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Situation Analysis and Adaptive Risk Assessment for Advanced Intersection Safety Systems

Dissertation
zur Erlangung des Doktorgrades
an der MIN-Fakultät
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vorgelegt von Dipl.-Inform. Bernd Rössler
aus Erlangen

Hamburg 2010

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Geheimhaltung

Veröffentlichungen über den Inhalt der Arbeit sind nur mit schriftlicher Genehmigung der Volkswagen AG zugelassen.

Die Ergebnisse, Meinungen und Schlüsse dieser Dissertation sind nicht notwendigerweise die der Volkswagen AG.

To my father.

Foreword

This thesis was developed during my three years activity at the Electronics Research Department of the Volkswagen AG in Wolfsburg. Parts of this work originated from the participation in the subproject INTERSAFE of the Integrated European project PReVENT and therefore were partly funded by the European Commission. The author of this thesis wants to thank the European Commission for the support in this project.
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Abstract

Motivated by accident statistics of these days, Intersection Safety Systems are a relative new but important research topic in the field of Advanced Driver Assistance Systems. Many vehicle manufacturers and research institutes have identified the need for driver assistance at intersections influenced by accident analysis work which identifies intersections as a critical environment concerning vehicle crashes with injuries and fatalities. Unfortunately, intersections are one of the most complex out of all traffic related scenarios which complicates the development of comprehensive assistance systems in this area.

This thesis presents the development of an Intersection Safety System with special focus on situation analysis and adaptive risk assessment algorithms which are suitable for online implementation in a vehicle. The developed demonstrator system is able to observe the intersection environment with several on-board sensors and to build an appropriate scene model including behaviors, intentions and interrelations of all traffic participants in the scene. The subsequent risk assessment judges the possible individual risks for the current driving task of the vehicle that is equipped with the safety system. Finally, the computed risk is presented to the driver through innovative warning strategy approaches. The whole system is tested for its functioning and user acceptance through appropriate test concepts in simulation as well as live in the demonstrator. These tests show that on the one hand the developed system is capable of properly assisting the driver at intersection driving maneuvers and on the other hand is also well accepted by people who are driving and evaluating the system.

On completion of this thesis, the underlying prototype demonstrator vehicle still is the first and unique independent Intersection Safety System demonstrator which is capable of assisting drivers in the most critical intersection scenarios. Thereby, it integrates the whole chain beginning with sensor data perception over situation analysis and adaptive risk assessment to innovative Human Machine Interfaces and test concepts.

Kurzfassung

Aktuelle Unfallstatistiken belegen, dass Kreuzungsassistenzsysteme ein sehr wichtiges Forschungsthema im Bereich der Fahrerassistenzsysteme darstellen. Motiviert durch dieses Statistiken, welche Kreuzungen als Schwerpunkt für Unfälle mit Verletzungen und Todesfolgen identifizieren, haben viele Automobilhersteller und Forschungsinstitute die Notwendigkeit zur Unterstützung des Fahrers in Kreuzungsbereichen erkannt. Leider stellen Kreuzungen aber auch eine der komplexesten aller Verkehrsumgebungen dar, was die Entwicklung von geeigneten Fahrerassistenzsystemen in diesem Bereich erheblich erschwert.

Die vorliegende Arbeit dokumentiert den Aufbau eines umfassenden Kreuzungsassistenzsystems. Der spezielle Fokus liegt hierbei auf online-fähigen Algorithmen für die Szenarieninterpretation sowie für eine adaptive Risikoanalyse. Das entwickelte Demonstratorfahrzeug ist in der Lage, die Umgebung der Kreuzung mit fahrzeugeigener Sensorik zu erfassen, um daraus ein bestmögliches Abbild der Umgebung zu erstellen. Dies beinhaltet sowohl die Verhaltensabschätzungen und Intentionen aller Verkehrsteilnehmer, wie auch die verkehrstechnisch relevanten Beziehungen dieser untereinander. Die nachgeschaltete Risikoanalyse bewertet die Gefährlichkeit der momentanen Fahrsituation für das mit dem Assistenzsystem ausgestattete Fahrzeug. Der so errechnete Risikowert wird dem Fahrer durch geeignete Warnstrategien präsentiert. Das gesamte System wird sowohl auf seine technische Funktionsweise als auch auf die Nutzerakzeptanz getestet. Dazu kommen adäquate Testkonzepte in einer Simulation sowie in dem realen Demonstratorfahrzeug zum Einsatz. Diese Tests zeigen, dass das entwickelte System zum einen sehr gut dazu geeignet ist den Fahrer in Kreuzungsbereichen zu unterstützen, sowie zum anderen auch eine breite Akzeptanz bei Testpersonen erreicht.

Bei Fertigstellung der vorliegenden Arbeit war das entwickelte System das erste und einzige bordautonome Demonstratorfahrzeug für Fahrerassistenz an Kreuzungen, welches die dortigen unfallträchtigsten Szenarien abdeckt. Dabei behandelt es den kompletten Bereich von Sensordatenerfassung über die Szenarieninterpretation sowie lernfähiger Risikobewertung bis hin zu innovativen Warnstrategien und Testkonzepten.

Contents

Chapter 1

Introduction

Along with the tremendous electronic vehicle equipment, increasing activities in the field of Advanced Driver Assistance Systems (ADAS) have taken place in the last few years. Beside systems that intent to increase driving comfort, safety systems play an important role within this development trend. One example of a driver comfort system is the Cruise Control (CC) system which automatically holds a drivers predefined speed for a vehicle. An extension to the CC is the Adaptive Cruise Control (ACC) which uses a radar or a laser sensor to additionally keep a safe distance to the preceding vehicle. Another example of a newer comfort system is the Park Assist (PA). The PA informs the driver about the free space of a parking spot, gathered e.g. by an ultrasonic sensor, and in some cases automatically steers the vehicle into this parking spot. Even if systems like ACC have the ability to smoothen traffic flow and therefore can also result in safer driving especially on motorways, comfort systems are not primarily designed to prevent accidents. This topic is addressed by ADAS for safety.

Safety functions like the well known Anti-Lock Braking System (ABS) or the Electronic Stability Control (ESC) are nowadays installed in nearly every new vehicle. By contrast, modern safety systems like Lane Departure Warning (LDW) or the Brake Assist System (BAS) can be found almost exclusively in luxury class vehicles. Nevertheless, the trend goes to an equipment of the mass-market. This can be seen from the example of the ABS system which was at its launch also restricted to luxury class vehicles. The need for such safety systems is also identified from other side than the vehicle manufacturers which include them in their product lines. As an example, the goal of the key action 'eSafety for Road and Air Transport' from 2004 of the European Union is 50% fewer accidents by the year 2010. Integrated research projects in the field of ADAS like the PReVENT project which was co-funded by the European Commission tried to contribute to this safety goal. In this project a consortium of automotive OEMs, suppliers, research institutes, public authorities and associations worked together using advanced sensors, communication and positioning technologies in order to develop advanced functions for Driver Assistance Systems. The use of modern sensors within the vehicle, that can gather broad information about the surrounding of the vehicle, allows Research and Development (R&D) activities of new safety functions for ADAS.

1.1 Intersection Safety Systems

Intersection Safety Systems (ISS) are a relative new research topic in the field of ADAS. Many vehicle manufacturers and research institutes have identified the need for assistance for intersection related driving tasks. This is mainly influenced by deep accident analysis work which identifies junctions as a critical environment concerning vehicle crashes with injuries and fatalities. Unfortunately intersections are one of the most complex scenarios out of all traffic related scenarios. Different road users are driving from nearly arbitrary directions and with different intentions at the same area. This complicates the development of such ISS a lot.

One problem is the lack of suitable sensors for the vehicles which are capable to precisely perceive the whole relevant area of a junction. Nowadays already installed sensors like e.g. radars for ACC or video cameras for LDW systems have a limited field of view. This is suitable for their regarded freeway scenarios where only the frontal area of the vehicle is taken into account. Unfortunately, as will be seen later in this work, monitoring of an intersection needs a much broader field of view in order to be able to detect traffic that is coming also from lateral directions. Beside the problem of the limited field of view of the sensors, especially the image processing of life outdoor video data (not to mention the high traveling speeds in the automotive area) is still a very challenging and complex task. Generally, such complex Driver Assistance Systems like ISS cannot get by with only one single sensor. In fact they need an integration of different sensor systems to perceive the complex environment. This necessitates a prior sensor data fusion so that it can be used by an integrated assistance system.

Another and even bigger challenge of ISS is the task of scenario interpretation and risk assessment. After the sensor data is fused into a common environmental representation, the specific situation at the intersection has to be analyzed. This means that interrelations and behaviors of all traffic participants have to be assessed in order to judge the overall situation and finally the potential risk for the driver of the assisted vehicle. Unfortunately, the analysis of the behavior of a driver at a junction and the resulting risk of the driving situation is a quite difficult task. Due to the high amount of possible actions that can be taken at an intersection and the sophisticated interrelationships between the behaviors of different drivers it is very difficult to find an appropriate system that can deal with all of these aspects. Furthermore, the processing power for the scenario interpretation and the risk assessment in this difficult area should stay reasonable in order to implement these algorithms on the limited hardware equipment of a normal vehicle.

Due to all these mentioned problems, most approaches that can be found in the literature are theoretical work and were not tested and evaluated in praxis, i.e. in a real prototype vehicle.

1.2 State of the Art

This section shows the state of the art in ISS and presents methods and research activities in the field of situation analysis and risk assessment in ADAS with focus on ISS. This collection consists of automotive research projects as well as scientific papers from notable and important conferences. Because ISS is a very young research topic in the field of ADAS, very few systems exist that show auspicious approaches. It is often noted that this lack of systems is attributed to the quite complex structure and goings at intersections why mostly theoretic and simulated approaches exist.

1.2.1 (Inter-)National Intersection Safety Projects

This section summarizes important national and international projects dealing with parts of the ISS topic. It consists of finished as well as ongoing and recently started research projects and therefore summarizes the overall state of the art in ISS on a global level.

The INVENT Project

The Intelligent Traffic and User-Friendly Technology (INVENT) initiative was a national research project from 2001 to 2005 funded by the Federal Ministry of Education and Research of Germany (BMWi). The most relevant subprojects for intersection assistance related research were VAS ("Anticipatory Active Safety"), FUE ("Detection and Interpretation of the Driving Environment") and FVM ("Driver Behavior and HMI").

The VAS subproject dealt with turning, stop sign and traffic light assistance at intersections as well as lane change assistance for freeway scenarios. The strategy of the system was either warning, autonomous braking or steering in order to assist the driver and help him to prevent an accident. The stop sign assistance was mainly based on GPS and map data information. In one demonstrator vehicle the stop sign as well as the current location of the assisted vehicle were determined so that the driver could be warned if the system detected a potential non observance of the traffic sign [MEH04]. In a second demonstrator vehicle the stop sign as well as the traffic light at the intersection were recognized by digital image processing systems [LKK04]. [GWF03] and [FGL04] used omnidirectional and active cameras in combination with custom digital maps in order to detect the status of the traffic lights. Vulnerable road users such as pedestrians and cyclists were protected by adaptive safety elements such as flexible bonnets or bumpers if a collision was unavoidable. Those elements were also developed within the subproject. An accident analysis was carried out in order to identify the most common accident types at intersections. Nevertheless, crossing traffic scenarios and communication for ISS were **not** considered in the VAS subproject.

In the horizontal subproject FUE, sensor data fusion and reliable traffic scenario interpretation was worked out for non-intersection environments.

The FVM subproject provided information about driver behavior especially in intersection scenarios.

The PReVENT Project

The Preventive Safety (PReVENT) project was an Integrated Project within the 6th Framework Programme of the European Commission. The aim of this project was to develop and demonstrate preventive safety applications in the context of driver assistance functions. Several number of applications were addressed by different subprojects: Safe Speed and Safe Following, Lateral Support and Driver Monitoring, Vulnerable Road Users and Collision Mitigation and last but not least Intersection Safety.

The development of these systems was based on in-vehicle systems and communication between vehicles and with the infrastructure [SNB05].

INTERSAFE

The subproject Intersection Safety (INTERSAFE) of the European Integrated Project PReVENT aimed to increase the safety at intersections [FR05], [RF06]. The running period of the project was from 2004 to 2007. The objectives of INTERSAFE were:

- Development of an Intersection Driver Warning System based on bidirectional V2I communication and on-board sensors.
- Demonstration of intersection driver assistance functions based on sensors and communication for relevant scenarios in demonstrator vehicles.
- Demonstration of advanced intersection driver assistance functions in a driving simulator.

INTERSAFE was based on two parallel approaches:

Basic System Approach – The basic system approach started with an accident analysis for intersection related accidents. Extraction of the most relevant scenarios led to the sensor requirements for the ISS. Based on these requirements a demonstrator vehicle was equipped with suitable sensors that fulfilled as much of these requirements as possible. The goal was to show what kind of functionality is possible in the context of driver assistance at intersections.

Note: The INTERSAFE related parts of this thesis are related to this basic system approach.

Advanced System Approach – The advanced system approach also started with the accident analysis like in the basic system approach. The basis for the function development was the assumption of an ideal sensor system. This was realized solely in an advanced driving simulator. The results were optimal requirements like range, coverage angles or accuracy for an advanced ISS.

ISS at the US Department of Transportation

The biggest ISS initiative in the United States is the Cooperative Collision Avoidance Systems (CICAS) initiative of the US Department of Transportation (USDOT). Together with automotive manufacturers the State and also local departments of transportation the USDOT is working on the Intersection Safety topic. Through vehicle-based and infrastructure-based technologies the driver of a vehicle should be warned about likely violations of traffic control devices and also helped to maneuver through the intersection. Most of the work done so far in this initiative focus on infrastructure-based techniques in order to detect oncoming vehicles (e.g. roadside mounted sensors) as well as to warn the driver of a potential hazard (e.g. electronic road-signs or communication with the vehicles) [FHW99].

In 1994 the National Highway Traffic Safety Administration (NHTSA) of the USDOT published a number of reports which emerged out of a multidisciplinary program to identify causal factors of intersection accidents, how they occur and what are potential Intelligent Vehicle Highway System (IVHS) countermeasure concepts. This program was a collaboration of the Office of Crash Avoidance Research (OCAR) of the NHTSA, the Research and Special Programs Administration (RSPA) and the Volpe National Transportation Systems Center. These reports were studied in detail during this thesis especially for the development of the system description part.

SAFESPOT

Cooperative Systems for Road Safety “Smart Vehicles on Smart Road” (SAFESPOT) is a European Integrated Project in FP6 running from 2006 to 2010. In-vehicle as well as infrastructure-based systems are used in order to warn the driver about potential hazardous situations. The goal is to develop a so called "Safety Margin Assistant" that will be an Intelligent Cooperative System based on V2V and V2I communication. The subprojects SCOVA (Cooperative systems applications vehicle based) and COSSIB (Cooperative safety systems infrastructure based) aim to develop, amongst others, Intersection Safety related functions. This includes warning about accidents at intersections, rudimentary support for turning/crossing maneuvers, red-light violation and emergency vehicle support. The functions within the SAFESPOT project are only focused on warning, i.e. no active vehicle intervention is considered.

AKTIV

The new and ongoing successor of the INVENT project is the Adaptive and Cooperative Technologies for the Intelligent Traffic (AKTIV) project. The running period is from 2006 to 2010. Among other things this project is a definite proof of the importance of Intersection Safety in those days. Among the projects dealing with active safety, AKTIV-AS, there is one subproject dedicated to Intersection Safety. The goal is to reduce the number of accidents at intersections by supporting the driver while entering, crossing or turning into an intersection. This should be reached by either on-board sensing, communication means or integration of digital map contents, positioning and comprehensive situation analysis. The driver should be informed and warned by the system as well as assisted by appropriate autonomous interventions. The function Cooperative Traffic Signal of the project AKTIV-VM uses bidirectional communication between vehicles and traffic signal systems. The main objectives are efficient traffic control, shorter waiting times at intersections as well as improved traffic flow.

INTERSAFE-2

The project Cooperative Intersection Safety (INTERSAFE-2) is the follow up project of the INTERSAFE project described above. This is the first single European funded project which exclusively deals with ISS. INTERSAFE-2 complements the INTERSAFE project by infrastructure sensing at the intersection as well as advanced warning and intervention strategies in the demonstrator vehicles.

The objectives of all these new ISS related projects show a strong relation to the INTERSAFE project and the work done in this thesis. The projects concurrently show the up-to-dateness and innovation of the ISS topic and the necessary parts like situation analysis and risk assessment for which a promising approach is presented in this work.

1.2.2 Communication Based Intersection Safety

If some boundary conditions are met, it is in principle possible to address the topic of ISS solely based on communication between vehicles. This is studied amongst others in [NR97], [BCN+05] and [LÖE05]. While [BCN+05] studies the communication to solely exchange vehicle data like e.g. position, [NR97] uses a simulation with autonomous agents to steer the vehicles without any danger through the intersection (a similar approach is also shown in [DS05]). However, on the one hand these approaches are highly dependent on the equipment rate of communication means in vehicles and on the other hand highly sophisticated control strategies would be needed in order to realize autonomous driving within intersections.

1.2.3 Driver Behavior Recognition and Risk Assessment

This section cites important contributions in the field of behavior recognition and risk assessment in ADAS which are in the focus of this thesis. If better applicable, additional citations are made in the chapters that are dealing in detail with these topics.

In [DBB02], [DR02] driver maneuvers like lane changes on freeway scenarios are predicted. With the use of Bayesian networks e.g. time gaps between the traffic participants and trajectories of the vehicles are used in order to derive the behavior of the drivers. With this approach a lane change can be recognized approximately 1.5s before the actual maneuver. A knowledge based approach for behavior decision is presented in [LGTH05]. The knowledge base is queried in order to assess the situation and to identify risky objects in a simulated environment. The advantage of such an approach is that common sense knowledge and traffic rules can be easily formulated and used for reasoning. However, no graduated risk assessment or learning strategies are used. Another and adaptive approach for LDW systems is shown in [KO03]. The LDW model is generated by a fuzzy-evolutionary algorithm after a training period. This can result in an improved warning system without e.g. frequently annoying alarms. The system was implemented and tested in a Hardware-in-the-Loop simulation. A Monte Carlo path planning approach for predicting future vehicle motions is presented in [BBK05]. However, only synthetic data for a few scenarios is used and no driver warning algorithms are connected. In [KSOA03] a Hidden Markov Model is used to predict the stop-probability of a vehicle in front of an intersection. The system shows quite good evaluation results for this one specific task based on velocity and pedal stroke data of real test drives. Another Hidden Markov Model approach is described in [BED08]. [WPTK05] as well as [JJG02] present a method for risk estimation for forward collision scenarios. The risk is estimated by calculating the probability of collision between two vehicles taking into account their individual positions. The systems are studied in simulation environments as well as in real vehicle demonstrators. In [STTT05] a fuzzy logic based decision making approach is presented for car following scenarios. It uses a few fuzzy rules and an inference engine without any learning functionality that is evaluated in a simulated traffic environment. Another fuzzy logic model is used in [MW04]. This work presents a decision support approach for left turn merging maneuvers based on a fuzzy rule base. For this, the concept of barrier crossing is implemented in a cognitive architecture. In [KKH+04] a simple method named SUPREME (Simple and Useful Perceived Risk Estimation Method) is proposed which uses driving behavior data in order to estimate the drivers perception of risk. The pedal and steering wheel operations are used as an indication for the assessment of a few traffic situations in a simulated environment. [OP00] employs Hidden Markov Models in order to recognize lane changes but used a batch algorithm that detected whole instances of a maneuver rather than continuous recognition of streaming, real-time data as would be needed in a real vehicle.

There are quite a few works which are dealing with adaptive strategies for behavior recognition and risk assessment. One example of a preliminarily realized approach is presented in [MHTM03]. Based on a driving simulator the driver model of an autonomous agent is refined offline with the data gathered from humans which were driving in the simulator beforehand.

1.3 Overview of this Thesis

As learned from Section 1.2 only a few limited online assistance functions for intersection related driving tasks were developed in the past. They are either limited in the complexity of sensor systems (e.g. no fully autonomous on-board systems) or in the functions they are addressing (e.g. only one dedicated function like for example traffic light assistance). In summary, no comprehensive and board autonomous ISS was realized so far. This is also reflected in the behavior recognition/prediction and risk assessment algorithms developed in the past. Most of the works which found their way into real demonstrator vehicles focus on tasks in less complex highway or freeway scenarios (e.g. recognition of lane changing maneuvers) and do not include any machine learning functionalities. Some dedicated works that address parts of ISS applications consider on the one hand only a subset of the most relevant scenarios or do not combine behavior recognition with subsequent risk assessment. On the other hand they were not implemented and tested in real demonstrator vehicles, which complicates the appraisal of suitability for online operation. Furthermore, for some works it seems very likely that an implementation of the proposed algorithms in a real demonstrator vehicle is not very promising. This is amongst others due to the fact that in the real world, sensor data is noisy and not a quarter as good as in a simulated environment. To the authors mind, the suitability of algorithm operability in real world scenarios can only be validated if a real demonstrator system is used during development.

1.3.1 Scientific Placement

The underlying work is embedded in the scientific context of ISS in the way that it is a development of a full functioning assistance system which offers a solution for the drawbacks of past systems which are mentioned above. In order to achieve this goal, the sensor requirements for such an ISS are derived from the most relevant accident scenarios. So far, based on the state of the author's knowledge, this was never analyzed in detail before. Based on the requirements, a generic architecture for modeling of intersection environments which includes a novel application driven simulator integration is developed. This architecture offers enhanced possibilities for algorithm development and testing procedures for ISS as well as many other ADAS applications. The special focus of this work is set on automatic situation analysis and adaptive risk assessment features and their proper and necessary combination as well as strategies for presenting the results to the driver. Therefore, an innovative approach is presented that integrates the above mentioned developed intersection modeling into a suitable online capable implementation for the demonstrator vehicle. The adaptive risk assessment algorithms are able to judge the considered critical situations in a junction and also allow for an automatically learning system (even online in the demonstrator) which can adapt its mode of operation to different drivers. This approach is abutted to human thinking in intersection driving tasks and therefore intuitively realizable. Through adequate and innovative developed Human-Machine Interface (HMI) elements the calculated risk is presented to the driver. One major progress of this thesis is that the system is not only theoretically designed but also implemented and tested in a real prototype vehicle which can gather environmental information from different on-board sensor sources. The work of this thesis contributed a lot to the first comprehensive on-board demonstrator vehicle which adequately combines situation analysis, adaptive risk assessment and innovative warning strategies and which is able to deal with a wide range of intersection safety applications.

1.3.2 Task Description

Following the scientific placement of this thesis stated above, the subsequent individual tasks are most relevant for this work:

1. derivation of sensor requirements for ISS
2. perception of the intersection environment
3. fusion of data into a common environmental model

4. **analysis of the traffic situation**

5. **adaptive risk assessment for the host vehicle**

6. **warning strategies for visualization of the results to the driver**

7. testing and evaluation of the whole system through appropriate test concepts

The developed system is able to observe the relevant environment of the intersection with several on-board and/or remote sensors which are identified to fulfill the requirements for this task. Out of these sensor data an appropriate scene model is build. Based on the scene model the behaviors, intentions and interrelations of all vehicles in the scene are derived and anticipated for a comprehensive situation analysis. Taking into account factors like the dynamics of the involved road users, the topology and right-of-way regulations of the considered intersection, possible dangerous situations are identified. The subsequent risk assessment judges their individual risks for the vehicle that is equipped with the safety system. Therefore, the behaviors and intentions from the situation analysis are compared and analyzed in time and space domain in order to identify possible collisions or dangerous maneuvers within the intersection. Once this task is performed the output is presented to the driver through appropriate warning strategies based on an innovative HMI in order to warn him against the potential dangerous situation for the relevant scenarios. Finally the whole system is evaluated and tested for its complete functioning. However, testing of safety related assistance systems without endangering the driver of the system and possibly other road users is not an easy task. Therefore, test concepts are developed which are suitable for such testing for each developed component of the ISS.

1.3.3 System Characteristics

In general there are mainly two approaches for the development of Driver Assistance Systems: systems with active and passive support. Assistance systems of the first kind are systems that provide active input to the dynamics of a vehicle (i.e. steering or braking) while the latter are systems that “solely” inform or warn the driver. Well known examples of active driver assistance systems are for example ESC or BAS. Further differentiation can be made into autonomous and semi-autonomous systems. While semi-autonomous systems always need a trigger of the driver (e.g. touching the brake pedal) before being activated, autonomous systems can perform their actions without any previous reaction of the driver. Still an issue of these fully autonomous systems may be legal aspects. The question of responsibility if such a system fails is not solved so far. For this reason nowadays safety relevant ADAS are almost always semi-autonomous or passive systems. Passive system support in the ADAS area is always done by informing or warning the driver against a possible dangerous situation. The control over the car fully remains in the hand of the driver. Warning and information is often done by acoustic, haptic or visual feedback. A famous example of such kind of passive systems is LDW where the driver receives either an acoustic or haptic feedback if he is unintentionally going to leave his driving lane on a motorway. However, the decision to steer the car back on track still remains the driver's responsibility. Figure 1.1 shows the described ADAS classification based on some selected systems. As long as this work deals with very new aspects on intersection support it

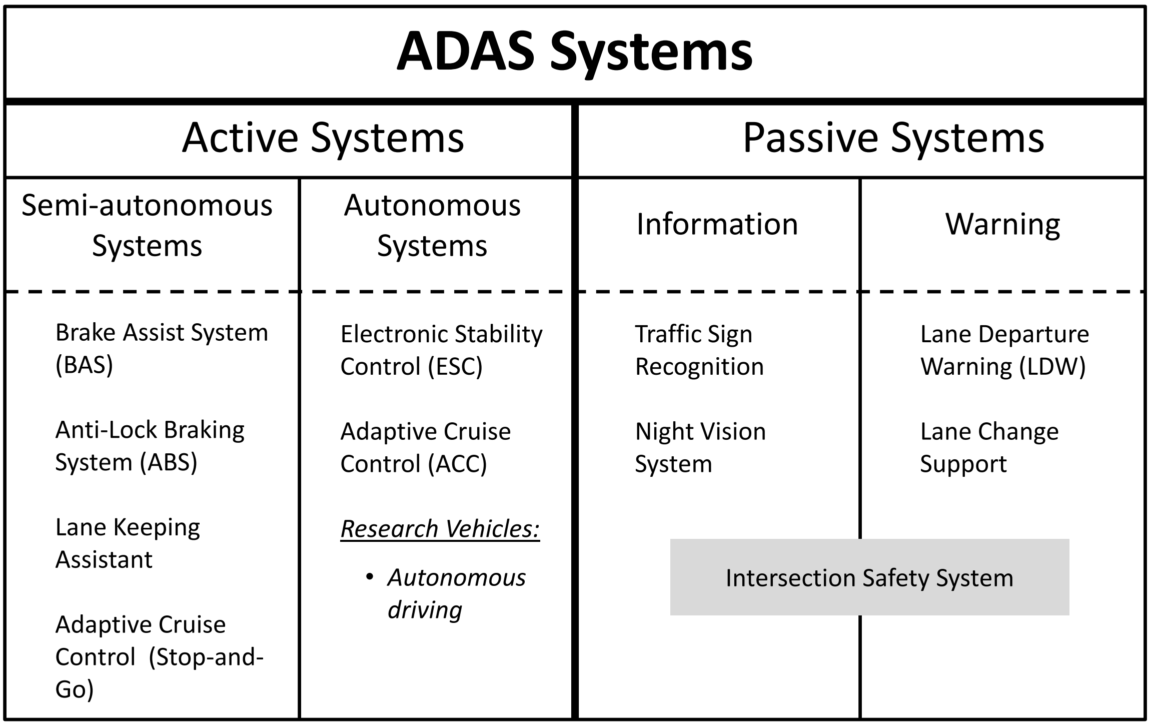


Figure 1.1: Classification of different ADAS systems. The scope of the ISS of this work is shown as a gray box.

was decided to focus only on information and warning strategies in order to support the driver in his decision making process or to inform him of potential dangerous situations. In comparison with an autonomous system, the current approach is more tolerant to possible false alarms that can inevitably occur in such a new research system. The outcome of this work is a complete and innovative ISS closing the chain from the sensor level through the perception level up to the application level like shown in Figure 1.2. On the sensor level the vehicle sensors and/or the remote sensors gather the information from the infrastructure and pass them after a preprocessing to the perception level. In the perception level all data from the different sensors is fused so that an overall environment model can be constructed. This environment model

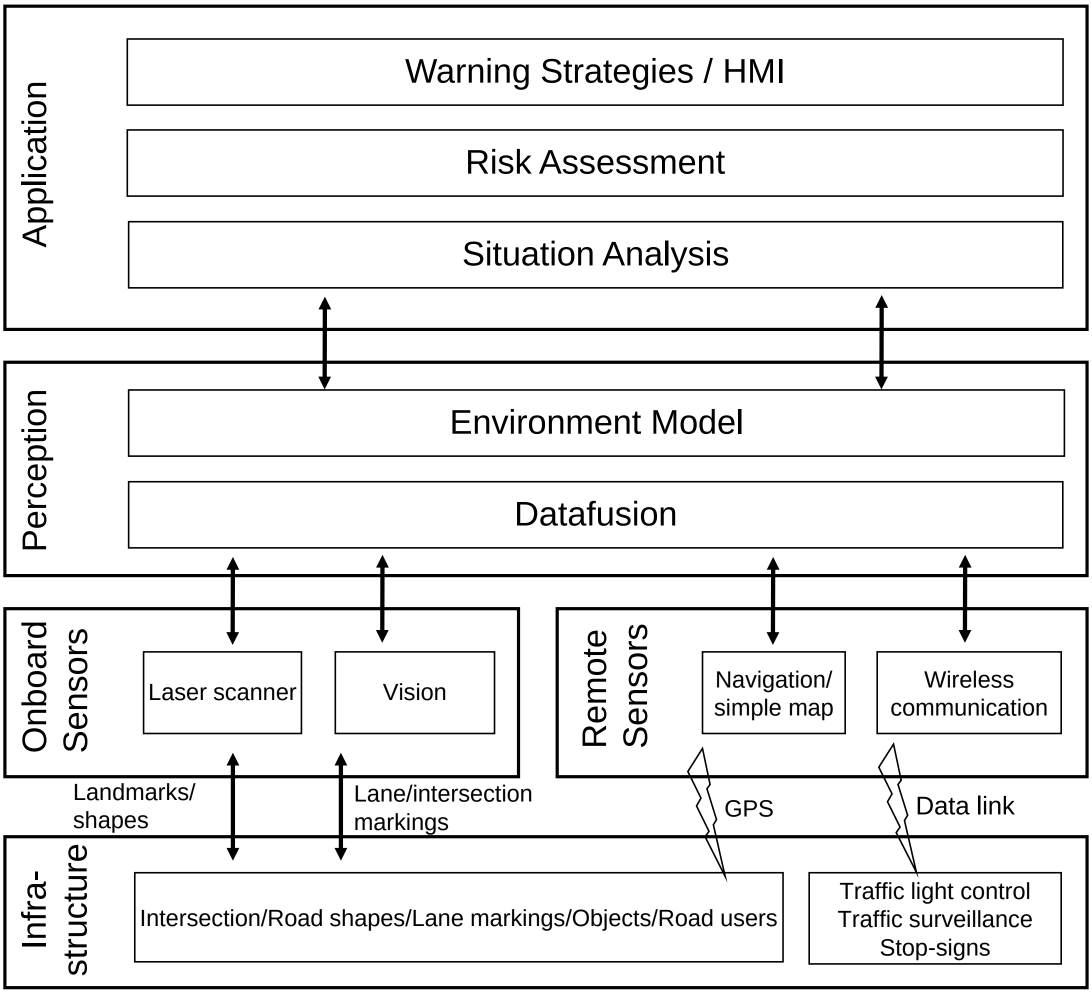


Figure 1.2: General architecture for the underlying Intersection Safety System.

is an image of the real surrounding with all its static and dynamic objects and other infrastructural information. Based on this environment model the application level can perform an appropriate situation analysis. The situation analysis computes the relationship between all objects from the environment model and identifies if there are possible conflicts in the current scenario configuration. A possible conflict is detected as soon as at least two objects in the scenario have the possibility to interfere in space domain (taking into account the dynamics of the objects, their constellations as well as the traffic regulations). The actual risk of such conflicts is appraised in the risk assessment. If a situation becomes too dangerous or needs to be communicated to the driver, the computed risk output is finally presented to the driver through appropriate warning strategies and HMI. This flow of information is shown in Figure 1.3.

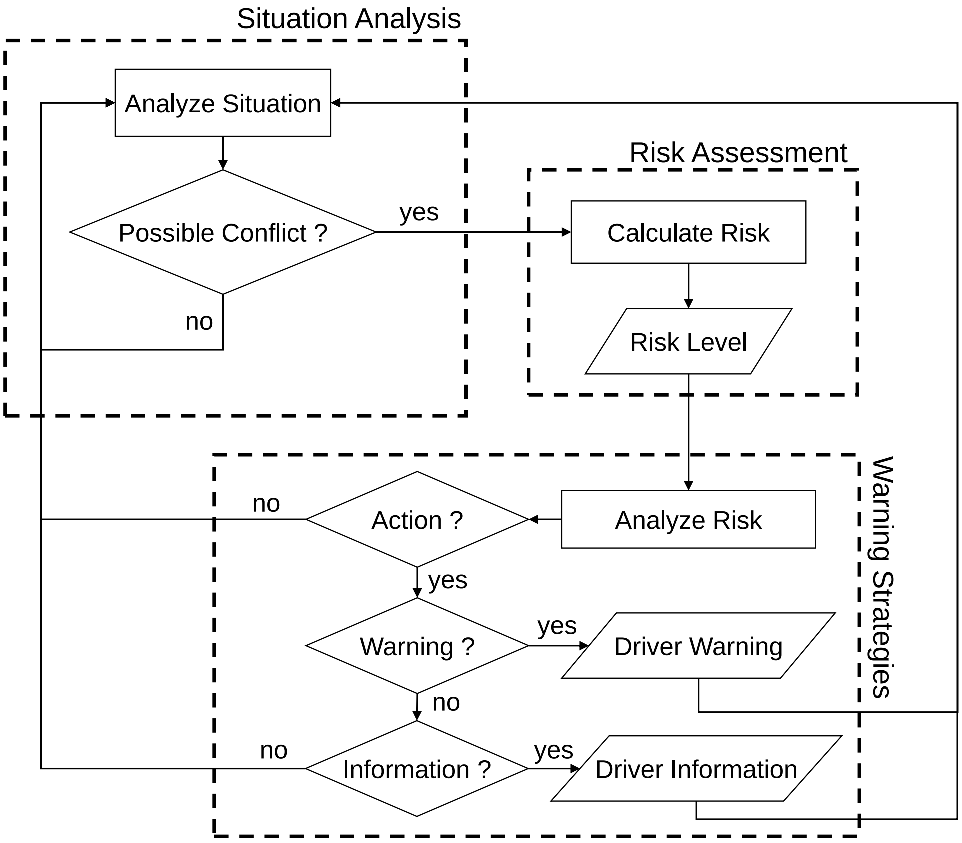


Figure 1.3: Application level off the ISS.

1.3.4 Structure of this Work

The structure of this work is closely abutted to the architecture shown in Figure 1.2. The different chapters in this work reflect to some extend the levels of this architecture.

Chapter 2 introduces the underlying system setups which were constructed as research and development basis for this work. Starting with a motivation from brief accident analysis data of intersection related accidents the system is described in its functions. After that, the sensor requirements for the selected functions are derived. Finally, the sensor platform and different characteristics of the demonstrator setups are shown. The developed demonstrators are a vehicle system which is based on on-board sensors to perceive the environment, an infrastructure supported approach where the sensors are located at the infrastructure as well as a simulated system which eases the development of the first two mentioned by the possibility to test the whole ISS and its different components for their functioning.

Chapter 3 describes the perception level and the overall framework of the system in more detail. The data fusion of the system sensor outputs is explained and how it results in the environment model of the intersection scene. Therefore, it is abstracted from the type of sensor which allows an open architecture for all characteristics of the demonstrator setups mentioned before. The environment model consists of the topology of the intersection as well as all dynamic and stationary objects that could affect the desired assistance task. For this purpose a suitable lane model description is introduced which enables an easy and real-time-compliant handling for the subsequent situation analysis and adaptive risk assessment tasks. The simulation and its application driven architecture integration into the used framework are further explained.

Based on the constructed environmental model of the scene and the online perception of the actual surrounding of the vehicle, the situation analysis is performed. This is described in detail in **Chapter 4**. Situation analysis includes the localization task of all vehicles, the behavior recognition and prediction of all traffic participants and the resulting possible traffic conflicts for the current intersection situation. An approach based on probabilistic networks that uses the advantages of the developed lane model description is introduced in order to fulfill these complex tasks.

Chapter 5 introduces an approach in order to identify if the current situations that were extracted from the situation analysis are critical according to some defined constraints or not. For this task human factors and ways of thinking are taken into account. This simplifies the formulation of expert knowledge which would otherwise be needed. Like in human thinking where different levels of risk or danger exist, the risk assessment output of the underlying system is also some kind of continuous level representation. To overcome the problem that the risk estimation differs from one situation to another or is not the same for different drivers – e.g. elderly drivers sometimes perhaps have a different appraisal of a critical situation than younger people – a machine learning approach is proposed that analyzes the behavior of the driver and computes the risk level in adaptation to his driving skills and attitude.

The problem of how and when to inform the driver of a possible risk is addressed in **Chapter 6**. This topic addresses several challenging questions like what kind of HMI interface could be appropriate for the proposed intersection safety system. Therefore, human factors are taken into account to differentiate between several characteristics of HMI approaches.

Chapter 7 completes this work with experimental results from the evolved test concepts. The different modules are tested separately by means of simulation and the whole system is additionally evaluated with the developed vehicle demonstrator. User test results are presented in order to judge the acceptance of such an ISS and the developed warning strategies.

A summary of the whole work as well as an outlook on possible future work and extensions of the system are finally given in **Chapter 8**.

Chapter 2

System Description

In this chapter the overall system is introduced. Starting with a motivation from a short accident survey the functions for the assistance system are derived. The aim is to concentrate on assistance for the driver in the most common and most severe accidents that occur at intersections, neglecting rare and uncommon types in order to reduce complexity where it is not needed. Based on this functional description the necessary sensor requirements for the assistance system are derived. The sensors that are going to be used have to fulfill several criteria (i.e. coverage area, resolution) in order to provide a basis for assistance for the selected functions. Finally, the different demonstrator setups (on-board, infrastructure based and simulation) that were designed and used for this work are shown and compared to each other.

2.1 Accident Survey

In the year 2007 in Germany 46.137.340 passenger cars were registered. This means that one passenger car was registered for more than every second inhabitant. Thereby, the German police counted a sum of 2.3 million accidents in 2007. This means that nearly every $20th$ registered vehicle was involved in an accident in this year. A view on the total number of accidents with personal injuries in Germany in 2007 shows that intersection related accidents rank among the most number of all these accidents [DES07]. Figure 2.1 shows the distribution of types of such accidents in Germany in 2007. The number of 96.418 collisions with another vehicle which turns into or crosses a road accounts for 28.7% of all accidents with personal injuries. Because of the high amount of intersections in urban areas these accidents mostly occur there. Detailed accident analysis shows that intersections are also a serious focal point for accidents in other countries [ROS+05b, BM03]. Common causes are violation of traffic lights/signs and disregarding others right of way either by fault or lack of information. Especially the violation of traffic lights or stop/yield signs leads to the most severe injuries out of these intersection accidents [CSN04]. Misinterpretation and inattention can be identified as the most common mistakes in these cases. Figure 2.2 shows the distribution of accidents with injuries in Europe separated into accidents occurring

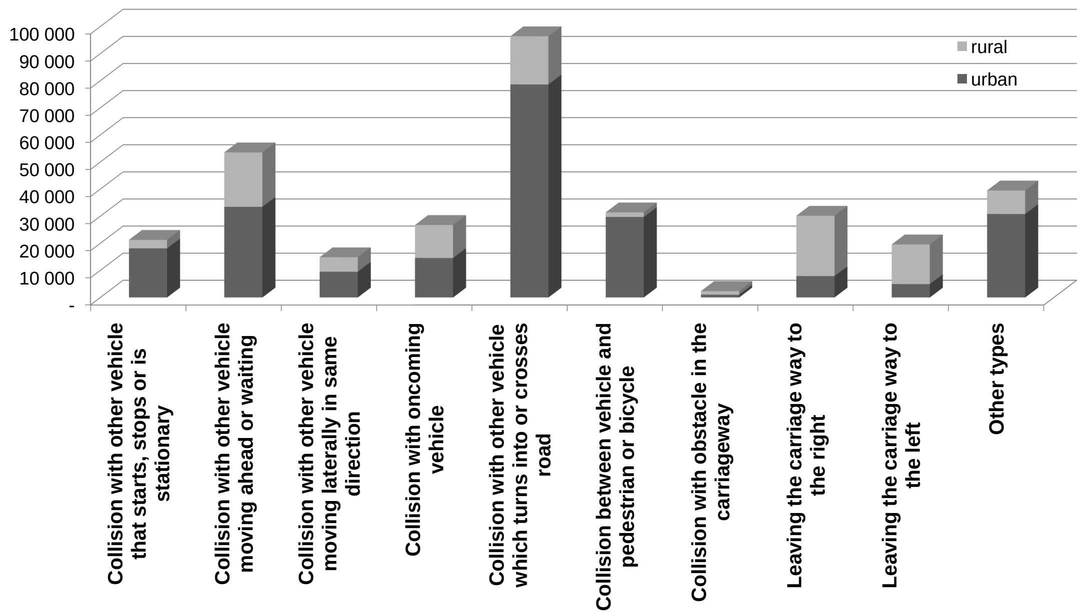


Figure 2.1: Number of accidents in Germany by accident type (year 2007).

at intersection and accidents occurring not at intersection. This simple figure alone, derived from the European Road Accident Database (CARE) 2006, expresses the need for action to increase safety at intersection. This short view on some statistical

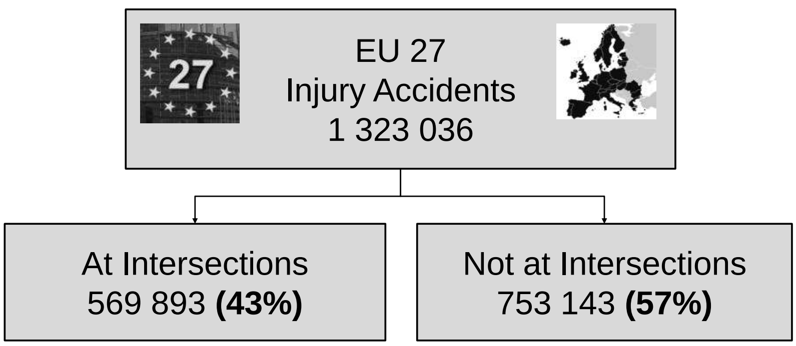


Figure 2.2: Distribution of accidents with injuries in Europe.

accident data shows that a well designed and approved ISS could help to reduce the number of accidents significantly.

Sometimes it is noted that it is sufficient to solely make structural measures like roundabouts in order to reduce accidents at intersections. Beside the high investments for the reconstruction of the existing intersections, [Voß94] showed in contrast an increasing number of accidents - indeed decreasing severities - after the reconstruction of defined intersections into roundabouts. Independent of this, the work found out compact roundabouts to be good for intersections with low or medium volume of traffic but bigger roundabouts (diameter > 50m) as inappropriate concerning traffic flow and road safety. Thus, a 100% secure type of intersection does not exist. Human factors like inattention or misinterpretation are not eliminated by other types of intersections. An ISS can assist the driver for several types of accidents independent of the type of the intersection. Therefore, it is assumed by many experts to be a good approach for a global reduction of accidents especially in urban areas.

2.2 Functional Description

The short accident review of the last section showed a need to assist drivers at intersections. From [ROS+05b] three main scenarios can be extracted which cover a crucial number of intersection accidents:

- left turn across path
- turn into/straight crossing path
- violation of a red traffic light

These scenarios define the basis for the ISS and its interpretation tasks in this work. Each situation is covered by separate assistance functions which are all described in this section. The first scenario, the “left turn across path scenario”, is covered by the *Turning Assistance* followed by the “turn into/straight crossing path scenario” which is covered by the *Right-of-Way Assistance*. Finally the *Traffic Light/Stop Sign Assistance* provides assistance for the “red light crossing scenario”. For the underlying system only mistakes that are possibly made by the vehicle with the installed ISS (i.e. the host vehicle) are considered by the assistance functions. This is due to the fact that the number of false alarms should be kept as small as possible. It is much harder to identify possible mistakes of other vehicles than mistakes from the host vehicle itself since data like position, speed, acceleration or turn indicator is needed in order to predict the maneuver of a vehicle. Unfortunately, in most cases if this data has to be derived from the data of on-board perception sensors this is more inaccurate and difficult to handle than the host vehicle data that is often directly available on the CAN bus. In the following, only German traffic regulations (i.e. right hand side traffic and right-before-left rule) are considered. Nevertheless, the developed strategies are with only minor adjustments transferable to other countries’ regulations like for example in the United Kingdom.

2.2.1 Turning Assistance

Left turn across path in an intersection is the first critical defined scenario. The vehicle which intends to turn left disregards the right of way of the oncoming vehicle and a crash occurs. In order to prevent such accidents, the first function is the Turning Assistance (TA) which warns/assists the driver in critical turning maneuvers at intersections. Accidents with Vulnerable Road Users (VRUs) like pedestrians and

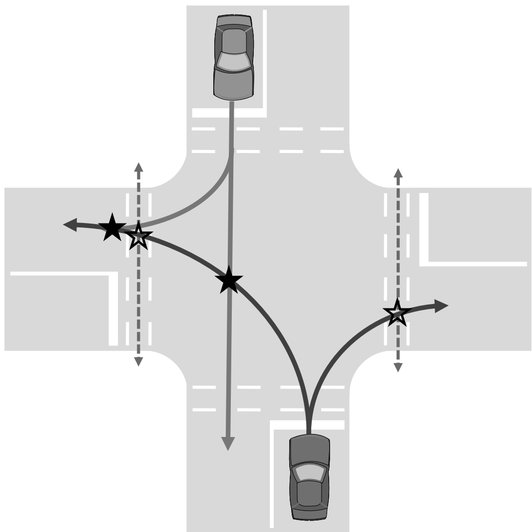


Figure 2.3: Scenario for the TA of the ISS. The stars define the possible conflicts. The dashed arrows are the paths of a pedestrian or bicyclist.

bicyclists are not among the most relevant intersection related accidents [ROS+05b]. They mainly occur in urban areas (see Figure 2.1) while most of the cases do not happen at intersections. Nevertheless, VRUs have a very high probability to get seriously injured in an accident with a car. For example, when turning right in an intersection with a car, it is quite easy to lose sight of a bicyclist which is coming from the back right. Therefore, the TA was designed to not only cover vehicle to vehicle accidents for this scenario but also the cases where pedestrians and cyclists are involved. A visual and auditory warning supports the driver in his decision making for turning in an intersection but can also directly prevent accidents that would occur because of inattention or occluded field of view of the driver. This warning is based on the predicted trajectories and behavior of the host vehicle and other nearby traffic participants. The scenario for the TA, together with the conflicting points the assistance system should be aware of, are shown in Figure 2.3.

2.2.2 Right-of-Way Assistance

The Right-of-Way Assistance (RoWA) pays special attention to lateral traffic. The system warns the driver if he seems to violate a right-of-way of another vehicle coming from either the left or right side. It supports the driver in finding a suitable gap between vehicles and the optimal speed in order to safely cross the intersection. Typical situations for the RoWA are intersections with a yield sign or crossings with right-before-left regulation like at a lot of German intersections without traffic signs or traffic lights. The scenario for the RoWA, together with the conflicting points the assistance system should be aware of, are shown in Figure 2.4.

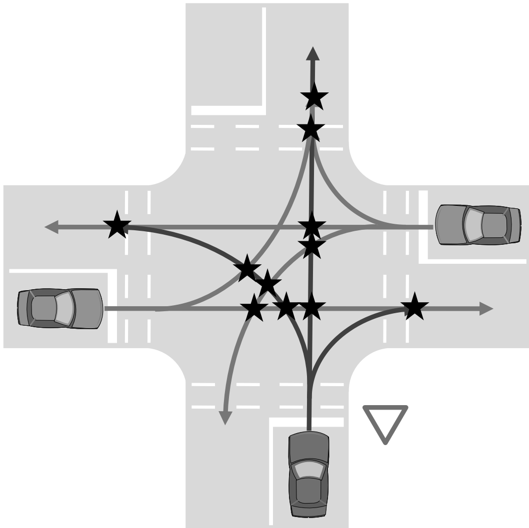


Figure 2.4: Scenario for the RoWA of the ISS.

2.2.3 Traffic Light/Stop Sign Assistance

As defined in the third of the three relevant scenarios mentioned above, drivers frequently have problems in approaching traffic lights. Predominantly the driver shall be prevented by the Traffic Light/Stop Sign Assistance (TLA) from violating neither a traffic light showing red nor a stop sign at his side of the intersection. For this purpose there is a visual and acoustic warning as soon as the system identifies a potential hazard. The scenario for the TLA, together with the conflicting points the assistance system should be aware of, are shown in Figure 2.5. In order that the driver can avoid such a conflict, a speed recommendation is given to him while approaching an intersection with traffic lights or stop signs. This depends on the current and predicted status of the traffic light or the presence of a stop sign. With

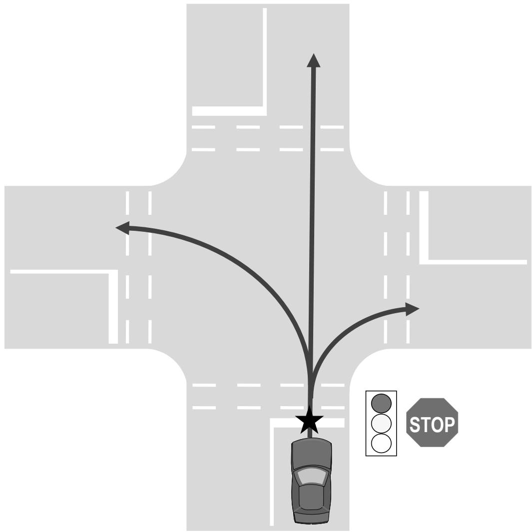


Figure 2.5: Scenario for the TLA of the ISS.

this additional information the driver is able to drive with adequate speed knowing in advance which situation he will be faced with when reaching the intersection. This warning/recommendation should result in less critical situations and better traffic flow at the intersections under consideration. One approach is to display a speed recommendation to the driver at intersections with traffic lights based on the assumption of a fixed phase control for the traffic signal system. Unfortunately, this assumption is not suitable for all nowadays traffic light controllers. More and more systems are equipped with highly dynamic phase control that does not offer the possibility to predict the signal state prior to arriving at the intersection with 100% reliability. Dynamic ascendancies like demands of a pedestrian or another vehicle made by either a button at the pedestrian light or induction loops in the street can change the signal plan from one moment to another. Nevertheless, it is a first approach to study the acceptance or suitability of such a speed recommendation until further studies or development are available for state of the art traffic light controllers.

2.2.4 Constraints for Intersection Safety Assistance

In order to ensure driver safety, the defined assistance functions have to respect some boundary conditions so that a possible warning can be raised early enough. These constraints directly influence the sensor requirements derived in Section 2.3. As shown in Section 1.3.3, in general one can differentiate between driver warning and driver information. In this work, a final acoustic warning is generated at the point where the driver is expected to decelerate the vehicle immediately to a full stop in order to just avoid an imminent danger. This point is called Last Warning Point (LWP). The according distance from the LWP to the calculated conflict point (distance needed to stop the vehicle before imminent danger) is called Minimum Warning Distance (MWD). It is important to mention that the LWP is not necessarily the point where the driver has to brake in order to avoid an imminent collision but rather the point where a hard (uncomfortable) braking has to be applied to stop at a reasonable distance to a possible conflict. This is primarily driven by the fact that the designed system generates warnings rather than applying autonomous interventions. With an autonomous intervention the system can calculate very precisely the braking distance for a defined deceleration. No human factors like response times or different applied braking levels have to be considered. In contrast, driver information is all kind of information that is given to the driver prior to the LWP. As will be discussed later in Chapter 6, the combination of driver warning and driver information is considered to be most helpful in case of an ISS. For the three assistance functions introduced above the host vehicle has to stop in front of or within the intersection in the following cases:

1. intersection with stop sign or traffic light that is red or will switch to red before the host vehicle enters the intersection (TLA).

2. the host vehicle intends to cross or turn-into a road with priority and another vehicle which has the right of way is coming either from the left or the right side (RoWA).

3. the host vehicle intends to turn left with a vehicle coming from straight ahead with the same road priority (TA).

As introduced above, warning in these described situations should be sent to the driver at a defined distance MWD from the intersection or calculated conflict point. This appropriate distance must take into account human factors, i.e. the response time of the driver and the deceleration value commonly applied by the driver. Of course such human factors can differ from one person to another. For the development of the ISS, as proposed in this work, it is a good starting point to use average values that were found out in different studies. One way to cope with the difference of those human factors is addressed later in Chapter 5.

Warning Constraints

For the RoWA and the TA a warning has to be raised if another vehicle is going to cross the conflict point or is going to enter the conflict zone (defined area around conflict point) at the same time as the host vehicle. Solely in this situation a warning should be raised. No warning should be raised if the host vehicle arrives at the conflict point/zone after the oncoming vehicle has already passed, which is expressed by the following equation:

$$t_{arrive} > \frac{D_o + 2W_l + L_v}{V_o} \tag{2.1}$$

or if the oncoming vehicle arrives at the conflict point/zone after the host vehicle has already passed it, which is expressed by the following equation:

$$t_{arrive} + t_{clear} < \frac{D_o}{V_o} \tag{2.2}$$

where V_o and D_o are the speed and distance to the intersection of the other vehicle, t_{clear} is the time the host vehicle needs in order to clear the intersection and t_{arrive} is the time for the host vehicle to reach the intersection.

Stopping in Front of Intersection

In the first two cases mentioned above the vehicle has to stop in front of the intersection (stop line). The minimum warning distance is calculated as follows:

$$\mathsf{MWD} = -\frac{V_h^2}{2a} + (t_{driver} + t_{system})V_h$$

where

V_h	velocity of the host vehicle
a	braking deceleration of host vehicle
t_{driver}	driver brake response time
t_{system}	braking system + warning system response time

Common values for t_{driver} and t_{system} are 2s and 0.5s respectively ([Tra94b], [CLE05]). Table 2.1 shows some values for the MWD calculated for a common velocity range of the host vehicle and three different deceleration values. Without reacting to a warning the time t_{arrive} for the host vehicle to arrive at the intersection and the time t_{clear} needed to clear the intersection are computed as follows:

$$t_{arrive} = \frac{MWD}{V_h} \tag{2.3}$$

$$t_{clear} = \frac{2W_l + L_v}{V_h}$$

Velocity (V_0)	**MWD** ($a=-0.3g$)	**MWD** ($a=-0.5g$)	**MWD** ($a=-0.7g$)
10	8	8	8
20	19	17	16
30	33	28	26
40	49	40	37
50	67	54	49
60	89	70	62
70	113	87	76
80	139	106	92
90	169	126	108
100	201	148	126

Table 2.1: Appropriate warning distances to stop “safely” before entering the intersection.

Stopping Within Intersection (Left Turn)

If the driver intends to turn left at an intersection the system has to watch out for oncoming traffic and warn the driver that he must possibly stop within the intersection to let the oncoming vehicle pass. The available time delay from the beginning of the deceleration (for the turning maneuver) to the point when the host vehicle has to brake immediately to come to a full stop no more than W_l meters beyond the intersection can be computed as follows:

$$t_d = \frac{\sqrt{(\frac{V_{max\_turn}^2}{2a} + W_l)(\frac{2aa^*}{a^*-a})} - V_h}{a} \tag{2.4}$$

where

V_h	initial travel velocity of the host vehicle
V_{max_turn}	maximum turning velocity to turn left within the intersection
a	"normal" braking level to slow down to V_{max_turn}
a^*	emergency braking deceleration
W_l	lane width for a simple intersection as shown in Figure 2.6.

Assuming again a delay for the driver and the machine of $t_d = t_{driver} + t_{machine} = 2.5$s, the minimum distance at which the driver has to be warned of a potential colliding vehicle can be computed solving Equation 2.4 for V_h and substituting into the following equation:

$$\mathsf{MWD} = \frac{V_{max\_turn}^2 - V_h^2}{2a}.$$

With

$$\begin{aligned} a &= -3\frac{\mathrm{m}}{\mathrm{s}^2}, \\ a^* &= -7\frac{\mathrm{m}}{\mathrm{s}^2}, \\ V_{max\_turn} &= 8\frac{\mathrm{m}}{\mathrm{s}}, \\ W_l &= 3.5\mathrm{m} \end{aligned}$$

(see e.g. [NH03], [Tra94a]) a warning distance of MWD $\approx$ 33m can be calculated. Notice, that this distance is not dependent on the initial travel velocity of the host vehicle but rather on the values a, a^*, V_{max_turn}, W_l and t_d. This is due to the fact that the driver of the host vehicle has to decelerate anyway at a defined distance to the intersection in order to reach his turning velocity V_{max_turn}. Here the times t_{clear} and t_{arrive} are computed differently since the host vehicle first has to slow down in his arrival phase (regardless a possible warning). Thereafter, it clears the intersection at a defined turning velocity on a curved path:

$$t_{arrive} = \frac{V_{max\_turn} - V_h}{a} \tag{2.5}$$

$$t_{clear} = \frac{R_m(\frac{\pi}{2}) + L_v}{V_{max\_turn}} \tag{2.6}$$

where R_m is the turning radius and L_v the length of the host vehicle. A visualization of this scenario is shown in Figure 2.6.

Passive vs. Active Support

As mentioned in Section 1.3.3 the system presented in this work is only a warning system. Therefore, human factors like the response time t_{driver} have to be taken into account when calculating the distances above. If such an ISS would be designed as an active system all derived distances would reduce quite a lot due to the distance the car travels during the response time of the driver. For example, if the car should automatically stop in front of the intersection the distance at a speed of $V_h = 100\frac{\mathrm{km}}{\mathrm{h}}$ for initializing the brake maneuver with $a = -0.7g$ would reduce by $V_h \cdot t_{driver} \approx 55$m. This fact becomes important when calculating the sensor requirements as done in the following section. Therefore, the sensor requirements for this system are higher than they would be for an automatic intervening system.

2.3 Sensor Requirements

In order to define the sensor equipment that is suitable for the ISS developed in this work, the sensor requirements have to be derived from the functionality which was

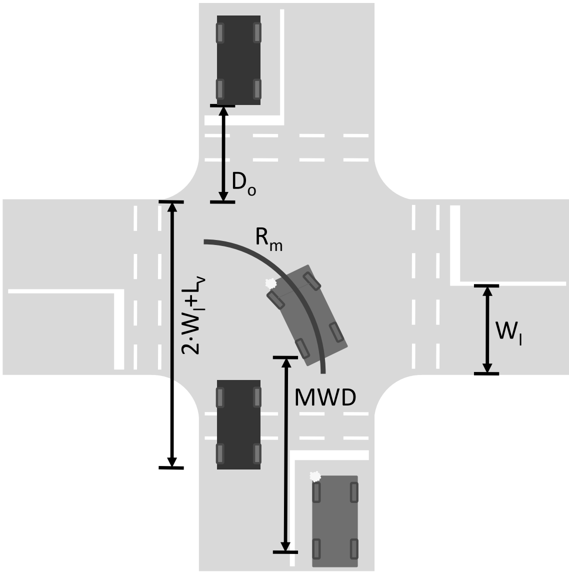


Figure 2.6: Visualization of left-turn maneuver.

described in Section 2.2 and especially the constraints defined in Section 2.2.4. All the described assistance functions from Section 2.2 should be realized by means of on-board sensors and/or remote sensors. Thus, the different tasks the sensors must be able to fulfill before performing the subsequent assistance applications are:

1. Localization of the host vehicle with respect to the intersection.

2. Localization and tracking of other traffic participants within the intersection.

3. Gathering of information from traffic signal systems.

4. Recognition of traffic rules for the actual intersection (standard rules, rules from traffic signs).

While the first two topics are solely achieved by "real sensors" it was decided to fulfill the latter two points with so called "remote sensors". Remote sensors in this case are a map of the intersection as well as communication means (see Figure 1.2). Even if it is possible to perceive certain information with e.g. a video sensor [FGL04], it is more convenient to store traffic rules in an additional map. Since these days navigation systems play a very important role, digital maps become more and more popular and therefore more and more detailed. So it is not unlikely that future digital maps include additional information like traffic signs and traffic regulations at intersections if a need exists.

When talking about camera-based traffic light recognition it is indisputable that communication based approaches offer more detailed information about the traffic signal system. While the video system can only recognize the current status of the traffic light, the communication solution can provide more information like the time to the next status change (if available in the controller of the traffic signal system). This offers the possibility to give the driver better advises like a speed recommendation as described in Section 2.2.3.

2.3.1 Accuracy Assumptions

For the TA and the RoWA it is of high interest to know in which driving lane a vehicle is located in order to predict the intended behavior and therewith the possible conflict points on the intersection (e.g. if a vehicle is located in a left-turning lane it is much likely that the driver intends to turn left). Chapter 4 provides more detailed information about the prediction of the driving behavior of a vehicle. Considering an average vehicle width of about 2m, an overall accuracy of 1m is needed in order to locate a vehicle in a particular driving lane. Otherwise it would for example not be possible to locate the upper vehicle in Figure 2.7 in its actual left turning lane – as it is driving at the right most lane marking – and therefore a false alarm could be raised. However, there are multiple possible sources of errors resulting from the task given above:

- the error of positioning of the host vehicle itself,
- the error of object detection of traffic participants (in the reference frame of the sensor, i.e. of the vehicle) and
- the error of the map (not corresponding perfectly to the reality).

Splitting the target error equally yields about 0.3m error for each source. Taking into account an ideal Gaussian distribution for errors, a standard deviation of 0.1m corresponds to a maximum error of 0.3m. Therefore the accuracy for each part should be 0.1m which is suitable as stated in the following. The accuracy assumption of 0.1m is suitable for all of the described assistance functions in Section 2.2 regarding the positioning problem:

TLA – When thinking about red light violation warning, it is important to have the exact position (distance to the stop line of the actual traffic light) to predict the potential braking distance so that the car can stop before the stop line without crossing it. As the typical width of a stop line painting in Germany is 0.5m([For93]) the above mentioned accuracy of 0.1m is adequate.

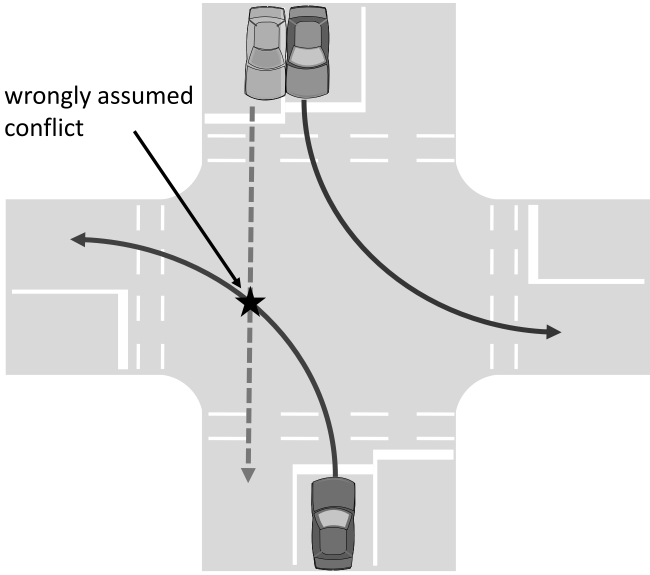


Figure 2.7: Possible false alarm due to low sensor accuracy. The host vehicle (lower vehicle) intends to turn left at the intersection. Normally no conflict exists since the other vehicle (upper vehicle) also intends to turn left. If the accuracy of the localization of both vehicles together with the map accuracy is too low, the other vehicle could also be assigned to the other lane (straight going lane) which could result in a false alarm since in this case a potential conflict could be assumed.

TA and RoWA – In order to predict the appropriate safe-gaps (time to collision) to another vehicle the resolution of ± 0.1m is adequate too. This is because in a warning system a free path can/should be computed with much higher margins. A path can considered to be safe if the host vehicle is able to clear the intersection before a potential colliding vehicle enters it. Depending on the size of the intersection these distances will not be less than 2m in every direction.

2.3.2 Object Detection and Tracking Requirements

This section derives the object detection and tracking requirements for the proposed ISS. This is the area the sensors have to cover in order to get a suitable overall view of the scene. Only if an adequate representation of the current scene is available, the risk assessment can be done and the driver can be warned about potential dangerous situations. Therefore it is important to detect and track the other vehicles in relative position to the host vehicle to a defined extent.

When talking about the needed coverage area for the described ISS one has to differentiate between two aspects. The first is a *wide-area-coverage* where the position of the host vehicle is important (but not with the accuracy assumptions made before) along with some kind of information about the next intersection and its traffic lights (this is addressed in Section 2.4). The second is the *local-area-coverage* where the exact positions (taking into account the accuracy assumptions from above) and dynamic behavior of all the road users in the intersection are of interest at the moment when approaching the closer area around the intersection. This section deals with the latter aspect. When approaching the intersection more closely the positions and dynamic behaviors of all road users, in particular all vehicles, currently in the local area of the intersection are of interest. Looking at the assistance functions described in Section 2.2 it can be directly seen, that it is most important to detect vehicles in the frontal view and also potential colliding objects coming from lateral direction (as for the RoWA). [1]

Angular Field of View

Since the detection of objects coming from lateral direction depends on the angles of the incoming roads and the yaw angle of the host vehicle, the horizontal field of view must be adapted to this fact. Looking at the accident analysis report in [ROS+05b] it can be stated that more or less simple intersection are important for an ISS. This means that the incoming roads can be assumed to be more or less perpendicular to each other and standard values from road construction regulations [For88] can be taken into account.

In order to derive the angular field of view for the ISS, three different situations have to be considered for the selected assistance functions:

1. Going straight ahead
2. Right turn
3. Left turn

Going straight ahead has nearly no influence on the angular field of view. In contrast, the right turn and left turn require an extended angular field of view because the vehicle sometimes already rotated slightly within the intersection while other vehicles still have to be monitored. The angular field of view for the three scenarios is calculated as follows.

[1] Only for extension of the TA (bicyclists coming from the back right) it is necessary to observe the back or side area of the host vehicle. Since this extension of the assistance function was reached by a lonely experimental setup with standard traffic surveillance video detectors, as will be described later, the realization did not depend on such accurate sensor requirement calculations as done in this chapter. Rather, this extension was just built and tested against the correct functioning and therefore it is not considered in these requirement derivations.

Going straight ahead: When a driver intends cross an intersection over a road with priority, the yaw angle of the vehicle, with reference to the approaching lane, is expected to be near zero. The resulting field of view should be therefore at least 180° so that traffic coming from the left or right side can be detected before entering the intersection (see Figure 2.8).

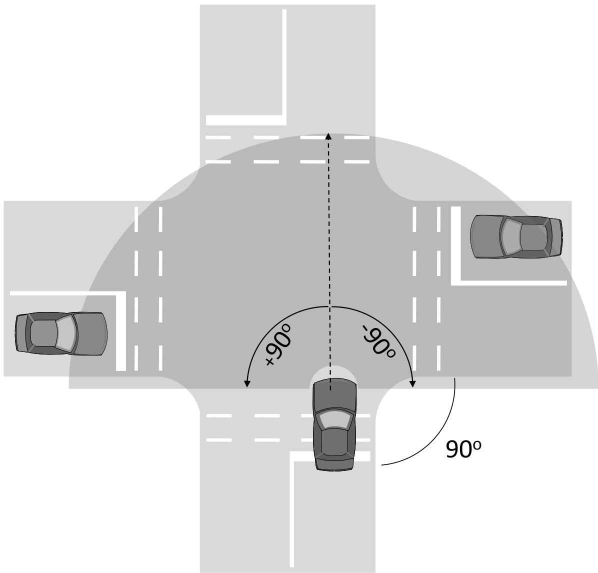


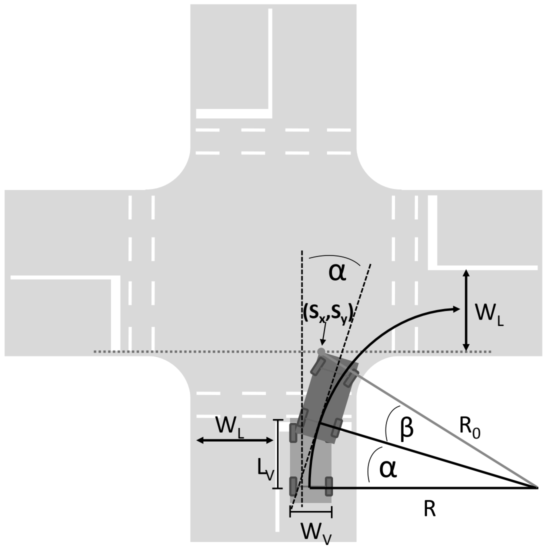
Figure 2.8: Field of view for going straight ahead (not in true scale).

Right turn: Especially for a right turn into a road with priority the driver has to stop in front of the intersection in order to watch out for potential traffic from the left. Depending on the type of the intersection (i.e. the construction of the intersection corners) a driver normally begins his right turn a little before the intersection so that when he has to stop the vehicle comes to rest with a yaw angle different from zero. This situation is shown in Figure 2.9(a). Assuming that the vehicle is driving normally in the middle of its lane, the maximum angle at which the vehicle has to stop can be estimated by Equation 2.7.

$$\alpha = \arctan(\frac{S_y}{S_x}) - \beta, \tag{2.7}$$

(S_x, S_y) is the point where the corner of the host vehicle enters the opponents lane, i.e. the last possible point to stop at. The coordinates of that point and the angle β are computed by:

$$S_y = R - \frac{W_l}{2}, \quad S_x = \sqrt{R_0^2 - S_y^2}, \quad \beta = \arctan(\frac{L_v}{R + \frac{W_v}{2}})$$



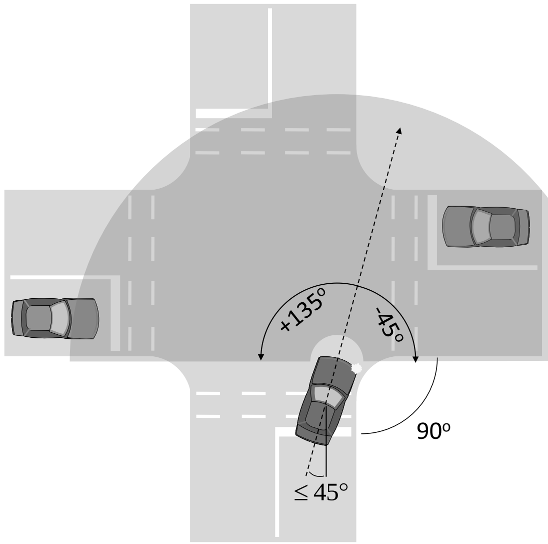


Figure 2.9: Computation of stopping angle for right turn and resulting angular field of view.

where

R Minimum turning radius of the host vehicle

W_v Width of the host vehicle

L_v Length of the host vehicle (i.e. distance from rear axle to the front of the vehicle)

W_l Width of the lane

and R_0 is the radius on which the front left corner of the host vehicle is turning according to the following equation:

$$R_0 = \sqrt{(R + \frac{W_v}{2})^2 + L_v^2}$$

The minimum turning radius R for a right turn is assumed to be the radius of the round road boundary (see Figure 2.9(a)) plus the half of the width of the lane. Due to German regulations for the construction of intersections [SL97] a commonly used radius for the road boundary is 12m. Taking a vehicle length L of 4.5m, a vehicle width W_v of 2m, and a lane width W_l of 3.5m, the minimum turning radius R is 13.75m and the resulting stopping angle computes to approximately 45° (43.36°). This results in a horizontal view of about 135° to the left and about 135° to the right of the vehicle (see Figure 2.9(b)).

Left turn: The computation of the stopping angle for a left turn is similar to Equation 2.7 and results in Equation 2.8. This is important for the TA where the host vehicle has to watch out for traffic coming from straight ahead before starting with a left turn maneuver.

$$\alpha = \arctan(\frac{S_y}{S_x}) - \beta, \tag{2.8}$$

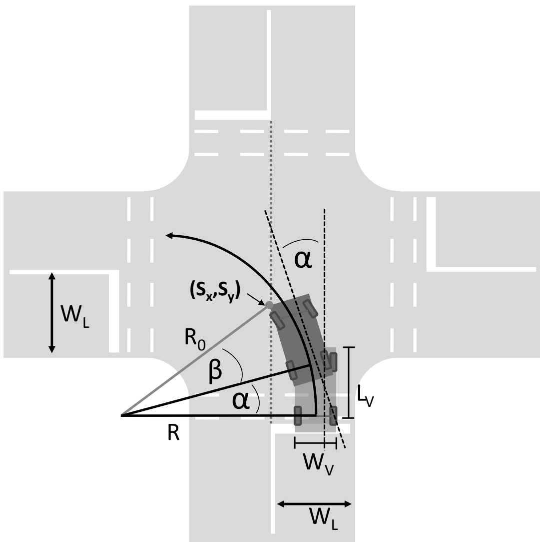
where

$$S_x = R - \frac{W_l}{2}, \quad S_y = \sqrt{R_0^2 - S_x^2}, \quad \beta = \arctan(\frac{L_v}{R - \frac{W_v}{2}})$$

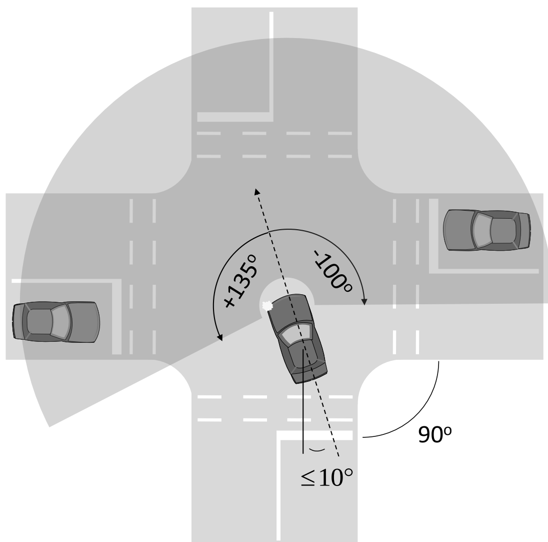
and

$$R_0 = \sqrt{(R - \frac{W_v}{2})^2 + L_v^2}$$

Here the minimum turning radius is set to 17.25m. The resulting stopping angle then computes to approximately 10° (7.7°). This results in a field of view of approximately 100° to the right (see Figure 2.10(a)). Since for a left turn off



(a)



(b)

Figure 2.10: Computation of stopping angle for left turn and resulting angular field of view.

a road with priority the field of view is less than for the right turn into a road with priority, because high attention lies in the traffic coming from straight ahead (see Figure 2.10(b)), the field of view to the left can be the same as for the right turn into a road with priority, i.e. the computed 135°.

Thus, an overall field of view of approximately 235° around the front of the vehicle (135° to the left and 100° to the right) is adequate for all three scenarios .

Object Detection Range

Beside the angular field of view of the host vehicle, the object detection range is of big interest. It has to be derived up to which distance a potential colliding object has to be detected in order to have enough time for a possible warning. In order to define the minimum required object detection range for the sensor system the following values for each of the functions are assumed (according to [Tra94a]):

V_{max_turn}	Maximum turning velocity	8m/s
a	Typical deceleration for left turning that driver will use to slow	-3m/s^2
a^*	Emergency braking deceleration applied after driver delay	-7m/s^2
L_v	Length of vehicle	4.5m
W_l	Lane width	3.5m

Turning Assistance (TA) According to Section 2.2.4 the distance at which a warning should be initiated for a left turn maneuver is at approximately 33m. The distance of the other vehicle that is on conflict with the host vehicle can be obtained by solving Equation 2.2 to D_o (this results in greater values for D_o than Equation 2.1):

$$D_o > (t_{arrive} + t_{clear})V_o,$$

where t_{arrive} and t_{clear} are computed according to Equation 2.5 and Equation 2.6. Adding this distance and a width of the intersection of about $2 \cdot W_l$ meters to the 33m the minimum required measurement ranges listed in Table 2.2 are obtained (dependent on the velocity V_o of the other vehicle).

Right-of-Way Assistance (RoWA) The worst case scenario for the right-of-way assistance is of course the situation where the host vehicle and another vehicle drive both at constant velocity. The host vehicle should give way to the other vehicle due to a traffic sign and the other vehicle is not able to clear the intersection before the host vehicle enters its path. If the host vehicle is traveling at V_h and the other vehicle is traveling at V_o the line of sight distance between the two vehicles can be computed according to Equation 2.9.

V_o[km/h]	Measurement range of the sensor [m]
30	96
40	114
50	133
60	151
70	170
80	188
90	207
100	225

Table 2.2: Minimum measurement ranges for TA.

$$D = \sqrt{(\mathsf{MWD} + 1.5 \cdot W_l)^2 + (V_o \cdot t_{arrive} + 2 \cdot W_l + L_v + 0.5 \cdot W_l)^2} \qquad (2.9)$$

where t_{arrive} is computed according to Equation 2.3.

With the MWD values computed according to Section 2.2.4 with $a = a^* = -7\frac{\mathrm{m}}{\mathrm{s}^2}$ and $t_{driver} + t_{machine} = 2.5\mathrm{s}$ the required minimum measurement ranges dependent on the velocities of the host (V_h) and the other vehicle (V_o) are listed in Table 2.3.

		V_h[km/h]							
		30	**40**	**50**	**60**	**70**	80	90	100
V_o[km/h]	**30**	50	58	68	80	93	107	123	139
	40	57	65	75	86	99	113	128	144
	50	64	72	82	93	105	119	134	150
	60	72	80	89	100	112	126	141	157
	70	80	88	97	108	120	134	148	164
	80	88	96	106	116	128	142	156	172
	90	96	104	114	125	137	150	165	180
	100	104	113	123	134	146	159	174	189

Table 2.3: Minimum required measurement ranges for RoWA in [m].

The worst case scenario occurs for the RoWA if both involved vehicles are driving with the maximum allowed speed of $100\frac{\mathrm{km}}{\mathrm{h}}$ (German speed limit on rural roads). In this case a minimum measurement range of approximately 190m is required.

When looking at Figure 2.11 it is clear that the direct line of sight will not be available in most cases. E.g. if the view is occluded by some building it will not be possible to detect the approaching car with an on-board sensor system at high

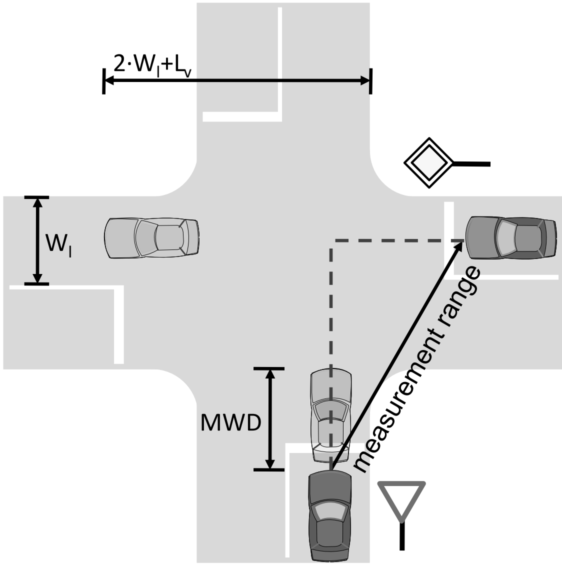


Figure 2.11: Computation of measurement ranges for RoWA.

distances. In this case, remote sensors can help to extend the field of view that is reached by solely on-board sensors.

It is important to notice that the computed measurement ranges from this section are all minimum requirements, i.e. the minimum distance at which another vehicle has to be detected in order to warn the driver of the host vehicle to decelerate immediately to a full stop. If some information should be given earlier to the driver e.g. an estimation of the momentous risk for a given situation the measurement ranges have to be increased. On the other hand, looking at the German traffic regulations it can be seen, that the maximum allowed speed at traffic light controlled intersections is $70\frac{\text{km}}{\text{h}}$ whereas in the cities a maximum speed of $60\frac{\text{km}}{\text{h}}$ is allowed at some places. This would result in a minimum measurement range for the TA of approximately 170m and 151m, respectively. For the RoWA this results in 120m and 100m, respectively. Furthermore, it is important, that the other vehicles needs not only to be detected at this computed distances but also to be tracked during the whole time to the intersection in order to predict their driving behavior and react appropriately to each situation. Also, detection in this case means not only that sensor data is available but in fact, that the data is classified at the calculated distance into the appropriate object class (e.g. vehicle).

2.4 Demonstrators

This section describes the different demonstrator setups that were developed for this work. They can be separated into three different systems.

On-board System The on-board system uses solely inner vehicle sensor technology to deal with the ISS topic. The installed sensors observe the environment to generate a comprehensive overall view of the surrounding scene. The on-board system is designed to work nearly independent of any other additional system. The only constraint is added by the TLA which uses Infrastructure to Vehicle Communication (I2V) communication as will be described later in this section.

Infrastructure Supported System The infrastructure supported system gathers its information through sensors that are installed on the intersection infrastructure i.e. on the traffic lights. This information is transferred by means of wireless communication to the approaching vehicles.

Simulated System In the simulated system the host vehicle and all other traffic participants are simulated in the same software framework that is used for the on-board and infrastructure supported system. Thus, scenario interpretation algorithms and warning strategies can be tested easily in an offline development process.

Each of the three systems works in principle separately from each other. Nevertheless, their architecture is developed universally and can be combined to different extents. For example the infrastructure supported system can amend the on-board system to get a better overall view around the vehicle. On the other hand, the simulated system can also be combined with the first two, e.g. in order to drive on a real intersection but with simulated other traffic participants. This combination offers the possibility to test the system in nearly real world conditions against critical situations but without endangerment for the test vehicle and its driver.

2.4.1 On-board System

The on-board system is the most innovative of the three demonstrators developed for this work. Two laser scanners are integrated into the two front corners of a Volkswagen Phaeton. An additional video camera is mounted inside the vehicle behind the windscreen. A communication module realizes the wireless communication with the traffic lights. Figure 2.12 shows the test vehicle with the mounting positions of each sensor. It can be seen that despite the vehicle is a prototype vehicle for ISS applications the sensors are installed within the vehicle not neglecting the design aspect. While many test vehicles in the past were equipped with sensors mounted on the roof of the vehicle or on an additional carrier in front of the bumper this vehicle was designed to show integration as it could look like in a series production car. Figure 2.13 shows the architecture of the on-board demonstrator system. It evolves

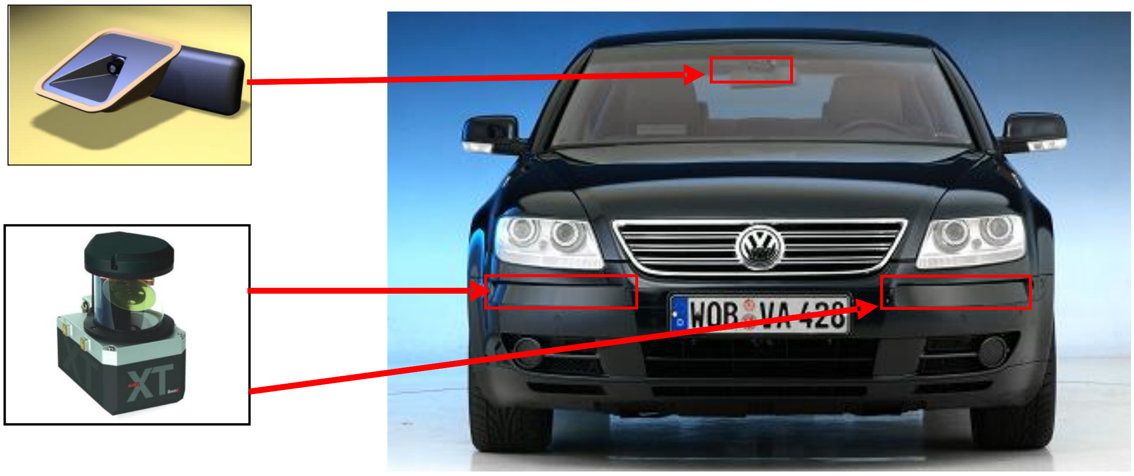


Figure 2.12: Sensor integration in the test vehicle.

from the general ISS architecture shown in Figure 1.2.

Sensor and Perception Layer

The sensor layer is the general data acquisition layer, where all data from the environment is perceived by different sensors and passed to the perception layer. The laser scanners are used for host vehicle landmark localization, object detection classification and tracking. The video camera also localizes the vehicle based on different road markings on the intersection. A time stamp based data fusion combines both localization outputs in order to gain a precise position and orientation of the host vehicle within the intersection (see Chapter 4). Both video camera and laser scanners are innovative approaches for vehicle localization in the intersection and the detection of the closer surrounding.

Laser Scanner
The Ibeo Automotive Laserscanner (ALASCA®XT) is a 4-channel laser range finder that was developed for the integration into automobiles. It is a high performance sensor suitable for a wide range of ADAS applications. The specifications of this sensor are listed in Table 2.4. Since the demonstrator is equipped with two laser scanners the overall field of view is about 240° around the front of the vehicle with an overlapping region in the middle. Therefore, the used laser scanners setup is highly suitable for the ISS since it mainly fulfills most of the requirements specified in Section 2.3. The

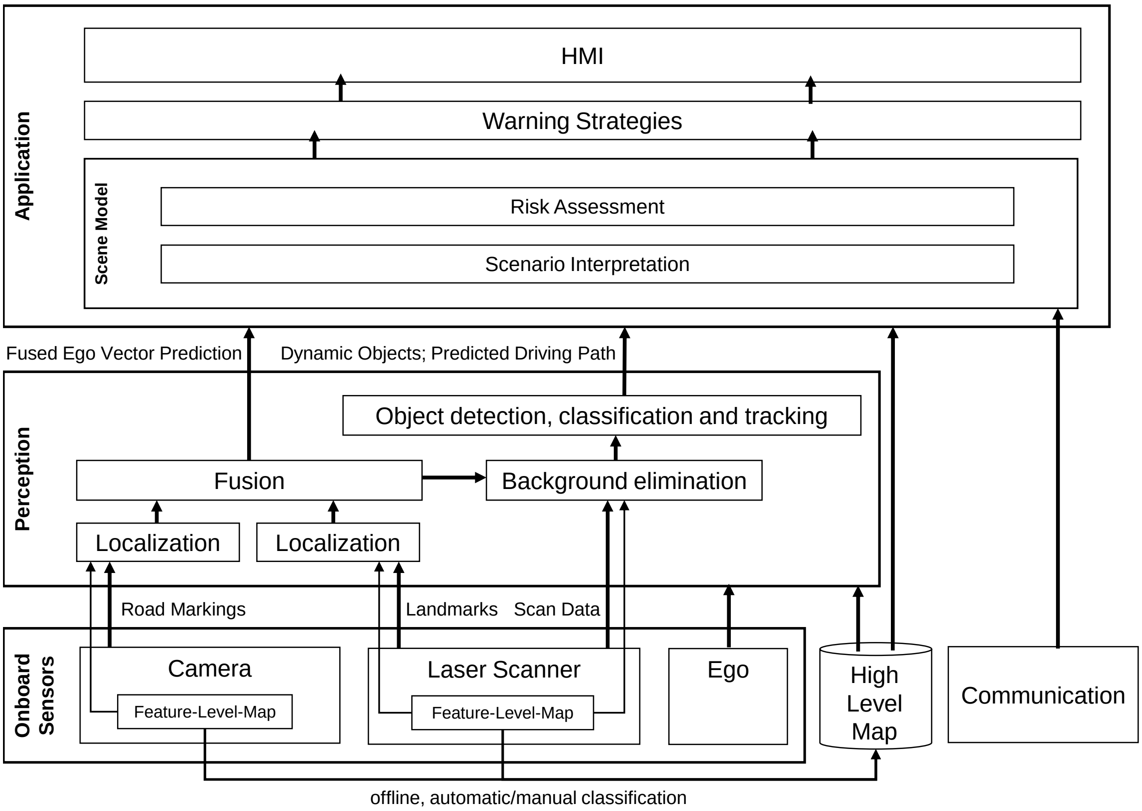


Figure 2.13: General architecture for the underlying ISS.

accuracy	±0.1m
max. range	200m
min. range	approx. 0.3m
object tracking	up to 200m
horizontal field of view	max. 240° (due to the mounting position)
horizontal angle resolution	0.25° or 0.5° or 1.0°
vertical field of view	approx. 3.2° (in driving direction)
vertical angle resolution	approx. 0.8° (in driving direction)
distance resolution	0.04m
scanning frequency	12.5Hz or 25Hz
sensor dimensions	$100 \times 127 \times 157$mm
sensor weight	1.3kg

Table 2.4: Specification of ALASCA®XT Laserscanner.

fusion of both scanners is based on synchronization to provide only one consistent scan. With this scan localization based on landmark navigation and object detection, classification and tracking is performed. Landmarks that are stored in a digital map, called Feature Level Map (FLM), like e.g. posts of traffic lights or traffic signs are matched to the current scan of the laser scanners. With this information a precise position and orientation can be derived with respect to a local coordinate frame. On the other hand, all dynamic objects in the scene can be detected and classified by the system. Due to the specifications (especially the high range) of the sensor listed in Table 2.4 it is clear that such a system produces a high amount of raw laser scanner data. Together with the map information of the intersection a high performance object classification and tracking can be reached since all scans outside the drivable area of the intersection are of no big interest for the ISS. The process of host vehicle localization and object detection is further described in Chapter 4.

Video Camera
The used video camera is a standard automotive video camera for LDW applications. The specifications of this sensor are listed in Table 2.5. In the proposed system the

position accuracy	0.01m (due to lane markings and dynamics of host vehicle)
heading accuracy	approx. 0,1 deg.
max. range	50 m
min. range	approx. 2,5 m (due to mounting pos. and vehicle dimensions)
horizontal field of view	approx. 45 deg.
imager size	640×480 pixels
used image	640×240 pixels
image acquisition rate	25 f.p.s.
target processing time	40ms
sensor dimensions	$95 \times 95 \times 50$mm

Table 2.5: Specification of the video camera.

video sensor is used as redundancy for host vehicle localization. White lines and other paintings on the intersection (e.g. turning arrows) are extracted out of the video image. These features are compared to road markings that are stored in a video sensor specific FLM (like the landmarks for the laser scanners). With this information a precise localization can be achieved with reference to a local coordinate frame. This coordinate frame matches to the coordinate frame of the laser scanner localization process. Therefore, both positions (laser scanner position and video position) can be fused to a common precise position and orientation information within the intersection (see Chapter 4).

Application Layer

At the application level, the scenario interpretation, the risk assessment and the warning strategies are executed based on the data from the perception level and direct input from the high-level map and the communication module. These steps are considered in detail in Chapter 4 and Chapter 5. As mentioned before, it was decided to use only warning strategies to assist the driver. These warnings are either expressed through a visual or an acoustic HMI. A common display is used to show information for the current analyzed situation (see Chapter 6)

Communication

As mentioned before, Car-to-Infrastructure Communication (C2I) is used to transfer required data from the Traffic Signal System (TSS) to the the vehicle equipped with the ISS. In general, communication with the TSS offers valuable functions for intersection safety systems:

1. Compared to intersection safety approaches that just use image processing techniques to get the status of a traffic light, communication with the TSS provides information to the on-board application for an estimation of the remaining time before light signal changes. An appropriate warning or intervention strategy can be derived in order to assist the driver.

2. Instead of only warning the driver in case of a possible traffic light violation, a more convenient system is able to give speed recommendations to the driver when he is approaching this intersection. Such a recommendation for reaching the green light phases enables better traffic flow and shorter stopping times at intersections. It can be very useful to prevent dangerous situations already in an early stage.

Both functions are realized by using just unidirectional communication from the traffic light to the cars. Extending this technique to bidirectional communication offers additional opportunities for driver assistance and driver comfort systems. Once, the approaching cars communicate bidirectional with the TSS, the following functions could be added:

- intersection preemption for emergency vehicles,

- intelligent traffic light control. This can be seen as an extension to the conventional induction loops where the TSS “knows” much more in advance how many cars are approaching the intersection at what time,

- approaching cars can propose their estimated time of arrival to the TSS (like for the intelligent traffic light control) and this information can be routed to all other cars in order to extend their survey area, i.e. to get information "around the corner".

Figure 2.14 shows the communication facilities for the C2I communication at intersections.

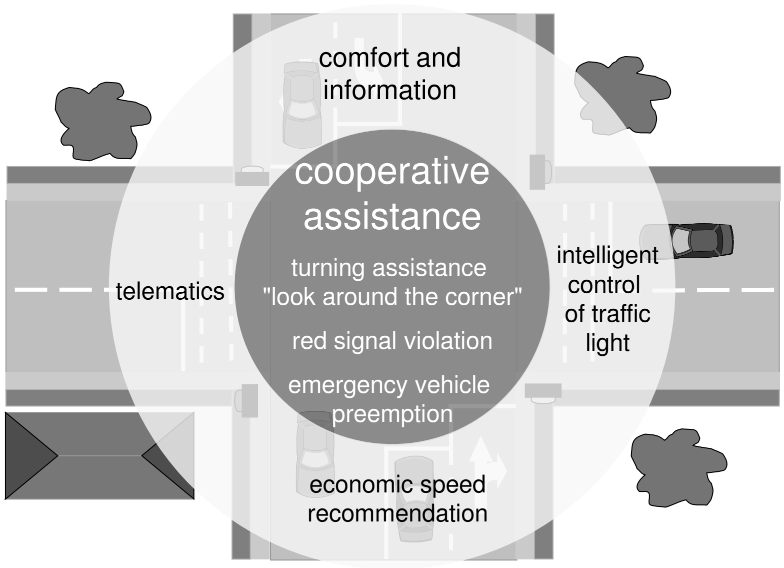


Figure 2.14: Possible communication functions for C2I communication at intersections.

Technological Basis According to the activities in the United States (Vehicle Safety Consortium (VSC)) and in Europe (Car-to-Car Communication Consortium (C2CCC)) in the field of Car-to-Car (C2C) and C2I communication the technological basis is IEEE 802.11a/b/g, also known as Wireless LAN. One goal of the activities is to get an exclusive frequency within the 5GHz range as it is realized in the US (frequency band from 5.85GHz to 5.925GHz) for safety relevant applications. The communication with the TSS should use the same band for its applications. For the underlying system the IEEE 802.11g as well as the IEEE 802.11a standard were used to show the operability of the presented approach.

Communication Properties Broadcasting the relevant information from the TSS to the vehicles in the range of the radio link seems to be suitable for the realization of unidirectional communication with the TSS. A maximum range of 200m showed to be sufficient. A vehicle driving at a speed of about $70\frac{\text{km}}{\text{h}}$ can receive the transmitted data more than 10s before arriving at the intersection. On streets with a lot of traffic lights equipped with communication modules the range of course can be shorter. A transmission rate of 100ms was used for the ISS. Based on the initial maximum range of about 200m there seems to be no need for additional repeaters or multi-hops. Nevertheless, if results from some testing sites in city areas with a lot of possible occlusions are available, there might be a need of multi-hop and repeaters setup. As for all safety related applications with wireless communication the data from the TSS is important. The media access and the handling of priorities should be done as specified in 802.11e. To guarantee, that the transmitted data has its seeds in the TSS, an authentication mechanism with certificates is needed. Transmitted messages are digitally signed before sending and verified using the public key read from the certificate when received. This safety topic is especially addressed in the INTERSAFE project and is not a main part of this system.

2.4.2 Infrastructure Supported System

In the Infrastructure Supported System information is gathered out of a commercial video detection system which is already in use in many cases nationwide, e.g. for presence detection in dynamic traffic light control at intersections [PJBM96]. Traffic information at a certain intersection is collected and sent to all approaching vehicles that are equipped with the installed ISS (see [ROS05a], [ROZ06]). The same communication module as for transferring the traffic light signal phases in the on-board system is used for transmitting the traffic information. Figure 2.15 shows a schematic view on this infrastructure supported system.

Video Surveillance System

Stationary cameras on the traffic lights are used to gather all the information about the other traffic participants in the intersection. This stationary setup has several benefits compared to a system that uses only on-board sensors. Due to their high mounting locations, the cameras can detect other road users even if they are occluded (from the drivers view) by other objects. They can also examine areas to detect e.g. a bicyclist who is possibly at risk during a left or right turn of a vehicle (see Figure 2.15). In [TKO05] a system is presented that uses such video surveillance cameras to display hidden areas to the driver in the shape of a virtual slope inside the car. The infrastructure supported system of this work is able to cope with the following functions of the TA and warn the driver in these cases:

1. left/right turn with crossing pedestrian,
2. left/right turn with bicyclist on the same road,
3. left turn with oncoming traffic.

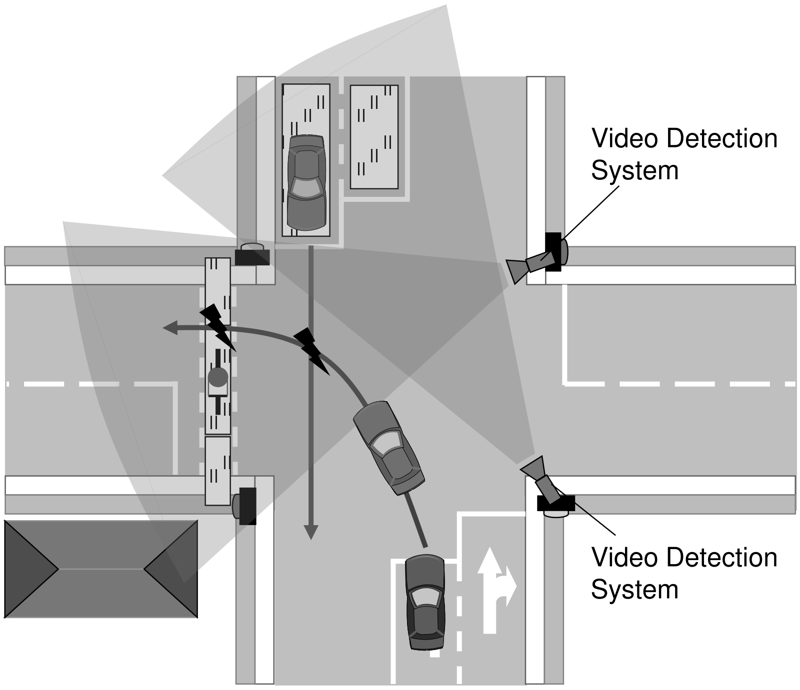


Figure 2.15: Schematic view on the used infrastructure supported system.

In all of these scenarios the driver has to yield the right of way to the other traffic participant. The cameras are mounted on top of the traffic lights. For a four-legged intersection one camera for each approaching road is needed. In this setup only two cameras are installed to show the functioning of such a system – one for oncoming traffic and bicyclists and the other one for crossing pedestrian detection.

The traffic surveillance camera system uses so called detection zones (see Figure 2.16) where obstacles are detected by a hardware video processing board. Usually, this system was designed for detection of cars, but with a clever placement of the detectors e.g. on the bicyclist lane (see Figure 2.15), it could be shown that this is sufficient for other obstacles, too. All gathered information of the detectors at the intersection is transferred wireless to the approaching vehicle. Every car equipped with C2I communication means can receive safety related information from the traffic signal system already without having on-board sensors installed.

The test vehicle is additionally equipped with a very high accurate differential GPS (DGPS). Together with the vehicle data like speed and acceleration and a precise map (like in the on-board solution) the system can estimate its own position within the intersection. Fusing this localization with the traffic information from the camera detectors the actual scenario interpretation and risk assessment is performed online.

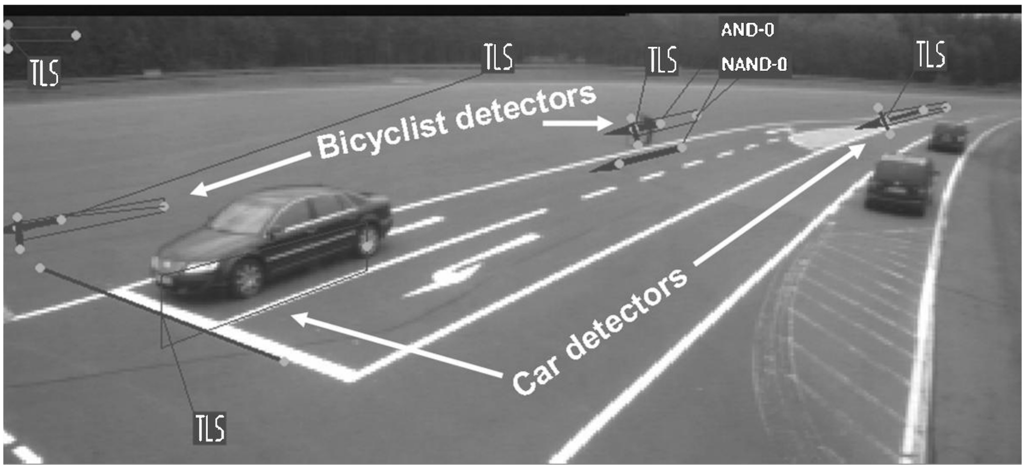


Figure 2.16: Example configuration for camera detectors.

2.4.3 Simulated System

In the simulator that was developed for this work all functions of the first two demonstrator setups can be reproduced or defined for specific needs. This system was mainly developed

1. to assist the development of the on-board and infrastructure supported system, and
2. to test the ISS for correct functioning.

If a system like the proposed ISS is developed, it can be very time consuming to traverse a complete development process with a real car. First of all the implementation of the algorithms has to be done before the system can be integrated into the vehicle. After that, usually (many) test drives are necessary in order to check the system functionality. At the end, an analysis of the testing has to be performed in order to identify possible enhancements for the system. Such enhancements have to be implemented and the development process starts again. The most time consuming component of this process is of course the test drive with the real vehicle. Simulation offers the possibility to perform each part of the cycle in an offline process at the workplace. The time consuming test drives can be skipped and run in the simulation environment. The exact reproducibility contributes to an easier and a precise development. The development cycle described above is demonstrated in Figure 2.17. The text in brackets shows the changes when using a simulation. When testing an ISS it is very difficult to generate dangerous situations within a real environment (intersection) without endangering the test drivers. In a simulated environment any situation can be constructed and potential failures of the ISS are unproblematic. Especially for

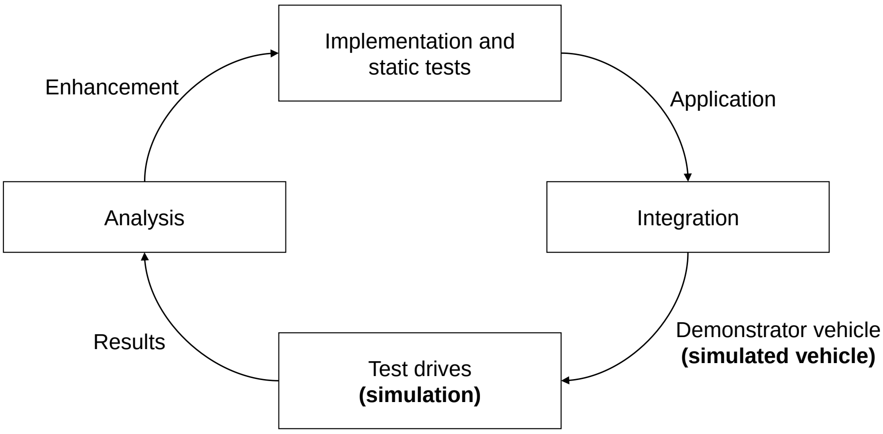


Figure 2.17: The typical ADAS development cycle with and without simulation.

the testing concept defined later in Chapter 7 it is essential to construct situations that lead into accidents. Nevertheless, a simulated system will never replace the (final) testing with a real system. Anyhow, it can dramatically ease the development effort needed to construct a new ADAS application. Since the developed simulation is directly integrated into the same software framework that is used for the on-board and infrastructure supported system the development process is further eased. The general framework is explained in the following chapter.

Chapter 3

Environmental Data Server

This chapter describes the framework and its extension that were made for the development of the proposed ISS. The framework is called Environmental Data Server (EDS) and was developed at the Electronics Research Group of the Volkswagen AG. The EDS offers the whole process from the sensor level to the application level as already quoted in Figure 1.2. The data flow of the EDS is exemplarily shown in Figure 3.1. The input for the data fusion layer is collected from different sources (e.g.

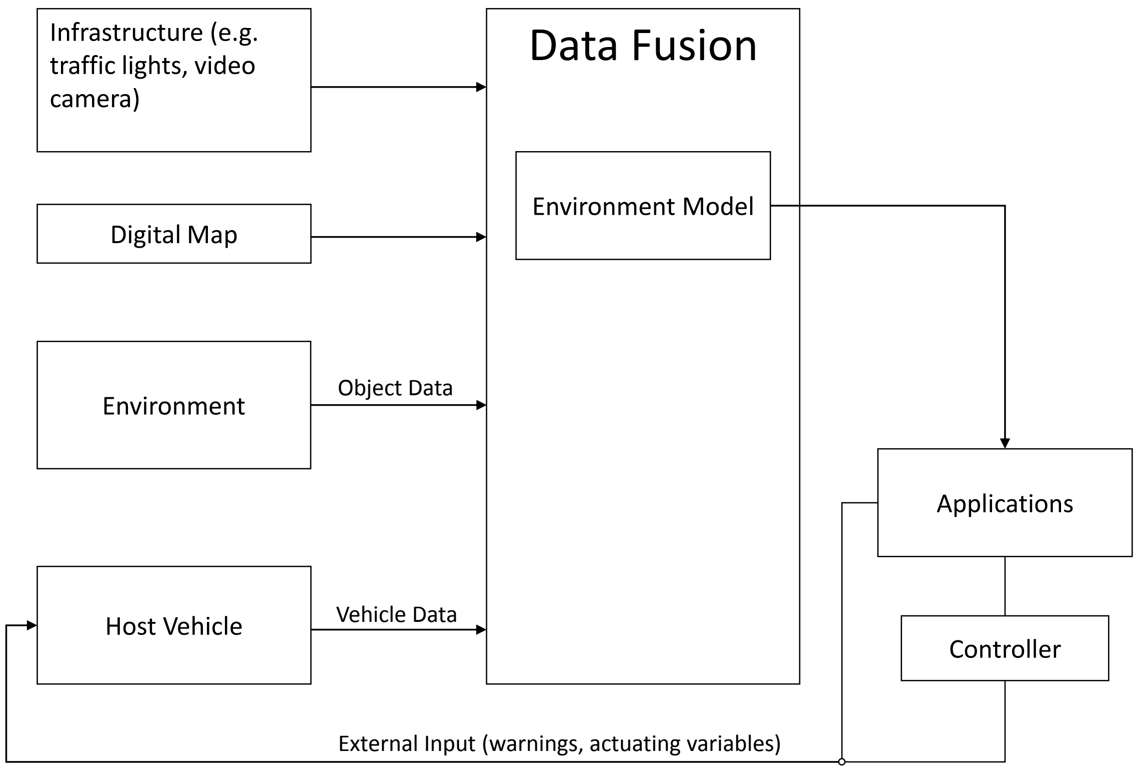


Figure 3.1: The EDS framework.

real environment, map, host vehicle) by several suitable sensors. The data fusion layer gathers all this information and fuses it into an Environmental Model (EM) which serves as an image of the current "real" environment. The better the sensor data is, the better is the EM of the real world. Ideally, the EM would include every part of the real dynamic scene around the equipped vehicle. This is strongly dependent on the used sensors and algorithms for sensor data processing. The EM serves as input to different ADAS applications (e.g. the ISS application of this work). The applications can drive different controllers which in turn can influence the vehicle dynamics or generate external inputs (e.g. warnings) for the driver of the host vehicle. It has to be stated that the process of building such an EM is not a situation analysis process (this will be described in Chapter 4). It solely takes the current sensor data, classifies the different objects of the scene (e.g. cars, pedestrians) and tracks those objects over time as soon as new sensor data arrives. In the following the construction process for the EM of the underlying ISS is described first. This includes the modeling of the road network (i.e. roads, lanes, intersections) and the road users present in the intersection scene. Additionally, the sensor data fusion as used in the EDS is described. Finally, the novel application driven architecture approach is presented which is used for the integration of the simulation into the EDS.

3.1 Environment Model

In order to build an ADAS application one needs to define the universe of discourse for the environment the system has to deal with. Therefore, this section deals with the modeling of objects and intersections including roads and lanes which serve as basis for the situation analysis and warning strategy algorithms of the proposed ISS. Thus, it forms the integral data model of the data fusion process - the Environmental Model. The structure of the EM is shown in a simplified Unified Modeling Language (UML) class diagram in Figure 3.2. To each object in the EM at least one dynamic model is assigned in order to predict its geometric and dynamic features with a Kalman filter [Kal60]. This can be e.g. stationary, described by a constant velocity or described by a constant acceleration model. This is described in more detail in Section 3.1.3. As long as in this work the road network, i.e. the intersection modeling, is formulated in terms of a digital map and is not gathered by a sensor system, the system does not make use of the prediction capabilities with the dynamic model `Lane`.

3.1.1 Coordinate Frame

In this work a global coordinate frame is used as reference for all objects in the EM. Other works like [Wei06] use a road or vehicle coordinate system whether a road is available or not. Here, where a digital map is used, a global coordinate frame is more adequate since it supersedes the transformation of the map information into a local

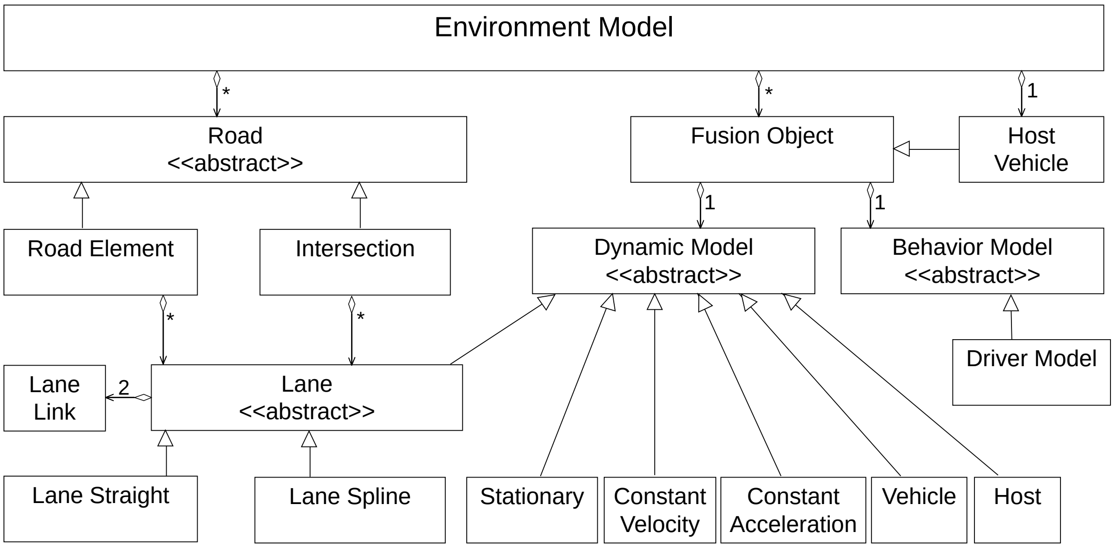


Figure 3.2: The EM in UML notation.

coordinate frame. The origin lies at a predefined point within the intersection. A right handed coordinate frame is used where the z axis can be omitted because the height is of no importance to the developed ISS (see Figure 3.3).

3.1.2 Road Network

Intersections are quite complex entities in terms of vehicular driving environments. They can include different lanes for different tasks (e.g. turning lanes), boundaries (e.g. curbstones, refuges, lane-markings) and last but not least complex right of way regulations (e.g. traffic-signs, traffic lights). Whereas freeway scenarios are very restricted in their complexity regarding driving maneuvers, intersections are very complex since all traffic participants can move in nearly arbitrary directions. This is the reason why intersections were neglected in the past and many situation analysis tasks for driver assistance applications were built upon freeway scenarios. In this thesis the complex structure of intersections is reduced to a lane model that allows the formulation of many assistance functions for intersection scenarios with only few restrictions. It will be seen later that this lane model is well suited for behavior recognition for the own and all other vehicles that are driving in the intersection.

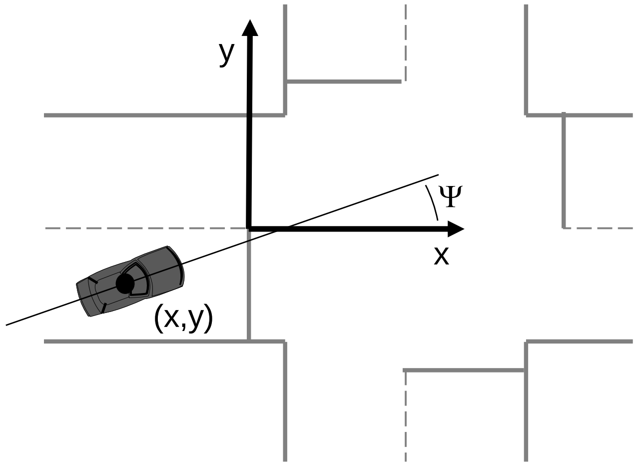


Figure 3.3: Example for a global coordinate frame.

GDF – Geographic Data Files

When talking about modeling of road networks one should look at existing specifications in this area. Geographic Data Files (GDF) [GDF02] is a standardized format for describing and exchanging road-related data. It is based on a three level description:

Level-0 This level describes the topology of the road-network in terms of nodes, edges and faces. This description is a common used and accepted Geographic Information System (GIS) format.

Level-1 This level is the feature level. The basis of this level are simple features like road elements, junctions, signposts or rivers which can include specific attributes (i.e. one way, number of lanes for road elements). Additionally, the features can be combined in relations which are commonly used in navigation systems. Such a relation can for example be formulated between two road elements in order to specify the allowed turning directions or the priority of the underlying roads.

Level-2 At Level-2 the features of Level-1 are aggregated into so called complex features. E.g. at Level-1 an intersection would be expressed by all road elements and junctions that are part of the whole intersection. At Level-2 these features would be aggregated to one point in order to formulate only one global intersection.

Figure 3.4 shows the data model for roads and ferries as they are used in GDF with the relations between Level-1 and Level-2 representation. The features which are

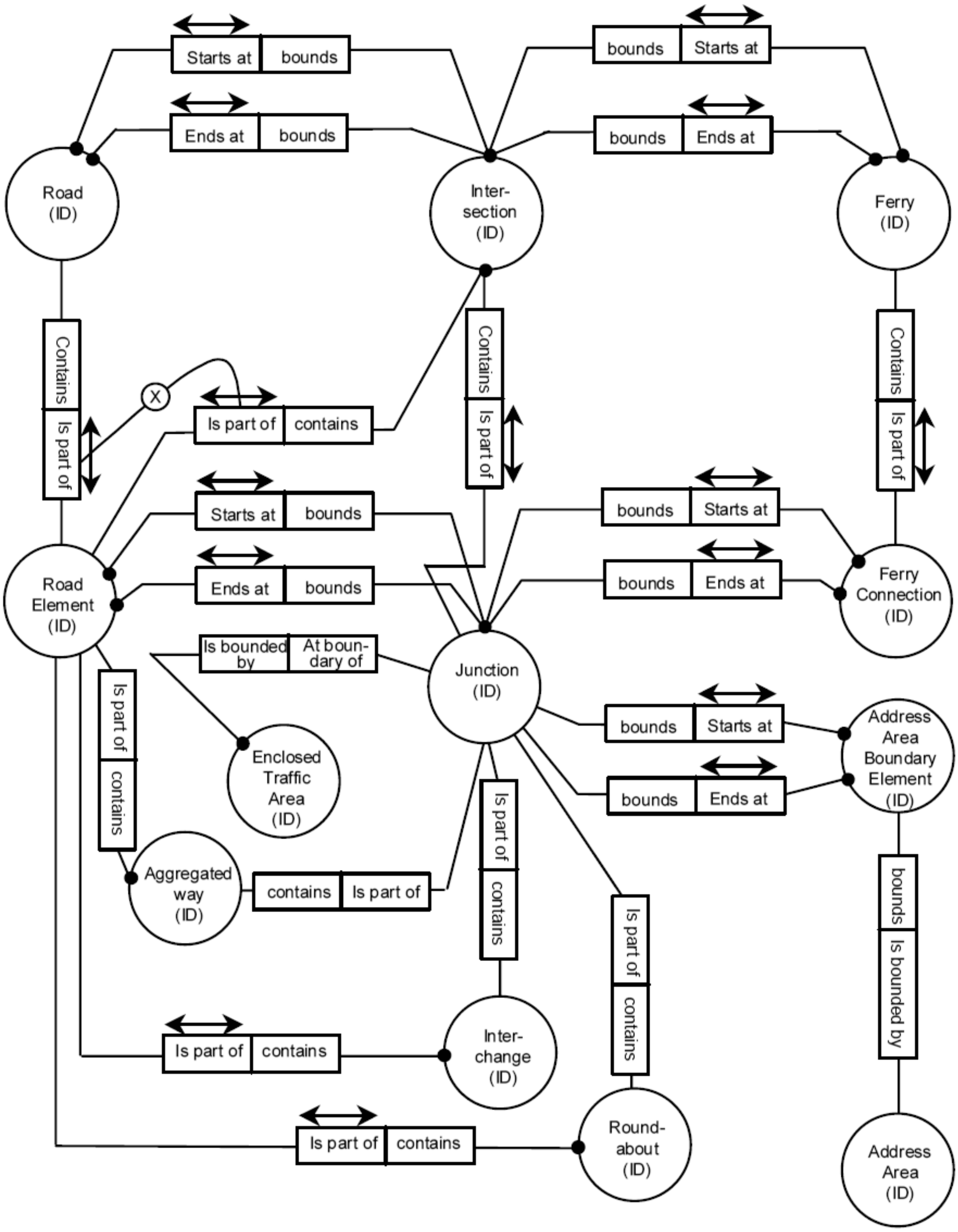


Figure 3.4: Data model for roads and ferries at Level-1 and Level-2 in GDF (source: [GDF02]).

important in this context are road elements, junctions, roads and intersections. As can be seen, this GDF format description is not suitable to describe the road network for an ISS as developed in this work because of the level of detail.

For an Advanced Driver Assistance System like the one developed in this thesis it is crucial to have exact information of the driving lanes of a road. Assistance systems in freeway scenarios use for example lane information in order to plan and to cope with lane changing maneuvers [WNK04]. As will be shown later, the here developed ISS uses lane information amongst others in order to recognize possible conflicts and to identify the road users aims while driving in the intersection. GDF does not offer this level of detail since the most basic feature at Level-1 is a road element and the lanes are only assigned to this feature via attributes. So the specific position of e.g. a turning lane cannot be expressed that easily. On the other hand the aggregated description like at Level-2 of GDF is not needed for assistance systems like in this thesis.

LMD – Lane Model Description

The modeling of the environment developed in this work is closely related to the GDF description mentioned in the previous section and is called Lane Model Description (LMD). The most significant difference to GDF is the level of detail. The idea of the LMD is to introduce the lane as the most basic feature of the description. This can be seen as a road element with only one lane in GDF. According to this description the LMD can be seen as a modification or a different interpretation of GDF. A road element in GDF turns into a lane in LMD and a junction into a lane link respectively. The road of GDF is interpreted as a road element in LMD. Figure 3.5 shows the LMD in a GDF like format in order to express the different approach. In the LMD a road element and an intersection contain a set of lanes. The lanes in a road element are always parallel to each other while in an intersection they can adopt arbitrary positions. As mentioned before, a lane is the smallest entity in the model where a vehicle can drive on. A lane is modeled by either a straight line or a curved spline and can have assigned a set of attributes. Figure 3.6 shows this modeling scheme of the environment. In this kind of visualization a lane is represented by only one line disregarding its width. This can be interpreted as the middle line of the corresponding lane. It can be seen that the lanes in an intersection are not necessarily *real* lanes with markings at each side. They are rather some kind of *virtual* lanes that describe the possible paths a vehicle can drive within the intersection as long as it acts on actual traffic rules. They provide an abstraction of the complex structure of an intersection by reducing it to the minimum required information. We will see later that this is highly suitable for high level assistance functions at intersections. For that reason all static road constructions (e.g. curbstones, refuges) within an intersection are not

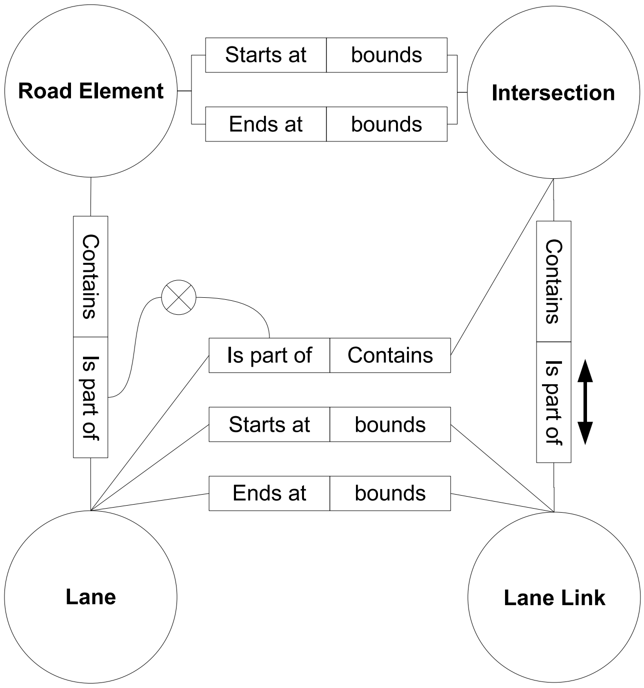


Figure 3.5: Data model in LMD.

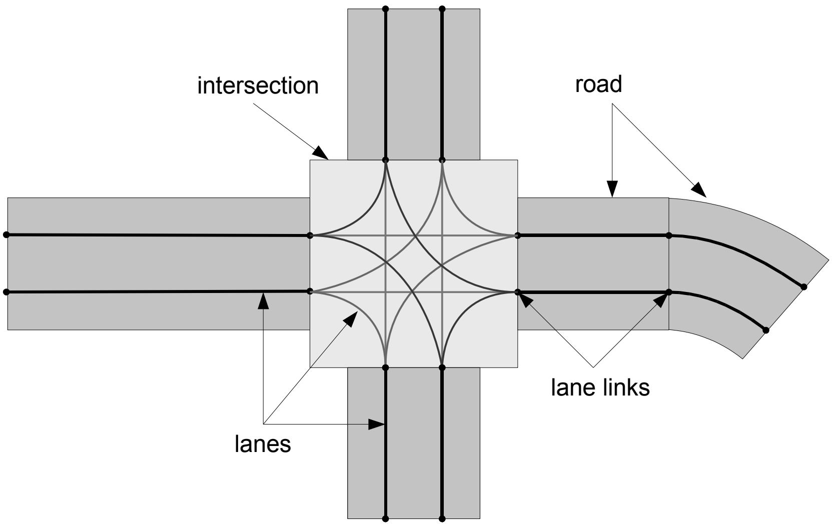
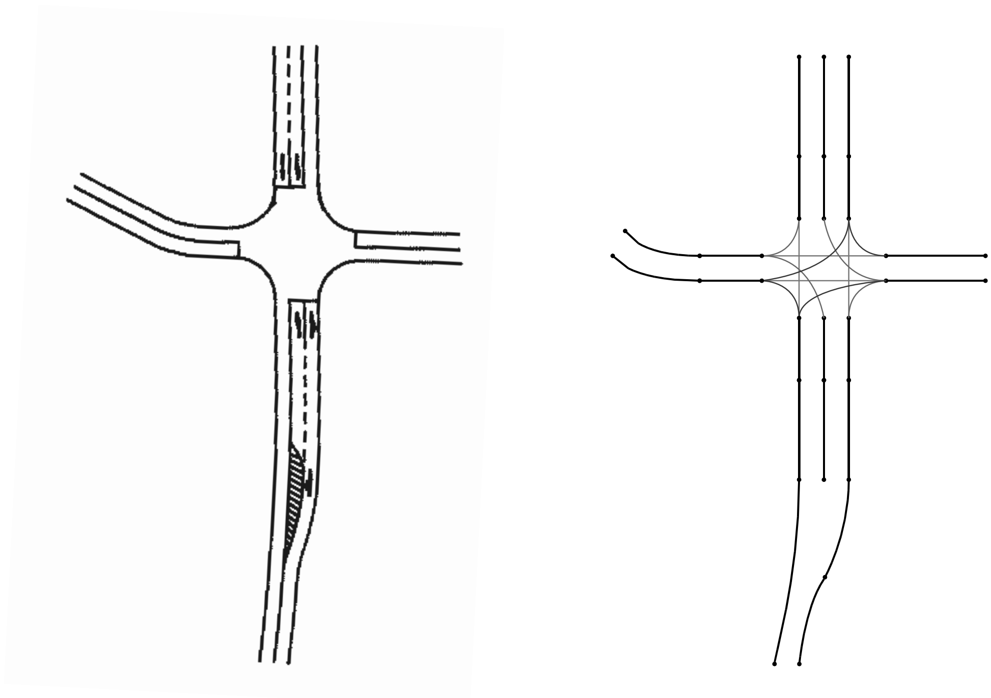


Figure 3.6: Modeling of roads and intersections.

explicitly modeled. A refuge would only be considered in that way that the lanes in the intersection would pass the non drivable part.

An example for a real intersection that is modeled with the LMD is shown in Figure 3.7. Figure 3.7(a) shows the test intersection frequently used during the development of the described system. The picture was created by measuring the lane markings with a precise GPS system. In Figure 3.7(b) the corresponding LMD is shown. It can be seen that the small refuge at the beginning of the lower road is considered by modeling the lanes around this area. Figure 3.8 shows how this LMD



(a) Appearance of real test intersection (measured with DGPS hardware).

(b) Corresponding LMD (not in true scale).

Figure 3.7: Real test intersection used during system development and corresponding LMD.

looks like when visualizing the different lanes in a 3D visualization. On the left side a camera view out of an approaching car towards the test intersection of Figure 3.7 is shown. The car is located in the left turning lane. In Figure 3.8(b) the corresponding LMD is shown as it can be used for environmental model visualization or simulation purposes. It can be seen that a similar 3D view than the one of the real camera can be generated. The darker lanes are the approaching lanes while the lighter ones are the lanes within the intersection. The orange lane indicates the current lane where the vehicle is assigned to by the system.

(a) Camera view. (b) Computer representation.

Figure 3.8: Visualization of LMD description.

Geometric Modeling

Road elements and intersections in LMD are containers for lanes and therefore contain no geometric information. The geometric information is stored in the lane links. Each lane is bounded by two lane links which are tuples $link = (X, Y, \Phi)$, where X, Y are coordinates in the global coordinate system and Φ is the rotation of the link which corresponds to the gradient of the bounded lanes in that point. As described before lanes are either curved or straight. A modeling scheme is needed to describe the geometry of such types of lanes. Straight lines are easy and straightforward to compute. Curved segments are a little bit more challenging. As a first approach one could simply use arcs of a circle in order to connect two different straight lane segments. Unfortunately, this is not suitable if dealing with control tasks on those curved segments which is done in the simulated system introduced in Section 2.4.3. At the connection points of a straight and a curved segment this would result in a jump of the curvature. Therefore, a geometric modeling is needed that is able to avoid such jumps of curvature.

Cornu's Spirals In road and railway construction the transition from a straight road element into a circle curve is modeled with clothoids also called as Cornu's spirals. A clothoid is defined as

$$a^2 = r \cdot l \tag{3.1}$$

where r defines the radius, l is the length and a the curvature parameter. This mathematic representation has the advantage of a constant slope of curvature within the arc length. Nevertheless, for control tasks it is difficult to handle as long as a desired position on the curve has to be computed by two times integration of Equation 3.1 [BSMM95]. The solution of these integrals needs high computational requirements and is not always possible to compute. Since a driver assistance system often deals with controlling of a vehicle and for this thesis a simulation environment was constructed where the simulated vehicles have to be *controlled*, the clothoid description turned out to be not suitable for the description of curved lanes in the environment. Therefore, a more easy to handle function was chosen which is described next.

Polar Splines Motivated by applications in mobile robotic navigation [Bre04] polar splines were used for describing curved lane elements in this work. Polar splines are expressed with polar coordinates so that a desired position for control tasks can be directly computed out of the spline description. With the polar coordinates $(\phi, r(\phi))$ a curve is constructed that describes an approximation to a circular arc between the control points P_i and P_{i+1} and radius R. The coordinates of the spline are expressed in a local coordinate system which has its origin in the center of the approximated circular arc and its orientation toward the control point P_i as shown in Figure 3.9.

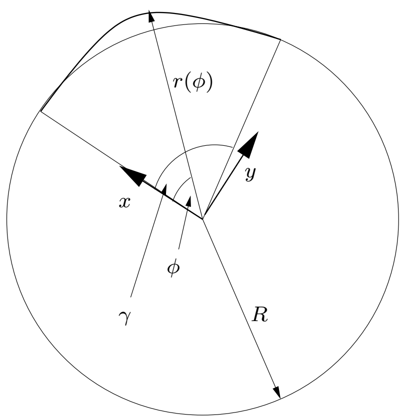


Figure 3.9: Illustration of a polar spline.

In order to construct a continuous run of the curves and their curvatures k in their connections the following boundary conditions have to be formulated:

$$\begin{aligned} r(\phi=0) &= R \qquad & r(\phi=\gamma) &= R \\ r'(\phi=0) &= 0 \qquad & r'(\phi=\gamma) &= 0 \\ k(\phi=0) &= 0 \qquad & k(\phi=\gamma) &= 0 \end{aligned} \tag{3.2}$$

In order to satisfy the six boundary conditions of Equation 3.2 the polar spline is constructed through a polynomial of order 5:

$$r(\phi) = a_0 + a_1\phi + a_2\phi^2 + a_3\phi^3 + a_4\phi^4 + a_5\phi^5$$

With the equation for the curvature for a function given in polar coordinates

$$k(\phi) = \frac{r^2(\phi) + 2r'^2(\phi) - r(\phi)r''(\phi)}{\sqrt{r^2(\phi) + r'^2(\phi)}^3}$$

it is possible to replace the last two boundary conditions of Equation 3.2 which postulate the curvature to be zero in the two control points P_i and P_{i+1} with the boundary conditions

$$r''(\phi = 0) = R, \quad \text{and} \quad r''(\phi = \gamma) = R.$$

This leads to the final equation for the polar spline $r(\phi)$ which is only dependent on the radius R and the apex angle γ:

$$r(\phi) = R\left(1 + \frac{\phi^2}{2} - \frac{\phi^3}{\gamma} + \frac{\phi^4}{2\gamma}\right).$$

With this geometric description it is possible to solve the control task for the simulation used in this work. On the other hand it is a good approximation to the real control behavior of a human driver for e.g. turning maneuvers. This becomes important when talking about drivers' behavior recognition as will be described later in Chapter 4. Since a polar spline is an approximation to a circular arc, some computational simplifications can be assumed for this task.

Lane Attributes

Along with the parameters of the curves a lane has additional attributes. Each lane has a right and a left lane marking which can be either dashed or solid. Those attributes become important when modeling the driving behavior at the intersection. Since the type of lane marking reflects the actual traffic rules in terms of possible lane changes, some initial assumptions can be made for the driving behavior of the traffic participants within the intersection (see Chapter 4.4). It is assumed that each dynamic object is respecting the current traffic rules (in terms of the drivable path). This means that a vehicle is not expected to drive on an area where it is not allowed (e.g. beside the road or crossing over a solid lane marking). Contrary to what can be easily guessed (i.e. that a lot of accidents occur because of illegal driving maneuvers), accident analysis shows that the most severe and fatal accidents at intersections happen because of disregarding others right of way by fault or lack of information (see Section 2.1). Therefore, the above assumption is justifiable when designing an ISS which primarily shall reduce injuries and fatalities at intersections.

Figure 3.10 shows the modeling of the LMD in the Environment Model in UML notation.

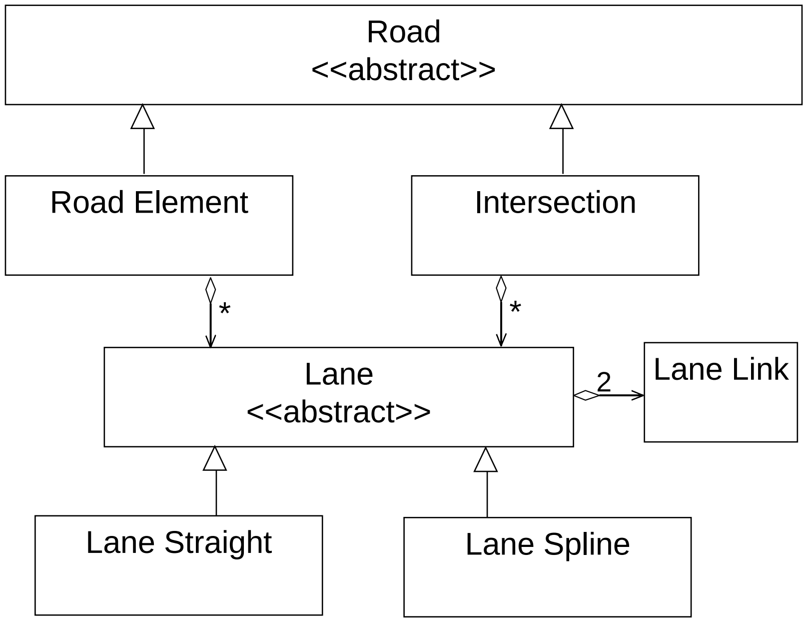


Figure 3.10: Road network description in the Environment Model in UML notation.

3.1.3 Object Description

The (fusion) objects of the EM mainly consist of two parts; the Dynamic Model (DM) and the Behavior Model (BM) which are both abstract classes in terms of programming. While the DM describes the dynamic behavior of an object, the BM includes intentions and behaviors which are used for situation analysis tasks as well as for simulation purposes. The BM is an extension to the initial EDS that was made especially for the system proposed in this work. The modeling of the objects is shown in UML notation in Figure 3.11.

Dynamic Models

The DM for the objects shown in Figure 3.11 differ in their feature vectors, their system equations as well as in the process noise. The DM used in this work is `Vehicle` which is used for the tracking of others cars at the intersection. The feature vector of `Vehicle` consists of the following components:

$$\mathbf{x}^V = (x, y, \psi, w, l, h, v, a, \dot{\psi})$$

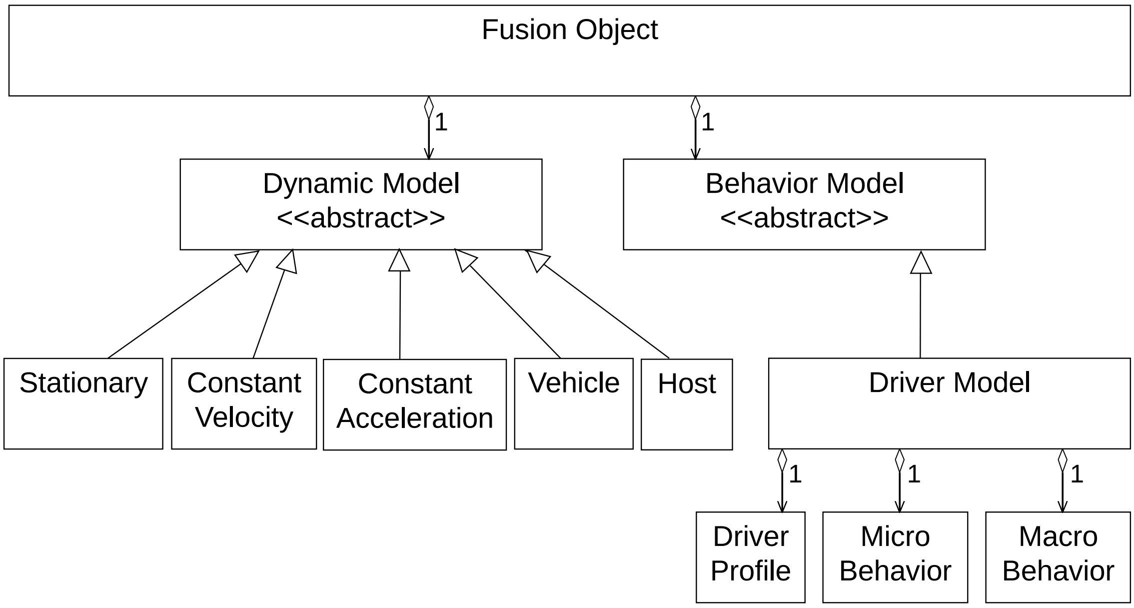


Figure 3.11: The model of the objects in the EM in UML notation.

where x, y describe the position and ψ the orientation and $\dot{\psi}$ the yaw rate with respect to the global coordinate frame. w, l, h are the geometric parameters width, length and height, respectively.

Within this model the movement of the vehicle is correlated with its orientation. Therefore, only the velocity v and the acceleration a in direction of the vehicle's roll axis are given. The system equation for the DM `Vehicle` which describes the movement of a vehicle for a time step T is given in Equation (3.3).

$$x^V(k+1|k) = F(k)x^V(k|k) \tag{3.3}$$

$$= \begin{pmatrix} 1 & 0 & -(Tv+0.5T^2a)\sin\psi) & 0 & 0 & 0 & T\cos\psi & 0.5T^2\cos\psi & 0 \\ 0 & 1 & (Tv+0.5T^2a)\cos\psi) & 0 & 0 & 0 & T\sin\psi & 0.5T^2\sin\psi & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & T \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & T & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} x^V(k|k)$$

The DM Host is solely used for the dynamics description of the host vehicle. It has the same feature vector as Vehicle except one additional parameter:

$$\mathbf{x}^H = (x, y, \psi, w, l, h, v, a, \dot{\psi}, a_l)$$

where a_l is the lateral acceleration.

Behavior Model

The BM in this work is implemented as a driver model. However, the structure allows the definition of additional behavior models for other road users like e.g. pedestrians or bicyclists. As can be seen in Figure 3.11, a driver model contains a Driver Profile (DP), a Macroscopic Behavior (MaB) and a Microscopic Behavior (MiB). The DP holds an individual model for human factors for each vehicle in the scene. Factors like response time, acceleration/deceleration values for normal and emergency situations or the range of vision are defined therein. These attributes can consist of predefined values (e.g. definition of simulation behavior) or can be predicted for situation analysis purposes. The same is the fact with the two behavior types described in the following. The MaB defines the global behavior of an object, i.e. which road elements are used before and after the intersection. This is comparable to a maneuver decision (e.g. left, right or straight) at an intersection. The MaB can be formulated as a graph with the road element as nodes and transition probabilities on the edges. The MiB is a more detailed view into the MaB. It defines the behavior in terms of lanes rather than roads. A graph representation of the MiB has lanes as nodes and transition probabilities at the edges. Both behavior models can be either predefined or predicted. Chapter 4 covers this issue in more detail.

3.2 Sensor Data Fusion

Sensor data fusion is an integral part of the EDS. The main idea is to combine several sensors in a vehicle (commonly used separately for a solely application) in order to get a condensed overall image of the current environment. The output is provided to the application level where each application can use the information of each sensor that is connected to the fusion architecture. Figure 3.12 shows the operation of the data fusion. The used data fusion is an event triggered process. Every time that a new sensor measurement is available a new fusion cycle is started. First the measured features are checked against validity. Features that are e.g. out of range are discarded. If a specific sensor measurement is valid, all objects in the EM are predicted toward the time of this measurement with the appropriate system equations. In order to associate the measured features from the sensors, the estimated features are predicted from the new object states. Through a Kalman filter [Kal60] the object states are

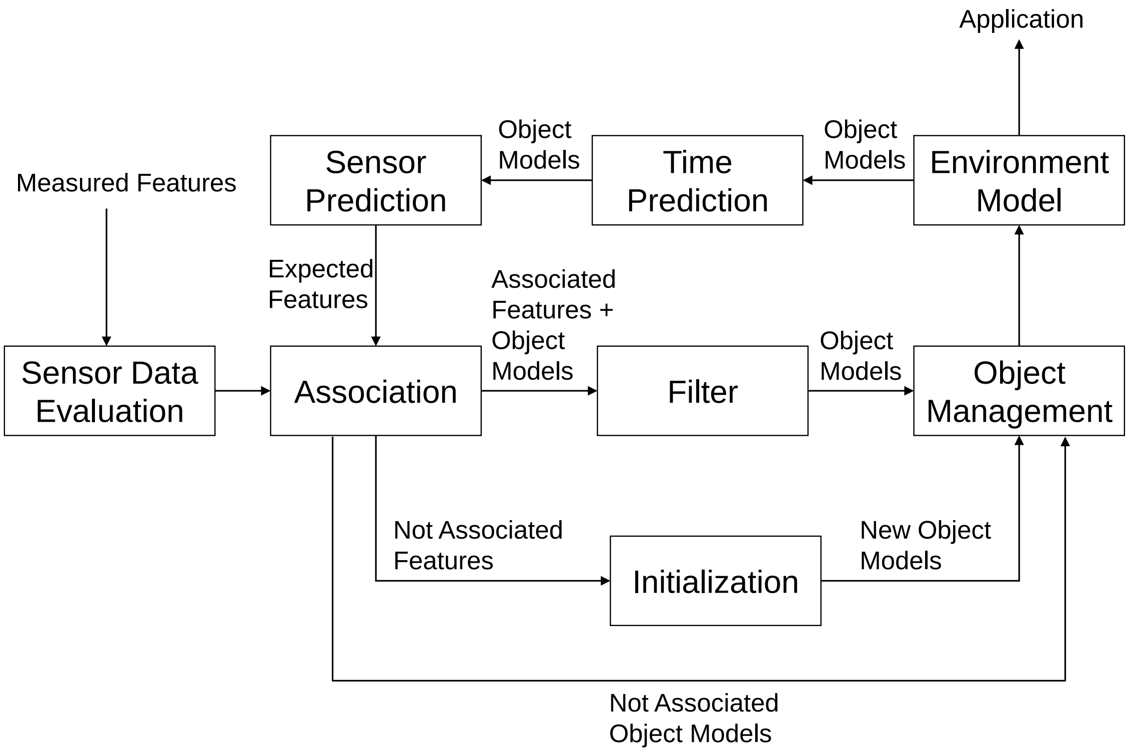


Figure 3.12: Flow chart of the sensor data fusion [Wei06].

updated from the associated sensor measurements. Sensor measurements that could not be associated initialize new objects. Finally, in the object management, objects are removed that were not updated over a defined time.

3.3 Simulation Integration

As introduced in Section 2.4.3 an additional simulator setup was developed for the proposed ISS. This simulation is integrated into the EDS so that every part of the ISS can be reproduced. Figure 3.13 shows this integration. The architecture looks similar to that in Figure 3.1 but has to be interpreted differently at some places. The main difference is that the "real" environment of the general EDS architecture is replaced by a Simulated Environment Model (SEM). For each simulation an initial SEM can be defined which includes all roads (retrieved from a digital map) and objects of a specific scene. As described in Section 3.1 the host vehicle is one part of the EM and therefore also part of the SEM. For the sake of clarity it is shown separately in Figure 3.13 also

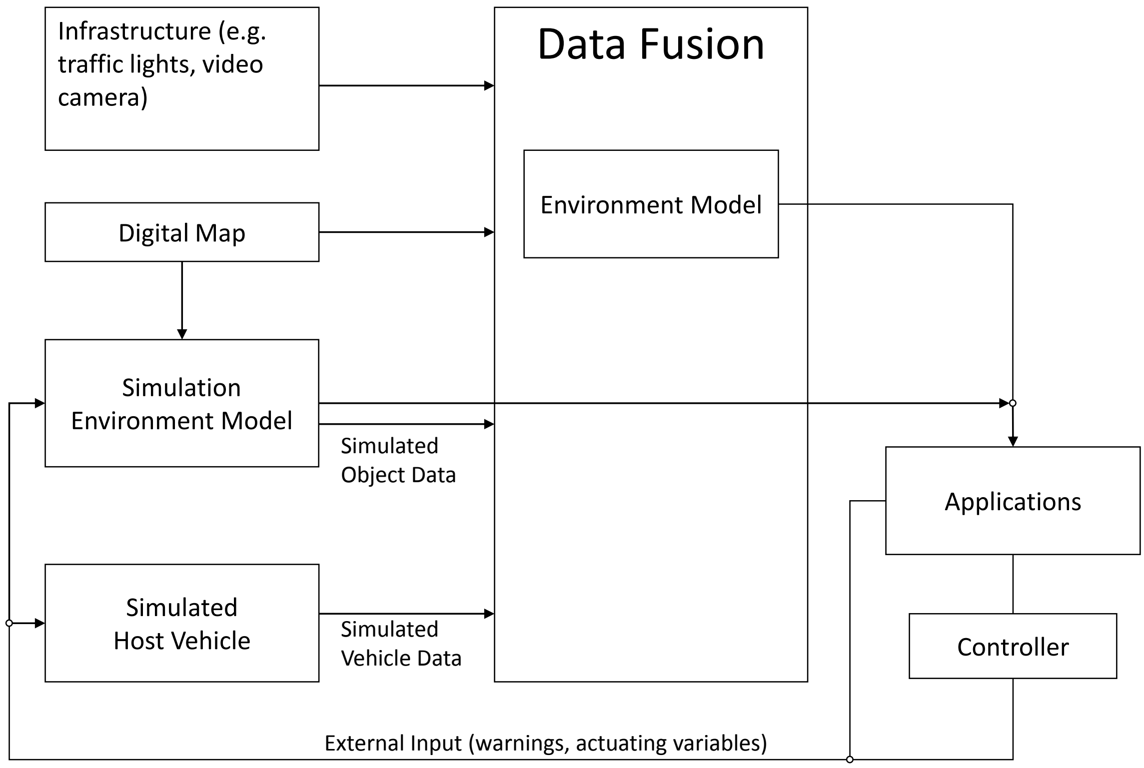


Figure 3.13: The EDS framework including simulation.

to state the affinity to Figure 3.1. The SEM itself is modified by the simulation so that a dynamic environment emerges. From the SEM (hence also from the simulated host vehicle) “virtual” sensor data is generated through appropriate sensor models. Those sensor models try to generate artificial raw sensor data based on the current scene of the SEM. This sensor data serves as input to the data fusion layer where the EM is build. The point is, that the data fusion layer does not “know” that the sensor data is just simulated data. It operates like normal, taking the simulated data as real sensor data. Therefore, the followed procedure is the same as described in the beginning of this chapter. Figure 3.14 shows a screenshot of the simulation. In the bottom one can see the SEM with parts of its roads and two objects driving towards an intersection. In the top of Figure 3.14 the EM is shown that was build out of the SEM.

3.3.1 Application Driven Architecture

The novel architecture approach in this work is to initially equip all the vehicles in the simulation only with rudimentary behavior:

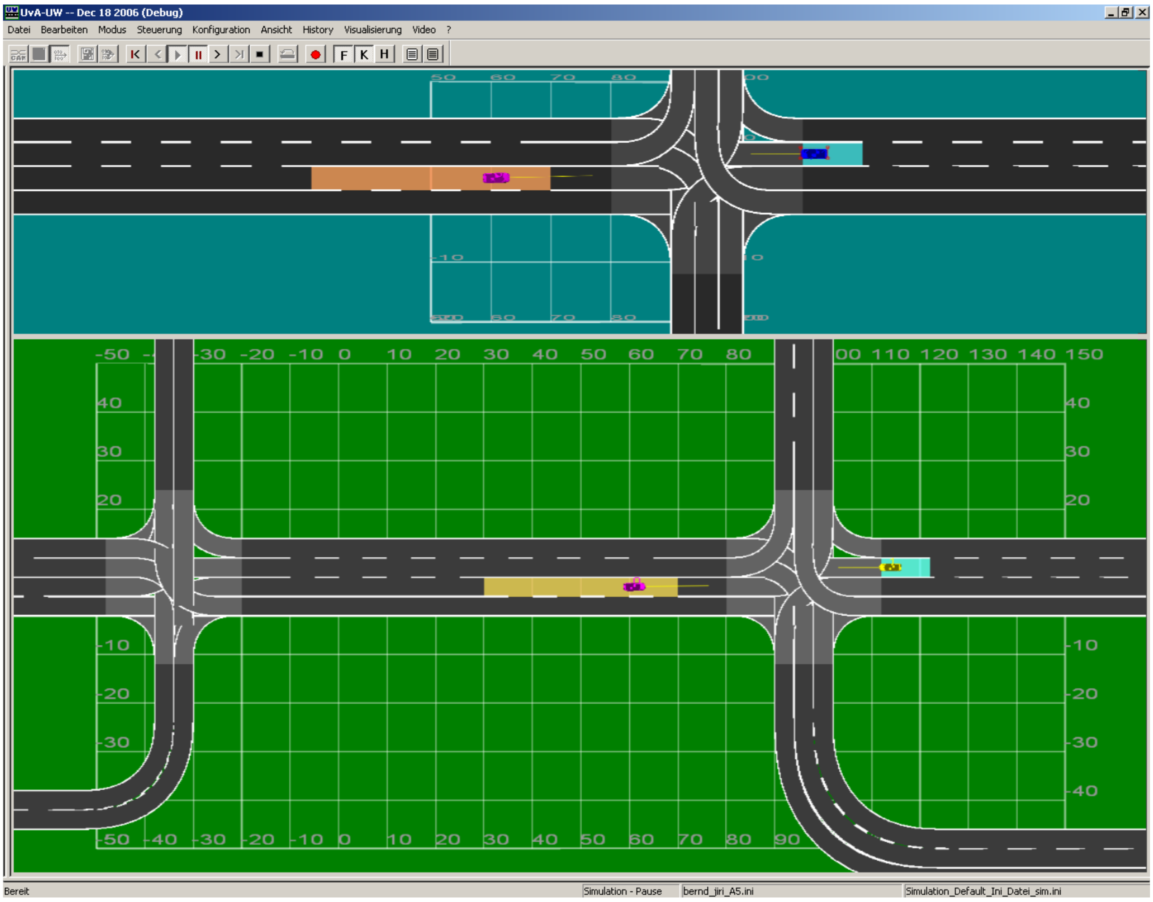


Figure 3.14: A screenshot of the simulation.

1. lane keeping/changing
2. deceleration/acceleration before/after a curve

This means that every vehicle in the simulation is able to drive on the roads of a defined world description (SEM). But initially the vehicles *do not care* about any other traffic participant. The more complex and advanced behavior is realized by the applications which can be assigned to a each object ([JR07]). The simulated objects are designed in a way that they act on each warning/information coming from the application and behave appropriately (e.g. stopping when receiving a warning before a left turn). This architecture approach offers the possibility to directly observe in the visualization of the simulation if an application is performing well or not. In the case of the ISS this means that all vehicles primarily behave like they were alone on the intersection (no other objects or infrastructure present). The procedure of linking an application to a simulated object is expressed by the arrow that is going across the data fusion box in Figure 3.13 since the before described process of building the EM is only used for the host vehicle. The simulated objects have direct access to the SEM. This can be interpreted as they were equipped with ideal sensors that are able to fully reconstruct the environment in every detail. Figure 3.15 shows that this application driven approach is based on three stages. In the first stage the different velocities v_{iA}

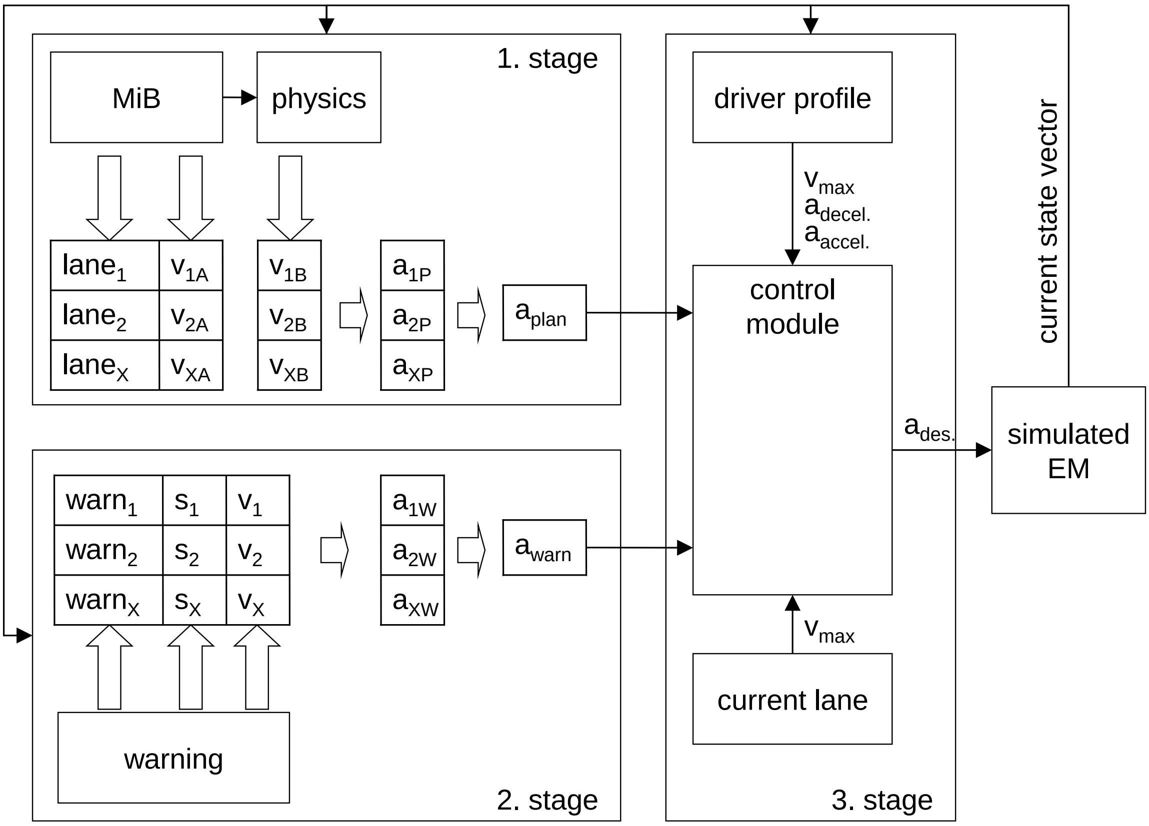


Figure 3.15: Structure of application driven simulation.

for each lane that can be extracted from the MiB are compared with the velocities v_{iB} that are physically possible for each of the lanes. Out of this comparison a resulting current acceleration a_{plan} is calculated. In the second stage the different applications can pass their warnings (expressed as desired velocity v_i after distance S_i) to the simulation. They are compared and a desired acceleration a_{warn} is calculated. Both acceleration values a_{plan} and a_{warn} are analyzed in the third stage. The current DP and the characteristics of the current lane are used in order to calculate a final desired acceleration a_{des} which is used to modify the SEM.

As an example, for a left turn the vehicle approaches with a defined speed, decelerates to an appropriate turning velocity and accelerates again up to the initial velocity after the performed maneuver without respecting other objects and their potential right of way. This results in a more and more chaotic behavior as the number of objects in the simulation is increased. When assigning different applications (e.g. Intersection Safety application) to the objects the behavior changes. Once an application generates a warning (normally presented to the "real" driver through an appropriate HMI) the simulated vehicles regard this as a demand and react according to their defined BMs. If the applications would cover the whole spectrum of safety functions and they would be assigned to every vehicle in the simulation no crash should occur anymore (assumed that the applications are performing correct). Varying the BM of a vehicle can test the application for different drivers. If for example for one BM (short reaction time, e.g. representing a young driver) a car is stopping in an appropriate distance to the conflict point during a left turn with oncoming traffic and for another BM (long reaction time, e.g. representing an elderly driver) it stops too late, a failure in the assistance function is detected and can be corrected. Indeed, there is an option to automate the application evaluation, resulting from the proposed application driven architecture. Beside the mentioned manual "observing" method, it is possible to use any user-defined evaluating algorithm to permanently check the application functionality and thus to rate its performance (e.g. monitoring the number of collisions). On the other hand this approach offers the possibility of automatically "learning" the correct behavior in the development phase of the applications. Since in the simulation it is possible to generate each type of situation (even accidents) without endangering a human being, the system (ADAS application) can adapt its behavior in order to avoid such critical situations in the future. This is described in detail in Chapter 5.

It is worth mentioning that the simulation was additionally enhanced by steering wheel and pedal interfaces in order to really drive the host vehicle within the simulation rather than only simulating it. Of course this is not comparable to a high-end driving simulator but it offers the possibility to test some of the developed concepts based on real driver input (realistic BM). Especially when testing the system in highly dangerous situations it is appropriate to do this in a simulated environment but with nearly realistic driver input.

Because it is generally applicable, simple and effective, the developed architecture can be widely used to support the development and testing of various ADAS applications even in their early development phase.

Chapter 4

Situation Analysis

The goal of the situation analysis in the context of an ISS is to reach a comprehensive view on the current scene at the intersection. In the last chapter the general framework for the situation analysis was presented. Within this framework, the following tasks have to be performed in order to achieve a complete understanding of the current situation:

1. localization of the host vehicle
2. detection and tracking of other road users
3. derivation of the driving behavior of all road users
4. identification of possible conflicts based on 1.-3. and current traffic rules
5. integration of infrastructure related data

The first step to be performed is the localization of the host vehicle within the intersection. Only if the position and orientation is known up to a defined accuracy (see Section 2.3), the current traffic situation can be analyzed for the host vehicle. The detection and tracking of other road users within the same reference is the basis for the important derivation of the driving behavior of all road users. Taking into account the interrelations between all road users, i.e. possible conflicts and the current traffic rules as well as other relevant infrastructure related data like traffic lights, a comprehensive view on the scene can be gained. Only if a complete understanding of the scene is reached the appropriate risk assessment and warning can be performed. The different tasks of the situation analysis stated above are described in the following.

4.1 Localization of Host Vehicle

The localization task is performed solely by the sensors installed in the car. As already introduced in Section 2.4, the sensors detect different types of natural or artificial landmarks such as posts and other similar fixed objects or lane markings in the scene and match them to prerecorded or manually stored features in a FLM. Compared to the localization based on GPS the landmark localization has advantages and disadvantages. Localization based on GPS is not always suitable to achieve sufficient accurate and reliable information since in many areas where intersections are located the free view to the sky and thus to the satellites is limited. Nevertheless, it needs no additional information like an on-board system that uses landmark positioning algorithms. On the other hand, the on-board solution works in nearly every situation since it is not dependent on any collaboration with an external system. But landmarks must be available and externally stored in a database in order to use them for the localization task. As stated in Section 3.1 a global reference coordinate frame is used. The LMD of the intersection (i.e. the map) and the positions of each traffic participant are based on this reference frame. As described above, the used sensor systems in the car (laser scanner, video) perform their individual localization. The output are two feature vectors including the position x,y as well as the orientation ψ of the host vehicle with respect to the global reference coordinate system. Both individual feature vectors are fused in order to gain one exact reliable position and orientation of the vehicle within the intersection. The fusion algorithm is embedded in the behavior prediction module which will be described in Section 4.5.3.

4.1.1 Laser Scanner Localization

As introduced above, the on-board system uses landmark positioning techniques in order to localize the host vehicle precisely within the intersection. Such landmarks, which can be detected by the laser scanners, are for example posts of traffic lights or traffic signs, trees or other artificial road construction. In an initial step an Occupancy Grid Map (OGM) [TBF05] is generated by moving the vehicle across the intersection. In this discretized image small cells with the size 5cm $\times$ 5cm are used. In each of these cells the number of measurement points of the laser scanner that hit that corresponding cell is accumulated. As mentioned before, all the coordinates are relative to a global reference system that has to be defined at the beginning. The resulting OGM is used to determine the position of all static objects in the scene with respect to this global reference frame. In Figure 4.1 such a sample OGM is shown. Each pixel corresponds to one cell of the discretization process where the color of the cell shows the number of measurements of the laser scan. The darker the pixel, the more hits were accumulated in that region. In the underlying system such a mapping process was used to store the desired landmarks for localization purposes. In future systems this could be done by manufacturers of digital maps who could store such additional features during their normal road mapping procedures. If the host vehicle approaches the intersection for a second time, the landmarks of the OGM are used to determine the exact position of the car with respect to the global reference frame. The challenging task is to match the current measurement points to the prerecorded

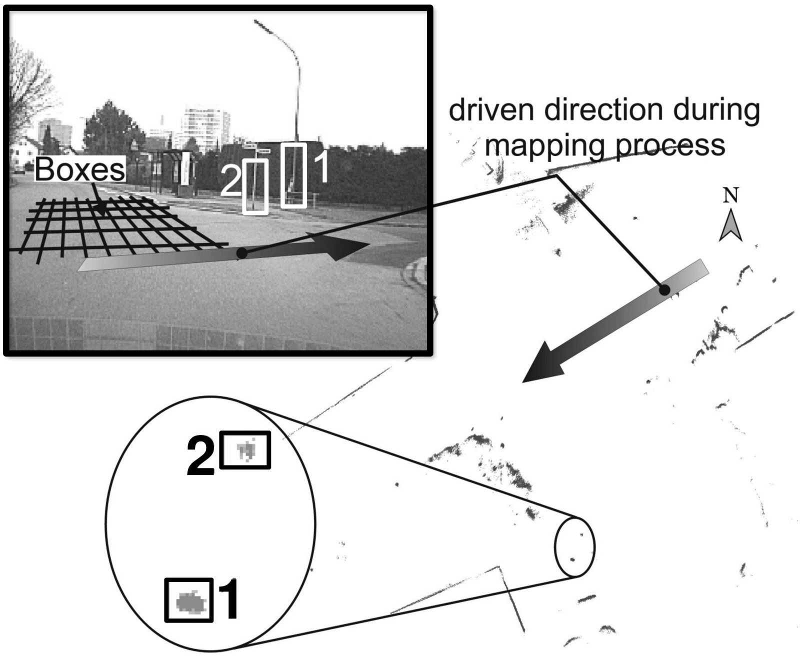


Figure 4.1: Laser scanner grid map and video reference image ([RF06]). The arrow shows the direction the vehicle drove along during the mapping process.

landmarks in the map. This is done by the algorithm proposed in [WKD05]. In order to reduce the search space for the landmark matching, GPS positioning is used for identification of the initial approaching direction toward the intersection. With this approximate position information, which normally lies within a range of ±10m, the detected features are transformed to the reference coordinate system. After the association of the measured features with the landmarks of the map, the precise position of the host vehicle can be determined within the reference coordinate frame. The resulting feature vector for the laser scanner localization which serves as input to the sensor data fusion is the following:

$$z^L = (x_L, y_L, \psi_L)$$

where x_L, y_L are the coordinates and ψ_L the yaw angle, all with respect to the reference coordinate frame. These are the parameters shown before in Figure 3.3.

4.1.2 Video Camera Localization

The video camera system uses a similar approach in order to localize the vehicle. Instead of features which are related to static objects in the scene it uses the road markings within the intersection. These can be normal solid or dotted lines along the lanes as well as arrows or stop lines from which the absolute positions are stored in the FLM. More precisely, the lane markings are extracted out of the image using proprietary feature extraction techniques. Line tracing and fitting algorithms are then used to extract parametric line descriptions from the raw image data. Inaccuracies in the line parameters that are caused by optical effects are corrected [HT06]. The overall process is the same as with the laser scanners. Initially, a feature level map is constructed from a free run over the intersection containing all relevant road markings that are suitable for localization within the intersection. These features are later mapped to the features which are extracted during the "live" run through the intersection in order to localize the vehicle. The resulting feature vector of the video system has the same components as the one from the laser system:

$$z^V = (x_V, y_V, \psi_V)$$

Figure 4.2 shows the results of a positioning test that was carried out at a test intersection. It shows the results of the video, the laser scanner as well as the final

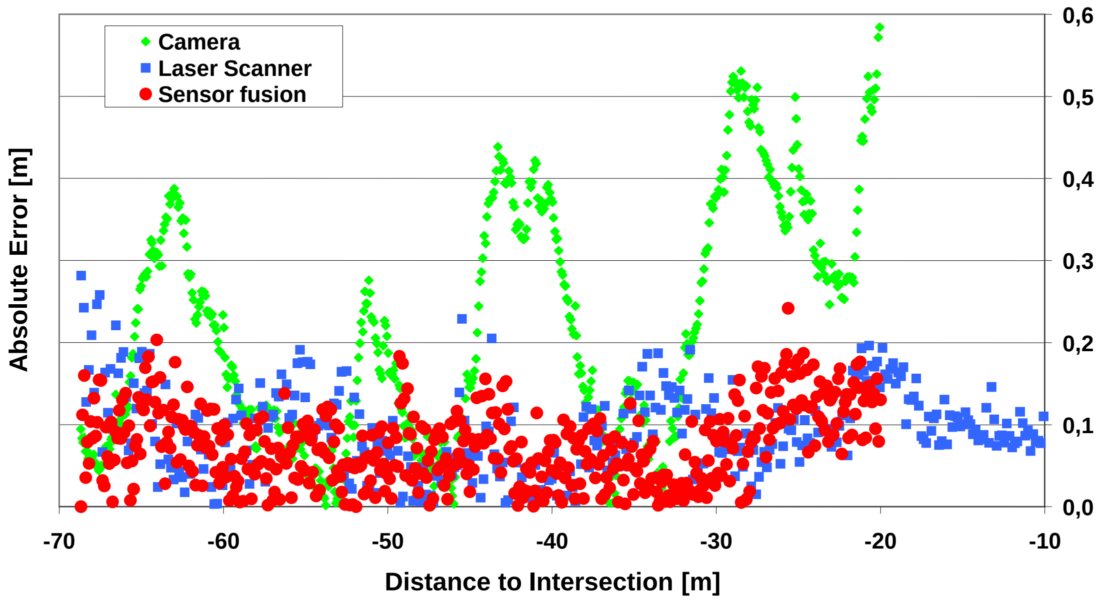


Figure 4.2: Results of positioning test.

fusion system. It is noticeable that the positioning error of the video camera is often higher than the error of the laser scanner system. This comes from the pitching of the host vehicle while approaching the intersection. Since a mono camera system was used, the video localization module is more susceptible to longitudinal positioning errors than the laser scanner module.

4.1.3 Localization in Simulated System

One has to differentiate between the simulation itself and the produced output. In the simulation itself the localization of the host vehicle is not worth mentioning since the position is well known in every simulation cycle. As described in Section 3.3 the output of the integrated simulation is the same as the output of the online data fusion process like e.g. in the on-board system. The simulation generates "virtual" sensor data that serves as input to the data fusion process. For the localization of the host vehicle the generated sensor data corresponds to the data received from the laser and video sensors. That means, the position (x, y) as well as the yaw angle ψ is generated out of the known position of the simulated host vehicle (see Figure 3.13).

4.2 Detection of Other Road Users

The detection of other road users within the intersection is performed differently in each demonstrator setup. For the on-board system solely the laser scanners are used for the detection and tracking task while in the infrastructure supported system the cameras on the traffic lights perceive the intersection environment. As described in Section 3.3 the detection and tracking of other road users in the simulation can be performed by the same algorithms like in the on-board system through the generation of simulated sensor data.

4.2.1 Detection of Other Road Users in On-Board System

The range profile that is generated by the laser scanner is initially clustered into segments. As introduced in Section 3.2, a Kalman filter is used to predict and update the objects' states based on these clustered segments. Segments that cannot be associated with previously recognized objects are initialized as new objects with default dynamic parameters. In order to classify the objects into different classes such as cars, trucks/buses, poles/trees, motorcycles/bicycles and pedestrians, typical object-outlines (static data) are used. The history and the dynamics of the tracked objects are also used to support this process. Figure 4.3 shows a sample intersection with road users detected by the laser scanner system. Since the object detection is not in the focus of this thesis and common techniques were already studied in detail in other works, e.g. [Stü04], no more details are given at this point. However, some test results regarding the object detection capabilities (see also Section 7.3 for more information on the real world testing) are given in the Table 4.1.

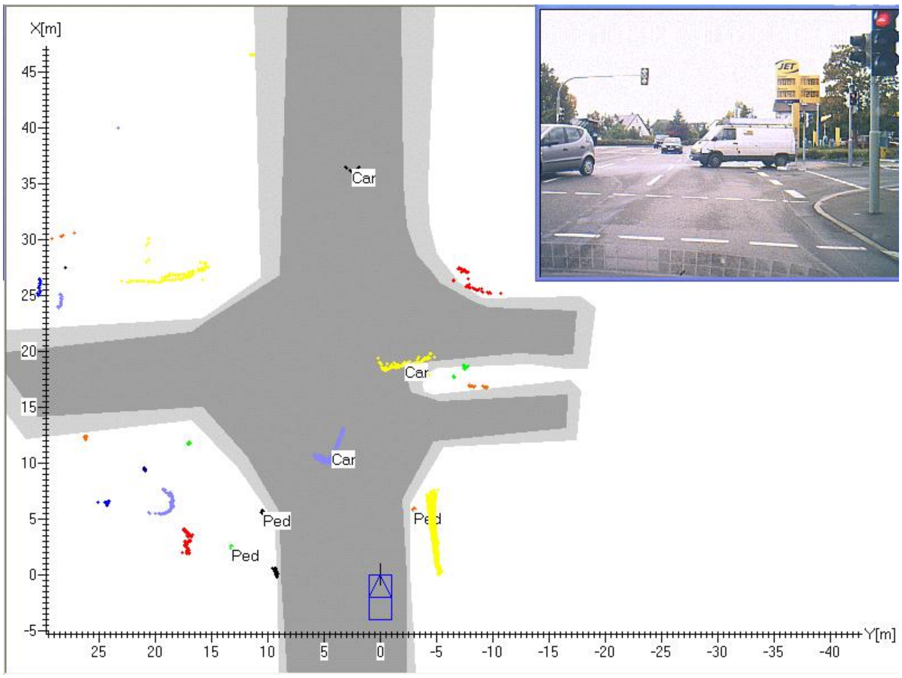


Figure 4.3: Object recognition using laser scanners: Road users crossing an intersection are tracked and classified. The shape of the intersection, registered in the feature-level map, is painted gray. The colored dots are measurements of the laser scanners at different objects. The host vehicle is drawn as a blue rectangle at position (0,0).

Test item	**Result**
Detection range to car	200m
Detection range to motorcycle	146m
Detection range to pedestrian	111m
Distance resolution	0.05m
Max. error of object velocity	-0.5%
Max. error of object position	-0.1m

Table 4.1: Real world test results for object detection.

4.2.2 Detection of Road Users in Infrastructure-Supported System

The detection of road users in the infrastructure supported system is treated totally different to the on-board system. As mentioned in Section 2.4 so called detection zones are used in order to detect the road users. Such detectors are also called

TLS detectors (Technische Lieferbedingunen für Streckenstationen) which refers to a German detector port communication protocol. A master/slave communication between a primary station and up to 254 secondary stations (roadway detectors) is supported. Based on the optical flow within these zones, it is possible to determine the presence and to some extent dynamic and static vehicle parameters like

- occupancy time of an object in the detection zone,
- operating class of the detected object (solely vehicle classes),
- speed of the detected object and
- length of the object.

It is obvious that such a detection zone offers only the possibility to detect a road user at one defined position, i.e. the placement position of the detector. If a road user has to be detected on a defined segment, i.e. the approaching road toward the intersection another strategy has to be found. In this work a queuing based technique with FIFO order was used to cover a defined road segment. This means that one detection zone is placed at the beginning and one at the end of the considered road segment. If a road user is detected on the first detector an object is inserted into the queue. Accordingly, the object is removed from the queue if the detector at the end notices a road user. The disadvantage of such a realization is that the exact position of a road user is not known within the considered road element. A prediction of the movement can be performed based on the dynamic data recognized by the detectors but this is not very accurate especially for pedestrians for which the detectors were not designed. Another possibility is the discretization of the considered road element by assigning several detectors at many places along the element. Depending on the discretization steps, the current position of a road user can be determined more or less accurate.

4.2.3 Detection of Road Users in Simulation

As can be seen in Section 3.3 the detection of other road users in the simulation can be performed similar to the process of the on-board system. Only an appropriate sensor model (including sensor noise) for the laser scanners has to be set up in order to produce “virtual” sensor data. Therefore, the beams of the laser scanner are calculated in each simulation step and intersected with each not occluded object in the simulation scene. The intersecting points become the “virtual” laser scanner measurements. Due to the simulation integration in the general data fusion framework the algorithms for object detection can be analyzed very easily.

4.3 Infrastructure Related Data (Traffic Lights)

As introduced in Chapter 2 wireless communication is used for C2I communication. In terms of integration into the EDS the traffic signal system is integrated as a (remote) sensor. This sensor gets its input via wireless LAN. In order to realize the addressed traffic light function described in Section 2.2.3, the following information is transmitted to the approaching vehicles and integrated in the situation analysis:

- identification of traffic lights
- current status of the traffic lights
- remaining state transition times for each traffic light

Different approaches exist in order to identify the relevant traffic light for the host vehicle so that is can be used for situation analysis purposes. One possibility is to store the traffic lights and their identifiers in the digital map. If the position of the host vehicle in the map is known, the relevant traffic light can easily be identified by matching the transferred identifier with the identifiers in the map. A more general approach that does not depend on a digital map was proposed by the author of this thesis in [RB06]. The relevant road segment for each traffic light is reproduced by a set of interpolation points that are transmitted together with the other traffic light data to the approaching vehicles.

4.4 Behavior Modeling

This section describes the general behavior modeling of this work. This was also shown in brief in the authors publication [RZ09]. The novel approach of this thesis is the representation of the driving behavior solely in terms of a few geometric entities. This eases the calculation of possible trajectories and therefore the identification of possible conflicts within an intersection. The computational complexity of the whole system is drastically reduced which makes it suitable for online analysis tasks. The entities for the behavior modeling are the driving lanes (real and virtual lanes) of the intersection. The idea is that each traffic participant only drives on predefined areas within the intersection, i.e. the lanes. This form of modeling can be interpreted as the definition of one common trajectory with a tolerance area to both sides which corresponds to the width of a lane. In order to represent the behavior of all traffic participants a common structure is needed. For this representation the LMD (see Section 3.1.2) is transferred into a probabilistic graph model for each object.

A **directed** graph is a tuple

$$G = (V, E)$$

where $V(G)$ is the set of vertices and $E(G) \subseteq V(G) \times V(G)$ the set of edges in the graph G, respectively. The graph G is called **undirected** if $E(G) = E(G)^{-1}$ with $E(G)^{-1} = \{(u,v)|(v,u) \in E(G)\}$. The k-th path $pa(v_s, v_e)$ of a directed graph G from vertex v_s to v_e is a tuple $(v_1, \ldots, v_{n_k})$ where $v_1 = v_s, v_{n_k} = v_e$ and $(v_i, v_{i+1}) \in E(G) \forall i \in (1, \ldots, n_k - 1)$. A graph is called a Directed Acyclic Graph (DAG) if there exists no path $pa_k = (v_s, \ldots, v_e)$ where $v_s = v_e \forall v_s, v_e \in V(G)$.

4.4.1 Probabilistic Behavior Network

In Section 3.1.3 the MiB was introduced. This MiB forms a probabilistic behavior network which is a directed graph with lanes as vertices and transition probabilities at the edges. Those transition probabilities from vertex v_1 to vertex v_2 are denoted by $prob(v_1, v_2)$. The MiB is build out of the LMD starting at the initial position of the appropriate traffic participant. The possible next lanes from the driving lane at initialization time are traversed and inserted into the graph (see Algorithm 1). Thereby, only the next lanes that can be reached, acting on the current traffic rules (e.g. allowed driving direction), are considered. The possible next lanes are

1. the lanes connected to the same link as the considered lane,

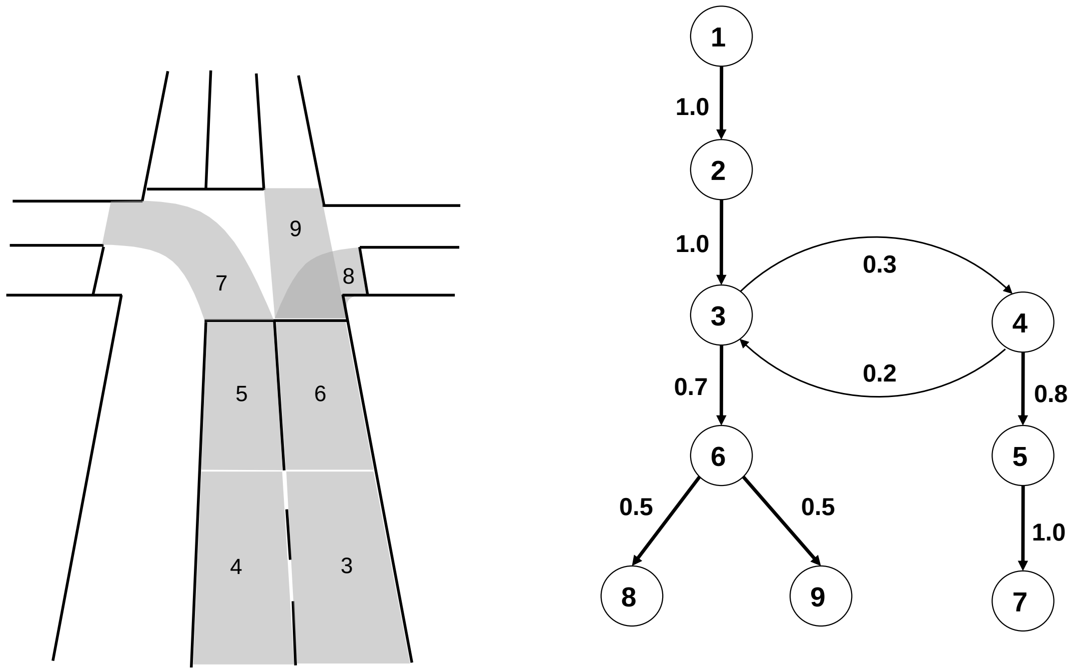
2. the neighboring lanes at the left and right side of the considered lane.

The transition probabilities describe the likelihood that a traffic participant moves from one lane to another. In general it could be stated that the unlikely behavior is the more dangerous behavior in intersection environments. As already mentioned most accidents do not occur because drivers are surprised by an unlikely maneuver taken by another road user but rather because they do not see other road users which are behaving correctly or because they misjudge available gaps. This fact legitimates to focus on conflict scenarios gained by prediction of the most likely behaviors.

Algorithm 1 buildMiB(v,dist)

```
if dist < dist_max then
  L =all possible next lanes
  for all l ∈ L do
    if l can be reached acting on actual traffic rules then
      add vertex V = l and edge E = (v,l) to MiB
      buildMiB(l,dist+dist(v,l))
    end if
  end for
end if
```

Initially, the likelihoods at the edges of the MiB are uniformly distributed over the number of outgoing edges for each vertex. However, they can also express terms like the most probable path by assigning different probabilities to the outgoing edges gained e.g. by statistical investigation of the driving behavior at an intersection. Nevertheless, the probabilities at the outgoing edges of one node must sum to 1. Figure 4.4 shows a sample intersection and the corresponding MiB for one approaching



(a) (b)

Figure 4.4: Visualization of one possible MiB.

direction. In Figure 4.4(a) the lanes which are used in the MiB of Figure 4.4(b) are shaded and numbered in order to state the relationship. In addition, the shown MiB has nodes which lanes are not shown in the intersection figure. These nodes are just the preceding lane elements of the lane with number 3. It can be seen that a new lane, i.e. a new node, is used if there are changes in the attributes of the corresponding lane. For example the lanes with the numbers 5 and 6 differ in their road markings at the right and left side from their preceding elements with the numbers 4 and 3, respectively. This is expressed by the missing edge between the nodes 5 and 6 in the MiB. The shown MiB also uses the mentioned deflection from the uniformly distributed probabilities at the edges. So, for this intersection it is more likely that a traffic participant is going straight ahead than turning left. The initial global probabilities for a maneuver at an intersection (e.g. straight, left, right) can be computed from the MiB, by summing the multiplied probabilities of all possible paths that lead to the destination starting from a specific vertex. This means to compute:

$$p(v_s \xrightarrow{*} v_e) = \sum_{k=0}^{n} p(v_s \xrightarrow{k} v_e)$$

where n is the number of possible paths from v_s to v_e and $p(v_s \xrightarrow{k} v_e)$ is the probability for reaching v_e beginning at v_s in the k-th path $pa_k(v_1 = v_s, v_{n_k} = v_e)$. As mentioned before, initially the probabilities at the edges are uniformly distributed or assigned due to some statistical background knowledge about the driving behavior at the intersection. Nevertheless, they can be modified by the application if the distribution changes due to some reason (e.g. different driving behavior at different day times).

Each MiB covers a specific maximum distance which can be seen as the range of vision for the appropriate traffic participant. Within this distance the behavior of the vehicle is described. In the simulation it is used for the local maneuver decisions while in the online application it is mainly driven by the field of view of the sensors and/or the map coverage. The wider the field of view the more extensive the maneuver decision as well as the behavior prediction can be. The high level maneuvers for the simulation are constructed by assigning a probability of 1 to every edge of the desired path. The *Dijkstra* algorithm (see [TCRC04]) is used to compute the optimal path on the MiB for each object. Therefore, a cost function is assigned to each edge in the MiB which has to be minimized over the whole path. In order to prevent the vehicle from doing needless lane change maneuvers but to change lanes as soon as possible when they are required the following cost function is used:

$$c_{ij} = \begin{cases} d_{ij} & \text{if the edge (i,j) is changed via a lane link} \\ d_{ij} \cdot d_{i,v} + b_{lc} & \text{if the edge (i,j) is a lane change} \end{cases}$$

where d_{ij} is the distance from the center points of lane i and lane j, $d_{i,v}$ is the distance from the position of the appropriate vehicle v to the center of lane i and b_{lc} are the basic costs for a lane change.

4.5 Behavior Prediction

This section describes the approach developed in this work in order to predict the behavior of the host vehicle and all other vehicles around the intersection. Prediction of human behavior is a very complex task. Within the field of Driver Assistance Systems intersections are one of the most complex scenarios, i.e. scenarios where a lot of different effects have to be considered when trying to predict the behavior of the drivers. In general, the behavior prediction can be classified into high-level and low-level behavior prediction. The high-level prediction considers global maneuver decisions like e.g. the intention to turn left or to stop in front of the intersection (e.g. due to a red traffic light). In the low-level prediction, trajectories or speed profiles are considers which are needed in order to perform the maneuvers from the high-level prediction. Especially this level is very complex because of a very big state space it has to deal with. If thinking of a "simple" left turn maneuver at the high-level the number of trajectories that can be used in order to actually turn left at the intersection is quite high. Different drivers use different trajectories and even different speed profiles for their maneuvers within an intersection. Trying to exactly predict those factors is nearly impossible.

This work uses a reduction of the state space with only little restrictions to the functioning of the ISS. The prediction module developed in this work is somewhat residing between the high-level and low-level prediction described above. Therefore, it it called *medium-level* behavior prediction here. This behavior prediction can be seen as the calculation of the probability $P(v_1 \stackrel{*}{\rightarrow} v_2)$ of two arbitrary vertices of the MiB in each time step. This approach has several advantages that make it very suitable for the proposed ISS. It offers the possibility to easily derive the appropriate maneuver as well as a boundary for possible trajectories for them (virtual lanes). Since the behavior prediction is based on the behavior network description which is defined on the real and virtual lanes of an intersection the current lane information of a vehicle is of very high importance. The developed model is capable of solving two problems in parallel:

- Computation of $P(x_t)$ for all lanes of the model. This can be interpreted as the lane assignment for the current time step.
- Computation of $P(x_{t+\delta})$ for all lanes of the model. This can be simply transferred into a maneuver prediction for a vehicle.

For the realization of this approach the theory of Dynamic Bayesian Networks is used. In order to enhance system performance and to make the application suitable for online processing a small network with only a few nodes was developed. The theory of the (Dynamic) Bayesian Networks is shortly introduced before the description of the prediction module of this system.

4.5.1 Bayesian Networks

A Bayesian Network (BN), also known as Belief Network or Causal Network, is a DAG $G = (V, E)$ where each node $v \in V$ represents a random variable X_v with the state space $\mathcal{X}_v$. For each node v a Conditional Probability Table (CPT) or a Probability Distribution Function (PDF) is given which describes the causal relationship between

v and its parent nodes in the form $p(X_v|parents(X_v))$. The CPT becomes the unconditional probability $p(X_v)$ if $parents(X_v) = \emptyset$. The advantage of a BN is that only the "real" causal relationships between the variables are modeled and therefore the full joint distribution can be expressed in a very compact form. The joint distribution of a set of variables in a BN $X_1, \ldots, X_n$ is computed by

$$p(X_1, \ldots, X_n) = \prod_{i=1}^{n} p(X_i|parents(X_i)) \tag{4.1}$$

This results in a saving compared to the full joint distribution computed by the chain rule

$$p(X_1, \ldots, X_n) = \prod_{i=1}^{n} p(X_i|X_1, \ldots, X_{i-1})$$

Figure 4.5 shows a simple Bayesian Network with five variables. It illustrates how likely it is that a driver misses a red light at an intersection if he is distracted and how this could result in an accident with another vehicle or a pedestrian both causing potential personal injuries. From this direct representation of the world reasoning can

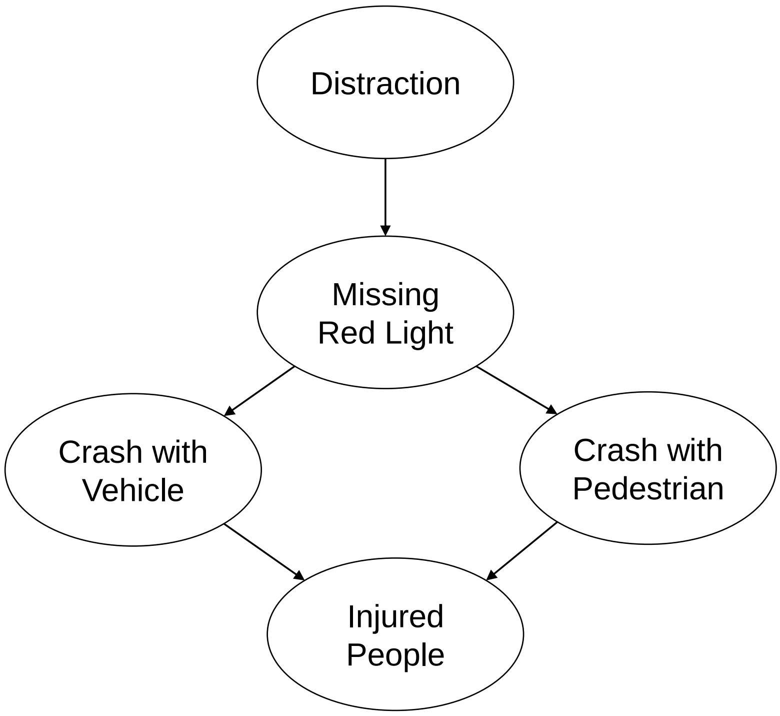


Figure 4.5: A simple BN with five variables.

be performed in any direction which is either a prediction (top down reasoning) or abduction (bottom up reasoning). For example, if an accident with another vehicle occurred there might have been some persons injured (prediction). On the other hand, if it is observed that people were injured at an intersection accident, makes it likely that there was an accident with a vehicle or a pedestrian and this was possibly caused by a red light violation (abduction). If an additional observation shows now that it was an accident with another vehicle, e.g. a side crash, the likelihood that there was an accident with a pedestrian is reduced (explaining away). This last form of reasoning in Bayesian Networks is a big advantage since in neural networks and rule based-systems it is very difficult to formulate such a form of explaining away in a natural way. Generally, the nodes in the network can be either observed or hidden. Observed nodes are nodes where evidence can be given at some time. Hidden nodes are the nodes where no evidence can be given but which are used for reasoning in the network.

For the inference in Bayesian Networks the Bayes' rule is use which is also the reason for the naming of the networks. If for example in Figure 4.5 it is observed that people were injured at an intersection it can be calculated whether it is more likely that this was caused by an accident with two vehicles or by an accident between a pedestrian and a vehicle. This can be done with the following equations:

$$p(VA = true|IP = true) = \frac{p(VA = true, IP = true)}{p(IP = true)}$$
$$= \frac{\sum_{PA=pa,RL=rl,D=d} p(IP = true, VA = true, PA = pa, RL = rl, D = d)}{\sum_{IP=ip,VA=va,PA=pa,RL=rl,D=d} p(IP = ip, VA = va, PA = pa, RL = rl, D = d)}$$

and

$$p(PA = true|IP = true) = \frac{p(PA = true, IP = true)}{p(IP = true)}$$

where the following names for the random variables were used: D=Distraction, RL=Missing Red Light, VA=Crash with Vehicle, PA=Crash with Pedestrian and IP=Injured people. The solutions for the equations given above are eased by the dependency of Equation (4.1).

4.5.2 Dynamic Bayesian Network

A Dynamic Bayesian Network (DBN) generalizes a Hidden Markov Model (HMM) and extends a "normal" BN as it is able to model uncertainty over time. This is done by storing multiple copies of the variables of a BN in different time slices. In other words each time slice of a DBN contains a single BN which variables can have causal dependencies within and over the different time slices. If the parameters and the structure of a DBN are not changing over time the network can be expressed by just drawing two BN (sometimes called 2TBN) for two time slices. This is also possible due to the assumption that the DBN represents a first-order Markov process where each variable depends only on the immediate predecessor slice and no earlier ones. If S_t and $S_{[a,b]}$ denote the variables in time slice t and the variables of the whole time slice interval $[a,b]$ respectively, the first-order Markov property is expressed by $P(S_t|S_{[0,t-1]}) = P(S_t|S_{t-1})$ for all t. For a sequence of length T the model can simply be "unrolled" by repeating this model T times. Figure 4.6 shows a sample DBN unrolled for three time slices.

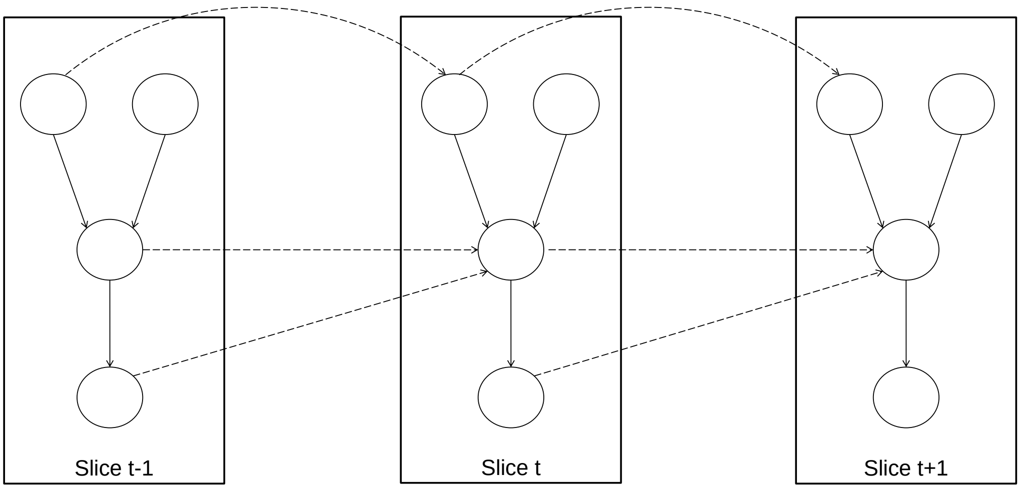


Figure 4.6: Sample DBN. The dotted arrows express the causal dependencies over the time slices.

Inference

The inference problem in a DBN is to compute:

$$P(x_{t_i}|y_{[t_1,t_2]})$$

where $x_{t_i} \in X_{t_i}$ is a hidden node at time t_i and $y_{[t_1,t_2]} \subseteq Y_{[t_1,t_2]}$ are all evidences given in the time interval from t_1 to t_2. In general it is assumed that $y_{[t_1,t_2]} = Y_{[t_1,t_2]}$. This formulation results in different inference procedures:

Filtering Filtering is the process to keep track of the current node x_t. This is done by taking into account all previous evidences. This results in the computation of

$$P(x_t|y_{[0,t]}) \tag{4.2}$$

Prediction Prediction is used to determine the distribution of some future node given all previous evidences, i.e. to compute

$$P(x_{t+\delta}|y_{[0,t]}) \tag{4.3}$$

where $\delta > 0$.

Smoothing In the smoothing process some distribution of a past node is determined given all evidences from the beginning up to the present. Formally, this is done by computing

$$P(x_{t_k}|y_{[0,t]})$$

where $t > t_k > 0$.

Most likely explanation Given a set of observations the sequence of variables that caused these observations is computed by

$$\operatorname*{argmax}_{x_{[0,t]}} P(x_{[0,t]}|y_{[0,t]}).$$

As will be seen below, the first two inference procedures are essential for the tasks performed in this work.

4.5.3 Prediction Module

As mentioned before, a DBN was used for the behavior prediction in this work. Generally, the network can be interpreted as an estimator for the lane a vehicle is driving on. This is comparable to a map matching algorithm e.g. for navigation purposes. Due to the modeling of this lane assignment as a dynamic process, not only the current lane but rather all future lanes the vehicle will drive on can be predicted. Due to the description of the vehicle's behavior solely by lanes, the intention of a driver can be inferred from the model. Figure 4.7 shows the DBN that is used for current lane estimation as well as behavior prediction. The observed states, i.e. the evidences in each slice, are the measured position x, y, the measured orientation ψ, the measured velocity v and the observed turn indicator state of the vehicle, as well as the current status of the traffic light. The hidden states are the actual position x, y, the actual orientation ψ, the actual velocity v as well as the current lane of the vehicle. Due to this intuitive representation of the model, additional nodes could be easily added to further enhance the prediction capabilities of the system. Through a filtering process (see Equation (4.2)) the actual lane can be estimated for the current time t. Here the big advantage of the formulation can be seen. The behavior

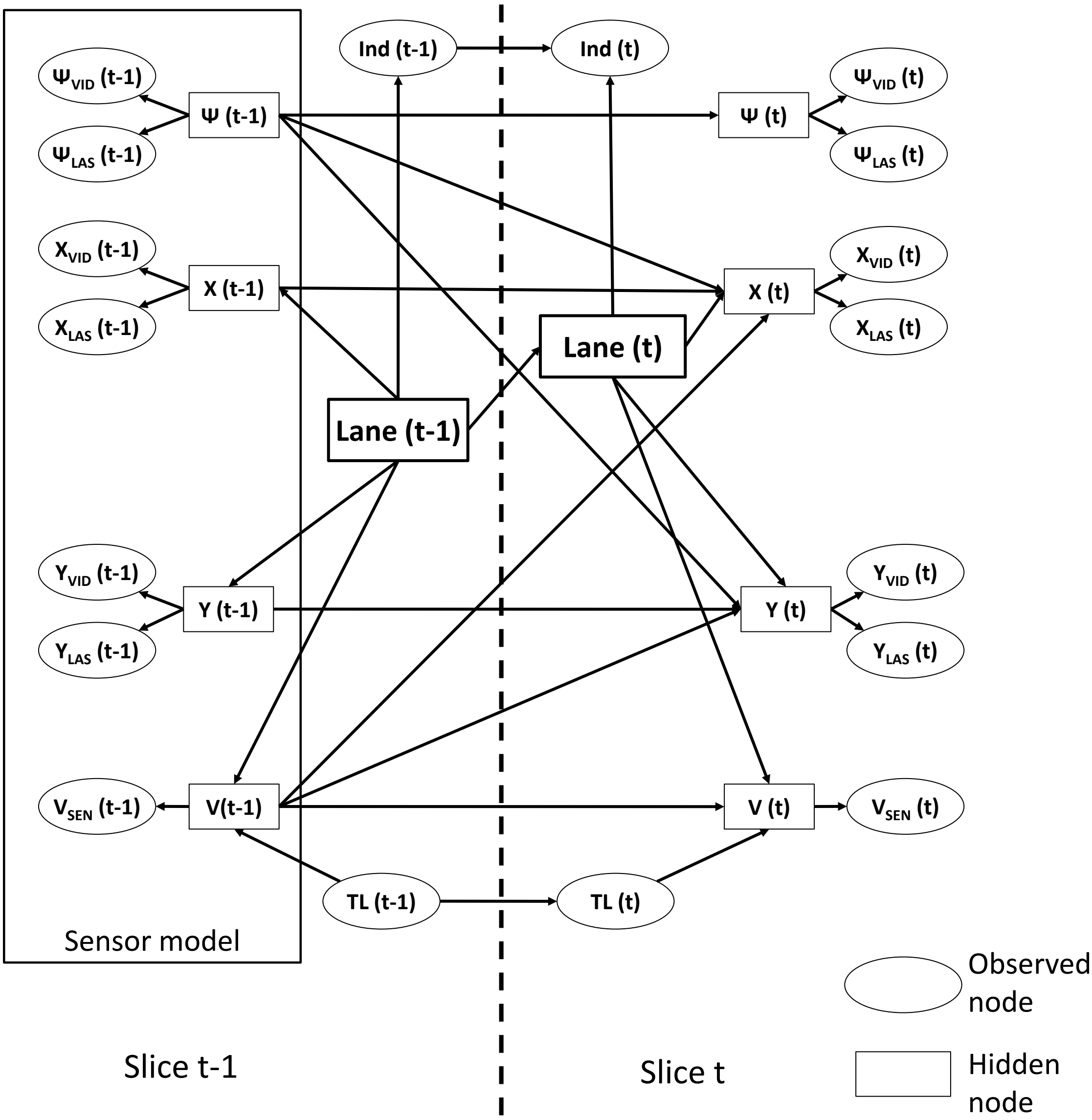


Figure 4.7: 2TBN for the behavior prediction module.

prediction in this model is simply the prediction (see Equation (4.3)) of the future lanes.

As can be seen in Figure 4.7 the DBN for the behavior prediction task also contains the sensor model for the host vehicle. This sensor model is a visualization for the sensor data fusion of the host vehicle localization (see Section 4.1) that is performed in the system. The sensor data fusion can be seen as a Kalman filtering process combining the different measurements of the installed sensors in order to achieve a precise localization of the host vehicle. Since a DBN is a general model and able to describe the theory of Kalman filtering, it is shown also in Figure 4.7 in order to visualize the whole process.

Let $x_t = (x_{1_t} \dots x_{n_t})$ be the state vector and $z_t = (z_{1_t} \dots z_{m_t})$ the vector of the sensor measurements, where n, m are the numbers of hidden nodes and evidence nodes in the sensor model of the BN. Then the prediction step of the Kalman filter, written probabilistically, is expressed by the following equation:

$$p(x_t|z_{[0,t-1]}) = \int p(x_t|x_{t-1}) p(x_{t-1}|z_{[0,t-1]}) dx_{t-1}$$

where $z_{[0,t-1]}$ are the sensor measurement from slice 0 up to slice $t-1$. The distribution $p(x_t|x_{t-1})$ for the state prediction based on the last state is defined by a Gaussian distribution function with state transition matrix F_t and process noise covariance matrix Q_t which are well known from the Kalman filtering theory:

$$p(x_t|x_{t-1}) = \mathcal{N}(F_t x_{t-1}, Q_t)$$

The probability density function of state x_{t-1} given all sensor measurements up to time $t-1$ is defined by:

$$p(x_{t-1}|z_{[0,t-1]}) = \mathcal{N}(\hat{x}_{t-1}, P_{t-1})$$

where $\hat{x}_{t-1}$ is the estimation of state x_{t-1}. As soon as a new sensor measurement is available the update step for the Kalman filter is performed by:

$$p(x_t|z_{[0,t]}) = \frac{p(z_t|x_t) p(x_t|z_{[0,t-1]})}{p(z_t|z_{[0,t-1]})}$$

where the sensor measurement prediction $p(z_t|x_t)$ is defined similar to the state prediction with the observation model matrix H_t and observation noise covariance matrix R_t by the following equation:

$$p(z_t|x_t) = \mathcal{N}(H_t x_t, R_t)$$

and

$$p(z_t|z_{[0,t-1]}) = \int p(z_t|x_t) p(x_t|z_{[0,t-1]}) dx_t.$$

Node Description

As described above the nodes for the position, orientation and velocity are part of the sensor model of the data fusion process for the host vehicle. For the current time slice the lane node describes the lane where a vehicle is currently driving on. For each lane a two dimensional Gaussian PDF $\mathcal{N}(\mu, \sigma)$ is used based on the position x, y

of the vehicle. The center of each PDF corresponds to the center of gravity of the according lane.

The velocity node in the model is dependent on the lane and traffic light node. Each lane has a maximum legal as well as a maximum possible velocity. While the legal velocity is depended on traffic regulations, the maximum possible velocity can be calculated based on the shape of the lane segment of the LMD (e.g. a turning lane has a much lower possible velocity than a straight one). In a similar way the traffic light node is influencing the speed node. Depending on the current status of the traffic light, the speed the driver is assumed to drive on each lane of the LMD can be defined. Consequently, e.g. a red traffic light results in reduced velocities on the approaching lanes. The indicator node defines the status of the turn indicator of the vehicle against the lanes of the intersection. E.g. the probability for activation of the left turn indicator is very high for lanes of the LMD which are describing a left turn in the intersection (e.g. lanes 4, 5 and 7 of Figure 4.4).

There is a difference between the observed and hidden nodes of the networks of different traffic participants. First of all it has to be mentioned that the non-observance of a specific node in the network is not equal to the evidence *false* of a binary node. This means that for example an observed turn indicator (e.g. through vehicle information on the CAN bus) which is turned off does not correspond to the hidden indicator node where the status of the turn indicator is not known. This becomes important for all other vehicles than the host vehicle since the turn indicator information of another vehicle cannot be observed by the installed sensors. This issue is further highlighted in Chapter 7. Technically, this drawback could be solved by C2C communication or possibly through highly complex video processing on a high resolution image but this was not considered in this work. Consequently, the indicator node can only give an advantage to the prediction of the host vehicle's behavior. If e.g. the intersection has only one approaching lane for every three directions (left, right, straight) it is very hard up to not possible (without the turn indicator state) to prematurely differentiate between a left and a right turn since the approaching behavior is nearly the same for both maneuvers. Not until both trajectories (i.e. virtual lanes) begin to separate from each other the difference in the probabilities becomes noticeable. For very small intersections this can be quite late. As will be seen later, such a situation could result into a false alarm of the system. If e.g. a vehicle that has the right of way is coming from the right and intends to turn right while the host vehicle intends to turn left, normally there would be no conflict. However, if the system assumes the other vehicle to turn left or to go straight ahead, there would be a conflict and the driver would possibly be warned of a potential right of way violation. The topic of conflict calculations is presented in the following.

4.6 Relational Road Network

When the behavior of all traffic participants is analyzed it has to be evaluated if the predicted plans are at odds with each other. As described in the beginning, in the underlying system only mistakes of the host vehicle should be considered, i.e. the system should warn the driver only of possible errors of his own. In a first step the possible conflicts that arise because of the construction of the intersection have to be identified (static part). In a second step the conflicts that can arise because of the current combination of the objects and their predicted plans have to be analyzed (dynamic part). At the end a comprehensive view on the scene is gained.

4.6.1 Conflict Graph

The Conflict Graph (CG) is a graph that results from the interconnection of the different MiB of each traffic participant currently in the scene. An interconnection between two vertices of two MiB exists if there is a potential conflict with the lanes belonging to these vertices. A potential conflict exists if two lanes have an overlapping area called conflict zone. For simplification, the conflict zone can often be reduced to the Conflict Point (CP) which is the intersection of the center lines of both lanes. The edges that represent a conflict are undirected edges in order to differentiate them from the transition edges of the initial MiB. The initial CG does not take into account the traffic control at the intersection, i.e. it cannot be seen which lane of the connection is preferred in terms of right-of-way regulations. Figure 4.8 shows a CG for a sample intersection which was computed for two vehicles in the scene.

4.6.2 Right-of-Way Computation

For the right-of-way regulation the German traffic regulation was considered. Nevertheless, the proposed approach can easily be reformulated for other traffic regulations like for example in Great Britain. For the implementation of the traffic rules the following features are assigned to the lanes of the CG:

Category To all lanes a category *cat* is assigned. This category defines the right-of-way regulation resulting from traffic signs or general traffic rules. The higher the category the more preferred is the lane. For an intersection without any traffic light or sign the category is the same for each lane in the intersection. Traffic lights are considered as *dynamic traffic signs*. Depending on the signal status of the traffic lights the categories are dynamically assigned to their according lanes.

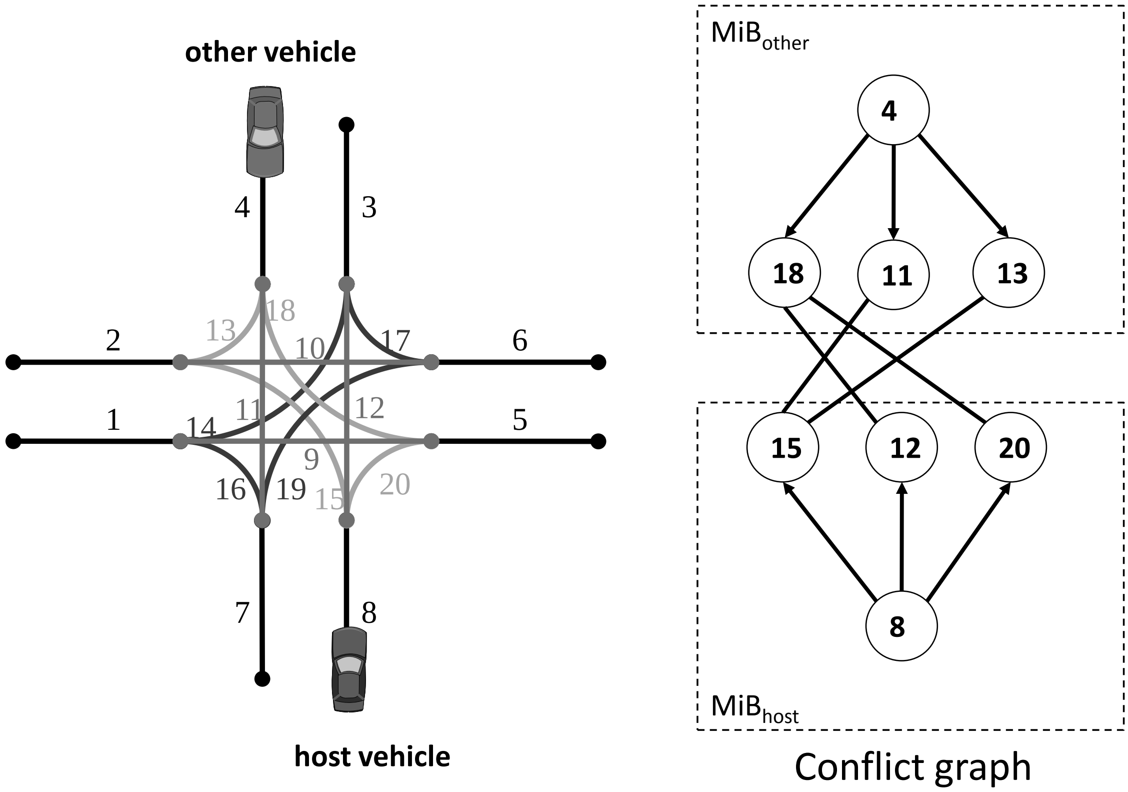


Figure 4.8: Conflict graph for a sample intersection.

Priority The priority of a lane defines the direction from where this lane can be reached with respect to the host vehicle.

$$prio(l) = \begin{cases} 1 & \text{if } dir(l) = right \\ -1 & \text{if } dir(l) = left \\ 0 & \text{otherwise} \end{cases}$$

where $l \in V(CG)$ and $dir(l) : V(CG) \rightarrow \{right, left, straight\}$ is a function that computes the direction from where a specific lane will be reached with respect to the host vehicle.

Intention The intention describes the aim of the host vehicle, i.e. if it wants to turn either left, right or intends to go straight ahead when it is on a specific lane l.

$$int(l) = \begin{cases} 0 & \text{if } l \notin V(MiB_{host}) \vee move(l) = straight \\ 1 & \text{if } move(l) = right \\ -1 & \text{if } move(l) = left \end{cases}$$

where $l \in V(CG)$ and $move(l) : V(CG) \rightarrow \{right, left, straight\}$ is a function that computes the direction where a specific object wants to go.

From the definition above it can be seen that only the following three points are important:

1. What are the categories of the conflicting lanes
2. From which direction (from the view of the host vehicle) the other vehicles arrive
3. Which direction the host vehicle intends to go

4.6.3 Right-of-Way Graph

If the computed CG is reduced to the conflicts where the host vehicle has to yield right of way to other vehicles, the Right-of-Way Graph (RoWG) is obtained. Algorithm 2 describes this procedure.

Algorithm 2 Construction of RoWG

```
for all C = (l1, l2) ∈ E(CG) & l1 ∈ MiB_host do
  if cat(l1) > cat(l2) then
    remove C from CG
  else
    if cat(l1) = cat(l2) then
      if prio(l1) > prio(l2) then
        remove C from CG
      else
        if prio(l1) = prio(l2) then
          if int(l1) ≥ int(l2) then
            remove C from CG
          end if
        end if
      end if
    end if
  end if
end for
```

The RoWG is only valid for the host vehicle. While the CG is a *static* graph, the RoWG is a *dynamic* graph that can change continuously during system operation. Every time a new vehicle is detected at the intersection or the categories of the lanes changes (e.g. due to a traffic light) the RoWG has to be updated. Figure 4.9 shows how the RoWG is obtained from the CG of Figure 4.8 taking into account no other traffic regulation than right-before-left. At the end, to each conflict $C_n = (l_i, l_j) \in$

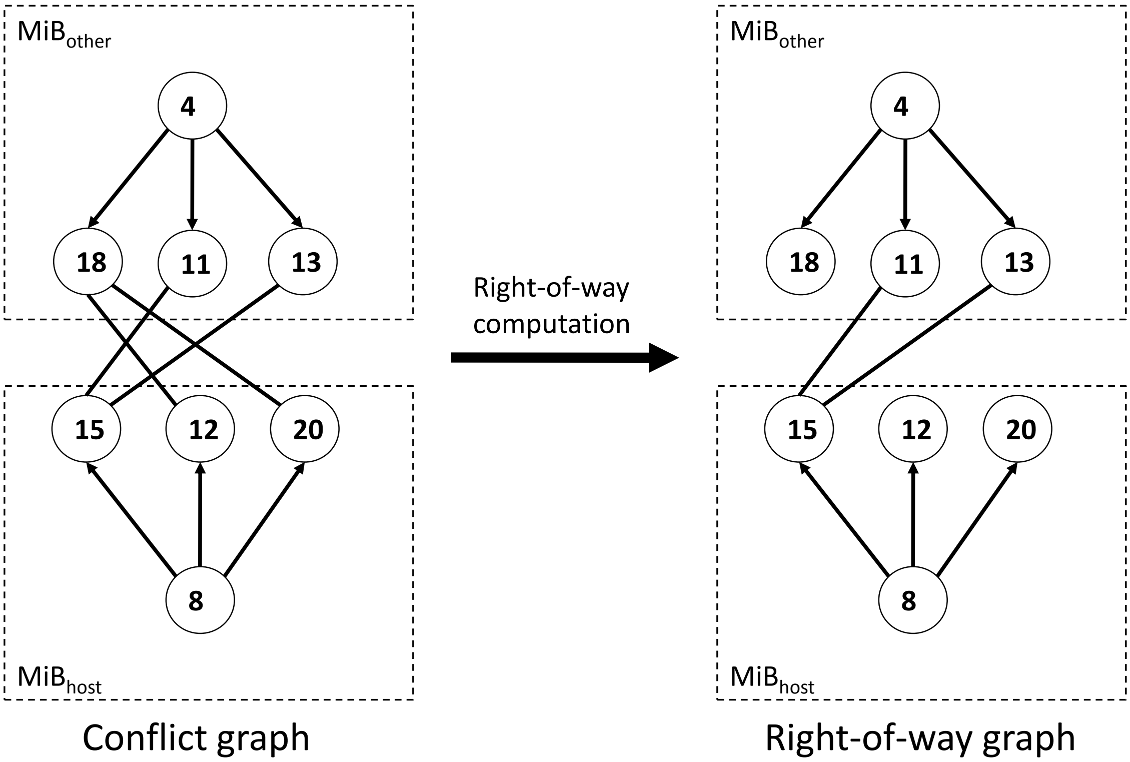


Figure 4.9: Right-of-way graph for the sample intersection of Figure 4.8.

E(RoWG) & $l_i \in MiB_{host}$ & $l_j \in MiB_{other}$ a probability p_{C_n} can be assigned which expresses the likelihood of the conflict of the MiB of the host vehicle with the MiB of the other traffic participant in the scene. This probability is computed by

$$p_{C_n} = p(l_{host} \xrightarrow{*} l_1) \cdot p(l_{other} \xrightarrow{*} l_2)$$

where l_{host} and l_{other} are the lanes where the host and the other vehicle are currently driving on.

It is important to mention that the probability p_{C_n} this is not the likelihood of the conflict in time AND space domain. It just expresses how likely a conflict between the host vehicle and another traffic participant is with respect to the space domain taking into account the behavior prediction of both parties. How this likelihood is used for a final risk assessment for the conflicts in the RoWG is described in the next chapter.

Chapter 5

Risk Assessment

This chapter describes the last step to be performed in the application level before presenting a warning to the driver - the risk assessment of the current situation. The risk assessment is the logical continuation of the performed situation analysis. Once a clear understanding of the scene is gained, the risk for the host vehicle can be calculated. This risk indicates how dangerous a current situation is for the driver of the host vehicle taking into account several parameters. Calculating the risk is a very complex task. The situation analysis provides all possible conflicts and the assigned probabilities of the driving behavior of the vehicles, but, as mentioned before, omitting the time domain. One possibility is to try to compute the occurrence of the conflicts analytically and try to find a measure for the preceding risk. In Section 2.2.4 several calculations were performed that could also be used for risk assessment for the different assistance functions. Nevertheless, these computations are not very suitable for a system like the one developed in this work. With an analytical approach it is very hard to cope with the fact of imperfect sensor data and to include aspects like the subjective assessment of the current risk of a specific driver. Risk assessment in general is a very subjective process that is dependent on different factors. One person can judge a situation as critical while for another one it is not critical at all or at least less critical. One possibility to cope with such a problem is a manually adjustable system that has a few settings to assure a system operation that fits to most drivers. For example there could exist settings like “sporty driver” or “defensive driver”. The problem with such an adjustable system is that it can never be designed to perfectly fit to each different user of the vehicle. Therefore, it would be better to have a system that automatically adapts to the current user, i.e. changes its behavior if the user does not react appropriately to the system outputs. The ability for such a “learning” system is presented at the end of this chapter.

In this work a fuzzy rule-base is built to reproduce “human thinking” for risk assessment so that an adequate strategy can be formulated in an easy way. Important input variables are speed, acceleration and distance to the conflict. But also inputs such as the type of the opponent could be of interest in order to translate it to a severity index for a possible crash as presented in [SUBW04]. Visibility, which can also affect the judgment of the risk, is an additional factor that can be easily modeled in such a fuzzy rule-base system. For example, the risk for an available time-gap for turning in an intersection could be assessed higher for a moment with poor visibility than for very good weather conditions. For this work the risk assessment takes the probabilities p_{C_n} of the behavior prediction as weighting factors and computes a risk level for each possible conflict in time and space domain (see Figure 5.1). Here, the time becomes important, because the risk of a conflict is highly dependent on the fact whether or not two vehicles are reaching the conflict point (i.e. a defined area around this conflict point) in the same time interval. The results of the risk assessment

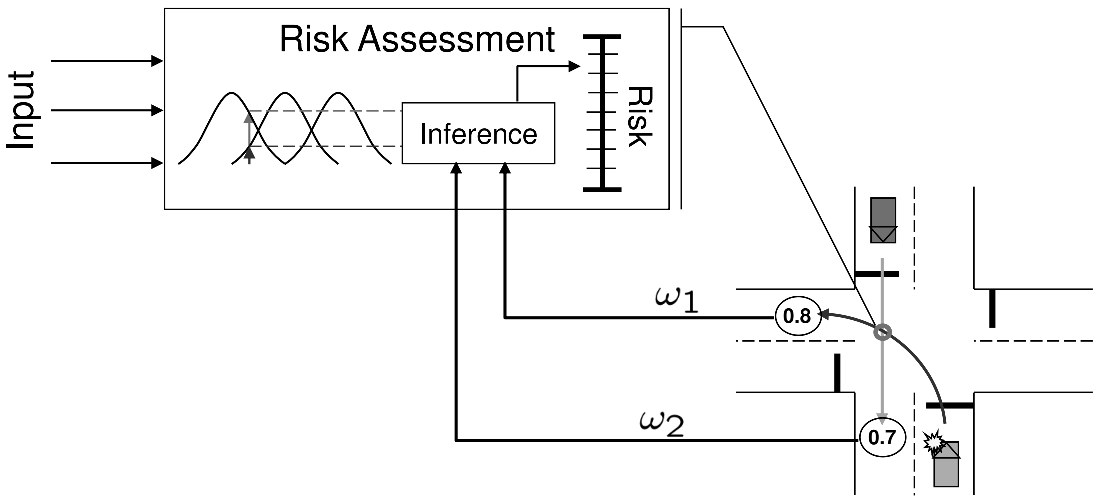


Figure 5.1: Schematic view on the risk assessment.

module are different risk levels for all possible conflicts in the scene (i.e. all conflicts of the RoWG).

5.1 Fuzzy Rule-Based Risk Assessment

A fuzzy-logic [Zad65] approach was used in this work to judge the risk of a possible conflict for the intersection scenarios. As mentioned before, this method has several advantages compared to an analytical approach:

- Risk assessment for ISS is uncertain in nature because it depends on several external factors that are not so easy to assess.
- The rules of such a fuzzy logic prediction system are all user-defined and therefore intuitively to understand and easy to modify.

- Using a neuro-fuzzy approach the rules of the inference system can be adapted in order to learn a warning strategy for a specific driver or in order to train the whole system rules from scratch.

Such a fuzzy-logic approach allows the formulation of the rules for the risk assessment in a very natural and easy way. No widespread expert knowledge is needed in order to define the rules so that the resulting system can work properly. Such a rule could for example be formulated as follows:

IF (v_h is HIGH) and (d_h is SHORT) and (v_o is MEDIUM) and (d_o is VERY_SHORT) THEN (*risk* is VERY_HIGH)

where v_h and d_h are the velocity and the distance to the conflict point of the host vehicle and v_o and d_o the velocity and distance of the other vehicle, respectively. This is just an example with possible input variables. As soon as one intends to add more input variables the rule-base can easily be extended.

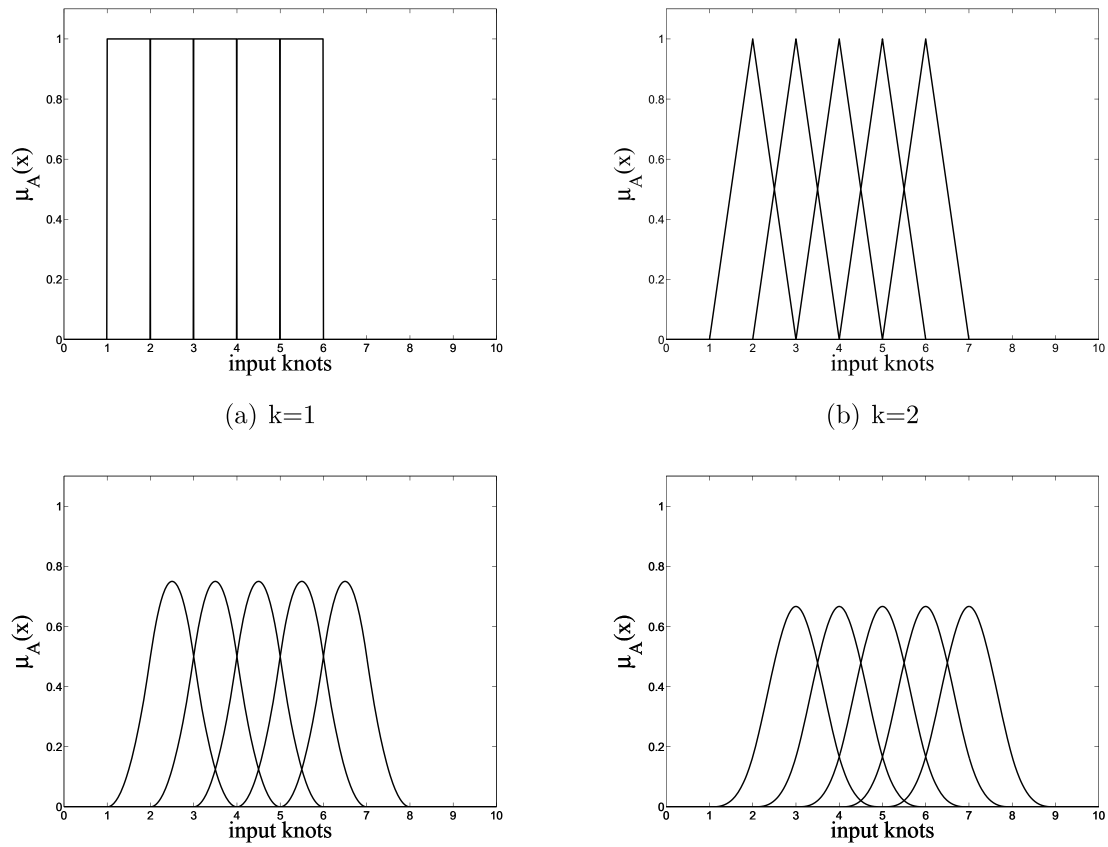
5.1.1 B-Splines as Membership Functions

Several different forms of membership functions are used for fuzzy inference systems. The most popular forms are the triangular or trapezoid functions since they are very easy to handle and to compute. Nevertheless, they are limited in their approximation ability for more complex systems. The B-Spline model is a natural generalization of coarse coding to continuous-valued features and can thus be used as well as function approximator for the risk assessment task. In order to solve the problem of numerical approximation for smoothing statistical data, "basis splines" (B-Splines) were introduced by [Sch46]. B-Splines were used later by [Rie73] and [GR74] in *Computer Aided Geometric Design* for curve and surface representation. Because of their versatility based on only low-order polynomials and their straightforward computation, B-Splines have become more and more popular. Nowadays, B-Spline techniques represent one of the most important trends in Computer Aided Design and Computer Aided Manufacturing. They have been extensively applied in modeling free shape curves and surfaces.

If x is a general input variable of a control system that is defined on the universe of discourse $[x_1, x_m]$ and given a sequence of ordered parameters (knots): $x_1, x_2, \ldots$, the ith B-Spline $X_{i,k}$ of order k (degree $k-1$) is recursively defined as follows:

$$X_{i,k}(x) = \begin{cases} \begin{cases} 1 & \text{for } x_i \le x \le x_{i+1} \\ 0 & \text{otherwise} \end{cases} & \text{if } k = 1 \\ \frac{x - x_i}{x_{i+k-1} - x_i} X_{i,k-1}(x) + \frac{x_{i+k} - x}{x_{i+k} - x_{i+1}} X_{i+1,k-1}(x) & \text{if } k > 1 \end{cases}$$

with $i = 1, \ldots, m-k$. Therefore m knots $x_i (i = 1, \ldots, m)$ form $l = m-k$ B-Splines. Figure 5.2 shows sample B-Splines from order 1 to 4. Figure 5.3 illustrates the



(a) k=1 (b) k=2

(c) k=3 (d) k=4

Figure 5.2: Visualization of B-Splines of different orders.

partition of a two-dimensional B-Spline model with 8 membership functions on each uniformly subdivided input interval and the activated B-Splines (slightly shaded) for a given input. Since learning one new part of the input space affects only a given number of controller response values (darkly shaded area of figure 5.3), fast online learning can be devised (see Section 5.2). By using the B-Spline model the approximation ability is only limited by the number of knots distributed over the input intervals. Regarding that most observed data is disturbed to a certain degree, the over-fitting problem may occur. Genetic algorithm optimized B-Spline models are promising approaches to find sparse models which are able to bridge the gap between high bias and high variance of the model.

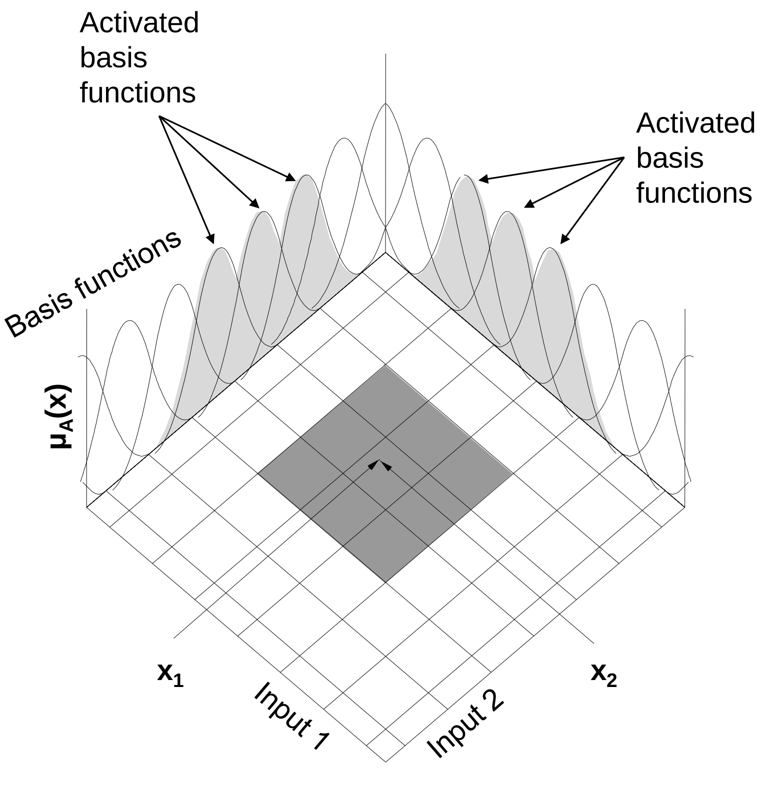


Figure 5.3: Illustration of two-dimensional B-Spline model.

5.1.2 System Concept

As introduced above the risk assessment approach used in this work is based on a fuzzy inference system. The membership functions of this system are constructed by B-Splines as described in Section 5.1.1. The overall design is as follows:

- B-Spline basis functions for system input
- fuzzy singletons as membership functions for system output
- fuzzy conjunctions by "product"
- defuzzification by "centroid" method

Each input is uniformly covered by five membership functions. This is due to a natural human partitioning of a specific linguistic variable. The linguistic variable *speed* would therefore be represented by the linguistic terms *very slow*, *slow*, *medium*, *high* and *very high*. The rules for the resulting Multiple Input Single Output (MISO) system with conjunctive terms in the IF-part are defined as follows:

$$\boxed{\text{IF } (x_1 \text{ is } X^1_{i_1,k_1}) \text{ and } (x_2 \text{ is } X^2_{i_2,k_2}) \text{ and } \dots (x_n \text{ is } X^n_{i_n,k_n}) \text{ THEN } y \text{ is } Y_{i_1 i_2 \dots i_n}}$$

where

x_j	j-th input $(j = 1, \dots, n)$
k_j	order of B-Spline basis function for x_j
$X^j_{i_j,k_j}$	i-th B-Spline membership function of x_j
$i_j = 1, \dots, m_j$	number of membership functions for the linguistic variable for x_j
$Y_{i_1 i_2 \dots i_n}$	fuzzy singleton for Rule$(i_1, i_2, \dots, i_n)$

This results in a risk computation as shown in Equation (5.1).

$$\begin{aligned} risk &= \frac{\sum_{i_1=1}^{m_1} \dots \sum_{i_n=1}^{m_n} (Y_{i_1,\dots,i_n} \prod_{j=1}^{n} X^j_{i_j,k_j}(x_j))}{\sum_{i_1=1}^{m_1} \dots \sum_{i_n=1}^{m_n} \prod_{j=1}^{n} X^j_{i_j,k_j}(x_j)} \\ &= \sum_{i_1=1}^{m_1} \dots \sum_{i_n=1}^{m_n} (Y_{i_1,\dots,i_n} \prod_{j=1}^{n} X^j_{i_j,k_j}(x_j)) \end{aligned} \tag{5.1}$$

The above risk assessment computation is performed for each conflict C which possibly can occur in the current situation. Since due to the number of road users currently at the intersection and their predicted driving behavior which will be most of the time less than 100%, a lot of possible conflicts can exist. Therefore an additional weighting factor ω is added to the risk computation which influences the overall risk for a specific conflict. Assuming $\mathcal{C} = (C_1, \dots, C_N)$ are the current conflicts of the RoWG for a specific situation the most critical conflict is computed by:

$$\theta = \underset{c_l \in \mathcal{C}}{\operatorname{argmax}} \left[\omega_{c_l} \sum_{i_1=1}^{m_1} \dots \sum_{i_n=1}^{m_n} (Y_{i_1,\dots,i_n} \prod_{j=1}^{n} X^j_{i_j,k_j}(x_{j,c_l})) \right]$$

where x_{j,c_l} is the j-th input and ω_{C_l} the weight for conflict C_l. Several procedures for the computation of the weight ω_{C_l} can be used. All are based on the probabilities calculated for the current conflict. The easiest way is to weight the risk computation simply by the probability for the conflict:

$$\omega_{C_l} = p_{C_l}$$

This has the effect that the risk changes if the probability for the conflict changes. If the risk should not change proportionally to the probabilities of the conflicts, the following weighting factor can be used:

$$\omega_{C_l} = \begin{cases} 1 & p_{C_l} > \frac{1}{N} \\ 0 & \text{otherwise} \end{cases}$$

where N is the number of calculated possible conflicts.

5.2 Learning of Fuzzy Risk Assessment System

The fuzzy-system approach introduced above can be extended with the ability for optimizing and generating rules by a machine learning approach [ZK99]. The practical suitability of this method was among others shown by the author of this thesis in the field of robotic grasp learning [RZ02], [ZR03]. The basic idea of the learning integration is based on a gradient descent method. The goal is to minimize the following squared error function:

$$E = \frac{1}{2}(risk_r - risk_d)^2 \tag{5.2}$$

where $risk_r$ and $risk_d$ are the current calculated risk and the desired outcome, respectively. The momentous risk level $risk_r$ is thereby calculated by Equation (5.1). In order to minimize Equation (5.2) the parameters $Y_{i_1,\ldots,i_n}$ of Equation (5.1) have to be adapted. For this purpose the gradient descent method is used:

$$\begin{aligned} \Delta Y_{i_1,\ldots,i_n} &= \epsilon \frac{\delta E}{\delta Y_{i_1,\ldots,i_n}} \\ &= \epsilon (risk_r - risk_d) \prod_{j=1}^{n} X^j_{i_j,k_j}(x_j). \end{aligned}$$

Since the second partial differentiation with respect to $Y_{i_1,\ldots,i_n}$ is constant, i.e.

$$\frac{\delta^2 E}{\delta^2 Y_{i_1,\ldots,i_n}} = (\prod_{j=1}^{n} X^j_{i_j,k_j}(x_j))^2 \geq 0,$$

it is guaranteed that the learning algorithm converges to the global minimum of the error function.

5.3 Adaption

The automatic adaption of the proposed risk assessment by machine learning techniques offers additional enhancement to the overall system. As stated in [GSB+08] most drivers will not accept ADAS warnings, i.e. the presentation of the risk assessment, unless they are in line with their own driving style (see also Chapter 6). Therefore, some kind of "soft" adaptation of warning thresholds is suggested. In this work, adaption can be understood as changing the internal parameters of the risk assessment algorithms in order to achieve a different behavior for specific situations. Two different adaptation procedures are used in this work:

- offline adaption with simulation,
- online adaption in the vehicle or in the simulation.

In both cases the adaption is used in order to adjust the parameters of the membership functions for the fuzzy rule base. In the offline risk adaption the parameters for the fuzzy rule base are generated automatically from scratch without designing the membership functions by means of expert knowledge. Just the number of the membership functions for each input is given. The online risk adaption is performed in order to adjust the warning system to a specific driving behavior or driver's skill. Here, an initial parameter set is already given and the system is performing well in most situations. Just for some specific situations, where a driver reacts noticeably against the warning or recommendations of the assistance system, the risk assessment is adapted to the driver. One drawback that has to be overcome with the described adaption is the sometimes missing transparency of the system behavior to the drivers of the vehicle. The driver who is driving the car has to be aware of the fact that the system is adapting to his behavior and will perhaps react differently from one situation to another. On the other hand if different drivers are driving the same vehicle they must know to which driver the system is currently adapted or at least need a switch to turn to a specific selectable profile.

5.3.1 Offline Risk Adaption

As described in Section 2.4.3 a simulator was designed for the proposed system. With this simulator approach it is possible to adapt the rules of the fuzzy inference system. The idea for the offline risk adaption is to generate a lot of different situations which do or do not result in an accident. From the conflict situation (e.g. accident, near accident, no accident) a corresponding feedback can be calculated and thus the parameters can be adapted.

The application driven architecture approach that was introduced in Section 3.3 is well suited for the adaption by machine learning. The fact that every vehicle is initially driving only with rudimentary behavior is utilized to randomly generate different conflict and conflict free situations. After analyzing each run of the host vehicle through the intersection the risk assessment is adapted accordingly. When adapting the whole risk assessment from scratch, the parameters of the fuzzy inference system must be initialized so that they produce for every situation the highest risk. This is due to the fact, that a “false positive” error is considered to be not as critical as a “false negative” one in this application. If the system is not fully trained for all situations it should warn in every of its “unknown” situations. Thus, it does not happen that a critical situation results in no alarm. Nevertheless, the number of both errors should be kept as small as possible in order to not reduce the system acceptance by the users. A big challenge is to find a good measure for the risk of a situation. Several possibilities are conceivable:

- distance based measures
- time gap based measures
- accident severity measures

It is important to define not only a risk measure that is adequate for the driver of the host vehicle but also for the driver of the other vehicle. This means that for one situation none of the involved drivers should assume the situation to be dangerous. The distance based measure simply uses the distance of the conflicting vehicles at the time when the host vehicle reaches the conflict point. The smaller the distance the higher is the assigned risk. The problem which arises is, that this measure does not take into account the speed of the vehicles. Normally, a driver would accept small distances to a conflicting object, if the speed is low and vice versa. A time gap measure defines the risk of a potential situation according to the “time gap” to the conflict. This is an often used measure in Driver Assistance Systems that takes into account the speed of the vehicle. For example, in modern ACC systems the user can define a time gap to the preceding vehicle which the system tries to keep. The lower the speed of the vehicle the smaller is the distance the systems keeps with the same time gap setting. The measure introduced in this system is called Conflict Time Gap (CTG). For the definition of this measure the Time-to-Conflict-Point (TTCP) is used in contrast to the well known term Time-to-Collision (TTC), used in Driver Assistance Systems [vdHH93]. For the TTC the time trajectories of two vehicles $(\mathcal{T}_h(x,y), \mathcal{T}_o(x,y))$ are intersecting exactly in one point $P = (x_c, y_c, t_c)$ in the time-space domain. Thus, the TTC is the same for both vehicles. This results in:

$$\mathsf{TTC} = \mathcal{T}_h(x_c, y_c) = \mathcal{T}_o(x_c, y_c). \tag{5.3}$$

In contrast, the TTCP is defined as the time to a conflict point (within an intersection) where a collision would occur if Equation (5.3) would be true. For the TTCP both trajectories are not necessarily intersecting in the time-space domain but at least in space domain, i.e. at $P = (x_c, y_c)$. This means that the TTCP is simply the time value of the time-space trajectory of the host vehicle h at a defined conflict point:

$$\mathsf{TTCP}_h = \mathcal{T}_h(x_c, y_c).$$

The TTCP for the host vehicle h becomes the TTC if another vehicle o exists where $\mathsf{TTCP}_o = \mathsf{TTCP}_h$. The CTG is defined as follows:

$$\mathsf{CTG} = |\mathsf{TTCP}_h - \mathsf{TTCP}_o|.$$

The CTG defines the time for a vehicle V_1 to reach a predefined point P after another

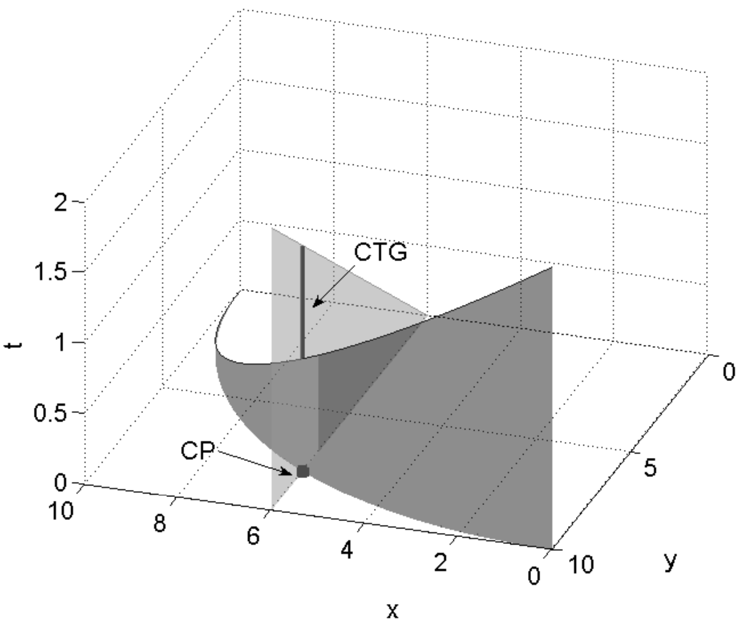


Figure 5.4: CTG for sample trajectories.

vehicle V_2 has already crossed it (see Figure 5.4). In other words, it describes the time gap between V_1 and V_2 if one vehicle is first at point P. This is not necessarily easy to compute since the vehicles' trajectories are initially not known. Thus, the simulation is run until one of both vehicles reaches the conflict point. Then the CTG becomes the TTCP of the other vehicle which is obtained by measuring the time during the simulation runs until the other vehicle reaches this point. The CTG is used to compute the risk of the situation and its conflict point:

$$risk_d = max(0., risk_{max} - \frac{CTG \cdot risk_{max}}{CTG_{max}})$$

where $risk_{max}$ is the maximum number of risk levels and CTG_{max} the highest CTG up to which a risk should be assigned.

5.3.2 Online Risk Adaption

As mentioned before, for assistance systems like the ISS proposed in this work it is difficult to ascertain parameters which are accepted by each driver. A sportier driver could be irritated by a warning signal because of oncoming traffic that arises during his (fast) left turning maneuver since he accepts the available gap as big enough. Whereas, an elderly person would possibly like to be warned in such a situation because he needs more time to perform a left turn within the intersection. Such a drawback can be overcome by an automatic risk assessment adaption for the online case. However, the adaption in the online case cannot be done in the same way as described before for the offline case. As mentioned above, the TTCP of the vehicles is not easy to compute since the trajectories of the involved vehicles are initially not known. On the other hand, the behavior of the driver has to be taken into account in order to do the adaption. For the adaption in the online case it is necessary to compare the computed risk of the system with the risk "felt" by the driver. This means that $risk_d$ of Equation 5.2 becomes the felt risk of the current driver. The challenge is now to estimate how the driver senses the risk of a specific situation. The strategy introduced in this work is as follows:

If a driver always disesteems the suggestion/warning of the assistance system in the car because from his point of view it is not suitable for his driving behavior the automatic risk assessment adaption adjusts to this behavior.

For the extremes like "dangerous" or "not dangerous" it is straightforward to use an adaption strategy like the one shown in Table 5.1.

System Output	**Driver Reaction**	**Adaption**
$risk_r$ = high risk	drive through	$risk_d = 0$
$risk_r$ = high risk	stop	$risk_d = risk_r$
$risk_r$ = low risk	stop	$risk_d = risk_{max}$
$risk_r$ = low risk	drive through	$risk_d = risk_r$

Table 5.1: Online adaption strategy.

This strategy can be explained by rules like the following ones.
First row of Table 5.1:

IF the computed risk is high, but anyhow the driver passes the conflict point without stopping, THEN the risk is changed to a lower risk.

Third row of Table 5.1:

IF the computed risk is low, but anyhow the driver stops in front of the conflict point, e.g. to let an oncoming vehicle pass, THEN the risk is changed to a higher risk.

In order to grade the risk level to more than 0 and $risk_{max}$ it is necessary to include more parameters. For example, the acceleration/deceleration used by the driver when disesteeming the current warning can be translated into a risk level between 0 and $risk_{max}$. However, this is not considered in this work. The proposed strategy can also be used for training the risk assessment from scratch. Like in the offline case there would be a training phase in which the systems shows no risk level output to the user but rather observes the driver's behavior in several typical intersection scenarios. After this training phase the system would switch to its operating phase where the computed risk is shown to the driver.

Chapter 6

Warning Strategies

When developing Advanced Driver Assistance Systems the design of a suitable HMI is a very crucial and challenging task. Without a good HMI design, i.e. if the user does not understand or does not rely on the system output, any underlying algorithm can become useless. HMI design is a very complex research field which solely can fill entire books and can easily create a controversial discussion on which is the best HMI solution. Whole European research projects like Adaptive Integrated Driver-vehicle InterfacE (AIDE) were set up which solely are engaged with the topic of HMI systems for ADAS. The HMI issue was also not neglected in this work and some promising approaches were developed that will be introduced in this chapter.

In [Var98] the HMI is basically described by the type of interactions which is shown in Table 6.1. Since all these kinds of support require or imply a form of dialog of the driver with the system, human factors have to be taken into account when designing the HMI. As already described in Section 1.3.3, the system in this work uses "Warning" as interaction type. As will be seen later in this chapter, this HMI is actually a combination of the "Information" and "Warning" support of Table 6.1. For systems like the one developed in this work, where a risk level is calculated, a strategy has to be found for how to present the result to the driver of the equipped vehicle. The selected HMI should

1. be intuitive, i.e. rapid and easy to understand,
2. be non-distractive, and
3. lead to an action to be performed by the driver that can avoid a critical situation.

It is obvious that a numeric display showing the current risk level is not an adequate mean. But what is an appropriate HMI for an ISS like the one developed in this work? In order to solve this question, a short insight into human factors for traffic safety is given. Based on this, the patented "Continuous Risk Assessment Visualization" (which takes into account important human factors), as well as the "Turn Indicator Modification"' that were developed in this work and implemented into the real demonstrator are presented.

Type of Interaction	**Procedure of Dialogue**	**Role of the driver**	**Examples**	**Physical Means**
Information	Dialogue about the status of the vehicle-traffic system or about a service the driver is asking for	Taking decision about the impact of the information on his / her task and possibly perform an action	Medium range preinformation, RDS-TMC; Travel information	Visual, audio
Warning	Signaling a situation of potential danger or deviation from the intended goal (typically if the driver does not take actions)	Taking decision about the action to be taken and possibly performing it	Collision warning; Driver status monitoring	Visual, auditory, haptic
Advice	Indications about actions to be performed to accomplish a stated goal	Following the advice and take actions or deciding to override it	Route guidance	Display, audio
Control	Parts of the driving task are taken over by the system	Supervising and possibly overriding the system	Adaptive cruise control	

Table 6.1: Different types of HMI (from [Var98]).

6.1 Human Factors Influencing HMI Selection

A big challenge for humans while driving a car is to assess parameters like speed and distance of other approaching vehicles [DO07]. Speed and distance of preceding as well as oncoming vehicles is often misjudged by many drivers. This results in an inability to adequately judge available gaps in intersection crossing scenarios [BM03]. Unfortunately, most of the time just these parameters (speed, distance and available time gaps) are directly linked to the risk level of a certain traffic scenario. Especially at intersections the appraisal of distance and speed is a very important task which sometimes has to be performed in fractions of a second.

When designing and HMI for ISS it is useful to study in advance also the user expectations regarding such a safety system. Therefore, it is even better if the interviewed persons were already involved in an intersection accident. In [HJJS07] drivers with accident experience at intersections sketched their ideas and expectations relating to ISS using the method of structure formation technique. The results of the study show that mainly mistakes of perception are leading to crashes. 95% of these drivers had the opinion that it is reasonable to assist the drivers at intersections in detecting other road users. When analyzing the desired type of assistance, most of the subjects favored acoustic warnings followed by visual warnings.

6.2 Continuous Risk Assessment Visualization

Nowadays Driver Assistance Systems mostly use warning strategies like appearing signals or sounds to alert the driver when a situation gets dangerous, i.e. when the computed risk rises over a defined level, e.g. [MRWC03], [KUA+04]. The system approach which is used in this work is using amongst others a warning interface that visualizes the risk level in a continuous manner for the time of an identified situation that could become dangerous. This way, the driver has a direct visual link to those parameters that are difficult to estimate when perceiving other road users. In order to prepare the driver for a potential dangerous situation at an intersection the presented system gives the driver an estimation of the risk for the current driving situation in advance to the last warning point where the only possibility is an emergency braking. The used technique for showing such graded warnings is similar to a progress bar. Here it shows the rising or decreasing risk for the current driving situation.

Usually, a user of such a driver assistance system is not only interested in the current risk but also in some further information, i.e. for what reason the risk is actually shown. In order to do so, the developed system shows some additional information that is necessary to point out for what kind of assistance function (TA, RoWA, TLA) the risk level is shown. The idea is to use common road traffic signs or slightly adapted ones that every driver of a car is familiar with. This can avoid additional interpretation time by the driver in which he cannot pay full attention to his driving task. In addition to the warning display an acoustic warning is given in order to direct the driver's attention to the assistance function. This can be a simple sound signal or a more complex speech output. The first acoustic sound is raised as soon as the system is activated for a specific situation. A convenient sound and the low risk at the beginning assure that the driver is not surprised and thus not led to an even more dangerous situation. From this time on the driver should be aware of the situation and the risk presented to him through the graphical display. If in spite of all the prior information the driver does not react appropriately a final haunting acoustic sound is raised if the last warning point is reached. Figure 6.1 shows a schematic sequence of the warning starting at the activation of the system up to the last emergency warning.

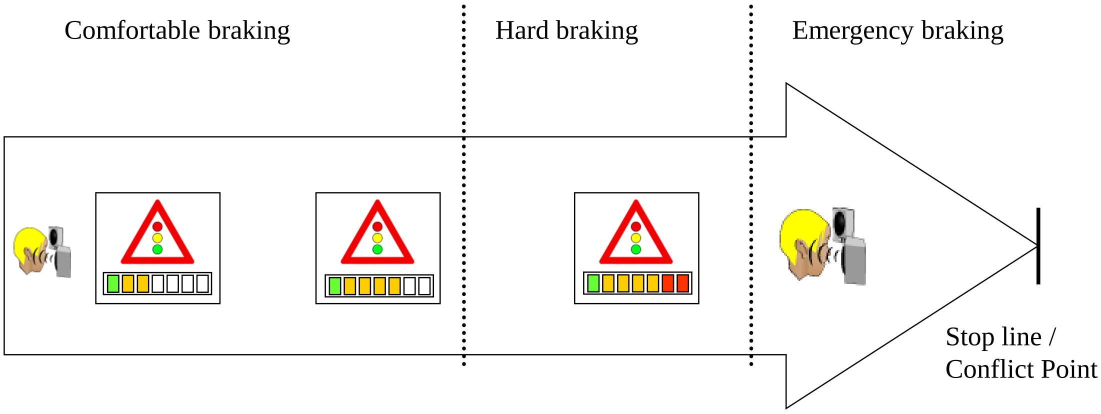


Figure 6.1: Schematic warning sequence.

For the visualization of the computed risk a color bar is used that is divided into seven segments with the colors green, amber and red. During the whole approaching time the driver has the direct link to the risk level computed by the system (i.e. momentous value and derivative). The advantage is that there is no possibility to get surprised by a flashing light that tells him suddenly that a situation gets dangerous. Due to the continuous HMI interface he will be prepared for the situation and can estimate the risk for his intended maneuver more easily by taking his own driving skills into account. This kind of HMI interface is also used for the red light violation-

Figure 6.2: Continuous risk visualization in the dashboard.

warning and the green light recommendation of the TLA. As mentioned before, due to the infrastructural communication approach all relevant data like the status times of the traffic lights are available in the car. However, it is not desirable to show these timings directly to the driver because this could lead to risky driving when approaching a signalized intersection. In fact, the risk assessment HMI can intuitively show the driver if he will safely reach the green light when arriving at the intersection or not. The higher the risk level, the more marginal the time to red light will be. In other words and looking again at Figure 6.1:

1. if the green light is shown the driver will safely reach green light at the intersection with his current driving profile

2. the increasing yellow lights indicate the decreasing remaining time for reaching the green phase

3. showing a red light indicates a red traffic light when arriving at the next intersection

User tests with this HMI concept have shown that it is very convenient for the driver to adapt his driving speed to the status of the risk assessment HMI in order to pass the signalized intersection safely and with smooth traffic flow. A visualization of the real HMI interface in a left-turn example scenario is shown in Figure 6.2. This innovative HMI concept was patented by the author and others under patent [RSSS06].

6.3 Turn Indicator Modification

As mentioned before the design of an appropriate HMI that is intuitive, easy to understand and not annoying or distracting for the driver is a challenging task. In addition to the HMI described before a small and simple innovative concept was developed for this work in order to visualize a potential hazard before a critical turning maneuver in an intersection. This is achieved by a modification of the turn indicator light in the dashboard of the vehicle. Normally, the indicator arrow is flashing in the well known green color. In this work two additional colors, amber and red, were used in order to signal a potential hazard. Intuitively, the red flashing arrow was used in order to signal a forthcoming hazard that makes it impossible to turn while the amber flashing arrow was used to visualize a potential hazard, i.e. a potential conflict that was identified but not yet regarded as critical. The three stages of the turn indicator color modification in the real demonstrator vehicle are shown in Figure 6.3. This simple add-on could also be used for other warning functions like for example a lane changing assistance which helps the driver in finding a safe moment for changing his lane. This additional warning HMI was patented by the author and others under patent [RS05].

Figure 6.3: Modification of the turn indicator color in the dashboard.

6.4 HMI Prioritization

An additional challenge that arises if an ADAS has several parallel working assistance function is the HMI prioritization, i.e. which of the individual HMI outputs for each assistance function should be displayed to the driver so that he will not be overloaded by too many information at the same time. In an intersection where the driver of the

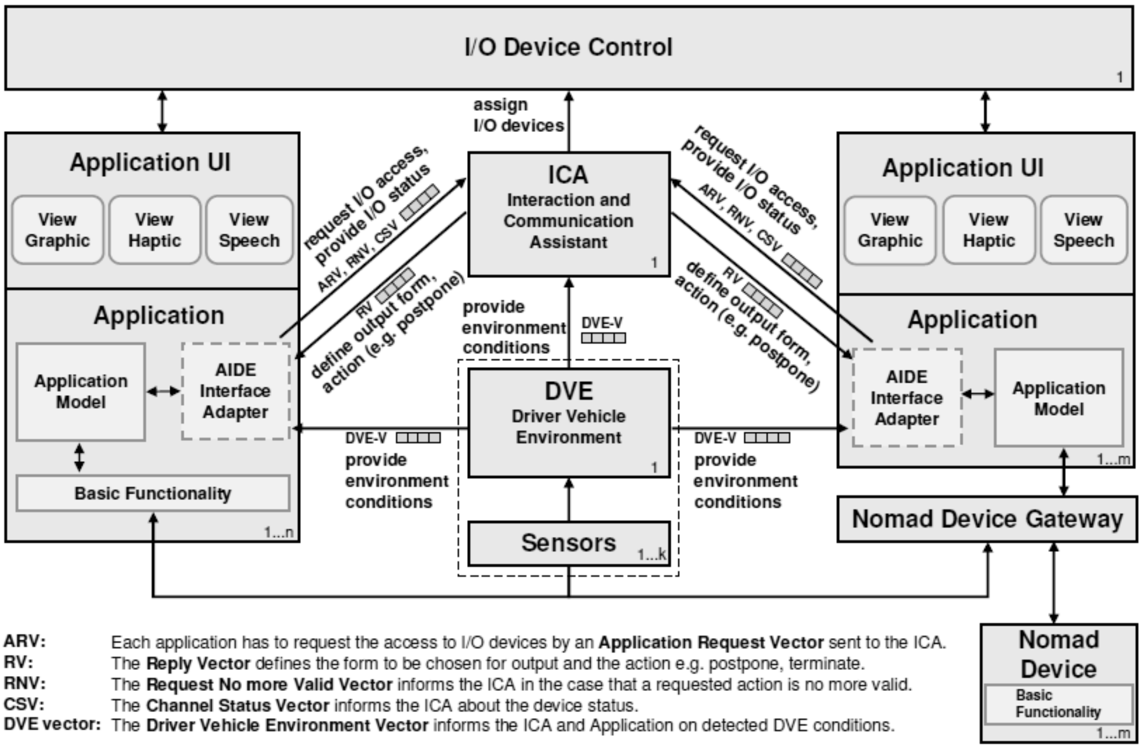


Figure 6.4: AIDE functional reference architecture (Source: [GSB+08]).

assisted vehicle intends to turn left, there could be e.g. two additional vehicles (one from the right and one from straight ahead) approaching the intersection. This could result in the TA and the RoWA to be activated and to generate individual warnings to the driver. In [GSB+08] an architecture is proposed that is controlled by two core elements, the Interaction and Communication assistant (ICA) and the Driver Vehicle Environment (DVE) modules (see Figure 6.4). The ICA has the main responsibility for HMI management functionality. It determines the global system behavior towards the user taking into account information gathered about the driver and the environment by the DVE modules. The DVE modules are also used by the applications in order to adapt the application specific functionalities. Since the developed system is based on individual risk level computations which use the same algorithmic basis and thus are comparable to each other, the solution for the ISS becomes straightforward. The ICA in this case chooses the function with the actual highest risk level to be displayed to the driver. Under normal operation this also assures that the visualization of the risk level as described in Section 6.2 always is a continuous color bar without any jerky leaps. The only issue that has to be assured by the ICA is that no frequented toggle between two or more of the attributive information displays (see Section 6.2) occur if they have similar risk level. This is solved by a simple hysteresis on the individual risk level. Figure 6.5 shows this selection based on two sample risk functions. As user tests which are further discussed in Section 7.3.2 will show, the above described HMI that was well accepted by the drivers of the system.

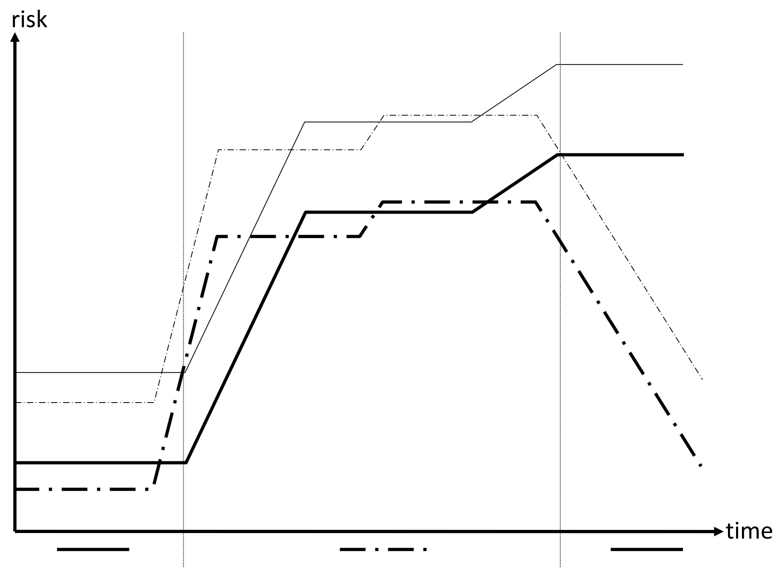


Figure 6.5: Example for the selection of risk functions. Each of the two individual functions has an additional hysteresis value. Only if one risk function becomes higher than the hysteresis value of the other risk function it is selected. Below the time axis the current selected risk function is shown.

Chapter 7

Experimental Results

This chapter describes the experimental results that were achieved by the different test procedures performed for this work. The experiments were carried out within the simulation environment and in the real demonstrator. Special test concepts were developed for the simulation that were used in order to separately test the different modules of the system. Furthermore, user tests were carried out in order to evaluate the acceptance of such a new ISS as well as the warning strategy concepts, i.e. the HMI. Therefore, a set of subjects was asked to drive the demonstrator in order to experience the assistance function. After the test drives they were asked to fill in a prepared questionnaire. The overall system performance was crosschecked against the results from the simulation tests.

7.1 Testing Measures

Global measures for testing an ADAS are the number of false alarms of the system. When talking about potential false alarms of an ADAS it is a common approach to differentiate between two kind of errors:

False Positive – Type 1 Error The application generates a warning although there is no current critical situation. As an example the host vehicle intends to turn left and the system generates a warning even if there was no oncoming vehicle or there was an oncoming vehicle but the driver behaved appropriately because he already recognized it.

False Negative – Type 2 Error The application generates **no** warning although there is a current critical situation. For the TA this would mean that the driver does not recognize an oncoming vehicle and starts to turn left and the system generates no warning which leads to a dangerous situation.

As an overall measure of quality of an ADAS the Correct Alarm Rate (CAR), the False Positive Alarm Rate (FPAR) and the False Negative Alarm Rate (FNAR) can be evaluated. It is obvious that the false negative errors are the most problematic errors for an ADAS since such a false behavior can easily result in a very dangerous situation, e.g. an accident. Nevertheless, a lot of false positive errors in a warning system will sooner or later result in a very annoyed driver and therefore in a reduced appraisal of the whole system. For an automatic ADAS even a false positive error can result in a dangerous situation, e.g. if the vehicle suddenly performs an emergency braking even if there is no dangerous situation at all and another car is close behind this vehicle.

7.2 Simulation Test Concept

There are several methods to test the correct functioning of a system by means of simulation. If the dimension of the state space is not too high a brute-force algorithm could test all possible states. Since this is not true in most cases a reduction of the state space has to be performed. Probabilistic methods are often used for very complex problems. Typically, probabilistic algorithms randomly generate states that are analyzed in order to get a statement on the whole system. One approach that uses this methods to analyze Driver Assistance Systems is described in [GSV05]. The disadvantage of such methods is that the reliability of a system cannot be fully guaranteed. If the states are limited only to the worst case scenarios of an application, the state space can often be reduced drastically so that a complete test becomes possible. The only drawback is that this approach is susceptible to pessimistic results. In the proposed ISS the final warning is highly dependent on the behavior prediction

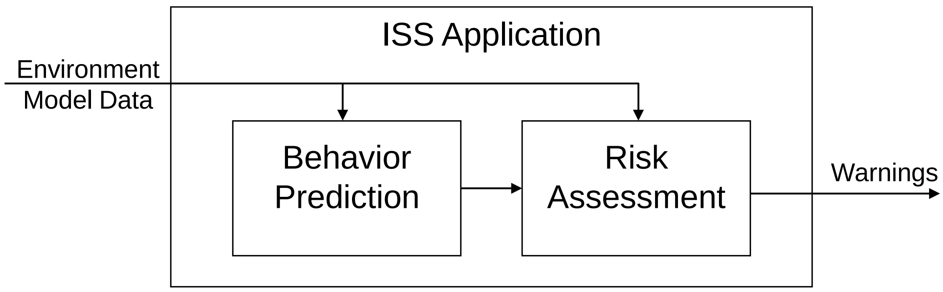


Figure 7.1: Different modules to be tested for correct functioning.

module that computes the plans for the own and all other vehicles (see Figure 7.1). If the application would be tested only against its warning outcomes it would not be possible to judge if a potential error has resulted from a wrong behavior prediction or if the risk assessment performed wrong. Therefore, the system can be separated into two different modules where each of them can be tested individually and the different results are combined later. With this procedure the analysis becomes more clear and the state space is reduced. In the following the different test concepts for each module are presented.

7.2.1 Warning Module

In order to test only the risk assessment module of the whole ISS it is important to fade out the behavior prediction algorithms. It is assumed that the behavior of each traffic participant is well known in every situation. This is a big advantage of the proposed system with its simulation integration. Within the simulation the plan of each traffic participant is well known at each point in time. Since the structure, i.e. the MiB, of the behavior of the traffic participants is equal for the simulation and the online application, the prediction module can be neglected in this case and the plans of the simulation serve as input for the risk assessment module (see Figure 7.2). In this case the test results are not influenced by possible false behavior prediction results.

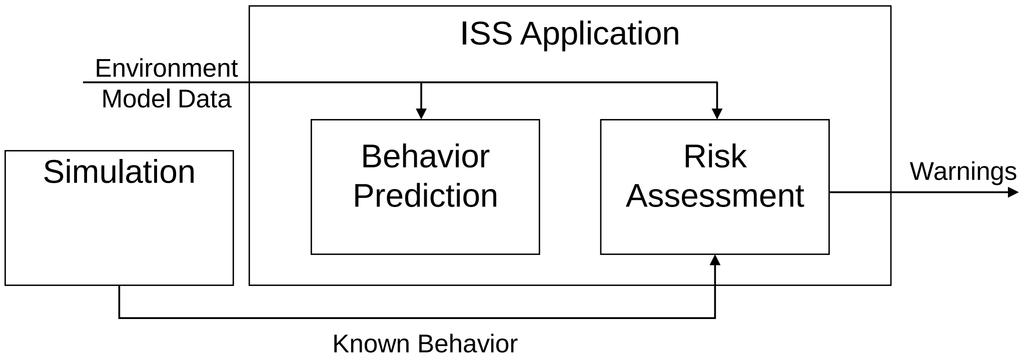


Figure 7.2: Test concept for the warning module.

State Space Reduction

The idea for a state space reduction is to divide each situation at an intersection into two-object scenarios. Figure 7.3 shows an example for such a separation. It is assumed that if the warning module is working well for the separated situations it is also working for the initial scenario, since it is a combination of them. In addition, each scenario with traffic lights is translated into a corresponding scenario with (dynamic) traffic sign regulation (see Section 4.6.2). It is important to extract all relevant and representative scenarios for the ISS as proposed in this work. They should cover the whole spectrum of conflict situations that can occur at an intersection. A similar extraction is done in [Tra01] but in this work a more detailed formulation is

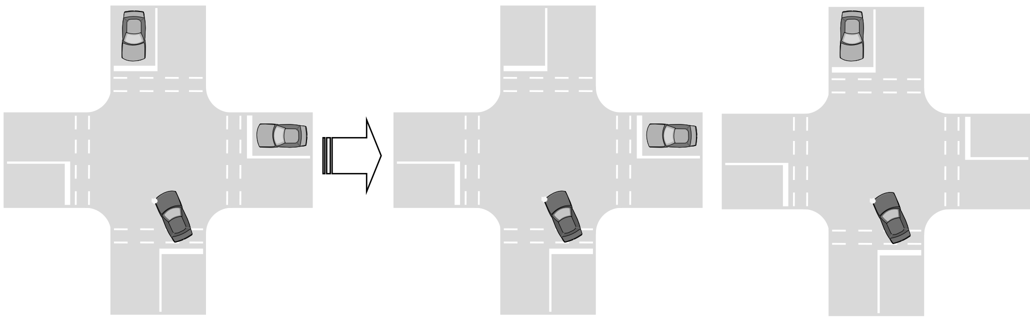


Figure 7.3: Separation of scenarios with 3 objects into 2 two-object scenarios.

needed. Considering all possible intersection situations it can be seen that the number of possible conflicts can be reduced to 14 different cases. Table 7.1 shows all of them. The field *Traffic Regulation* indicates the traffic rule for the host vehicle while

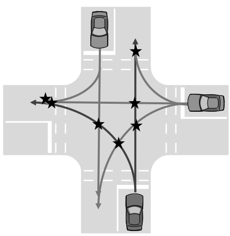
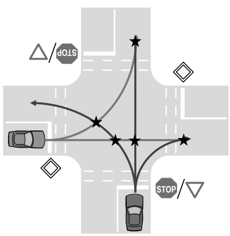
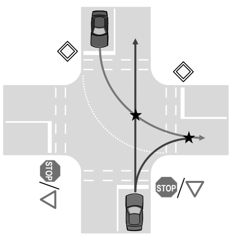
Traffic Regulation	**Opponent Location**	**Host Vehicle Intention**	**Opponent Intention**
	right	left	left
		left	straight
		straight	left
		straight	right
		straight	straight
	ahead	left	right
		left	straight
	left	left	left
		left	straight
		right	straight
		straight	left
		straight	straight
	ahead	right	left
		straight	left

Table 7.1: Conflict scenarios for testing of the ISS.

Opponent Location is the relative location of the opponent vehicle with respect to the host vehicle. *Host Vehicle Intention* and *Opponent Intention* refer to the driving intentions of both vehicles at the intersection.

Strategy

In order to test the situations defined above with the simulation, the host and the opponent vehicle are placed in an appropriate distance to the intersection. This distance must be greater than the overall stopping distance of both vehicles. As described in Section 3.3.1, the two vehicles are driving at constant velocity only reducing their speed if they are going to turn (rudimentary behavior). The ISS application is assigned to the host vehicle while the application feedback (see Figure 3.13) is intercepted by the test module. Table 7.2 shows the situations for which the different error types have to be tested. In order to test all possible conflict scenarios with the

		Opponent Vehicle		
		Right-of-Way	**No Right-of-Way**	**Absence**
Host Vehicle	**Right-of-Way**		False Positive	False Positive
	No Right-of-Way	False Positive/ Negative		False Positive

Table 7.2: Error types for ISS scenarios.

suggested approach the velocities of the vehicles are varied in a range that is typical for intersections. The simulation is run as for the risk assessment adaption described in Section 5.3.1. Therefore, not only the occurrence of a warning but also its timing is analyzed. As described in Section 2.2.4 the warning should be shown to the driver at a distance $D \geq D_{warn}$ to the conflict point. The decision if a warning should be shown or not is achieved by analyzing the CTG value as presented in Section 5.3.1. As a border for this value a minimum of 1.5s is taken according to [vdHH93] where no warning is shown. In addition to the 14 scenarios of Table 7.1, it has to be analyzed if the ISS application does not warn for the 14 *inverse* scenarios, i.e. for the view of the opponent vehicle. This can be done easily with the presented approach. Since it is possible to equip all vehicles in the simulation with appropriate applications (see Section 3.3.1), the ISS application is also assigned to the opponent vehicle. So for each of the 14 scenarios it has to be verified that there is no warning for the opponent vehicle.

Results

Here some exemplarily chosen results of the warning module tests are shown. Figure 7.4 demonstrates the 3-D graphs that are used for visualization of the results.

The starting velocities of both vehicles are plotted against the CTG for the potential

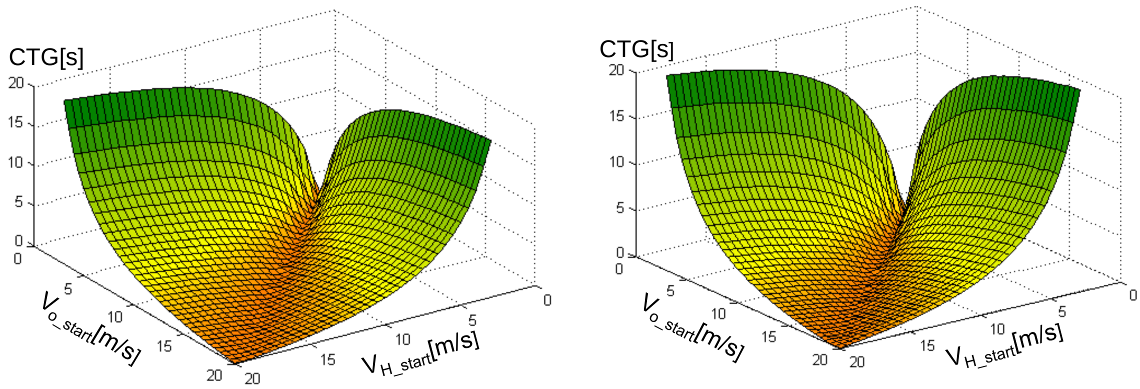


Figure 7.4: CTG visualization for RoWA straight crossing path scenario with other vehicle coming from left and right, respectively.

conflict. The application has to warn in situations where the minimum CTG of 1.5s is not reached. On the other hand, for situation where the CTG is greater it should not warn. For this definition one has to define what a warning is for the ISS developed in this work. As described in Chapter 6 a continuous level visualization was used

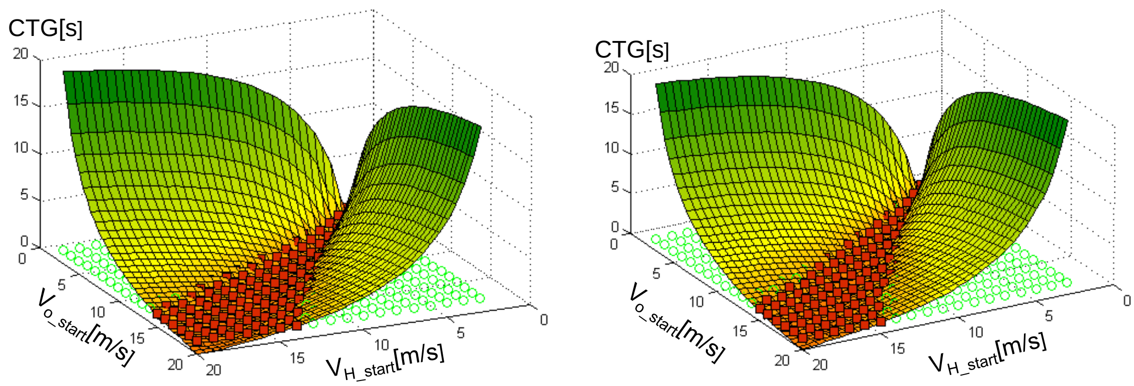


Figure 7.5: Visualization of the system warnings for the scenarios of Figure 7.4. Warnings are expressed by red dots, no warnings are shown as green dots.

in order to express the current risk of a specific situation. The big advantage was amongst others that there is no suddenly appearing signal that shows a hazardous situation. Nevertheless, for the evaluation of the warning module one level has to be selected from which on the risk is regarded as a warning. This was set to the last amber section before the red segments, i.e. risk level five. The situations where the application has generated a warning are marked with red dots in the graph so that they are forming a plain. In the case of no warning, a green dot is used (see Figure 7.5). In the ideal case, the plain should exactly fill the CTG graph at a value of 1.5s. As can be seen in the 2-D projections of Figure 7.5 on the velocity-axes shown in Figure 7.6, the ISS application performed very well in the tested scenario.

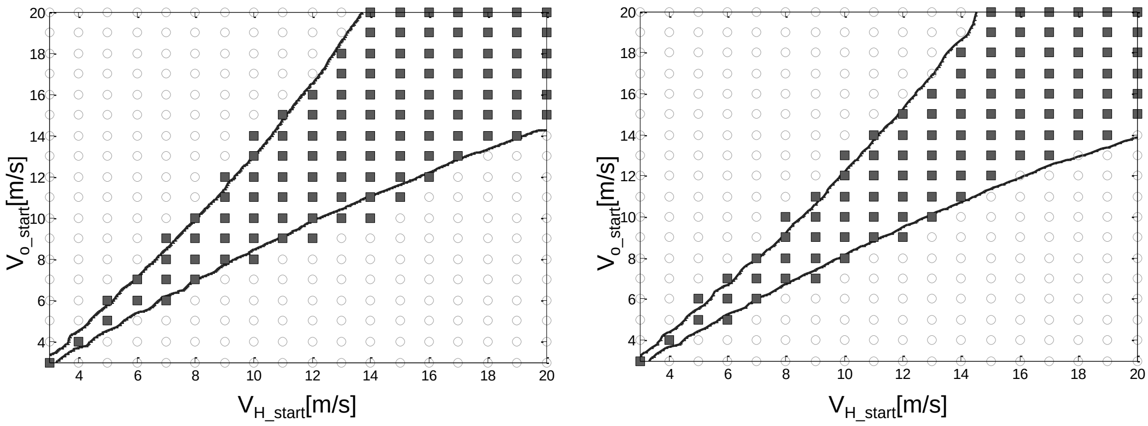
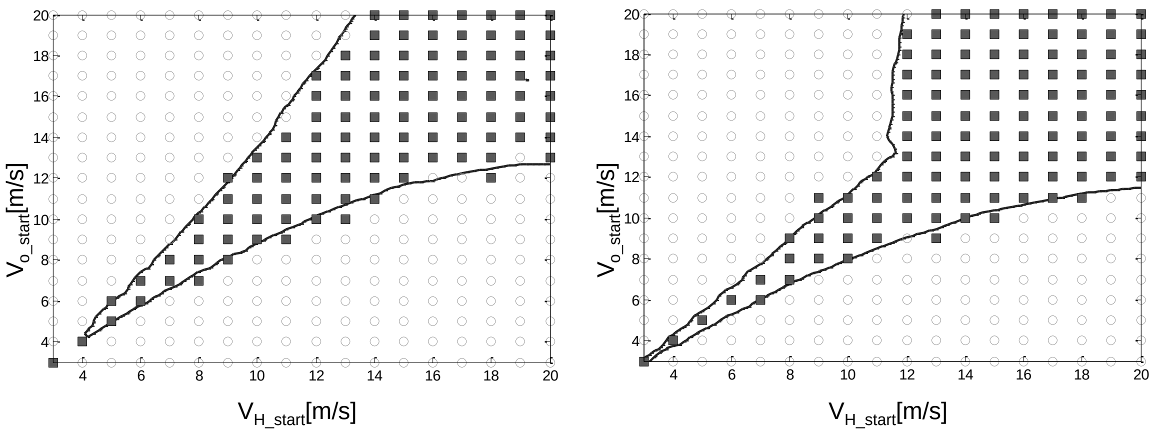


Figure 7.6: Projection of the graphs of Figure 7.5 on the velocity-axes.



(a) Left turning with lateral traffic from left.

(b) Left turning with oncoming traffic.

Figure 7.7: Warning results for two scenarios of the TA.

An additional scenario that was tested is the left turning in the TA. As can be seen in [ROS+05b] these accidents are very important regarding all intersection accidents.

Figure 7.7 shows two of those accident types. In Figure 7.7(a) a left turning scenario with lateral traffic from the left is shown, while in Figure 7.7(b) the host vehicle is turning left with an oncoming vehicle. Also in these scenarios the inverse case was tested and it resulted in no warning for the opponent vehicle. With the described kind of evaluation and visualization it can be seen if a necessary warning is generated by the system as well as if it is raised in due time. Of course, this is a very important factor. Furthermore, it is of interest if the continuous risk level computation is performing well. Otherwise, the system could also simply use one warning level which, as described before, is not a desirable solution. Figure 7.8 shows the different risk level for the left turning scenario. It can be seen that it forms a good continuous hill

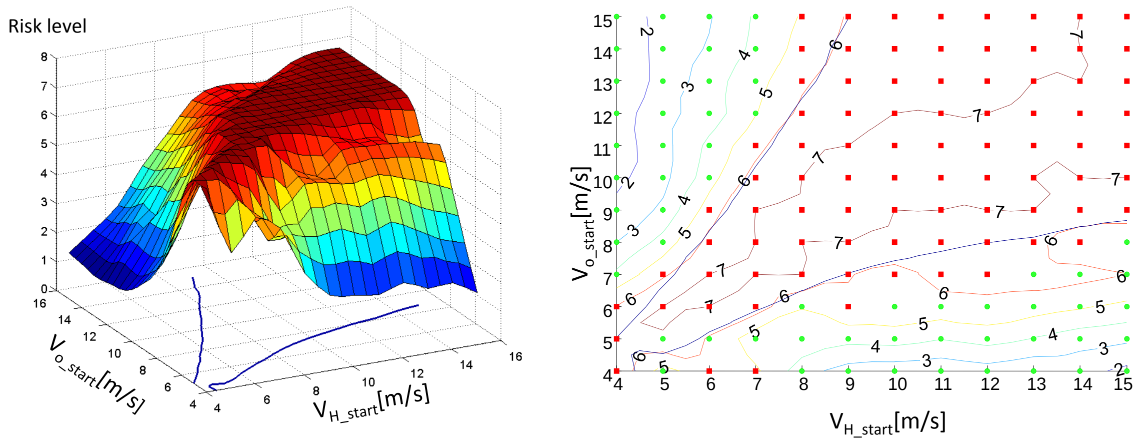


Figure 7.8: Visualization of the risk level computation in the left turning scenario. On the left the two-dimensional risk level is presented. On the right a projection of the seven risk levels to the velocities plane is shown.

with the maximum in the important warning area.

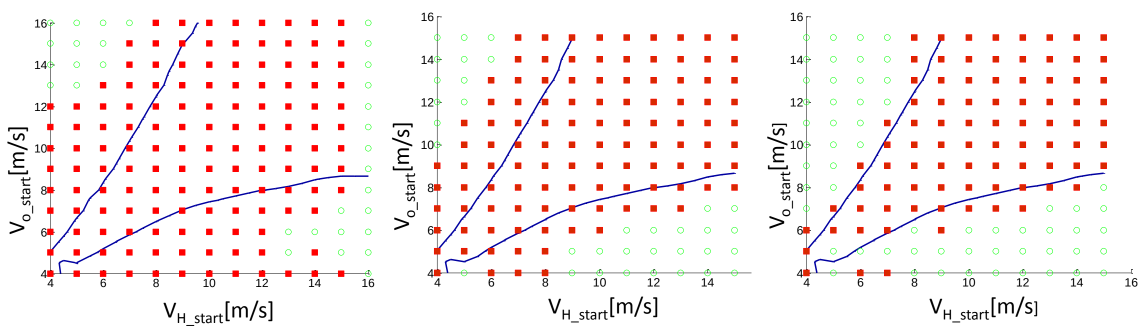


Figure 7.9: Sequence of warning module analyses during adaption phase.

Adaption

In order to show the results of the adaptive risk assessment as described in Section 5.3 the same visualization means as described in the previous section can be used. For this purpose, the analysis of the warning module is performed after each learning cycle with separated training and evaluation data sets. Figure 7.9 shows a sequence of individual warning module analyses. As can be seen, over time the red markers reduce more and more to the desired warning region of the projected images (as described above).

7.2.2 Behavior Prediction Module

The here described module tests the behavior prediction capabilities of the proposed system. As described before, the ISS is capable of predicting the driving behavior of all relevant objects in the current scene. In Section 4.5.3 it was shown, that it is normally easier to predict the behavior of the host vehicle since there is much more (sensor) data available than for the other objects within the intersection. In the simulation this is not the case, i.e. the information is the same for all vehicles. Nevertheless, one can omit specific data fields in order to reach a realistic representation of the environment. Because this module solely tests the behavior prediction capabilities, the warning generation of the ISS can be turned off or skipped (see Figure 7.10). Furthermore, a state space reduction to one-object scenarios is performed in this module, so that there is no warning for the host vehicle at all.

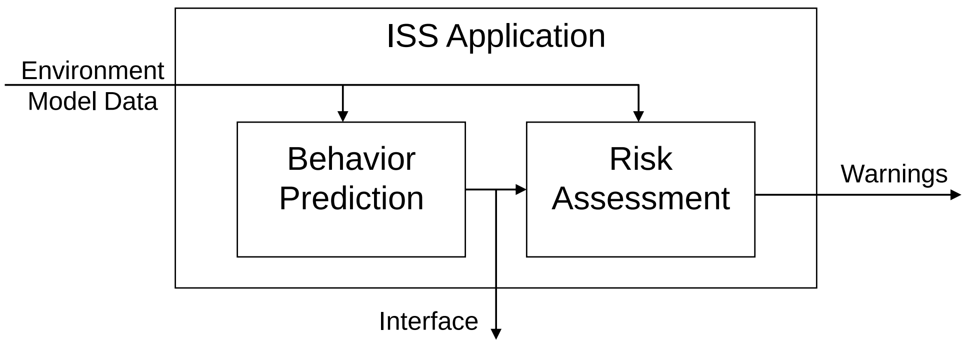


Figure 7.10: Test concept for behavior prediction module.

State Space Reduction

The performance of the behavior prediction of the ISS is highly dependent on the topology of the considered intersection. There can be a single lane for all driving directions or separate lanes for different directions. Since the rudimentary behavior of all vehicles is independent of the existence of other vehicles the scenarios are separated into one-object scenarios. Due to the ideal sensor system in the simulation it is sufficient to test all scenarios only with the simulated host vehicle. It is possible to omit specific data (e.g. the information about the turn indicator) in order to cope with the other vehicles. Similar to the testing of the warning module, all the 14 conflict points described in Section 7.2.1 are considered also in the behavior module testing.

Strategy

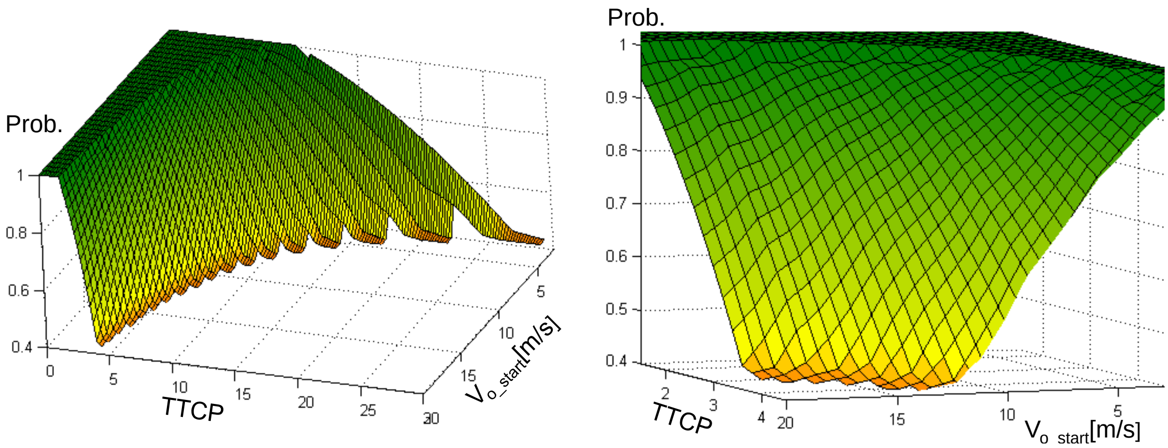
The host vehicle is placed in an appropriate distance in front of the intersection. The velocity is varied in a range from $3\frac{\mathrm{m}}{\mathrm{s}}$ to $20\frac{\mathrm{m}}{\mathrm{s}}$. In each run of the simulation the vehicle is driving up to the considered conflict point. During such a simulation run the required data is collected for later analysis. These are mainly the actual system time, the probabilities of the behavior prediction and the actual distance to the conflict point. One important measure for the evaluation of the system performance is the fact to which grade the behavior was predicted at the last possible point of warning D_{warn}. From the collected simulation data the TTCP is known for each D_{warn}. A situation is considered to be dangerous if the CTG in the moment when the host vehicle is at D_{warn} reaches a defined value. This value is set as a minimum acceptable gap to 1.5s (see [vdHH93]). At least at this stage it is important to analyze the predicted behavior of the host vehicle and the other traffic participants correctly.

Results

Here, some exemplarily chosen results from the analysis of the behavior prediction module are shown. The chosen scenarios are the same as described in Section 7.2.1. Two different layouts of the intersection were chosen:

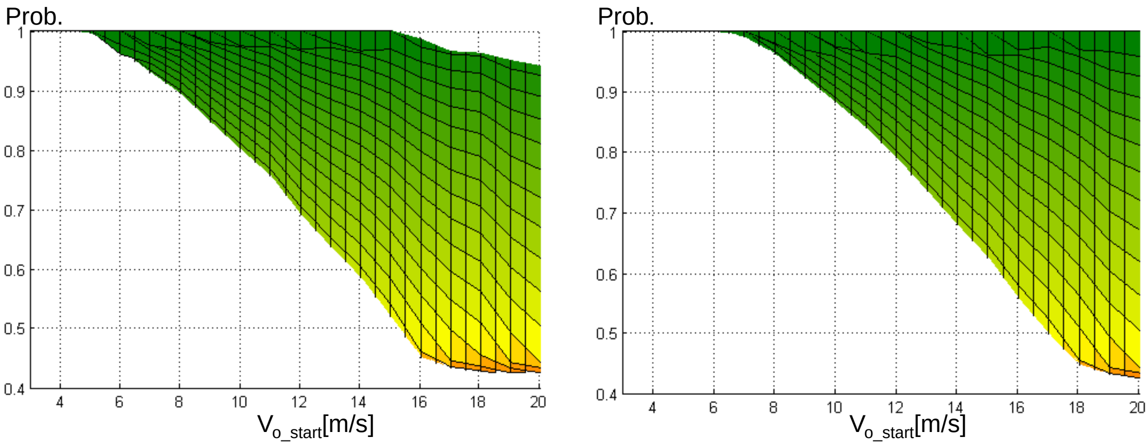
1. intersection with only one approaching lane
2. intersection with separate approaching lanes for each direction

In each case the intersection was considered to be symmetric in its layout of the approaching lanes. Figure 7.11 shows the probabilities for the host vehicle to go straight in the RoWA scenario where a vehicle is coming from the left. The analysis of the other vehicle's probabilities at D_{warn} is an extract of Figure 7.11(a). E.g. if the TTCP of the host vehicle at D_{warn} is 3s a TTCP range in the interval $< 1.5\text{s}; 4.5\text{s} >$ for the other vehicle has to be considered as being dangerous. This is shown in Figure 7.11(b). A projection of Figure 7.11 in the probability-velocity plane allows an analysis of the worst case situation of the behavior prediction module. This is shown in Figure 7.12. Especially in intersection scenarios with only one approaching



(a) (b)

Figure 7.11: Probabilities for going straight in the RoWA scenario and vehicle coming from the left.



(a) (b)

Figure 7.12: Projection in the probability-velocity plane for the RoWA scenario with (a) other vehicle coming from the left and (b) other vehicle coming from the right.

lane, the turn indicator is expected to bring additional performance in the prediction of the driving behavior. From the speed profile alone it is not possible up to a specific point in time to accurately predict if the vehicle is going to turn left or right without the turn indicator state known (not observed). This fact can be seen in Figure 7.13.

From Figure 7.14 it can be seen that a not observed turn indicator is not the same as an indicator that is observed but turned off. An observed turn indicator that is

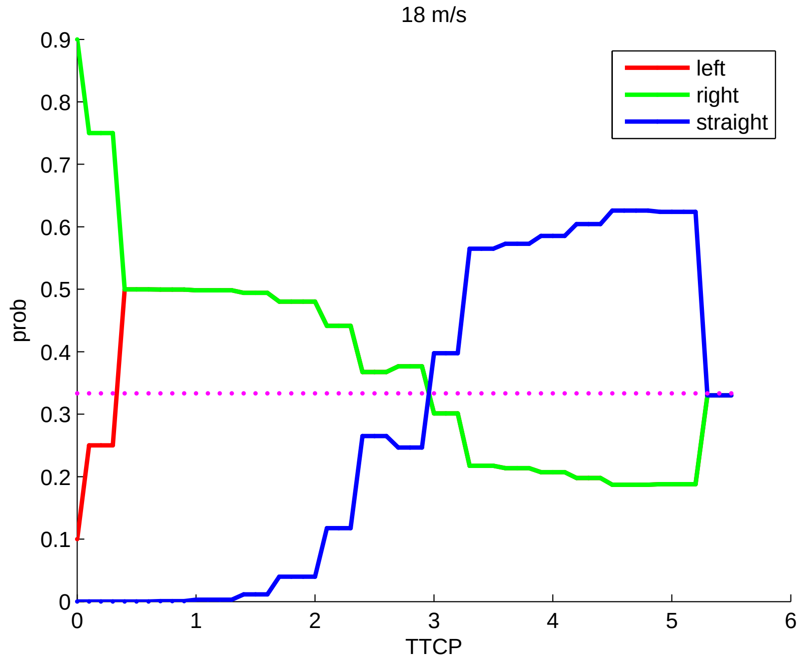
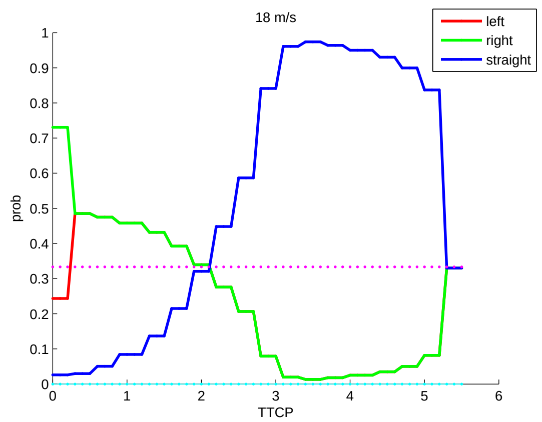
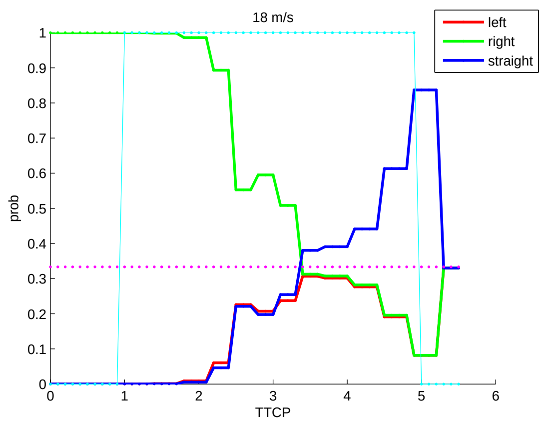


Figure 7.13: Probability for right turning with indicator not observed for an intersection without separate turning lanes.



(a) Indicator observed and turned OFF.



(b) Indicator observed and turned ON.

Figure 7.14: Probability for right turning with observed indicator at intersection without separate turning lanes.

turned off increases the probability of a vehicle to go straight over the intersection. If the driver of a vehicle forgot to turn on the indicator while intending to turn right the correct behavior will be recognized later as shown in Figure 7.14(a). As soon as the indicator is turned on correctly (right indicator for turning right) the performance of the behavior prediction increases drastically as shown in Figure 7.14(b).

7.3 Real World Testing

As part of the INTERSAFE project (see Section 1.2) wherein the system described in this work was used, real world tests were performed together with the “Institut für Kraftfahrwesen Aachen (ika)” in order to judge the performance of the demonstrator vehicle. Therefore, a test intersection was constructed that follows the German guidelines for the construction of intersections [SL97]. This was necessary since the usage of a “real” public intersection is quite cost-intensive because the required intersection needs to be closed for public traffic in order to not endanger other traffic participants for the time of the testing. On the other hand one needs a “clean” surrounding so that all tests can be performed target-oriented. In the real world testing it was not possible to separately test the individual modules of the application like it was done with the simulation. Here, only the final output (warning) to the driver was evaluated. This is a sufficient procedure since the user is experiencing the final HMI and is not interested in the individual modules. The testing procedure was separated into three different tasks:

1. sensor tests
2. system tests
3. user tests

These tasks are directly related to the general architecture as shown in Figure 1.2. The working point of each testing step is illustrated in Figure 7.15. The sensor tests were performed in order to analyze the performance of the used sensor system and the suitability for ISS applications. Since the sensors itself are not in the focus of this work, this testing procedure is not further described. The only thing that can be mentioned is that it turned out that the sensors and the kind of integration is well suited for general ISS applications. The last two testing schemes will be described a little bit more detailed as they are directly linked to the application developed here. The performed testing is very innovative since it was the first known testing of a real demonstrator vehicle equipped with an ISS application in the field of ADAS. As mentioned before, the real world testing does only test the application against its final outcome, i.e. warning or no warning. A separation due to the different application modules as performed in the simulation test concept (see Section 7.2) was not performed within the demonstrator vehicle. Therefore, the analysis of a

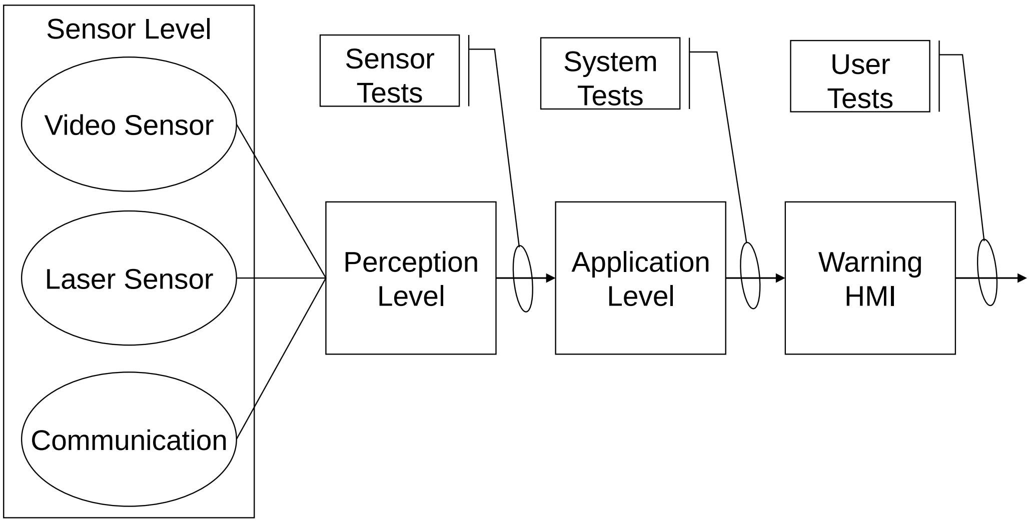


Figure 7.15: Working points of the real world testing.

potential false alarm is not that easy, i.e. to figure out where the false alarm comes from, and for this reason can only be speculative.

7.3.1 System Tests

The system tests analyzed the overall performance of the demonstrator vehicle for different scenario setups. Warning timings and false alarm rates were considered. For each addressed scenario that was described in Section 2.2 several tests were performed.

Testing of the Turning Assistance

The TA was tested with two vehicles. The host vehicle which approaches the intersection intends to turn left and is faced to another oncoming vehicle. This vehicle can either represent a potential conflict for the host vehicle (see Figure 2.3) or itself intend to turn left so that no alarm should be raised. Different dynamic behaviors of the host vehicle were analyzed:

Starting Up – Warning Situation The host vehicle stands still before the left turn and suddenly starts its turning maneuver across the path of the oncoming vehicle. This is motivated by a prior stopping in front of a red traffic light or a stopping because the driver let other oncoming vehicles pass before starting its turning maneuver. The start-up testing was always performed for a situation where a warning should occur.

No braking – Warning Situation The host vehicle approaches the intersection with constant speed and without (or very late) braking. The oncoming vehicle always drives so that a warning should be raised.

Braking – No-Warning Situation The host vehicle approaches the intersection and decelerates in order to let another oncoming vehicle pass. In this situation there should be no warning since the driver behaves like he correctly recognized the other car in the front.

Table 7.3 shows a summary of the performed tests for the TA with the dynamic behavior stated above. The last row shows the no-warning situation where both vehicles intend to turn left and therefore no conflicts occur. In total 44 test runs

Host behavior	**Opponent intention**	**Host speed** $[\frac{km}{h}]$	**Situation**	**# correct behavior**	**# wrong behavior**	**CAR**	**FNAR**
No braking	straight	30	warning	7	0	100%	0%
No braking	straight	50	warning	7	0	100%	0%
Braking	straight	30	no warning	6	1	86%	0%
Braking	straight	50	no warning	5	2	71%	0%
Start up	straight		warning	11	0	100%	0%
No braking	left	30	no warning	5	0	100%	0%

Table 7.3: Test results for the TA.

were performed. For 41 test runs the system behaved correctly while in three runs a false alarm occurred. As a summary it can be stated that an average CAR of 93%, an average FPAR of 7% and an average FNAR of 0% was reached. A very positive result is the FNAR of 0% since those false alarms are the most problematic ones as stated in the beginning of this chapter. The false alarms during the TA testing most likely occurred due to a not optimally adapted risk assessment. The TA was trained with the simulation and a standard DM and was not adapted to the driver who drove the host vehicle during the system tests. As stated by this driver in the cases of the happened false alarms he braked very lately which was most likely different to the assumed DM during testing.

Testing of the Right-of-Way Assistance

For the testing of the RoWA a similar setup as for the TA was used. The host vehicle is approaching the intersection or stands still in front of it while another vehicle is approaching either from the left or the right side on the main road, i.e. it has the right-of-way. Again the different types of errors were analyzed. The results are shown in Table 7.4. A total of 54 test runs were performed for the RoWA where all of them

Host behavior/ intention	**Opponent from**	**Host speed** $[\frac{km}{h}]$	**Situation**	**# correct behavior**	**# wrong behavior**	**CAR**	**FNAR**
No braking/ straight	left	30&50	warning	6	0	100%	0%
No braking/ left	left	30&50	warning	5	0	100%	0%
No braking/ right	left	30&50	warning	6	0	100%	0%
No braking/ straight	right	30&50	warning	6	0	100%	0%
No braking/ left	right	30&50	warning	5	0	100%	0%
Standing	left&right		no warning	8	0	100%	0%
Start up/ straight	left&right		warning	6	0	100%	0%
Braking/ straight	left&right	30	no warning	6	0	100%	0%
Braking/ straight	left&right	50	no warning	6	0	100%	0%

Table 7.4: Test results for the RoWA.

were treated correctly by the system. This results in an average CAR of 100% and consequently in an average FPAR and FNAR of 0%.

Testing of the Traffic Light Assistance

The last system test analyzed the behavior for the scenarios with traffic lights. Again different dynamic behaviors of the host vehicle were analyzed. In contrast to the tests of the TA and the RoWA only the host vehicle was on the intersection for the testing of the TLA. As can be seen in Table 7.5 again good results with an average

Host behavior	**Traffic light status**	**Host speed** $[\frac{km}{h}]$	**Situation**	**# correct behavior**	**# wrong behavior**	**CAR**	**FNAR**
Standing	all 4 phases		no warning	40	0	100%	0%
Start up	red		warning	8	0	100%	0%
Start up	green		no warning	7	0	100%	0%
Start up	red yellow		no warning	7	0	100%	0%
No braking	red	30&50	warning	16	0	100%	0%
No braking	green	30&50	no warning	17	0	100%	0%
Braking	red	30	no warning	6	2	75%	0%
Braking	green	30	no warning	7	0	100%	0%
Braking	red	50	no warning	1	6	14%	0%
Braking	green	50	no warning	8	0	100%	0%

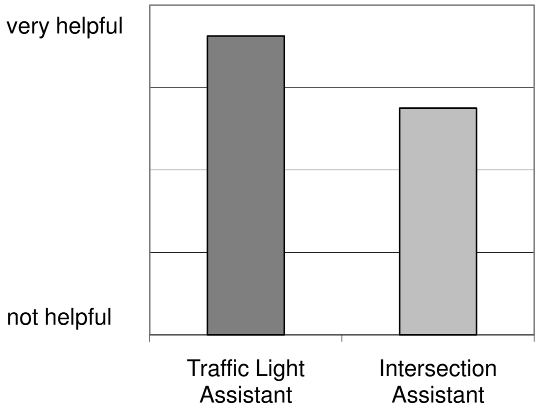
Table 7.5: Test results for the TA.

CAR of 94%, an average FNAR of 0% and an average FPAR of 6% could be achieved. The relative high FPAR in the situation when the host vehicle braked in order to stop in front of the red light can be explained again by a not correctly adapted risk assessment like in the testing of the TA.

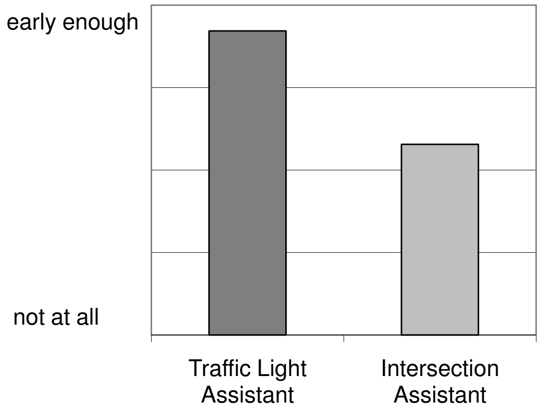
7.3.2 User Tests

As mentioned in the beginning of this chapter, user tests were carried out in order to analyze the acceptance of the developed ISS by "normal" drivers. Therefore, a set of 16 subjects was asked to drive the demonstrator for all the different scenarios and to fill in a questionnaire at the end. For this user tests the different assistance functions were grouped into two applications. The first was called the "Intersection Assistant" which covers the TA and RoWA while the second one was named "Traffic

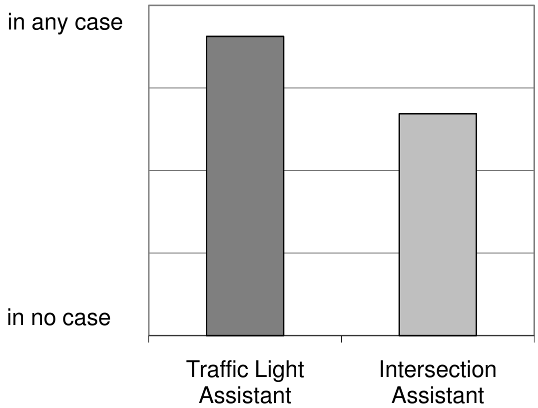
Light Assistant" that covers the functions of the TLA. This separation was made in order to compare the different parts of the ISS to each other. Figure 7.16 shows some of the result from the users' evaluation of the system. The subjects should rate the different questions within a scale from one to five. In Figure 7.16 the median values out of all answers are listed. Figure 7.16(a) displays the general users' evaluation of the whole system. The subjects could rate the applications in a scale from *not helpful* to *very helpful*. As it can be seen, both applications are rated helpful up to very helpful. The Traffic Light Assistant is rated even more helpful than the Intersection Assistant. This can be explained with the informative concept of the application. Since in daily driving one is faced more with red traffic lights than to dangerous traffic situations at intersections the knowledge of the timing of the traffic lights or the speed recommendation for reaching the green light is rated more helpful than an application for solely safety reasons. Asking the subjects how far before a critical situation the system indicates a potential danger to the driver they judged the Traffic Light Assistant better than the Intersection Assistant as can be seen in Figure 7.16(b). This is due to the very exact and early information gained by wireless communication rather than the information of the on-board sensors. This fact is also reflected in the estimation of the possibility to brake in good time after the warning as shown in Figure 7.16(c). Nevertheless, a good functioning is assigned to both applications. Considering the information of the HMI, a good comprehensiveness is assigned to both functions as well as an easy to understand design of the warning signs (see Figure 7.16(d), Figure 7.16(e)). The number of warning steps is not rated as too little as well as not too much but with a small tendency to the latter one as can be seen in Figure 7.16(f). This is reflected also by a comment that was given by one subject, that it is not clear why two red steps were used in the color bar of the HMI.



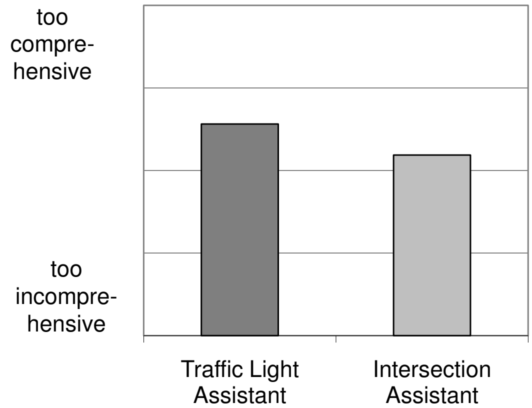
(a) Users' evaluation of the system.



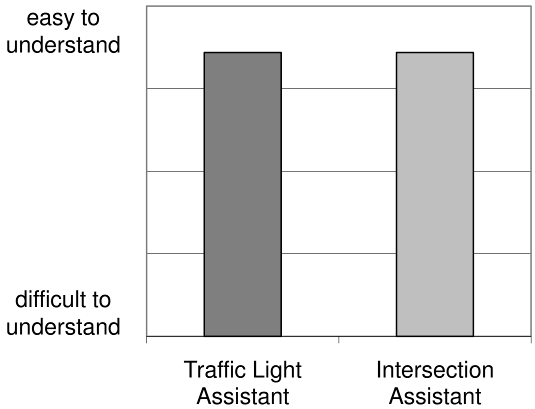
(b) Indication of potential danger.



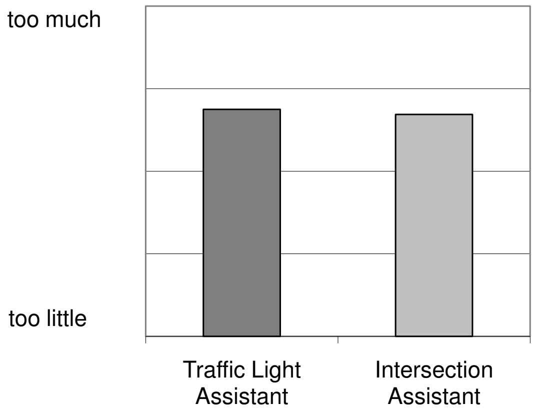
(c) Possibility for braking after the warning.



(d) Information content of the display.



(e) Design of warning signs in the display.



(f) Number of warning steps in the display.

Figure 7.16: Detailed users' evaluation results.

Chapter 8

Summary and Outlook

Intersection Safety is a very hot research topic. Nearly every automobile manufacturer and also some of the suppliers have recognized that future ADAS have to deal to some extend with the topic of ISS. This is mainly due to the fact that intersections are a black spot in term of vehicle accidents. When thinking of the development of such systems the need for adequate sensor systems and also suitable situation analysis and risk assessment algorithms rise. This work has shown a promising approach for all of the tasks that need to be solved in order to build a comprehensive ADAS for ISS.

Starting with the identification of the most important accident configurations at intersections, the systems requirements for an ISS were derived. It was shown that a broad field of view around the front of the vehicle is needed in order to cope with all of the most relevant intersection scenarios. Based on these system requirements the ISS demonstrators were designed. This includes an independent on-board demonstrator vehicle, the extension of infrastructure sensing and communication means as well as a simulated system for development and testing support. For all of these demonstrators, a common generic architecture for modeling of the intersection environment based on a LMD was developed. Within this environmental model the application driven simulator integration was shown which offers a good possibility for algorithm development and testing procedures for ISS as well as other ADAS. The developed situation analysis based on the integration of the LMD approach into a DBN algorithm turned out to be a suitable and applicable method for ISS in terms of intuitive implementation which is capable of running online in a vehicle. The subsequent risk assessment algorithms which are based on an adaptive fuzzy logic approach allowed for an automatically learning system which was abutted to human thinking and therefore was intuitively realizable. The calculated risk was presented to the driver of the demonstrator vehicle through adequate and innovative HMI elements like the continuous risk level visualization color bar and a colored turn indicator. System and user tests at the end showed the possibility of the developed system to reduce accidents at intersections while being accepted by real drivers. The system was rated as helpful and able to relieve driver workload. The subjects stated that the realized system would have helped them in their daily driving and it was agreed that it would improve traffic safety.

Needless to say, all the mentioned results apply only to the here developed Intersection Safety System which consists of an on-board demonstrator vehicle and for some functions also comprises infrastructure measures. However, the system of this work contributed a lot to the world-wide first comprehensive on-board demonstrator vehicle dealing with a wide range of intersection safety applications.

8.1 Outlook

As stated several times throughout this thesis, ISS is a very active research activity. This means that this subject will not be neglected in future research as well as in final ADAS products. Most likely, at first smaller Intersection Safety subsystems will enter the marked before introducing a comprehensive system like studied in this work. This could be e.g. a particular left-turn or traffic light assistance. Nevertheless, the here developed architecture, algorithms and techniques can be used and extended in future ISS implementations in order to get closer to the vision of injuries and fatalities free driving. Some possible future work will be described in the following aligned to the structure of this work.

8.1.1 Overall System Enhancements

Even if the proposed equipment of the demonstrator vehicle and the extensions made concerning infrastructure sensing turned out to be highly suitable for the ISS, even more enhancements could be considered. In order to extend the proposed systems it could be enriched with more comprehensive infrastructure equipment. Sensors installed at the infrastructure, e.g. cameras, radars or laser scanners, could monitor the traffic on the intersection from the infrastructure side in order to emend the detection, tracking and classification of road users within this area. This data could be either used for direct warning applications at the infrastructure itself (e.g. adjustable warning road signs) or could be transferred remotely to the approaching vehicles in order to extend their detection capabilities or even provide them with such data if they are not equipped with onboard sensors. Furthermore, additional onboard sensor techniques could be investigated which are able to cope with the requirements derived in Section 2.3 and maybe have even a larger field of view (e.g. omnidirectional vision systems). Finally, the requirements for integration into series vehicle should also not be neglected.

8.1.2 Future Work on Situation Analysis

In order to localize the host vehicle within the intersection an approach based on high detail digital maps was used. When thinking of possible market introduction of such an ISS, such detailed information will not be available in the near future. Thus, other approaches for localization are needed. One possibility could be a system that solely uses on-board sensors, e.g. (stereo) video camera, radar or laser scanners, in order to identify each kind of intersection and thus to localize the host vehicle on it. Therefore, adequate algorithms have to be developed so that the system is able to detect and classify different intersection feature like e.g. road markings, curbstones and side roads. Based on adequate fusion techniques these features need to be combined in order to build a representative model/map of the intersection that can be used for subsequent applications. In such work it could be worth studying suitable machine learning techniques like artificial neural network in order to cope with these challenging tasks of incorporating imperfect sensor data.

Another extension to the proposed system could study the problem of analyzing the most common behavior of traffic participants within a specific intersection, i.e. to learn the probabilities that are stored in the graphs for the MaB and the MiB. Such an analysis could benefit from an additional sensor equipment at the intersections like proposed in Section 8.1.1. In brief, this would include learning of most probable paths, typical turning velocities and even study the impact of indicator usage for turning maneuvers. Such an analysis could provide benefit to the proposed behavior prediction module in terms of using realistic driving data for a specific intersection.

8.1.3 Future Work on Risk Assessment

Especially in the topic of risk assessment adaptation the author sees a lot of enhancement possibilities.

The approach for online adaption of the risk assessment showed in this work turned out to be well suited for the proposed ISS. However, it does not allow for a detailed analysis of driver reaction to the provided risk estimation. In a more comprehensive future work one could try to build a system that is able to observe the driver of the equipped vehicle with suitable sensor systems. So, the driver response to a given warning or information, e.g. response time, acceleration behavior or viewing direction, could be more deeply analyzed and used for an even more realistic adaptation of the risk assessment system.

Furthermore, as a combination of situation analysis and risk assessment, a totally unsupervised learning system that constantly monitors the behavior of the driver would be of high interest. Such a system should learn how to drive safely through an intersection in order to warn the driver if he is not driving as usual or even to support him in his driving task (see Section 8.1.4).

Ideally, these extensions could be developed and studied in a highly sophisticated driving simulator where it is no problem to create dangerous situations without any danger for the involved persons.

8.1.4 Future Work on Warning Strategies

As mentioned throughout this work, warning is an adequate mean when developing a totally new and innovative Driver Assistance function like an ISS. However, in times of increasing stimulus satiation of the driver with numerous information and warning elements, autonomous vehicle interaction is sometimes (especially in very time critical situations) the only adequate mean to assist the driver. Thus, as an extension to this system, adequate HMI strategies should be studied and developed to benefit from autonomous vehicle intervention system. Such active safety function (see Figure 1.1) could be e.g. automatic braking or active steering of the equipped vehicle. A more challenging task would be a fully autonomous guided drive through the intersection (like an autopilot). The driver would give the control to the vehicle in front of an intersection and henceforward would be autonomously driven safely through the intersection. After this maneuver he would again take over the control of the vehicle. Even for larger areas of a city this would be an interesting enhancement in order to extend nowadays ACC systems to something that could be called City ACC. Such a system, which could be based on the algorithms and techniques proposed in this work, would definitely contribute to much safer driving within urban areas.

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Nomenclature

ABS	Anti-Lock Braking System
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
AIDE	Adaptive Integrated Driver-vehicle InterfacE
AKTIV	Adaptive and Cooperative Technologies for the Intelligent Traffic
BAS	Brake Assist System
BM	Behavior Model
BMWi	Federal Ministry of Education and Research of Germany
BN	Bayesian Network
C2C	Car-to-Car
C2CCC	Car-to-Car Communication Consortium
C2I	Car-to-Infrastructure Communication
CAR	Correct Alarm Rate
CC	Cruise Control
CG	Conflict Graph
CICAS	Cooperative Collision Avoidance Systems
CP	Conflict Point
CPT	Conditional Probability Table
CTG	Conflict Time Gap
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Network
DGPS	Differential Global Positioning System
DM	Dynamic Model
DP	Driver Profile
DVE	Driver Vehicle Environment

EDS	Environmental Data Server
EM	Environmental Model
ESC	Electronic Stability Control
FLM	Feature Level Map
FNAR	False Negative Alarm Rate
FPAR	False Positive Alarm Rate
GDF	Geographic Data Files
GIS	Geographic Information System
HMI	Human-Machine Interface
HMM	Hidden Markov Model
I2V	Infrastructure to Vehicle Communication
ICA	Interaction and Communication assistant
INTERSAFE	Intersection Safety
INVENT	Intelligent Traffic and User-Friendly Technology
ISS	Intersection Safety Systems
IVHS	Intelligent Vehicle Highway System
LDW	Lane Departure Warning
LMD	Lane Model Description
LWP	Last Warning Point
MaB	Macroscopic Behavior
MiB	Microscopic Behavior
MISO	Multiple Input Single Output
MWD	Minimum Warning Distance
NHTSA	National Highway Traffic Safety Administration
OCAR	Office of Crash Avoidance Research
OGM	Occupancy Grid Map
PA	Park Assist
PDF	Probability Distribution Function
PReVENT	Preventive Safety
R&D	Research and Development

RoWA	Right-of-Way Assistance
RoWG	Right-of-Way Graph
RSPA	Research and Special Programs Administration
SAFESPOT	Cooperative Systems for Road Safety “Smart Vehicles on Smart Road”
SEM	Simulated Environment Model
TA	Turning Assistance
TLA	Traffic Light/Stop Sign Assistance
TSS	Traffic Signal System
TTC	Time-to-Collision
TTCP	Time-to-Collision-Point
UML	Unified Modeling Language
USDOT	US Department of Transportation
VRUs	Vulnerable Road Users
VSC	Vehicle Safety Consortium