calculus and inference procedures used. One of the simplest kinds of logics is *Propositional logic*. Propositional logic, also called *Boolean logic* or *sentential logic*, consists of bi-valent propositions inter-related by truth-functional connectives. Propositions can be either `true` or `false`. Basic connectives are *negation* $\neg$, *conjunction* $\wedge$ and *disjunction* $\vee$ whereas already the combinations $\{\neg, \vee\}$ or $\{\neg, \wedge\}$ are functional complete. Functional completeness follows from the ability of a set of connectives to express every function of the respective logic [138]. Further connectives which can be build from the basic connectives are *implication* $\rightarrow$, *biconditional* $\leftrightarrow$, *xor* $\nleftrightarrow$, *nor* $\downarrow$ or *nand* $\uparrow$. The latter two ($\downarrow$ and $\uparrow$) are already functional complete by themselves as it is shown in [262] or [138]. A proposition using these connectives is for instance: `Raining` $\rightarrow$ `RoadIsWet` which is equivalent to the proposition $\neg$`Raining` $\vee$ `RoadIsWet` and is true whenever antecedent and consequence both are `true` or the antecedent `Raining` is `false` (see table 2.1).

A knowledge base consisting of the two sentences:

- `Raining` $\rightarrow$ `RoadIsWet` $\Leftrightarrow$ $\neg$`Raining` $\vee$ `RoadIsWet` and
- `RoadIsWet` $\rightarrow$ `IncreasedWheelSlip` $\Leftrightarrow$ $\neg$`RoadIsWet` $\vee$ `IncreasedWheelSlip`

restricts the valid possible worlds as depicted in table 2.1.

Raining	RoadIsWet	Raining $\rightarrow$ RoadIsWet
false	false	true
false	true	true
true	false	false
true	true	true

RoadIsWet	Increased WheelSlip	RoadIsWet $\rightarrow$ Increased WheelSlip
false	false	true
false	true	true
true	false	false
true	true	true

Table 2.1: Truth tables for the two logical sentences `Raining` $\rightarrow$ `RoadIsWet` and `RoadIsWet` $\rightarrow$ `IncreasedWheelSlip`

Given this knowledge base the proposition $Raining \wedge \neg RoadIsWet$ cannot be concluded because $KB, Raining \not\models \neg Raining \wedge RoadIsWet$. Logical entailment would require that in every possible world in which $KB, Raining$ is true $Raining \wedge \neg RoadIsWet$ is true which is not the case as can be seen in table 2.2. Thus the possible world in which $Raining \wedge \neg RoadIsWet$ is true is not consistent with the knowledge base.

Similar to the possible world $Raining \wedge \neg RoadIsWet$ all other possible worlds can be evaluated in the context of the knowledge base in order to decide whether they are valid or not. *"The fact that inference in propositional logic is NP-complete suggests that,*

Raining	RoadIsWet	$(\neg Raining \vee RoadIsWet) \wedge Raining$	$Raining \wedge \neg RoadIsWet$
false	false	false	false
false	true	false	false
true	false	false	true
true	true	true	false

Table 2.2: Possible worlds for the logical entailment $KB, Raining \not\models \neg Raining \wedge RoadIsWet$

in the worst case, searching for proofs is going to be no more efficient than enumerating models" [226], i.e. all possible worlds.

If the logical knowledge base contains the rule ¬`Raining` ∨ `RoadIsWet` and a sensor reports `Raining`, the inference process concludes on the logical consequence `RoadIsWet` because `Raining` ∧ `RoadIsWet` is the only valid possible world. And with the rule ¬`RoadIsWet` ∨ `IncreasedWheelSlip` the occurrence of an increased `Wheel Slip` can be inferred from `Raining`. This consecutive conclusion is logically sound because propositional logic is transitive. But it is not able to reflect cause-effect relations with uncertainty: "Rain only increases the probability of occurrence of a wet road which increases the probability of occurrence of an increased wheel slip". The "hard" implication in the proposed knowledge base, which makes rain a sufficient condition for an increased wheel slip, does not reflect the characteristics of the real-world in the required detail. Adding the additional rules `Raining` ∧ ¬`RoadIsWet` and `RoadIsWet` ∧ ¬`IncreasedWheelSlip` eliminates the sufficiency condition but on the other hand makes the model completely useless because no value whatsoever is encoded in the knowledge base any more.

If the initial knowledge base is used in reverse direction, e.g. inferring from an observed `Wheel Slip`, a conclusion that the `RoadIsWet` and it is `Raining` may be obvious. This is called the fallacy of *affirming the consequent* which is an invalid conclusion in propositional logic. It is not given by the rule set ¬`Raining` ∨ `RoadIsWet` and ¬`RoadIsWet` ∨ `IncreasedWheelSlip` because no statement on the premise can be made based on a true consequence. A true premise as well as a false premise might be the reason. The mere valid conclusion in reverse direction is that in the absence of the consequence (¬`IncreasedWheelSlip`) the premise needs to be false (¬`RoadIsWet`). Informally this can be translated to "`RoadIsWet` *is only* true, if `IncreasedWheelSlip` is true" which again does not reflect a cause-effect relation with uncertainty because an `IncreasedWheelSlip` is necessary for `RoadIsWet` which is not true in reality.

All sentences in the knowledge base as introduced above have the following form:

$$\neg antecedent \vee consequent$$

This rule validates the following possible worlds:

- $antecedent \wedge consequent$
- $\neg antecedent \wedge consequent$
- $\neg antecedent \wedge \neg consequent$

Thus, the implication rule can also be written in the form:

$(antecedent \wedge consequent) \vee (\neg antecedent \wedge consequent) \vee (\neg antecedent \wedge \neg consequent)$

For the above example the possible worlds thus are:

$$\begin{aligned} &(\texttt{Raining} \wedge \texttt{RoadIsWet} \wedge \texttt{IncreasedWheelSlip}) \quad \vee \\ &\qquad\vdots \\ &(\neg\texttt{Raining} \wedge \neg\texttt{RoadIsWet} \wedge \neg\texttt{IncreasedWheelSlip}) \end{aligned}$$

Now all possible worlds as a conjunction of situational information are combined in a disjunction. This form is called a *Disjunctive Normal Form (DNF)*. Every knowledge base in propositional logic can be transformed in a DNF. Similar to the DNF, a knowledge base can be transformed to a *Conjunctive Normal Form (CNF)*, i.e. a conjunction of clauses, where a clause is a disjunction of literals, and in particular to the 3-Conjunctive Normal Form (3-CNF) where each clause consists of three literals each being a situational information [226]. It has been shown in [52] that the Boolean satisfiability problem (SAT) in 3-CNF can be transformed to a probabilistic causal network within linear effort. Thus, Bayesian networks are at least as expressive as propositional logics but as a consequence also NP-hardness for the inference has been passed on.

2.4.1.2 Predicate Logic

An extension to propositional logic with more expressive power has its origins in Freges predicate logic [86]. The elementary units in predicate logic are the predicates which, in contrast to the propositions in propositional logic, may include variables which can be quantified. Quantification is done by the *universal quantifier* $\forall$ and the *existential quantifier* $\exists$. Additionally, predicate logic introduces the concepts of objects and functions. Depending on how the new concepts are used, one can differentiate between different types of predicate logic which are mainly first-order logic (FOL), second-order logic or in general higher-order logics.

First-order logic introduces additional symbols which are constants (e.g. *Road*), predicates (e.g. *isWet*) and functions (e.g. *atPosition*). With this kind of logic a sentence such as $isWet(atPosition(Road, (48.06°, 11.35°)))$ to express that the road at location $(48.06°, 11.35°)$ is wet can be formed. Using such a sentence, additional logical statements can be formulated which were not possible by simple propositional logic: $\forall x, y : isWet(atPosition(Road, x, y)) \rightarrow isWet(atPosition(Road, x + 5, y + 5))$ which means that if the road at location (x, y) is wet, the road will also be wet at location $(x + 5, y + 5)$ and this rule is valid for all locations. Thus, with predicate logic is it possible to define relations between possible worlds instead of explicitly naming the facts as it is required in propositional logic. In contrast to propositional logics where a possible world is defined by mere facts, a *"possible world, or model, for first-order logic is defined by a set of objects, the relations among them, and the functions that can be applied to them"* [226].

Although predicate logic is much more expressive than propositional logic, a general problem of all classical logics (propositional logics, first-order logics, higher-order logics, etc.) is that classical logical reasoning is monotonic. That means that *"if a sentence φ can be inferred in FOL from a set Γ of premises, then it can also be inferred from any set Δ of premises containing Γ as a subset"* [6]. The same applies of course in propositional logic because *"a clause [of Γ] is true if any literal is true, even if the other literals do not yet have truth values; hence the sentence as a whole could be judged true even before the model is complete"* [226]:

$$\Gamma \models \varphi \quad \wedge \quad \Gamma \subseteq \Delta \quad \rightarrow \quad \Delta \models \varphi$$

This fact makes classical logics unreasonable to model dynamic real-world problems where sequential reasoning often requires that jumping to a conclusion and subsequently retracting that conclusion as further information becomes available has to be feasible. This requires the support of non-monotonic reasoning and which is a crucial requirement for future ITS applications.

Furthermore, monotonic reasoning makes the estimation of the worth of information unfeasible because information contained in $\Delta \backslash \Gamma$ which has a high relevance becomes completely irrelevant if Δ already renders φ true. If we consider the example depicted in figure 2.15, a knowledge base for abduction may contain among others the following sentences:

$$\texttt{IncreasedWheelSlip1} \leftrightarrow \texttt{RoadIsWet}$$
$$\texttt{IncreasedWheelSlip2} \leftrightarrow \texttt{RoadIsWet}$$
$$\texttt{IncreasedWheelSlip3} \leftrightarrow \texttt{RoadIsWet}$$

Then, the observation of `IncreasedWheelSlip1` entails `RoadIsWet` because:

$$KB, \texttt{IncreasedWheelSlip1} \models \texttt{RoadIsWet}$$

An additional observation, e.g. two other sensors reporting ¬`IncreasedWheelSlip2` and ¬`IncreasedWheelSlip3`, will not affect the conclusion since `IncreasedWheelSlip1` already made the conclusion true. Therefore, if the outcome of the abduction does not depend on the incorporation of additional evidence, the worth of the additional evidence is zero. Thus, classical logic is not able to treat information according to its real worth.

2.4.1.3 Non-monotonic Logics

The lack of non-monotonic reasoning is tackled by various kinds of non-classical logics, e.g. *default logics* [218], *modal logics* or *probabilistic logics*.

Default logics try to solve the problem of the lack of default knowledge. Classical logic cannot assume default sentences, for instance, if nothing else is known, the observation of an `IncreasedWheelSlip` is caused by `RoadIsWet`, because due to the monotonicity new observations, such as a `Race Start` cannot remove the conclusion `RoadIsWet`. Thus, default logics extend classical logics by the capability of using default rules. A simple default logic which is used in the logical programming language Prolog is *negation as failure* [48]. Here, every sentence which cannot be proved to be true is considered as false by the closed world assumption. Thus, every sentence that cannot be proved has a default rule which assigns it to false. In general, default logic $\langle$D, W$\rangle$

extends the classical logic W by a set of default rules D also called the background theory. With the introduction of the background theory a useful new concept has been developed for logical systems, but it has to be considered that if *"one allows hypothetical reasoning [,i.e. probabilistic reasoning] then there is no need to define a new logic to handle nonmonotonic reasoning"* [202]. Thus, by using probabilistic reasoning which allows non-monotonicity, the concept of explicit default rules is not required.

Modal logics extends classical logics by two additional modal operators, namely *Necessarily* $\Box$ and *Possibly* $\Diamond$. Necessarily and possible are not truth-functional in contrast to the connectives *and*, *or*, etc. of classical logics. A connective is truth-functional *"whenever we are given the truth-value of the argument or arguments, we can deduce the truth-value"* [113] of the whole sentence which may be a complex sentence consisting of several arguments. The evaluation of non-truth-functional modal operators requires taking into account how things *might* have been, of the conceivable possible worlds alternative to the actual one. Then, $\Diamond p$ counts as true if and only if p is true in at least one possible world, and $\Box p$ is true if and only if p is true in every possible world.

Another step to non-monotonicity is probabilistic logic. *"Perhaps the simplest type of probability logic is a propositional logic in which the logical implication relation $\models$ is generalised to partial entailment $\models_y$"* [263]. Thereby, $KB \models_y X$ means that given the knowledge base KB X is implied with probability $P(X|KB) = y$. If the premise *"is empty we get a concept of degree of partial truth which corresponds to unconditional probability"* [263]. Propositional entailment is given by $y = 1$, thus, propositional logic is a subset of probabilistic logic. A further expansion to probabilistic entailment results in the following definition:

$$\Theta_1 : x_1, \ldots, \Theta_k : x_k \models \Phi : y$$

which means Θ_1 with probability x_1 and ... and Θ_k with probability x_k entail Φ with probability y.

The concepts given by default rules, modal operators and probabilistic implication provide fundamental extensions to classical logics that allow non-monotonic reasoning and opens the expressiveness of logical systems to sequential reasoning in dynamic problem domains. But still one of the major principles of classical and non-classical logics holds, the *Principle of Bivalence*. Based on this principle each valid sentence can merely be ascribed to one of the two truth values: *true* or *false*. The evaluation of a valid sentence will result in exactly one of these values, e.g $\texttt{Raining} = true$, $\texttt{Raining} \land \neg\texttt{RoadIsWet} = false$, which does not allow the expression of vagueness or uncertainty. This problem has been tackled by many-valued logics.

2.4.1.4 Many-valued Logics

Two-valued logics were unique until Lukasiewicz came up with three-valued logics in the 1920th and extended the two-valued logics with the third value *possible* [159]. This value was used for cases where neither *true* nor *false* can unambiguously be assigned. This can be the case for instance when no evidence is set or contradictory premises, which are always false in classical logic, are made. Four-valued logics defined by Belnap differentiated these two additional values ending up with four different states

$\mathcal{P}(\{true, false\}) = \{\emptyset, true, false, \{true, false\}\}$ [30]. A further extension, the N-valued logics or many-valued logics facilitate the adoption of an arbitrary number of values.

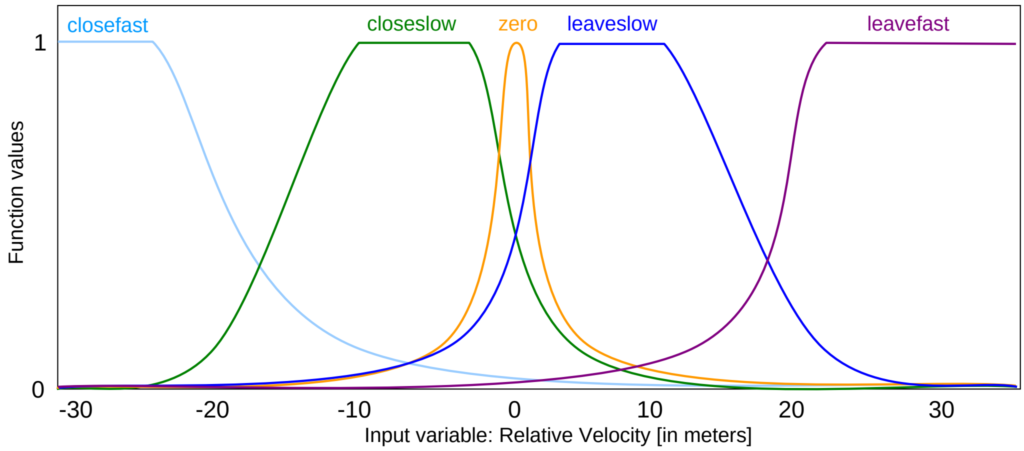


Figure 2.21: Membership function for change in distance in an ACC (figure adapted from Lanik [151])

The usage of N-valued logic is for instance applied in fuzzy logic [267]. Fuzzy logic has significantly been influenced from fuzzy set theory where a sentence can adopt several values simultaneously. For instance the situational information `Temperature` can be in the state *warm* and *cold* at the same time, e.g. at the freezing point. This can be used to specify fuzziness in the expressions *warm* and *cold*, and *warm* and *cold* become so called *fuzzy sets*. *"Fuzzy sets are an instrument of modelling inexact predicates appearing in natural languages"* [167]. The strength of having a certain value in fuzzy logic is expressed by a so called membership function. The membership function maps the degree of membership to a certain state on the interval $[0; 1]$ whereas 0 means no membership and 1 means full membership. For the longitudinal control function of a driver assistance system, the change in distance between the preceding and the following vehicle can for instance be expressed as a fuzzy set {*close-fast*, *close-slow*, *zero*, *leave-slow*, *leave-fast*} with a membership function as shown in figure 2.21 [151].

Fuzzy logic has for instance been proposed for vehicular longitudinal control in [177, 184, 229, 170, 34, 44], for lateral vehicle control in [183, 106], for hazardous situation detection in [115, 155], for traffic jam detection in [201] or for automatic parking system [221]. A summary of the application of fuzzy logic in ITS can be found in [250].

2.4.1.5 Evaluation of Formal Logics against Probabilistic Causal Networks

The concepts introduced by non-monotonic reasoning and many-valuedness allow a very flexible new type of implication which gets close to the indication between cause and effect in probabilistic causal networks. But there is one major difference which is not foreseen in the logical calculi introduced so far. All connectives are static and thus do not change according to the information in the knowledge base. Thus, a logical rule that renders the influence of `Black Ice Warning` on the occurrence of `Wheel Slip` will always influence the `Wheel Slip` if a `Black Ice Warning` is received. Evidence on the `Pavement Condition` causes conditional independence of `Black Ice Warning` and `Wheel Slip` (see figure 2.18). The causal influence between `Black Ice Warning` and `Wheel Slip` has to be eliminated in this case which is not foreseen in the logical calculi. Thus, logical systems miss the ability of dynamically adapting the strength of the logical connectives. Of course, one might argue that the strength of the influence can be explicitly coded to every logical connective but *"explicit encoding is clearly impractical [. . .] because relevance and dependency are relationships that vary depending on the information available at any given time"* [194] and thus will produce an enormous control overhead which can only hardly be solved for large problem domains.

Although the membership function in fuzzy logics which assigns values between zero and one seems to be similar to the concept of probabilistic causal networks, the functionality is still quite different. *"Consequently, logical probability must not be identified with logical values of many-valued logic. The reason is that probabilistic intensionality is incompatible with logical extensionality"* [167]. In contrast to extensional approaches which treat uncertainty as a generalized truth value, in intensional approaches, also known as declarative or model-based approaches, uncertainty is inherent to possible worlds. For a more detailed analysis the reader is referred to [194].

Furthermore, although a probabilistic implication appears to be similar to the causality concept in probabilistic causal networks, the functionality is quite different. Indeed, the inequality of probabilistic causality expressed by $P(A|B)$ and the logical implication $B \rightarrow A$ has been shown by Lewis and Jeffrey in [153, 124]). Additionally, the implication in logical calculi is uni-directional by definition, even if extensional probabilistic concepts are introduced, and therefore does not allow a bi-directional reasoning. In summary, the intensional usage of probability in probabilistic causal networks has not been achieved by any extensional probability handling so far which makes probabilistic causal networks predominant to logical systems [194] for the problem domain of interest of this work.

2.4.2 Neural Networks

A further knowledge representation and inference concept for intelligent systems are *Neural Networks*. A neural network is supposed to model circuits of biological neurons similar to the behavior of human brains. Gurney defines neural networks as: *"A neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the interunit connection strenghts, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns"* [96]. In most cases neural networks are applied to complex systems to solve complex relationships between input and output parameters or to find patterns in the input data [226, 118, 144]. Neural networks in intelligent transportation systems are for instance used for road detection in [80], longitudinal or lateral control functionality in [56, 87, 121] or driver behavior recognition in [190, 265].

Generally, a neural network consists of a set of artificial neurons inter-connected with each other. A neuron is activated or "fires" when a linear combination of its inputs exceeds some threshold [226]. The linear combination simply sums over all input connections of the neuron which are either 1 (fired) or 0 (not-fired) in case of binary neurons. Thereby, each input connection can individually be weighted:

$$in_i = \sum_{j=0}^{n} w_{j,i} a_j$$

with a_j being the activation from neuron j to neuron i, and $w_{j,i}$ the weight of this connection. The weight $w_{j,i}$ is allowed to be negative which allows non-monotonicity. The neuron i then fires according to the activation function:

$$a_i = g(in_i) = g\left(\sum_{j=0}^{n} w_{j,i} a_j\right)$$

The activation function g activates neuron i according to the input of its predecessor neurons $j = 1, \ldots, n$. $w_{0,i}$ in this case is the so called *bias weight* which is the main control possibility of a neuron. If a_0 is assigned to -1, the bias weight can be adjusted to represent the connectives of propositional logic (1.5 for an *and*-neuron, 0.5 for an *or*-neuron and -0.5 for a *not*-neuron). Accordingly, a neural network can represent every proposition in propositional logic [172].

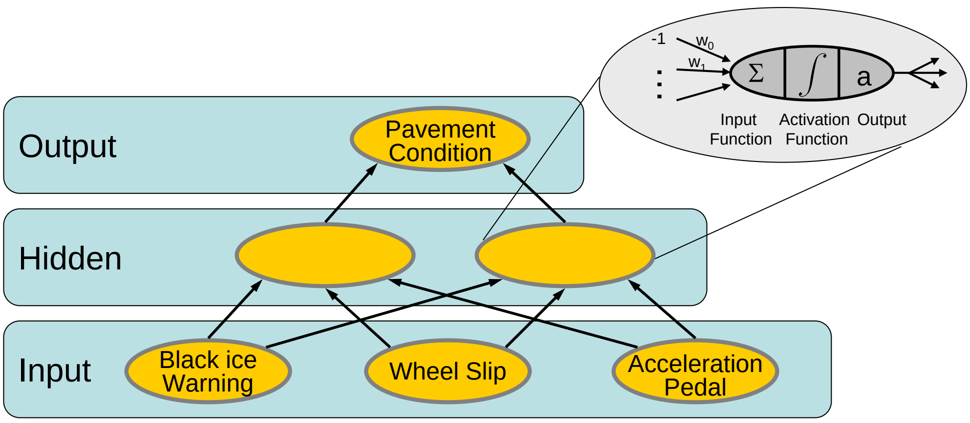


Figure 2.22: Example neural network for the estimation of the pavement condition

The operation of the neural network depends on the number of artificial neurons it has, and on the way they are connected. Neurons that are activated from conditions outside the network are called *input neurons*, neurons that provide their activation outside the network are called *output neurons* and the remaining intermediate neurons are called *inner neurons* [144]. For a clear structuring neurons sometimes are assigned to a layered topology. Input neurons belong then to the *input layer*, output neurons to the *output layer* and inner neurons to the *hidden layer*. The hidden layer can be subdivided to multiple instances representing intermediate processing steps.

A neural network consisting of six neurons in three layers is shown in figure 2.22. The input layer comprises neurons which are triggered by processes outside the network, e.g. sensors. Their activation is subsumed in the two hidden neurons and finally converges in the pavement condition neuron which represents the variable of interest. If the structure is known, in the learning phase the network can be trained to a given training sequence which consists of input information and the according output information. In the learning phase with fixed network structure the weights of the individual inputs in the combination function is adapted which *"is formulated as an optimization search in weight space"* [226]. If the structure is unknown, neural networks emerge as a quite complex construct with lots of unknowns [226].

Beyond that point, when structure and weights are assigned, neural networks have a fixed structure with a fixed information flow from input neurons over inner neurons to output neurons (in case of feed-forward networks). Thus, in contrast to probabilistic causal networks, they are bound to a strict uni-directional reasoning sequence without clearly distinguishable causal dependencies. The greatest strength of probabilistic causal networks is *"causal reasoning which in turn facilitates reasoning about actions, explanations, counterfactuals and preferences. Such capabilities are not easily implemented in neural networks"* [197]. For instance *"a neural network for character recognition may be able to recognise an 'A' from a bitmap, but could not say what an 'A' looks like"* [203]. The reason for this is that neural networks mainly are used for mere abductive or mere predictive purposes and are not capable of reasoning in both directions which limits their functionality for a flexible usage in future ITS applications.

A further disadvantage is that the structure of a neural network cannot be easily extended without a consecutive learning phase. Therefore, if the structure is subject to change, e.g. due to a variable amount of vehicles, congested traffic segments or black ice warning messages, the network has to go through a continuous learning phase which will significantly reduce the performance of the network.

2.4.3 Data Mining

Another knowledge representation concept which has been used in the context of ITS [266] are data bases, in particular relational data bases. The first similarity of data bases and probabilistic causal networks appears in the graphical notation. Data base system are often described by the *Entity-Relationship-Model (ERM)* [45] which is similar to the notation of probabilistic causal networks. Figure 2.23 shows one of the previous examples in an ERM [4]. `Temperature` causally influences `Pavement Condition` with a $N : 1$ relation meaning that a state of `Temperature` determines exactly one state of `Pavement Condition` (*dry*, *wet* or *icy*) but not vice versa. This state of `Pavement Condition` then determines exactly one state of `Wheel Slip` (*yes* or *no*).

The data model used in relational data bases can be traced back to Codd's work in [49, 50]. The core is a collection of predicates over a finite set of n predicate variables,

[4] In the ERM of the figure no attributes are shown for simplification. Thus, every entity comprises a single attribute being the entity name with its assigned domain

Figure 2.23: Example of an Entity-Relationship-Model

called *n-tuples*, describing constraints on the possible values and combinations of values. Each element of a tuple is a triple $\langle$A, V, v$\rangle$ consisting of the attribute name A, the domain V and a value v [57] which is similar to the already described situation model with situational information S_i and its value s_i in the respective domain. The valid set of n-ary relations R which inter-relates n variables is equivalent to a possible world description in the purpose of this work.

The data base design according to the ERM of figure 2.23 with some initial relations is shown in table 2.3.

Temperature	Pavement Condition
...	...
+2	dry
+1	dry
0	wet
-1	icy
-2	icy
...	...

Pavement Condition	Wheel Slip
dry	no
wet	yes
snow	yes

Table 2.3: Data base design according to functional dependencies

In order to translate an Entity-Relationship-Model into a data base design every inter-relation becomes a data base table and every entity with its attributes is translated to a data base table in case of more than one attribute per entity. Inter-related tables are references by foreign keys shared between these tables. This results in a lot of tables if the data is highly inter-related. The number of tables for the inter-relations can be reduced by exploiting ontological constraints in the data. Ontological constraints in inter-relations between predicate variables in relational data bases are based on functional dependencies. A functional dependency constrains the relations of states between variables. That means:

$$\text{Y is functional dependent on X} \quad \text{or} \quad X \rightarrow Y \quad \text{i.f.f.}$$

$$\forall \quad \text{tuples } t_1, t_2 \in R: \quad t_1[X] = t_2[X] \Rightarrow t_1[Y] = t_2[Y]$$

For instance, the `Pavement Condition` is functional dependent on `Temperature`, i.e. `Temperature` $\rightarrow$ `Pavement Condition`, and `Wheel Slip` is functional dependent on `Pavement Condition`, i.e. `Pavement Condition` $\rightarrow$ `Wheel Slip`. Due to the transitivity of functional dependency, `Temperature` $\rightarrow$ `Wheel Slip` is true. Table 2.3 shows valid relations that fulfill the constraint of this functional dependency. But this functional dependency is not true anymore in case if there is no $1:1$ or $N:1$ relation thus having an ambiguity in the relations. For instance, it is not determined whether the `Pavement Condition` is dry, wet or *icy* if the `Temperature` has zero centigrade. Furthermore, it might even be *dry* if the `Temperature` is below zero centigrade without precipitation. The $N:1$ relation therefore has to be eliminated. Thus, there are three valid relations with `Temperature=0` but different states for `Pavement Condition` (see table 2.4). The same is true for the inter-relation of `Pavement Condition` and `Wheel Slip` resulting in a plethora of possible relations and eliminating uniqueness and simple data base designs.

Temperature	Pavement Condition
...	...
+1	dry
+1	wet
0	dry
0	wet
0	icy
-1	dry
-1	icy
...	...

Pavement Condition	Wheel Slip
dry	yes
dry	no
wet	yes
wet	no
icy	yes
icy	no

Table 2.4: Data base design without functional dependencies

Using data bases to model complex real-world problems as they are targeted in this work is not trivial and straightforward. A critical limitation is the usage of hard state descriptions. Furthermore, the high number of ambiguous inter-relations complicates the data base design which will result in complex system design and high storage consumption as well as complex inference procedures. Whereas data bases can perfectly be used to model "man-made" environments, such as customer lists with clear states and inter-relations (e.g. every customer has a unique ID), data bases are not suitable to model complex real-world environments.

2.5 Concluding remarks and evaluation

This chapter introduced a situation model and the according inference which can be considered as the fundamental basis of this work. It was shown that other approaches cannot fulfill the requirements of future ITS applications as introduced in the beginning of this chapter. The main problems are the difficulties as described by Pearl in [194]:

- Improper handling of bidirectional inference,
- difficulties of retracting conclusions, and
- improper treatment of correlated sources of evidence

Probabilistic causal models together with the according inference opposed to other knowledge representations use probability as an intensional measure to express the system inherent uncertainty. Thus, it is often called nondeterministic or inaccurate because the outcome is not a single discrete value. But if a real-world problem has to be modeled, uncertainty is inevitable because it is impossible to model every single detail and inter-relation unless we are targeting a model which has a greater extent than the problem itself. Uncertainty hence is fundamentally given in models expressing real-world problems.

Therefore a detailed picture of the world requires taking into account the uncertainty of the world within the model. Probabilistic causal models exactly do that by expressing uncertainty with a probabilistic measure. Together with the probabilistic inference which is based on an axiomatic deterministic set of rules (i.e. Kolmogorov axioms and Bayes rule) a way to calculate uncertainty is given. Pearl simply states this in [195] as by probabilistic causal networks "causality has been mathematized". Thus, it can be argued that not the probabilistic models are nondeterministic and inaccurate but the models that do not take into account the problem's inherent uncertainty. If an explicit neglect of uncertainty is desired, *"we obtain the deterministic theory by letting all the probabilities in question be either 1 or 0"* [248]. Thus, systems neglecting uncertainty can simply be considered as a subset of probabilistic one's and *"to switch from strict causality to probabilistic causality, we simply replace implication by weight of evidence"* [92].

It has to be noted that probabilistic models and inference must not be equalized with calculating by chance. They merely express problems that are or seem to be occupied by a certain extent by chance. Foot states this as follows: *"when actions or choices are called 'chance' or 'accidental' this has anything to do with the absence of causes, and if it has not we will not be saying that they are in the ordinary sense a matter of chance if we say that they are undetermined"* [82]. By the mathematization of probabilistic causal models they are based on deterministic mathematical axioms and thus are completely non-ambiguous and traceable. Thus, it is important to note that **Probability is not Chance.**

Probability in this work is considered as a subjective measure for belief. This concept was mainly influenced by Ramsey 1926 in [206], deFinetti 1937 in [60] and Savage 1972 in [231]. Subjective probability in this sense means the probability describes the personal belief of an agent regarding a specific situation in its intellectual world and not the situation in the physical world.

In contrast to the subjective interpretation of probability, the objective probability interpretation is used by frequentists and propensity theory [204]. Objectivists argue that probability is ontologically given and independent of one's belief. *"The difficulty in the objectivistic position is [...] [that] probabilities can apply fruitfully only to repetitive events [...] and it is either meaningless to talk about the probability that a given proposition is true, or this probability can be only 1 or 0, according as the proposition is in fact true or false"*. Thus, frequentists have difficulties to answer questions like "what is the probability of rain tomorrow?" or "what is the probability of an icy pavement condition in the headway of the vehicle when it reaches it?" because the probability refers to a single event which frequency is either one or zero.

In contrast to this, sources for subjective probabilities are given by measurements, *"(statistical) data, literature, and human experts"* [63] and can automatically be utilized to derive network structure and probability distributions by learning algorithms [101, 226], manually by domain experts [134] or a combination of both. Since these probability distributions sometimes are hard to determine, uncertainty in the probabilities of the situation model may occur. This uncertainty can again be expressed by a probability distribution, i.e. *probabilities of probabilities* [194]. Inference then can be based on *Bayesian model averaging* [108]. Therefore, a probability distribution $P(M)$ is assigned to the set of possible models $M = \{M_1, \ldots, M_k\}$. The posterior probability of a situational information S_i given evidence E and taking into account the models M can be determined by:

$$P(S_i|E) = \sum_{j=1}^{k} P(S_i|M_j, E)P(M_j|E)$$

It is *"an average of the posterior distributions under each of the models considered, weighted by their posterior model probability"* [108].

According to the algorithms used for the inference, in particular approximating algorithms as they will be used later in this work, a certain amount of chance can be induced which makes the outcome partially dependent on chance (see chapter 5). This is not the case if exact inference algorithms are used. The application of exact algorithms only depends on available computation resources. If sufficient computation resources are disposable for the problem complexity exact algorithms are preferable over approximation. If not, approximating inference algorithms often can provide a sufficient approximation of the exact inference.

A major goal of this work is to show that situational information cannot be regarded independent of all other situational information. "Making effective use of information about dependencies is essential in reasoning" [194]. In particular if physical worlds are represented by the situation model, it is required to take relevant situational information into account that has influence on the situational information of interest. The relevance of information thereby is the critical point which has to be considered when talking about distributed systems which allow to exchange information between entities. If this exchange is constricted by bandwidth, latency, reliability, etc. the worth of information has to be considered before the inference process. "In other words, before we examine

B, we need to know if its truth value can generate new information that is relevant to A and is not available from K" [194], with K being the knowledge we already acquired. To achieve this, the actual information content in the current context has to be considered, whereas, according to MacKay [162] *"Information content, surprise value, and log likelihood or log evidence are the same thing"*. Especially the second definition, the surprise value, reflects the intention of this work. In order to communicate efficiently and effectively between vehicles and between vehicles and infrastructure the surprise value shall be high for the receivers of a message, otherwise the worth to communicate it should be put into question.

3 Forward Integration

A wise man, therefore, proportions his belief to the evidence. In such conclusions as are founded on an infallible experience, he expects the event with the last degree of assurance, and regards his past experience as a full proof of the future existence of that event.

David Hume (1711 -1776)

3

From Evidence to Decisions

In the previous chapter the concepts of probabilistic causal networks have been defined. By using these concepts it is possible to model situations with a set of situational information which describe different aspects of the physical universe. Conditional probability distributions quantify their coherencing causal dependencies. Inference can be used to derive implicit knowledge incorporating explicitly given evidence and prior knowledge. With this they already provide the basic functionality which is required throughout this work and therefore serve as the fundamental basis for all concepts which will be introduced subsequently to provide additional problem-specific model extensions. As the final objective is to make the best decision given all evidences, these extensions comprise the network structuring for the incorporation of various kinds of evidences over time and the decision-making functionality. Whereas the former is used to cope with the specifics of dynamic environments, different kinds of information sources, and sequential reasoning, the latter is required to decide in favour of an optimal action which is based on evidence of the past and has an effect in the future.

3.1 System Model

A crucial problem of probabilistic causal networks describing real-world problems is that they quickly reach complex proportions and seem to be highly unstructured. Even for simple problem spaces the situation model quickly reaches great dimensions like the one shown in figure 3.1. Such a situation model mainly has drawbacks in terms of storage and computation complexity and is difficult to interpret and analyse by humans because of the complex inter-dependency structure. Thus, a clear structure would be beneficial which utilizes a clear separation of concerns.

According to the proposed situation modelling concepts, situational information is used to describe an aspect of interest of the physical universe. Observations, which concatenate the physical universe with the intellectual universe by the introduction of evidence, are capable of assigning values to situational information. For instance,

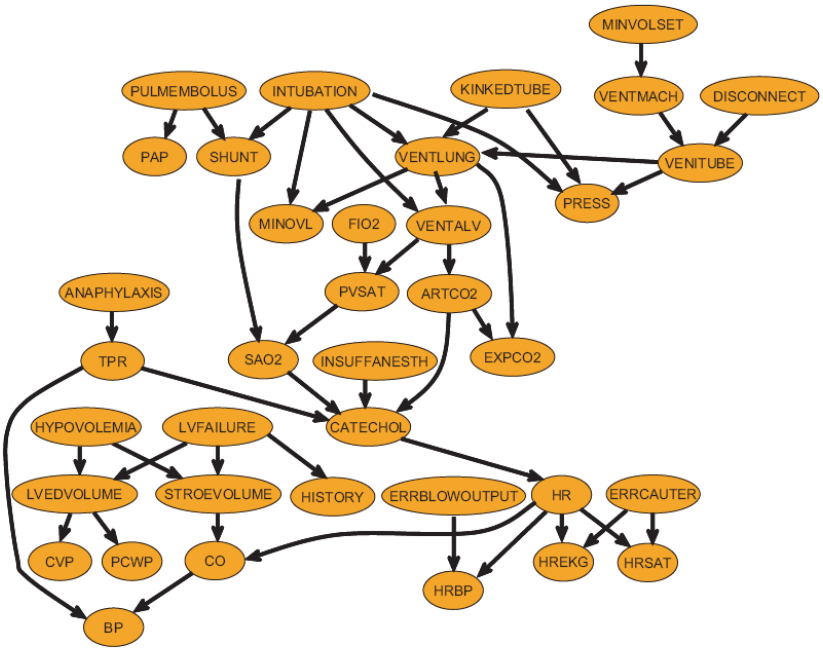


Figure 3.1: Complex Bayesian network (source: Murphy [181])

evidence can be used to assign the situational information `Pavement Condition` an *icy* state. But in reality this situational information represents a state of the physical universe which can only be hardly observed directly because there is no simple sensor that is capable of accurately observing the `Pavement Condition`. Thus, `Pavement Condition` can be characterised as “hidden” in the situation model. However, it can be inferred by means of other situational information as it has been explained in the previous chapter.

Indeed it can be said that generally no hidden aspect of a situation at all can be observed directly. From a philosophical point of view the Kant’s “thing in itself” is a comparable construct which is an objective instance independent of any observer. It becomes accessible by the perception of evidences. The perception provides a subjective estimation of the objective aspect specific for the perception entity and shaped by its background knowledge. This fact holds for aspects of situations such as pavement condition, temperature, precipitation or position of other vehicles and their dynamics as well. The attribute velocity of a vehicle, for instance, is an objective concept as the actual vehicle is moving through the environment with a definite velocity. There are different observation techniques that allow to estimate this velocity. It can be achieved by counting the number of wheel rotations, by differentiation of subsequent GPS position fixes or by using the Doppler shift of a reflected radar signal. The perception of these evidences allows a subjective estimation of the objective situational information. It is subjective in the sense that it depends on the evidence in the context of the background knowledge. Without any evidence no further assertion than given by the prior knowledge can be made. Given evidence, further assertions actually depend on the actual weight of the evidence (see section 2.3.3). Therefore, the estimated situational information does not reflect the objective situational information but provides the best estimation which is accessible through the manifested evidence. Accessibility is accomplished in the probabilistic causal network by the perception of evidence gathered by sensors, data bases, human interactions, etc. The most important sources of information for observing the environment belong to the category of sensors. Norton defines sensors as *"devices that transform (or transduce) physical quantities such as pressure or acceleration (called measurands) into output signals (usually electrical) that serve as inputs for control systems"* [186]. Thus, sensors gather evidence in form of physical quantities from a system-external process which is the ITS environment in this work and transforms it to an other type of signal by means of a transducer. Often the output is an electrical signal. The inclusion of evidence from the ITS environment by sensors measuring aspects of the situation strongly relies on the type of observation, which is subject to different:

- measurands: acceleration, pressure, mass-flow, angular rate, rotational-speed, phase, etc. [169]
- observable: e.g. magnetism, microwaves, acoustic waves, temperature, light, power, etc. [76]
- reporting mechanisms: push or pull/poll
- measurement trigger: time-triggered or event-triggered
- locality: **cooperative sensing** using remote sensor measurements from other vehicles/infrastructure or **autonomous sensing** using measurements from the local sensor domain, e.g. in-vehicle sensors [212, 210]

Since the cooperative sensing is a rather new field in this area, in the following a short introduction will be given. In a distributed system wireless communications can be utilized to distribute evidence gathered from the local sensor system to other entities within the system. This opens up a much broader sensing horizon significantly extending the field of view of local sensors.

There are three major types of wireless communications systems relevant for ITS: broadcast communications, cellular communications and ad-hoc communications (see figure 3.2). **Broadcast communications** are for instance FM radio, Digital Audio Broadcast (DAB), Digital Multimedia Broadcast (DMB) and Digital Video Broadcast (DVB). Besides these land-based broadcast systems, also satellite-based broadcast systems have to be mentioned although their role in vehicular transportation is rather low. Generally, broadcast systems simply propagate information by broadcasting. The addressees are all entities which are in reception range of the signal. No explicit addressing of receivers takes place. Broadcast systems normally merely allow simplex communications and have a range in the order of $\sim 10^4 - 10^5$m or even more.

Cellular communications as the name implies are based on cells which are established by fixed infrastructure. This infrastructure acts as a master which holds control functionality for the respective cell and allows half- or full-duplex communications. The size of cells normally is smaller than in broadcast systems ($\sim 10^3 - 10^4$m). Due to its nature cellular communications relies on the availability of cost incurring infrastructure, may be subject to long delays, mainly caused by management functions (authentication,

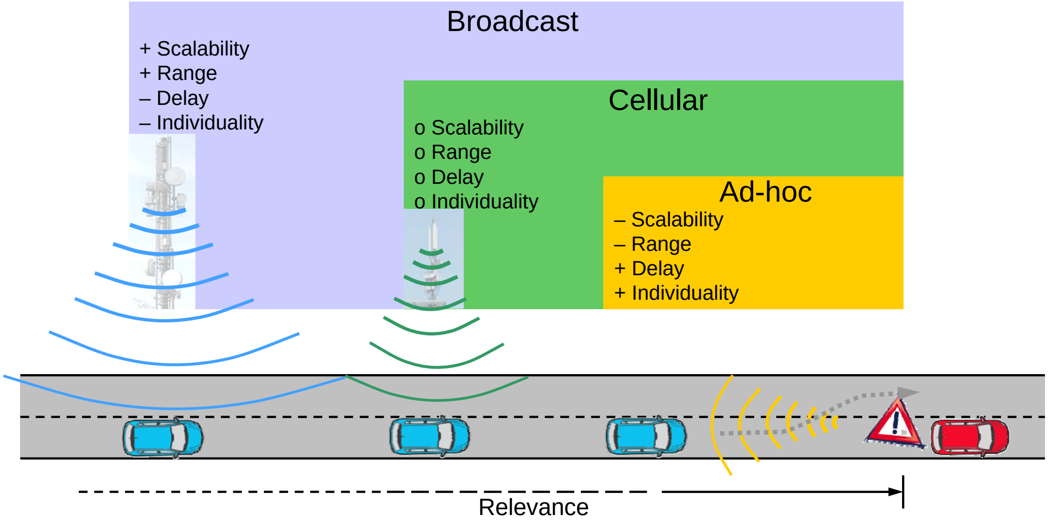


Figure 3.2: Broadcast, cellular, ad-hoc communications

handover, etc.), and do not scale well with an increasing number of nodes, even if they are only listening[1]. The great benefit in contrast to broadcast systems is the additional uplink which even allows a connection to the global internet and the possibility of directly addressing specific nodes by unicast communications. The latter significantly increases the reliability of data transmission. Examples for cellular communication systems are GSM, UMTS or WLAN hotspots.

The third type of communication system is denoted as **ad-hoc communications**. Ad-hoc in this sense means that two or more entities can communicate without the need for a central control unit. In ad-hoc communications each entity is a self-contained, self-organizing communication station which is capable of dynamically forming a temporary network with other stations in the vicinity [230]. All entities are principally equal in their capabilities except for some technological differences. Communication equipment may be mounted in any kind of vehicle, carried by pedestrians, or deployed as stationary infrastructure often called road-side units (RSU). In the remainder ad-hoc communications in the context of ITS is also denoted as **Vehicle-to-Vehicle (V2V)**, **Vehicle-to-Infrastructure (V2I)** (equal to **Infrastructure-to-Vehicle (I2V)**) or in general **Vehicle-to-X (V2X)** communications depending on the respective communication endpoints. In contrast to broadcast and cellular communications, ad-hoc communications has a much shorter range (up to $\sim 10^3$m) but stand out with very short delay. Ad-hoc communications for ITS is currently under standardization by ETSI TC ITS [2] and IEEE802.11p/1609.1-4/SAE2735 [8, 14, 15, 13, 12, 18].

This work mainly focuses on the last type of communications, the ad-hoc communications, but can be applied to the other types of communications as well. For the cooperative sensing the ad-hoc communication paradigm allows to exchange evidence between entities whenever they are in communication range. In order not to overload

[1]The Multimedia Broadcast Multicast Service (MBMS) may provide a useful extension for future UMTS systems to overcome scalability issues

the channel and reduce scalability problems, respective criteria for an adaptive exchange of evidence need to be defined. Such concepts will be presented in the next chapter (chapter 4). For the entities which receive evidence by means of wireless communications appropriate mechanism to incorporate this evidence into their situation model have to be defined. In particular, the entity has to *"proportion his belief to the evidence"* as it was stated in the introductory chapter quotation and shall handle this evidence with an appropriate weight in the context of the background knowledge.

As an important fact it has to be noted that we will not use two independent situation models for the local sensor domain and the remote sensor domain. It is of particular importance to use both types of sensor domains with a single situation model since in the other case coherencing causal dependencies will be neglected and hence essential knowledge ignored. Thus, cooperative sensing is by no means meant to substitute for autonomous sensing. Indeed, both may profit from one another [210]. This often is neglected in the current state of the art [19, 55, 2] where novel applications are designed and adjusted merely based on cooperative sensing with totally disregard of autonomous sensors which are already mounted to our everyday vehicles and thus can be used "out of the box".

> Cooperative sensors which reside on remote entities and communicate evidence wirelessly can be considered as nothing more than additional sources of information in a distributed system. They have to be used in tight coupling with local sources of information in order to exploit their full worth.

Cooperative Positioning

A basic evidence which is anticipated to play a major role in future ITS is position information. Position information will be used to denote the current location of vehicles, any kind of black spots (icy road segment, traffic jams, etc.) or other points of interest such as parking lots or fuel stations. Evidence for the situational information `Position` can for instance be gathered by satellite navigation systems such as GPS, Glonass or Galileo (in the following referred to as *Global Navigation Satellite System (GNSS)*). All of these systems make use of a lateration of nondirectional *Time of Arrival (ToA)* measurements of microwave signals emitted from the satellites [242, 212, 210]. The position calculation of all of these systems is subject to measurement errors which emerge due to satellite clock offset, satellite orbit dislocation, ionospheric and tropospheric refraction, receiver clock offset and multipath propagation. The former two error types, i.e. satellite clock offset and orbit dislocation, are specific to a certain satellite and depend only on this specific satellite (*satellite-based*). Atmospheric refraction errors depend on satellite and receiver position (*atmosphere-based*). Receiver clock errors and multipath errors strongly depend on the receiver and its local environment and therefore are specific for each individual receiver (*receiver-based*). If only the distance between both entities is of interest, satellite-based and atmosphere-based errors are compensated since the errors only provide an equal offset for both receivers [141].

The distribution of GNSS positions to nearby vehicles by utilizing V2V communications together with the evaluation of the position information is referred to as **coop-**

If conditional independence holds, the computation and storage complexity can be reduced significantly because all situational information of the past time slices $S^{0:k-1} = \{S_1^{0:k-1}, \ldots, S_n^{0:k-1}\}$ as well as past evidences $E^{1:k-1} = \{E_1^{1:k-1}, \ldots, E_m^{1:k-1}\}$ can be neglected in the computation and also removed from the memory. Only information from the recent time slice has to be carried along when the next time slice is inspected. As depicted in figure 3.6, the approach can be considered as a sliding window and the window including the situation model of the recent and the previous time slice is shifted further in time at every time instant of interest which includes the advancement of the situational information (prediction) and the situation update every time new evidence becomes available (update).

Given a set of evidences which is gathered at each time slice and which can be used to calculate the posterior distribution of the situational information, the inference process can be separated in the two well known Bayesian filter equations [46, 226]:

1. **Prediction**
   Prediction of the situational information S^{k+1} of time slice $k+1$ given past evidences from time slice 1 to k:

$$\begin{aligned} P(S^{k+1}|E^{1:k}) &= \frac{\sum_{S^k} P(S^{k+1}|S^k, E^{1:k}) \cdot P(S^k, E^{1:k})}{P(E^{1:k})} = \\ &= \frac{\sum_{S^k} P(S^{k+1}|S^k, E^{1:k}) \cdot P(S^k|E^{1:k}) \cdot P(E^{1:k})}{P(E^{1:k})} = \\ &= \sum_{S^k} P(S^{k+1}|S^k, E^{1:k}) \cdot P(S^k|E^{1:k}) =^{(*)} \\ &= \sum_{S^k} P(S^{k+1}|S^k) \cdot P(S^k|E^{1:k}) \end{aligned} \tag{3.6}$$

   The equation makes use of the Markov condition (3.4) in $^{(*)}$ which allows to reduce the probability $P(S^{k+1}|S^k, E^{1:k})$ to $P(S^{k+1}|S^k)$.
   Accordingly, the prediction with continuous random variables is defined by:

$$P(S^{k+1}|E^{1:k}) = \int_{S^k} P(S^{k+1}|S^k) P(S^k|E^{1:k}) dS^k$$

   For discrete or continuous state descriptions $P(S^{k+1}|S^k)$ represents the state transition from time slice k to $k+1$. It specifies the situation dynamics from one time slice to the next time slice. This can be for instance a **movement/motion model** of a vehicle or the decay of a time variant information such as wetness on the road. Concrete examples for state transitions will be given in chapter 5.
   The second factor in the prediction equation is the estimation of the situation which has been made in the previous time slice k given all evidences gathered in the time slices 1 to k. It is defined by the conditional probability distribution $P(S^k|E^{1:k})$ and can be calculated as follows.

2. **Update**
Update of the predicted situational information of time slice k by the evidences from time slice k taking into account all previously gathered evidences:

$$\begin{aligned}
P(S^k|E^{1:k}) &= \frac{P(E^{1:k}, S^k)}{P(E^{1:k})} = \\
&= \frac{P(E^k, E^{1:k-1}, S^k)}{P(E^k, E^{1:k-1})} = \\
&= \frac{P(E^k|E^{1:k-1}, S^k) \cdot P(E^{1:k-1}, S^k)}{P(E^k, E^{1:k-1})} = \\
&= \frac{P(E^k|E^{1:k-1}, S^k) \cdot P(E^{1:k-1}|S^k) \cdot P(S^k)}{P(E^k|E^{1:k-1}) \cdot P(E^{1:k-1})} = \\
&= \frac{P(E^k|E^{1:k-1}, S^k) \cdot P(S^k|E^{1:k-1}) \cdot P(E^{1:k-1}) \cdot P(S^k)}{P(E^k|E^{1:k-1}) \cdot P(S^k) \cdot P(E^{1:k-1})} = \\
&= \frac{P(E^k|E^{1:k-1}, S^k) \cdot P(S^k|E^{1:k-1})}{P(E^k|E^{1:k-1})} =^{(*)} \\
&= \frac{P(E^k|S^k) \cdot P(S^k|E^{1:k-1})}{P(E^k|E^{1:k-1})} = \\
&= \alpha \cdot P(E^k|S^k) \cdot P(S^k|E^{1:k-1})
\end{aligned} \tag{3.7}$$

Again the Markov condition (3.5) allows a reduction of the dependencies in $^{(*)}$ for the probability $P(E^k|E^{1:k-1}, S^k) = P(E^k|S^k)$. α in the update equation can be considered as a normalization constant which ensures that the posterior probability over the entire state space sums up to one. $P(E^k|S^k)$ is the likelihood of evidence E^k in situation S^k, i.e. the likelihood of perception (see section 3.3). The second factor $P(S^k|E^{1:k-1})$ is a prediction of the situation at time k given all previously gathered evidences. Thus, the prediction equation 3.6 for the previous time slice is performed which results in a recursive call of prediction and update (see figure 3.7). With this recursive function definition prediction and update of time slice k can be calculated merely based on the outcome of the prediction-update of the previous time slice which again merely is based on the prediction-update of the previous time slice and so forth.

Starting with the prior probability $P(S^0)$ at time slice 0, every further step of the prediction-update recursion integrates new evidence into the situation model (see figure 3.7). First the prediction step predicts the situation for the time slice given all previously gathered evidence, then the update step updates the situation model with the recently gathered evidence. Based on the belief outcome of the previous prediction/update counterpart, i.e. $P(S^k|E^{1:k})$ or $P(S^k|E^{1:k-1})$, the additional factors $P(S^{k+1}|S^k)$ or $P(E^k|S^k)$ for the prediction or the update respectively form the newly generated belief in the situation. Since $P(S^{k+1}|S^k)$ is based on predictive inference, it usually widens the probability distribution and thus increases the uncertainty. The abduction with the likelihood of the perception $P(E^k|S^k)$ in the update usually lets the probability distribution be more focused and thus reduces the uncertainty.

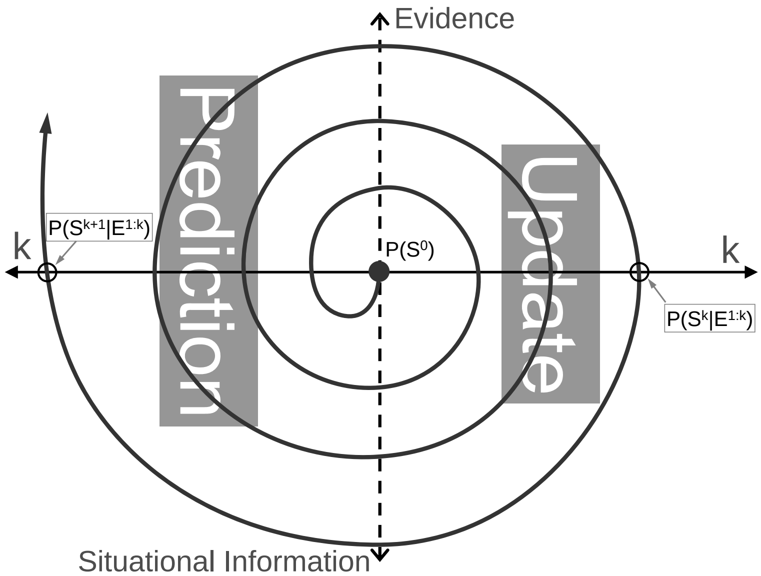


Figure 3.7: Prediction-Update Spiral: The spiral starts with the prior probability $P(S^0)$ for the situational information S. The next step is a prediction $P(S^1|S^0)$ for the transition to time slice 1. Then the situational information is updated by $P(S^1|E^1)$ with the evidence E^1 of time slice 1. After that the spiral starts over with a prediction based on the outcome of previous update.

Figure 3.8 exemplarily shows the variation of the probability density functions for a longitudinal distance estimation influenced through prediction and update. In the left figure the red PDF depicts the prior probability which can be the prior probability $P(S^0)$ of the whole estimation process or the posterior probability $P(S^k|E^k)$ of the previous time slice k which goes down as the prior probability in the next time slice. The PDF in the example is given by the normal distribution $N(2, 0.6)$ with mean $\mu_p = 2$m and a standard deviation of $\sigma_p = 0.6$m. In the prediction step the prior probability is influenced by the state transition probability $P(S^{k+1}|S^k)$ which is for instance a motion model for vehicle movement (depicted in magenta) which incorporates the acceleration uncertainty. In the example it is given by the normal distribution $N(1, 0.7)$ with mean $\mu_m = 1$m and a standard deviation of $\sigma_m = 0.7$m. The result of the prediction step $P(S^{k+1}|E^k)$ is the blue PDF which is calculated by convolution. $P(S^{k+1}|E^k)$ is proportional to the normal distribution $N(\mu_p + \mu_m, \sigma_p + \sigma_m) = N(3, 1.3)$ with mean $\mu_e = 3$m and a standard deviation of $\sigma_e = 1.3$m.

In the update step (right figure) $P(S^{k+1}|E^k)$ (shown in blue) is updated by the evidence which goes down with its sensor/measurement model $P(E^{k+1}|S^{k+1})$ which expresses the uncertainty inherent to the evidence (depicted yellow). It is represented by the normal distribution $N(5, 0.6)$ with mean $\mu_s = 5$m and a standard deviation of $\sigma_s = 0.6$m. The outcome of the update step $P(S^{k+1}|E^{k+1})$ which results from the multiplication of the prediction and sensor model PDFs is visualized in green. It is given by the normal distribution $N(\frac{\sigma_e^2\mu_s+\sigma_s^2\mu_e}{\sigma_e^2+\sigma_s^2}, \frac{\sigma_e^2\sigma_s^2}{\sigma_e^2+\sigma_s^2}) = N(4.65, 0.57)$. As can be seen

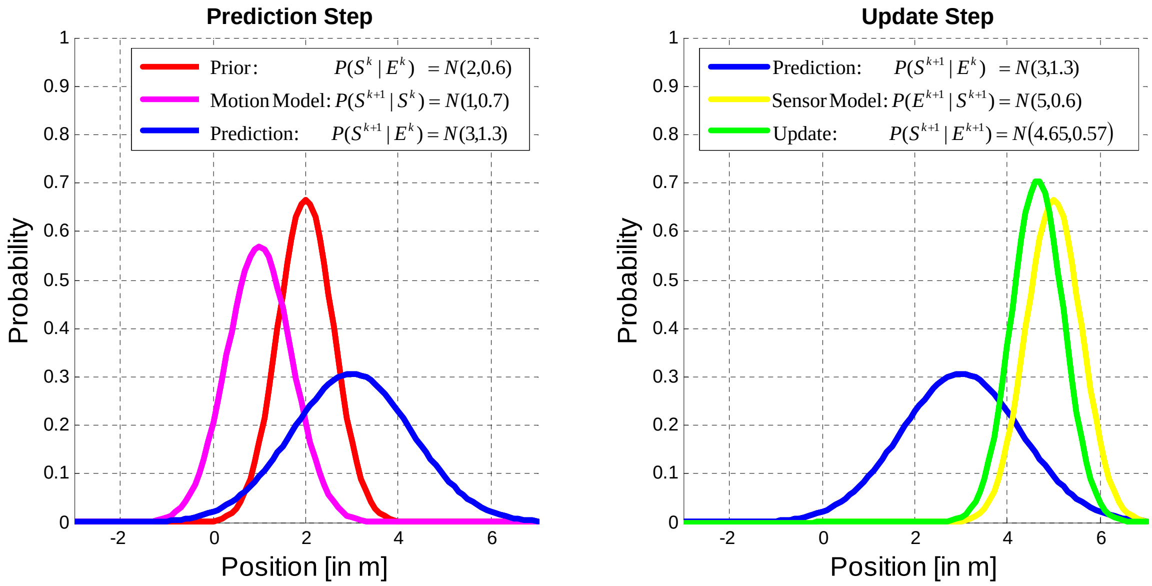


Figure 3.8: Variation of the probability density functions in the prediction and update step (based on Durrant-Whyte [64])

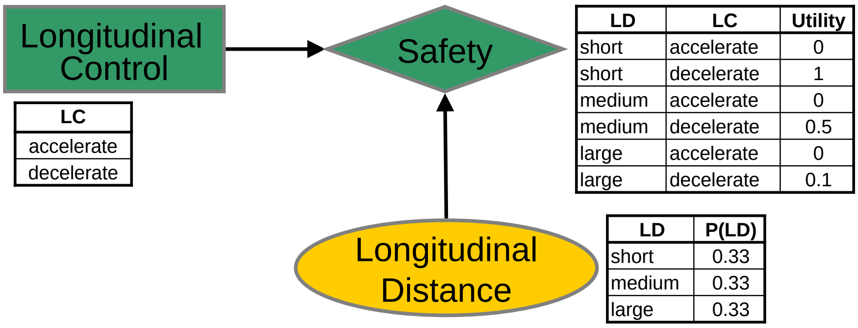
the prediction widens the prior probability (from sharp red PDF to the wider blue PDF) and the update focuses the PDF again (from wide blue PDF to sharp green PDF).

Process control

From the temporal perspective each prediction step periodically moves the inspection window to a new time slice and the following update step incorporates the evidence gathered in this time slice. Each inspected time slice normally has an equal length and an equal set of situational information and evidences. This is the standard procedure as it is normally found in literature [62, 226]. It requires that the information sources regularly provide evidence in a period that is identical to the time slice duration. This will result in an equidistant time slice structure as depicted in figure 3.6.

As equidistant time-slices do not allow a suitable incorporation of evidence which does not comply with a constant update rate, this approach is not suitable for distributed systems. A black ice warning, for instance, which serves as evidence for an icy pavement condition will not comply with a constant update rate as it normally is event-triggered. In this case evidence has to be incorporated whenever it becomes available. Thus, the constant shift of the inspection window to the next time slice will be foiled with a prediction-update every time new evidence becomes available. What is needed is an event-triggered prediction-update process that follows the occurrence of evidence. The prediction $P(S^{k+1}|S^k)$ therefore has to take into account the duration between time slice k and $k+1$.

Reconsidering the objective of the situation model to provide an estimation of the situation at every time instant of interest, whereas the interest strongly depends on the kind of application, triggering the next prediction-update process only in case new evidence is gathered is not suitable. As an example, consecutive losses of V2V messages will



LC
accelerate
decelerate

LD	LC	Utility
short	accelerate	0
short	decelerate	1
medium	accelerate	0
medium	decelerate	0.5
large	accelerate	0
large	decelerate	0.1

LD	P(LD)
short	0.33
medium	0.33
large	0.33

Figure 3.25: `Longitudinal Control` decision with safety objective (short form of the decision network as depicted in figure 3.24)

If we model a driver assistance system that shall maintain a safe distance to the preceding vehicle by penalizing acceleration in case the distance to the preceding vehicle is short, the maximum expected utility estimation will result in constant deceleration. The distributions of figure 3.25 always show *decelerate* as the best action $EU(LC = \{accelerate, decelerate\}) = \langle 0, 0.53\rangle$ with

$EU(LC|LD = short) = \langle 0, 1\rangle$,

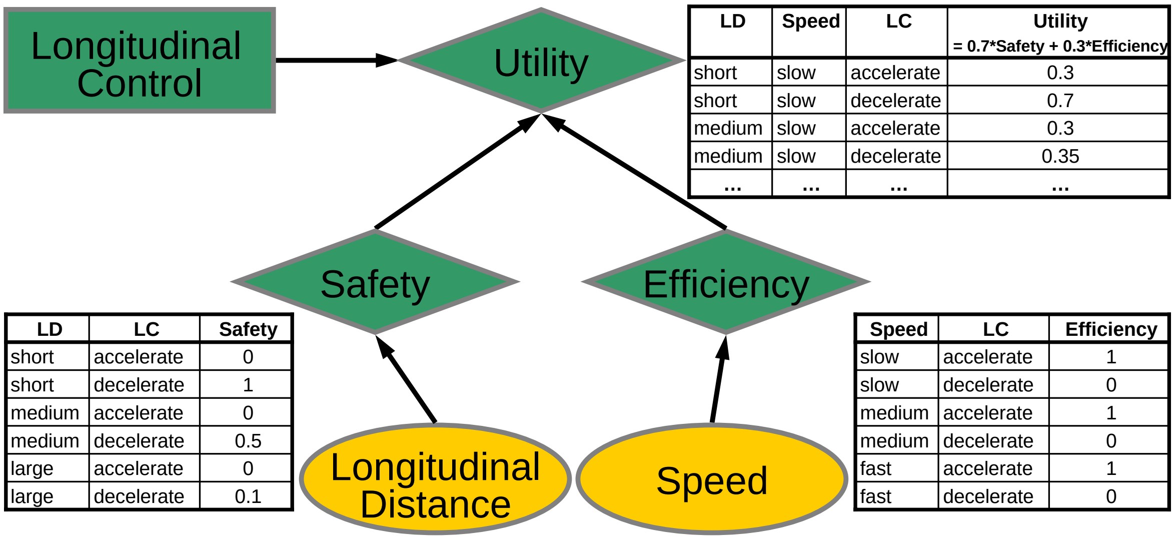
$EU(LC|LD = medium) = \langle 0, 0.5\rangle$ and

$EU(LC|LD = large) = \langle 0, 0.1\rangle$

This is obvious because only the safety aspects have been modeled as objective and every acceleration is penalized, so the safest situation is not to move at all. Thus, to eventually reach the destination, an additional objective has to be incorporated in the decision-making. The additional objective is the efficiency of movement which provides a positive incentive with higher speeds. Figure 3.26 shows the decision network with the additional `Efficiency` utility node which, together with the `Safety` utility, is combined in a higher layer utility node with a weighting of 0.3 : 0.7. For simplicity reasons the dependence of the `Safety` utility on the `Speed` as introduced in figure 3.21 is neglected.

Rational decisions with temporal situation dynamics

Up to now, the decision problem was considered as a temporarily static problem. An action was chosen on the utility of its consequence given the recent evidence. That means no progression over time was taken into account. In dynamic system environments not only the situation has to be observed over time but also the decision-making process. Evidently, this is required because a decision made at the current point in time influences the situation in the future. E.g. pressing the accelerator pedal will result in a higher speed in the upcoming time slice. By performing a certain action we want to change the upcoming situation towards the targeted objectives. Thus, the value emerges from the situation that will be achieved in the future. This has to include a prediction based on the current situation and the action that will be performed which has an impact on the situation transition. Thus, the alternative actions have to be compared by the



LD	Speed	LC	Utility = 0.7*Safety + 0.3*Efficiency
short	slow	accelerate	0.3
short	slow	decelerate	0.7
medium	slow	accelerate	0.3
medium	slow	decelerate	0.35
...	...	...	...

LD	LC	Safety
short	accelerate	0
short	decelerate	1
medium	accelerate	0
medium	decelerate	0.5
large	accelerate	0
large	decelerate	0.1

Speed	LC	Efficiency
slow	accelerate	1
slow	decelerate	0
medium	accelerate	1
medium	decelerate	0
fast	accelerate	1
fast	decelerate	0

Figure 3.26: `Longitudinal Control` decision with utility functions `Safety` and `Efficiency` which take into account the situational information `Longitudinal Distance` and `Speed`

expected utility of the future situation given the evidence which has been perceived. According to Russel and Norvig [226], *"for each possible percept sequence, a rational agent should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has"*. Thus, a decision in a dynamic system environment shall not merely be based on the current evidence but on the whole *"percept sequence"*. Therefore, the MEU has to be calculated in the context of the evidence gathered in the time slices 1 to k by:

$$\begin{aligned} MEU(A|E^{1:k}) &= \max_A EU^{k+1}(A|E^{1:k}) = \\ &= \max_A \sum_{S^{k+1}} U(S^{k+1}) \cdot P(S^{k+1}|A, E^{1:k}) \end{aligned} \tag{3.23}$$

In the dynamic inspection the consequence S_a is the situation which occurs in the upcoming time slice S^{k+1}, thus, $S_a = S^{k+1}$. $MEU(A|E^{1:k})$ thus provides the utility which can be achieved in the next time slice by performing the best action according to all the evidence which has been observed up to now (see figure 3.27).

$P(S^{k+1}|A, E^{1:k})$ in this equation is the probability of the predicted situation given the evidence observed up to now and given that action A has been performed. Thus, it is a prediction as defined in equation 3.6 but with the additional condition that A is performed:

$$
\begin{aligned}
P(S^{k+1}|A, E^{1:k}) &= \frac{\sum_{S^k} P(S^{k+1}|S^k, A, E^{1:k}) \cdot P(S^k, A, E^{1:k})}{P(A, E^{1:k})} = \\
&= \frac{\sum_{S^k} P(S^{k+1}|S^k, A, E^{1:k}) \cdot P(S^k|A, E^{1:k}) \cdot P(A, E^{1:k})}{P(A, E^{1:k})} = \\
&= \sum_{S^k} P(S^{k+1}|S^k, A, E^{1:k}) \cdot P(S^k|A, E^{1:k}) =^{(1)(2)} \\
&= \sum_{S^k} P(S^{k+1}|S^k, A) \cdot P(S^k|E^{1:k})
\end{aligned}
\tag{3.24}
$$

In (1) conditional independence has been exploited which states that a future situation is independent of the evidence observed up to now given the current situation and the action which has been performed recently: $P(S^{k+1}|S^k, A, E^{1:k}) = P(S^{k+1}|S^k, A)$. And, second, in (2) additional conditional independence of the current situation S^k being independent of the action A given evidence $E^{1:k}$ is used: $P(S^k|A, E^{1:k}) = P(S^k|E^{1:k})$.

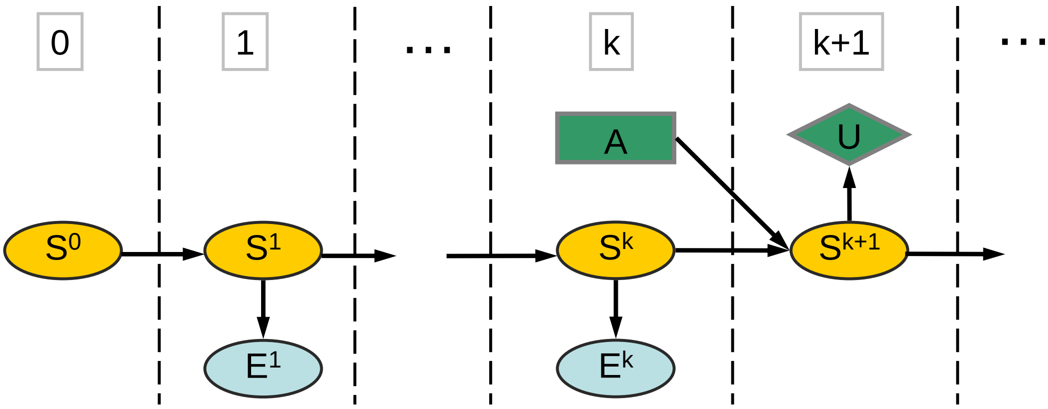


Figure 3.27: Dynamic Decision-making

For the deliberation of the best action in time slice k, the upcoming expected utilities for each alternative action are evaluated in the context of all observed evidences and the action which is subject for deliberation:

$$
\begin{aligned}
MEU(A|E^{1:k}) &= \max_A EU^{k+1}(A|E^{1:k}) = \\
&= \max_A \sum_{S^{k+1}} U(S^{k+1}) \cdot \sum_{S^k} P(S^{k+1}|S^k, A) \cdot P(S^k|E^{1:k})
\end{aligned}
\tag{3.25}
$$

This MEU determination for dynamic systems calculates the maximum utility which can be expected for the time slice $k+1$ by the utility comparison of the consequences of each action weighted by the probability of the consequence which is based on the action prediction marginalized over the possible current situations. Thus, it takes into account the uncertainty in the current situation and the uncertainty in the action function.

$P(S^k|E^{1:k})$ in the equation is given by the update of evidence in time slice k as defined in equation 3.7.

It is worth to note here that the prediction of equation 3.24 does not substitute for the prediction introduced in dynamic system equation 3.6. Equation 3.24 assumes that a concrete action has been performed. This action does not represent an act. It is a concept merely used for deliberation which does not represent the act and, thus, also neglects the selection uncertainty which would be the case if an act would be considered because the system has no certainty in the implementations within the physical universe.

Planning

In the above described dynamic decision-making the relevant utility of an action was merely inspected at the next time slice. Thus, the optimality of an action is only valid for the next time slice. In the ITS environment an action such as the *acceleration* operation influences not only the next time slice but influences also subsequent time slices (see figure 3.28). The utility for such kind of operations therefore has to summarize the whole duration of influence of this action:

$$MEU_h(A|E^{1:k}) = \max_A \sum_{i=1}^{h} EU^{k+i}(A|E^{1:k}) \tag{3.26}$$

Thus, the utility of performing an action is the additive utility of performing the action for the time horizon h. *"In open or continuous environments, deciding what is best depends on a time horizon - it is usually impractical for agents to reason infinitely far into the future or to consider an infinite number of intermediate states"* [114]. Thus, we will only consider finite time horizons in this work.

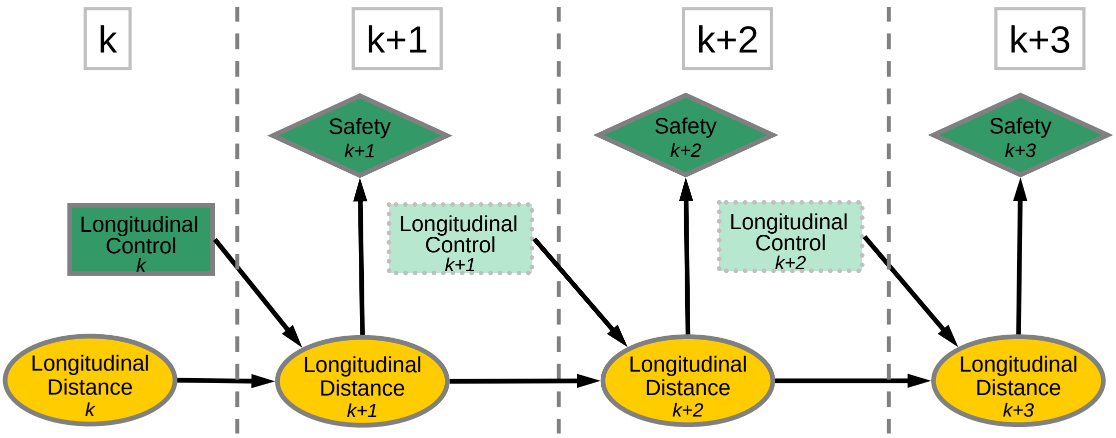


Figure 3.28: `Safety` utility evaluation of the `Longitudinal Distance` for a duration of influence of the decision `Longitudinal Control` of $h = 3$

It has to be noted that in equation 3.26 the best action is not determined independently for every time slice but a single best action is determined which is optimal for all future time slices of interest. Thus, it is no decision policy with action sequences for a specific time horizon as introduced in [226]. As dynamic systems in ITS environments often have no terminal state or the terminal state is far away in time, the state-action space is too complex for decision policies. Future utility hence is generated by performing a single action which is chosen in time slice k and its influence lasts for the duration h (see figure 3.28).

In order to determine the recent best action, rational decision-making has to evaluate the expected utility for the future duration of influence given past evidence

3.5 Concluding remarks and evaluation

This chapter introduced a holistic system model which incorporates the whole process from gathering evidence to making elaborate decisions. The system model features a clear structuring consisting of three layers: input layer, hidden layer and decision layer. Thereby, complex probabilistic network structures are clearly separated of concerns.

It is worth to note that *"systems that reason about real-world problems can represent only a portion of reality. It is clear that any computational representation must be a dramatic simplification of the objects and relations in the universe that may have relevance to a decision problem. The inescapable incompleteness in representation leads to unavoidable uncertainties"* [111]. Thus, the situation model only takes into account the portion of reality which is relevant for decision-making and ignores all other unnecessary information.

The system model allows the usage of evidence from any kind of information source by any kind of application. In contrast to the *"one single sensor per application"* this work contributes to the concepts of a single information platform [143, 104] which incorporates a **dynamic extendible multi-sensor multi-application** handling. It incorporates temporal dynamics in the situation by introducing the dynamic filter equations for prediction and update which add the temporal coherence required for an adequate estimation of time-persistent situational information. The concepts for dynamic process control with time-triggered as well as event-triggered update mechanisms are vital for the decision-making capability.

Event-triggered updates are initiated by new evidence which is the link between the physical universe and the intellectual universe. The proper perception of evidence which is generated by various kinds of sources of information which may reside on the local entity (autonomous sensing) as well as on remote entities (cooperative sensing) in a distributed ITS is the major challenge. Evidence has to be regarded against the background of accuracy and reliability. In order to protect the system from drawing false conclusions, a key feature is the exploitation of the actual worth of information which is based on the general evidence likelihood, prior knowledge on the situational information and contextual information, e.g. further sources of information. This can serve as confidence check with autonomous sensing or majority vote with an increasing number of supportive entities. Sensor fusion thus provides a major cornerstone in the proposed system. With the multi-state concept the problems of an unknown number of targets, unknown measurement-target associations and unknown states are tackled. Instead of explicitly associating measurements to targets the scenario-based approach for the perception of composite evidence avoids the problem of mis-association and enables a $1 : T$ relation of measurements and targets. Since applications are not interested in explicit associations but require only a valid estimation of the current environment, an association-free approach perfectly copes with the requirements.

Based on an update-to-date situation estimation actions and utilities provide the required concepts for making elaborated decisions. The decision on the recent best action takes into account all evidence gathered up to now and deliberates the impact of an action for the future duration of influence. The key concept is to account for uncertainty in the situation and in the consequences of actions which results in a **probabilistic causal decision network**. The decision-making as proposed in this work uses the probabilistic causal decision network as a mental model for the deliberation of actions. *"Mental models are adaptive belief constructs, used to describe, explain and predict situations"* [54], for instance, by simulation. This *"mental simulation can be used to project a course of action forward in time, and it also can be used to look backwards in time as a way of making sense of events and observations. Here, the decision maker is trying to find the most plausible story, or sequence of events, in order to understand what is going on - a process of diagnosis that is intended to result in situation awareness."* [145]

4 Backward Integration

A little knowledge that acts is worth infinitely more than much knowledge that is idle.
Kahlil Gibran (1883-1931)

4

Decisions for optimized evidence exchange

In the previous chapters it has been shown that by using probabilistic causal decision networks, situations and the according best actions can be inferred from inaccurate and incomplete evidence by explicitly taking into account the inherent uncertainty. Particularly, the integration of remote sensor data which has been communicated from other entities[1] in the ITS network, provides a significant knowledge improvement for each individual node and allows a timely, accurate and reliable decision-making. In this chapter we will focus on the specific **integration of Vehicle-2-X ad-hoc communications as an adaptive source of information which can be used actively to reduce the uncertainty in the situation estimation**. Whereas in the previous chapters it was assumed that information is received whenever it is required by each entity via broadcast, cellular or ad-hoc communications and then serves as evidence for the situation estimation, this chapter focuses on the underlying communications and introduces concepts to exploit communications for an optimal exchange of information.

The fundamental input and output parameters utilized within the communication optimization algorithms are the information included in the situation model and therefore the approach can be characterized as **information-centric communications**. This will close the cycle from communications to information and back to communications (see figure 1.3).

Messaging characteristics

In future ITS systems single entities are expected to host a multitude of different applications [19, 223, 18]. A vehicle may include for instance an application for Vehicle-Based Road Condition Warning, Intelligent Traffic Flow, Lane Change Warning and Cooperative Adaptive Cruise Control (CACC) running in parallel. According to a

[1]In this work the term "entity" generally represents everything that is capable of sending and/or receiving information, e.g. a car, motorcycle or truck with an on-board unit, an ITS road-side unit, a UMTS node B, a pedestrian carrying an ITS-enabled device, etc.

study of CAMP VSC [55] these applications require a minimum set of information which is listed for each application in the following:

- *Vehicle-Based Road Condition Warning*: position, heading, road condition parameters (∼2Hz)
- *Intelligent Traffic Flow*: position, velocity, heading (1Hz)
- *Lane Change Warning*: position, velocity, acceleration, heading, turn signal status (∼10Hz)
- *Cooperative Adaptive Cruise Control*: position, velocity, acceleration, heading, yaw rate (∼10Hz)

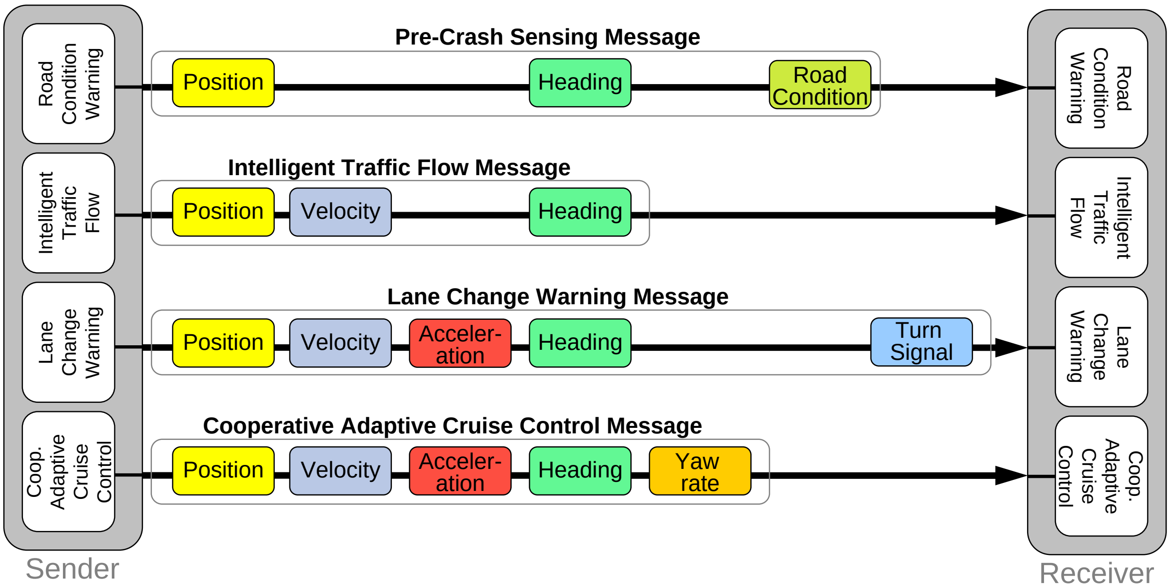


Figure 4.1: Independent communication of V2X messages

All of these applications[2] require at least the position, heading and velocity of the vehicle. Two of the four applications require information on acceleration and yaw rate. Thus, if every application independently sends its information within a dedicated message (*single application messaging* [18]), this results in a considerable amount of redundancy in the transmitted data [223] (see figure 4.1). Redundancy in the transmitted data is equivalent to an uncertainty update in the situational information of zero because the evidence includes no additional information. Although this would increase reliability, for instance, if a message gets lost due to a packet collision, the independent handling of single application messages will not allow to utilize this redundancy.

A solution to reduce redundancy is achieved by combining all situational information of all applications inside a single message which refuses redundant information (see

[2]Although we will focus on these applications in the following paragraphs, the same conclusions hold for a multitude of the applications defined by [55], [19], [70] etc.

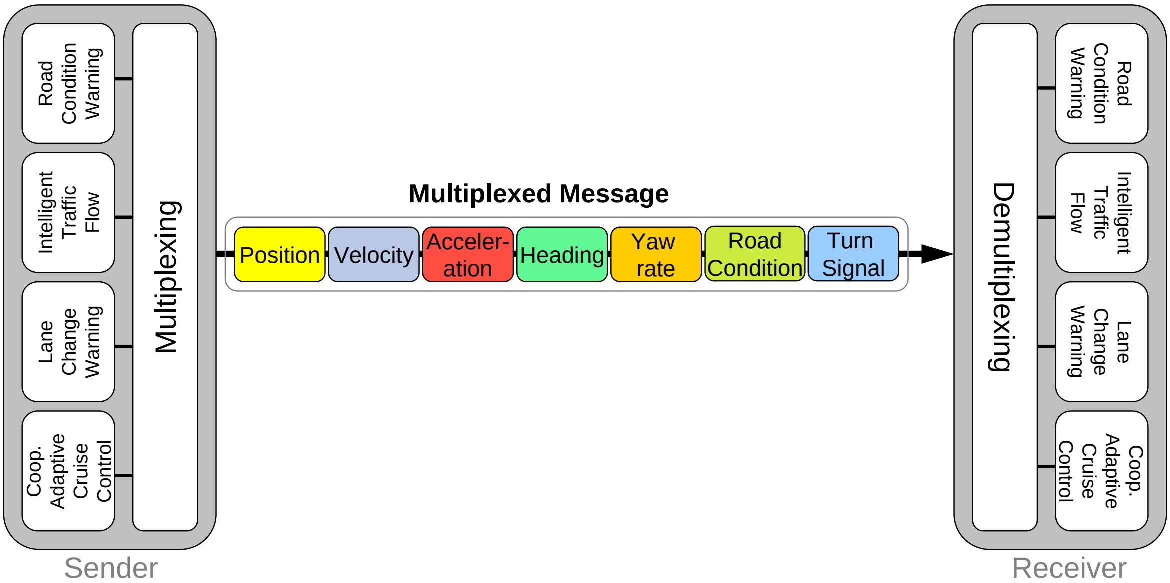


Figure 4.2: Multiplexed single V2X message

figure 4.2) and with the highest required update rate (10Hz for the examples). Using a single "all-in-one" message with a common update rate according to the highest requirements may again cause unnecessary updates of situational information which is only required with a low update rate, e.g. road condition parameters, and hence results in an unneeded bandwidth allocation. As long as the bandwidth is not fully used to capacity this is not problematic but if less important information (e.g. unchanged road conditions or position updates of a standing vehicle) is sent with high frequency at the cost of highly important information which will not get its bandwidth share, such kind of resource management strategy is up to discussion. Thus, this chapter is targeted on a message exchange which takes into account the actual worth of transmitted information for the receivers and the costs which emerge due to a limited resource availability.

For a good bandwidth utilization it is reasonable to send messages adaptively generated and individually charged with information according to the application requirements set union. This process has to be executed by a cross-application function which is called a *Message Dispatcher* in the work of Robinson et al. [223] or *Safety Message Handler* in SAE J2735 [18]. It is located within a common building block for all applications and provides a common interface to the applications that have an information transmission demand (see figure 4.3). The message dispatcher collects the demands of all applications and eventually sends a message containing all the information requested for transmission.

A weakness of this approach emerges due to the characteristics of an open, distributed system such as future cooperative ITS. In such systems it cannot be assumed that sender and receiver have an identical set of applications, especially in the course of the continuous deployment but also afterwards by the development of novel applications. As can be seen in figure 4.3, if an application is installed on the sender which is not installed on the receiver, the respective information simply is ignored by the receiver

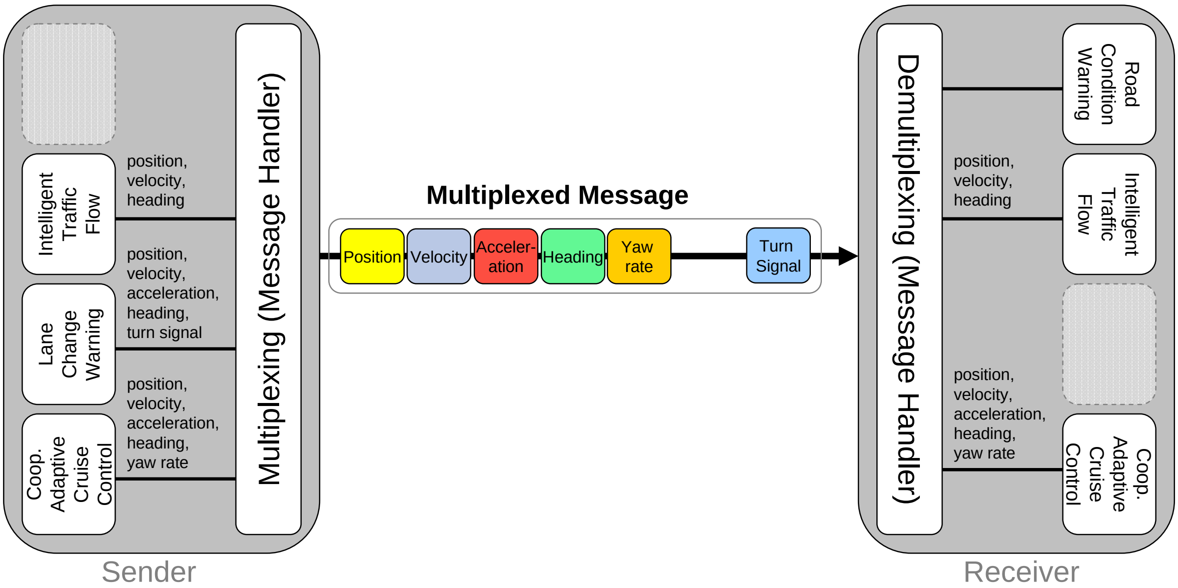


Figure 4.3: Multiplexed message exchange with Message Handler [18] and differing application sets on sender and receiver

(turn signal in figure 4.3). But this approach does not work in the opposite direction, i.e. an application running in the receiver but not in the sender. Thus, the receiver will not receive the required information although the information (road condition in figure 4.3) may be available at the sender but is not sent because of the absence of an appropriate application.

Therefore one of the basic contributions of this work which differs from state of the art is the consideration of applications only on receiver side. The sender is reduced to a simple **evidence distributor**[3]. The main task of the evidence distributor is to set up the message similar to the message dispatcher but without the need for specific applications on the sender side. Furthermore, the evidence distributor is responsible to determine the worth of information in order to perform a suitable message prioritization in the communications part. Thus, what is proposed in this work, is a much stronger emphasis on the information itself leaving behind pre-defined message sets and message characteristics as used in classical communications systems. This proposition is based on the fact that the overall goal of a distributed system in the context of safety/efficiency-related ITS shall be the **timely distribution of relevant information** whereas this relevance is a receiver-based criteria. Thus, it is more an **information-centric receiver-oriented communication** than conventional *message-centric sender-oriented* communication which dominated in the past.

> Information-centric receiver-oriented communication distributes information according to the worth of the information for the receivers

[3] *Sender* and *receiver* are only logical roles of ITS entities taken during a message exchange, thus, an ITS entity can be sender and receiver, even in parallel

In this work we break down our concept for information-centric receiver-oriented communications into three messaging types:

- **Information dissemination**: An entity decides on its current state of knowledge to disseminate information which it gathered from local sensors.
- **Information gathering**: An entity detects that a specific kind of information would be of high importance and thus initiates a request.
- **Information forwarding:** An entity receives information from another entity and decides to forward it.

Each messaging type will be set up with novel concepts for information-centric receiver-oriented communication strategies in one of the following sections.

4.1 Information Dissemination

Generally, information is more interesting for an entity if it does not know it, or, for the case of intelligent entities, if it cannot predict it. This fact applies for human beings as well: the outcome of tossing a coin has a very high relevance to interested people because nobody can predict the outcome. If this coin is loaded and in the majority of cases shows the same side, the outcome is only less surprising and, hence, less relevant to the observers. If we transfer this example to the cooperative situation estimation in future ITS, disseminating information which is obvious to other nodes because it is fully predictable is not worth sending it. It would consume bandwidth and may collide with other messages which may be more relevant. So, an intelligent system has to differentiate the degree of "surprise" which is the level of uncertainty reduction of the information it can communicate to other nodes.

Postulating that nodes in each others' communication range are aware of the same information and have the same prior knowledge about the information dynamics, they will anticipate similar situations using the prediction equation 3.6 on page 74. Every time new evidence is generated by autonomous sensing, e.g. by a new GNSS position measurement, the dynamic situation estimation updates the prediction of the situational information with the likelihood function using the update equation 3.7 on page 75. The difference in the uncertainty before and after incorporating the evidence is a measure for the worth of the evidence in the current situation. Hence, the prediction creates uncertainty in the situational information and the update reduces uncertainty as it was shown in figure 3.8 (equation 4.8 provides the respective proof). Thus, the prediction of a future vehicle position increases the uncertainty and the GNSS measurement update decreases the uncertainty.

> The worth of information has to quantify the strength the situation estimation utilizing this information differs from pure prediction

A common measure for uncertainty is the **entropy** as it has been identified by Shannon in his seminal article *"A Mathematical Theory of Communication"* [237]. Shannon defined the entropy $H(X)$ for a discrete random variable X with a probability distribution $P(X)$ by:

$$H(X) = -\sum_{x \in X} P(x)\ \log P(x) \tag{4.1}$$

With $\mathbb{E}_X$ being the expectation over the random variable X (or simply $\mathbb{E}$ if the respective random variable is unambiguous)[4], the entropy also can be written as:

$$H(X) = -\mathbb{E}_X \log P(X) = \mathbb{E}_X \frac{1}{\log P(X)} \tag{4.2}$$

For a uniformly distributed random variable $X_U = \{x_1, \ldots, x_n\}$ the entropy can be calculated by:

$$H(X_U) = -\sum_{i=1}^{n} \frac{1}{n} \log \frac{1}{n} = \log n \tag{4.3}$$

A uniform distribution has the maximum entropy because all states are equiprobable and a prediction would be a complete leap in the dark. On the other extreme the minimum entropy is zero which reflects a random variable with a certain outcome. Thus, $0 \leq H(X) \leq \log n$.

For continuous random variables the entropy (*differential entropy*) can be approximated, e.g.:

$$\textit{Uniform distribution:} \quad H(f(x)) = log_2(b-a) \qquad \text{for} \quad f(x) = \frac{1}{b-a}\ ,\ a \leq x \leq b \tag{4.4}$$

$$\textit{Normal distribution:} \quad H(f(x)) = log_2(\sigma\sqrt{2\pi e}) \qquad \text{for} \quad f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{(-\frac{(x-\mu)^2)}{2\sigma^2}} \tag{4.5}$$

Additionally to the entropy definition for prior probability distributions, the entropy can also be regarded in the context of background knowledge as **conditional entropy** *"of a random variable given another as the expected value of the entropies of the conditional distributions, averaged over the conditioning random variable"* [53]:

$$\begin{aligned} H(X|Y) &= \sum_{y \in Y} P(y) H(X|y) = \qquad (4.6)\\ &= -\sum_{y \in Y} P(y) \sum_{x \in X} P(x|y) \log P(x|y) = \\ &= -\sum_{y \in Y} \sum_{x \in X} P(y,x) \log P(x|y) = \\ &= -\mathbb{E}_{X,Y} \log P(X|Y) \end{aligned}$$

[4]The symbol $\mathbb{E}$ is used for *expectation* in order to clearly distinguish it from the evidence symbol E

Chapter 4

Thus, the difference in the entropy of X with and without the knowledge of the random variable Y can be calculated by:

$$\begin{aligned} I(X:Y) &= H(X) - H(X|Y) = \\ &= -\mathbb{E}\log P(X) + \mathbb{E}\log P(X|Y) = \\ &= \mathbb{E}\log\frac{P(X|Y)}{P(X)} \end{aligned} \tag{4.7}$$

$I(X:Y)$ is called **mutual information** [237, 189]. *"It is the reduction in the uncertainty of one random variable due to the knowledge of the other"* [53]. The mutual information represents the expectation of the logarithm of the *relevance quotient* which was introduced in equation 2.10 as the ratio of the posterior probability to the prior probability as part of the Bayes rule. A general rule is that the mutual information is non-negative:

$$\begin{aligned} I(X:Y) &= \mathbb{E}\log\frac{P(X|Y)}{P(X)} \\ &= -\mathbb{E}\log\frac{P(X)}{P(X|Y)} \\ &= -\sum_{X,Y} P(X,Y)\log\frac{P(X)}{P(X|Y)} \\ &\geq^{(*)} -\log\sum_{X,Y} P(X,Y)\frac{P(X)}{P(X|Y)} \\ &= -\log\sum_{X,Y} P(X,Y)\frac{P(X)P(Y)}{P(X,Y)} \\ &= -\log\sum_{X,Y} P(X)P(Y) \\ &= -\log 1 = 0 \end{aligned} \tag{4.8}$$

$$\Leftrightarrow \; H(X) \geq H(X|Y) \tag{4.9}$$

In $^{(*)}$ the Jensen inequality $\mathbb{E}f(x) \geq f(\mathbb{E}x)$ for convex functions f [162] has been used. The mutual information is equal to zero if and only if X and Y are unconditionally independent (equation 2.3):

$$I(X:Y) = \mathbb{E}\log\frac{P(X|Y)}{P(X)} = \mathbb{E}\log 1 = 0 \tag{4.10}$$

Thus, **additional information, in particular evidence from a source of information, never increases the entropy**. Although the logarithm of the relevance quotient can be negative, its expectation is always greater or equal zero. Figure 4.4 graphically shows the composition of entropy, conditional entropy, mutual information, etc.

5 Cooperative ACC

Truth in science can be defined as the working hypothesis best suited to open the way to the next better one.

Konrad Lorenz (1903-1989)

5

The previous chapters introduced the theoretical basis for layered probabilistic causal decision networks and the respective inference algorithms as well as different kinds of messaging types in order to optimally exchange information between distributed entities. To show the practical applicability, in this chapter an exemplary application named *Cooperative Adaptive Cruise Control (CACC)* will be described in detail. CACC has been chosen as application because it makes use of the whole functionality introduced so far and thus is perfectly suited to evaluate the overall system performance.

From CC to CACC

Driving a vehicle across wide open roads with constant speed can be very monotonous for the driver. Thus, in 1958 Chrysler produced a respective automation system called cruise control (CC) for the first time. By switching it on at a certain speed, cruise control automatically maintains this speed constantly as long as the driver makes no interaction that overrules the automatic control. If the vehicle experiences an external change in speed, e.g. when approaching an ascent or descent, cruise control accelerates or decelerates the vehicle according to the desired velocity. Cruise control merely targets for comfort increasing purposes.

In the last years an improvement of the conventional cruise control has been developed which further increases the comfort and also increases safety aspects by maintaining a safe following distance to the preceding vehicle. It is known under the name of *Adaptive Cruise Control (ACC)* [260, 222] or *Autonomous Adaptive Cruise Control (AACC)* [258]. In contrast to conventional cruise control, ACC adapts the velocity according to the distance to the preceding vehicle. Thus, if the preceding vehicle, in remainder called the target vehicle, gets closer, by a lower speed of the target vehicle or a higher speed of the ego vehicle, ACC automatically reduces the speed of the ego vehicle. If the distance gets larger and the desired maximum speed adjusted by the driver has not already been reached, ACC accelerates the ego vehicle. If no target vehicle is detected, ACC speeds up the ego vehicle to the desired velocity which has been chosen by the driver when the system was switched on.

Conventional ACC uses radar technology to measure the distance to the preceding vehicle. Although todays radar systems provide distance measurements with a high accuracy and reliability most of the time, radar technology has disadvantages in certain situations due to the limitation to the line of sight horizon and susceptibility to undesired reflections. That is why the functionality is limited in areas with strong bends or slopes, if the target vehicle is not in line of sight, or simply if the target vehicle is too far apart to be detected. Furthermore, radar is only capable of detecting effects of movement changes. That means radar can only detect a preceding vehicle already coming closer and not the cause for the movement change which is for instance the driver pressing on the brake pedal because she/he approaches the end of a traffic jam. This situation cannot be handled with conventional ACC appropriately since radar distance measurements are limited to the directly preceding vehicle, and thus, the system cannot infer movement changes of vehicles in front of the preceding vehicle.

Figure 5.1a) shows a target vehicle which is not detectable by the radar system due to a distance exceeding the maximum field of view of the radar. Conventional ACC radar systems have a field of view of around 100-200m in longitudinal direction [240]. With a speed of 180km/h which is not unusual on the German Autobahn a deceleration of 6.25m/s^2 is required to bring the ego vehicle to a halt if the target vehicle is for instance the end of a traffic jam. Such a deceleration is hardly achievable on wet or icy roads and is much more than the maximum comfortable deceleration of $2\text{-}3\text{m/s}^2$ [255, 43].

In figure 5.1b) the target vehicle is leaving the radar field of view in a sharp bend and thus cannot be detected any more. Accordingly, the ACC system will accelerate the ego vehicle if the maximum velocity has not already been reached.

Figure 5.1c) shows a highway approach. The target vehicle is located on the on-ramp and may cut in but cannot be detected by the radar. For all three examples (figure 5.1a-c) the same detection problems are to be expected in case lidar or camera-based systems are used for ACC instead of radar.

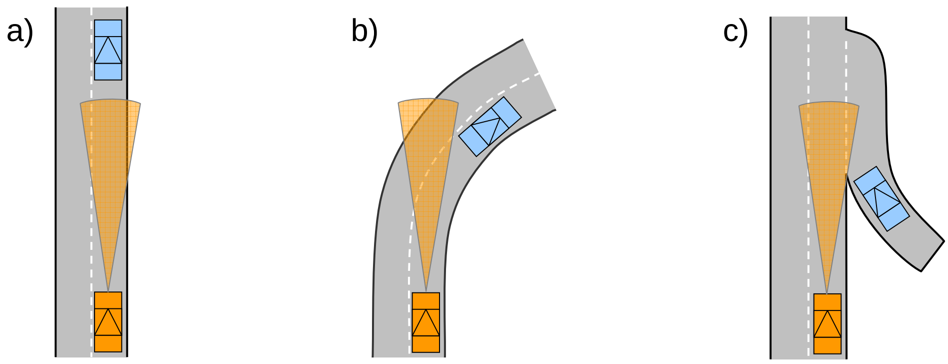


Figure 5.1: Critical ACC situations: a) Target vehicle too far away b) Target vehicle behind bend c) Target vehicle on adjacent on-ramp

These problems can be tackled by the usage of V2X communications which allows to exchange various situational information between vehicles independent of their relative direction and thus can provide additional sensor information, e.g. position, heading and velocity, to the ego vehicle whenever the vehicles are in communication range. We denote an ACC implementation that is capable of utilizing V2X communications as *Cooperative ACC (CACC)* [211, 210, 258, 257]. In diverse literature [133, 103] ACC systems which integrate the use of inter-vehicle communications in the control loop are considered as the next step towards autonomous vehicle control systems.

5.1 Objectives and Impact

Besides commercial profits CACC will provide a benefit in terms of safety, efficiency and comfort of driving in the following ways:

Safety

Almost 50% of all road fatalities in Germany per annum can be ascribed to collisions with other vehicles (see figure 5.2). The 2353 road fatalities in 2007 are caused by collisions with other vehicles which are more than 60% of all accidents with injured happened in this year. Thus, a reduction of the vehicle collisions will have a significant impact on the traffic injured and fatalities. Due to the general functionality of the CACC system to regulate the distance to the preceding vehicle, CACC has the potential to reduce the number of collisions. Falling below the safe distance which includes at least the reaction time if the vehicles move with the same velocity is automatically prevented by the system and thus the risk of rear-end collisions with the target vehicle is decreased. By having a larger detection range using V2X communications critical situations can be anticipated much earlier than in the case only autonomous sensing technology is used. This is also justified by the capability to exchange causes, e.g. a driver of one of the preceding vehicles pressing on the brake pedal, which enables a much earlier preparation of appropriate measures than if only effects, i.e. the position changes, are observed. Furthermore, a more timely reaction of the system avoids fast slow down maneuvers which otherwise would increase the probability of rear-end collisions with the pursuing vehicle. According to Abele et al. CACC has the potential to reduce the number of rear-end collisions by 25% [22]. Additionally, a shift in the accident severity is anticipated. Hence, *"20% of fatalities become severe injuries and 20% of severe injuries become slight injuries"* [22].

Efficiency

The avoidance of fast slow down and fast acceleration maneuvers also increases the efficiency of traffic, not only because collisions are prevented which otherwise would decrease traffic flow efficiency, but also because string stability will be kept [41, 154] and shock waves will be avoided [257]. Thus, inadequate accelerations/decelerations can be reduced, the average vehicle distance can be shortened and the average velocity can be increased. *"Higher average velocity means higher traffic throughput, lower RMS [root mean square] value of acceleration means lower fuel consumption and lower air pollution"* [154] which cannot be achieved to this extent by conventional ACC systems (see figure 5.3). Furthermore, noise emissions and material wear and tear can be reduced. The latter is achieved for instance by an appropriate selection of braking devices, e.g. the wheel brake, the engine brake or a recuperator, in accordance with the anticipated future movement.

Comfort

The avoidance of unnecessary accelerations and decelerations also improves the comfort for the driver and passengers and account for an improved driving experience. Bringing about an artificial attenuation of strong accelerations or decelerations by limiting the maximum allowed acceleration/deceleration force to a comfortable value will increase the safety risk potential and jeopardize string stability respectively. Thus, the avoidance of strong accelerations and decelerations can only be achieved by prospective situation analyses which is achieved by a much broader and timelier sensing horizon.

A more technical objective of the proposed CACC application is to incorporate already existing sources of information within modern vehicles and in parallel be open for new kinds of sensors which will be established in vehicular environments in the future. This can for instance be lidar technology or a camera system or the incorporation of infrastructure-2-vehicle communications [257, 140]. V2X communications which can be considered as another "virtual" sensor [211] shall be integrated into the existing sensor system seamlessly not delimiting the functionality of any other system inside the vehicle.

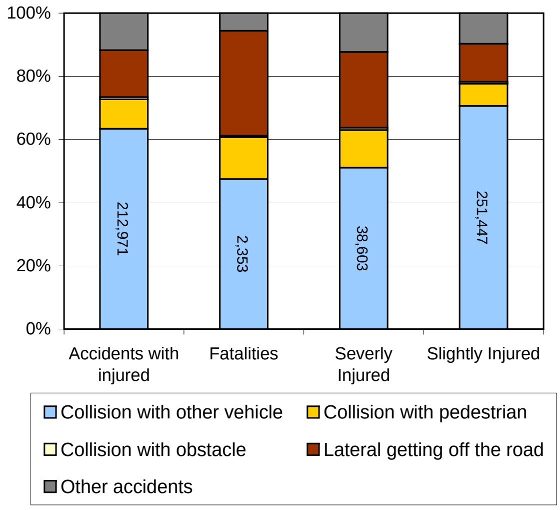


Figure 5.2: Accident statistics broken down to injured severity [2007] (numbers from German Federal Statistical Office [243])

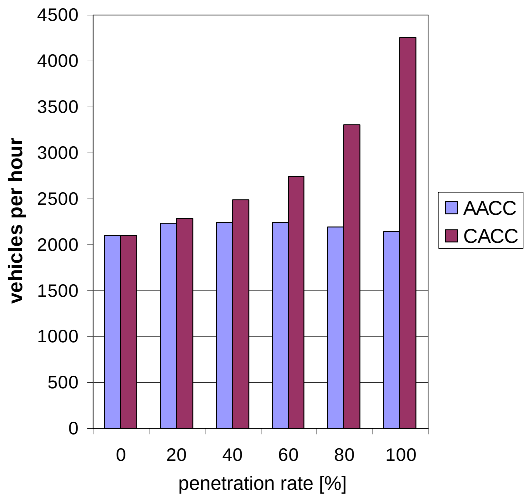


Figure 5.3: Flow rate in vehicles per hour against penetration rate of AACC and CACC (source: VanderWerf et al. [259])

Furthermore, although this chapter focuses on CACC, the general architecture shall facilitate a simple implementation of additional applications, such as Cooperative Collision Avoidance or Pre-Crash Sensing [19, 55].

1. **Initialization**: Set $k = 0$ and draw N samples $\{S^k_{(j)}\}^N_{j=1}$ with equal weight $w^k_{(j)} = \frac{1}{N}$ from the proposal distribution $P(S^0_{(j)})$
2. Increment k
3. **State transition**: Draw sample set $\{S^k_{(j)}\}^N_{j=1}$, from $\{S^{k-1}_{(j)}\}^N_{j=1}$, $j = 1, \ldots, N$ using the state transition distribution $P(S^k_{(j)}|S^{k-1}_{(j)})$
4. **Weight update**: Compute the importance weight for each sample $w^k_{(j)} = P(E^k|S^k_{(j)})$, $j = 1, \ldots, N$
5. **Normalization**: Normalize the importance weights $\tilde{w}^k_{(j)} = \frac{w^k_{(j)}}{\sum_{l=1}^N w^k_{(l)}}$
6. **Resampling**: Generate a new sample set $\{S^k_{(j^*)}\}^N_{j^*=1}$ with $w^k_{(j^*)} = \frac{1}{N}$ by resampling with replacement of the N samples from $\{S^k_{(j)}\}^N_{j=1}$, where the probability of resampling from each $S^k_{(j)}$ is proportional to $\tilde{w}^k_{(j)}$
7. **Restart**: Iterate to item 2

Figure 5.13: SIR particle filter algorithm [46, 136, 26]

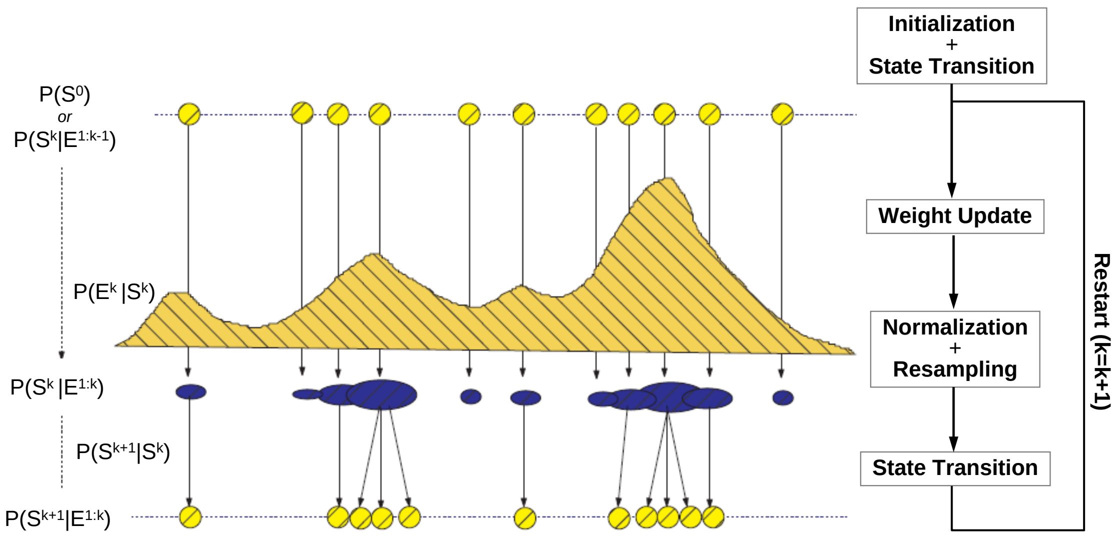


Figure 5.14: Evolution of the particle distribution (based on [46])

Sample Importance Resampling (SIR) algorithm which is a special case of the *Sequential Importance Sampling (SIS)* algorithm. The approach is also called "Survival of the fittest" because only particles with high weights survive.

Thus, a particle filter recursively performs the three essential steps:

1. **State Transition**: Prediction of the state of the next time slice given the state of the current time slice. For the first time slice the prior distribution is used.

2. **Weight Update**: Weighting of each individual particle according to the evidence received (multiple times in case of multiple sources of information)

3. **Normalization & Resampling**: Resampling of the whole particle set according to their weights

The complete algorithm is given in figure 5.13.

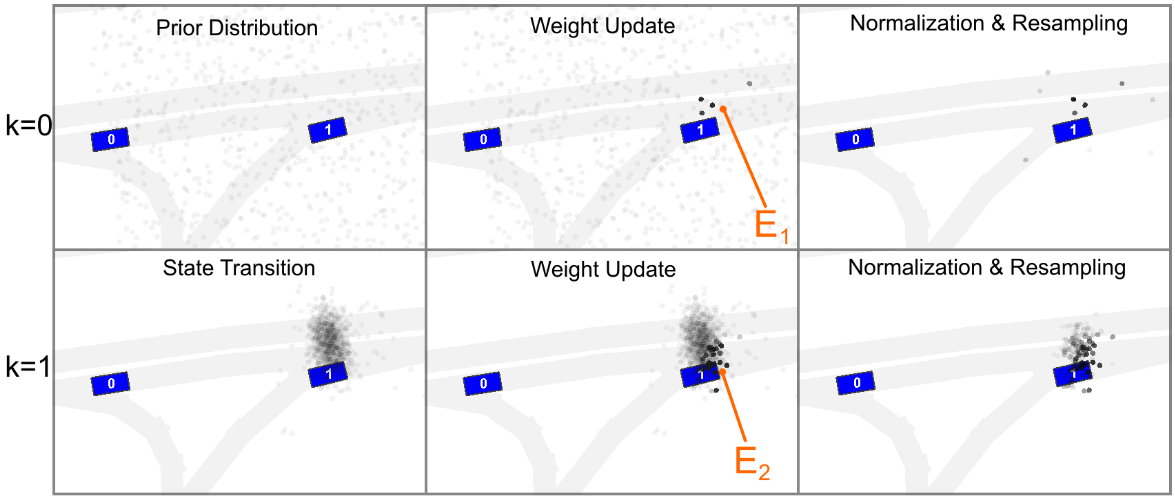


Figure 5.15: Graphical depiction of state transition, weight update, normalization and resampling with a particle filter used for target tracking

Figure 5.14 shows an abstract evolution of the particle distribution according to the SIR particle filter steps. The first line shows the particle distribution according to the probability distribution of the previous time slice $P(S^k|E^{1:k-1})$ or the prior $P(S^0)$. When new evidence E^k becomes available, the update process assigns weights to the particles according to the likelihood of the evidence given the current situation $P(E^k|S^k)$. Normalization and resampling generates new particles according to their weights with more particles in areas with high weights and less particles in areas with low weights. The state transition predicts new particle states given the current particle states and the algorithm is restarted.

In the concrete case of target tracking, the three steps *state transition*, *weight update* and *normalization/resampling* are shown in figure 5.15 for the time slices $k = 0$ and $k = 1$. In this figure one can see two vehicles: vehicle 0 as the ego vehicle (left) and vehicle 1 (right) as the target vehicle. In the first depiction (top-left), the particle distribution according to the prior probability is rather wide with lots of possible hypotheses as long as no measurement has been incorporated. When the first measurement E_1 arrives particles near the measurement get high weights (top-center). After the first normalization and resampling (top right) already most of the hypotheses were rejected and only a few possible hypotheses are left. The estimation process restarts with a state transition based on the latest particle set (bottom-left). After a new measurement E_2 has been received, particles near the measurement get high weights (bottom-center). After normalization and resampling the particle distribution is centered around the real target vehicle position (bottom-right).

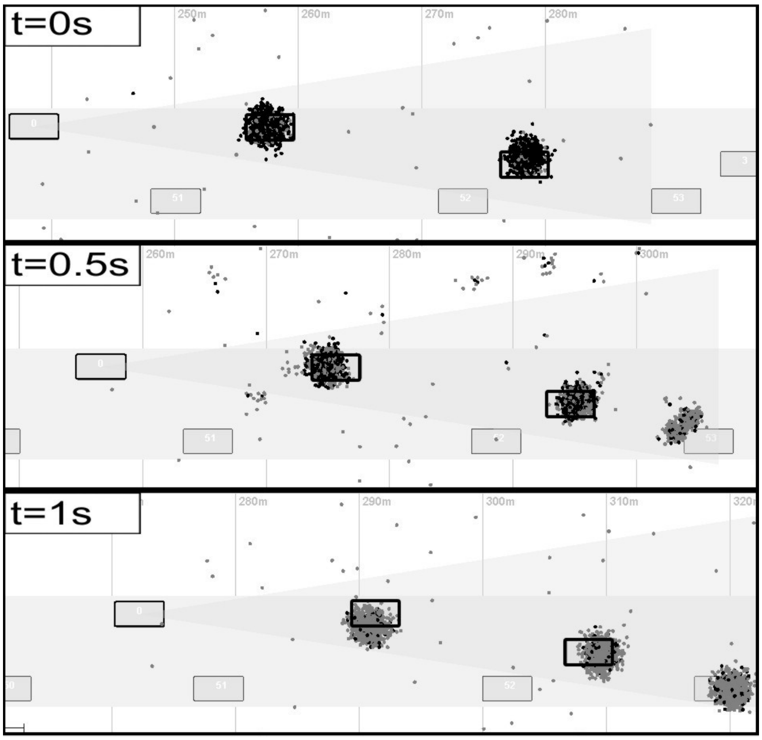


Figure 5.16: Snapshots of the particle distribution for t=0s, t=0.5s and t=1s in a multi-target tracking scenario (source: Röckl [216])

The inclusion of additional targets using JMPD for multi-target tracking adds additional states to the state space of a particle. Thus, instead of using one particle per target, one particle per scenario is used as proposed by Kreucher et al. [148]. A scenario in this case is the whole vehicle constellation in the vicinity (see figure 5.16 and [216]).

5.4.2 CODAR Architecture

Since the objective of this work is to provide general concepts for cooperative situation awareness for future ITS systems, a general architecture shall be defined which enables the support of various kinds of applications which utilize these concepts. The concrete system setup which is used for CACC is shown exemplary. The general system architecture, called *Cooperative Object Detection And Ranging (CODAR)* basic architecture, consists of 4 major modules (see figure 5.17):

Sources of information
: The sources of information module provides information source specific elements (e.g. sensor drivers, data base connections) as well as general functionality (e.g. general sensor measurements, simple unit conversions, sensor discovery) for any kind of information source, e.g. radar, GNSS, odometer, compass, V2X communications. The source of information module provides a standard interface to the CODAR Engine module.

CODAR Engine
: The CODAR Engine module encapsulates all algorithms for the situation estimation. This includes the particle filter implementation, various measurement models for diverse evidences, different state transition models, timers, etc. Depending on the state space, i.e. the set of situational information, used within the state transition model, sources of information providing evidence which causally depends on the situational information are automatically discovered and the respective measurement models are loaded. The CODAR Engine provides a standard interface to the Application module.

CODAR Application Framework
: The CODAR application framework either allows standalone applications to register for certain situational information or functionality for general decision-making support. For instance, the *CODAR Visualisation* as depicted in figure 5.18 registers for situational information of type *Target Vehicle*. Every time situational information of type *Target Vehicle* is updated within the CODAR Engine, the *CODAR Visualisation* is informed. On the other hand, applications such as CACC can register a decision space and utility functions to the CODAR application framework. In this case, the framework connects to the appropriate situational information, evaluates the utility functions when new situational information becomes available and informs effectors of the best action.

Effectors
: The effectors module provides general functions to connect applications to effectors. An effector in general is any kind of output device such as a vehicle accelerator, brake, steering, dashboard display or V2X communications. The module includes effector specific software (e.g. drivers) and general functionality (e.g. effector discovery). Effectors provide a standard interface to the CODAR application framework.

Each of the above presented modules of the CODAR basic architecture encapsulates a specific system functionality. This strong encapsulation provides a clear separation of concern which allows a flexible inter-linkage of modules. This is of particular importance in the vehicular environment since each vehicle provides different types of information sources and effectors from different suppliers with evolving interfaces. Furthermore, a static inter-linkage would be disadvantageous regarding system reliability in case of sensor failures. From an efficiency perspective a static inter-linkage has to be managed and maintained even if the sensor/effector is not required and, thus, has to be avoided.

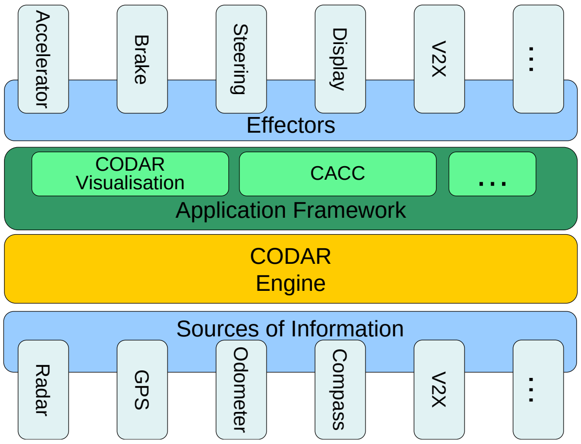


Figure 5.17: CODAR Basic Architecture

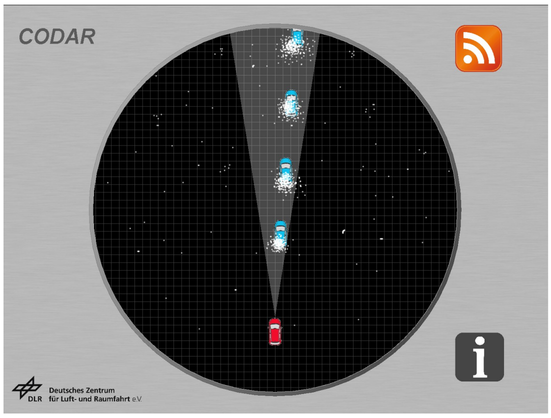


Figure 5.18: CODAR Visualisation with uncertainty representation

All of these disadvantages can be tackled by a loose coupling of dynamic loadable modules. In this case each module exposes a standardized interface by which it identifies itself to other modules. The actual implementation is considered as a black box for other modules. Herby, the CODAR Engine provides filtered situational information to applications. The application does not need to know which kind of filtering has been applied. It merely knows the filter service interface.

Service oriented architecture

The interaction between two modules is based on the usage of a service whereas one module has the role of a service provider and the other as a service user (also known as service consumer). If all interaction between modules is based on services, the architecture is called a *service-oriented architecture (SOA)* [173, 245]. In a service-oriented architecture every logical function which can be used by external modules is considered as a service whereas a service is self-contained, modular, loosely coupled, location-transparent, dynamically bound and exposes a network-addressable, coarse-grained interface [173]. Thus, every sensor, processing algorithm, visualisation component, etc. can be regarded as a service. Services interact by exchanging messages whereas a message is triggered by an event. An event can be a sensor measurement update, the availability of a new sensor, a user interaction, the detection of a critical situation or a timer that triggers a certain process. Some of the services are required over the whole runtime of the system, others only have a temporarily relevance. In order to allow such a flexible service composition, a framework is required that allows a loosely coupling of service instances. Furthermore, dependencies between services have to be resolved during runtime and a service lifetime management is required.

Thus, the CODAR implementation is based on the application framework OSGi (*Open Services Gateway initiative*) [3, 21]. OSGi introduces a dynamic module system which allows a loading and unloading of so called *bundles* during runtime. The bundles

6 Evaluation

I have not failed. I've just found 10,000 ways that won't work.

Thomas A. Edison (1847-1931)

6

In order to show the functionality of the algorithms and concepts which have been introduced in this work, various simulations have been performed. For the performance evaluation simulation is preferable to field operational tests because it allows reproducibility in a fully controllable environment with no external disturbances. The evaluation criteria have been chosen according to the specifics of Cooperative Adaptive Cruise Control (CACC) but are also applicable to any application which requires position information of the vehicles in the vicinity. The evaluation criteria are the accuracy of positioning, the reliability against diverse failures, the CACC decision-making functionality and the communication optimization.

6.1 Simulation Environment

For the evaluation of the different capabilities of the algorithms presented in this work, in particular for the CACC application, a simulation environment provides the required input to the sensor interfaces of the CODAR system (see section 5.4.2) and listens on effector commands initiated by the CODAR application framework. Thus, instead of real sensor drivers the simulation environment provides simulated sensor data through the same interface as the sensor driver. Thus, no changes have to be made in the CODAR bundles. In fact, the bundles are not aware whether they are running within a real vehicle with real sensors and effectors or within the simulation environment with simulated sensors and effectors.

The simulation environment called **m3** which has been implemented to study the performance of the proposed algorithms simulates a set of vehicles, drivers, the environment and telematics [214, 215] in the simulation loop. Vehicles are specified by their maximum velocity, acceleration and deceleration and the drivers which control the acceleration and deceleration act according to the Krauss model (see section 5.3.2.3 on page 153, more details follow in section 6.1.2). The vehicles are bound to the roads and thus no lateral control of the vehicles is required. Additionally, *m3* provides software components for timing, configuration, remote control, debug visualisation and logging (see figure 6.1).

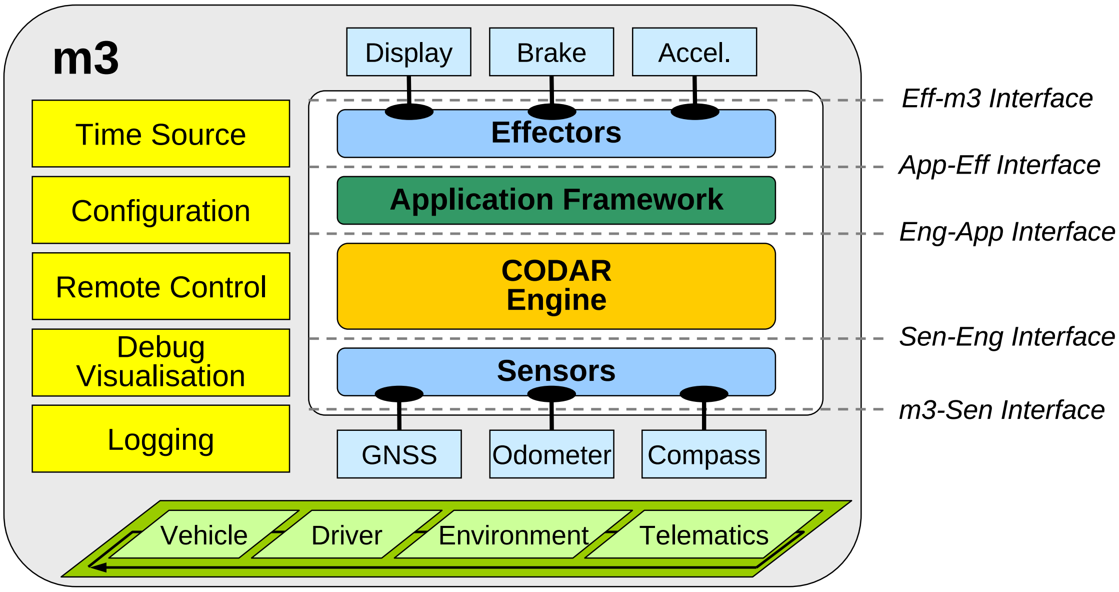


Figure 6.1: CODAR running in the simulation environment m3

For every vehicle a set of sensors and effectors can be deployed. In the following analyses every vehicle is equipped with a GNSS receiver, an odometer and a compass and is capable of transmitting and/or receiving remote evidence (i.e. position, heading, velocity) via V2V communications. Some of the vehicles are also equipped with a radar which observes objects in the front of the vehicle. The effectors mounted to each vehicle are the acceleration control, the brake and/or a display which visualizes the estimated situation for each vehicle (see figure 5.18). The sensor simulations and the scenarios which have been implemented will be explained in detail in the following. A tabular listing is given in the tables 6.1-6.4.

6.1.1 Sensor Simulation

Global Navigation Satellite System (GNSS)

The simulated GNSS receiver uses the real position of the vehicle and adds a Gaussian distributed error according to the normal distribution $N(0, 3)$ with mean 0m and a standard deviation of 3m independent in X and Y direction. The update rate of the GNSS receiver is 10Hz.

Radar

The simulated radar sensor has an opening angle of $\frac{\pi}{20}\text{rad} = 0.157\text{rad} = 9°$. The radar is mounted at the front of vehicle (in center) observing the headway of the vehicle with 4.5° to the left of the vehicle and 4.5° to the right. The maximum range is limited by 100m. If a target vehicle is located within the radar beam, its real position is altered by a Gaussian distributed error according to the normal distribution $N(0,1)$ in meters. The update rate is 10Hz.

Compass

The simulated compass provides heading information of the vehicle. It adds a Gaussian distributed error to the real heading of the vehicle according to the normal distribution $N(0,0.15)$ in radians. The update rate of the compass is 10Hz.

Odometer

The simulated odometer provides the velocity of the vehicle with a Gaussian distributed error according to the normal distribution $N(0,2)$ in m/s. The update rate is 10Hz.

V2V Communications

The simulated V2V communications allow to exchange information between vehicles up to a range of 300m. The value is gathered from real-world measurements with V2V communication hardware which is currently used for initial field operational tests. Communication errors are modeled by a random packet loss model which can be adjusted to the specific simulation interests between 0 (no packet loss) and 1 (100% packet loss). Lower layer influences (e.g. fading due to multi-path propagation and Doppler effect) are not simulated explicitly. These influences are only relevant for lower layer analyses which are not part of this work.

6.1.2 Scenarios

The simulations are based on four different scenarios. Two artificial scenarios and two real-world scenarios. The first scenario is a single-lane straight road with a length of 5km (see figure 6.2). The second scenario is a single-lane road formed as octagon with an arc length of 130m (see figure 6.3). Furthermore, two real-world scenarios obtained from the *Openstreetmap* project [4] have been used. The third scenario is a highway section between *Inning am Ammersee* and *Oberpfaffenhofen* on the highway *A96* (Lindau-Munich) in southern Germany (see figure 6.4) and the fourth scenario is a curved mountain road between *Bayrischzell* and *Unteres Sudelfeld* in southern Germany (see figure 6.5).

Each of these scenarios contains two vehicles, vehicle 0 (ego vehicle) and vehicle 1 (target vehicle), which move on the road network. Each vehicle has a length of 4m and a width of 2m and acts according to the Krauss model or the decision-making algorithm presented in the previous chapter.

Scenario 1 (Straight Road)

The straight road scenario contains a single-laned straight road with a length of 5km (see figure 6.2). The lane width is 3m. In the startup constellation both vehicles are separated by 50m. Vehicle 1 (target vehicle) drives in front of vehicle 0 (ego vehicle). Both vehicles drive from left to right. Vehicle 1 (right) accelerates with an acceleration of 2m/s^2 (desired velocity of the movement model) to its maximum desired velocity of 20m/s (see table 6.1). If not specified explicitly vehicle 0 follows according to the deterministic version of the Krauss model with a desired velocity of 20m/s, a reaction time of 2s and a safety distance of 5s (in the table abbreviated by *Krauss model (20,2,5)*).

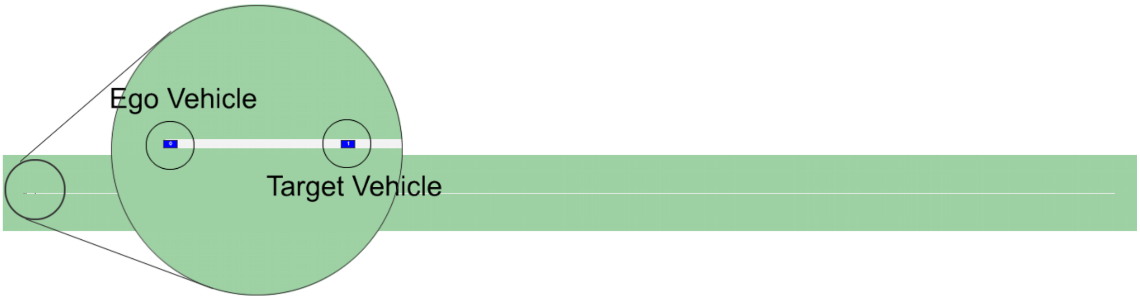


Figure 6.2: Scenario 1: Straight Road

Scenario 2 (Octagon Road)

Scenario 2 (Octagon Road) is a single-laned road formed as octagon with an arc length of 130m and rounded curves approximated by 3 short road segments. The lane width is 3m. Vehicle 1 is located in front of vehicle 0 and both vehicles drive clock-wise on the octagon. If not specified explicitly, the vehicles behave according the parameters of table 6.2.

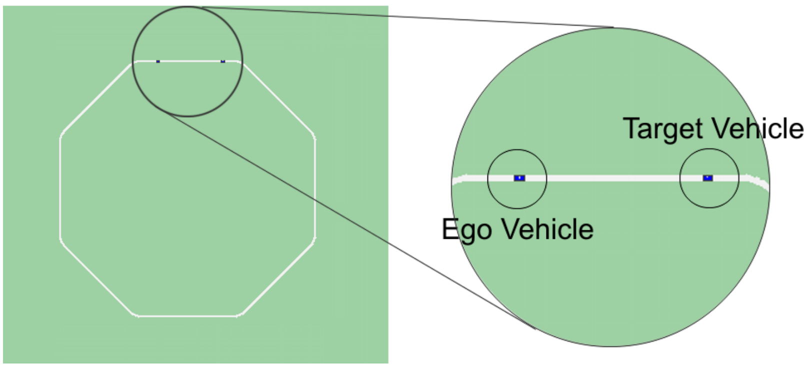


Figure 6.3: Scenario 2: Octagon

Scenario 3 (A96)

The third scenario is a highway section between *Inning am Ammersee* and *Oberpfaffenhofen* on the highway *A96* (Lindau-Munich) in southern Germany. The length is 10.7km. The scenario is located within the bounded box spanned by the latitude/longitude coordinates (48.03° N/11.12° E) and (48.10° N/11.30° E) in WGS84. Since no lateral control of the vehicles is intended the highway is reduced to a single lane with a lane width of 3m. In the startup constellation vehicle 0 is already located on the highway 30m in front of the approach 30 Inning am Ammersee. Vehicle 1 is located on the highway approach. In contrast to the previous scenarios the vehicles drive with high speed (up to 36m/s). If not specified explicitly, the vehicles behave according to the parameters given in table 6.3.

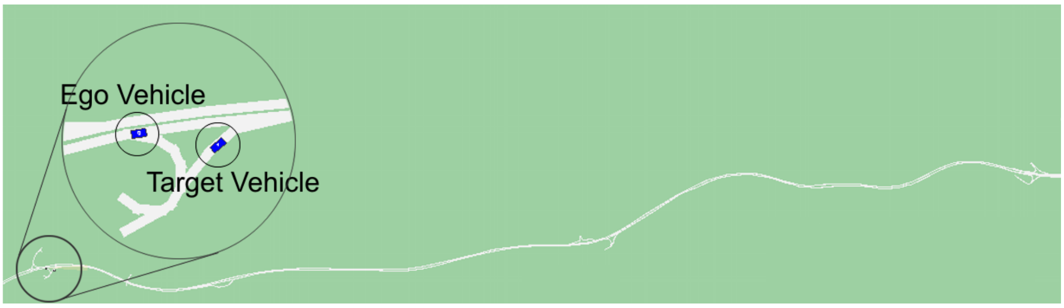


Figure 6.4: Scenario 3: Highway A96

Scenario 4 (Tatzelwurm)

Scenario 4 is a curved mountain road with a length of 4.7km from *Bayrischzell* to *Unteres Sudelfeld*. The route also called *Tatzelwurm* is located within the bounded box spanned by the latitude/longitude coordinates (47.74° N/11.96° E) and (47.65° N/12.01° E) in WGS84. In contrast to the previous scenarios, Tatzelwurm has sharp curves (up to 180°, marked with 1 and 2 in the figure). In the startup constellation both vehicles are located on the *Alpenstrasse*. Vehicle 0 starts behind vehicle 1 with a distance of 100m. If not specified explicitly, the vehicles behave according to the parameters specified in table 6.4.

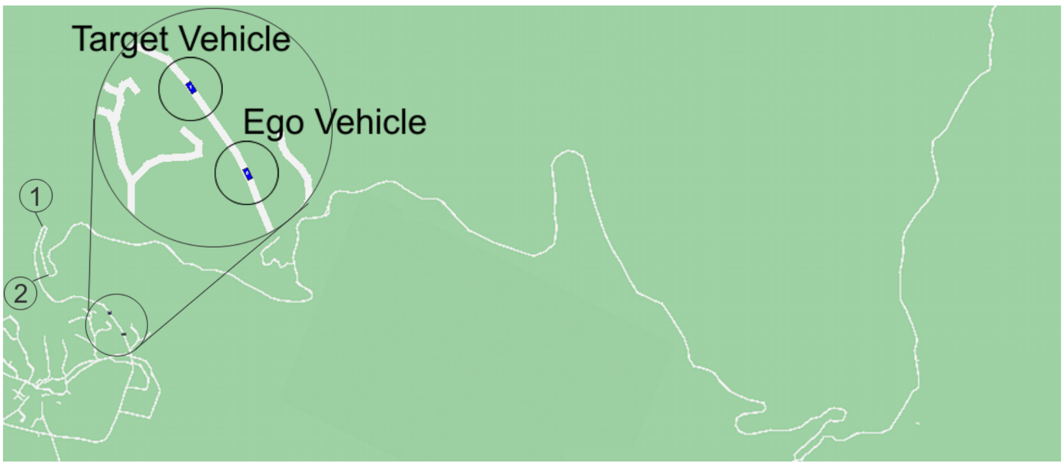


Figure 6.5: Scenario 4: Tatzelwurm

Vehicle 0 (ego vehicle)	
Start position	(0m,0m)
Max. velocity	25m/s
Max. acceleration	3m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Krauss Model (20,2,5)
Sensors	Radar, GNSS, Compass, Odometer, V2X (10Hz)
Effectors	Acceleration (10Hz)
Vehicle 1 (target vehicle)	
Start position	(50m,0m)
Max. velocity	15m/s
Max. acceleration	3m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Krauss Model (20,2,5)
Data dissemination	Position-Heading-Velocity (10Hz)
Sensors	GNSS, Compass, Odometer (10Hz)
Effectors	V2X (10Hz)

Table 6.1: Scenario 1 (Straight Road)

Vehicle 0 (ego vehicle)	
Start position	(0m,0m)
Max. velocity	15m/s
Max. acceleration	2m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Krauss Model (15,2,5)
Sensors	Radar, GNSS, Compass, Odometer, V2X (10Hz)
Effectors	Acceleration (10Hz)
Vehicle 1 (target vehicle)	
Start position	(200m,0m)
Max. velocity	10m/s
Max. acceleration	2m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Krauss Model (10,2,5)
Data dissemination	Position-Heading-Velocity (10Hz)
Sensors	GNSS, Compass, Odometer (10Hz)
Effectors	V2X (10Hz)

Table 6.2: Scenario 2 (Octagon Road)

Vehicle 0 (ego vehicle)	
Start position	(48.084638° N lat, 11.15198m/s^2 lon) WGS84
Max. velocity	36m/s
Max. acceleration	3m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Krauss Model (20,2,5)
Sensors	Radar, GNSS, Compass, Odometer, V2X (10Hz)
Effectors	Acceleration (10Hz)
Vehicle 1 (target vehicle)	
Start position	(48.083939° N lat, 11.153827°E lon) WGS84
Max. velocity	30m/s
Max. acceleration	3m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Random Speed Model
Data dissemination	Position-Heading-Velocity (10Hz)
Sensors	GNSS, Compass, Odometer (10Hz)
Effectors	V2X (10Hz)

Table 6.3: Scenario 3 (A96)

Vehicle 0 (ego vehicle)	
Start position	(47.67685°N lat, 12.020348°E lon) WGS84
Max. velocity	17m/s
Max. acceleration	3m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Krauss Model (17,2,5)
Sensors	Radar, GNSS, Compass, Odometer, V2X (10Hz)
Effectors	Acceleration (10Hz)
Vehicle 1 (target vehicle)	
Start position	(47.677931° N lat, 12.019417° E lon) WGS84
Max. velocity	15m/s
Max. acceleration	3m/s^2
Max. deceleration	5m/s^2
Driver behaviour	Random Speed Model
Data dissemination	Position-Heading-Velocity (10Hz)
Sensors	GNSS, Compass, Odometer (10Hz)
Effectors	V2X (10Hz)

Table 6.4: Scenario 4 (Tatzelwurm)

6.2 Simulation Results

In the following, various simulation results will be shown using these scenario definitions. The results show the improvements of the situation estimation, the improvements of the decision-making functionality, the improvements in the communications and runtime performance analyses.

The evaluation criteria will be explained in the individual sections. In case point estimations are compared, the point with the *minimum mean square error (MMSE)* [46, 122] has been used:

$$MMSE(S|E) = \sum_{S} S \cdot P(S|E) = \sum_{p \in ParticleSet} p.S \cdot p.weight \tag{6.1}$$

If not stated explicitly, the position-heading-velocity movement model of section 5.3.2.1 has been used for the situation estimation.

6.2.1 Runtime Performance

In order to evaluate the runtime performance of the algorithm, various simulation runs with different numbers of particles have been performed. The simulation hardware was a standard Fujitsu-Siemens Lifebook (E-Series) with Intel Core^{TM} 2 Duo T7500 (2.2GHz) CPU and 2GB RAM. The operating system was a Windows XP Professional with service pack 3 and Sun Java 1.6.0. The results are shown in table 6.5.

# of Particles	**Total runtime** (in s)	**Real time ratio** (in %)	**Memory** (in MB)	**Accuracy** (in m)
100	18.781	3.13	7.57	1.18
200	35.250	5.88	8.17	0.91
500	89.937	15.00	8.17	0.68
1000	182.500	30.44	8.54	0.66
2000	405.593	67.64	9.73	0.64
5000	1061.969	177.11	13.30	0.60

Table 6.5: Runtime performance comparison

The simulations used scenario 2 (Octagon) because of the circular road course and ended automatically after a duration of 600000ms (10 minutes) of simulation time. The simulation time source incremented the time immediately after the whole time step has been processed without any additional waiting time. Thus, the runtime (in real time) merely depended on the problem complexity. The runtime in real time is shown in the second column of the table. The average ratio between simulation time and real time is shown in the third column of the table. It almost increases linearly. In order to gain real-time capabilities[1] not more than 2000 particles shall be used with

[1] Real-time capability is achieved if *real time ratio* ≤ 1 which means that a certain amount of time required for calculation (i.e. runtime) is less or equal to the real time

this system configuration. The memory required to perform the simulation is shown in the fourth column of the table. The numbers are based on the Java measures which can be requested from the API. Due to the automatic garbage collection the numbers are only partially meaningful. The last column of the table shows the distance error between real distance and estimated distance between ego and target vehicle. The error decreases with an increasing number of particles. With particle numbers less than 1000 a strong accuracy gain can be detected with every increment. With higher number of particles the gain gets smaller.

A trade-off between accuracy and real-time capability is given by a number of 2000 particles. Thus, the particle filter used to perform the simulations in the following sections was implemented with 2000 particles in vehicle 0 (ego vehicle) for the estimation of the state of the ego and the target vehicle. In section 6.2.4 also vehicle 1 runs a particle filter. This particle filter will only track the state of vehicle 1. Thus, the state space has only half the cardinality and we limited the number of particles to 1000 for vehicle 1.

6.2.2 Improved Situation Estimation

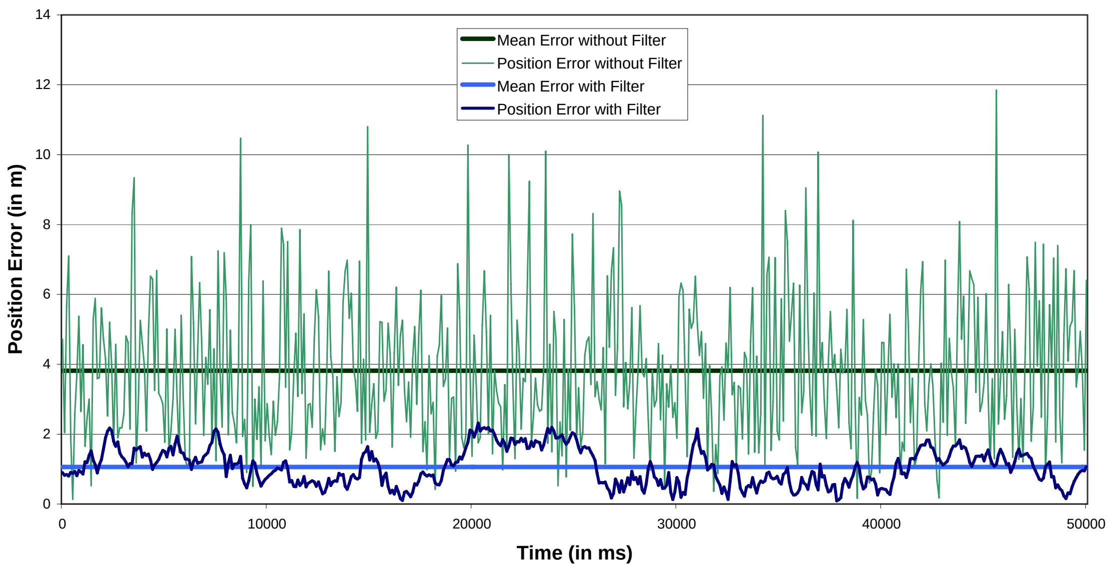


Figure 6.6: Ego position error with and without filter application in scenario 1 (Straight road)

6.2.2.1 Increased accuracy

In the following sections the accuracy gain in terms of position accuracy is evaluated. The gain is achieved by the application of the filter to the inaccurate and incomplete evidences from GNSS, odometer and compass. Since the main focus of these analyses is the evaluation of the position accuracy, the gain of the filter is evaluated in contrast to the raw GNSS position measurements which can be tapped from the *m3-Sen interface*

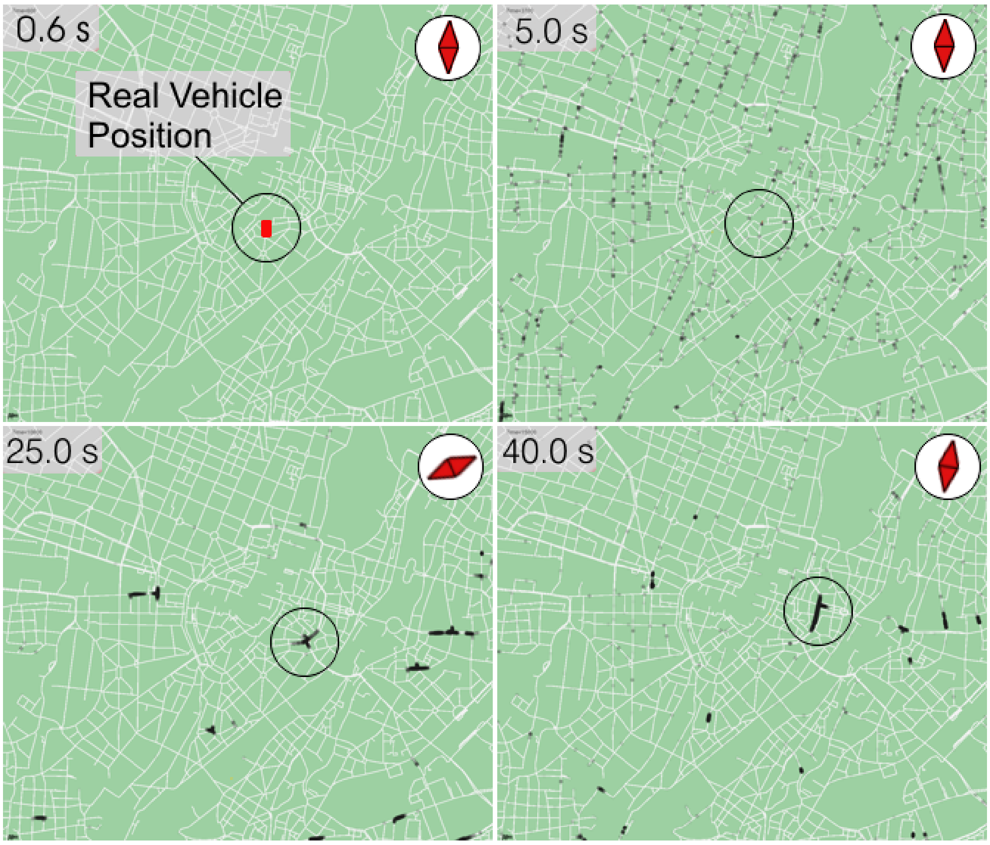


Figure 6.15: Positioning solely based on compass measurements (1Hz update rate) and road network as soft indication for vehicle location

According video files which show the whole simulation run can be found on the CODAR website [209].

Message loss

Figure 6.16 shows the distance error between ego and target vehicle for the message loss ratios 0.5, 0.7, 0.9 and 0.95 using scenario 1 (Straight Road). A message loss ratio of 0.5 means that of all the evidence updates generated from the 10Hz-sensors of the sender only an average of 50% is actually received by the receiver. The accuracy of the distance estimation for this receiver is depicted in the figure. Evidently, the mean error grows with an increasing message loss ratio (1.78m → 2.18m → 2.27m → 6.27m). The standard deviation increases accordingly (1.28m → 1.84m → 2.28m → 8.30m).

6.2.3 Improved Decision-making

Up to now, the ego vehicle only performed a situation estimation without decision-making functionality. In the following simulations the ego vehicle evaluates the situation according to the decision-making algorithms introduced in section 5.3.3 and actually controls the acceleration of the ego vehicle in the simulation environment. Thus, the

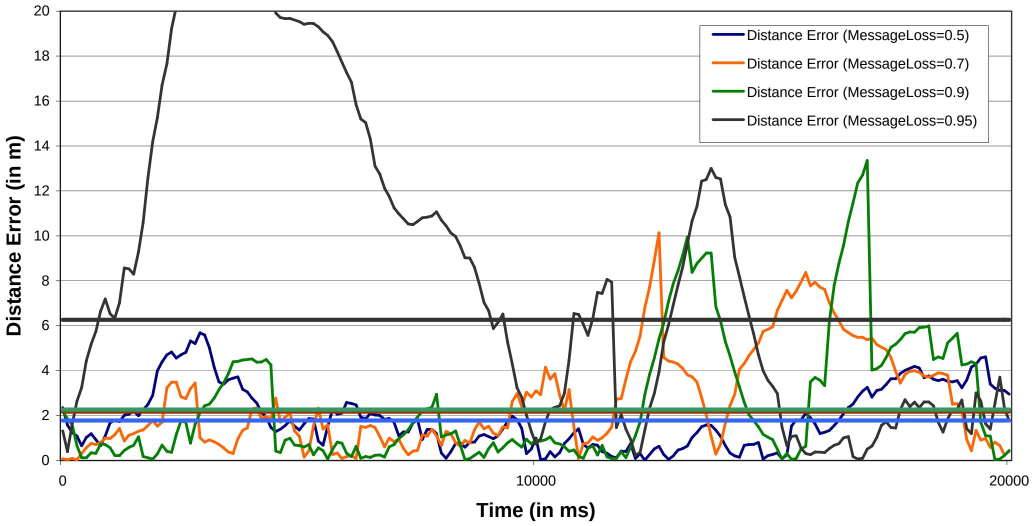


Figure 6.16: Ego-Target distance error with with filter application and different message loss ratios (Scenario 1)

CACC system runs in a closed loop which perceives the environment, estimates the situation, derives best actions, changes the environment by accelerating or decelerating and starts over.

The sensors used in the ego vehicle in the following simulations are odometer, compass, GNSS and cooperative sensing via V2V communications. The target vehicle provides compass, odometer and GNSS measurements via V2V communications. The decision-making algorithm differentiates two actions *accelerate* and *decelerate* which control the acceleration/brake effector with an acceleration of 2m/s^2 and the brake with a deceleration of 2m/s^2 [170].

Figure 6.17 shows a simulation run with a duration of 30s using scenario 1 (Straight Road). The target vehicle moves with a constant speed of 10m/s. The figure shows the real distance between the vehicles which circulates around 19.82m with a standard deviation of 0.88m. Changes in the distance result from a varying acceleration of the ego vehicle based on the maximum expected utility which is calculated from the estimated speed of the ego vehicle and the estimated distance between ego and target vehicle. The estimated distance error is depicted in the figure as well. In the upper part of the figure the difference in the expected utilities (equation 3.20 on page 104) for the *acceleration* and the *deceleration* action is depicted:

$$\text{Utility Difference} = EU^{k+1}(accelerate|E^{1:k}) - EU^{k+1}(decelerate|E^{1:k}) \qquad (6.2)$$

A utility difference greater than zero, will accelerate the vehicle and a utility difference less than zero, will decelerate the vehicle according to the maximum expected utility principle for dynamic systems (equation 3.26 on page 110). Due to the constant movement of the target vehicle the difference in the expected utility between both actions is rather low.

Figure 6.19 shows a similar simulation run. Again the duration is 30s and the scenario is scenario 1 (Straight Road). The difference to the previous simulation is the

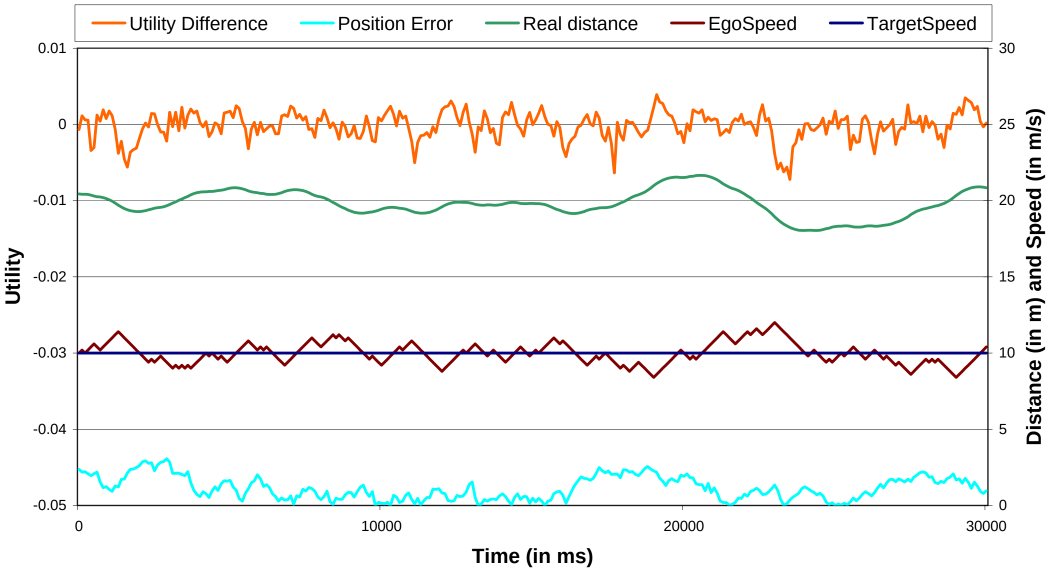


Figure 6.17: Expected utility difference, distance estimation error, real distance, and speeds (target vehicle moves with constant speed of 10m/s in scenario 1)

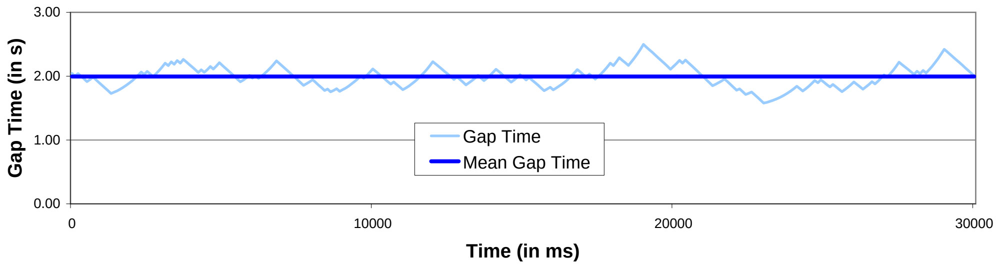


Figure 6.18: Gap time (target vehicle moves with constant speed of 10m/s in scenario 1)

changing speed of the target vehicle. First the target vehicle accelerates from 1m/s to 8m/s, then it decelerates to 3m/s, then it accelerates to 7m/s and decelerates to 3m/s. In this simulation run a clearer separation between the expected utilities of the *accelerate* and the *decelerate* action becomes visible. This can be explained due to the changing velocity of the target vehicle. During a deceleration of the target vehicle the *accelerate* action often has a considerable lower expected utility than the *decelerate* action.

In contrast to the previous simulation, the distance strongly varies between 3m and 14m. In order to provide a better comparison, figure 6.18 and 6.20 show the gap time calculated by $GapTime = Distance/EgoSpeed$ (with real values obtained from the simulation environment) for both simulation runs. As it was mentioned in section 5.3.3 the maximum expected utility shall be around 1.8s gap time using the proposed utility functions. The simulation runs show a mean gap time of 1.99s and 1.86s with a standard

1.3Hz. Thus, in order to have an error below 3.8m, a reduction of the required update rate of 87% (or 75%) is achieved with the filter application.

6.2.4.2 Information Gathering

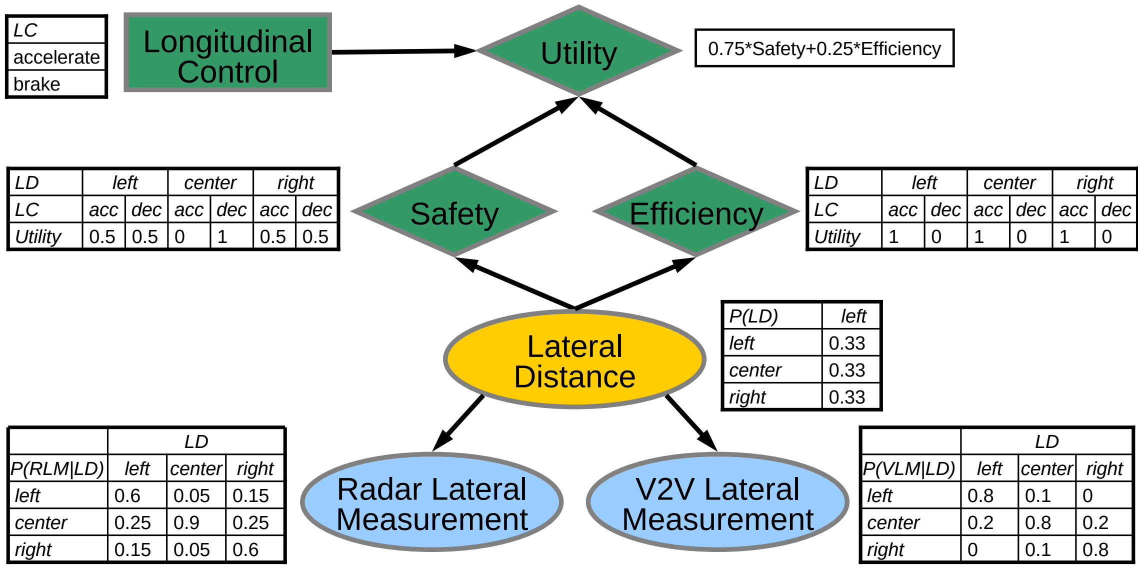


Figure 6.31: *Longitudinal Control* decision based on the *Lateral Distance* with evidence from radar and V2V

In the following the decision algorithm for interest propagation as introduced in section 4.2 will be analysed for multi-lane roads. On a road with multiple lanes in the same direction the ego vehicle has to determine the actual lane the target vehicle is driving on. If for instance the ego vehicle is located on the center lane of a three-laned road, the target vehicle can be located on the same, the right or the left lane. These three states are denoted as *center*, *right* and *left* of the situational information `Lateral Distance` `(LD)` in the following. Evidence to determine the situational information is given by `Radar Lateral Measurements (RLM)` and `V2V Lateral Measurements (VLM)` (with GNSS information transmitted via V2V communications plus heading measurement or map-matching alternatively) with the same states as `Lateral Distance`. Additionally, a utility hierarchy with three utility functions is specified which take into account the state of `Lateral Distance`. One utility function determines the traffic `Safety` utility. Another utility function determines the traffic `Efficiency` utility. The third utility function calculates a weighted average of `Safety` and `Efficiency` utility with a 3:1 weighting. The decision to make differentiates the two states *accelerate* and *decelerate*. The whole probabilistic decision network is depicted in figure 6.31.

In the example, the radar sensor quality is very high for target vehicles located in the center of the radar beam. False estimations only occur with a probability of 0.1 (0.05 left and 0.05 right). On the other hand, if the target vehicle is located on the left or the right lane, the sensor quality is worse, e.g. due to reflections on the guard rails. False estimations occur with a probability of 0.3 (0.25 center and 0.05 for the opposite

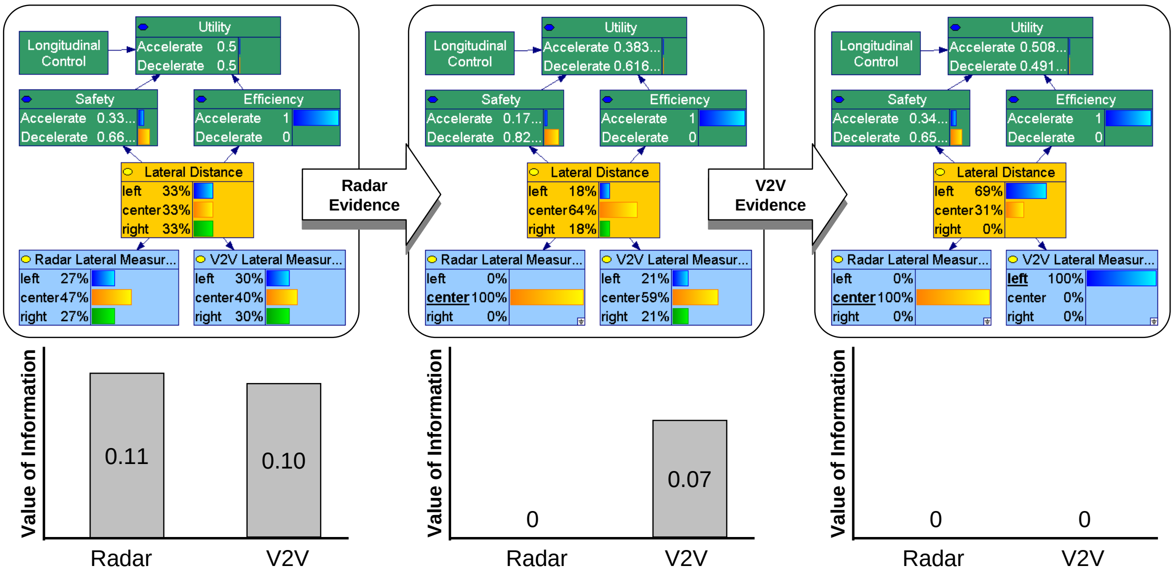


Figure 6.32: Variation of the Value of Information with evidences from radar and V2V communications

lane). For the cooperative sensing with GNSS position information transmitted over V2V communications, the sensor quality is independent of the target position since it is not based on relative vehicle constellations. False estimations occur with a probability of 0.2. The situational information `Lateral Distance` has a uniform distribution since the usage of the lanes is assumed to be equal. The `Safety` utility is uniformly distributed in case the target vehicle is located on another lane because this vehicle will not pose any safety threat. If the target vehicle is located on the same lane, the `Safety` utility is high for the deceleration and low for the acceleration. A more detailed dependency, e.g. with speed and longitudinal distance, will go beyond the scope of this example and is therefore omitted. Thus, a (0/1) distribution for (*accelerate*/*decelerate*) is defined. The `Efficiency` utility assigns a value of 1 to the *accelerate* action and a 0 to a *decelerate* action independent of the `Lateral Distance`.

If no evidence is available, the state of `Lateral Distance` is uniformly distributed, each state with a probability of 1/3 (see left-most depiction in figure 6.32). In this case there is a tie between the actions *accelerate* and *decelerate*. Both have a utility of 0.5. The value of information (VoI) calculation provides a value greater than zero to both evidences. A `Radar Lateral Measurement` has a value of 0.11 and thus carries more information than a `V2V Lateral Measurement` of 0.10. These calculations are independent of the actual state of the evidence which is unknown up to now. Thus, the decision algorithm requests a radar measurement (e.g. by sending the according CAN RTR frame [117] on the respective CAN bus) or listening for an appropriate CAN frame on the respective CAN bus.

When the radar measurement is received, the input node `Radar Lateral Measurement` can be updated with the new evidence. If, for instance, the radar measured a *center* state, the VoI of the `V2V Lateral Measurement` reduces to 0.07 because both

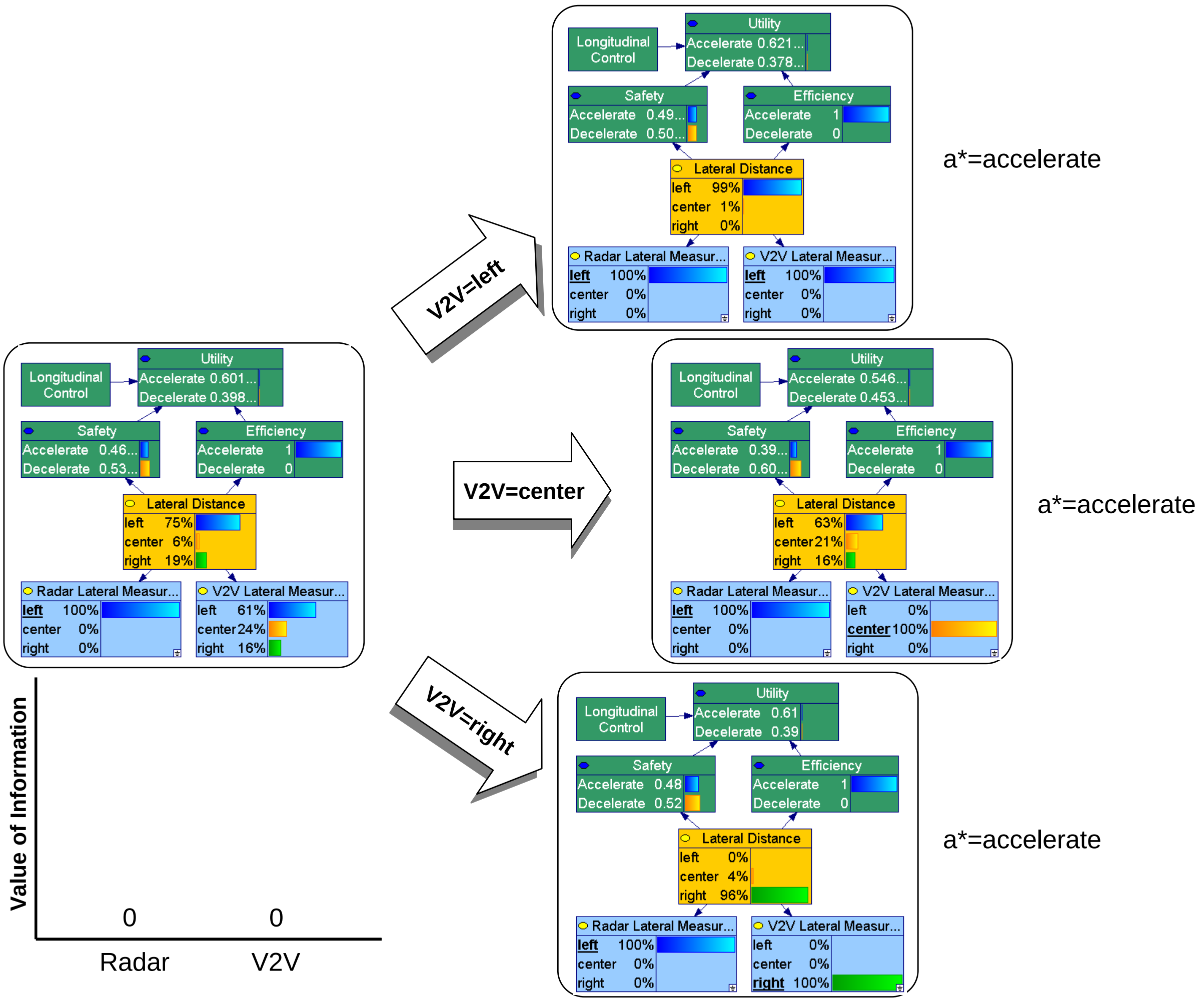


Figure 6.33: Variation of the maximum expected utility (MEU) with different outcomes of the V2V evidence after observing the radar evidence *left*

evidences are dependent due to the common cause `Lateral Distance`. Thus, the belief in the *center* state as the actual outcome of the `V2V Lateral Measurement` already has a probability of 59%. But the VoI of `V2V Lateral Measurement` is still positive and thus is expected to provide a value for the decision-making. This is justified since after the incorporation of the *center* state from `Radar Lateral Measurement` the expected utility (EU) for the *decelerate* action raises from 0.5 to 0.62 and thus represents the maximum expected utility (MEU) but in case the additional acquisition of `V2V Lateral Measurement` provides a different state than *center* (*left* in the right-most depiction of figure 6.32) the MEU switches to 0.51 for the *accelerate* action. Thus, the best action changes from *decelerate* to *accelerate* by the acquisition of the `V2V Lateral Measurement`. Thus, in this example requesting position information from the target vehicle via V2V communications may provide a valuable benefit for the action decision-making.

It has to be noted that the VoI is not a general evaluation on a per-sensor basis but is based on the actual outcome level as explained in section 4.2. This can be seen in figure 6.33. The figure is based on the same parameters as the previous evaluation but instead of the *center* state as the outcome of the `Radar Lateral Measurement` the radar provided a *left* measurement. The best action a^* accordingly is *accelerate* with a MEU of 0.60. In this case the VoI for the `V2V Lateral Measurement` is 0 whereas in the previous analysis it was 0.07. The figure also shows the situation after the acquisition of `V2V Lateral Measurement`. If it provides as well the *left* state the best action evidently is *accelerate*. If it provides the *center* state still *accelerate* is the best action and even if it provides a *right* measurement the best action is *accelerate*. Thus, independent of the outcome of the `V2V Lateral Measurement` the best action is always *accelerate* and thus the VoI is zero.

The simulation results of this section showed that an information-centric data dissemination approach as introduced in this work enables a very flexible bandwidth utilization which takes into account the actual worth of information. Figure 6.30 showed that a reduction in the information dissemination is feasible with slightly increasing but manageable loss of accuracy. Jumping to the conclusion to finally reduce the update rate to a lower constant value without an information-centric priority handling will be dramatic since important evidence may be discarded by a static scheme. As it was shown in figure 6.27 and 6.28 worth may reside in a single evidence in case this evidence provides for instance a turning maneuver (figure 6.27) or the evidence has a infrequent update rate (figure 6.28). In this case an information-centric data dissemination approach shows its exceptional potential.

In the interest propagation the value of information algorithm even takes into account actual outcomes and thus determines the worth of information for decision-making of individual receivers. The results depicted in figure 6.32 and 6.33 confirmed the functionality and showed that a static evaluation on a per-sensor level cannot cope with the targeted objectives.

7 Conclusion

Research is to see what everybody else has seen, and to think what nobody else has thought.

Wernher von Braun (1912-1977)

7

In conclusion, some final remarks will highlight the major achievements that have been accomplished in this work and point out potential future continuations.

7.1 Summary

This work was devoted to elaborate the cooperative situation awareness in the field of information-theoretic research required in future ITS systems with a plethora of wirelessly interconnected entities. Single entities normally cannot perceive all information from their local sources of information which is required to perform optimal actions. To extend the perception horizon, cooperative situation awareness is required. It is achieved by the purposive exchange of information between the entities. Information from other entities serves as evidence to improve the situation assessment performed in each individual entity. Chapter 2 showed that situation models based on probabilistic causal networks have the expressive power to represent and infer situations which are inherently subject to uncertainty. They outperform other solutions in their capabilities and thus represent a promising basis for future ITS systems.

In order to make the theoretical concept of probabilistic causal networks applicable to future ITS systems, the tailoring of the network to the problem-specific domain has been presented in chapter 3. The chapter accompanies the information forward along its path from the generation in the sources of information through the dynamic probabilistic causal decision network to the selection of the concluding action with the maximum expected utility. Along the whole path it is taken care that no information is neglected, the uncertainty inherent to the information is utilized appropriately and herewith the actual worth of the information is exploited.

Chapter 4 reverses this path and attempts to maximize the utility outcome by cooperatively controlling the information flow from remote sources of information. This is achieved by an exploitation of the knowledge within the dynamic probabilistic causal decision network. The result is an information-centric receiver-oriented communications approach which is shown to be a promising solution in future ITS systems. A prioritised utilization of the wireless channel based on the worth of information finally yields an optimal usage of the communications resource.

An exemplary application named *Cooperative Adaptive Cruise Control (CACC)* which is considered as one of the most promising, purposeful and enabling applications has been identified. It improves safety, efficiency and comfort of transportation with every additional vehicle equipped with V2X communications facilities. Chapter 5 provided configuration and implementation details. The enabling framework called *Cooperative Object Detection And Ranging (CODAR)* is based on a particle filter running inside a self-configuring application framework. These concepts provide the required capabilities for future extensions to enable a simple deployment of further applications.

The performance of the whole system and of CACC in particular is presented in the evaluations of chapter 6. The evaluations have been performed by simulations and showed in the respective analyses on situation estimation, decision-making and communication optimization that the implementation significantly increases accuracy, reliability and overall functionality. The pre-assigned requirements are met and the system performs as expected.

7.2 Outlook

Evidently, this is just the beginning of information-theoretic research for future ITS. In order to tap the full potential of the presented concepts further studies taking into account additional sources of information (e.g. acceleration and brake pedal), state transition models (e.g. anticipated driver behavior), elaborated utility functions (e.g. cooperative long-term planning), etc. have to be performed.

The hidden state space which was introduced for CACC in section 5.3 included only a minimum set of situational information required to perform first results. In the future more situational information can be included (e.g. pavement condition, movement histories of other vehicles, vehicle models, common positioning errors) in order to gain an improved situation awareness and an improved decision-making. For instance, movement histories of preceding vehicles can be used to learn the road course in order to improve the position accuracy and improve the movement prediction even without an explicit road topology map. The estimation of common positioning errors (e.g. atmospheric effects) in the hidden state space allows a better relative positioning to entities which are exposed to identical errors and thus it is worth to be studied more in detail for an improved relative positioning.

In the communications optimization we limited the work to inspections of application and network layer of the ISO OSI reference model. Definitely, this is not the only contact point of information-centric communication optimizations. Further starting points are improvements for medium access control (e.g. application-layer controlled adaptation of the contention window) and even physical layer (e.g. channel coding depending on the worth of information). Both have to be analysed more in detail and the identification of further potential improvements based on a cooperative situation awareness shall not fall into oblivion.

The prototype implementation of CACC already showed promising results but by far is not complete to transfer into production. Further analyses are required, in particular with field operational tests that inspect the performance in real-world environments before a market introduction can take place in the upcoming years.

The CODAR architecture has been designed having in mind a plethora of cooperative ITS applications. It can be considered as an enabling technology for various kinds of applications. Next steps are the implementation of further applications such as *Cooperative Collision Avoidance* or *Pre-Crash Sensing* which, besides CACC, will provide a considerable improvement for future road transport.

Finally, it remains to look ahead in anticipation what the future of transportation holds. I am convinced fascination and suspense continues.

-MR-

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Glossary

AACC	Autonomous Adaptive Cruise Control
ABS	Anti-lock Braking System
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
AODV	Adhoc On-demand Distance Vector Routing
AP	Acceleration Pedal
B	Bayes factor (Likelihood ratio)
BW	Black ice Warning
$C(\cdot)$	Costs
CACC	Cooperative Adaptive Cruise Control
CAN	Controller Area Network
CBR	Contention-Based Forwarding
$CNetNI(\cdot)$	Cumulative Net Normalized Mutual Information
CO_2	Carbon Dioxide
CODAR	Cooperative Object Detection And Ranging
CPU	Central Processing Unit
DAB	Digital Audio Broadcast
DBN	Dynamic Bayesian Networks
DSDV	Destination-Sequenced Distance Vector Routing
DSR	Dynamic Source Routing
DVB	Digital Video Broadcast
E	Evidence
ECA	Event Condition Action
$EMEU(\cdot)$	Expected Maximum Expected Utility
ERM	Entity Relationship Model
$EU(\cdot)$	Expected Utility
$EW(\cdot)$	Expected Weight of evidence
FM	Frequency Modulation
FOL	First-Order Logic
GNSS	Global Navigation Satellite System
GPCR	Greedy Perimeter Coordinator Routing
GPS	Global Positioning System
GPSR	Greedy Perimeter Stateless Routing
GSM	Global System for Mobile communications
$H(\cdot)$	Entropy
HMM	Hidden Markov model
$I(\cdot)$	Mutual Information
I2V	Infrastructure-to-Vehicle (communications)
ICT	Information and Communications Technology
IEEE	Institute of Electrical and Electronics Engineers
IETF	Internet Engineering Task Force
ISO	International Organization for Standardization
ITS	Intelligent Transportation System

JMPD	Joint Multi-target Probability Density
JPDA	Joint Probabilistic Data Association
KB	Knowledge Base
LC	Longitudinal Control
LD	Longitudinal Distance
LDS	Linear Dynamical System
MAP($\cdot$)	Maximum A Posteriori
MCMC	Markov Chain Monte Carlo
MEU($\cdot$)	Maximum Expected Utility
MHT	Multiple Hypotheses Tracking
minCNetNI	Minimum Cumulative Net Normalized Mutual Information
ML($\cdot$)	Maximum Likelihood
MMSE	Minimum Mean Square Error
MNetVoI($\cdot$)	Maximum Net Value of Information
MORA	Movement-Based Routing Algorithm
N(μ,σ)	Normal Distribution with mean μ and standard deviation σ
NetNI($\cdot$)	Net Normalized Mutual Information
NetVoI($\cdot$)	Net Value of Information
NI($\cdot$)	Normalized Mutual Information
OSGi	Open Services Gateway initiative
OSI	Open Systems Interconnection
P($\cdot$)	Probability
PC	Pavement Condition
PDA	Probabilistic Data Association
PDF	Probability Density Function
PMF	Probability Mass Function
Pr	Precipitation
R	Probability factor (Relevance quotient)
RAM	Random Access Memory
RDS-TMC	Radio Data System - Traffic Message Channel
RMS	Root Mean Square
RS	Race Start
RSU	Road-Side Unit
RTR	Remote Transmission Request
S	Situation, Situational Information
SEU	Subjective expected utility
SIR	Sample Importance Resampling
SIS	Sample Importance Sampling
SMC	Sequential Monte Carlo
SOA	Service-Oriented Architecture
T	Temperature
TJ	Traffic Jam
TMC	Traffic Management Center
ToA	Time of Arrival
U($\cdot$)	Utility

UML	Unified Modeling Language
UMTS	Universal Mobile Telecommunications System
UTM	Universal Transverse Mercator
V2I	Vehicle-to-Infrastructure (communications)
V2V	Vehicle-to-Vehicle (communications)
V2X	Vehicle-to-X (communications)
VMS	Variable Message Signs
VoI	Value of Information
$W(\cdot)$	Weight of evidence
WGS-84	World Geodetic System 1984
WLAN	Wireless Local Area Network
WS	Wheel Slip

Index

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Intelligent Transportation Systems (ITS) became a fast moving field of research in the last decades, in particular in the context of continuously growing mobility and a high employment of resources starting from energy and material consumption to travel time and finally the human life. As it has already been experienced in other application areas, the introduction of communications technology is able to bring a revolutionary change in structures and behaviors long-believed to be carved in stone.

This thesis provides concepts and strategies that push forward the exploitation of information in a cooperative way within a probabilistic framework that allows to make various kinds of decisions with maximum utility. For the evaluation of the proposed concepts, the exemplary application Cooperative Adaptive Cruise Control (CACC) has been implemented on the basis of a particle filter which is used for the situation estimation. Initial simulations provided promising results and hence constitute a solid basis for future work in the field of Cooperative Situation Awareness in Transportation.

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