Situation understanding and risk assessment framework for preventive driver assistance

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Situation Understanding and Risk Assessment Framework for Preventive Driver Assistance

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Abstract

Modern vehicles include advanced driving assistance systems for comfort and active safety features. Whilst these systems contribute to the reduction of road accidents, their deployment has shown that performance is constrained by their limited situation understanding capabilities. This is mainly due to perception constraints and by ignoring the context within which these vehicles evolve. It results in last minute risk assessment, and thus in curative assistance in the form of warning alerts or automatic braking. This thesis focuses on the introduction of contextual information into the decision processes of driving assistance systems. The overall purpose is to infer risk earlier than conventional driving assistance systems, as well as to enhance the level of trust on the information provided to drivers. Several factors govern the vehicle behaviour. These include the road network and traffic rules, as well as other road users such as vehicles and pedestrians with which the vehicle interacts. This results in strong interdependencies amongst all entities, which govern their behaviour. Further, whilst traffic rules apply equally to all participants, each driver interacts differently with the immediate environment, leading to different risk level for a given behaviour. This information must be incorporated within the decision-making processes of these systems. In this thesis, a framework is proposed that combines a priori information from digital navigation maps with real time information from on board vehicle sensors and/or external sources via wireless communications links, to infer a better situation understanding, which should enable to anticipate risks. This tenet is similar to the task of a co-pilot when using a priori notated road information. The proposed approach is constrained by using only data from close to production sensors.

The framework proposed in this thesis consists of two phases, namely situation understanding and risk assessment. The situation understanding phase consists in performing a high level interpretation of all observations by including a priori information within the framework. The purpose is to understand how the perceived road entities interact, and how the interactions constrain the vehicle behaviour. This phase establishes the spatio-temporal relationships between the perceived entities to determine their relevance with respect to the subject vehicle motion, and then to identify which entities to be tracked. For this purpose, an ontology is proposed. It stores a priori information about the manner how different road entities relate and interact. This initial phase was tested in real time using data recorded on a passenger vehicle evolving in constrained environments. The risk assessment phase then looks into the perceived situation and into the manner how it becomes dangerous. To demonstrate the framework applicability, a use case applied to road intersections was chosen. Intersections are complex parts in the road network where different entities converge and most accidents occur. In order to detect risk situations, the manner how the driver reacts in a given situation is learned through Gaussian Processes. This knowledge about the driver is then used within a context aware Bayesian Network to estimate whether the driver is likely to interact as expected with the relevant entities or not. The probabilistic approach taken allows to take into consideration all uncertainties embedded in the observations. Field trials were performed using a passenger vehicle to validate the proposed approach. The results show that by incorporating

drivers' individualities and their actuations with the observation of the vehicle state, it is possible to better estimate whether the driver interacts as expected with the environment, and thus to anticipate risk. Further, it is shown that it is possible to generate assistance earlier than conventional safety systems.

Résumé

Les nouvelles voitures sont pourvues d'aides à la conduite qui améliorent le confort et la sécurité. Bien que ces systèmes contribuent à la réduction des accidents de la route, leur déploiement montre que leurs performances sont encore limitées par leur faible compréhension de situation. Cela est principalement lié aux limites des capteurs de perception, et à la non prise en compte du contexte. Ces limites se traduisent par des détections de risques tardives, et donc en assistances sous forme d'alertes ou de freinages automatiques. Cette thèse se concentre sur l'introduction d'informations contextuelles dans le processus de décision des systèmes d'aides à la conduite. Le but est de détecter des risques plus tôt que les systèmes conventionnels, ainsi que d'améliorer la confiance qu'on peut avoir dans les informations générées. Le comportement d'un véhicule dépend de divers éléments tels que le réseau routier, les règles de la circulation, ainsi que de la cohabitation avec d'autres usagers de la route. Ces interactions se traduisent par une interdépendance forte entre chaque élément. De plus, bien que chaque conducteur doive suivre les mêmes règles de circulation, ils peuvent réagir de façon différente à une même situation. Cela implique qu'un même comportement peut être considéré comme sûr ou risqué, selon le conducteur. Ces informations doivent être prises en compte dans le processus de prise de décision des systèmes. Cette thèse propose un cadre qui combine les informations a priori contenues dans les cartes de navigation numériques avec l'information temps réel fournie par les capteurs de perception et/ou communications sans fil, pour permettre une meilleure compréhension de situation et ainsi mieux anticiper les risques. Ce principe est comparable aux tâches qu'un copilote doit accomplir.

Ces travaux se répartissent en deux principales étapes : la compréhension de situation, et l'estimation des risques. L'étape de compréhension de situation consiste à donner du sens aux différentes observations réalisées par les capteurs de perception, en exploitant des informations a priori. Le but est de comprendre comment les entités perçues interagissent, et comment ces interactions contraignent le comportement du véhicule. Cette étape établit les relations spatio-temporelles entre les entités perçues afin d'évaluer leur pertinence par rapport au véhicule, et ainsi extraire les entités les plus contraignantes. Pour cela, une ontologie contenant des informations a priori sur la façon dont différentes entités de la route interagissent est proposée. Cette première étape a été testée en temps réel, utilisant des données enregistrées sur un véhicule évoluant en environnements contraints. L'étape de détection des risques s'appuie sur la situation perçue, et sur les signes annonciateurs de risques. Le cas d'usage choisi pour cette étude se concentre sur les intersections, puisqu'une grande majorité des accidents de la route y ont lieux. La manière de réagir d'un conducteur lorsqu'il se rapproche d'une intersection est apprise par des Processus Gaussiens. Cette connaissance à priori du conducteur est ensuite exploitée, avec les informations contextuelles, par un réseau Bayésien afin d'estimer si le conducteur semble interagir comme attendu avec l'intersection. L'approche probabiliste qui a été choisie permet de prendre en compte les incertitudes dont souffrent chacune des sources d'information. Des tests ont été réalisés à partir de données enregistrées à bord d'un

véhicule afin de valider l'approche. Les résultats montrent qu'en prenant en compte les individualités des conducteurs, leurs actions sur le véhicule, ainsi que l'état du véhicule, il est possible de mieux estimer si le conducteur interagit comme attendu avec l'environnement, et donc d'anticiper les risques. Finalement, il est montré qu'il est possible de générer une assistance plus préventive que les systèmes d'aide à la conduite conventionnels.

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Contents

Chapter 1

Introduction

Contents

1.1 Context

Safe, accessible and convenient mobility has always been one of mankind's challenges. Whilst disruptive solutions were imagined, society had to wait for progress in science and engineering during the last two centuries to reach the development of modern transportation modes. The impact of the steam engine in the 19th century enabled the transformation of energy into mechanical power which allowed for industrial machinery, but also for steam trains. Man left horse carriages and the redefinition of travel distance began. Trains represented the first revolution in the transportation domain. Toward the beginning of the 20th century, the mass production of automobiles started the notion of individual transportation and of freedom to travel, at any time and as often as desired. Ground mobility has transformed our lives, however it has brought other concerns such as pollution, congestion and safety.

The increasing number of vehicles lead to the progressive modernisation of driving spaces with the construction of new roads, and with the installation of traffic lights, signs, roundabouts, etc. The whole is governed by different laws and regulations, and the most common one among nations is the Vienna convention [1]. The automotive industry is also working to reduce the number of fatalities and therefore to enhance safety. Whist initial efforts were centred on passive devices such as seat belts, today's efforts centre on active systems designed to avoid accidents, or at least to reduce their effect.

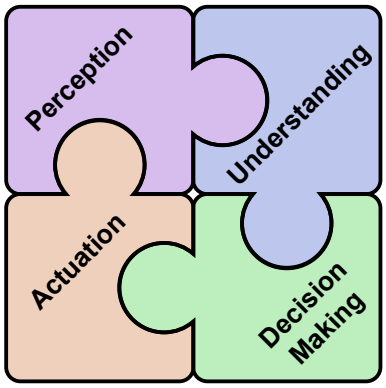


Figure 1.1: Driving process: major driving tasks.

The research addressed in this thesis is centred on active devices designed to assist drivers, usually known as Advanced Driving Assistance Systems (ADAS). The work centres on the area of situation understanding for decision making by such systems. In this Chapter, the context of the thesis is represented from the driver perspective and from the new generation of vehicles known as intelligent vehicles. The emphasis is to understand how the complexity of the driving task increases the risk of road accidents, and how intelligent vehicles using robotics technology offer new perspectives for road safety. The problem is then formally stated, and the contributions of the thesis are given.

1.2 Overview on the Driving Process

Driving a vehicle implies the simultaneous performance of several tasks. Shortcomings on the ability to perform them often lead to risk situations, and to accidents. Solutions to avoid accidents and to reduce their effect have been investigated for several decades. This Section aims to provide an overview of what driving is, in order to understand how risk situations arise. Further, it briefly presents how some passive solutions deployed on road networks and vehicles were a first step towards safer traffic.

1.2.1 Driving

For most people, driving after a few years becomes a collection of mechanical tasks. However, driving is complex, as different tasks are performed in parallel, each responding to the different situations encountered. For the purpose of this thesis, four major tasks have been identified for a driver to safely control a vehicle. These are Perception, Understanding, Decision-Making and Actuation, as represented in Figure 1.1.

Figure 1.2: Example of a typical driving environment. Entities of different types cohabit in the same area.

Perception

When driving, the first question to be answered is *What is around my vehicle?* The driver must be capable to observe the surroundings, to classify the scene into the relevant entities. This is done despite the clutter and occlusions that might occur. The Perception task is complex, where experience enables drivers to consider mainly the most relevant entities.

Understanding

Once the driver has a mental model of the perceived world, it is then necessary to understand the spatio-temporal relationships between the vehicle and the perceived entities. Those which are relevant are inferred first, and then classified into entities that are in motion, and those that are likely to move. Then, road features that constrain vehicle motions like road signs are considered. Within this context, the driver takes into account all likely interactions and constraints posed by all surrounding entities on his vehicle. Drivers need to gain a full understanding of their situation wherever possible. Failure to do this often results in driver errors, which may lead to conflicting and dangerous situations.

Decision-Making

Once the driver gains an understanding of his current situation by identifying the relevant entities with regard to his future direction of motion, a process of risk assessment starts. This includes the estimation of the future state of the interacting entities, his own intention, the knowledge of the vehicle capabilities, etc. The collected mental model allows drivers to decide the immediate motion of the vehicle. This implies split-second decisions, particularly in case of difficult driving situations. Extreme situations, e.g. bad weather, hazardous surrounding vehicles may lead to inappropriate decisions favoured by poor driving experience or insufficient situation awareness.

Actuation

Once the decision on the next vehicle manoeuvre is taken, the driver acts on the vehicle controls, e.g. accelerates, brakes, turns the steering wheel. The vehicle then responds accordingly and completes the manoeuvre. This again is subject to driver capabilities, as any latency might hamper the manoeuvre and might result in hazardous situations.

The four tasks are required all the time as drivers have to adapt the vehicle response according to the situations encountered. Note that whilst localization is an important task, it is not mentioned in this chapter as it is not considered as a major requirement to ensure safe driving.

In the driving process, time and space are very relevant. These driving tasks are executed almost in parallel, with Actuation being the result of the previous three. The starting time at which the driver observes his surrounding environment and concluding at the moment he acts on the vehicle control is incompressible. This time is known as the Reaction Time (RT). It is the result of a humans physiological limitations in sensing, understanding, deciding and acting. It is usually estimated between 1 and 1.5 seconds [145, 125]. Further, it depends on several parameters related to the situation complexity and the driver (i.e. age, experience, gender, conditions, etc.) [50].

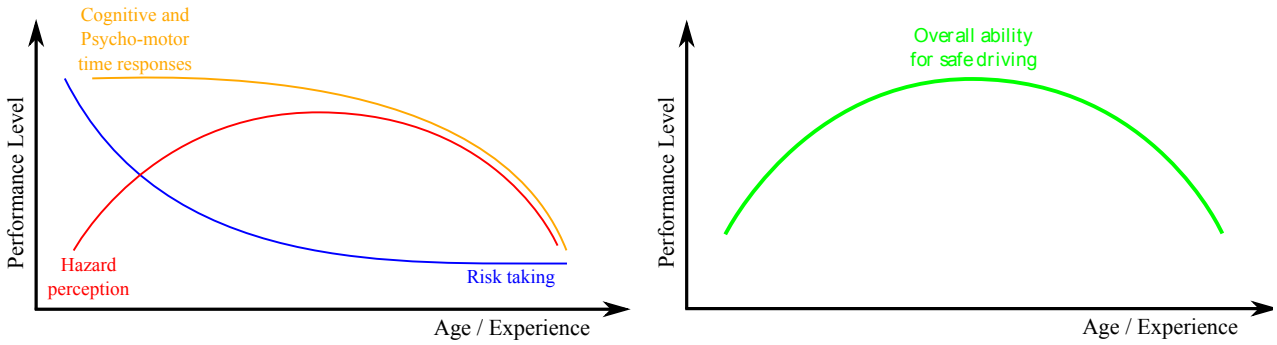
1.2.2 Influence of Age and Experience on Driving

Everyone drives differently, the differences depend on several parameters. There are strong driving style differences between countries; these differences reflect culture, demography, and gender [40, 119]. The driver emotional and mental state have a major role in the manner how drivers behave [141, 37]. Whilst the trend would be to generalize, their influence on the same driver may vary from day to day.

Studies have shown that the most influential parameters in terms of safety concerns are Experience and Age. Table 1.1 shows the summary of dependencies that age and experience have on the major driving tasks. Figure 1.3a shows the dependencies of age and experience on cognitive and physiological performances of drivers, and Figure 1.3b shows the overall driving capabilities with respect to age and experience. They are detailed in the following paragraphs.

Table 1.1: Influence of age and experience on the major driving tasks.

	Perception	**Understanding**	**Decision**	**Action**
Younger, Novice	OK	Lower Hazard Perception Ability	More Risk Taking	OK
Middle Age, Experimented	OK	OK	OK	OK
Elderly	Lower Vision Ability	Lower Processing Time	Lower Processing Time	Lower Psycho-motor Ability



(a) Parameters affecting driving performance

(b) Overall driving performances

Figure 1.3: Effect of age and experience on driving performances.

Perception

Age has a significant effect on the perception abilities of drivers. People usually suffer from progressive narrowing of the field of view as they age. It implies that older drivers have more difficulties with perceiving the environment. Moreover, it results in having difficulties with perceiving road entities which might represent hazard [68, 159]. Whilst their ability to perceive is usually good, young and inexperimented drivers more often fail to understand their driving situations, resulting in hazardous conditions. Driver experience progressively solves this problem by improving the visual search strategy [83].

Hazard Perception

Drivers differ mainly in their situation understanding which allows them to anticipate traffic situations. This is known as the Hazard Perception Ability which is one of the parameters needed for comfortable and safe driving. The earlier the hazard is detected, the earliest the driver could decide and act to keep the situation under control. Age and driving experience have a significant influence on this parameter [100]. As shown in Figure 1.3, younger and older drivers have more difficulties to perceive hazards. Older drivers would need longer processing times to understand the situation, decide and act, whilst novice drivers are likely to have difficulties for understanding the relevance of the perceived entities [143, 21]. Moreover, as vision capabilities diminishes, the ability of drivers to perceive and thus to infer likely collisions decreases with age [9].

Risk Taking

Investigations into the causes of accidents showed that young drivers are more likely to take risks, often stimulated by their overconfidence and sensation seeking [77]. Speeding is the most common traffic rule violation [46, 159], as well as risky overtaking and close following [33]. By contrast, as drivers get older, risk taking is decreased. Figure 1.3 shows the variation of risk taking with age and experience. Further, younger drivers usually respond to hazard later than other drivers, as they favour risky situations [135].

Cognitive and Physical Capabilities

For elderly drivers, statistics reveal that they are often involved in accidents at road intersections, because of decision-making difficulties [159, 2, 32]. In addition, they may suffer from altered psycho-motor functioning affecting their reaction time and on the manner they act. Experiments in simulated environments highlighted dependencies between lower driving performances the elderly suffer from, and collision occurrence [143]. Often, elderly drivers become aware of their decreasing driving capabilities. They will decide either to stop driving, or to reduce the effects of their age-related decline and thus to diminish risks. For example, to suit with their abilities, some will avoid specific situations such as left turning, roundabouts, or will decide to drive slower, to increase following time, etc. [106, 146].

Younger, novice and older drivers show lower driving capabilities than experienced and middle aged drivers. Road accidents statistics seem to confirm this hypothesis. Moreover, demographic trends in OECD countries show an inversion in the pyramidal age structure. Over the next years, the number of elderly drivers shall increase very much. Consequently, accident risks shall also increase unless special measures are taken. This is an opportunity for new technical solutions.

1.2.3 Accidentology

Background

Accessibility to motor vehicles has provided freedom of movement and have changed society. However, they have also brought social and economical costs, large road networks, pollution and most of all road accidents. Currently, road accidents kill more than 1.2 millions people per year across the world, and represent the first cause of death of young adults aged 15-24. Further, for every road accident fatality, at least 20 individuals sustain non-fatal injuries . Emergent countries accident fatalities are very high with 20 deaths for 100 000 population. In OECD countries, the death rate is much lower with less that 9 deaths for 100 000 population [118].

Road accidents lead to significant government spendings. For example, in France, the government estimates the cost of a road fatality to be greater than 3 million Euros, while all road injuries and fatalities cost 22 billions Euros per year in 2014 [110]. In the US, the

American Automobile Association estimated that in 2011, the annual societal cost of traffic accidents was close to 300 billions US Dollars [101].

Road Accidents

In Europe, 57% of road accidents and 79% of road fatalities occur in stabilized situations. Problems mostly happen because of lane departure, unexpected violation manoeuvres from other vehicles, or unexpected pedestrian appearance. The other 43% of road accidents occur at road intersections resulting in 21% of road fatalities. Moreover, for the elderly drivers, fatalities at road intersections are very high. Safety at road intersection is therefore of much concern [105].

Accidents Risk Factors and Causes

Accidents are caused by the combination of several factors related to the environment, the vehicle and the driver. Statistics show that the great majority of accidents are due to endogenous events (i.e. related to the driver). Out of road intersections, most of accidents are caused by anticipation failures and bad manoeuvre planning [105]. At road intersections, more than 80% of accidents are caused by human errors due to impaired internal conditions (e.g. violations of traffic rules), driver behaviour (e.g. perception failures) and driver state (e.g. tiredness, alcohol) [105, 104]. Driver errors are therefore the first cause of road accidents, hence efforts have to be made to minimize their occurrence or at least to fix them before situations become hazardous.

1.2.4 Primary Strategies for Road Safety Improvements

The constant increase in injuries and fatalities due to road accidents raised the alarm in advanced economy countries. This led to several changes on road design and equipments, but also in vehicles with the aim of improving safety and protecting vehicle occupants when accidents occur [45, 128]. Measures for road safety can be classified into two groups: 1) Measures aiming at helping drivers to better understand the situation and to reduce risks 2) Measures related to passive safety.

Facilitating Situation Awareness

Accidents are often related to poor environment perception, therefore efforts have been made to install equipments on roads to inform drivers about relevant oncoming road features. Traffic signs and road markings had a significant influence on the reduction of accidents at dangerous road sections. Further, several road intersections were redesigned to limit risk of bad visibility, or also to limit the number of conflict points, provided by conversion of crossroads into roundabouts. Their introduction reduced considerably the number of accidents at road intersections [132].

Passive safety

Despite all efforts made to limit risks, accidents still occur. It is therefore of importance to limit the extent of damage resulting from such situations. In this way, guard rails and crash cushions have showed their utility in motorways or mountain roads. Car manufacturers contributed to the reduction of damages implied by road accidents by improving vehicles passive safety. The seat belt was one of the first devices which made possible to significantly improve passive safety in cars [34]. Moreover, the democratisation of airbags, and the significant improvement of vehicle chock absorption offer additional protection to car occupants. Since 1997, the Euro NCAP requirements for passive safety represent major guidelines to car manufacturers for safety improvements [164].

Accidentology statistics show that passive safety solutions contributed to indisputable results, especially in OECD countries. However, a plateau was soon reached. It is insufficient to protect passengers after a road accident, the aim is now to prevent accidents. This has led onto technologies that started as driving assistance systems and moved towards intelligent vehicles.

1.3 Intelligent Vehicles

Motor vehicles are undergoing a rapid transformation from essentially electromechanical systems to computer controlled complex systems. That is, the control of vehicles is progressively being taken over by computer systems. Further, it can be said that modern vehicles are becoming complex, software dependent, sensor-based platforms at an accelerated pace [74]. For example, ABS (from the German Antiblockiersystem) which is mandatory in commercialized vehicles in Europe since 2007, prevents wheels from blocking during emergency braking [23].

In this Section, a summary introduction is provided on the evolution of vehicles from Advanced Driving Assistance Systems (ADAS) to fully computer controlled vehicles known as autonomous vehicles. Figure 1.4 shows how the introduction of intelligence in vehicles results on a reduction on the degree of human intervention, and leads to autonomous vehicles and zero driver intervention [75].

1.3.1 Advanced Driving Assistance Systems

Current ADAS aim to help the driver in the driving process. They can be classified into three types: 1) ADAS addressing driver deficiencies and comfort 2) ADAS addressing dangerous situations 3) Autonomous navigation. A quick overview of such systems is presented in this Section.

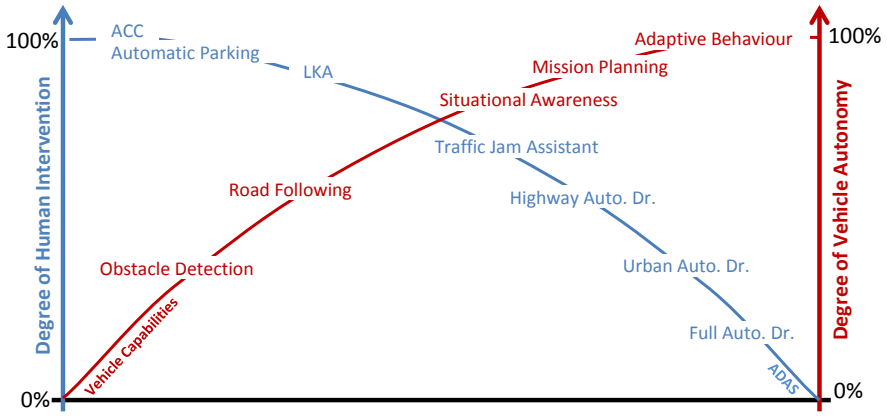


Figure 1.4: Impact of the introduction of intelligence and ADAS in vehicles on the degree of human intervention. After [75].

Comfort ADAS

Several driving tasks can be stressful and/or difficult, and as presented in Section 1.2.2 the degree varies according to age and experience. Perceiving the vehicle surrounding is in particular a difficult task. Several systems have been developed to address this problem. For example, Blind Spot Information Systems informs drivers when a vehicle is located to their side and rear. Further, providing in a bird's eye point of view around the subject vehicle is the function of Around View Monitor which aims to facilitate close manoeuvres. Such systems can be used by parking assist systems for the detection of parking slots, and then to either indicate the manoeuvres to follow or for the most sophisticated systems to automatically perform the manoeuvre. Comfort can also be improved by systems such as Adaptive Cruise Control (ACC) which allows the vehicle to automatically regulate the vehicle speed, and to maintain safe distance from the vehicle ahead. Whilst they help drivers to perform some driving tasks, comfort ADAS are not designed to assist drivers in case of hazardous situations.

Safety ADAS

Driving may lead to dangerous situations and thus to accidents. In a limited number of situations, ADAS may provide assistance to avoid accidents or to limit their consequences. Nowadays, most of vehicles are equipped with electronic systems such as ABS and ESC (Electronic Stability Control), using proprioceptive sensors to help the driver keep the vehicle control in emergency situations. A new generation of ADAS using exteroceptive sensors starts to be widely used within new vehicles.

Image processing techniques allow for the detection of lane markings and thus for the detection of lane departure. The function Lane Departure System will for example assist the driver when inopportune lane departures arise, by informing the driver for Lane Departure Warning systems (LDW) or by automatically actuating on the vehicle lateral control for Lake Keeping Assistants (LKA). Driver Monitoring Systems (DMS) can observe the driver,

determine whether there is drowsiness, and then provide warning to the driver if necessary. Such systems may be coupled with Lane Departure Systems (LDS) to ensure that drivers are in control.

Collisions with other road users are also addressed by ADAS. The Automatic Emergency Braking Systems (AEB), also known as Precrash systems, automatically stop the vehicle if a collision is perceived as imminent. Such systems operate with perception sensors which estimate the state of front obstacles. By considering the state of the subject vehicle and braking capabilities, it is possible to estimate whether a collision is likely to happen if no action is taken. Field trials show that the validation of these systems is difficult as inopportune automatic braking may have serious consequences. AEB is becoming mandatory for vehicles to be awarded a 5 star Euro Ncap qualifications [164].

Towards Autonomous Driving

Most vehicle OEMs have running programs and product-road maps for the development of Autonomous Vehicles (AV). These represent a disruptive technology in the automotive industry and shall provide accessibility to a part of society that is not able to drive. They shall improve road safety, optimize traffic flows and improve productivity by letting drivers focus on other tasks rather than driving. Rapid developments in sensors and algorithms have been integrated into always more impressive demonstrators of autonomous driving.

The combination of some ADAS enables to delegate driving to the vehicle in well structured situations. For example, the combination of ACC and LKA systems allows for lateral and longitudinal control of the vehicle, and thus would allow for automated driving in situations such as highways or traffic jams. However, urban situations are much more complex, as the cohabitation with other road users is difficult to understand for a machine. Poor situation understanding would lead to risks for the vehicle passengers, but also for the nearby road users. This is mainly why autonomous driving in complex situations remains a challenge for car manufacturers.

Several research projects have demonstrated that autonomous driving is no longer science fiction. One of the first notable demonstrators was Navlab (National Autonomous Vehicle Laboratory) developed by Carnegie Mellon University in 1986 [151]. The first version which had lateral and longitudinal control performed by computer navigated more than 300 miles at 20 mph maximum. In 2004 and 2005, 23 teams participated to the first edition of the DARPA Challenge [73]. For each team, the rule was to develop an AV able to navigate autonomously on a dirt road, in a limited time with the other participants. This was followed by the DARPA Urban Challenge in 2007. In this edition, the participants had to manage urban situations such as intersections and parking manoeuvres [29].

The DARPA challenges represent a springboard for research in AV, and motivated universities and industry. In 2007, VisLab travelled 16000 km from Parma to Shanghai, aboard four driverless vehicles [19]. In 2010, the New York times announced that Google developed vehicles with full autonomous capabilities operating autonomously on Californian roads [96].

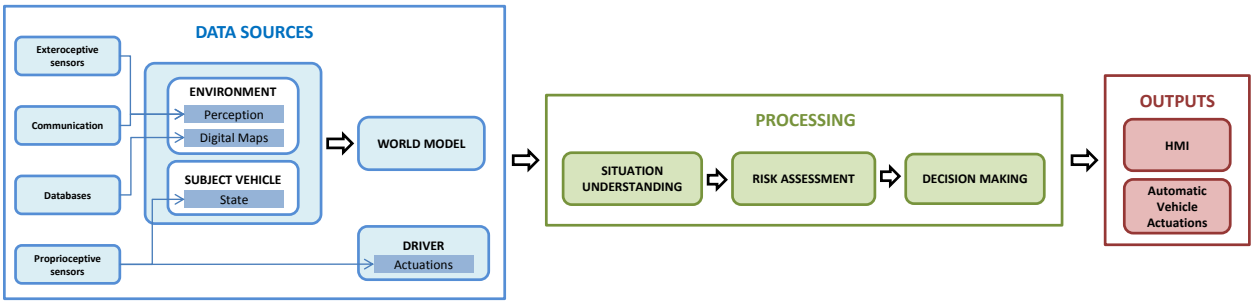


Figure 1.5: Intelligent vehicles functions. After [90].

Moreover, they claimed that the vehicles travelled more than 800000 km on Californian roads without accident. In 2013, VisLab successfully tested PROUD in Parma, in urban situations [28]. Moreover, Daimler, FZI and KIT successfully tested their Bertha prototype on the 103 km famous German Bertha Benz Memorial Route [176]. In 2015, Delphi's driverless car covered 3400 miles from San Francisco to New York City without human intervention for more than 99% of the time [41]. In 2015 also, Renault presented his autonomous valet parking service and their vehicle accumulated 90km of autonomous driving without anybody sat behind the steering wheel during the international ITS congress. Finally, in the same year, Tesla Motor became the first car manufacturer to propose a hand free driving function. This autopilot function allows the vehicle to manage speed and steer on highways [25].

From comfort ADAS to autonomous navigation, the requirements in terms of data sources and embedded intelligence are more and more challenging. Moreover, technologies developed for autonomous navigation should contribute to the improvement of safety ADAS. The structure of intelligent vehicles is composed by several functions which are quickly described in the following Section.

1.3.2 Intelligent Vehicles Functions

An Intelligent Vehicle can be regarded as replicating the driver tasks (c.f. Section 1.2.1) through sensors and computers. These are split into several functions which are classified into Data Sources, Processing and Outputs. The first comprises all the data and information used in the driving task. The second is concerned on the processing of the collected data. Finally, the third applies the processed information to control the vehicle or to inform the driver. Figure 1.5 shows the functional components required for a typical intelligent vehicle.

Data Sources

The data sources needed on board an intelligent vehicle include information about the driver, the vehicle and the surrounding environment. These data sources can be classified into four groups: 1) Proprioceptive sensors 2) Exteroceptive sensors 3) Databases 4) Communication.

Proprioceptive sensors provide information about internal status and state of the subject vehicle. The internal status describes the working conditions, in particular the vehicle accessories like the turn signal, the pedals, the air conditioning, etc. The vehicle state describes the vehicle kinematics and dynamics state, namely velocity, heading, accelerations, etc. Whilst the vehicle velocity and accelerations can be measured with low cost odometry and inertial sensors, estimating the vehicle location is a difficult task. Knowing the vehicle location is a very important function. In commercialized vehicles, this is usually estimated based in the use of GNSS (Global Navigation Satellite System), sometimes coupled with the vehicle dynamics. Whilst much progress have been achieved, estimating the vehicle pose all the time using automotive type components remains a challenge [112].

Exteroceptive sensors provide information about the environment in which the subject vehicle navigates. They can be classified into two types, namely passive sensors and active sensors. Passive sensors comprise different types of cameras, monocular, stereo and infrared. For these cameras, the trend is to have embedded intelligence which extracts from raw data a list of detected objects and lane markings with their attributes (position, speed, type, etc.). Whilst much progress have been achieved, several constrains exist due to the physics involved. The field of view and resolution are limited, there are uncertainties on the object attributes, and performances are even reduced in extreme weather conditions [18, 52]. Active sensors comprise two main technologies: RADAR (RAdio Detection And Ranging) and LIDAR (LIght Detection And Ranging). RADAR sensors have become very common in modern vehicles as they are cheap and offer excellent performances for the perception of vehicles. However their field of view is narrow and offer low performances for the detection of non-metallic objects due to the technology they exploit [7]. LIDAR sensors (also known as Laser scanners), whilst they are not yet common is commercialized vehicles, offer more precise measurements than RADARS with a wider field of view. However, they are still expensive, and as cameras, their performances are reduced under unfavourable weather conditions [7].

Databases provide *a priori* information about the context. The most used are digital maps. They store information about the road network features (e.g. road curvature, position of intersections, speed limits, etc.) and enable to contextualize information about the subject vehicle and other entities sharing the same road network. Databases may contain information about the driver such as his driving style, his favourite roads, habits, etc. Whilst the quality of navigation maps is very important as erroneous data may result in inappropriate assistance, most of navigation maps embedded in commercialized vehicles are far from being perfect [129, 177].

Communications allows the subject vehicle to perceive beyond the limits of its on board sensors. For example, the navigation system can get real-time information about traffic conditions through cellular communications. Moreover, Vehicle-to-Vehicle (V2V) and Vehicle-

to-Infrastructure (V2I) communications provide an opportunity to enlarge the subject vehicle perception of the environment [10, 76]. For example, at road intersections, V2V enables to perceive hidden vehicles, and V2I enables to inform about the state of traffic lights. Whilst communications are of much interest, systems exploiting them must handle the latency and the loss of signal which may occur.

In general, data regarding the subject vehicle state and the surrounding environment is fused into a unified framework that represents a digital representation of the world. Sensor fusion techniques enable to reduce uncertainty on measurements and to improve the robustness of the systems. However, due to the layout of sensors and the technologies used (limited in cost), perception systems have incomplete and inaccurate representations of the world. As a consequence, the world model suffers from the same shortcomings. That means that the Processing function which exploits the information returned by the data sources have to deal with them.

Processing

The Processing function aims to exploit the information returned by the data sources, in order to provide assistance. This function is usually performed through three main steps: 1) Situation Understanding 2) Risk Assessment 3) Decision Making.

Situation Understanding aims to interpret the data stored in the world model. That is, the world model needs to be understood with respect to the subject vehicle response and motion needs. One major situation understanding task is to determine in what road context the vehicle is (e.g. is it approaching to an intersection? is it on the highway? etc.). Further, situation understanding implies giving sense to perception data by contextualizing it, and by taking into consideration the relationships and interactions between the subject vehicle and the relevant perceived entities.

Risk Assessment aims to estimate the likelihood that the subject vehicle will be implied in a hazardous situation or in a collision in a near future. For example, in precrash systems, risk assessment consists in estimating whether a collision will happen with a pedestrian or a vehicle if no action is taken. The most used method is based on the estimation of the time remaining before a collision, also known as the Time-To-Collision (TTC) [88]. In conventional ADAS, risk situations are usually assessed very late. This is partly due to the limited amount of information that is exploited to estimate the risk, as situation understanding is generally rather poor.

Decision-Making aims to determine whether assistance should be provided in order to avoid a collision, or at least to mitigate the consequences of a collision. Further, it aims to select the most appropriate action to handle a risk situation that has been assessed. For

example, in the case of precrash systems, Decision Making consists in deciding if automatic emergency braking should be performed. In most of conventional safety systems, assistance is triggered using decision thresholds.

Outputs

Outputs consist of the assistance that may be provided to the driver once decision has been taken. Conventional assistance is usually provided under two forms: Human Machine Interfaces (HMI) and since more recently in commercialized vehicles, automatic vehicle control. HMIs aim to enhance the driver's situational awareness by providing information though sound signals and/or pictograms displayed on the dashboard. Their design is a difficult task as they have to assist the driver without distracting him from the driving task. Automatic vehicle control aims to apply actions directly on the vehicle through the vehicle controller, e.g. automatic emergency braking in the case of precrash systems.

Intelligent vehicles represent a new perspective for the improvement of road safety. Whilst safety ADAS represent indisputable progress with respect to passive safety systems, they still suffer from several technical limitations. The next Section aims to present the problem that is addressed in this thesis, related to some of these limitations.

1.4 Problem Statement

The last Sections showed that the introduction of intelligence in modern vehicles through safety type ADAS represents new perspectives for road safety. Nevertheless, conventional ADAS can be regarded as *Curative Systems* as they provide assistance at the last minute. Studies showed that curative systems are not sufficient for safety and driver comfort, as they may become intrusive and make situation uncomfortable for drivers and passengers [93, 95].

In most of conventional ADAS, assistance is triggered using decision thresholds. Figure 1.6, Part A illustrates how thresholds are set on a scale of risk as it is assessed. These thresholds are set so that assistance is provided when the likelihood that an accident will occur is high enough. At the same time, the likelihood of inopportune assistance must be at its lowest. Part B of Figure 1.6 shows that this second constraint delays the moment at which assistance can be provided. Further, as presented in Section 1.2.2, drivers have different perception of hazard. Thus, the most relaxed drivers usually react early to handle a given situation, while the most aggressive drivers usually react late to the same situation. However, most of conventional ADAS do not consider the differences which may exist between drivers as it would require to learn customized driving styles. Therefore, for safety ADAS, the decision thresholds have to be set so that they are compatible with all types of drivers, i.e. most of aggressive drivers do not undergo inopportune assistance. As a consequence, assistance is generally provided as last resort.

By contrast to *Curative Systems*, this thesis addresses what can be named *Preventive Systems*, that is, systems which will operate in anticipation. The purpose is to look towards

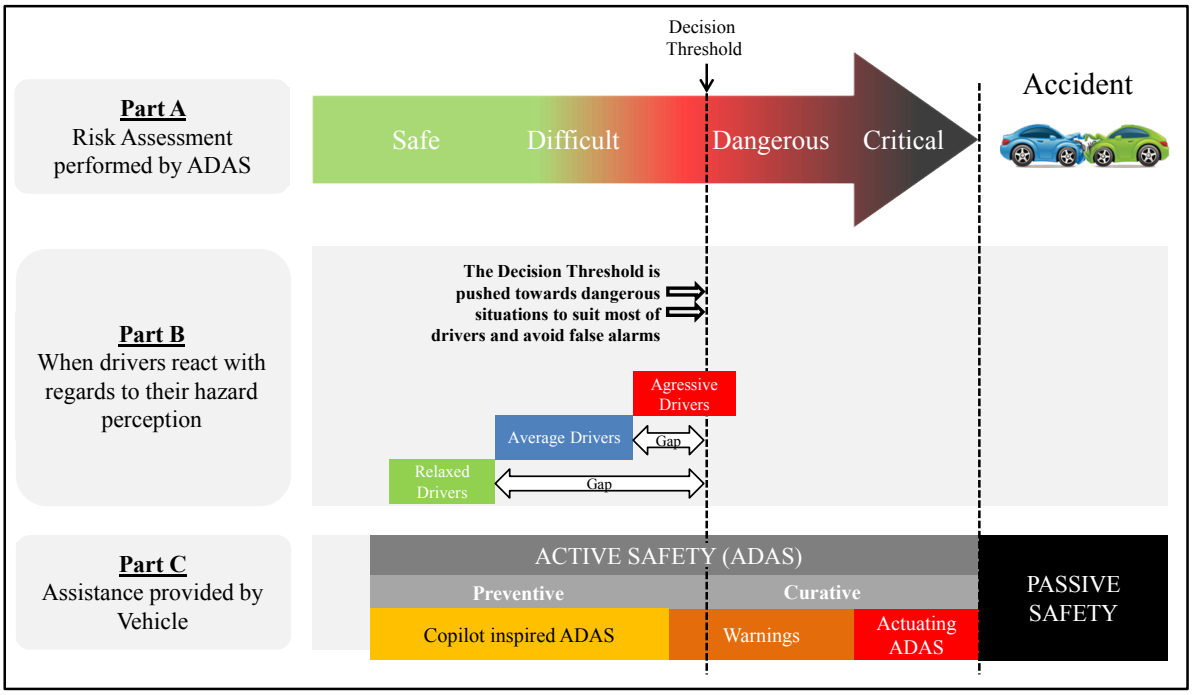


Figure 1.6: Assistance strategies for safety ADAS.

better driving safety and comfort by providing pertinent anticipatory assistance in order to help drivers to avoid making errors, and thus to reduce the likelihood that hazardous situations arise. The analogy is made to the action of the copilot in a rally vehicle. He has advantageous situational awareness by using his *a priori* knowledge of the road and his perception of the world. Moreover, as all drivers are different (c.f. Figure 1.6, Part B), he can adapt his assistance to the drivers capabilities and preferences. Within the context of ADAS, it leads to the term *Copilot Inspired ADAS*, as shown in Figure 1.6, Part C. A Copilot Inspired ADAS aims to provide assistance which comes early, to be taken by the driver as advice or recommendation. The driver should have enough time to understand the information, to make new decisions and then to react comfortably in order to avoid the situation to become hazardous.

The thesis aims to propose solutions to detect when it is pertinent to improve the situational awareness of the driver through assistance that takes the form of recommendation. This is done by relying on the data available on board modern passenger vehicles, namely proprioceptive sensors, navigation maps and perception sensors. As road intersections remain a challenge for road safety (c.f. Section 1.2.3), they have been chosen as case study.

1.5 Approach and Objectives

This thesis was driven in an industrial context, therefore the contributions have to be compatible with car manufacturers constraints. All data sources which are used have to be representative of data sources available on board commercialized vehicles. In this way, in-

formation about the subject vehicle state is provided by the vehicle CAN-bus and by a standard GNSS receiver. Information about the environment is provided by a standard front perception sensor such as a smart camera or a smart RADAR. It is assumed that this sensor performs all processing necessary to output the type and the state of all detected road users (vehicles and pedestrians). The digital map which is used is of low definition (as most of commercialized maps) and is used within a navigation function that provides the contextual information. All data sources offer limited performances and suffer from noise which has already been quantified.

A copilot must be able to adapt his assistance to the driver's driving style in order to ensure reliable assistance. He therefore needs to observe the driver so as to learn how he usually behaves and negotiates road situations. In the case of a vehicle approaching to an intersection, the driver's driving style is showed through the evolution of the vehicle velocity. The first objective was to propose an algorithm that enables to learn velocity profiles, and that takes into account the constraints imposed by the low performances of the sensors. The second objective was to develop an algorithm that enables to assess risk situations, and that exploits learnt velocity profiles to adapt assistance to the driver. Whilst the contribution of customized driver patterns was shown, observing the driver's actuations in addition to the vehicle state enabled to perform faster risk assessment.

Performing risk assessment in real road conditions implies that the most appropriate risk assessment algorithms have to be selected, according to the situation. This requires a situation understanding step, which is preliminary to the risk assessment. In the case of conventional safety ADAS, this step is usually simplified as a basic selection of a single and context independent entity among the others. For example, current precrash systems do not consider that the motion of a monitored entity may depend on a contextual element, or on the motion of another entity. Figure 1.7 shows that considering the context can change the understanding that a system may have of a perceived world. The third objective of the thesis was to give sense to the information returned by the various data sources in order to understand what surrounding road entities are reliable from the point of view of the subject vehicle. Moreover, it aims to provide guidelines on how these entities should be monitored to ensure a safe navigation.

The approach that was followed for this thesis lead to the framework presented in Figure 1.8. This framework is composed by three main parts, namely the Data Sources, the Electronic Copilot and the Outputs. The Electronic Copilot is composed by two blocks, namely Situation understanding and Risk assessment. The Situation understanding block exploits information about the subject vehicle and the environment (i.e. the other road users and the road features). The Risk assessment block needs the guidelines returned by situation understanding as well as information about the driver actuations and driving style. This block estimates if it is pertinent to assist the driver, and returns what type of assistance is the most relevant for the situation. The outputs consists of dedicated HMIs which aim to provide the assistance to the driver. The thesis covers the generation of the trigger signal for advice assistance, however it does not cover the development of the HMIs.

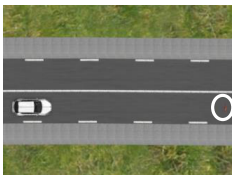
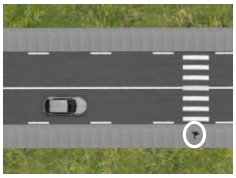
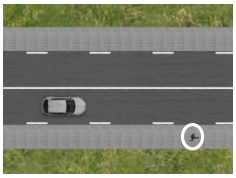
Situation Number	Situation which can be perceived by onboard sensors	Situation considered by conventional ADAS
1	 The pedestrian is not on the vehicle trajectory as he is on the pavement. He is not a pertinent entity.	 The ADAS does not consider the intersection. The pedestrian seems pertinent as he seems on the vehicle trajectory.
2	 The pedestrian is on the pavement, but goes towards crossings. He is a pertinent entity as he has probably the intention to cross the road.	 The ADAS does not consider the zebra. The pedestrian does not seem pertinent as he is not on the vehicle trajectory.

Figure 1.7: The importance of interactions between road entities for reliable situation understanding. Pedestrians are circled by white circles.

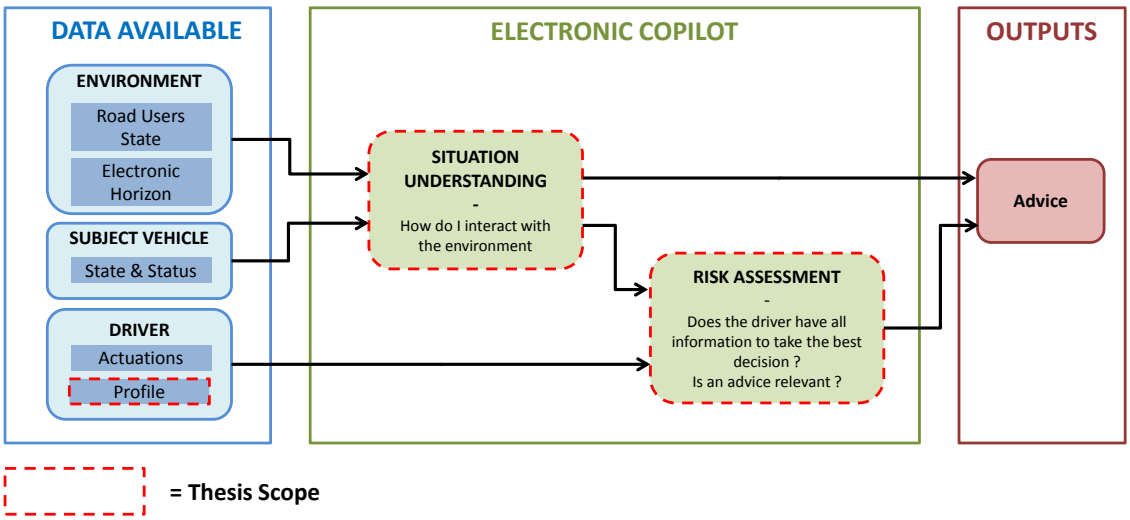


Figure 1.8: The proposed concept of Electronic Copilot in the thesis framework.

1.6 Contributions

The problem addressed in this thesis is the early detection of risk situations that enable to provide early assistance in the form of advice or recommendations. This is achieved through the definition of the Electronic Copilot framework, and through contributions in the domains of situation understanding and risk assessment. The contributions are as follows:

1. A novel semantic-based approach for situation understanding which allows to:
   - Conceptually model the static and dynamic road entities which may be met by vehicles, and the interactions which are likely to exist between all of them.
   - Represent the environment as it is perceived by a vehicle equipped with vehicle type sensors and databases.
   - Reason on the environment that is perceived by a vehicle, in order to extract the most relevant entities and to give guidelines to risk assessment frameworks.
2. A mathematical framework that allows to model personal velocity profiles. This framework:
   - Takes into account the uncertainties of the sensors.
   - Takes into account the variability of the drivers behaviour as they approach to stop intersections.
3. A risk assessment framework based on the "comparing intention and expectation" framework developed by [90]. The extended framework allows to:
   - Exploit personal velocity profiles to customize risk assessment to the driver's driving style.
   - Take into consideration the driver's actuations as well as the vehicle state for risk assessment. It allows for a fast detection of unexpected behaviours, and thus of risk situations.
   - Estimate the most relevant type of assistance between automated actuations, warning and advices.
   - Diminish the risk of rear-end collisions when the driver is provided with advice assistance in case of risk situation.

The work carried out during the thesis gave rise to 5 publications presented in international conferences and a patent registered at INPI[1]:

- A. Armand, D. Filliat, and J. Ibanez-Guzman. Modelling stop intersection approaches using gaussian processes. *Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on. IEEE*, 2013.

[1]Institut National de la Propriété Intellectuelle.

- A. Armand, D. Filliat, and J. Ibanez-Guzman. Detection of unusual behaviours for estimation of context awareness at road intersections. *in Proceedings of the 5th Planning, Perception and Navigation for Intelligent Vehicles Workshop (IROS 2013)*, 2013.
- A. Armand, D. Filliat, and J. Ibanez-Guzman. Ontology-based context awareness for driving assistance systems. *Intelligent Vehicles Symposium Proceedings, 2014 IEEE. IEEE*, 2014.
- A. Armand, D. Filliat, and J. Ibanez-Guzman. A framework for proactive assistance: Summary. *Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on. IEEE*, 2014.
- A. Armand, D. Filliat, and J. Ibanez-Guzman. A Bayesian Framework for Preventive Assistance at Road Intersections. *Intelligent Vehicles Symposium Proceedings, 2016 IEEE. IEEE*, 2016.
- A. Armand, J. Ibanez-Guzman and D. Filliat. Système d'aide à la conduite et procédé mis en œuvre dans un tel système, *Pattent WO2016020598*, issued date February 11th, 2016.

1.7 Thesis Content

The remaining of the thesis is organised as follows:

Chapter 2 gives an overview of the related work in the domains of perception and contextual data handling, and risk assessment. The Chapter is driven through three parts. The first one presents with Scene representation methods, that is, methods for the representation of road environments. The second part presents works dealing with Situation understanding, that is, how to give sense to the Scene from the point of view of the subject vehicle. The third part deals with Scenario prediction. In the context of the thesis, this last part presents the existing methods for risk assessment.

Chapter 3 presents an ontology-based framework for situation understanding. After a brief presentation of principles of ontologies, the proposed ontology is described. It consists of a conceptual description of the road entities which are usually met on the road. This description includes the interactions which are likely to exist between the entities. The ontology is used within a framework that enables to reason on the environment perceived by the subject vehicle, and to generate guidelines intended for risk assessment frameworks. The approach is validated through an experimental evaluation performed with real vehicle data.

Chapter 4 presents an extension of the Bayesian Network framework developed by [90], which relies on the vehicle state for the detection of risk situation. The extension aims to make the framework able to adapt to the driver's driving style, and to estimate what type of assistance is the most pertinent (between automated actuation, warning and advice) in case of risk situation. An algorithm to learn personal velocity profiles which can be used within the risk assessment framework is presented. Finally the ability of the framework to trigger

advice assistance is evaluated with real vehicle data. The contribution of using personal driver profiles for risk assessment is shown.

Chapter 5 presents a second extension of the Bayesian Network framework which aims to detect risk situations earlier. This extension consists of the incorporation within the Bayesian Network, of observations of the driver's actuations. The ability of the extended framework to trigger advice assistance is evaluated with real vehicle data. It is shown that considering the driver's actuations enables to detect risk situations earlier, and therefore to increase the performances for triggering pertinent advice assistance.

Chapter 6 presents an experimentation which aims to estimate the added value of the system presented in Chapter 5 for other vehicles interacting with the subject vehicle. This was performed from the point of view of a vehicle following the subject vehicle in which the driver is provided with an advice. It is shown that assistance provided in the form of advice to the driver of the lead vehicle is also beneficial for the driver of the following vehicle, as it allows to reduce the deceleration necessary to avoid rear-end collision.

Chapter 7 finally concludes by summarizing the thesis, and by providing perspectives for further work.

Chapter 2

From Road Scene Representation to Risk Assessment: State of the Art

Contents

2.1 Introduction

Chapter 1 showed that intelligence embedded in modern vehicles can contribute to the improvement of comfort and safety on roads. The ability that vehicles have to be aware of their surroundings through perception sensors, databases and communication services represent one of the essential elements. However, the major part of intelligence is represented by the ability to give sense to this data in order to detect risk situations, and thus to avoid accidents.

In the literature that deals with the exploitation of perception data, 3 terms are generally used, namely *Scene*, *Situation* and *Scenario*. The meaning of each of these terms in the context of intelligent vehicles is rather vague, and it is not rare to meet conflicting definitions. Geyer *et al.* formally defined the meaning of these terms in the context of assisted and automated driving guidance [48]. These definitions are rather abstract, therefore they were interpreted with respect to the problems addressed in this thesis:

– A Scene is a snapshot of a collection of cohabiting road entities, including the subject vehicle and the surrounding static and dynamic entities. Each entity is defined by its type and state. A Scene can therefore be represented by all data returned by the data sources.

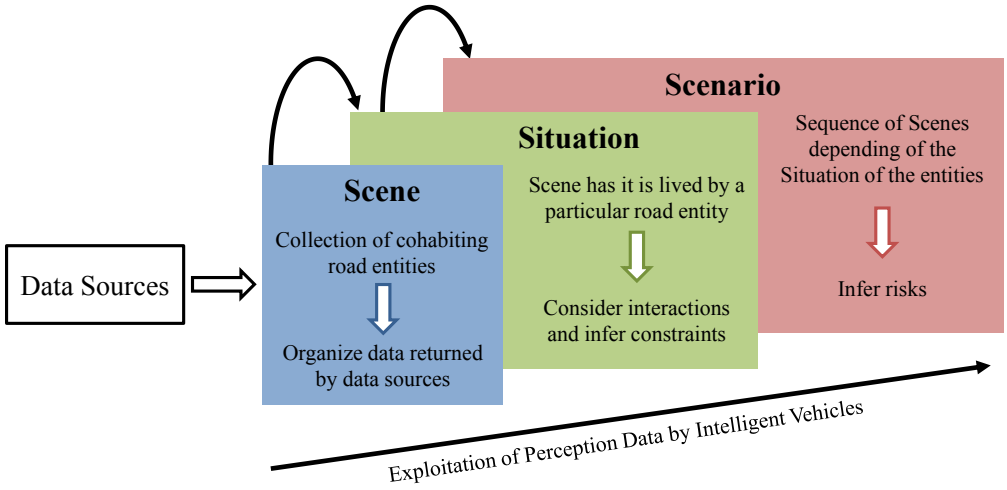


Figure 2.1: Definitions of Scene, Situation and Scenario as they are used in this thesis.

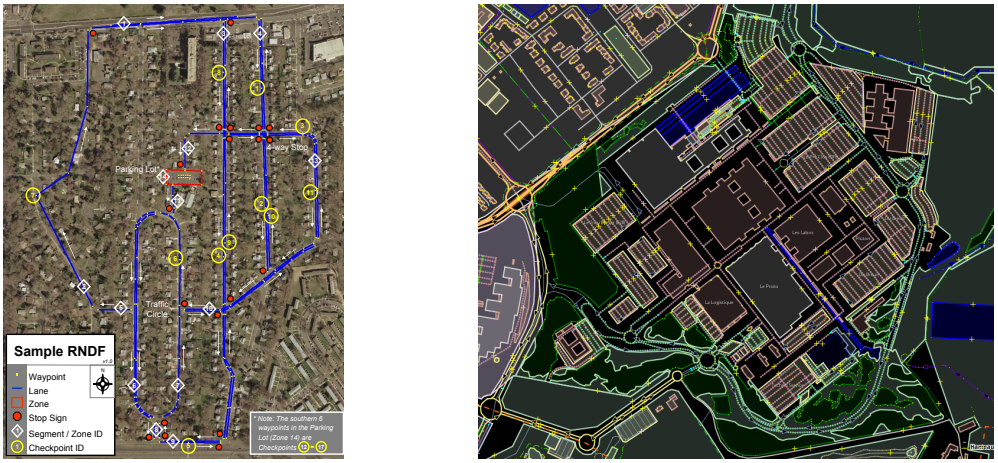
- A Situation is the Scene as it has to be understood by a particular dynamic entity of this scene (i.e. the subject vehicle). This consists in understanding how the interactions between all entities of the Scene are propagated to this entity and constrain it in its navigation. Therefore, Situation understanding consists in giving sense to a Scene.
- A Scenario is understood as a sequence of Scenes which is the consequence of the Situation of all interacting road entities present in a primary Scene. In the context of this thesis, predicting a Scenario consists in predicting the future state of the participating entities in order to estimate the risks lead by the Situation.

Figure 2.1 shows how these 3 terms are linked together. A Situation is based on a Scene, and a Scenario is based on the primary Scene and on the Situation of each entity present in the Scene. The exploitation of the perception data can therefore be split into 3 main steps: the Scene representation, the Situation understanding and the Scenario prediction for risk assessment.

This Chapter aims to provide an overview of the existing methods dealing with road Scenes, road Situations and road Scenarios. Existing situations understanding methods are strongly linked to the manner how to represent the scene, thus the first Section presents conventional methods for scene representation which are not well suited for situation understanding. The second section presents how Situation understanding can be performed, and therefore introduces other approaches for scene representation. Finally, the last section presents how risks can be inferred from the Scene representation and the Situation understanding.

2.2 Scene Representation

The Scene representation consists of the statement of the nearby environment, with respect to the surrounding road entities which are perceived by the subject vehicle. The simplest scene representation consists of the raw data as it is returned by data sources, such as point



(a) RNDF maps used for the DARPA Challenge.

(b) OSM map of the Renault Technocentre in Guyancourt, France.

Figure 2.2: Graphical Representation of Road Networks.

clouds provided by laser range sensors, or lists of objects returned by smart laser, radars or cameras. This Section aims to provide an overview of the conventional techniques for the representation of road Scenes for intelligent vehicles purposes. Two main categories were identified: the representation of the road network only, and the representation of the road network plus other dynamic road entities.

2.2.1 Representation of the Road Network

Maps represent a solution for the representation of the road network and static entities, as they allow for the compilation of geographical knowledge. In the domain of intelligent vehicles, they have become a strategic issue to store *a priori* information about environments and context. For commercial use, their primary function was for path planning and guidance of human driven vehicles through Personal Navigation Device (PND). In that way, the digital maps contains a graphical representation of the road network and some basic semantic information such as the streets names or the direction of navigation. The navigation systems which exploit these maps are generally black boxes, therefore a direct access to the databases is usually not possible.

The progresses in the research towards intelligent vehicles progressively lead to frameworks requiring always more prior information about the environment. New formats allowing for quick and simple edition of digital maps were developed. The Route Network Definition Format (RNDF) has been developed and used by the participants of the DARPA challenges for autonomous navigation [30]. This format specifies road segments, and contains information such as the lane width, the position of stop signs, the position of parking slots, particular zones, etc. Figure 2.2a shows the map that was used for the Urban DARPA Challenge. An other format regularly used by intelligent vehicle frameworks is the collaborative and open

source Open Street Map (OSM) format [58]. This format represents the road network in the form of geolocalized nodes and ways. Semantic information can be stored in the map through the edition of attributes on the nodes and ways. Figure 2.2b shows an example of OSM map representation.

Whilst digital maps enable to store a large amount of prior information about the environment (i.e. static road entities), they cannot contain information about dynamic entities such as other road users. Next Section presents techniques for the representation of dynamic road entities.

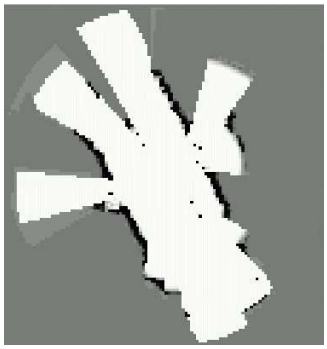
2.2.2 Representation of the Road Network and Dynamic Road Entities

Information about nearby dynamic entities is generally provided by exteroceptive sensors. In the domain of intelligent vehicles, a very popular approach for the representation of the navigable space and of obstacles is the occupancy grids [169, 38, 82]. Also known as evidential grids, occupancy grids are map-based representation of environments initially developed and used in the field of robotics [153]. They consist of maps of the environment in the form of arrays of cells. The range of the cells usually varies from one to several dozens of centimetres, depending on the required precision, and on the sensors resolution. For each cell of the grid, the aim is to compute the probability that it is occupied by an object, i.e. that the cell is full or empty.

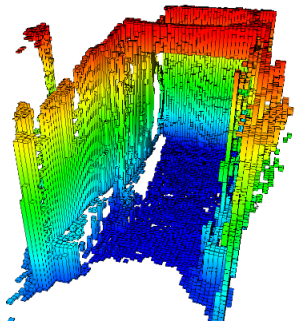
Conventional occupancy grids are built after processing the raw data that is returned by sensors delivering point cloud representation of the environment (i.e. laser range sensors or sonar sensors). They consist of 2 dimensional grids [107, 152]. An example of representation of a 2D occupancy grid is given in Figure 2.3a. The concept was extended to allow for a 3D mapping of the environment, which is mostly used by aerial vehicles [171]. Figure 2.3b shows an example of 3D occupancy grid. From point clouds representation, it is possible to extract obstacles and dynamic entities.

The handling of dynamic obstacles in cluttered environments requires to perform additional multi-target tracking, as it is done by Bayesian Occupancy Filtering (BOF) [35]. Whilst some approaches prefer to map static and dynamic obstacles on different grids [161, 162], others fuse both representations into a single grid [38]. Multiple data sources can be used, for example to exploit information about lane markings [63, 97], to exploit prior knowledge stored in digital maps [85, 113], or also to improve the tracking of the dynamic objects [24]. This allows to establish more reliable occupancy grids which can then be exploited by ADAS. Figure 2.3c shows an example of occupancy grid representing the road course.

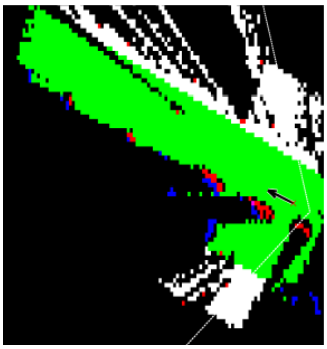
Recently, Dynamic Occupancy Grids have become more and more popular and reliable. For instance, the Hybrid Sampling Bayesian Occupancy Filter (HSBOF) allows to represent the environment as a mix static and dynamic occupancy, in order to improve the accuracy of the results [111]. This approach can be extended by adding new features, such as empty spaces and unknown areas, allowing for great improvement of the performances [134]. Note



(a) 2D Occupancy grid. After [152]



(b) 3D Occupancy grid. After [171]



(c) Road course based on occupancy grid. After [85]

Figure 2.3: Occupancy grids.

that credibilist approaches can also be used for occupancy grids representation [154, 85]. As probabilistic approaches, credibilist approaches consider data uncertainties, but their distinctive characteristic is their capability to consider data imprecision.

Whilst occupancy grid methods represent a straightforward method for sensor fusion, they usually require high computational efforts and high memory consumption. This is because the computation of the probability of occupancy has to be performed for each cell, at each time-step. Scalability is therefore a major problem. Further, semantic information about obstacles is often restricted to a "static object" or a "dynamic object" labels.

The smart sensors which are embedded in modern vehicles are for most of them black boxes which return information about detected objects. As well as the state of the objects, these sensors are usually able to classify the objects, that is, they are able to return additional semantic information. Fusion between multiple sensors can be performed, such as fusion between a camera and a radar. This allow to take benefit of the advantages of both sensors in order to get more precise and reliable estimation of the type and state of the objects. However, a major part of the systems which exploit data provided by these sensors or returned by sensor fusion represent the environment as a list of objects present in the subject vehicle field of view. Projects such as RoadGraph aimed to integrate information from exteroceptive sensors, digital maps and V2X communication data into a single graphical structure [80]. However, this scene representation does not enable to reason on the information that it stores in a straightforward manner.

The techniques presented in this Section enable to provide Scene representations, however the manner how the environment around the subject vehicle is represented do not enable to understand the interactions which may exist between the entities present in the scene. For this purpose, more elaborated techniques have to be used to 1) Represent the scene, 2) Reason on the scene, i.e. to understand the situation of the subject vehicle.

2.3 Situation Understanding

Situation understanding consists in reasoning on the Scene representation, i.e. in giving sense to the information stored in the Scene representation. From the point of view of a subject vehicle, it consists in inferring how it is constrained by the surrounding environment. This therefore helps to understand what surrounding entities are the most pertinent to monitor. For this purpose, the interactions which exist between road entities have to be considered. Whilst Situation understanding aims to provide essential information for risk assessment, it has not yet been extensively studied. This Section aims to present the few related works which have been published so far. Two main categories were identified: probabilistic approaches and semantic based approaches. Table 2.1 presents a comparative review of the works which are presented in the remaining of this Section.

2.3.1 Probabilistic Approach

Road situations are often subject to high complexity and variability of situations, especially in urban environments. Vehicles are able to perceive plenty of surrounding entities, however most of the time a major part of these entities is not pertinent to be considered by the subject vehicle. It is with this perspective that Platho *et al.* proposed to decompose situations into "parts of situations" or in an other term "configurations" [122]. This enables to simplify the Scene by selecting only the entities which are pertinent for the subject vehicle. The notion of relationship between road entities is introduced by, for example, considering that the behaviour of a perceived vehicle can be affected by the presence of a red traffic light, or by another vehicle which is stopped because of another entity. Figure 2.4 shows an example of configuration. The recognition of configurations is performed through a Bayesian Network. The approach was tested in simulated environments, and was used to predict the velocity profiles of other road users in intersection situations [123]. However, in that state, the approach only allows to consider direct relationships between entities. Therefore, chain reactions are not considered. For example, if the subject vehicle follows a vehicle that approaches to a pedestrian, the interaction between the lead vehicle and the pedestrian is not taken into account by the subject vehicle. If chain reactions which may occur are not considered, the situation understanding may be partially performed only.

Whilst probabilities allow to take into account uncertainties on perception data, so far they can only be used to model basic situations based on scenes represented with conventional methods. The amount of possible situations which may occur makes it difficult to define a generic probabilistic model which would be well suited for all situations, and which would be capable of considering interactions between road entities. This may explain why the literature does not propose other probabilistic frameworks for Situation understanding than the one presented above.

Table 2.1: Comparative review of works on situation understanding.

Reference	Description of Road Network	Description of Road Users	Interactions Between Road Entities	Purpose
Platho *et al.* [123]	✓	✓	✓	Selection of the most pertinent entities of the scene.
Schamm *et al.* [138]	✓	✗	✓	Situation of the subject vehicle.
Hummel *et al.* [72]	✓	✗	✗	Model concepts of road networks as a complement of vision sensors.
Regele [131]	✓	✗	✗	Conflict assessment between vehicles.
Hülsen *et al.* [71]	✓	✗	✗	Model intersections for conflict assessment between vehicles.
Vacek *et al.* [157]	✓	✓	✗	Recover already met situations.
Zhao *et al.* [175]	✓	✓	✓	Gather information from multi sources. Estimation of risk.
Kohlhaas *et al.* [81]	✓	✓	✓	Model interactions between vehicles and road network. Include traffic rules.
Pollard *et al.* [124]	✓	✓	✗	Infer best automation level for intelligent vehicles.

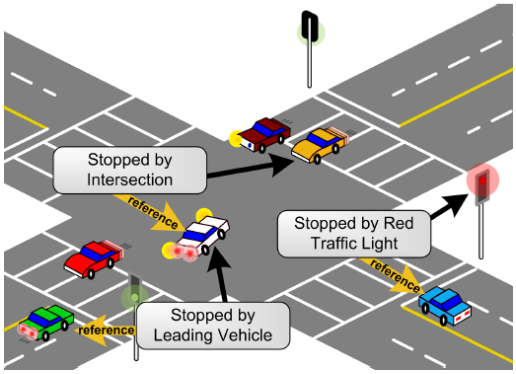


Figure 2.4: Example of a configuration as it is defined in [122].

2.3.2 Semantic based Approaches

Some of the approaches which were presented so far for the representation of road Scenes take into consideration semantics, for description purposes only. Semantic based approaches for Situation understanding aim to focus on semantics for description, but also for reasoning. This Section provides an overview of these approaches as they are used in the intelligent vehicle domain for scene representation allowing for straightforward situation understanding. Most of them use either First-order Logics [149] and Description Logics (DL) [14], for representation of concepts in the form of ontologies (c.f. Chapter 3 for more details on ontologies). At first, semantic based approaches were used to model and understand the road network from the point of view of the subject vehicle, and then they were also used to model and understand the whole interaction between road network and dynamic entities.

Road Network

One of the first works exploiting DL for situation understanding was done by Hummel *et al.* [72]. The ontology that is proposed introduces the concepts of road networks (roads, lanes, dividers, road markings and junctions) and is used as a complement of vision sensors and digital maps to retrieve relevant information about intersections. For example, when the precision of the localisation sensors do not enable to determine on what lane the vehicle is navigating, this information can be inferred by the ontology from map and camera data. Whilst this formalism does not take into account cohabiting road entities (vehicles, pedestrians, etc.), it enables to show that ontologies can be used to reason, at least partially on road situations.

The representation of road intersection networks through ontologies was introduced by Regele [131]. It was used to solve the traffic coordination problem of autonomous vehicles, i.e. to handle conflicts between vehicles reaching the same intersection or cohabiting in the same area. This work inspired Hülsen *et al.* who proposed a generic description of road intersections for situation understanding at the approach to road intersections [71]. This ontology enables to infer conflicts and thus potential risk situations for vehicles reaching the same intersection. Figure 2.5 illustrates how the relationships which may exist at road intersections are represented. The framework was tested on several intersections and its efficiency was proved even for very complex intersections. A real time implementation of the framework in simulated environments was successfully performed [70]. In these ontologies, vehicles and other road entities are not formally represented.

Road Network and Other Entities

Within ontologies, the representation of road entities other than those related to the road network was introduced by Vacek *et al.* [157]. In that way, semantic information about road entities (i.e. types, etc.) were defined in an ontology which is used within a case-based

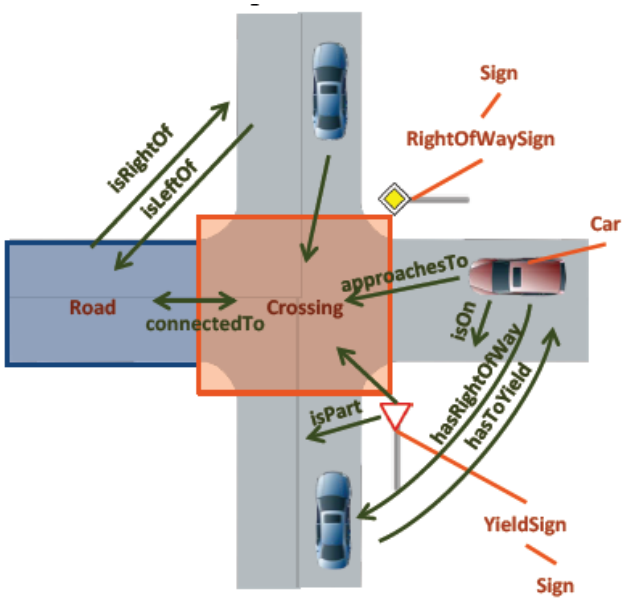


Figure 2.5: Example of semantic representation of an intersection. After [71].

reasoning framework to perform scene understanding. The tenet was to recover similar or resembling situations as those already met, in order to infer the behaviour which seems to be the most appropriate to negotiate the situation. Whilst the ontology allows to represent different types of road entities, relationships between them are ignored, which finally prevents from understanding the situation as a whole. Moreover, the ontology was actually used to model the context, and was not used to perform proper reasoning on the road situations.

First-order probabilistic languages (FOPL) was used by Schamm *et al.* to perform situation assessment [138]. A FOPL knowledge base was used to model driving situations and interactions. This *a priori* knowledge is thus used with sensor information to automatically create a probabilistic network, and then to infer the situation in a structured manner. Whilst the interest of the approach is demonstrated through collision risk estimation, it does not enable to sufficiently consider semantics. That is, all entities are conceptually of the same type, which prevents from considering interactions between entities of different types. Moreover, first order logic suffers from poor expressivity, which therefore prevents from editing complex rules in the knowledge base. Further, it seems difficult to extend such a system for more complex situations than those presented in [138].

Zhao *et al.* built a knowledge base which contains information about maps and traffic regulation, and which is used within safety ADAS to take decision at road intersections in case of over speed [175]. Three ontologies were defined for this purpose. The first one aims to describe information which may be stored in a digital map, the second aims to describe control strategies and the last one aims to describe vehicles. Interactions between road entities are considered only between vehicles reaching the same intersection, for the generation of collision warning.

An ontology that models traffic scenes in order to establish the state space of the subject vehicle with respect to other vehicles and the road network was proposed by Kohlhaas *et al.* [81]. Two categories of objects are considered, namely the environment objects (related to the road network) and the dynamic objects (related to vehicles). The interactions between the vehicles and the road network are formally stated, as well as the lateral and longitudinal interactions between vehicles. Further, the ontology contains information about traffic rules through defined conditions.

Finally, Pollard *et al.* proposed an ontology that represents features of the road network, environmental conditions, sensors states, subject vehicle state and presence of moving obstacles [124]. This ontology enables vehicles to perform self assessment on their automated driving capabilities, with the aim to decide what automation level (from fully manual to fully automated) is best adapted to the situation.

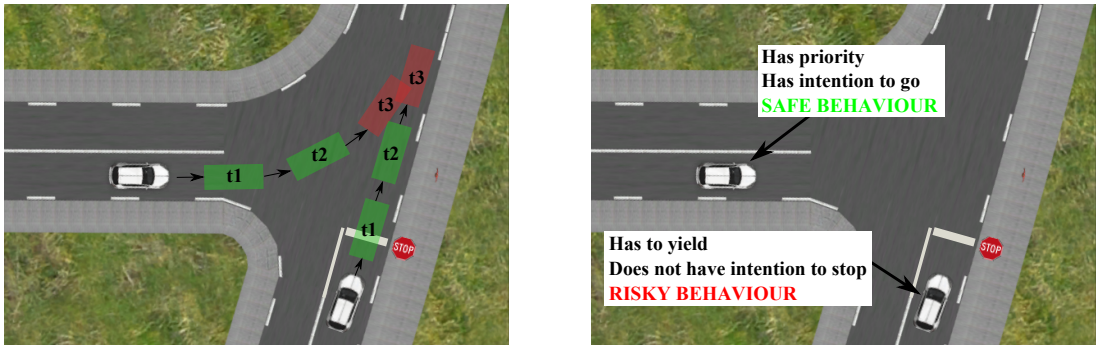
Whilst semantic based approaches enable to model road scenes, to model the interactions between entities, and then to reason in a straightforward manner on situations, their main limitation is their inability to take into account data uncertainties. FOPL enables to fill this gap, however it does not enable to model complex situations because of the low expressivity of the language.

2.4 Scenarios Prediction and Risk Assessment: Focus on Road Intersections

The two last Sections presented how information returned by the data sources can be used in order to represent road Scenes and to understand road Situations. Whilst these methods enable to provide relevant information about the subject vehicle in its surrounding environment, they are not sufficient for an accurate estimation of the risks lead by the situation.

For a vehicle, a situation is said to be at risks if a collision between this vehicle and another road entity is likely to happen in a near future. In the literature, two main approaches are generally used for collision detection. The first approach consists in predicting the future states of the concerned entities, and then in estimating the likelihood that a collision will happen between these entities. The second approach consists in estimating the intention of the concerned vehicles, and then in detecting unexpected or conflicting intentions. Figure 2.6 illustrates these two approaches.

Lefèvre *et al.* published a survey of the existing methods used for prediction of vehicle motions and for risk assessment [91]. This survey covers the state of the art in terms of scenario prediction aiming to assess risks lead by a situation. In this Section, it is proposed to provide an overview of this state of the art, focussed on the problem of this thesis. The first part presents the literature that exploits the first approach for collision detection, and the second part presents the second approach. Table 2.2 presents a compilation of the methods used for risk assessment that are presented in the remaining of the Section, classified by approach and abstraction levels.



(a) Collision detection through trajectory prediction. Collision is detected at timestep $t3$.

(b) Detection of unexpected or conflicting intentions.

Figure 2.6: The two main approaches for risk assessment.

Table 2.2: Compilation of risk assessment approaches and related techniques.

Approach	**Abstraction Level**	**Methods**	**Mathematical Tools**	**Customization for drivers ?**
Trajectory Prediction and Collision Detection	1	Basic motion models	KF, PF	✗
	2	Trajectory	Parametric functions	✓
			GMM, GP	✓
		Manoeuvre recognition	MLP, SVM, HMM	✓
			BN, DBN	∼
	3	Trajectory	Parametric functions, GMM, GP, etc.	✗
		Sophisticated motion models	BN, DBN	∼
		Hierarchical scenario	SMT	✗
Detection of Unexpected Manoeuvres	3	Manoeuvre recognition	Machine learning	✓
			BN, DBN	∼

2.4.1 Collision Detection based on Trajectory Prediction

Prediction of vehicles motion navigating in road environments can be performed through three levels of abstraction. In Level 1, it is assumed that the motion of the subject vehicle is not constrained by neighbouring entities. In Level 2, it is assumed that the subject vehicle is constrained by the road network only, while in Level 3 it is assumed that the vehicle is constrained by both the road network and other road users. This Section presents the most popular methods for trajectory prediction classified by levels of abstraction followed by the manners how to use these trajectories for estimation of collision.

2.4.1.1 Trajectory Prediction of Unconstrained Vehicles

When vehicles are assumed to be independent from their surroundings, the most common method to predict their trajectories is to use classical motion models.

Motion Models

Motion models can be classified through several levels of complexity, depending on the physical parameters which are taken into consideration. Kinematic models assume that the vehicle motion is only constrained by the vehicle state and movement, i.e. its position, speed, acceleration, etc. That is, external forces such as road and air friction are not considered. In the family of kinematic models, linear models are the simplest as they assume either a Constant Velocity (CV) of a Constant Acceleration (CA) over time. These models assume straights motions and therefore cannot consider rotating motions. Curvilinear models including Constant Turn Rate and Velocity (CTRV) and Constant Turn Rate and Acceleration (CTRA) models aim to fill this gap by taking into account the motion around the Z axis. These motion models and other more complex kinematic models are detailed in [140].

By contrast to kinematic motion models, dynamic motion models take into consideration the forces and parameters which affect the vehicle motion. These models can, for example, consider the lateral acceleration that the vehicle undergoes in curved road, or the tire forces, etc. The amount of parameters which can be taken into account by dynamic models can be large, and therefore make the models very complex. Such complexity is most of the time not pertinent for trajectory prediction, therefore simple models such as the well known "bicycle model" are preferred. The vehicle is assumed to be a two wheel vehicle with front wheel drive moving on a rigid flat horizontal surface [59].

These motion models are very generic, and the parameters which are used only depend on the initial vehicle state. That means that these models do not allow to use parameters which are *a priori* known, that is, it is not possible to use parameters which are specific to the driver. Therefore, the trajectory prediction methods which are presented below cannot take into consideration the driving style of the driver.

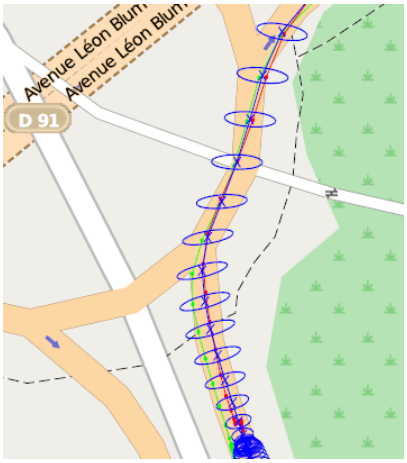


Figure 2.7: Example of vehicle trajectory estimation using EKF tracking. Ellipsoids represent the uncertainty on the estimated locations. After [177].

Trajectory Prediction

Trajectory prediction is generally performed by exploiting a kinematic or a dynamic motion model. The simplest manner to perform this is to directly apply the motion model using the current state of the vehicle as initial values. This assumes that there is no uncertainty neither on the initial values of the parameters, neither on the motion model that is used. Whilst such a basic method is simple to implement and computationally efficient, these assumptions are too strong to ensure reliable and long term predictions. Taking into consideration uncertainties helps to improve the reliability of the prediction.

The uncertainties on the vehicle state and on its evolution can be handled in a straightforward manner through recursive filters such as Gaussian Filters or Monte Carlo simulations. Recursive filters work in two steps: the *Prediction* and the *Update*. The *Prediction* consists in predicting the state of the vehicle at time $t+1$ using the selected motion model and the state at time t. The *Update* consists in combining the sensors measurements performed at time $t+1$ with the predicted vehicle state. These filters allow to take into account uncertainties on the inputs, but also enable to return the predicted vehicle state as a distribution. Among Gaussian filters, it is worth citing the well known Kalman Filter (KF) [174, 153]. The basic version of this filter assumes that the uncertainties follow a normal distribution, and that the motion and sensor models are linear. Non linear models can be handled by more sophisticated versions of the KF such as the Extended Kalman Filter (EKF) [153]. Monte Carlo sequential simulations, also known as Particle Filtering (PF) allow to avoid the assumption of normal distribution made on uncertainties and on the linearity of motion models [44, 153]. All estimations are performed through a set of random variables (i.e. a set of particles) which represent the potential locations of the vehicle. The main disadvantage of PF-based trajectory prediction is their computational cost, as the computation has to be performed at each step for each entity. Figure 2.7 gives an example of vehicle trajectory estimation using a recursive filter.

Tracking consists in looping on the Prediction and the Update steps when measurements are available. These filters can also be used to predict the evolution of the motion of the vehicle, even if there is no measurement available [39]. This will result in a progressive rise of the uncertainties on the estimated state, therefore the accuracy on the predicted motion will progressively decrease. Such prediction methods are therefore usable only for short term motion prediction. Further, the motion models exploited for prediction do not enable to predict changes on the vehicle motion which can be due to external constraints such as those implied by the road network or other road users. Therefore, in case of manoeuvre (i.e. lane change, stop or turn at road intersections, etc.) the methods presented above cannot be used. The next section presents how constraints imposed by the road network can be taken into consideration for vehicle motion prediction.

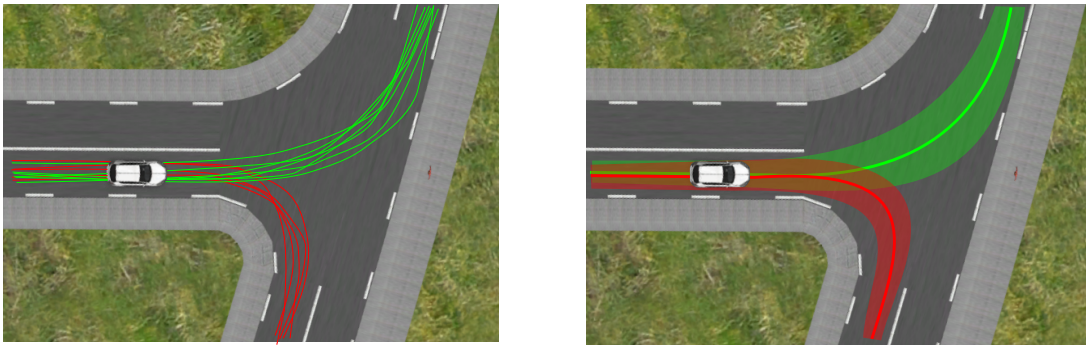
2.4.1.2 Trajectory Prediction of Vehicles Constrained by the Road Network

When navigating, vehicles are constrained by the road network which governs their motion. It is therefore pertinent to take into account the road network and the possible trajectories and manoeuvres that vehicles can follow in order to predict their motion. In that way, trajectory prediction can be performed simply by using Recursive filtering (i.e. KF, PF, etc.) which exploits the shape of the path that the vehicle is likely to follow. The information about the road is generally *a priori* known and extracted from digital maps. In that way, the road network can be taken into account during the Prediction step [168] or during the Update step [121]. More sophisticated methods are proposed in the literature. There are those based on trajectory prototypes and those based on manoeuvre recognition.

Trajectory based motion prediction

Trajectory based motion prediction consists in comparing the vehicle current trajectory to a stored dataset of prototype trajectories which represent typical motion patterns. By selecting the prototype trajectory that suits best the current vehicle trajectory, it is possible to predict the vehicle motion several seconds ahead by using the prototype trajectory as a model. In general, the trajectories are preliminary learnt and used as *a priori* knowledge for the trajectory prediction. Therefore, this allows to learn trajectories for each driver, and therefore to customize trajectory prediction for each driver.

Several techniques exist for the representation of the prototype trajectories as a parametric function $T(t) = \Phi$, with Φ the vehicle state. Φ is generally composed by spatial points on the xy 2D plane, or/and by the vehicle yaw angle $\varphi(t)$ and velocity $v(t)$. Among all techniques, polynomial descriptors, curve signatures and Chebyshev decompositions are the most popular [109, 36, 61, 170]. Figure 2.8a shows an example of clustered prototype trajectories. The current vehicle trajectory is then compared to all prototype trajectories available in the database. For this purpose, several metrics have been used in the literature, such as Longest Common Subsequence (LCS), Quaternion-based Rotationally Invariance LCS (QRLCS), Hausdorff, Levenstein, Dynamic Time Warping (DTW) and others [57, 16, 160, 61].



(a) Cluster of prototype trajectories.

(b) Prototype trajectories modelled by GMM or GP.

Figure 2.8: Prototype trajectories.

In some situations, prototype trajectories can be classified by manoeuvres that the vehicle can perform. For example at road intersections, the classes can be "go straight", "turn left", "turn right", etc. It can therefore be relevant to model one prototype trajectory per class using the cluster of training prototypes which is available. For that purpose, Gaussian Mixture Models (GMM) represent a solution to model trajectories as parametric probability density functions [170]. Another probabilistic manner to model vehicle trajectories is based on Gaussian Processes (GP) regressions [31, 78]. GP consist in fitting a Gaussian distribution over a training cluster of the training trajectories. By contrast to GMM, GP enable to model trajectories as non-parametric probability functions. As shown in Figure 2.8b, using either GMM or GP enable to predict trajectories which consist of the mean trajectory together with the uncertainty on the prediction (variance). Therefore, from the current partial trajectory of the subject vehicle, it is rather simple to compute and select the most likely prototype trajectory.

Manoeuvre based motion prediction

Manoeuvre recognition followed by prediction of manoeuvre execution represent an alternative to trajectory prototypes for trajectory prediction. In the context of road intersections, the most obvious feature to observe to estimate the intention to go straight or to turn is the blinker indicator. However, in practice recognition of manoeuvre intention needs to be performed through the exploitation of proprioceptive vehicle information (state, status, etc.), and sometimes through road network information (geometry, topology, etc.). Manoeuvre recognition actually consists in classifying the intended manoeuvre among a set of possible manoeuvres. For this purpose, discriminative learning algorithms are popular such as Multi-Layer Perceptrons (MLP), Support Vector Machines (SVM) or more recently Latent Dynamic Discriminative Models [47, 12, 116]. These techniques are usually used for binary classification problems, such as, for example, classification of compliant vs. violating drivers.

Hidden Markov Models (HMM) represent a generative approach and are a popular alternative to discriminative algorithms [12, 17]. They model manoeuvres as chains of consecutive events, the transition between events being modelled through conditional probabilities. Intended manoeuvres can be estimated by comparing the likelihood of the observations for each HMM. These algorithms need to undergo a preliminary training step. For this purpose, data recorded in vehicles is generally used, which makes it possible to customize the systems for a given driver. It therefore allows to customize the systems for each driver by taking into consideration the manner how they usually negotiate given situations.

Bayesian Networks (BN) represent another solution for the estimation of intended manoeuvres. In [89], the driver intention is not estimated through learned data, but through the exploitation of the road network that is stored in digital maps. By contrast to the other discriminative and generative techniques, this solution does not take into account the drivers driving style, however it provides a generic method which adapts to all intersection layouts. While this method does not allow for a straightforward customization for the driver, customization may be conceivable by tuning for each driver the conditional probabilities defined in the BN.

Once the intended manoeuvre has been identified, the prediction of the vehicle trajectory can be performed with respect to the manoeuvre. Again, several methods have been explored in the literature. Trajectories can be predicted using GPs or Rapidly exploring Random Trees (RRT) [31, 12]. An alternative consists in computing reachable states [6, 51].

Whilst taking into account the constraints imposed by the road network to navigating vehicles enables to enhance the prediction of motion, this is not sufficient for most of situations. The approaches presented above assume that vehicles are not constrained by other vehicles, that is, they cannot result in realistic predictions for situations in which the subject vehicle cohabits with other vehicles. The next Section presents how the constraints imposed by cohabiting vehicles can be taken into consideration for vehicle motion prediction.

2.4.1.3 Trajectory Prediction of Vehicles Constrained by the Road Network and Other Road Users

Frameworks which take into consideration the constraints that the subject vehicle undergoes from the road network and the other road users are rather rare. Because of the infinite number of situations which may occur, it is not possible to model each possible situation. Therefore, generic approaches have to be preferred. One of the main approaches is, again, based on trajectories learned on road network without cohabiting vehicles. Assuming that most of drivers have tendencies to avoid collisions, prototype trajectories leading to collisions are rejected during the matching process [87]. The main limitation of this approach is that the direct constraints imposed by the other vehicles are not formally modelled. Moreover, the manner how drivers usually negotiate these constraints is not taken into consideration to customize the trajectory prediction.

Parametric motion models represent a solution to model the influence of the motion of cohabiting entities on the motion of the subject vehicle. For example, the Intelligent Driver Model which is usually used for traffic flow simulations can be used to model vehicle motion in following situations [155]. Used within a BN, it represents a convenient tool to estimate the manoeuvre intention of vehicles following other vehicles approaching to a road intersection [92]. One limitation of this model is that it does not natively reject unrealistic vehicle motions, such as motions implying decelerations which are physically impossible for a vehicle.

By far, Dynamic Bayesian Networks (DBN) are the most popular approach for modelling the motion of interacting vehicles. Two main approaches have been investigated. The first one models pairwise dependencies between interacting vehicles through Coupled HMM (CHMM), or through asymmetric HMM which assume that interaction between entities exist in only one way [26, 117]. Further, it is possible to model traffic rules which, as well as the road network, influence the motion of cohabiting vehicles [5]. The second approach consists in modelling the mutual influences that exist between vehicles. This approach was implemented in highway situations, but also in intersection situations [49, 90]. In [90], the manoeuvres that the vehicles are expected to performed with respect to the road network, the traffic rules and the cohabiting vehicles are considered within the motion model.

Recently, an approach based on Scenario Model Trees (SMT) have been developed for the prediction of manoeuvre for the surrounding vehicles [20]. Scenes are categorized into a hierarchy, from the most simple to the most complex scene. From vehicle observations, the most likely scene is selected from the SMT. Then, it allows to select the most relevant behaviour models for the surrounding vehicles, and thus to predict their future behaviour.

This Section presented an overview of the techniques currently used to predict the motion of vehicles as they are navigating on roads. Next Section aims to present how these trajectory prediction techniques can be exploited for risk assessment.

2.4.1.4 Detection of Collision Using Predicted Trajectories

A major part of the pre-crash systems embedded in commercialized vehicles are based on the computation of the so called Time To Collision (TTC) [150, 27, 8]. This indicator represents an estimation of the time remaining before that a collision with another entity occurs.

The Velocity Obstacle concept usually used in the robotics field for navigation planning, can also be used to predict collisions. This geometrical approach consists in computing a set of velocities that the subject vehicle should not follow in order to avoid collision with another moving vehicle [158].

Collisions can be detected by predicting the trajectories of the vehicles cohabiting in the same area, and then by detecting conflicting points for pairs of vehicles. This can be done by computing the intersection point between 2 trajectories, using the linear equations of motion of 2 vehicles [62]. In practice, this solution is difficult to implement because solving the equations can be a difficult task. The most popular solution consists in approximating

trajectories by piecewise-straight line trajectories. Then, trajectories are discretized and collisions are iteratively checked.

Representing the vehicles by simple points is not realistic, therefore vehicles are generally shaped either by polygons [27, 31], either by the ellipses which represent the Gaussian uncertainty on the vehicles positions [8, 15]. Figure 2.6a (page 35) illustrates collision detection based on this approach. These algorithms enable to classify vehicles situations by returning binary information, i.e. by returning whether or not a collision will occur. Only a few works aimed to perform a probabilistic detection of collision, and most of them where based on reachable states [51].

The approach presented in this Section in rather low level as the trajectories of the concerned vehicles are directly used to estimate whether a collision will occur. Next Section presents the second approach which is higher level as the intended vehicle manoeuvres enable to detect risk situations and collisions.

2.4.2 Collision Detection based on Detection of Unexpected Manoeuvres

As presented in Chapter 1, a major part of road accidents is caused by driver errors. These errors lead to inappropriate manoeuvres, such as priority violation, dangerous lane change, etc. Therefore, the detection of inappropriate manoeuvres represents a coherent manner to detect risk situations. Works dealing with this approach are rather recent, and thus still rather rare.

One technique relies on the notion of expected behaviours. For a given situation, a set of vehicle behaviours which ensure a safe handling of this situation is defined. In general, the expected behaviours are defined through safe vehicle velocities which match with the road network constraints and traffic rules. They can either be defined manually [76], either by using machine learning techniques (GMM, HMM, etc.) to learn from data the typical behaviour of road users [136, 12]. If an unexpected behaviour that may lead to a risk situation is detected, then the situation is classified as a risk situation.

Another technique consists in evaluating the expected manoeuvres of all cohabiting vehicles, and to detect pairs of vehicles which have conflicting intentions. This approach was implemented in the context of road intersections, exploiting a DBN based motion model. This model estimates the risk by computing the probability that at least one vehicle does not intend to do what it is expected to do with respect to the cohabiting road users, the road network and the traffic rules [90]. By contrast to the other approaches presented above, this one jointly addresses motion model and risk assessment. Further, according to the authors of [90], this concept can be extended to other road situations, such as lane change on highways.

2.5 Discussion and Conclusion

This Chapter presented an overview of the approaches and techniques used within the processing of perception data for risk assessment, in particular at road intersections. The process was split into three main tasks, namely the Scene representation, Situation understanding and Scenario prediction for risk assessment. From this literature review, it is possible to highlight several things.

Whilst techniques for risk assessment have been extensively studied, Scene representation and Situation understanding techniques remain limited. Further, it is noticeable that the state of the art frameworks for scene representation are generally not used by the state of the art frameworks for situation understanding. That is, occupancy grids and graphical representation of environments do not make part of probabilistic nor semantic based frameworks for situation understanding. Further, except partially in [157], there is no framework for risk assessment which takes advantage of preliminary situation understanding performed through ontology or probabilistic inferences.

The review of risk assessment techniques showed that some of them use machine learning in order to model trajectories, or to learn how drivers usually behave in given situations. In addition to be a solution for the avoidance of design issues, it enables to adapt the systems to drivers in a straightforward manner. Moreover, the review showed that taking into consideration the interaction that may occur between cohabiting entities by far provides more reliable detection of risk situations. Further, frameworks which jointly address motion model and risk assessment also provide improvement in this field. We argue that such frameworks which would take benefits on the manner how the driver usually drives would probably provide even more reliable and pertinent detection of risk situations.

All the models which were presented for risk assessment were designed for specific contexts. Even if some of them are generic for road intersections or highway situations, in their state they cannot suit all possible road situations. The best solution would be to design a universal model that would be able to model in a generic manner all possible road situations, that takes uncertainties into account, and that is able to detect risks situations. Overall the difficulty that it would be to design such a model, it would probably require very high computational resources. This would be incompatible with car manufacturer constraints. As claimed by Platho *et al.* [122], we argue that a realistic and reliable solution would be to make a compromise between a unique generic model and a set of simplified models.

If risk assessment is performed through a set of simplified and generic models, it is necessary to know what model(s) match(es) with the situation. This implies a case based approach. A preliminary situation understanding is therefore necessary. It aims to give sense to the Scene by understanding what entities interact (directly and indirectly) with the subject vehicle. Further, this step has to make it possible to extract the entities which are the most pertinent to monitor, and therefore what risk assessment model to employ in order to ensure safe navigation. The literature review on situation understanding showed that only [122] worked towards such a framework. A probabilistic approach was investigated, however it was

shown that it is difficult to represent all direct and indirect interactions lead by the situation. Further, in case of complex situations, probabilistic approaches will suffer from scalability. It is from this point of view that we argue that semantic based approaches represent pertinent tools for situation understanding. Their inability to deal with uncertainties is not an issue as, in the context of this thesis, situation understanding is made at a very high level which will make uncertainties negligible.

The following Chapters of this thesis will present contributions on Situation understanding and risk assessment. A novel approach based on ontologies is presented as a solution for the extraction of the most relevant entities of the Scene. This aims to give directions for risk assessment. Further, solutions for early detection of risk situations for vehicles approaching to road intersection are presented. These solutions are based on the model which was developed by Lefevre [90], which was extended to take into account differences between drivers.

Chapter 3

Ontology Based Situation Understanding

Contents

3.1 Introduction

Chapter 2 showed that reliable risk assessment frameworks shall consist of a compromise between a unique generic model a set of simplified models. This implies that a preliminary step that allows to select the most relevant model is necessary. For this purpose, the relevant entities of the situation have already been extracted from the available data sources. Further, it has been understood how they should be monitored to ensure a safe navigation. This preliminary step, called situation understanding, remains a complex task for intelligent systems.

In a driving space, different entities including vehicles and vulnerable road users cohabit in the same area. This cohabitation implies constant interactions between these entities, and governs their behaviour. Smart sensors and navigation maps embedded in modern vehicles enable awareness about the surrounding entities and about the context. However, systems exploiting all this information usually do not consider the spatio-temporal relationships which may exist between all entities. This limitation restrains the ability to properly understand road situations.

Associating information about surrounding entities together with contextual information appears as a solution towards the improvement of situation understanding of intelligent

vehicles. For this purpose, the use of ontologies is introduced and presented in this Chapter. The tenet is to define a semantic description of the entities which are commonly met by vehicles in driving environments. This description includes the interactions which are likely to happen, with respect to the variety of entities that exists. The knowledge hold by this description would enable to consider as a whole all information provided by the data sources. Further, it would enable to extract the most pertinent features of the situation which could be used as guidelines for risk assessment.

This Chapter is organized as follows. At first, the principles of ontologies are given as a background necessary for a good understanding of the rest of the Chapter. The experimental setup is then presented as the constraints implied by the experimental facilities will govern the design of the framework for situation understanding. Then, the framework, that exploits an ontology is presented. The ontology that intervenes is defined, and its functioning is described through the understanding of a given situation. Further, the implementation of the framework for the real time situation understanding on board an experimental vehicle under controlled conditions is presented. The added value of the information inferred thanks to the use of the ontology is finally discussed.

3.2 Ontologies Principles

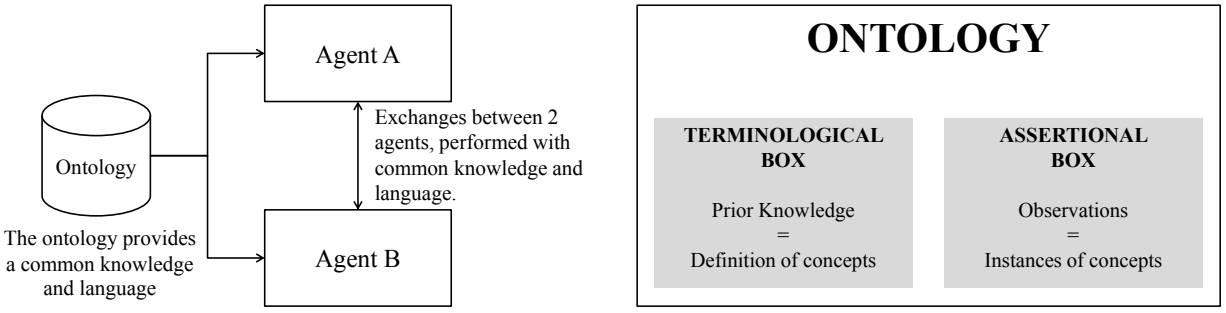
For intelligent systems, both natural and artificial, knowledge is an essential element. In that way, intelligence can be defined as the faculty to capture, process, reuse and share this knowledge. Whilst performing these tasks is a natural thing for living being gifted with intelligence, it remains complex for machines. As a technical solution, ontologies represent an Artificial Intelligence tool (AI) which enables to artificially perform these tasks. This Section aims to present the principles of ontologies.

3.2.1 Definition

The term *ontology* was first introduced by the philosophers to designate the study of being of existence. It is from the beginning of research in AI that this term started to be employed by researchers of the domain to designate computational models which enable automated reasoning [60]. From this point of view, several definitions of the term were published; the three following are those which are the most often admitted by the literature:

- An ontology is an explicit *specification of conceptualization* [54].
- An ontology is *a theory of vocabulary or concepts* used for building artificial systems [53].
- An ontology is *a body of knowledge* describing some domain [103].

A comparison of these three definitions was done [114]. Whilst these definitions do not mean exactly the same, the principles of ontologies come down to the first definition. It



(a) Ontology used by agents (e.g. software) for communication.

(b) Structure of an ontology based on description logic.

Figure 3.1: Ontology.

is therefore important to understand both terms *specification* and *conceptualization* in the good way. The conceptualization of a domain is the manner how a domain is perceived and understood, and the specification of this conceptualization is actually a formal description of this conceptualization.

More concretely, an ontology is a description of the concepts and relationships that are relevant to model a domain of interest. It specifies the vocabulary that is necessary to make assertions, and which may be inputs/outputs of knowledge agents (e.g. software, etc.). Moreover, it provides the language for communication between agents [55]. Figure 3.1a illustrates this definition.

3.2.2 Description Logic

Ontologies are based on Description Logics (DL) which is a formal language for Knowledge Representation [14]. A DL enables to model Concepts, Roles and Individuals through its two functional parts, namely the Terminological Box (TBox) and the Assertional Box (ABox). Figure 3.1b illustrates this structure, and the description of these two parts is given below.

Terminological Box (TBox)

The TBox consists of the definition of all the concepts that the ontology aims to describe. An analogy can be done between the TBox and the knowledge that human have. The knowledge that humans acquire along their life is used to understand and to interpret the world. The ontology TBox represents prior knowledge, and the definition of it is performed through the definition of Concepts, Roles and Relations. The following definitions were established after [65].

- **Concepts** (or classes) are concrete representations of the concepts of the domain that the ontology aims to describe. These concepts can be organized into a superclass-subclass hierarchy, which is generally called *Taxonomy*.

- **Roles** are properties which can be defined and assigned to concepts. Roles can be classified into two groups:

  - **Object Properties** aim to define axioms in the form of *Triples*. In other words, they are binary relationships between two concepts in the form *Concept1 - Object Property - Concept2*. Characteristics may be attributed to object properties, such as symmetry or transitivity with respect to other object properties.

  - **Data Properties** are used to assign properties to single classes or instances of classes in the form *Concept1 - Data Property - Property Value*.

- **Relations** between concepts are defined with taxonomic relations (hierarchical relations), axioms (classes linked by object properties) and rules. The definition of rules can be done using basic description logic axioms which only enables the definition of basic class equivalence. More sophisticated languages enable to define more complex and expressive rules. Among these languages, the Semantic Web Rule Language (SWRL) is one of the most common [66].

Assertional Box (ABox)

The ABox consists of the definition of instances of classes previously defined in the TBox. These instances, commonly called *Individuals*, represent real life data that the ontology aims to interpret. Again, an analogy may be done with humans as the ABox can represent objects that humans observe, and understand thanks to prior knowledge their acquired with experience (TBox). Further, in the same way as properties can be attributed to concepts defined in the TBox, Object and Data Properties can be attributed to individuals defined in the ABox.

Description Languages

Several DL languages exist, the differences between each rely on the concept constructors that they provide. Concept constructors are actually operators which enable to build complex descriptions [14]. The language $\mathcal{AL}$ (Attributive Language) provides foundations for most of the other DL languages. Table 3.1 shows the operators which present the syntax of $\mathcal{ALC}$ (Attributive Language with Complement) which is an extension of $\mathcal{AL}$.

It is proposed to illustrate the syntax and expressivity with a simple example. Let's define two atomic concepts: Human and Male. The intersection of these two concepts $\mathsf{Human} \sqcap \mathsf{Male}$ is a concept that describes men, that is, humans who are male. Similarly, $\mathsf{Human} \sqcap \neg\mathsf{Male}$ represent humans who are not male, that is, women. Now let's define $\mathsf{hasChild}$ as an atomic role. The expression $\mathsf{Human} \sqcap \exists\mathsf{hasChild}.\top$ describes humans (not all) who have a child. By contrast, $\mathsf{Human} \sqcap \forall\mathsf{hasChild}.\top$ describes all humans who have a child.

Syntax	Comment
N_C	Set of Atomic Concepts
N_R	Set of Atomic Roles
C, D	Concept Descriptions
R	Role Description
$\top$	Top Concept (Most general in Taxonomy)
$\bot$	Bottom Concept (Most Specific in Taxonomy)
$\neg C$	Negation
$C \sqcap D$	Intersection
$C \sqcup D$	Union
$\forall R.C$	Universal Restriction
$\exists R.C$	Existential Restriction

Table 3.1: Logic syntax of $\mathcal{ALC}$ language.

3.2.3 Tools and Exploitation

Reasoner

The interest of using ontologies is the possibility they offer to reason on the knowledge that they store. For this purpose, *Reasoners* have to be used. Reasoners are pieces of software able to infer logical consequences from a set of asserted facts or axioms [3]. In other words, they aim to exploit information stored in the TBox in order to infer new information and knowledge which are not specifically expressed, about the *Individuals* defined in the ABox.

Plenty of software solutions for ontology reasoning exist, including the most popular such as Pellet, FACT++, HermiT, Racer and others [148, 67, 144, 56]. All reasoners present different characteristics and performances, therefore several surveys have been produced and published [94, 42, 3]. Among all features which characterize a reasoner, the following have been identified as the most important (all are presented in details in [42]):

- **Reasoning methodology.** The methodology refers to the algorithm that is used for the reasoning task. Several algorithms exist, namely the tableau-based and the hypertableau algorithms for the most common [142, 108]. Methodology has a significant influence on computational efforts required for reasoning.
- **Expressivity and Rule support.** Expressivity is the capability of the reasoner to understand different sorts of Description Logic axioms which may be defined in an ontology TBox. In the same way, as rules are extensions to DL to improve expressivity, the capability to consider them is also a relevant characteristic for reasoners.
- **Performances.** The computational time necessary to reason on an ontology is one of the major limitation of today's reasoners as all existing reasoning methodologies are computationally complex and expensive. This is therefore a significant parameter that is taken into consideration to estimate reasoners performances. Moreover, per-

formances are also defined by soundness and completeness which is the capability to correctly perform all inferences which should be done in theory.

Inferences

Several types of inferences can be performed by reasoners. The following list, which is not exhaustive, gathers some examples of typical inferences:

- **Consistency checking.** In the TBox, consistency checking consists in making sure that there is no contradiction in the concepts definitions. In the ABox, it aims to make sure that individuals do not violate descriptions and axioms defined in the TBox.
- **Individual class and property checking.** In the ABox, it consists in checking what concepts an individual belongs to, and what data properties it is assigned.
- **Class subsumption checking.** In the TBox, it consists in checking whether a concept A includes another concept B.
- **Query answering.** It gives the possibility to answer queries such as, for example "what individuals belong to concept A, with data property B equal to C?".

3.3 Experimental Facilities

3.3.1 Test Vehicle and Embedded Sensors

All experiments presented in this Chapter were performed using data recorded in a standard passenger vehicle, a 2008 Renault Espace IV. This vehicle benefits from various electronic equipments, therefore a large amount of data is available on the Controller Area Network (CAN) which is the vehicle internal network commonly known as the vehicle CAN-bus [22]. Thus, information such as the vehicle dynamics (i.e. speed, acceleration, etc) or the state of internal devices (i.e. the state of the pedals, of the turn signals, etc.) are easily accessible in real time at high frequencies (20 to 50 Hz, depending on the sensors).

The localization of the vehicle was performed by a standard single frequency Ublox 6T GPS receiver. This is a standard automotive sensor subject to external perturbations, and it therefore provides estimations of the vehicle pose suffering from significant noise. All experiments were performed in open sky conditions, therefore the uncertainty of measurements in the north and east directions is assumed to be constant. It was set such as $\sigma_{North} = \sigma_{East} = 3m$. Outputs are provided following the standard NMEA format, with a $5Hz$ frequency.

The vehicle is equipped with two perceptions sensors. The first one is an Ibeo Alasca XT LIDAR sensor that is installed on the front of the vehicle. This smart sensor allows for the detection, the classification and the tracking of both vehicles or pedestrians with a field of view of 170°. The second sensor is a Mobileye smart camera that is installed on the vehicle windscreen. This sensor is able to provide information about vehicles, pedestrians, traffic

signs and road markings with a field of view of about 30°.

3.3.2 Navigation System

A navigation system similar to those available in commercialized vehicles was used to take benefits from navigation maps which store contextual information. Field trials were performed on closed roads, therefore commercialized navigation maps were not available. Thus, maps had to be edited, and the Open Street Map (OSM) format was chosen for this purpose. A navigation system was developed in order to exploit the OSM maps, and thus to generate and provide in real time the information about the coming road features such as the distance to the next intersection, the speed limit, etc. This information is called the Electronic Horizon (EH).

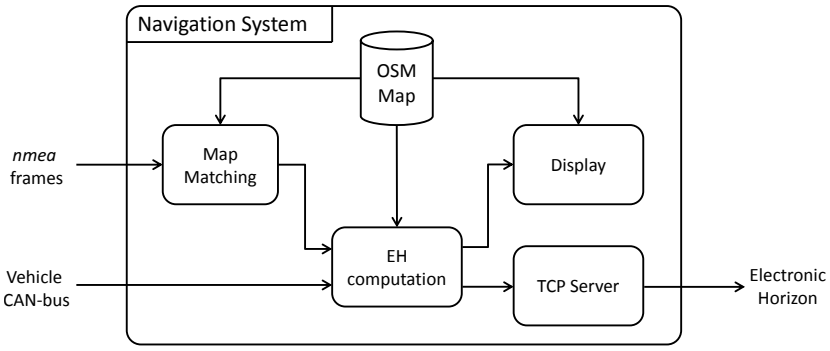
Figure 3.2a shows the structure of the navigation system. An OSM digital map which has previously been edited is required. The edition of the map is illustrated by Figure 3.2b. Moreover, the system requires the vehicle position in the NMEA format to perform map matching. The map matching is based on algorithms inspired from [115]. The computation of the EH is based on the map matched vehicle position and consists in extracting from the digital map all data referring to the close vehicle environment. The EH is finally accessible on a TCP server.

Figure 3.2d shows how the distance to the stop intersection that is available in the EH is defined. This distance P is the vehicle curvilinear abscissa along the carriageway, taking as reference the next stop intersection stored in the map.

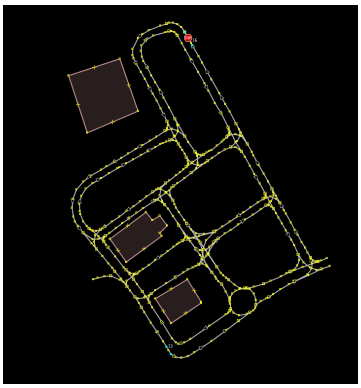
The uncertainty σ_P of the vehicle curvilinear abscissa P cannot be provided by the navigation system. It is therefore set with respect to the uncertainty of the vehicle pose that is estimated by the GNSS used for the experiments. The later is represented by an ellipsoid, according to σ_{North} and σ_{East}, the uncertainties of the vehicle pose measured in the north and east directions. Figure 3.2e shows how an isotropic approach is used is used to estimate the value of σ_P.

3.4 Ontology Based Approach

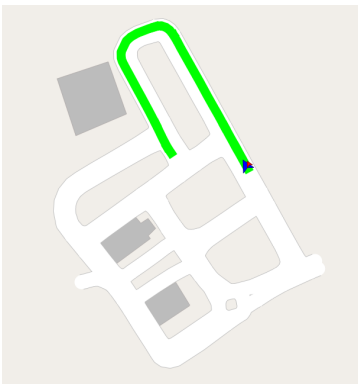
This Section aims to present the ontology based approach that is used for situation understanding. The framework in which the ontology intervenes is introduced, followed by description of the ontology strictly speaking. What is important to retain from this Section is the approach that is proposed, and the possibilities that ontologies may offer to solve the problem. Therefore, it is important to keep in mind that the ontology which is presented is not exhaustive, and must be considered as a draft that is used to confirm the coherence of the approach. Further extensions and optimisations would be necessary if the approach is validated.



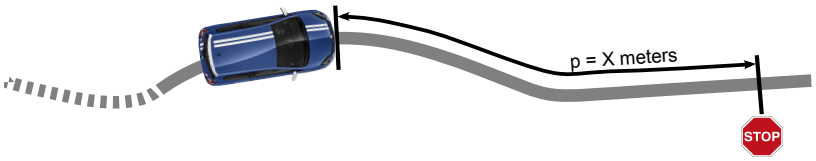
(a) Structure of the navigation system.



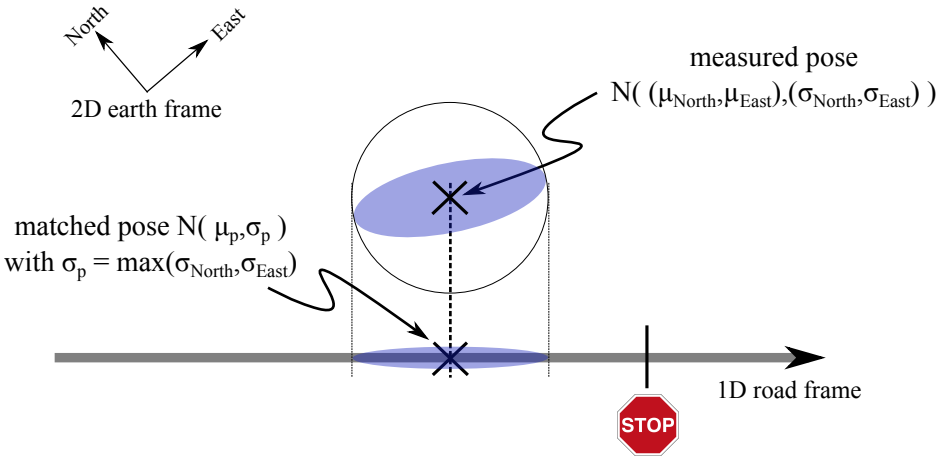
(b) Edition of the OSM map used for the experiments.



(c) Navigation system display.



(d) Vehicle pose defined as the curvilinear abscissa between the vehicle and the stop.



(e) The uncertainty of the measured pose $Pobs_t$ relies on the uncertainty of the pose (North/East) measured by the GNSS.

Figure 3.2: Navigation system.

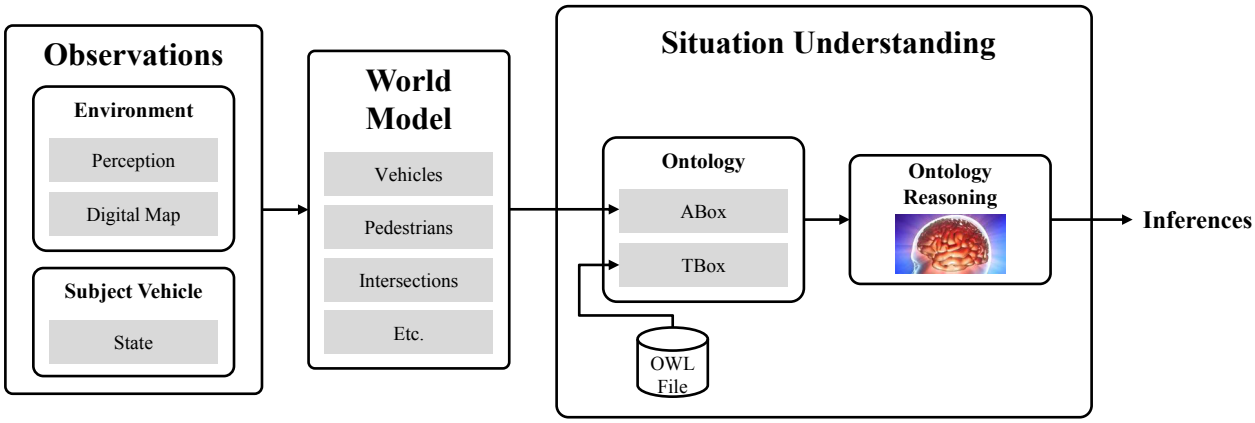


Figure 3.3: Exploitation of the ontology within a framework.

3.4.1 Framework Overview and Structure

The ontology that was developed makes part of an overall framework for situation understanding. Figure 3.3 shows the structure of the framework which is presented in the following of this Section.

Observations

The first prerequisite for the framework is information about the presence of surrounding entities. This step is represented by the Observations box in Figure 3.3. Two types of data sources are considered for the awareness of the environment. Modern vehicle sensors such as smart cameras, radars or lasers allow for the real time perception of moving entities. Most of them are able to perform classification on the perceived entities, and provide an estimation of their state with respect to the subject vehicle on which they are embedded. Further, digital maps can store and provide contextual information about the road network features. For instance, this *a priori* information can contain information about the coming road intersections, about coming pedestrian crossing, etc. Figure 3.4 shows an example of situation as it may be perceived by a vehicle.

World Model Principles

All this information is provided in a piecemeal manner as most of time all sources of information work independently from the others. It is therefore necessary to organize this data in the form of a list of surrounding entities. As part of this thesis, this structured and organized list is called the *World Model*. Table 3.2 provides an example of what could be the corresponding world model for the situation shown in Figure 3.4.

The edition of this world model may require some preliminary processing on perception data. For example, a same entity may be perceived at the same time by several sensors, it is therefore necessary to consider this entity only one time (i.e. to perform data association). Moreover, as sensors may not be synchronized, asynchronous data has to be handled. For

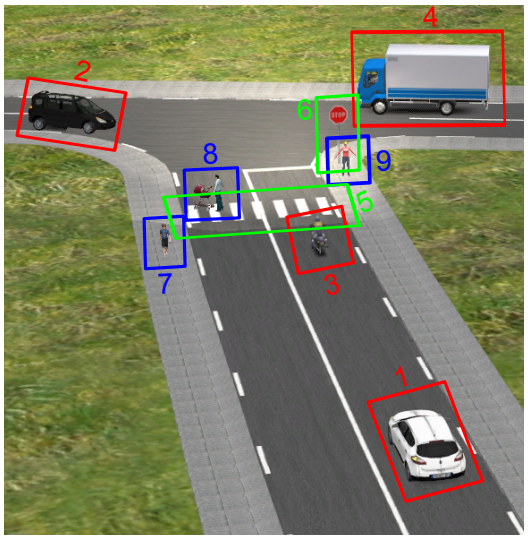


Figure 3.4: Example of perceived world. The perceived entities are given IDs.

Table 3.2: World presented in Figure 3.4 in the form of World Model table.

#	Type	Information
1	Car	Subject Vehicle
2	Car	Coming from the left Turning right
3	Motor Bike	Same lane x meters ahead
4	Truck	Coming from the right x meters before intersection
5	Pedestrian Crossing	x meters ahead
6	Stop Intersection	x meters ahead
7	Pedestrian	x meters ahead On left pavement
8	Pedestrian	x meters ahead On the road
9	Pedestrian	x meters ahead On right pavement

these purposes, data and sensor fusion techniques have to be employed [86]. These problems are complex to solve and today they remain a meaningful challenge for the data fusion community. However they are not the subject of this thesis, therefore these problems are not addressed. Instead, perception is considered as a black box performing sensor and data fusion on the data returned by a set of perception sensors.

Situation Understanding

All the situation understanding is performed through the use of the ontology, as shown in Figure 3.3. Like every ontology, the ontology that has been developed consists of two fundamental parts, namely the TBox and the ABox.

- The TBox consists of a conceptual description of the entities and contextual objects which can be met by a vehicle in a navigable space. In other words, it enables to define the types of entities which can be met, and the relationships and interactions which are likely to exist between them. An analogy can be done with the knowledge that drivers acquire when they learn driving at driving school, which is fundamental to makes them able to understand situations. The TBox is the permanent part of the ontology.
- The ABox can be considered as the conversion of the *World Model* into the ontology language. That is, for each entity that is present in the *World Model*, an instance of the corresponding concept is created. The ABox is the changing part of the ontology and is updated at each update of the *World Model*.

After each update of the ABox, reasoning can be performed on the whole ontology. The aim

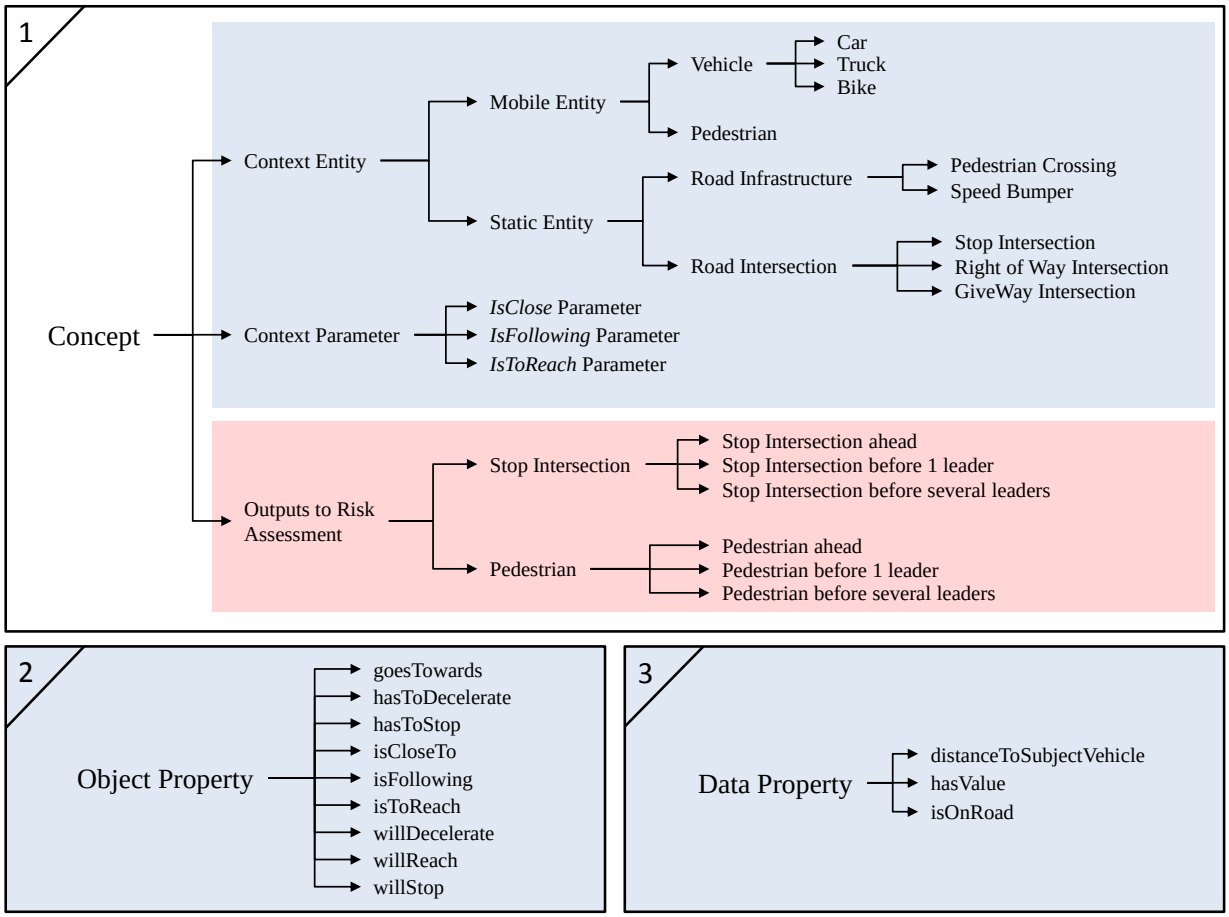


Figure 3.5: Ontology Concepts, Object Properties and Data Properties.

of the Reasoning step is to give more sense to the data present in the World Model. In other words, it is to take into consideration the interactions which are likely to exist between the entities, and also chain reactions which may happen as a consequence of these interactions. At the end, the purpose is to infer a high level interpretation of the perceived situation in order to select the risk assessment algorithms which suit the situation best.

3.4.2 The TBox

The ontology TBox was developed with respect to the Description Logic specifications which were presented in Section 3.2.2. That is, the TBox was designed through the definition of concepts, object and data properties, and relations. Figure 3.5 shows the taxonomy which defines the ontology. In this ontology, the focus is done only on situations which can be represented in 1 dimension in space. In other words, the ontology is able to represent road entities which are all located on the same navigation lane.

Concepts

Box 1 of Figure 3.5 presents the taxonomy on the ontology concepts. Three major concepts were defined, namely Context Entity, Context Parameter and Output to Risk Assessment. They were defined as described below.

The first major concept, Context Entity, aims to list and classify the road entities which may be met in a driving space. Road entities were classified into two sub-concepts, namely Mobile Entity and Static Entity. From the point of view of an intelligent vehicle, information about a mobile entity cannot be a-priori known. That is, this information has to be obtained in real time from perception sensors. Therefore, the ontology defines pedestrians and vehicles as mobile entities. Further, static entities are assumed to make part of the road network, therefore their presence is perfectly predictable. Thus, information about a static entity can be a-priori known and stored in digital maps. In the ontology that is presented, two categories of static entities are represented. The first one gathers Road Infrastructures which have an effect on vehicles behaviours such as Speed Bumpers and Pedestrian Crossings. The second one gathers Road Intersections which are classified into three categories: Stop, Right of Way and Giveway Intersections.

The second major concept, Context Parameter, aims to define spatio-temporal thresholds which allow to decide whether interactions between two entities are likely to exist. To illustrate the IsFollowing Parameter, let imagine two vehicles (the leader and the follower) navigating at the same speed, on the same road and in the same direction. If the two vehicles are separated by 90m, the interaction between them depends on their speed. If they are moving at 30km/h, the leader is 6s ahead of the follower, so it may be considered that there is no interaction between them. However, if they are moving at 90km/h, the leader is only 2s ahead. It can therefore be considered that interaction between the two vehicles is established. The IsFollowing Parameter allows to set the threshold in the form of time duration which enables to consider if a vehicle is following another one. Following the same logic, the IsClose Parameter and the IsToReach Parameter are also defined. Numerical values are given to these concepts through Data Properties, which are detailed a bit later in this paragraph.

The last major concept, Outputs to Risk Assessment, is presented in the red shaded area in Figure 3.5. It aims to store concepts which describe the situation of vehicles. Further, these concepts are guidelines for embedded risk assessment systems as they state what entities and what associations of entities are pertinent to be monitored to ensure safety. The purpose is to infer class equivalences on the subject vehicle in order to chose what risk assessment algorithm suits best the situation. The ontology that is described emphasises on Stop Intersections and Pedestrians. For example, if after reasoning it is inferred that the subject vehicle is actually an instance of the concept Stop Intersection Ahead, it would mean that an algorithm that aims to ensure safety at the approach to a stop intersection would the best adapted to perform risk assessment on the subject vehicle. In that way, the algorithm presented in Chapter 5 would be well adapted.

Object Properties

Box 2 of Figure 3.5 presents the taxonomy on the ontology object properties. These properties aim to define the relationships and interactions which may happen between two concepts of Context Entities. They were defined as described below.
The state of a mobile entity with respect to another one can be described through the goesTowards, isCloseTo, isToReach, and isFollowing properties. Further, expected behaviours are defined through the hasToStop and hasToDecelerate properties. Finally, near future behaviours are defined through the isToReach, willDecelerate and willReach properties.

These object properties will be used within inferred triples such as Car - goesTowards - Stop Intersection, or Pedestrian - isCloseTo - Pedestrian Crossing, or Car - isToReach - Stop Intersection.

Data Properties

Box 3 of Figure 3.5 presents the taxonomy on the ontology data properties. These properties aim to assign properties to individuals which will be defined in the ontology ABox. They were defined as described bellow.
All individuals which will be defined in the ontology ABox have to be defined with their position in the scene. For this purpose, a reference frame had to be chosen. As most of observations are performed with respect to the subject vehicle, the subject vehicle was chosen as the reference frame. Further, since the world is represented in one dimension in the ontology, the positions of entities with respect to the subject vehicle are defined as curvilinear abscissas along the road (in the same manner as the position of static entities are defined in the Electronic Horizon, cf. Figure 3.2d in Section 3.3). In that way, the property distanceToSubjectVehicle was created. This property expects arguments in the form of a numerical values.

Further, some entities such as pedestrians can be either on the road, either on the pavement. From the point of view of a vehicle evolving on the road, this has a significant consequence on how pertinent it is to consider these entities. Therefore, the parameter isOnRoad enables to define in the ontology whether a pedestrian is on the road. This property expects arguments in the form of boolean variables.

Finally, the Context Parameter concepts require to be set. For this purpose the data parameter hasValue was created. This property expects arguments in the form of numerical value.

Relations

Ontology concepts, object properties and data properties alone cannot provide added value to information present in the World Model. Relations are defined for this purpose, and can therefore be considered as the core of the ontology. The aim of the relations is to provide *a priori* knowledge about road entity concepts and about interactions which may exist between

them, and then to extract the most relevant features of the situation. Relations consist of axioms aiming to affect object properties to the individuals which are stored in the ontology ABox.

Relations were edited in two steps. The first step aims to edit the axioms which enable to infer the likely interactions between the road entities stored in the ABox. These axioms are for most of them too expressive for using the basic Description Logic language, therefore SWRL rules were preferred for this purpose. The second step aims to edit additional axioms to exploit the interactions which were inferred during the first step, and thus to extract for all vehicles the most relevant features of the situation. For this purpose, it was possible to use the DL language as the corresponding axioms are simple. Note that SWRL could have been used, however reasoning on SWRL rules is more expensive than reasoning on DL axioms. It was therefore preferred to use DL axioms for this second step.

For the first part, 14 SWRL rules were edited. Table 3.3 presents in details 3 of these rules, and the rest is available in Appendix A. These rules aim to make it possible to infer spatio-temporal relationships between entities, near future behaviours of mobile entities and expectation about mobile entities manoeuvres. In Table 3.3, the rule labelled as number 1 is one of the 5 rules dealing with spatio-temporal relationships. Further, the rule labelled as number 2 is one of the 3 rules dealing with near future behaviours of the mobile entities. Finally the rule labelled as number 3 is one of the 6 rules dealing with expected manoeuvres of the mobile entities. Some of these rules were defined to take into consideration chain reactions which can happen in road situations. For example, a vehicle that is following another vehicle that has to stop has also to stop in order to avoid a collision.

For the second part, one basic DL axiom was edited for each Output For ADAS concept. That is, 6 axioms were edited for the ontology presented in this Chapter. They are all listed in Appendix A, but two of them are presented in Table 3.4 in order to help the reader understand the principles. The axiom labelled as number 1 aims to define that if a single vehicle expected to stop at a stop intersection, it is pertinent to run an ADAS that makes sure that the driver is aware of the stop intersection. Further, the axiom labelled as number 2 aims to define that if a vehicle following another vehicle expected to stop at a stop intersection, it is pertinent to run an ADAS that makes sure that the driver is aware that the lead vehicle will stop soon.

3.4.3 The ABox

The ontology ABox contains two types of individuals. There are those which are mandatory and created independently from the World Model, and those which are created according to the World Model contents.

Table 3.3: Example of 3 SWRL rules edited in the ontology.

#	SWRL Rules	Meaning
1	1 vehicle(?v1) ∧ vehicle(?v2) 2 ∧ distanceToSubjectVehicle(?v1,?d1) 3 ∧ distanceToSubjectVehicle(?v2,?d2) 4 ∧ subtract(?sub,?d2,?d1) 5 ∧ isFollowingParameter(?fParam) 6 ∧ hasValue(?f,?fParam) 7 ∧ lessThan(?sub,?f) 8 → isFollowing(?v2,?v1)	The position *d1* and *d2* of the vehicles *v1* and *v2* are known thanks to the *distanceToSubjectVehicle* parameter. By performing a subtraction (line 4), it is possible to determine the distance *sub* between both vehicles. By comparing this distance with the threshold of the *isFollowingParameter* (line 7), it is determined whether one vehicle is following the other one (line 8).
2	1 vehicle(?v1) 2 ∧ StopIntersection(?stop1) 3 ∧ willReach(?v1,?stop1) 4 → willStop(?v1,?stop1)	The vehicle *v1* will reach the stop intersection *stop1*. This condition means that *v1* will probably stop at *stop1* (line 4).
3	1 vehicle(?v1) 2 ∧ StopIntersection(?stop1) 3 ∧ isToReach(?v1,?stop1) 4 → hasToStop(?v1,?stop1)	The vehicle *v1* is about to reach the stop intersection *stop1*. This condition means that *v1* has to stop at *stop1* (line 4).

Table 3.4: Example of 2 Description Logic Axioms edited in the ontology.

#	DL Axioms	Meaning
1	$\mathsf{StopIntersection} \doteq \mathsf{Vehicle} \sqcap \exists \mathsf{hasToStop} \cdot \mathsf{StopIntersection}$	If an instance of concept *Vehicle* is linked to an instance of concept *StopIntersection* through the object property *hasToStop*, then the instance of concept *Vehicle* is also an instance of the *StopIntersectionAhead* concept.
2	$\mathsf{StopIntersectionBefore1Leader} \doteq \mathsf{Vehicle} \sqcap \mathsf{isFollowing} \cdot \mathsf{StopIntersectionAhead}$	If an instance of concept *Vehicle* is linked to an instance of concept *StopIntersectionAhead* through the object property *isFollowing*, then the instance of concept *Vehicle* is also an instance of the *StopIntersectionBefore1Leader* concept.

Mandatory Individuals

Even if the World Model does not include any information about surrounding road entities, the ontology ABox requires four individuals to be defined. These individuals enable the ontology to work properly, and are defined as follows.

The World Model will always contain information about the subject vehicle that perceives its surrounding environment. Therefore, the ontology ABox has to store one instance of the *Vehicle* concept, representing the subject vehicle. This entity is taken as the origin of the frame, so the distanceToSubjectVehicle data property is affected to this individual and is set at 0.

The three other individuals refer to the three concepts included in the Context Parameter major concept. These individual aim to activate the context parameters in the ontology, and thus to assign a value to the three of them. In that way, one instance of the isCloseParameter concept has to be created. This individual is given the hasValue data property which sets the maximum distance between a pedestrian and a static entity to consider them close enough to interact. Further, one instance of the isFollowingParameter concept has to be created with the hasValue data property. The value of this property sets the distance between two vehicles from which it is considered that the following vehicle is no longer following the leader. This value depends on the vehicle speeds in stabilized conditions. Finally, one instance of the isToReachParameter concept has to be created, again with the hasValue data property. This parameter sets the distance of a vehicle to a static entity from which it is considered that the vehicle is about to reach the static entity. This parameter also depends on the vehicle speed in stabilized conditions.

World Model Dependant Individuals

These individuals can be considered as the conversion of the World Model contents into the ontology language. Thus, each entity stored in the World Model has its equivalent in the ontology ABox. For each entity, one instance of the corresponding concept is created, and is affected the distanceToSubjectVehicle data property. The value of this property is the position of the concerned entity, with respect to the subject vehicle. Note that uncertainties on the position of entities are not considered by the ontology. Finally, the isOnRoad data property has to be attributed to all instances of the Pedestrian concept to declare whether the corresponding pedestrians are on the road or on the pavement.

3.4.4 Illustrative Example

The ontology which is described in the previous Section was tested to verify that it is able to infer pertinent information about a road situation. It was edited in the Protégé software (TBox and ABox), version 4.3, developed by the Stanford Center for Biomedical Informatics

Research [165, 166]. This ontology editor enables the edition of SWRL rules.

Case Study

Figure 3.6a on Page 58 describes the situation that was manually edited in the ontology. This situation consists of three vehicles (called *Subject Vehicle*, *Vehicle 2* and *Vehicle 3*) going towards a stop intersection (called *Stop 1*). *Vehicle 3* is the closest to the intersection, and just passed a pedestrian crossing (called *Pedestrian Crossing 1*). *Vehicle 2* goes towards *Pedestrian Crossing 1*, and *Subject Vehicle* follows *Vehicle 2*. Finally, a pedestrian (called *Pedestrian 1*) is walking next to *Pedestrian Crossing 1*.

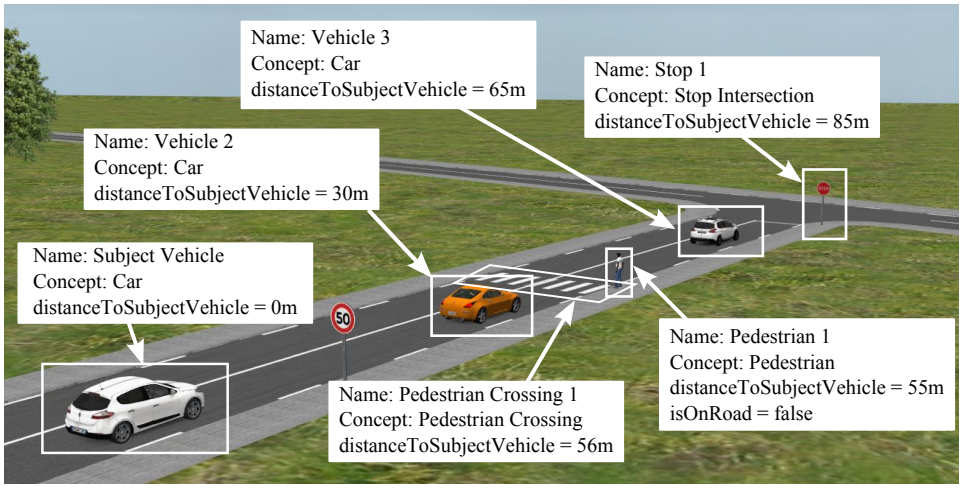
Section 3.4.3 presented that the ontology ABox contains four mandatory individuals, including one for the subject vehicle and the three others for the context parameters. In this case study, the highest allowed speed is 50 km/h, therefore the context parameters are set according to this speed. In that way, it was set that a vehicle is following another one if the following time is lower than 3 seconds. Therefore, an individual of the isFollowingParameter concept was created with the hasValue data property set at 42m (distance travelled in 3 seconds at 50 km/h). Further, it was set that a mobile entity is about to reach a static entity if at constant speed it is reaching it within 5 seconds. Therefore an individual of the isToReach concept was created with the hasValue data property set at 70m. Finally, an instance of the isCloseParameter concept was created with the hasValue property set at 3m.

Results

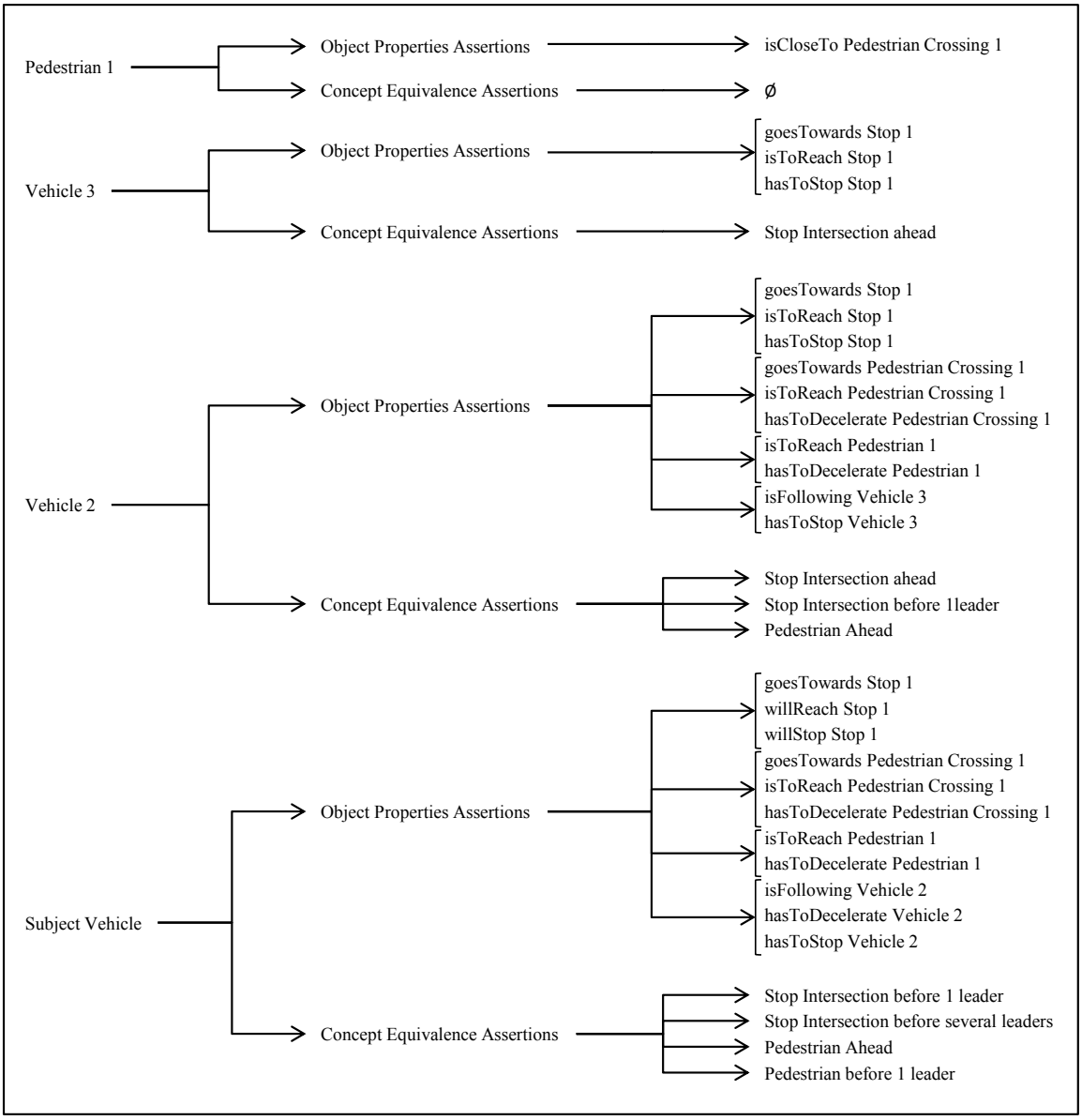
Reasoning was performed through the Protégé software that proposes a collection of reasoners, however the SWRL rules which define the ontology restrain the number of compatible reasoners. Pellet was chosen as it is compatible with SWRL, and offers good performances [42]. Figure 3.6b shows the object properties and concept equivalence assertions performed by Pellet for the chosen case study. These inferences are detailed below.

Pedestrian 1 is inferred to be close to *Pedestrian Crossing 1*. The reasoner computes the distance between these two entities according to the distanceToSubjectVehicle data parameter set on the two corresponding individuals. This distance is of 1m, and satisfies the condition (that depends on the isClose context parameter) that was set in the ontology to claim that a pedestrian is close to a pedestrian crossing. It implies that the pedestrian is likely to have the intention to cross the road, therefore it means that a vehicle that would approach to the pedestrian would have to take care of the pedestrian. No concept equivalence is asserted on *Pedestrian 1* because there is no axiom for concept equivalence defined in the TBox for the Pedestrian concept.

Three object property assertions are inferred for *Vehicle 3*. These assertions concern interactions between this vehicle and the stop intersection *Stop 1*. Thanks to the position of these two entities, is was inferred that *Vehicle 3* passed all the static entities except *Stop 1*. Therefore, it is inferred that *Vehicle 3* goes toward *Stop 1*. Further, the distance between these two



(a) On the left, an illustrative picture of the case study (scale is not respected). In the boxes on the right, the World Model Dependant Individuals stored in the ABox.



(b) Object properties and concept equivalence assertions after reasoning.

Figure 3.6: Case study.

entities is low enough to consider that *Vehicle 3* is about to reach *Stop 1*. Moreover, since it was defined in the ontology that all vehicles about to reach a stop intersection have to stop at the intersection, it is inferred that *Vehicle 3* has to stop at *Stop 1*. Finally, it is inferred that *Vehicle 3* is an instance of the Stop Intersection Ahead concept. This is performed using the first DL axiom presented in Table 3.4, Page 55.

Ten object property assertions are inferred for *Vehicle 2*. The ontology infers that this vehicle passed neither *Pedestrian Crossing 1* and *Stop 1*, therefore it is inferred that it goes towards these two static entities. Moreover, *Vehicle 2* is close enough to *Pedestrian Crossing 1* and *Stop 1* to say that it is about to reach them. Since all vehicles have to stop at stop intersections, it is inferred that *Vehicle 2* has to stop at *Stop 1*. This assertion implies *Vehicle 2* to be an instance of concept Stop Intersection Ahead. Moreover, all vehicle have to decelerate before reaching a pedestrian crossing, therefore *Vehicle 2* has to decelerate for *Pedestrian Crossing 1*. Further, as it was inferred that *Pedestrian 1* is close to *Pedestrian Crossing 1*, and since *Vehicle 2* is about to reach *Pedestrian 1*, it is inferred that it has to decelerate for the pedestrian. This assertion implies *Vehicle 2* to be an instance of concept Pedestrian Ahead. Finally, *Vehicle 2* is close enough to *Vehicle 3* to claim that it is following this latter. However, it was inferred that *Vehicle 3* has to stop at *Stop 1*, and since *Vehicle 2* is following *Vehicle 3*, *Vehicle 2* has to top behind *Vehicle 3*. This chain reaction implies *Vehicle 2* to be an instance of concept Stop Intersection before 1 leader.

Eleven object property assertions are inferred for *Subject Vehicle*. Like *Vehicle 2*, *Subject Vehicle* passed neither *Pedestrian Crossing 1* and *Stop 1*. It is therefore inferred that it goes towards these two entities. Moreover, *Subject Vehicle* is too far from *Stop 1* to consider that it is about to reach it. However it is inferred that *Subject Vehicle* will reach *Stop 1*, and therefore that it will stop at *Stop 1*. Further, as it is close enough to *Pedestrian Crossing 1*, *Subject Vehicle* is about to reach it, and thus has to decelerate. In addition, as it is for *Vehicle 2*, the chain reaction with *Pedestrian 1* and *Pedestrian Crossing 1* implies that *Subject Vehicle* has to decelerate for *Pedestrian 1*. This implies Subject Vehicle to be an instance of concept Pedestrian Ahead. Further, *Subject Vehicle* is close enough to *Vehicle 2* to claim that it is following it. This implies several chain reactions with the other context entities. First, *Subject Vehicle* is following *Vehicle 2* that is an instance of Stop Intersection ahead. This implies *Subject Vehicle* to be an instance of concept Stop Intersection before 1 leader. In addition, *Vehicle 2* is also an instance of concept Stop Intersection before 1 leader, therefore is also implies that *Subject Vehicle* is an instance of concept Stop Intersection before several leaders. Finally, *Vehicle 2* is an instance of concept Pedestrian Ahead, it therefore implies that *Subject Vehicle* is an instance of concept Pedestrian before 1 leader.

These results show that the proposed ontology enables to perform coherent reasoning on global road situations as they may be perceived by a vehicle. It shows that interactions between road entities can be understood and considered to anticipate the behaviours of the mobile entities, and to know how they are expected to behave. This test was performed with an ontology whose ABox was filled manually, the next step is to test the ontology with data recorded from sensors embedded on an experimental vehicle.

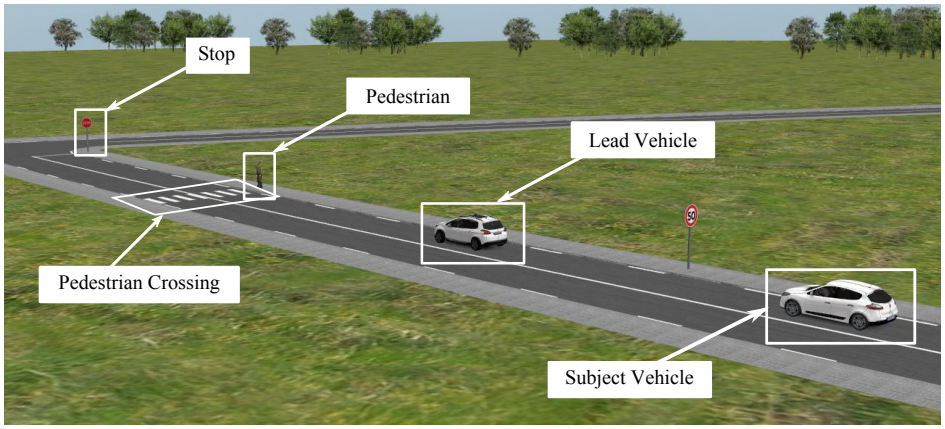


Figure 3.7: Case study for real time evaluation of the ontology.

3.5 Implementation and Experimental Evaluation

Last Section presented the ontology based framework for situation understanding. The approach used to define the ontology was detailed, and results of reasoning on a situation manually edited in the Protégé software were presented. This Section aims to present how the framework was exploited in real time with data recorded on an experimental vehicle.

3.5.1 Case Study and Implementation

Figure 3.7 shows a representation of the case study that was chosen for the evaluation of the ontology in real time conditions. It consists of the subject vehicle that is following a lead vehicle. Both vehicles are navigating towards a pedestrian crossing that precedes a stop intersection. Ten meters separate the pedestrian crossing and the intersection. Finally, a pedestrian is located next to the pedestrian crossing.

Data Sources and Software

Figure 3.8 presents the framework that was used for the real time exploitation of the ontology.

The framework requires several data sources. *A priori* information about the position of the pedestrian crossing and of the stop intersection were stored in a digital map in the Open Street Map format. In addition to this map, the localisation data returned by the GPS receiver was used by the Navigation System in order to generate the Electronic Horizon in real time. Real time information about leading vehicles and pedestrians are provided by the Lidar sensor. Finally, the ontology TBox was stored in a Ontology Web Language (OWL) file [98]. This file format is the reference for the storage of ontologies.

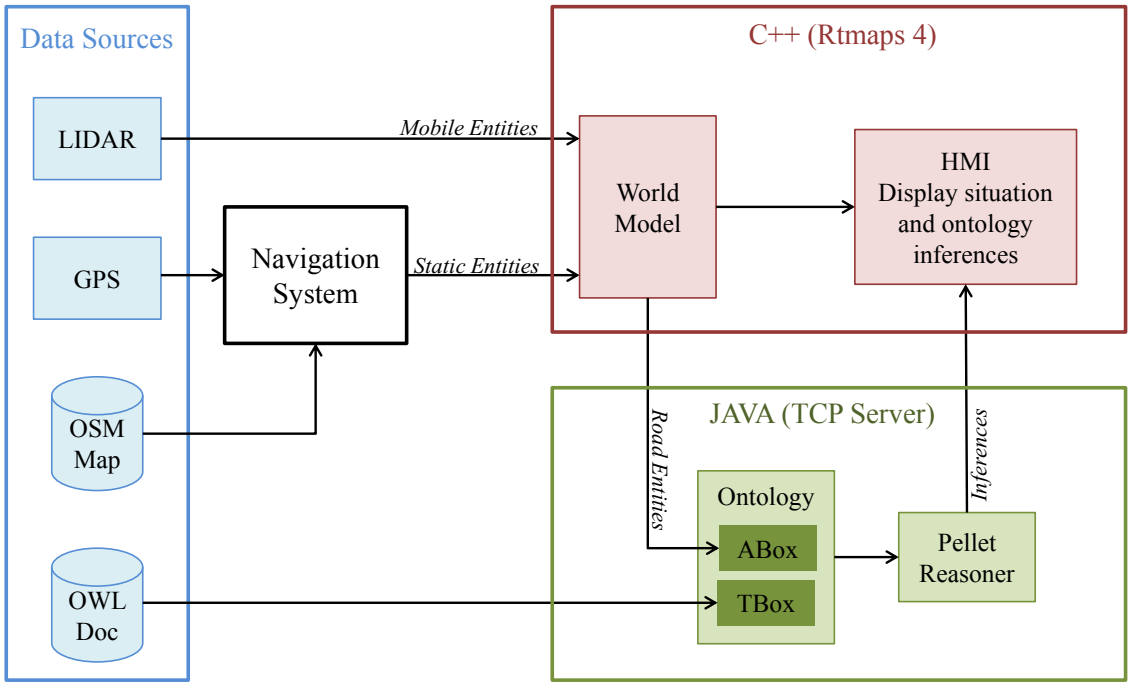


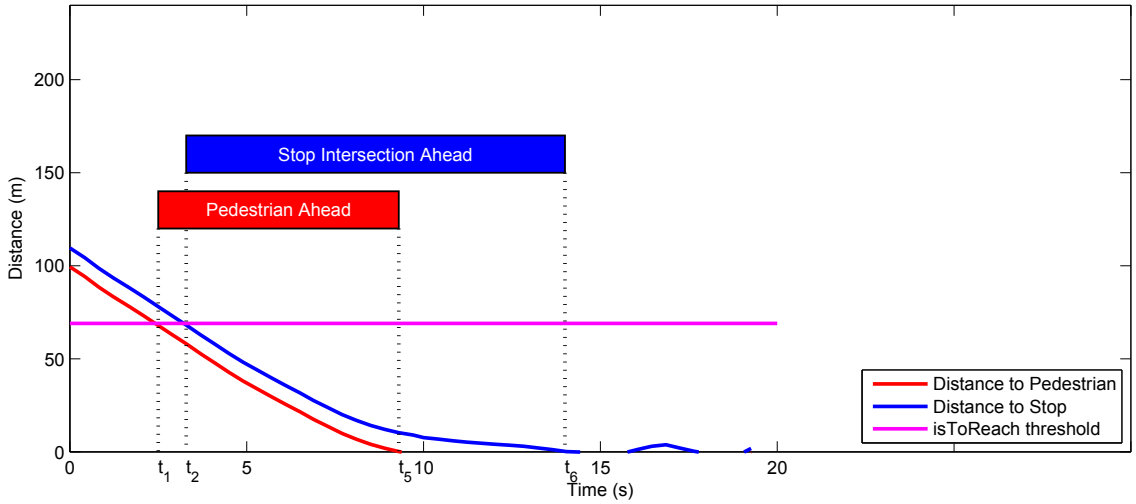
Figure 3.8: Framework for real time situation understanding.

Software

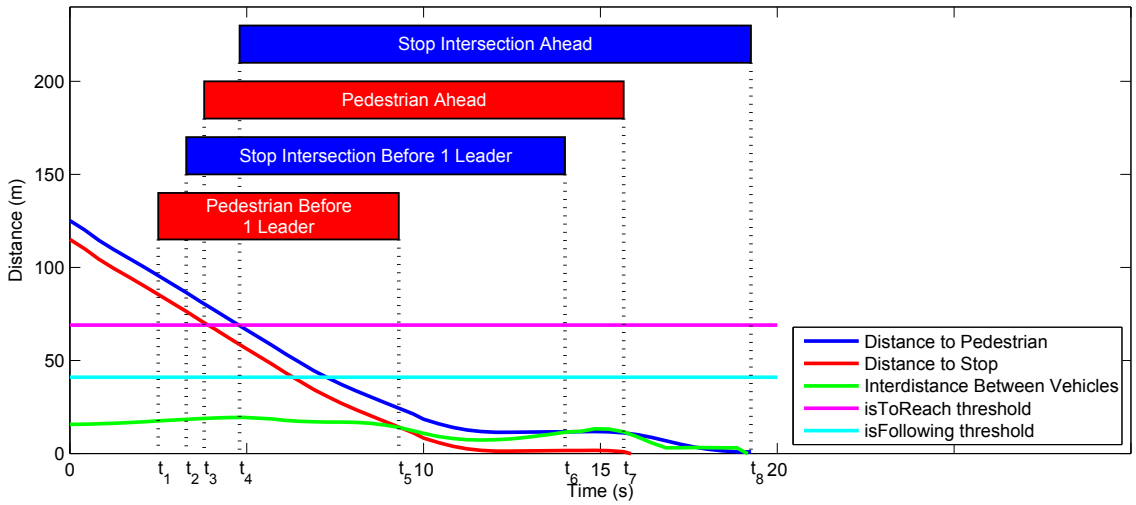
Three pieces of software were necessary to exploit the ontology in real time. The first one is the navigation system that exploits the OSM digital map and that returns the Electronic Horizon at each new measurement of vehicle location. That is, it provides information about the static entities, i.e. the distance of the subject vehicle to the pedestrian crossing and to the stop intersection.

The second piece of software was developed in the C++ programming language for the RTMaps 4 middle-ware. This software allows to get information about the mobile and static entities as they are returned by the data sources. A RTMaps component was developed to feed the World Model structure according to the information about road entities.

The last piece of software was developed in the Java programming language. It enables to exploit the ontology and thus to reason about the World Model. Even if the Java language is not the best language for real time functions, it was chosen to use it as it was the only programming language that proposes accessible libraries for ontologies handling. For this purpose, the OWL API library was used [64]. Moreover, the software was developed as an ontology server, that is it communicates with clients which need to reason about World Models. The communication between the server and RTMaps is performed through the TCP protocol, and the World Model structure is exchanged after having been serialized using the Protobuf library [167]. After reception of the World Model structure by the server, ontology individuals are created, completing the core ontology that was preliminary loaded from the OWL file. Reasoning is then performed through the Pellet reasoner, and inferences are sent back to the TCP client. The inferences can therefore be exploited by an ADAS, which is, in



(a) Situation of the lead vehicle with respect to the static entities, and ontology inferences.



(b) Situation of the subject vehicle with respect to the static entities, and ontology inferences.

Figure 3.9: Results of the experimental evaluation.

this Chapter, an HMI that displays the ontology inferences.

3.5.2 Results

Figure 3.9 presents the results of the experimental evaluation of the ontology. Figure 3.9a shows the state of the lead vehicle and the inferred class equivalences over time for the corresponding ontology individual. Further, Figure 3.9b shows the state of the subject vehicle and the inferred class equivalences over time for the corresponding ontology individual. From the point of view of the subject vehicle, the situation evolves over time through eight main events happening at times t_1 to t_8. These events are detailed hereafter.

From the beginning of the experiment, the interdistance between the subject vehicle and the lead vehicle is lower than the isFollowing threshold (see Figure 3.9b). The ontology therefore considers that the subject vehicle is following the lead vehicle. It means that as soon as the

lead vehicle interacts with at least one other road entity, this interaction is propagated to the subject vehicle.

At time t_1, the distance between the lead vehicle and the pedestrian becomes lower than the isToReach threshold (see Figure 3.9a). Therefore, the ontology considers that there is interaction between the lead vehicle and the pedestrian, and that the lead vehicle is about to reach the pedestrian. However, the pedestrian is close to the pedestrian crossing, therefore it is inferred that the lead vehicle individual becomes an instance of the Pedestrian Ahead concept (see Figure 3.9a). Moreover, since the subject vehicle is following the lead vehicle, the interaction between the lead vehicle and the pedestrian is propagated to it. The subject vehicle individual therefore becomes an instance of the Pedestrian Before 1 Leader concept (see Figure 3.9b).

At time t_2, the distance between the lead vehicle and the stop intersection becomes lower than the isToReach threshold (see Figure 3.9a). Thus, the ontology considers that the lead vehicle is about to reach the stop intersection. The lead vehicle individual therefore becomes an instance of the Stop Intersection Ahead concept. Further, since the subject vehicle is still following the lead vehicle, the subject vehicle individual becomes an instance of the Stop Intersection Before 1 Leader concept (see Figure 3.9b).

At time t_3, the distance between the subject vehicle and the pedestrian becomes lower than the isToReach threshold (see Figure 3.9b). Since the pedestrian is still close to the pedestrian crossing, the subject vehicle starts to interact with him and therefore the subject vehicle individual becomes an instance of the Pedestrian Ahead concept. Note that at this time the lead vehicle did not pass the pedestrian, therefore the subject vehicle individual is still an instance of the Pedestrian Before 1 Leader concept.

At time t_4, the distance between the subject vehicle and the stop intersection becomes lower than the isToReach threshold (see Figure 3.9b). Therefore, the ontology considers that the subject vehicle starts to interact with the intersection, and thus the subject vehicle individual becomes an instance of the Stop Intersection Ahead concept. Note that at this time the lead vehicle did not pass the stop intersection, therefore the subject vehicle individual is still an instance of the Stop Intersection Before 1 Leader concept.

At time t_5, the lead vehicle passes the pedestrian (see Figure 3.9b). As a consequence, the lead vehicle individual is no longer an instance of the Pedestrian Ahead concept. Further, that implies that the subject vehicle is no longer following a vehicle that is about to reach a pedestrian. Therefore, the subject vehicle individual is no longer an instance of the Pedestrian Before 1 Leader concept (see Figure 3.9b). It means that the subject vehicle no longer indirectly interacts with the pedestrian.

At time t_6, the lead vehicle passes the stop intersection. As a consequence, the lead vehicle individual is no longer an instance of the Stop Intersection Ahead concept (see 3.9b). Therefore, the subject vehicle is no longer an instance of the Stop Intersection Before 1 Leader concept (see Figure 3.9b).

At time t_7, the subject vehicle passes the pedestrian. Therefore, the subject vehicle indi-

vidual is no longer an instance of the Pedestrian Ahead concept (see Figure 3.9b). The stop intersection therefore becomes the only pertinent road entity for the subject vehicle.

Finally, at time t_8, the subject vehicle reaches the stop intersection. Therefore, the subject vehicle individual is no longer an instance of the Stop Intersection Ahead concept (see Figure 3.9b). The ontology no longer infers any concept equivalence, therefore there is no more pertinent perceived surrounding entity that have to be monitored by the subject vehicle.

This Section showed that the proposed ontology based framework can be used to understand the situation in which the subject vehicle is navigating. The ontology inferences change over time as the situation change and can be used as guidelines for risk assessment systems. For this experiment, the average processing time necessary for reasoning was $71ms$ on a 4GB RAM laptop with a dual core 1.9GHz processor. The framework can therefore work in real time with the data acquired from the sensors which are used. The next Section aims to discuss about the results of the experimental evaluation of the framework.

3.6 Discussion

It was shown that the proposed ontology enables to reason on road environments as they can be perceived by a vehicle. Reasoning on road environments can be performed with respect to the types of the entities which are concerned, while considering the interactions which are likely to happen between entities. The ontology enables to consider chain reactions in a straightforward manner, that is, the interaction between two entities can have consequences on the behaviour of another entity. In comparison, most of conventional ADAS would have considered each perceived entity independently from the others, and would have monitored the closest entity only. In the case of the case study of Section 3.4, Paragraph 3.4.4, the lead vehicle *Vehicle 2* alone would have been considered by a conventional ADAS.

The proposed ontology cannot be exploited to reason on every road context. Only situations compatible with it can be understood, that is, situations which only meet entities which have been described in the ontology TBox. It means that if the World Model contains an entity that is not formally described in the ontology, the latter will not be able to reason about this entity. If in real life this entity has influence on other entities known by the ontology, a great part of the reasoning will not be representative of reality and thus will not be consistent. Further, for the experiments which were presented, the values of the Context parameters were set in an ad hoc manner. This was because no studies aiming to define conditions for which entities can be considered as interacting were found in the literature. It would therefore be pertinent to carry out studies to fill this gap.

In addition to the quality of the knowledge that is stored in the ontology, the consistency of the inferred information depends on the quality of the information stored in the World Model. If a pertinent entity of the situation misses in the World Model, reasoning about the situation cannot be coherent. Moreover, if the World Model contains incoherent information about the situation, reasoning will neither be coherent. For instance, let's consider a situation for

which the World Model contains an intersection and a lead vehicle in addition to the subject vehicle. If the distance between the subject vehicle and the intersection is under-estimated, the ontology may understand that the lead vehicle already passed the intersection while it did not. The consequence would therefore be that no interaction between both entities is inferred, therefore the situation would be misunderstood by the subject vehicle.

In the current state of research, one weak point of ontologies is their inability to take uncertainties into account. Again, this means that the precision of the data stored in the World Model is of great importance. This implies that all perception and localisation sensors must provide precise and accurate measurements, and that navigations maps are precise and up to date. In addition, this lack of uncertainty implies that it has to be assumed that drivers comply with rules, and that it is not considered that rules can be violated. Finally, neither uncertainties on interactions between entities, neither uncertainties on concept equivalence assertions can be estimated. Such uncertainties could be of great interest, especially for the risk assessment systems which may have to exploit the ontology inferences.

Finally, the time necessary to reason on an ontology is significant and has to be considered. For the experimental evaluation presented in Section 3.5, the average processing time necessary for reasoning was 71ms on a 4GB RAM laptop with a dual core 1.9GHz processor. For a same machine, this processing time depends both on the complexity of the ontology TBox (number of axioms, and especially the number and complexity of the SWRL rules), and on the number and types of road entity individuals stored in the ontology ABox. If the ontology has to be extended, an effort would have to be made in order to limit the number of axioms and rules and thus to limit the complexity of the reasoning step. For real time applications, if the processing time is too high in comparison with the frequency at which the World Model returns data, it would be conceivable to reason on the ontology asynchronously with the rest of the system as it was done in [69].

3.7 Conclusion

This Chapter presented a framework to perform situation understanding. This framework aims to give sense to perception data by considering the perceived environment as a whole, and not only as a collection of road entities. Further, it enables to extract the most pertinent features of the situation in order to provide guidelines to risk assessment systems. The implementation of the framework, and results of real time situation understanding were presented.

The framework is based on the exploitation of an ontology which is a semantic description of entities currently met in road situations. This description contains *a priori* knowledge about interactions which are likely to happen between entities. Further, it also contains information about the behaviours that mobile entities are likely to have in a near future, with respect to the interactions which are likely to exist with nearby entities. All this *a priori* knowledge allows to reason about the data that the subject vehicle is able to collect

about its nearby environment (from perception sensors and databases). Further, it allows to understand what entities are the most pertinent, and how to monitor them and the subject vehicle to perform risk assessment.

The evaluation of the framework was performed in two steps. The first one consisted in exploiting the ontology for a static situation, in order to verify that it allows for a coherent understanding of the situation and moreover to detail the functioning of the approach. The second step aimed to exploit the framework in real time with data recorded aboard an experimental vehicle. This step allowed to analyse the evolution of the ontology inferences over time, and thus to check the pertinence of these inferences for risk assessment. The results showed that the proposed approach allows to give sense to perception data by considering interactions, and chain reactions which may happen. Pertinent features can be extracted from perception data, and then be used as guidelines for ADAS which perform risk assessment.

Whilst promising results were presented, it is of importance to keep in mind that the proposed framework is a preliminary draft which principally aimed to check the coherence of the approach. Further work should therefore be carried out. The ontology, in its current state, enables to consider only entities which are on the same navigation lane than the subject vehicle. One pertinent perspective would be to extend the ontology so that it is able to consider entities which are on other lanes (adjacent and crossing lanes). Taking into consideration vehicles coming from the right or from the left will imply to make the ontology TBox more complex. Such extension must be performed with care in order to avoid to make the ontology too complex, and thus to ensure a moderate processing time for reasoning. Further, fundamental research on ontologies towards a solution to make them able to consider uncertainties would be of great relevance. This would allow for an even more coherent situation understanding as uncertainties on the state of the perceived road entities, on the likely interactions and on behaviours would be taken into account. Nevertheless, such a possibility would require to know the conditional probabilities which describe dependencies between observations, interactions and likely behaviours.

Chapter 4

Bayesian Risk Assessment Using Vehicle State Observations

Contents

4.1 Introduction

Last Chapter presented a situation understanding framework which aims to give sense to the perception and context data. The framework aims to extract the entities which are the most pertinent to be considered by the subject vehicle. Further, it enables to give guidelines for risk assessment by stating what entities should be monitored, and how they should be monitored to ensure safe situations. The framework which is presented in this Chapter constitutes the next step after situation understanding, that is, risk assessment.

The moment at which an ADAS infers that a situation is dangerous is a fundamental parameter. This has a strong impact on the manner how to solve the problem. As presented in Chapter 1, three types of assistance can be considered, namely automated actuation, warnings and assistance in the form of advices or recommendations. The choice of using one type of assistance instead of another one depends on the time remaining before a probable collision, considering the driver reaction time and the vehicle time response.

The risk that a situation turns wrong can be estimated through different approaches. While collision assessment is usually performed by computing the time remaining before collision,

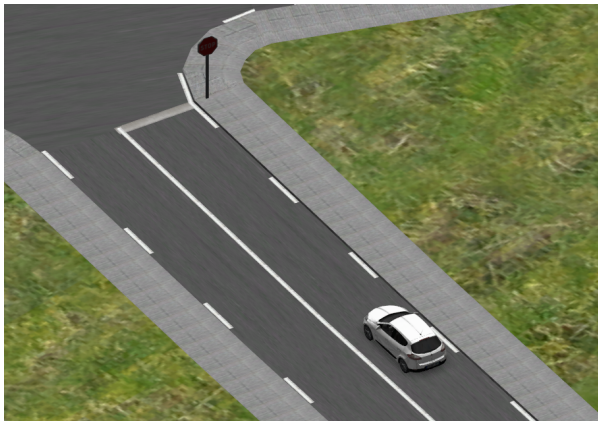


Figure 4.1: Case study: approach of a single vehicle to a stop intersection.

the literature showed that the detection of conflicting intentions which may lead to risky situations offers promising performances. A Bayesian framework was developed in [90] to estimate the risk that a driver manoeuvre intention does not match with the manoeuvre he is expected to perform.

This Chapter aims to evaluate the capabilities of this framework to detect risky situations early enough to provide with pertinence each of the three possible types of assistance. For this purpose, two hypothesis are tested. One considers that all drivers are the same, and uses generic driver profiles to estimate the driver intention. The second one considers that all drivers are different, and thus uses personal driver profiles. Car manufacturers constraints are considered, therefore only automotive sensors can be used.

As presented in Chapter 1, road intersections are of much concern since they account for more than 40% of road accidents in Europe. The simplest intersection scenario was chosen for this study: the approach of a single vehicle to a stop intersection. Figure 4.1 illustrates the chosen case study.

This Chapter is organized as follows. An overview of Bayesian models for vehicle motion is presented as a background for the following of the Chapter. The adaptations performed on the Bayesian network proposed in [90] are then detailed, followed by the presentation of how Gaussian Processes are used to model drivers personal velocity profiles. The ability of the Bayesian framework to provide the three types of assistance, using generic and personal driver profiles is then evaluated. The obtained performances are finally discussed.

4.2 Bayesian Models for Vehicle Motion

Representing vehicle motions is a complex task as motions highly depends on the manoeuvre the driver intends to perform. Markov State Space Models (MSSM) have often been used in the literature with the advantage of being very flexible to considering the vehicle manoeuvre in a straightforward manner [11, 49, 102, 90]. They consist of:

- A set of **measurement variables**. These variables are observable.
- A set of **state variables**. These variables are hidden (not observable) and are estimated from the measurements.
- A set of **conditional probability functions** which specify dependencies between measurements and state, and which specify the evolution of the state in the time.

A brief description of existing models is proposed below.

4.2.1 Considering Manoeuvre Intention

The great majority of MSSMs used to model vehicle motion consider the vehicle state and the manoeuvre intention as state variables. The literature proposes two manners to model vehicle motions with MSSMs: using single MSSMs, or using sets of MSSMs.

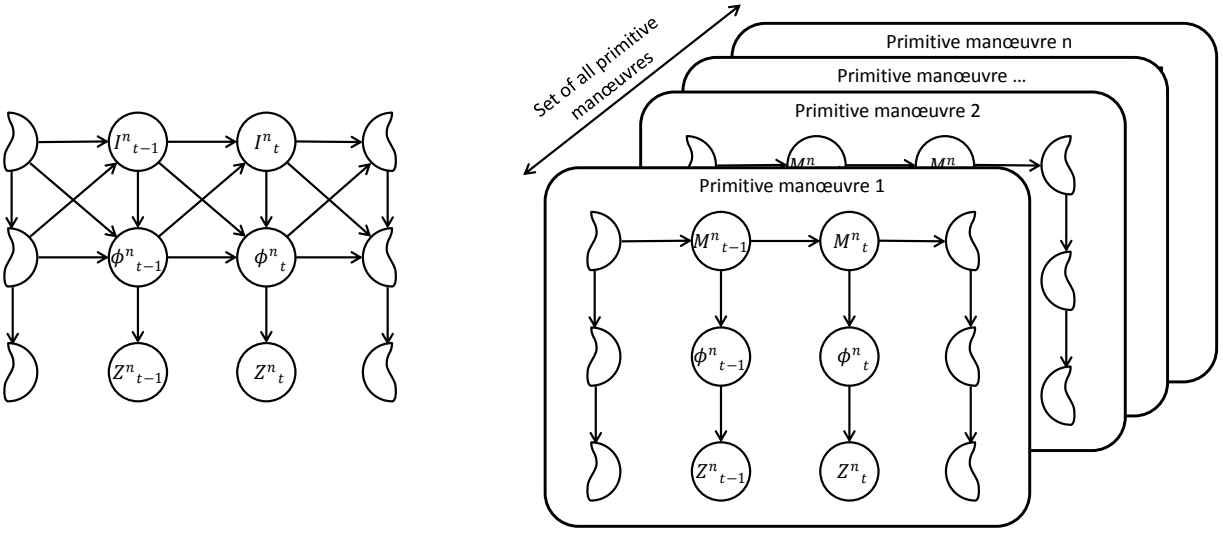
Single MSSMs

Single MSSMs which consider the manoeuvre intention usually model the vehicle motion through three layers:

- **Manoeuvre Intention $\boldsymbol{I}$.** This is the highest level that represents the manoeuvre that is performed by the vehicle (for example go, stop, turn left, etc.). These variables are discrete and are hidden. $\boldsymbol{I}_t^n$ represents the manoeuvre intention of vehicle n at time t.
- **Vehicle State $\boldsymbol{\phi}$.** This is the middle level of the model and represents the **estimation** of the physical state of the vehicle (for example its velocity, acceleration, position, etc.). These variables are hidden and are either discrete or continue. $\boldsymbol{\phi}_t^n$ represents the state of vehicle n at time t.
- **Measurements $\boldsymbol{Z}$.** This is the lowest level of the model and usually represents the noisy version of the Vehicle State. These variables are observable and either discrete or continue. $\boldsymbol{Z}_t^n$ represents the measurements performed about the state of vehicle n at time t.

Figure 4.2a presents a graphical representation of a typical single MSSM. These models are said *Generative*, unlike *Discriminative* models, as the observable variables depend on the hidden variables.

One of the main advantages of MSSMs is their ability to account for the context. They actually offer the possibility to make the intended manoeuvres of the subject vehicle depend on other entities it is interacting with. For example, in the case of vehicles A and B crossing at an intersection, the intended manoeuvre (go or stop) of vehicle A may depend on the intended manoeuvre of vehicle B [49].



(a) Graphical representation of a single MSSM.

(b) Graphical representation of a set of MSSMs.

Figure 4.2: Graphical representation of MSSMs considering the manoeuvre intention. The layers are represented by nodes, conditional probabilities are represented by arrows linking nodes together.

Set of MSSMs

A set of MSSM consists in modelling manoeuvres as a sequence of "primitive manoeuvres", and in having one MSSM model for each. As a consequence, the highest level Manoeuvre Intention is replaced by the primitive manoeuvre $\boldsymbol{M_t^n}$ performed by the vehicle n at time t. The sequences of primitive manoeuvres are constrained in order and duration. Figure 4.2b shows a graphical representation of a set of MSSMs.

Dependencies can be taken into consideration by this type of models. It consists in representing all possible interactions between vehicles by HMMs. It actually requires a high number of models as interactions between all primitive manoeuvres of vehicle A and all primitive manoeuvres of vehicle B have to be modelled. As a consequence, inferences made through such models are time consuming a lot.

4.2.2 Considering Manoeuvre Expectation

The models presented so far only account for manoeuvre intentions, and lack in considering traffic rules which are supposed to govern intentions. For example, in the case of an approach to a stop intersection, the driver's intention to stop at the intersection highly depends on the fact that making a stop is mandatory.

As a solution, Lefevre proposed to extend single MSSMs by integrating a new layer **Manoeuvre Expectation** as the top layer of the model [90]. Like the variables of the Manoeuvre Intention layer, these variables are hidden and discrete. $\boldsymbol{E_t^n}$ represents the manoeuvre that

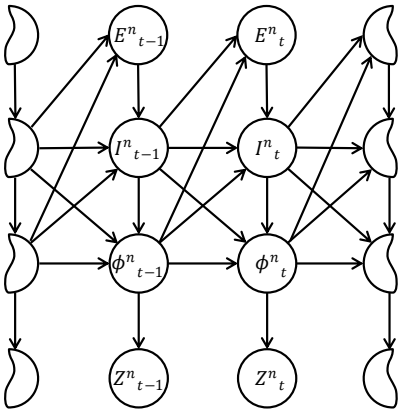


Figure 4.3: Graphical representation of the MSSM proposed in [90] which considers expected manoeuvres.

vehicle n is expected to perform at time t, according to traffic rules. Figure 4.3 shows a graphical representation of this model. The expected manoeuvre is derived from the previous situation (manoeuvre intention and vehicle state), and has an effect on the intended manoeuvre.

This model enabled a new manner to perform risk estimation by computing the probability that the driver intends to perform a manoeuvre that he is not expected to do. This approach was tested in the context of road intersections and showed high performances in the detection of risky situations.

4.3 Bayesian Network Framework For Risk Assessment

The Bayesian model that is used is the Markov State Space Model (MSSM) that is presented in [90]. It allows to consider the vehicle manoeuvres which are expected for a given context, and therefore to infer risk situations by comparing the intended manoeuvre with the expected manoeuvre.

In this thesis, the use of the MSSM differs from the manner it is used in [90]. Table 4.1 summarizes these differences. First of all, the case study is different. While [90] aims to detect imminent collisions between vehicles at intersections, the case studied in this thesis consists in monitoring a single vehicle when it approaches to a stop intersection in order to detect suspicious behaviours which may lead to dangerous situations. In addition, the sensors and maps used in this thesis are compatible with vehicle manufacturer constraints, while this problem did not stand in [90]. Finally, when risk is detected, [90] does not consider the type of assistance that would be the most pertinent for the situation. The model presented in this Chapter aims to estimate how pertinent each type of assistance is when a risk is detected.

This Section aims to detail all adaptations and extensions performed on the original BN in order to make it suited for the imposed constraints and the chosen case study.

Table 4.1: Comparisons between the use of the MSSM in [90] and in this Chapter.

	MSSM used in [90]	**MSSM used in this thesis**
Case study and risk assessment	Approach to intersections. Detection of collisions.	Approach to stop intersections. Detection of suspicious behaviours which may lead to uncomfortable or dangerous situations.
Number of vehicles	n vehicles can be considered	Only 1 vehicle needs to be considered
Localization	Precise and accurate GNSS	Noisy GNSS
Digital map	Precise and designed at lane level	Not precise and designed at road level
Assistance	The relevance of each type of assistance is not considered	Estimation of the type of assistance that would be the most pertinent

4.3.1 Variables Definition

The graphical representation of the Bayesian Network is shown in Figure 4.4. It is the same as the one used in [90], however a conjunction node that represents the driving assistances which can be provided has been added. This node and the relationships it has with the other nodes of the BN are represented with dotted lines. The ensemble of variables present in the BN is presented in Table 4.2. The shaded area represents the variables which were added to those already present in the original BN. This paragraph aims to define all these variables and the relationships they have with each other.

Expected Manoeuvre

The framework would allow for the representation of the expected vehicle manoeuvre through a separation of the longitudinal manoeuvre (go or stop) and of the lateral manoeuvre (choice of the navigable lane). Considering the lateral manoeuvre requires to perform lane level localisation. However, the limits of the GNSS and of the navigation system prevent from considering lane level localisation:

- The GNSS which is used suffers from noise and cannot guarantee measurement of position with an uncertainty lower than $\sigma_P = 3m$, even in ideal conditions (open sky, no external perturbations, etc.). These performances are too low to perform accurate map matching on maps designed at lane level, and therefore to extract the corresponding Electronic Horizon. Localization at lane level would need $\sigma_P < 1m$.
- The performances of the navigation system which is used can be considered as similar as those of navigation systems embedded in commercialized vehicles. It means that maps were not designed at lane level, but at road level. Therefore, it is technically impossible to localize the vehicle at lane level.

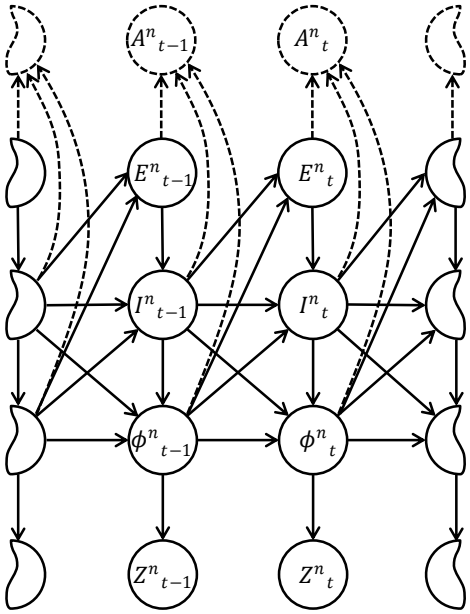


Figure 4.4: Graphical representation of the Bayesian network.

Table 4.2: Detail of all variables present in the BN. The variables added to the initial BN are shown in the blue area.

Conjunction Nodes	Variables Present in Conjunction Nodes		
$A^n{}_t$ Assistance	$Act^n{}_t$ Actuation	$War^n{}_t$ Warning	$Adv^n{}_t$ Advice
$E^n{}_t$ Expectation	$EM^n{}_t$ Expected Manœuvre: Go / Stop		
$I^n{}_t$ Intention	$IM^n{}_t$ Intended Manœuvre: Go / Stop		
$\phi^n{}_t$ Vehicle Physical State	$S^n{}_t$ Real Vehicle Speed	$P^n{}_t$ Real Vehicle Position	
$Z^n{}_t$ Observations	$Sobs^n{}_t$ Observed Vehicle Speed	$Pobs^n{}_t$ Observed Vehicle Position	

The variable that describes Expectation E_t^n is composed by only one node that represents the expected longitudinal manoeuvre of the vehicle, EM_t^n. For a vehicle n, two manoeuvres can be defined with respect to the vehicle longitudinal motion, such as $EM_t^n \in \{go, stop\}$.

- $EM_t^n = go$ means that at time t, the vehicle n is not constrained by context elements (i.e. traffic rules, other road cohabitants) that would impose it to stop at the coming intersection.
- $EM_t^n = stop$ means that at time t, the vehicle n is constrained by context elements that impose it to stop at the coming intersection. In the chosen case study, as the intersection is a stop intersection, the vehicle is expected to stop as it approaches to the intersection.

Intended Manoeuvre

The variable that describes the driver intention I_t^n corresponds to the variable that describes expectation on the driver E_t^n. In that way, the driver intention relies only on the intended longitudinal manoeuvre IM_t^n. For the driver of vehicle n, two intended manoeuvres can be defined with respect to the vehicle longitudinal motion, such as $IM_t^n \in \{go, stop\}$.

- $IM_t^n = go$ means that at time t the driver of vehicle n does not have the intention to stop at the coming intersection.
- $IM_t^n = stop$ means that at time t the driver of vehicle n has the intention to stop at the coming intersection.

Vehicle Physical State

The variable that describes the physical state of vehicle n at time t is represented by $\phi_t^n = (S_t^n, P_t^n)$, with:

- $S_t^n \in \mathbb{R}$ the true speed of vehicle n at time t.
- $P_t^n \in \mathbb{R}$ the true pose of vehicle n at time t, which is represented in one dimension as the distance to the coming intersection. It is the curvilinear abscissa from the vehicle front extreme point and the position of the intersection stopping point as it is edited in the map. This distance was presented in Chapter 3, Figure 3.2d.

Observations

The variable that describes the observations corresponds to the variable that describes the vehicle physical state. In that way, observations on vehicle n at time t are represented by $Z_t^n = (Sobs_t^n, Pobs_t^n)$, with:

- $Sobs_t^n \in \mathbb{R}$ the measured vehicle speed of vehicle n. This data is collected to the vehicle CAN-bus.
- $Pobs_t^n \in \mathbb{R}$ the measured pose of vehicle n. This data is returned by the navigation system with respect to the digital map and the vehicle position provided by the GNSS. More details were given in Chapter 3, Section 3.3.2.

Assistance

Assistance can be provided in 3 forms: automatic actuation, warning and advice. Thus, A_t^n, the relevance of providing assistance to the driver of vehicle n at time t is defined by $A_t^n = (Act_t^n, War_t^n, Adv_t^n)$, with:

- $Act_t^n \in \{not\,pertinent, pertinent\}$ the relevance of performing automatic emergency actuation on vehicle n at time t. $Act_t^n = not\,pertinent$ means that automatic actuation at time t is not pertinent and $Act_t^n = pertinent$ means that automatic actuation at time t is pertinent.
- $War_t^n \in \{not\,pertinent, pertinent\}$ the relevance of warning the driver of vehicle n at time t. $War_t^n = not\,pertinent$ means that providing a warning at time t is not pertinent and $War_t^n = pertinent$ means that providing a warning at time t is pertinent.
- $Adv_t^n \in \{not\,pertinent, pertinent\}$ the relevance of giving an advice to the driver of vehicle n at time t. $Adv_t^n = not\,pertinent$ means that providing the driver with an advice at time t is not pertinent and $Adv_t^n = pertinent$ means that giving an advice at time t is pertinent.

4.3.2 Joint Distribution

For N vehicles, the joint distribution of the general model is given by the following equation, according to the graphical representation shown in Figure 4.4:

$$\begin{aligned} P(A_{0:T}, E_{0:T}, I_{0:T}, \phi_{0:T}, Z_{0:T}) &= P(A_0, E_0, I_0, \phi_0, Z_0) \\ &\cdot \prod_{t=1}^{T} \cdot \prod_{n=1}^{N} [P(E_t|I_{t-1}, \phi_{t-1}) \cdot P(I_t^n|\phi_{t-1}^n, I_{t-1}^n, E_t^n) \\ &\cdot P(\phi_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(Z_t^n|\phi_t^n) \cdot P(A_t^n|E_t^n, I_t^n, \phi_t^n)] \end{aligned} \tag{4.1}$$

This paragraph aims to develop this equation with all variables presented in last paragraph.

Expected Manoeuvre

The conjunction node that represents the expected manoeuvre E_t^n stores only one variable which is the expected longitudinal manoeuvre of the vehicle EM_t^n. This variable depends on the intention and of the vehicle state at time $t-1$. The probability on the expected manoeuvre of vehicle n at time t can therefore be written as follows:

$$P(E_t|I_{t-1}, \phi_{t-1}) = P(EM_t|I_{t-1}, \phi_{t-1}) \tag{4.2}$$

Intended Manoeuvre

The conjunction node that represents the intended manoeuvre I_t^n stores only one variable which is the intended longitudinal manoeuvre of the vehicle IM_t^n. This variable depends on the intention and of the vehicle state at time $t-1$, and of the expected manoeuvre at time t. The probability on the intended manoeuvre of vehicle n at time t can therefore be written as follows:

$$P(I_t^n|\phi_{t-1}^n, I_{t-1}^n, E_t^n) = P(IM_t|\phi_{t-1}, I_{t-1}, E_t) \tag{4.3}$$

Vehicle Physical State

The conjunction node that represents the vehicle state ϕ_t^n stores two variables which are the true vehicle speed S_t^n and the true vehicle pose P_t^n. These two variables are assumed to be conditionally independent given the variables they depend on. They depend on the vehicle state and the intended manoeuvre at time $t-1$ and on the intended manoeuvre at time t. The probability on the vehicle state can therefore be written as follows:

$$P(\phi_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) = P(S_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(P_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \tag{4.4}$$

Observations

The conjunction node that represents the observations Z_t^n stores two variables which are the observed vehicle speed $Sobs_t$ and the observed vehicle pose $Pobs_t$. These two variables only depend on the physical quantities they rely on. The probability on the observations can therefore be written as follows:

$$P(Z_t^n|\phi_t^n) = P(Sobs_t|S_t) \cdot P(Pobs_t|P_t) \tag{4.5}$$

Assistance

The conjunction node that represents the pertinence of providing assistance A_t^n stores three variables which are the pertinence of performing automatic emergency braking Act_t^n, the pertinence of warning the driver War_t^n, and the pertinence of giving an advice to the driver Adv_t^n. These variables depend on the expected manoeuvre, on the intended manoeuvre and on the vehicle state at time t. They are assumed to be conditionally independent given the variables they depend on. The probability of the pertinence of providing assistance in vehicle n can therefore be written as follows:

$$P(A_t^n|E_t^n, I_t^n, \phi_t^n) = P(Act_t^n|E_t^n, I_t^n, \phi_t^n) \cdot P(War_t^n|E_t^n, I_t^n, \phi_t^n) \cdot P(Adv_t^n|E_t^n, I_t^n, \phi_t^n) \tag{4.6}$$

Final Joint Distribution

Considering all these assumptions and simplifications, the joint distribution given by Equation 4.1 becomes, for the given case study:

$$\begin{aligned} P(A_{0:T}, E_{0:T}, I_{0:T}, \phi_{0:T}, Z_{0:T}) &= P(E_0, I_0, \phi_0, Z_0) \\ &\cdot \prod_{t=1}^{T} \cdot [P(EM_t|I_{t-1}, \phi_{t-1}) \cdot P(IM_t|\phi_{t-1}, I_{t-1}, E_t) \\ &\cdot P(S_t|\phi_{t-1}, I_{t-1}, I_t) \cdot P(P_t|\phi_{t-1}, I_{t-1}, I_t) \\ &\cdot P(Sobs_t|S_t) \cdot P(Pobs_t|P_t) \\ &\cdot P(Act_t|E_t, I_t, \phi_t) \cdot P(War_t|E_t, I_t, \phi_t) \cdot P(Adv_t|E_t, I_t, \phi_t) \end{aligned} \tag{4.7}$$

4.3.3 Parametric Forms

This part aims to detail all conditional probability terms whose general equations were given in the previous part.

Expected Longitudinal Manoeuvre

The evolution model of the expected manoeuvre is very simple as the case study consists of the approach to a stop intersection. Thus, the expected longitudinal manoeuvre is always to make a stop at the intersection, independently from the vehicle state and the intended manoeuvre at previous timestep. The conditional probabilities for the expected manoeuvre are therefore defined as follows:

$$\begin{cases} P(EM_t = go) & = 0 \\ P(EM_t = stop) & = 1 \end{cases} \tag{4.8}$$

Moreover, the conditional probability that describes the expected longitudinal manoeuvre can be simplified such as:

$$P(EM_t|I_{t-1}, \phi_{t-1}) = P(EM_t) \tag{4.9}$$

Table 4.3: Conditional probabilities describing the intended manoeuvre I_t.

I_{t-1}	E_t	$P([I_t = go]\|I_{t-1}, E_t)$	$P([I_t = stop]\|I_{t-1}, E_t)$
go	*go*	P_{comply}	$1 - P_{comply}$
go	*stop*	0.5	0.5
stop	*go*	0.5	0.5
stop	*stop*	$1 - P_{comply}$	P_{comply}

Intended Manoeuvre

The evolution model of the intended longitudinal manoeuvre is the same as the one used in [90]. That is, it is based on the comparison between the expected manoeuvre at time t and the intended manoeuvre at time $t-1$. Therefore Equation 4.3 can be simplified as follows:

$$P(IM_t|\phi_{t-1}, I_{t-1}, E_t) = P(IM_t|I_{t-1}, E_t) \tag{4.10}$$

Table 4.3 shows the conditional probabilities. The evolution model assumes that drivers mostly respect traffic rules, that is, they make a stop at the intersection when they reach a stop intersection. In that way, the variable P_{comply} is defined to model how much drivers comply with rules. A low value set for P_{comply} means that most of the time drivers do not respect rules, while a high value means that drivers usually respect rules. If the intended manoeuvre at time $t-1$ and the expected manoeuvre at time t do not match, a uniform prior is assumed. In the following of the thesis, P_{comply} is set such as $P_{comply} = 0.9$, which means that drivers respect traffic rules most of the time.

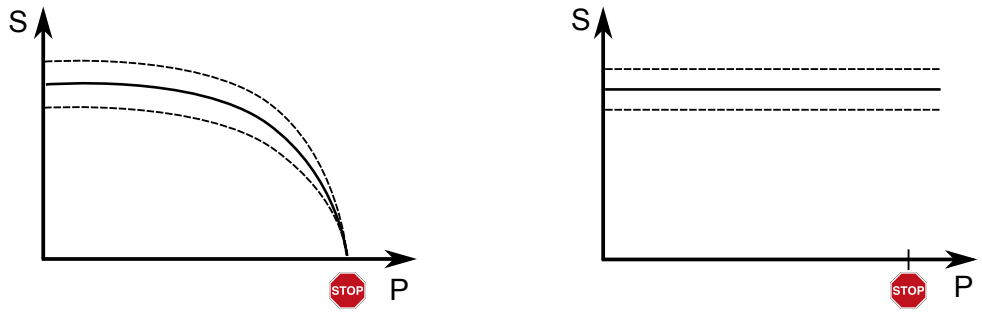
True Vehicle Pose

The evolution model of the true vehicle pose P_t at time t depends on the true vehicle pose P_{t-1} and speed S_{t-1} at time $t-1$. Therefore the conditional probability that describes P_t can be simplified as follows:

$$P(P_t|\phi_{t-1}, I_{t-1}, I_t) = P(P_t|P_{t-1}, S_{t-1}) = \mathcal{N}(\mu_P, \sigma_P) \tag{4.11}$$

with:

- μ_P the mean of the pose. For the sake of simplicity, it is computed following a constant velocity model, using the value of P_{t-1} and S_{t-1} , and the duration between timesteps $t-1$ and t.
- σ_P the standard deviation of the pose. It is manually set such as $\sigma_P = 1m$.



(a) Speed profile shape for $I_t = stop$.

(b) Speed profile shape for $I_t = go$.

Figure 4.5: Example of speed profile shapes depending on the intended manoeuvre. The solid line corresponds to the mean μ_S and the dashed lines corresponds to the standard deviation σ_S.

Observed Vehicle Pose

The evolution model of the observed vehicle pose $Pobs_t$ at time t is based on a classic sensor model as the measurements of the vehicle pose suffer from noise. The measurements follows a normal distribution centred on the true vehicle pose. The conditional probability that describes $Pobs_t$ can therefore be written as follows:

$$P(Pobs_t|P_t) = \mathcal{N}(P_t, \sigma_P) \tag{4.12}$$

In the following, this parameter was set such as $\sigma_P = 3m$, with respect to the performances of the GPS receiver (Ublox 6T) that was used for the experiments.

True Vehicle Speed

The evolution model of the true vehicle speed S_t at time t depends on the true vehicle pose P_{t-1} and speed S_{t-1} at time $t-1$, and of the intended longitudinal manoeuvre at time t. P_{t-1} and S_{t-1} are used to predict the vehicle pose P_t at time t, assuming constant speed between $t-1$ and t. S_t is then based on the velocity profile corresponding to the intended longitudinal manoeuvre IM_t.

Figure 4.5a shows the shape of the velocity profile referring to situations in which the driver intends to stop at the intersection. It describes a deceleration until a null speed at the position of the intersection. Figure 4.5b shows the shape of the velocity profile referring to situations in which the driver does not intend to stop. It describes a constant speed all along the run. These velocity profiles are assumed to follow normal distributions.

The likelihood of the true vehicle speed is defined as following a normal distribution such as:

$$P(S_t|\phi_{t-1}, I_{t-1}, I_t) = P(S_t|P_{t-1}, S_{t-1}, I_t) = \begin{cases} \mathcal{N}(\mu_S^{go}, \sigma_S^{go}) & \text{if } I_t = go \\ \mathcal{N}(\mu_S^{stop}, \sigma_S^{stop}) & \text{if } I_t = stop \end{cases} \tag{4.13}$$

These two distributions can be defined following two different strategies. The first one considers that all drivers are the same, therefore generic speed profiles are used. The second strategy considers that all drivers are different, therefore customized speed profiles are used. Both strategies are tested and compared in the remaining of this Chapter.

Note that even if the case study does not consider lateral manoeuvres, situations in which the driver intends to make a turn at the intersection are absorbed by the cases in which the driver intends to stop. Turning at an intersection imposes to adapt the vehicle speed to the road curvature, therefore decelerations are usually observed. This will be understood by the BN as an intention to stop.

Observed Vehicle Speed

The measurements of the vehicle speed is collected from the vehicle CAN-bus and is accurate enough to ignore uncertainties. A Dirac function is used to model the vehicle speed measurements, such as:

$$P(Sobs_t|S_t) = \delta(S_t - Sobs_t) \tag{4.14}$$

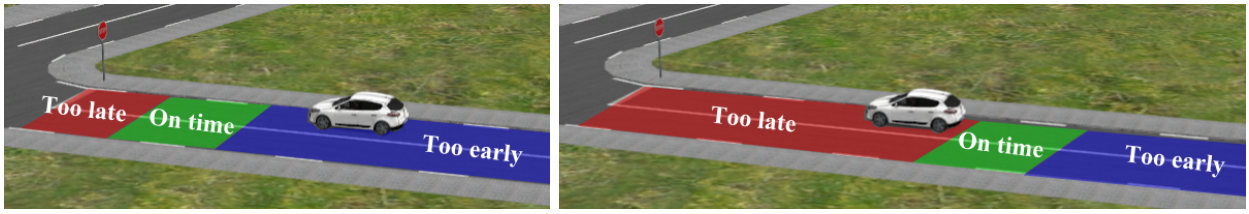
Note that if this measurement had suffered from noise, a normal distribution centred on the true vehicle speed would have been chosen to model the sensor.

Pertinence of Assistance

Assistance is necessary if a risk has been detected. However, the choice of the type of assistance that has to be provided depends on the constraints imposed by the vehicle state. Actually, providing an advice does not make sense if after reaction, the driver has to undergo a too hard deceleration. Moreover, performing automatic braking is not pertinent if the deceleration that the vehicle has to undergo is too smooth. This is illustrated by Figure 4.6. Conditions have therefore to be specified to estimate if a given type of assistance would be pertinent at time t, with respect to the vehicle state.

For this purpose, indicator $\tau_t^{assistance}$ with $assistance \in \{advice, warning, actuation\}$ is defined in order to evaluate the pertinence of each type of assistance in case of risky situations, with:

- $\tau_t^{advice} \in \{good, too\,late, too\,early\}$ indicates if it would be time, or if it is too late or too early to give an advice to the driver.



(a) For automatic actuation assistance (b) For advice assistance

Figure 4.6: The importance of choosing the right moment to provide assistance.

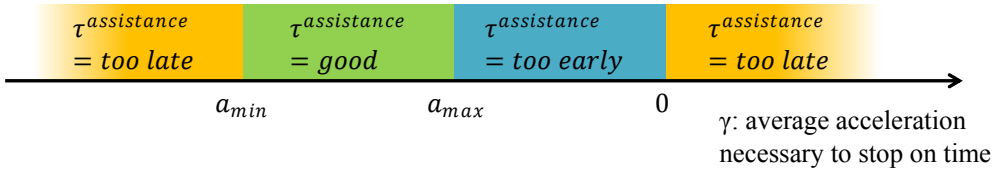


Figure 4.7: Determination of the state of $\tau_t^{assistance}$ given γ.

- $\tau_t^{warning} \in \{good, too\,late, too\,early\}$ indicates if it would be time, or if it is too late or too early to warn the driver.
- $\tau_t^{actuation} \in \{good, too\,late, too\,early\}$ indicates if it would be time, or if it is too late or too early to perform automatic emergency braking.

The state of $\tau_t^{assistance}$ depends on:

- The value of the average acceleration γ that the vehicle would have to undergo to stop on time if assistance was provided. This acceleration is computed by Equation 4.15, considering the vehicle true speed S_t, the vehicle true pose P_t and reaction time RT.
- An acceleration interval defined by the variables a_{min} and a_{max}. Figure 4.7 presents how γ is compared to this interval to get the state of $\tau_t^{assistance}$. If $\tau_t^{assistance}$ is greater than 0, or smaller than a_{min}, it is considered that it is too late to provide the assistance to the driver. If $\tau_t^{assistance}$ is included between 0 and a_{max}, it is considered that it is too early to provide assistance. Finally, if $\tau_t^{assistance}$ is included between a_{min} and a_{max}, it is considered that it is the right moment to provide assistance. Table 4.4 presents the time and physical constraints imposed by each type of assistance. Note that warning and automatic braking assistances allow for harder acceleration (low values of γ, with $\gamma < 0$) than advice assistance.

$$\gamma = -\frac{S_t^2}{2(P_t - S_t \cdot RT)} \tag{4.15}$$

Table 4.4: Time and physical constraints

	Reaction Time $\boldsymbol{RT}$	Minimum tolerated acceleration a_{min}	Maximum tolerated acceleration a_{max}
Automatic Braking	$RT_{machine}$	a_{min}^{hard}	a_{max}^{hard}
Warning	$RT_{machine} + RT_{driver}$	a_{min}^{hard}	a_{max}^{hard}
Advice	$RT_{machine} + RT_{driver}$	a_{min}^{smooth}	a_{max}^{smooth}

Finally, for all three types of assistance, assistance is considered as pertinent if and only if the situation is considered as risky, i.e. $I_t = go$ and $E_t = stop$, while the time and physical constraints are compatible with the given assistance, i.e. $\tau_t^{assistance} = good$.

The probability that it would be pertinent to provide the driver with assistance can therefore be written as follows:

$$P([Assistance_t = pertinent]|IM_t, EM_t, S_t, P_t) = \begin{cases} 1 & if \begin{cases} ([IM_t = go], ... \\ [EM_t = stop], ... \\ [\tau_t^{assistance} = good]) \end{cases} \\ 0 & otherwise \end{cases} \tag{4.16}$$

with $assistance \in \{Adv, War, Act\}$.

The conditional probability that represents assistance A_t at time t can be simplified as follows:

$$P(A_t|E_t, I_t, \phi_t) \quad = P(Adv_t|E_t, I_t, S_t, P_t) \cdot P(War_t|E_t, I_t, S_t, P_t) \cdot P(Act_t|E_t, I_t, S_t, P_t) \tag{4.17}$$

In the following of the thesis, the parameters presented in Table 4.4 are set as follows:

- $RT_{machine} = 0.4sec$, the vehicle brakes time response.
- $RT_{driver} = 1.5sec$, the driver reaction time.
- $a_{min}^{hard} = -8m/s^2$, the hardest acceleration that the vehicle can undergo during emergency braking.

- $a_{max}^{hard} = -5m/s^2$, the smoothest acceleration that the vehicle can undergo during emergency braking.
- $a_{min}^{smooth} = -3m/s^2$, the hardest acceleration which can be considered as comfortable for a driver when he reacts to an advice.
- $a_{max}^{smooth} = -1.5m/s^2$, the smoothest acceleration which can be considered as pertinent for a driver when he reacts to an advice.

Simplified Joint Probability

The joint probability can finally be simplified as follows:

$$\begin{aligned} P(A_{0:T}, E_{0:T}, I_{0:T}, \phi_{0:T}, Z_{0:T}) &= P(E_0, I_0, \phi_0, Z_0) \\ &\cdot \prod_{t=1}^{T} \cdot [P(EM_t) \cdot P(IM_t|I_{t-1}, E_t) \\ &\cdot P(S_t|P_{t-1}, S_{t-1}, I_t) \cdot P(P_t|P_{t-1}, S_{t-1}) \\ &\cdot P(Sobs_t|S_t) \cdot P(Pobs_t|P_t) \\ &\cdot P(Adv_t|E_t, I_t, S_t, P_t) \cdot P(War_t|E_t, I_t, S_t, P_t) \cdot P(Act_t|E_t, I_t, S_t, P_t) \end{aligned} \tag{4.18}$$

4.4 Learning Velocity Profiles for Exploitation by the Bayesian Network Framework

The previous section presented the Bayesian network framework and the adaptation it underwent to fit with the case study requirements. It was explained that the manner how the true vehicle speed S_t is defined depends on the strategy that is chosen. It can either be modelled using generic velocity profiles, either be modelled using profiles depending on the driver driving style. This Section aims to describe how Gaussian processes were used to learn drivers velocity profiles, which will be used within the BN to model the true vehicle speed when the driver intends to stop.

4.4.1 Problem

Learning velocity profiles which can be used as part of the BN framework comes down to a regression problem. As repeatability for driver behaviour can differ very much, it is of importance to take into account this wide spread during the regression process. In the ITS domain, regression problems have been solved with Gaussian Mixture Regression (GMR) [170], Locally Weighted Projection Regression (LWPR) [47] or also Gaussian Processes (GP) [31]. These techniques were used for very different purposes, therefore it is difficult to perform a relevant comparison. Nevertheless, the robotics field has often used regression

algorithms for different problems, such as learning of mechanical models of robots. Sigaud *et al.* published a survey on regression algorithms [147]. Among all algorithms presented in this survey, LWPR is identified to be the most popular regression algorithm in the robotics literature. However, whilst it is an efficient algorithm, it cannot provide information about its confidence on the outputs, such as a variance. By contrast, GMR and GP allow to return confidence on the outputs, and according to the survey they have rather equivalent performances. However, GP seem to represent a more straightforward algorithm as it does not require to partition the training dataset into subregions. This algorithm was therefore preferred for the modelling of velocity profiles. Appendix B presents the principles of GP.

4.4.2 Gaussian Processes Based Pattern Extraction

Training Data

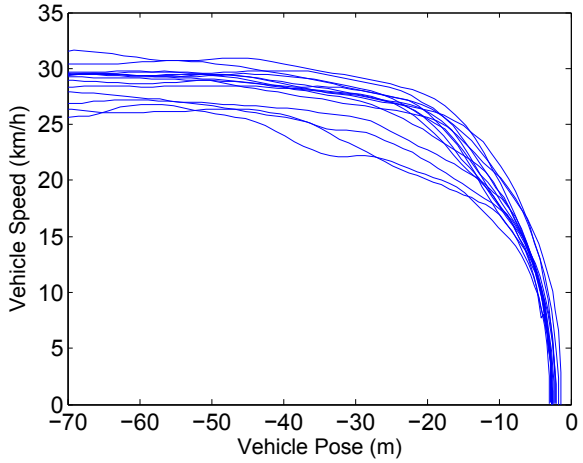
As the purpose is to learn velocity profiles, training data is necessary. It consists of n datasets recorded using the experimental facilities described in Chapter 3, Section 3.3. These datasets are defined such as $\mathcal{D}tr_i = \{Xtr_i, Ytr_i\}_{i=1}^{n}$ (see Figure 4.8a), with:

- Xtr_i the input training vector which corresponds to the measured vehicle pose P_t during approach i.
- Ytr_i the input training vector which corresponds to the measured vehicle speed S_t during approach i.

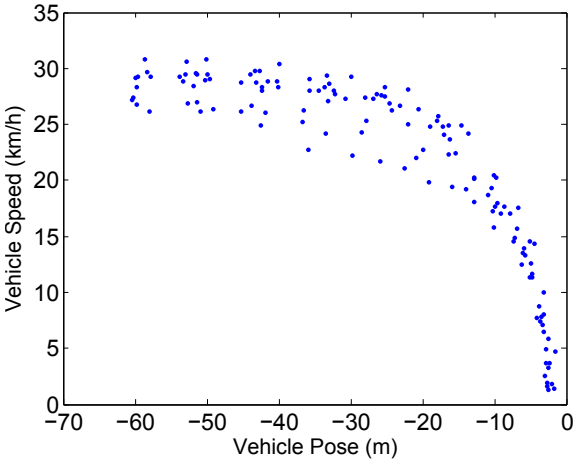
Each dataset $\mathcal{D}tr_i$ is sampled with a frequency f, and starts l seconds before the driver starts showing a reaction with regards to the stop intersection, i.e. l seconds before he starts to push the brake pedal.

The full dataset $\mathcal{D} = \{X, Y\}$ that stores the n training datasets $\mathcal{D}tr_i$ (see Figure 4.8b) is defined such as:

- $X = \begin{bmatrix} Xtr_1 \\ Xtr_2 \\ ... \\ Xtr_m \end{bmatrix} = \{x_j\}_{j=1}^{m}$
- $Y = \begin{bmatrix} Ytr_1 \\ Ytr_2 \\ ... \\ Ytr_m \end{bmatrix} = \{y_j\}_{j=1}^{m}$
- $m = \sum_{i=1}^{n}(\text{sizeof}(Xtr_i)) = \sum_{i=1}(\text{sizeof}(Ytr_i))$ the size of vectors X and Y.



(a) Example of a dataset $\mathcal{D}tr_i$ containing 15 approaches.



(b) Example of dataset $\mathcal{D}$, storing all datasets $\mathcal{D}tr_i$ after sampling ($f = 1Hz$).

Figure 4.8: Example of a dataset before and after sampling.

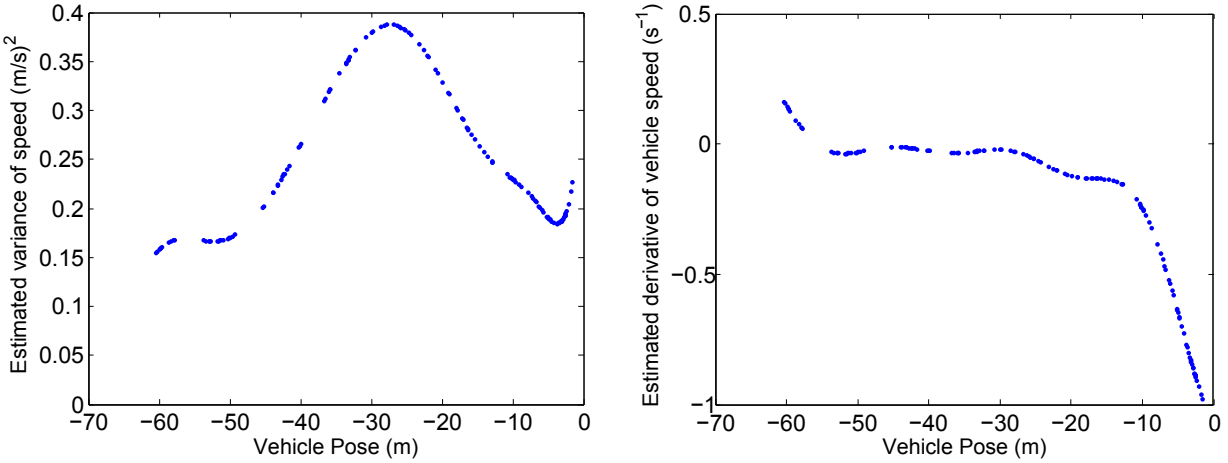
Correction Matrix R

As presented in Appendix B Section B.2, basic Gaussian Processes assume that output variance is constant over all the dataset. This assumption is rarely valid on real life case studies, it was therefore chosen to consider heteroscedastic variance.
To generate the variance correction matrix R, it is necessary to estimate the output variance $r_j(x_j)$ for each input x_i of the training dataset $\mathcal{D}$. For this purpose, the same method as the one proposed by [139] is used. This method can be described through the following steps:

1. A basic Gaussian Process $\mathcal{GP}tr_i$ is modelled for each of the n training datasets $\mathcal{D}tr_i$.
2. For each training input x_j from dataset $\mathcal{D}$, n output predictions $y^*_{i,j}$ are computed using the n GP $\mathcal{GP}tr_i$.
3. The empirical variance $r_j = \frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{y_j} - y^*_{i,j}\right)^2$ is then computed for each training input x_j, with $\bar{y_j}$ the mean of the n predicted values $y^*_{i,j}$. Figure 4.9a gives an example of graphical representation of $r_j = f(x_j)$.
4. The vector $V = \{r_j\}_{j=1}^{m}$ is then obtained and used to define the $m \times m$ matrix $R = \text{diag}(V)$, the covariance correction matrix related to input dependent variance.

Correction Matrix P

As presented in Appendix B, Section B.3, basic Gaussian Processes assume that inputs do not suffer from noise. This assumption is, by far, not valid for the chosen case study as GP inputs are fed by the noisy vehicle pose measurement $Pobs_t$. The noise σ_x is assumed to be constant.
To generate the variance correction matrix P related to the noise σ_x that all inputs x_j of dataset $\mathcal{D}$ suffer from, the same method as the one proposed in [99] is used. This method



(a) Example of graphical representation of variance on vehicle speed function of vehicle pose ($r_j(x_j)^2$).

(b) Example of graphical representation of derivative of vehicle speed function of vehicle pose ($\delta_{yj}(x_j)$).

Figure 4.9: Example of estimated variance and derivative functions necessary for the computation of the covariance correction matrices R and P.

can be described through the following steps:

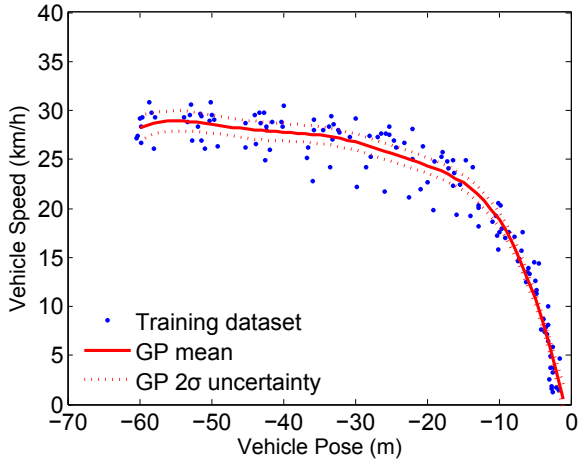
1. A basic Gaussian Process $\mathcal{GP}d$ is performed on the dataset $\mathcal{D}$ to get the prediction output vector $Y^* = \left\{y_j^*\right\}_{j=1}^m$ with respect to the input vector X.
2. The output derivative $\Delta Y^* = \left\{\delta y_j^*\right\}_{j=1}^m$ are then computed with respect to Y^*. Figure 4.9b gives an example of graphical representation of $\delta y_j^* = f(x_j)$.
3. The $m \times m$ matrix $P = \text{diag}(\Delta Y^* \Sigma_x \Delta Y^{*T})$ is then computed as the covariance correction matrix related to noisy inputs, with $\Sigma_x = \text{diag}(\sigma_x)$ and ΔY^{*T} the transpose of ΔY^*.

4.4.3 Results

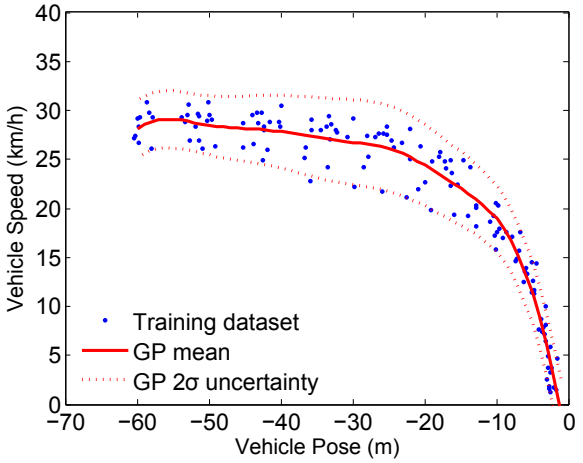
The results presented in this Section were obtained through data recorded in an experimental vehicle, using the facilities described in Chapter 3, Section 3.3. The dataset contains more than 320 approaches to stop intersections performed by 4 different drivers who have different driving styles. From this data, only a limited number of runs were used to learn velocity profiles.

Extracted Pattern

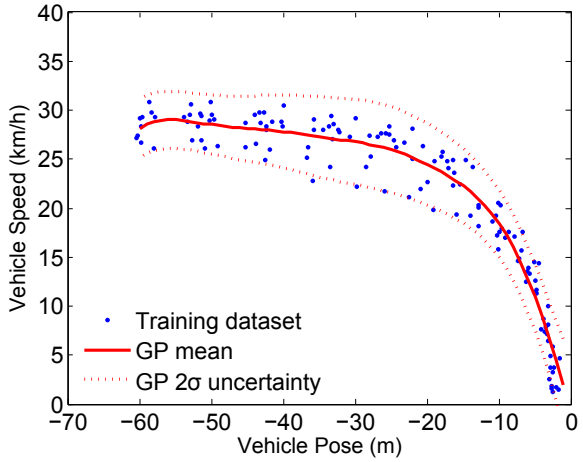
The three GP solutions (GP without correction matrix, GP with correction matrix R, and GP with correction matrices R and P) which would enable to learn velocity profiles were applied. Figures 4.10a, 4.10b and 4.10c show a comparison of the three GP regressions applied on a dataset composed by $n = 15$ randomly chosen runs, which were performed by the same driver. It is noticeable that:



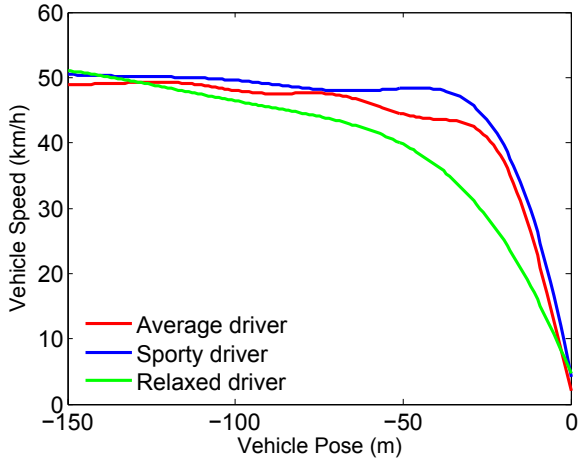
(a) Basic homoscedastic Gaussian Process regression with noiseless inputs.



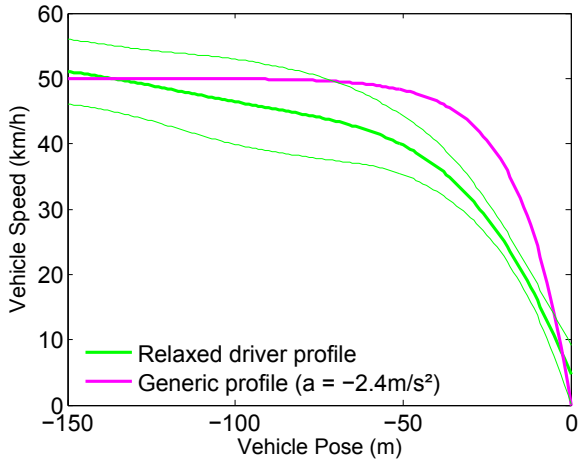
(b) Heteroscedastic Gaussian Process regression with noiseless inputs.



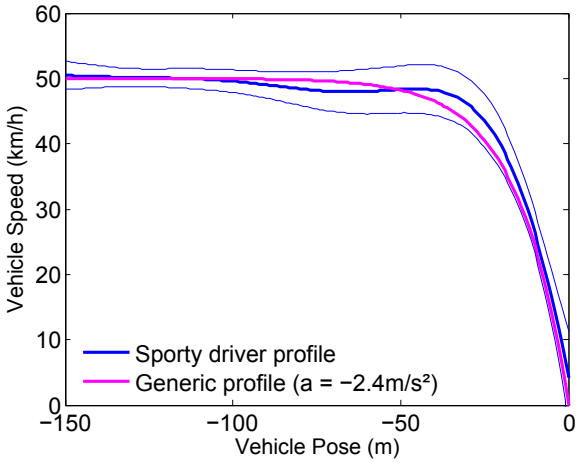
(c) Heteroscedastic Gaussian Process regression with noisy inputs.



(d) Comparison of GP regressions performed for 3 different drivers with different driving styles. For the sake of clarity, variances are not represented.



(e) Comparison of the profile of a relaxed driver with a generic profile.



(f) Comparison of the profile of a sporty driver with a generic profile.

Figure 4.10: Results of GP regressions. The dataset is represented by blue dots. The GP mean is represented by thick lines, and 2σ uncertainty is represented by thin lines.

- All 3 methods enable to compute continuous and smooth curves describing the average vehicle speed (the mean μ) with respect to the distance to the intersection. Moreover, at first glance, these mean curves are coherent with the training dataset.
- The basic homoscedastic GP regression shows an underestimated variance as several points of the dataset are not included inside the variance envelope (the noise level σ_n was set such as $\sigma_n = 5$, see Figure 4.10a). It would be possible to increase the value of the noise level, but it would certainly result in an overestimated variance for some areas of inputs x^*.
- The heteroscedastic GP regression which does not considers noisy inputs shows a variance that models the dispersion of the training points better than the basic homoscedastic GP, as most of training points are included inside the variance envelope. However, the projection of the variance on the x axis (called σ_{proj_x}) when $x \approx 0$ is low ($\sigma_{proj_x} < 1m$ on the example given in Figure 4.10b). This value may be smaller than σ_x, the uncertainty on the measurement of the vehicle pose. In the given example, $\sigma_x = 3m >> 1m$, it is therefore pertinent to consider this noise during the GP training.
- As expected, the differences between GP which consider noisy inputs and GP which consider noiseless inputs are visible only when the derivative of the mean is different from 0. Thus, during the deceleration phase ($x \approx 0$), the projection of the variance on the x axis is greater than if noiseless inputs were considered. In the example given in Figure 4.10c, this value was measured such as $\sigma_{proj_x} \approx 3m$. This matches with $\sigma_x = 3m$, the uncertainty on vehicle pose measurements.

Comparison Between Drivers

The main motivation to learn velocity profiles is to make it possible to easily customize ADAS for each driver. Figure 4.10d shows the learnt velocity profiles of 3 drivers, with different driving styles, approaching to the same intersection. Large differences between these three profiles are visible, as the sportier the driver, the later he starts to decelerate. Gaussian processes therefore enable to take into consideration the differences which may exist between drivers.

Comparison with Generic Profiles

The most conventional velocity profiles which are used by ADAS are generic, therefore it it proposed to compare them with profiles learnt from drivers. The generic profile that is used for this comparison assumes a constant acceleration $a = -2.4m/s^2$ until the vehicle stops. This acceleration is the average deceleration that vehicles undergo when drivers intend to stop at an intersection [163].

Figure 4.10e shows the comparison between a generic profile and a profile learnt for a rather relaxed driver. It is noticeable that the generic profile was designed overestimating the deceleration rate of the driver. If such a profile was used by an ADAS to perform risk

assessment, in the case of dangerous situations, the situation would be detected as dangerous much later than if a customized profile was used.

Figure 4.10f shows the comparison between a generic profile and a profile learnt for a rather sporty driver. It is noticeable that the generic profile was designed underestimating the deceleration rate of the driver. Contrary to the case of relaxed drivers, if such a profile was used by an ADAS to perform risk assessment, in the case of dangerous situations, false alarms may occur often.

Finally, when generic profiles are used, it is difficult to quantify the variance on the vehicle velocity. Most of the time, the only solution is to define it manually, without pertinent justification. The problem no longer exists when GP are used to model velocity profiles, as they enable to quantify uncertainty on the learnt vehicle velocity in a straightforward manner.

4.4.4 Discussion

The results show that Gaussian Processes represent a tool that is well suited to learn velocity profiles of individual drivers. They enable to model accurately the driver patterns, considering uncertainties which exist due to the driver and the quality of the sensors. In that way, heteroscedastic GP which consider noisy inputs seem to be the most suitable version of GP to solve the problem.

For real time application, it is of importance to keep in mind that the computational cost of GP may be high, due to the necessary inversion of covariance matrix K (or $K + R + P$ if the most elaborate version of GP is used), coming at the cost $\mathcal{O}(n^3)$. The bigger the training dataset, the more expensive GP predictions. A compromise has therefore to be found between a large amount of training data (i.e. that leads to more accurate trained models) and a reasonable computational cost. An alternative that consists in separating the training data into several regions and in applying GP to each region can be used. This solution is called Local Gaussian Processes (LGP) [139], but is not investigated in this thesis.

Finally, learnt velocity profiles must not be considered as perfect driver models, and must be used with caution if they are exploited within other frameworks (e.g. risk estimation). As discussed in Chapter 1, the driver behaviour may depend on several factors, such as his general state or external conditions. For pattern learning purposes, it is therefore better to use a training dataset that is representative of different driving situations. This would make it necessary to use a wide dataset, implying significant time necessary to collect data, and the use of techniques such as LGP to limit the computational cost of GP. Nevertheless, as it would be too long and difficult to get enough data covering all driving situations, it is better to use a limited dataset for the learning phase, and to design the stakeholder systems so they do not over-trust customized patterns, and only use them as indicators.

4.5 Experimental Evaluation of the Bayesian Network Framework

4.5.1 Experiment

Purpose

This section aims to evaluate the Bayesian framework ability to provide each of the three types of assistance in case of situations leading to dangerous situations. This evaluation is performed twice, considering the two following approaches:

- Assuming that all driver are the same, and therefore using generic velocity profiles to set the parametric equation of the true vehicle speed $\mathcal{N}(\mu_S^{stop}, \sigma_S^{stop})$ and $\mathcal{N}(\mu_S^{go}, \sigma_S^{go})$ given by Equation 4.13. The manner how to generate generic velocity profiles is the same as the one used by [90]. It is detailed in Appendix C. In the following of this Chapter, the BN designed with this approach will be called *Model 1*.

- Considering that all drivers are different, and therefore use customized velocity profiles to set the parametric equation of the true vehicle speed $\mathcal{N}(\mu_S^{stop}, \sigma_S^{stop})$ given by Equation 4.13. Velocity profiles learnt with Gaussian Processes are used. For each driver who participated to the experimentation, a number $n = 15$ runs where used for the training process. As violating a stop is a rare event, it is not pertinent to learn velocity profiles when the driver does not intend to stop. Generic profiles are therefore used to model $\mathcal{N}(\mu_S^{go}, \sigma_S^{go})$. In the following of this Chapter, the BN designed with this approach will be called *Model 2*.

Inferences

A dataset containing 260 runs (130 for which the driver intends to stop, 130 for which the driver intends to go), recorded with 4 different drivers, with different styles was used. For each recorded run, the following probabilities were computed through the Bayesian network:

- $P([Act_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$, the probability that performing automatic actuation at time t is pertinent.

- $P([War_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$, the probability that providing a warning to the driver at time t is pertinent.

- $P([Adv_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$, the probability that providing an advice to the driver at time t is pertinent.

All inferences were performed using a particle filter running with $N = 400$ particles.

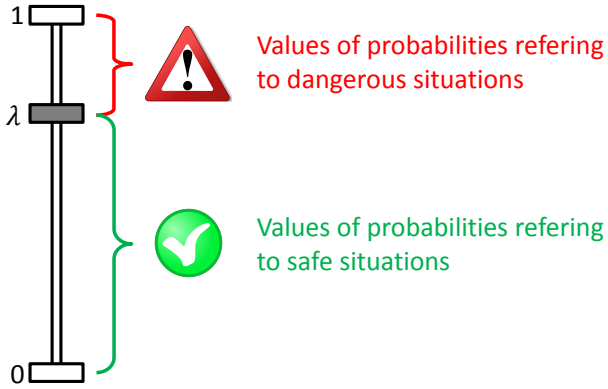


Figure 4.11: Sensitivity of the risk assessment.

4.5.2 Performance Evaluation

Metrics

To take the decision to provide assistance or not, binary outputs are necessary. It is therefore necessary to define a threshold $\lambda \in [0, 1]$ that will define the values of probabilities referring to dangerous situations and those referring to safe situations. It is illustrated by Figure 4.11. The performances of such systems are highly dependent on the value that is set for λ. To evaluate these performances, metrics have to be used. Those are defined as follows:

A too low value will favour the rate of true detections of dangerous situations, but will also favour the rate of inopportune detections. On the contrary, a too high value will favour the rate of true detections of safe situations, but will also favour the rate of missed detections of dangerous situations. As a consequence, a compromise has to be found for the value of λ to get a maximum of True Positive detections of dangerous situations while keeping low the number of False Positive.

One common manner to optimize the value of λ consists in computing the so-called Recall and Precision indicators for a given dataset. They are computed as follows:

$$Recall(\lambda) = \frac{TP(\lambda)}{TP(\lambda) + FN(\lambda)} \tag{4.19}$$

$$Precision(\lambda) = \frac{TP(\lambda)}{TP(\lambda) + FP(\lambda)} \tag{4.20}$$

with:

– TP the number of True Positive, i.e. the number of correct detections of dangerous situations.

- FN the number of False Negative, i.e. the number of missed detections of dangerous situations.
- FP the number of False Positive, i.e. the number of inopportune detections of dangerous situations.

Strategies

Optimized values of λ are reached when $Recall(\lambda) = 1$ and $Precision(\lambda) = 1$. For the dataset containing safe and dangerous situations, it means that all dangerous situations are classified by the model as dangerous situations, and that all safe situations are classified by the model as safe situations. It may happen that there is no value of λ that satisfies this criterion. In this case, one strategy has to be chosen between:

1. Choosing λ so that a maximum of dangerous situations are detected (i.e. take λ when $Recall(\lambda)$ is at its greatest)
2. Choosing λ so that a minimum of inopportune detection of dangerous situations happens (i.e. take λ when $Precision(\lambda)$ is at its greatest).
3. Choosing λ so that a compromise between TP, FN and FP is found.

In this thesis, priority is given to the 2nd strategy when $Precision(\lambda) = 1$ can be reached. Otherwise, a compromise between TP, FN and FP is found. As far as possible, a maximum rate of 5% of false positive is tolerated, otherwise the value of λ for which the precision is the greatest is selected.

4.5.3 Qualitative Results

This paragraph aims to show and explain how the Bayesian Network behaves. All details are given in the case of a safe situation, then in the case of a risk situation. As curves obtained with generic velocity profiles are rather similar to curves obtained with customized velocity profiles, only BN results obtained with customized profiles are shown.

Safe Situation

Figure 4.12 presents all observed and inferred data in the case of a safe situation.
Figure 4.12a shows the vehicle speed and the velocity profile that is expected when the driver intends to stop at the intersection. It is noticeable that the vehicle speed matches with the velocity profile, therefore it means that the probability that the driver intends to stop $P([IM_t = stop]|obs)$ is high.

Figure 4.12b shows intermediate probabilities which are inferred within the BN. The probability that the situation is risky, defined by $P([IM_t = go], [EM_t = stop]|obs)$ stays low all along the run. This is expected has the vehicle speed leads to believe that the driver has the intention to stop.

Figure 4.12b also shows the probabilities on the state of indicators $\tau^{assistance}$. The probability $P([\tau_t^{advice} = good]|obs)$ starts to increase from $P \simeq 40m$ and reaches its top at $P \simeq 25m$. This happens because the vehicle speed and position satisfy the conditions for $\tau^{assistance} = good$ (c.f. Figure 4.7 in Section 4.3.3). By contrast, $P([\tau_t^{warning} = good]|obs)$ stays rather low, and $P([\tau_t^{actuation} = good]|obs)$ is equal to zeros all along the run.

Finally, Figure 4.12c shows for each type of assistance, the probability that assistance is pertinent. It is noticeable that the probabilities $P([Act_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$, $P([War_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ and $P([Adv_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ stay low all along the run. This is because no risk is detected, since $P([IM_t = go], [EM_t = stop]|obs)$ stays low. Therefore, for this example of safe situation, the BN estimates that it is not pertinent to assist the driver.

Risk Situation

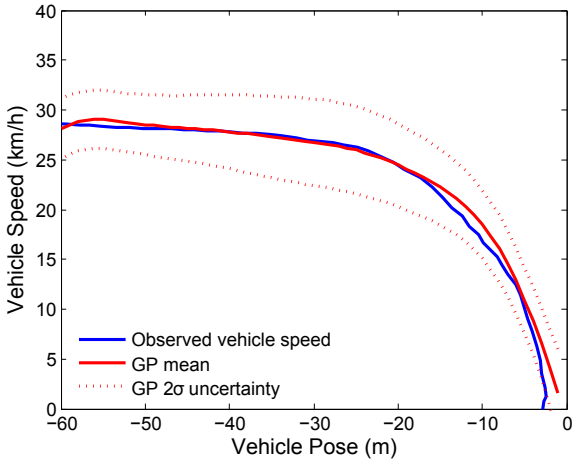
Figure 4.13 presents all observed and inferred data in the case of a risk situation.

Figure 4.13a shows the vehicle speed and the velocity profile that is expected when the driver intends to stop at the intersection. It is noticeable that the vehicle speed does not match with the velocity profile, therefore it means that the probability that the driver intends to stop $P([IM_t = stop]|obs)$ is low.

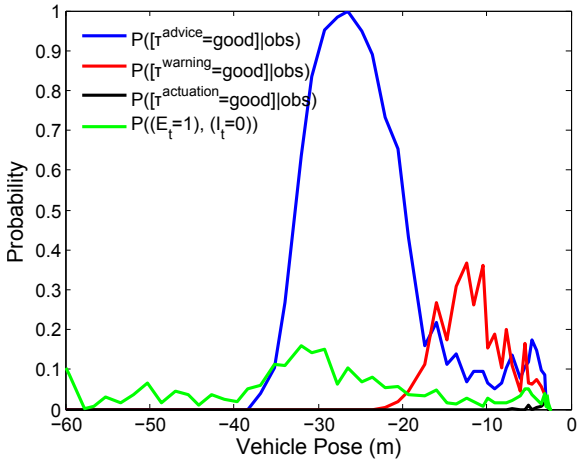
Figure 4.13b shows intermediate probabilities which are inferred within the BN. The probability that the situation is risky, defined by $P([IM_t = go], [EM_t = stop]|obs)$ is high ($\simeq 0.7$) and increases to 1 from $P \simeq 30m$ as the vehicle velocity leaves the velocity profile envelope shown in Figure 4.13a. It is inferred that the driver does not have intention to stop, and thus that the situation is risky.

Figure 4.13b also shows the probabilities on the state of indicators $\tau^{assistance}$. The probability $P([\tau_t^{advice} = good]|obs)$ starts to increase from $P \simeq 45m$ and reaches its top at $P \simeq 35m$. Moreover, $P([\tau_t^{warning} = good]|obs)$ starts to increase at $P \simeq 25m$, and reaches its top at $P \simeq 20m$. Finally, $P([\tau_t^{actuation} = good]|obs)$ starts to increase at $P \simeq 15m$ and reaches its top at $P \simeq 10m$. Therefore, in case of inferred risk situation, each type of assistance would be considered as pertinent at different times.

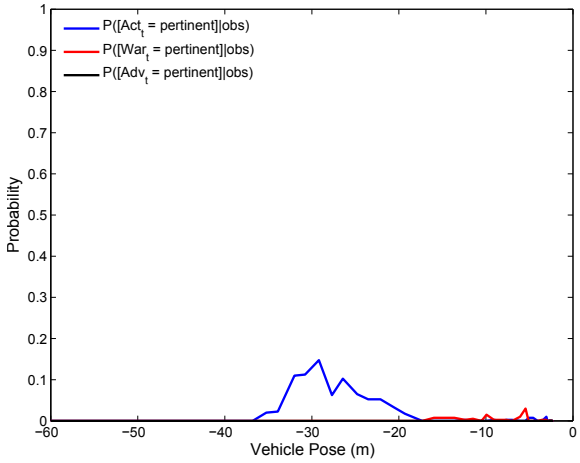
Finally, Figure 4.13c shows the probability that assistance is pertinent, for each type of assistance. It is noticeable that the probabilities $P([Act_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$, $P([War_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ and $P([Adv_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ are high at different times. Moreover, all of them are high during short time intervals. Therefore, for this example of risk situation, the BN estimates that it would be pertinent to assist the driver through the three types of assistance.



(a) Vehicle speed and velocity profile with respect to the vehicle pose.

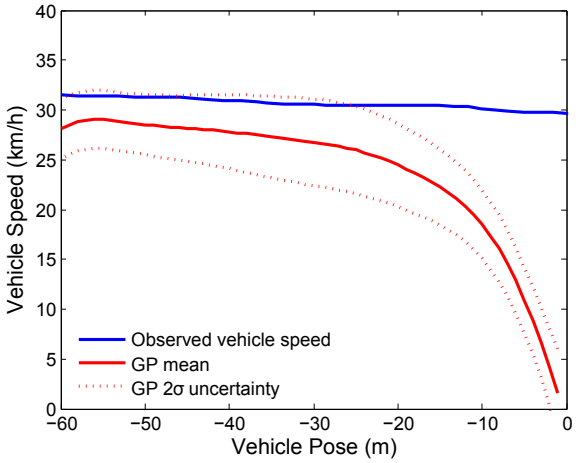


(b) Transitional probabilities with respect to the vehicle pose.

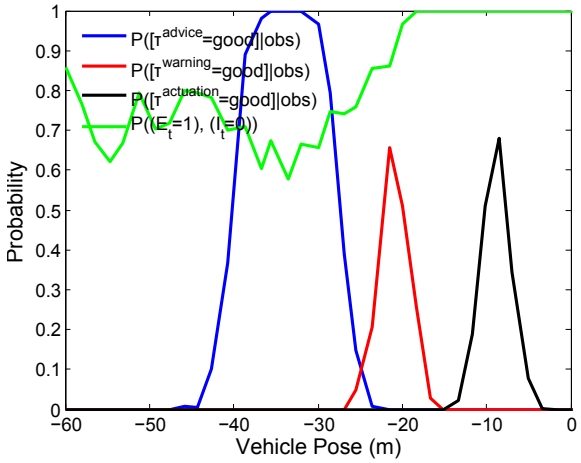


(c) Probabilities that assistance is pertinent with respect to the vehicle pose.

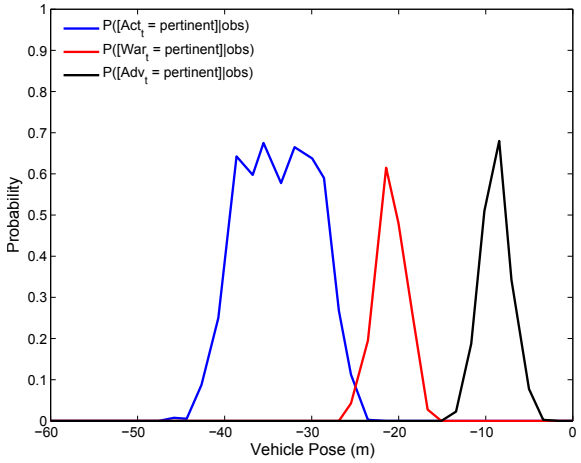
Figure 4.12: Example of observed and inferred data in the case of a safe situation.



(a) Vehicle speed and velocity profile with respect to the vehicle pose.



(b) Transitional probabilities with respect to the vehicle pose.



(c) Probabilities that assistance is pertinent with respect to the vehicle pose.

Figure 4.13: Example of observed and inferred data in the case of a risk situation.

Discussion

In the examples presented above, the BN behaves as it was expected to behave. In the case of a safe situation, the probability that any type of assistance is pertinent stays low all along the run. On the contrary, in the case of a risk situation, the BN is able to determine precisely the time laps at which each type of assistance is pertinent. The probabilities which represent the pertinence of each type of assistance have a clear peak indicating the best time to provide assistance.

In Figure 4.13c, the curve which describes $P([Adv_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ has an average width of about $15m$, which represents a time of $1.8sec$ as the vehicle moves at $30km/h$. In addition, the curves which describe $P([War_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ and $P([Act_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t})$ have an average width of about $8m$ which represents a time of $1sec$. It shows that time lapses during which assistance can be considered as pertinent are short.

4.5.4 Quantitative Results

4.5.4.1 Performance Evaluation

Each run present in the dataset was used as input of the Bayesian Network. For each piece of data, the BN was used twice: once exploiting *Model 1* (i.e. generic velocity profiles), and once using *Model 2* (i.e. customized velocity profiles). A velocity profile was previously learnt for each driver. When customized velocity profiles are used, the profile learnt for the corresponding driver is used.

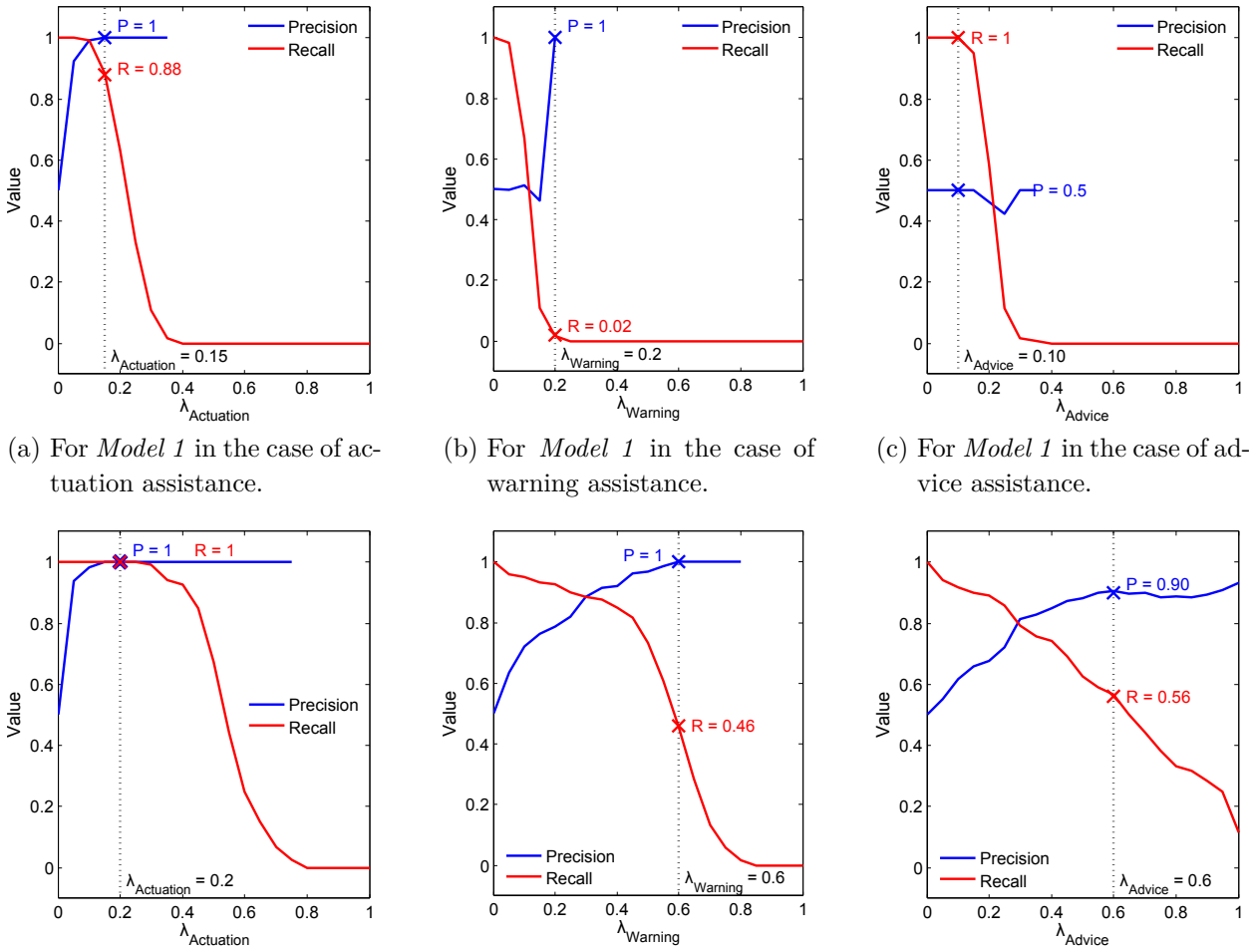
Optimized values of the threshold λ, which represent the sensitivity of the risk assessment had to be found. All runs available in the dataset are labelled either safe or dangerous, therefore it was possible to evaluate TP, FN and FP, and thus the value of the Recall and of the Precision for a given value of λ. Figure 4.14 shows the evolution of the Precision and of the Recall for the three types of assistance, for *Model 1* and *Model 2*.

For *Model 1*

Figure 4.14a shows that the optimized value for the threshold is obtained for $\lambda_{actuation} = 0.15$, leading to $Precision(\lambda_{actuation}) = 1$ and $Recall(\lambda_{actuation}) = 0.88$.

Figure 4.14b shows that the optimized value for the threshold is obtained for $\lambda_{warning} = 0.20$, leading to $Precision(\lambda_{warning}) = 1$ and $Recall(\lambda_{warning}) = 0.02$.

Figure 4.14c shows that there is no value of λ_{advice} for which $Precision(\lambda_{advice}) = 1$. The highest value for Precision is 0.5, so λ_{advice} was chosen so the Recall is the highest. Thus, $\lambda_{advice} = 0.10$ was chosen, leading to $Precision(\lambda_{advice}) = 0.5$ and $Recall(\lambda_{advice}) = 1$. This "optimized" value of λ_{advice} leads to a rate of 100% of true positive, with a rate of 100% of false positive. It means that for all approaches to an intersection (safe and risky), the system will provide assistance. This makes it totally useless as the driver cannot trust it.



(a) For *Model 1* in the case of actuation assistance.

(b) For *Model 1* in the case of warning assistance.

(c) For *Model 1* in the case of advice assistance.

(d) For *Model 2* in the case of actuation assistance.

(e) For *Model 2* in the case of warning assistance.

(f) For *Model 2* in the case of advice assistance.

Figure 4.14: Recall and Precision curves for optimization of threshold $\lambda_{Assistance}$.

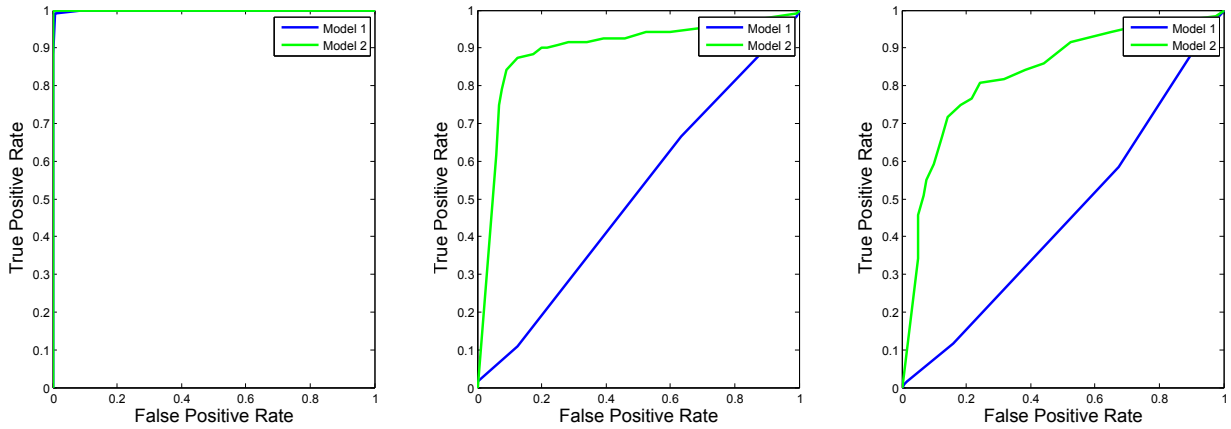
It is therefore considered that advice assistance cannot be provided by *Model 1*, thus both rates of true positive and false positive are set to 0%. This is illustrated by Figure 4.16e.

For *Model 2*

Figure 4.14d shows that there is a a large range for which the value of $\lambda_{actuation}$ allows for $Precision(\lambda_{actuation}) = 1$ and $Recall(\lambda_{actuation}) = 1$. Finally $\lambda_{actuation} = 0.2$ was chosen as an average value of this range.

Figure 4.14e shows that there are several values of $\lambda_{warning}$ leading to $Precision(\lambda_{warning}) = 1$. $\lambda_{warning}$ was therefore chosen so that $Recall(\lambda_{warning})$ is the highest. Thus, $\lambda_{warning} = 0.6$ was chosen, leading to $Precision(\lambda_{warning}) = 1$ and $Recall(\lambda_{warning}) = 0.46$.

Figure 4.14f shows that there is no value of λ_{advice} for which $Precision(\lambda_{advice}) = 1$. A compromise between TP, FN and FP was found for $\lambda_{advice} = 0.6$ which leads to $Precision(\lambda_{advice}) = 0.9$ and $Recall(\lambda_{advice}) = 0.56$.



(a) For actuation assistance (b) For warning assistance (c) For advice assistance

Figure 4.15: ROC curves

4.5.4.2 Results

Figure 4.15 shows the ROC curves for each type of assistance (Automatic Actuation, Warning and Advice), for *Model 1* and *Model 2*. It is noticeable that the performances obtained with *Model 2* are better than those obtained with *Model 1*, as the curves are closer to the point (False Positive Rate = 1, True Positive Rate = 1).

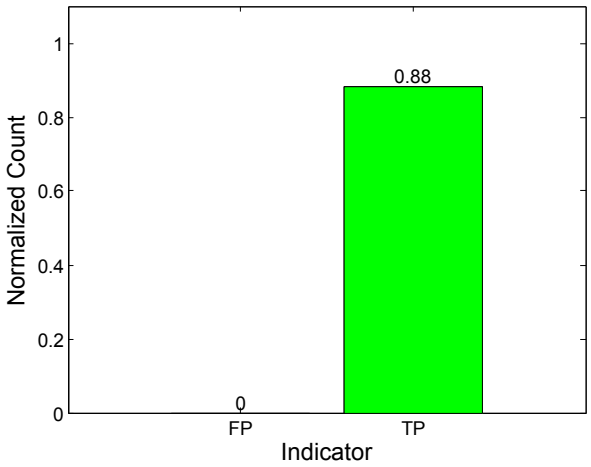
The results obtained with values of λ chosen in last Paragraph are shown by Figures 4.16 and 4.17.

Automatic Actuation Based Assistance

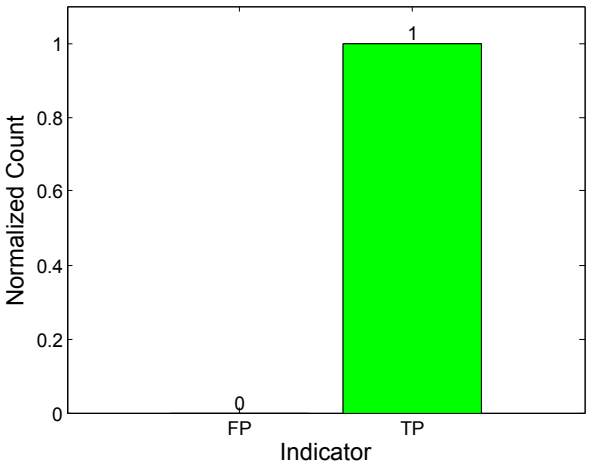
Figure 4.16a shows the performances of *Model 1* obtained for the detection of dangerous situations, leading to the activation of automatic emergency braking. The performances are very good as the rate of 88% of true positives is reached, with a rate of false positives at 0%.

Figure 4.16b shows the same performances for *Model 2*. They are better than those obtained for *Model 1* as the rate of true positives reached 100%, with a rate of false positives at 0%. Therefore, it is noticeable that using customized velocity profiles improves the performances of the BN for the detection of dangerous situations, leading to the activation of automatic emergency braking.

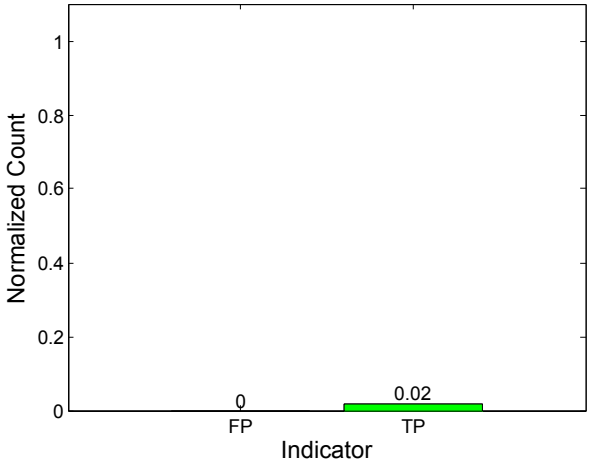
Figures 4.17a and 4.17b show the repartition of the acceleration that would be necessary to stop on time once decision has been taken to perform automatic emergency braking in the case of *Model 1* and *Model 2*. These accelerations match with the acceleration which are expected (see red windows on Figures), even if they are a bit smoother than expected.



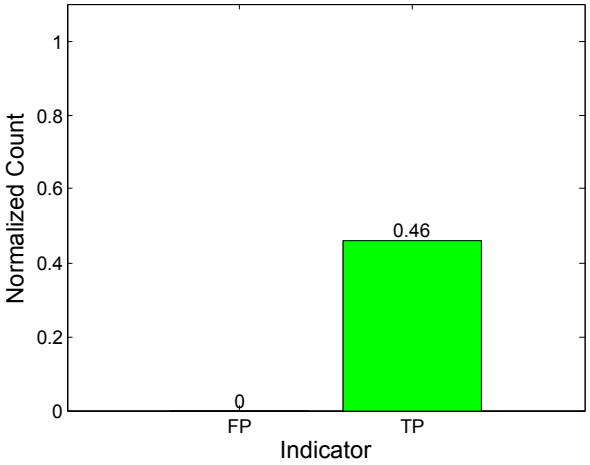
(a) Performances of the BN with *Model 1* in the case of automatic actuation assistance.



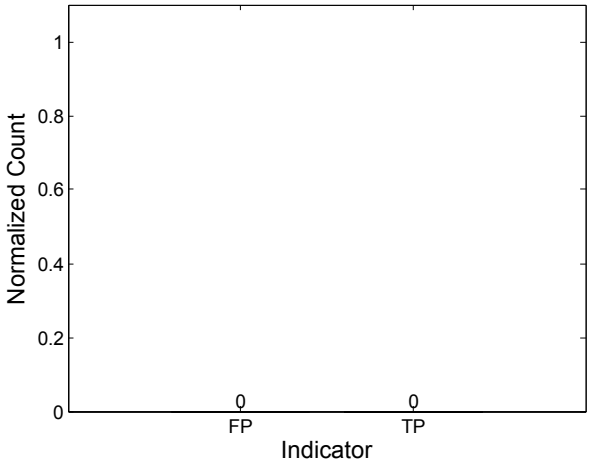
(b) Performances of the BN with *Model 2* in the case of automatic actuation assistance.



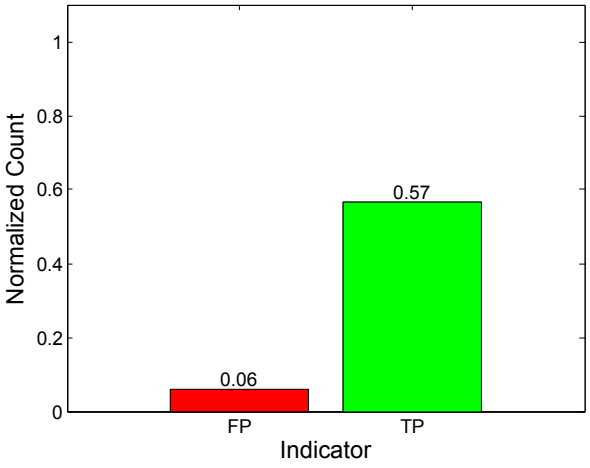
(c) Performances of the BN with *Model 1* in the case of warning assistance.



(d) Performances of the BN with *Model 2* in the case of warning assistance.

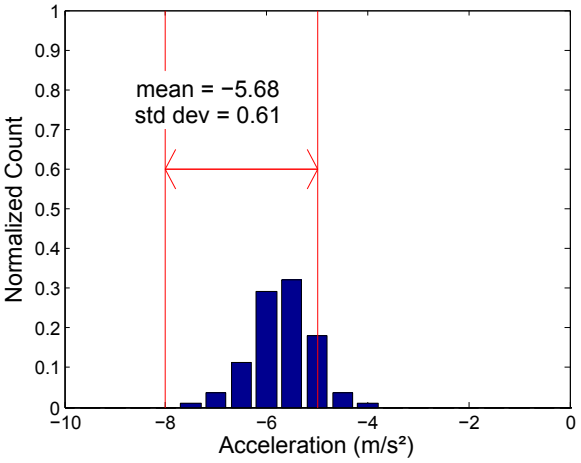


(e) Performances of the BN with *Model 1* in the case of advice assistance.

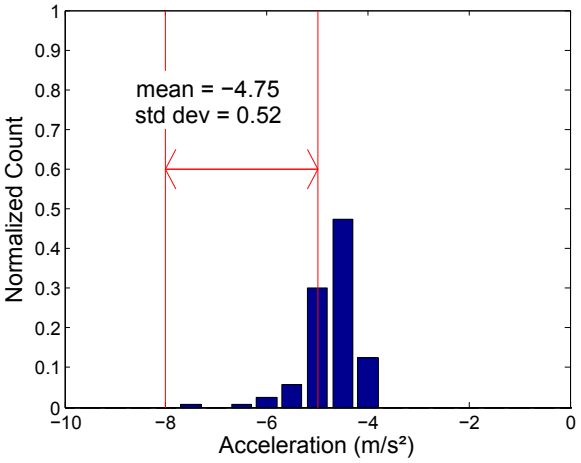


(f) Performances of the BN with *Model 2* in the case of advice assistance.

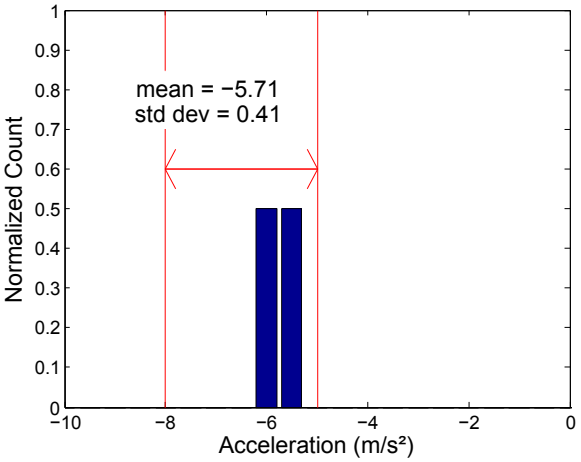
Figure 4.16: Comparison of the performances of the BN for the three types of assistance, considering *Model 1* and *Model 2* for the velocity profiles.



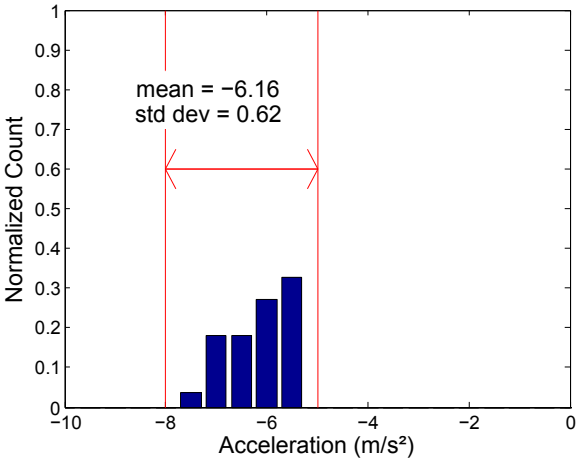
(a) Repartition of acceleration necessary to stop on time, using *Model 1* in the case of automatic actuation assistance.



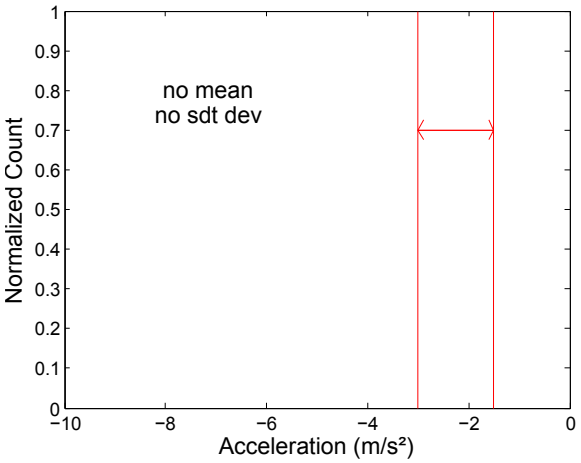
(b) Repartition of acceleration necessary to stop on time, using *Model 2* in the case of automatic actuation assistance.



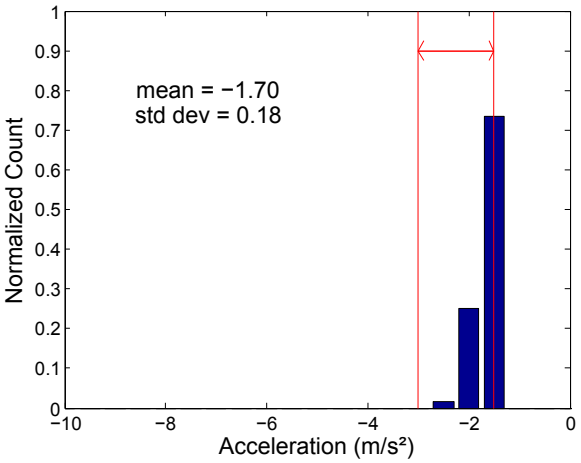
(c) Repartition of acceleration necessary to stop on time, using *Model 1* in the case of warning assistance.



(d) Repartition of acceleration necessary to stop on time, using *Model 2* in the case of warning assistance.



(e) Repartition of acceleration necessary to stop on time, using *Model 1* in the case of advice assistance.



(f) Repartition of acceleration necessary to stop on time, using *Model 2* in the case of advice assistance.

Figure 4.17: Comparison of the repartition of acceleration that the vehicle has to undergo for the three types of assistance, considering *Model 1* and *Model 2* for the velocity profiles.

Warning Based Assistance

Figure 4.16c shows the performances of *Model 1* obtained for the detection of dangerous situations, leading to assistance in the form of warning. The performances are bad as the rate of only 2% of true positives is reached, with a rate of false positives at 0%.
Figure 4.16d shows the same performances for *Model 2*. They are better than those obtained for *Model 1* as the rate of true positives reached 46%, with a rate of false positives at 0%. Therefore, it is noticeable that using customized velocity profiles improves the performances of the BN for the detection of dangerous situations, leading to assistance in the form of warnings.

Figures 4.17c and 4.17d show the repartition of the acceleration that would be necessary to stop on time ones decision has been taken to warn the driver, in the case of *Model 1* and *Model 2*. These accelerations match with the acceleration which are expected (see red windows on Figures).

Advices Based Assistance

Figure 4.16e shows the performances of *Model 1* obtained for the detection of dangerous situations, leading to assistance in the form of advices. As explained a few paragraphs above, there is no values of Precision and Recall that allow for acceptable performances. Therefore, it is assumed that the system cannot be used, and the rate of true positive and false positive were both set to 0%.

Figure 4.16f shows the same performances for *Model 2*. They are better than those obtained for *Model 1* as the rate of true positives reached 57%, with a rate of false positives of 6%. Therefore, it is noticeable that using customized velocity profiles improves the performances of the BN for the detection of dangerous situations, leading to assistance in the form of advices.

Figures 4.17e and 4.17f show the repartition of the acceleration that would be necessary to stop on time once decision has been taken to provide the driver with an advice, in the case of *Model 1* and *Model 2*. As *Model 1* cannot provide advice assistance, no repartition of acceleration can be shown. However, for *Model 2*, the accelerations match with the acceleration which are expected (see red windows on Figures).

4.5.5 Discussion

The results presented above show that using customized velocity profiles to infer the driver intention has a significant impact on the performances of the BN. While differences are not meaningful in the case of automatic actuation assistance, differences are indisputable in the case of warning and advice assistance. Using *a priori* information about the driver usual manner to approach to a stop intersection helps estimate his intention to stop more

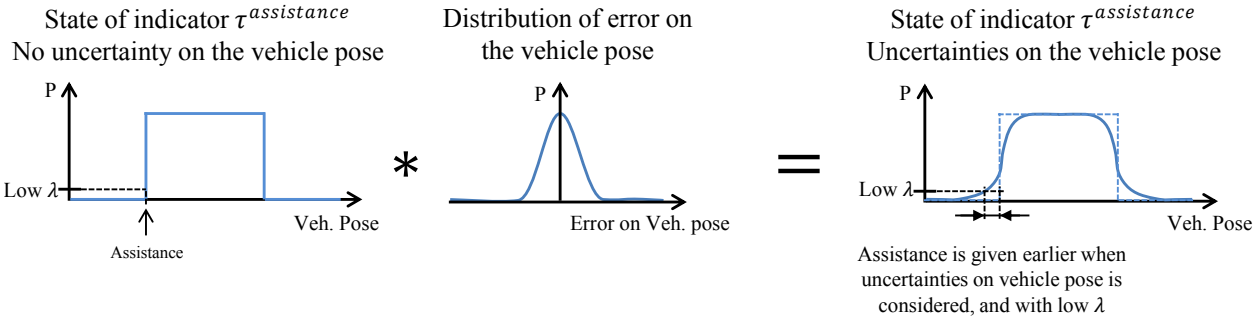


Figure 4.18: Influence of the uncertainties on the vehicle pose on the position at which assistance is triggered.

accurately than if generic profiles are used. Therefore, the detection of risks is also performed with more accuracy.

The accelerations which would be necessary to stop on time once decision has been taken to provide assistance may be smaller than expected. It is particularly visible in Figures 4.16a and 4.16b. This is not an issue as it is better to undergo smaller accelerations than higher accelerations, however it is interesting to understand why this happens. Figure 4.18 illustrates these reasons. The probability that assistance is pertinent at time t depends on the state of the indicator $\tau_t^{assistance}$. This indicator, when it is represented with respect to the vehicle pose, ignoring uncertainties on position, looks like a rectangular function. However, in real life there is a significant uncertainty on the vehicle pose. The state of indicator $\tau_t^{assistance}$ is therefore the convolution of the rectangular function (no uncertainty on vehicle pose) with the Gaussian curve that represents the distribution of error on the vehicle pose. The curve that represents the state of $\tau_t^{assistance}$ is thus wider than the rectangular one, which means that for low values of threshold $\lambda_{assistance}$, assistance is triggered earlier. The acceleration necessary to stop on time is therefore reduced.

In the case of *Model 2*, the learning of velocity profiles and the evaluation were performed using data recorded on the same intersections. These intersections are similar, as both are preceded by straight lines with same speed limitation. If the system was tested on other intersections with different characteristics, but using the same learnt velocity profiles, the performances would be poorer since the velocity profiles would not be well suited for the intersections. Therefore, two approaches may be considered concerning the learnt velocity profiles. The first one consists in learning a velocity profile for each intersection, which means that risk assessment can be performed only on intersections located on roads on which the driver is used to drive. The second one consists in taking benefits from repetitive journeys to learn velocity profiles which can be used for risk assessment at unknown intersections. It would be possible to store in a database several velocity profiles according to intersection characteristics, and then to select the profile that suits best the intersection at which risk assessment has to be performed.

Finally, while it was shown that using customized velocity profiles instead of generic profiles shows promising performances, these performances are too poor to plan on taking bene-

fits on them for warning and advice assistance. Therefore, other improvements should be investigated.

4.6 Conclusion

This Chapter presented the extension of the Bayesian Network framework developed by [90] for risk assessment. The extension was carried out to make the framework suitable for industrial constraints, and for the case study consisting of approaches of a single vehicle to stop intersections. The performances of the framework for the detection of risk situations, and for the estimation of the pertinence of providing assistance were presented.

The extension of the BN framework was performed following two main guidelines. The first one was to allow for the use of data sources compatible with car manufacturer constraints. In this way, the use of low cost and noisy GNSS and of road level navigation maps imply that only longitudinal manoeuvres could be considered by the framework. The second guideline was to make the framework able to evaluate the pertinence of providing assistance (either advice, warning or automatic actuation), based on the comfort of the driver and on the braking limitations of the vehicle. The pertinence of assistance is therefore represented by a conjunction variable present in the Bayesian Network.

Two approaches were considered in this Chapter. The first one assumes, as most conventional systems, that all drivers react and behave in the same manner for a given situation. This translates into the use of generic profiles to model the vehicle behaviour. The second approach rejects this assumption and assumes that each driver has his own manner to react and to behave for a given situation. This translates into the use of profiles, customized for each driver, to model the vehicle behaviour. A method to learn velocity profiles, based on the use of Gaussian Processes was proposed. It was shown that the method allows to model driver patterns with precision and accuracy, considering the uncertainties the sensors suffer from.

For both approaches, the framework was tested on its ability to trigger each of the three types of assistance in case of risk situations. For this purpose, a dataset recorded in a standard passenger vehicle was used. For the dataset that was used, it is noticeable that the framework is very good at triggering automatic actuation assistance with both generic and customized driver profiles. On the contrary, when generic profiles are used, the framework is not able to detect risk situation on time to trigger warning and advice assistance. When customized profiles are used, performances are better as the framework is able to trigger warning and advice assistance in about 50% of the cases. The interest of using customized driver profiles for risk assessment purposes was therefore demonstrated, however the performances shown is this Chapter are still too low to consider implementing the framework in that state in a commercial vehicle. Chapter 5 proposes another extension of the Bayesian Network framework which considers the driver actuations with the aim of improving performances.

The intervals or allowed acceleration which define the pertinence of providing an advice in case of risk situation were set manually. It was assumed that accelerations which can be considered as comfortable for the driver depend on the acceleration he usually undergoes when the situation is not a risk situation. As a perspective for the work led in this chapter, it would be pertinent to set these intervals according to drivers feedbacks about what accelerations they consider as comfortable. It is likely that such tuning will help to ensure the pertinence of the advices which will be provided.

Chapter 5

Bayesian Risk Assessment Using Vehicle State Observations and Driver Actuations

Contents

5.1 Introduction

Chapter 4 showed that the use of vehicle state observations did not allow to provide the driver with advice assistance with sufficient anticipation in many cases. This is due to the limits of the observations and of the model which do not enable to infer risk situations early enough. As shown in Figure 5.1, the purpose is to push the limits imposed by the vehicle state observations in order to shift the moment at which it is possible to detect that it is likely that the situation is at risk.

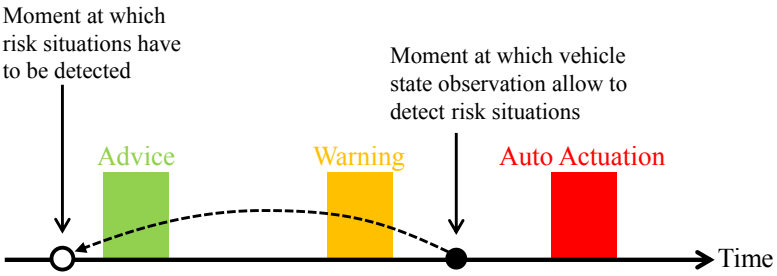


Figure 5.1: Time diagram showing time gaps dedicated to each type of assistance and moments of detection of risk situation.

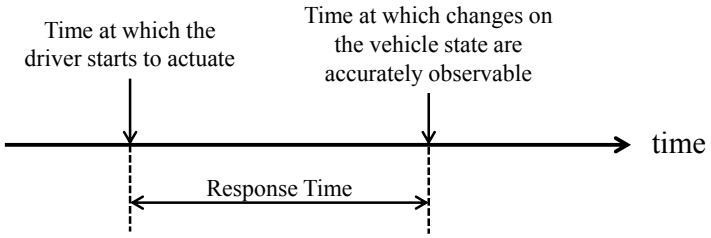


Figure 5.2: Response time.

When a vehicle is driven manually, there is a response time to accurately observe changes on the vehicle state after the moment at which the driver actuates on the vehicle commands (pedals and steering wheel). This is illustrated by Figure 5.2. In the case studied in Chapter 4, three main causes affect this response time: the vehicle response time, uncertainties on the vehicle pose and uncertainties on the evolution models used within the Bayesian Network. One manner to shorten this response time would be to reduce uncertainties on the evolution models, but it would probably affect the performances of the Bayesian network.

Taking into consideration the driver as well as the vehicle and its environment at the same moment helps to better infer driver intentions and therefore risk situations [156]. Thus, by observing the manner how the driver is actuating on the vehicle commands through vehicle CAN data, it would be possible to bypass the response time, and therefore it would help to anticipate earlier what the vehicle will likely do. By incorporating the observations of the driver's actuations in the Bayesian network presented in Chapter 4, it would be possible to detect risk situations early enough to provide the driver with advices instead of warnings or automatic actuations. This hypothesis is applied for the same case study as the one chosen in last Chapter, that is to say the approach of a single vehicle towards a stop intersection.

This Chapter is organized as follows. The manner how the Bayesian network is extended to incorporate observations of the driver's actuations is presented. Then, the model is evaluated using data recorded in an experimental vehicle. All inferences are presented in details in the case of a safe situation and of a risk situation. The performances of the new model for the detection of risk situations that could lead to assistance in the form of advices are finally presented and discussed.

5.2 Extension of the Bayesian Network Framework

This Section aims to detail how the Bayesian Network presented and discussed in Chapter 4 was extended to consider the driver actuations as part of the observations. The initial BN does not consider the lateral motion of the vehicle, therefore it would be useless to consider actuators having effect on the vehicle lateral dynamics. As a consequence, actuations on the steering wheel were ignored, giving way to the state of the gas and brake pedals.

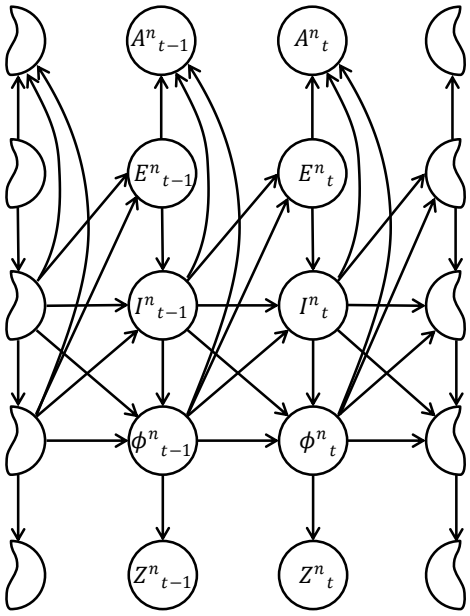


Figure 5.3: Graphical representation of the Bayesian network.

Table 5.1: Detail of all variables present in the BN. The variables added in Chapter 4 are shown in the blue area. The variables added in this Chapter are shown in the green area.

Conjunction Nodes	Variables Present in Conjunction Nodes			
$A^n{}_t$ Assistance	$Act^n{}_t$ Actuation	$War^n{}_t$ Warning	$Adv^n{}_t$ Advice	
$E^n{}_t$ Expectation	$EM^n{}_t$ Expected Manœuvre: Go / Stop		$ER^n{}_t$ Expected Reaction: Reaction / No reaction	
$I^n{}_t$ Intention	$IM^n{}_t$ Intended Manœuvre: Go / Stop		$IR^n{}_t$ Intended Reaction: Reaction / No reaction	
$\phi^n{}_t$ Vehicle Physical State	$S^n{}_t$ Real Vehicle Speed	$P^n{}_t$ Real Vehicle Position	$B^n{}_t$ Real Brake Pedal State	$G^n{}_t$ Real Gas Pedal State
$Z^n{}_t$ Observations	$Sobs^n{}_t$ Obs. Vehicle Speed	$Pobs^n{}_t$ Obs. Vehicle Position	$Bobs^n{}_t$ Obs. Brake Pedal State	$Gobs^n{}_t$ Obs. Gas Pedal State

5.2.1 Variable Definition

The graphical representation of the Bayesian framework is shown in Figure 5.3. It is similar to the one used in Chapter 4, however the variables present in the conjunction nodes now include the expected and intended reactions of the driver, plus the state of the control inputs to the vehicle. The ensemble of the variables present in the Bayesian network is presented in Table 5.1. The green shaded area represents the variables introduced in this Chapter, while the blue shaded area represents the variables added to the initial BN in Chapter 4. Below, the variables present in the initial BN are reminded, and the new variables are detailed.

Expected Manoeuvre

The term "manoeuvre" has to be cleared up, as from now, it concerns either the vehicle or the driver. A manoeuvre related to the vehicle has to be understood as a the vehicle behaviour impacting its physical state. For example, turning right, or making a stop are considered as manoeuvres related to the vehicle. A manoeuvre related to the driver has to be understood as an action, or an operation that the driver is performing. For example, pushing a pedal, or turning the steering wheel are considered as manoeuvres related to the driver.
In that way, the expected manoeuvre conjunction node stores one manoeuvre related to the

vehicle, and one manoeuvre related to the driver, such as, at time t, $E_t^n = (EM_t^n, ER_t^n)$. They can be explained as follows:

- $EM_t^n \in \{go, stop\}$ the expected longitudinal manoeuvre of vehicle n. It is the same variable as the one detailed in Chapter 4, Section 4.3.1. The vehicle can either be expected to stop, or expected to go at the stop intersection.
- $ER_t^n \in \{reaction, no\,reaction\}$ the expected manoeuvre of the driver of vehicle n. Here, the term "driver manoeuvre" has to be interpreted as the reaction that the driver shows when he starts to interact with the stop intersection. Depending on the context, the driver can therefore be expected, or not, to react.

Intended Manoeuvre

The variable that describes the intended manoeuvre I_t corresponds to the variable E_t that describes the expected manoeuvre. In that way, the intended manoeuvre at time t is defined such as $I_t^n = (IM_t^n, IR_t^n)$, with:

- $IM_t^n \in \{go, stop\}$ the intended longitudinal manoeuvre of vehicle n. The driver can either have the intention to stop, or to go at the stop intersection.
- $IR_t^n \in \{reaction, no\,reaction\}$ the intended reaction of the driver of vehicle n. The driver can either react, or do not react to the stop intersection.

Vehicle Physical State

The physical state of vehicle n at time t is represented by $\phi_t^n = (S_t^n, P_t^n, B_t^n, G_t^n)$, with:

- $S_t^n \in \mathbb{R}$, the true speed of vehicle n.
- $P_t^n \in \mathbb{R}$, the true pose of vehicle n, which is represented in one dimension as the distance to the coming intersection. More details were given in Chapter 3, Figure 3.2d.
- $B_t^n \in \{on, off\}$, the true state of the brake pedal of vehicle n. It is assumed that the state of the brake pedal is binary. State *on* means that the driver pushes the brake pedal, and state off means that the driver does not push the brake pedal.
- $G_t^n \in \{on, off\}$, the true state of the gas pedal of vehicle n. It is assumed that the state of the gas pedal is binary. State *on* means that the driver pushes the gas pedal, and state off means that the driver does not push the gas pedal.

Observations

The variable that describes the observations corresponds to the variable that describes the physical state the vehicle. In that way, $Z_t^n = (Sobs_t^n, Pobs_t^n, Bobs_t^n, Gobs_t^n)$ the measurements performed on vehicle n at time t are defined such as:

- $S^n obs_t \in \mathbb{R}$ the measured vehicle speed of vehicle n. This data is collected to the vehicle CAN-bus.
- $P^n obs_t \in \mathbb{R}$ the measured pose of vehicle n. This data is returned by the navigation system with respect to the digital map and the vehicle position provided by the GNSS.
- $B^n obs_t \in \{on, off\}$, the observed state of the brake pedal of vehicle n. This data is collected from the vehicle CAN-bus.
- $G^n obs_t \in \{on, off\}$, the observed state of the gas pedal of vehicle n. This data is collected from the vehicle CAN-bus.

Assistance

The Assistance conjunction node stores the same variables as in Chapter 4, namely:

- $Act_t^n \in \{not\, pertinent, pertinent\}$ the relevance of performing automatic actuation on vehicle n at time t..
- $War_t^n \in \{not\, pertinent, pertinent\}$ the relevance of warning the driver of vehicle n at time t.
- $Adv_t^n \in \{not\, pertinent, pertinent\}$ the relevance of providing the driver of vehicle n with an advice at time t.

5.2.2 Joint Distribution

For N vehicles, the joint distribution of the general model is given by Equation 4.1 (reminded below). This paragraph aims to develop this equation with all variables presented in last paragraph.

$$\begin{aligned} P(A_{0:T}, E_{0:T}, I_{0:T}, \phi_{0:T}, Z_{0:T}) = \; & P(A_0, E_0, I_0, \phi_0, Z_0) \\ & \cdot \prod_{t=1}^{T} \cdot \prod_{n=1}^{N} [P(E_t^n | I_{t-1}^n, \phi_{t-1}^n) \cdot P(I_t^n | \phi_{t-1}^n, I_{t-1}^n, E_t^n) \\ & \cdot P(\phi_t^n | \phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(Z_t^n | \phi_t^n) \cdot P(A_t^n | E_t^n, I_t^n, \phi_t^n)] \end{aligned}$$

Expected Manoeuvre

The conjunction node representing the expected manoeuvre E_t stores two variables which are the expected vehicle manoeuvre EM_t and the expected driver reaction ER_t. These variables depend on the intended manoeuvre and on the vehicle state at time $t-1$. Moreover, they are assumed to be conditionally independent given the same variables. The distribution on the expected manoeuvre of vehicle n can therefore be written as follows:

$$P(E_t^n | I_{t-1}, \phi_{t-1}) = P(EM_t^n | I_{t-1}^n, \phi_{t-1}^n) \cdot P(ER_t^n | I_{t-1}^n, \phi_{t-1}^n) \tag{5.1}$$

Intended Manoeuvre

The conjunction node representing the intended manoeuvre I_t stores two variables which are the intended vehicle manoeuvre IM_t and the intended driver reaction IR_t. These variables depend on the intended manoeuvre and the vehicle state at time $t-1$, and on the expected manoeuvre at time t. Moreover, they are assumed to be conditionally independent given the same variables. The distribution on the intended manoeuvre of vehicle n can therefore be written as follows:

$$P(I_t^n|\phi_{t-1}^n, I_{t-1}^n, E_t^n) = P(IM_t^n|\phi_{t-1}^n, I_{t-1}^n, E_t^n) \cdot P(IR_t^n|\phi_{t-1}^n, I_{t-1}^n, E_t^n) \tag{5.2}$$

Vehicle Physical State

The conjunction node that represents the vehicle physical state ϕ_t stores four variables which are the true vehicle speed S_t, the true vehicle pose P_t, the true brake pedal state B_t and the true gas pedal state G_t. All these variables depend on the vehicle state at time $t-1$, and on the intended manoeuvre at times t and $t-1$. The distribution on the state of vehicle n can therefore be written as follows:

$$\begin{aligned} P(\phi_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) = \quad & P(S_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(P_t^n|\phi_{t-1}^n, I_{t-1}^n, I^n{}_t) \\ & \cdot P(B_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(G_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \end{aligned} \tag{5.3}$$

Observations

The conjunction node that represents the observations Z_t stores fours variables which are the observed vehicle speed $Sobs_t$, the observed vehicle pose $Pobs_t$, the observed brake pedal state $Bobs_t$ and the observed gas pedal state $Gobs_t$. All measurements are conditionally independent given the physical quantities they are associated with. The distribution on the observations on vehicle n can therefore be written as follows:

$$P(Z_t^n|\phi_t^n) = P(Sobs_t^n|S_t^n) \cdot P(Pobs_t^n|P_t^n) \cdot P(Bobs_t^n|B_t^n) \cdot P(Gobs_t^n|G_t^n) \tag{5.4}$$

Assistance

The conjunction node that represents the pertinence of providing assistance A_t stores three variables which are the pertinence of performing automatic emergency braking Act_t, the pertinence of warning the driver War_t, and the pertinence of providing the driver with an advice Adv_t. These variables depend on the expected manoeuvre, on the intended manoeuvre and on the vehicle state at time t. They are assumed to be conditionally independent given the variables they depend on. The probability that providing assistance in vehicle n is pertinent can therefore be written as follows:

$$P(A_t^n|E_t^n, I_t^n, \phi_t^n) = P(Act_t^n|E_t^n, I_t^n, \phi_t^n) \cdot P(War_t^n|E_t^n, I_t^n, \phi_t^n) \cdot P(Adv_t^n|E_t^n, I_t^n, \phi_t^n) \quad (5.5)$$

Final Joint Distribution

Equation 4.1 can finally be developed as follows:

$$\begin{aligned} P(A_{0:T}, E_{0:T}, I_{0:T}, \phi_{0:T}, Z_{0:T}) = \quad & P(A_0, E_0, I_0, \phi_0, Z_0) \\ & \cdot \prod_{t=1}^{T} \cdot \prod_{n=1}^{N} P(EM_t^n|I_{t-1}^n, \phi_{t-1}^n) \cdot P(ER_t^n|I_{t-1}^n, \phi_{t-1}^n) \\ & \cdot P(IM_t^n|\phi_{t-1}^n, I_{t-1}^n, E^n{}_t) \cdot P(IR_t^n|\phi_{t-1}^n, I_{t-1}^n, E_t^n) \\ & \cdot P(S_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(P_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \\ & \cdot P(B_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \cdot P(G_t^n|\phi_{t-1}^n, I_{t-1}^n, I_t^n) \\ & \cdot P(Sobs_t^n|S_t^n) \cdot P(Pobs_t^n|P_t^n) \cdot P(Bobs_t^n|B_t^n) \cdot P(Gobs_t^n|G_t^n) \\ & \cdot P(Act_t^n|E_t^n, I_t^n, \phi_t^n) \cdot P(War_t^n|E_t^n, I_t^n, \phi_t^n) \\ & \cdot P(Adv_t^n|E_t^n, I_t^n, \phi_t^n) \end{aligned} \quad (5.6)$$

5.2.3 Parametric Forms

This part aims to detail all conditional probability terms whose general equations were not given in the previous part. The proposed BN is an extension of the one presented in Chapter 4, therefore some conditional probability terms were already detailed. They are reminded while the new probability terms or those which were modified are detailed.

Conditional Probabilities Already Defined in Section 4.3.3

- $EM_t \in \{go, stop\}$, the expected vehicle manoeuvre at time t. See Equation 4.8.
- $IM_t \in \{go, stop\}$, the intended vehicle manoeuvre at time t. See Equation 4.10 and Table 5.2.

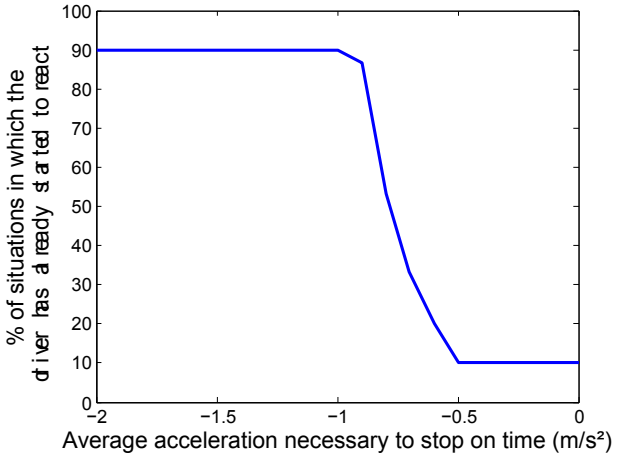


Figure 5.4: Example of output of Algorithm 5.1 for a particular driver.

- $S_t \in \mathbb{R}$, the true vehicle speed at time t. See Equation 4.13.
- $P_t \in \mathbb{R}$, the true vehicle pose at time t. See Equation 4.11.
- $Sm_t \in \mathbb{R}$, the measured vehicle speed at time t. See Equation 4.14.
- $Pm_t \in \mathbb{R}$, the measured vehicle pose at time t. See Equation 4.12.

Expected Driver Reaction

The evolution model of ER_t, the expectation that the driver is reacting at time t, depends on how early the driver usually reacts to a stop intersection. The moment at which a driver reacts depends on γ, the average acceleration that he will have to undergo to stop on time. The later the driver reacts, the higher the acceleration that he has to undergo is. This acceleration depends on the driver driving style.
The approach that was chosen considers that in normal situations, drivers start to react as early as they usually do. In other words, it means that drivers usually look to undergo accelerations that they are used to undergo, i.e. accelerations that they consider as comfortable. The tenet is that if a time t the average acceleration that would be necessary to stop at the intersection is higher than accelerations the driver usually undergoes, the driver is expected to start to react at the same time.

It is therefore necessary to learn when drivers usually start to react to a stop intersection. For this purpose, the average accelerations that the driver usually does not have to undergo to stop are learnt. This is performed using Algorithm 5.1. It enables to determine the relationship between average accelerations γ, and ψ the percentage of situations in which the driver did not have to undergo average acceleration γ. This relationship is defined as the driver dependent function f, defined such as $\psi = f(\gamma)$. Figure 5.4 shows an example of function f learnt for a particular driver.

At time t, the probability that the driver is expected to react, i.e. should be reacting, is therefore derived from function f such as $P(ER_t|I_{t-1}, \phi_{t-1}) = f(\gamma_t^*) = f(S_{t-1}, P_{t-1})$. The

Algorithm 5.1 Computation of percentage of situations in which the driver does not have to undergo acceleration γ when he stops at an intersection.

Inputs: n training datasets $\mathcal{D}_n$ containing the vehicle State $\phi_t(P_t, S_t, G_t, B_t)$.

Outputs: Vehicle acceleration vector $\Gamma^{average}$ and Percentage of situations vector $\Psi^{average}$ such as $\Psi^{average} = f(\Gamma^{average})$.

Begin

$\Gamma^{average} = \{\gamma_m^{average}\} = 0 : -0.1 : -10$
$\Psi^{average} = \{\psi_m^{average}\} = zeros(sizeof(\Gamma))$
For each value of n
  $\Gamma_n = \{\gamma_{n,m}\} = \Gamma^{average}$
  $\Psi_n = \{\psi_{n,m}\} = \Psi^{average}$
End For

For each dataset $\mathcal{D}_n$
  Find time t at which the driver starts to react (i.e. $G_t = off$)
  Compute $\gamma_{n,t} = -\frac{S_t^2}{2 \cdot P_t}$
  For each value of m
    If $\gamma_{n,t} \geq \gamma_{n,m}$ **Then** $\psi_{n,m} = 1$
    Else $\psi_{n,m} = 0$
  End For
End For

For each value of m
  Compute average value of $\psi_m^{average} = \frac{1}{n} \sum_{n=1}^{n} \psi_{n,m}$
End For

Return $\Gamma^{average}$ and $\Psi^{average}$

End

Table 5.2: Conditional probabilities describing the intended driver reaction IR_t.

IR_{t-1}	ER_t	$P([IR_t = reaction]\|IR_{t-1}, ER_t)$	$P([IR_t = no\,reaction]\|IR_{t-1}, ER_t)$
$reaction$	$reaction$	P_{comply}	$1 - P_{comply}$
$reaction$	$no\,reaction$	P_{comply}	$1 - P_{comply}$
$no\,reaction$	$reaction$	0.5	0.5
$no\,reaction$	$no\,reaction$	$1 - P_{comply}$	P_{comply}

vehicle pose P_{t-1} and speed S_{t-1} at time $t-1$ are used to predict the vehicle pose P_t^* and speed S_t^* at time t, considering constant speed between $t-1$ and t. The value of γ_t^* can therefore be estimated and used to determine the probability $P(ER_t|I_{t-1}, \phi_{t-1})$.

The conditional probability can be simplified as follows:

$$P(ER_t|I_{t-1}, \phi_{t-1}) = P(ER_t|P_{t-1}, S_{t-1}) \tag{5.7}$$

Intended Driver Reaction

The evolution model of IR_t, the driver's intention to react to the stop intersection at time t is based on the comparison between the expected driver's reaction at time t and the intended driver's reaction at time $t-1$. The conditional probability is therefore simplified as follows:

$$P(IR_t|\phi_{t-1}, I_{t-1}, E_t) = P(IR_t|IR_{t-1}, ER_t) \tag{5.8}$$

This model assumes that the driver mostly complies with the behaviour he is expected to have. This is represented through the parameter P_{comply}. A high value of P_{comply} means that drivers usually react as early as usual. In the following, this parameter is set such as $P_{comply} = 0.9$.

In that way, it is modelled that if intention at time $t-1$ and expectation at time t are similar, the probability is high that intention at time t is the same as the one at time $t-1$. Moreover, it is modelled that if the driver starts reacting at time $t-1$, the probability that he will keep on reacting at time t is high. However, there is no prior assumption on intention at time t when the driver was not reacting at time $t-1$ while he is expected to react at time t. Table 5.2 summarizes these conditional probabilities.

Table 5.3: Conditional probabilities describing the true state of the brake pedal B_t.

IR_t	$P([B_t = on]\|IR_t)$	$P([B_t = off]\|IR_t)$
$reaction$	P_{comply}	$1 - P_{comply}$
$no\,reaction$	0.5	0.5

True Brake Pedal State

The evolution model of B_t, the state of the brake pedal at time t is based on IR_t, the intention to react at time t. The conditional probability is therefore simplified as follows:

$$P(B_t|\phi_{t-1}, I_{t-1}, I_t) = P(B_t|IR_t) \tag{5.9}$$

The model assumes that pushing the brake pedal is a sign of reaction. It means that if the driver intends to react, the probability that he pushes the brake pedal is high. The parameter $P_{comply} = 0.9$ is used to model this probability. However, if the driver does not intend to react, no prior assumption is done about the state of the brake pedal. Table 5.3 summarizes these conditional probabilities.

Observed Brake Pedal State

The measurement of the state of the brake pedal is collected from the vehicle CAN-bus. The accuracy of the measurement is high enough to ignore uncertainties. A Dirac function is used to model the measurement of the brake pedal state, such as:

$$P(Bobs_t|B_t) = \delta(B_t - Bobs_t) \tag{5.10}$$

True Gas Pedal State

The evolution model of G_t, the state of the gas pedal at time t is based on IR_t, the intention to react at time t. The conditional probability is therefore simplified as follows:

$$P(G_t|\phi_{t-1}, I_{t-1}, I_t) = P(G_t|IR_t) \tag{5.11}$$

The model assumes that pushing the gas pedal is a sign of no reaction. It means that is the driver pushes the gas pedal, the probability that he is not reacting is high. The parameter $P_{comply} = 0.9$ is used to model this probability. However, if the driver intends to react, no prior assumption is done on the state of the gas pedal. Table 5.4 summarizes these conditional probabilities.

Table 5.4: Conditional probabilities describing the true state of the gas pedal G_t.

IR_t	$P([G_t = on]\|IR_t)$	$P([G_t = off]\|IR_t)$
$reaction$	0.5	0.5
$no\,reaction$	P_{comply}	$1 - P_{comply}$

Observed Gas Pedal State

The measurement of the state of the gas pedal is collected from the vehicle CAN-bus. The accuracy of the measurement is high enough to ignore uncertainties. A Dirac function is used to model the measurement of the gas pedal state, such as:

$$P(Gobs_t|G_t) = \delta(G_t - Gobs_t) \tag{5.12}$$

Pertinence of Advice

To estimate the pertinence of providing an advice, a similar approach as the one used to estimate the pertinence of assistance in the BN presented in Chapter 4 is used. In that way, indicator $\tau_t^{advice} \in \{good, too\,late, too\,early\}$ is determined following the method described in Section 4.3.3. To best adapt the assistance to the driver, the variables a_{min}^{smooth} and a_{max}^{smooth} which define the tolerated acceleration interval for advice assistance are learnt from the driver and are set as follows:

- a_{max}^{smooth} is set with the hardest deceleration that the driver is used to undergo when he stops at a stop intersection. It is collected from training data.

- $a_{min}^{smooth} = \eta \cdot a_{max}^{smooth}$ with $\eta > 1$, which enables to tolerate deceleration a little bit harder than the usual maximum deceleration. In the following, η is set manually such as $\eta = 1.5$.

The estimation of risk is performed by checking whether the driver behaviour is suspicious. Chapter 4 showed that comparing the intended and expected vehicle manoeuvre IM_t and EM_t does not enable to detect risk situations early enough to assist the driver in the form of advices. Thus, it was chosen not to use these variables to estimate the pertinence of providing the driver with an advice.

Instead, a behaviour is considered as suspicious when the driver does not show any sign leading to think that he is aware that he has to stop at the intersection. This is done by comparing the intended driver reaction IR_t and the expected driver reaction ER_t. In that way, the driver's behaviour is considered as suspicious at time t as soon as $IR_t = no\,reaction$ and $ER_t = reaction$.

The probability that it would be pertinent to give an advice to the driver can therefore be written as follows:

$$P([Adv_t = pertinent]|IR_t, ER_t, \tau_t^{advice}) = \begin{cases} 1 \quad if \begin{cases} ([IR_t = no\,reaction], ... \\ [ER_t = reaction], ... \\ [\tau_t^{advice} = good]) \end{cases} \\ 0 \quad otherwise \end{cases} \tag{5.13}$$

The conditional probability describing the pertinence of providing the driver with an advice at time t can be simplified as follows:

$$P(Adv_t|E_t, I_t, \phi_t) = P(Adv_t|ER_t, IR_t, S_t, P_t) \tag{5.14}$$

Pertinence of Warning

It is considered that warning the driver is pertinent as soon as these two conditions are satisfied at the same time:

- The comparison between the driver's intended reaction IR_t with the expected reaction ER_t shows that the driver's behaviour is suspicious, i.e. the driver does not react while he is expected to react. Moreover, the state of indicator $\tau_t^{warning}$ has to be *good*. It is computed with values of a_{min}^{hard} and a_{max}^{hard} set manually with same values as those described in Chapter 4, Subsection 4.3.3.

- Risk has been detected by comparing the intended vehicle manoeuvre IM_t with the expected one, EM_t, i.e. by inferring that the driver does not have intention to stop while he is expected to stop. Moreover, the state of indicator $\tau_t^{warning}$ has to be *good*.

The probability that it would be pertinent to warn the driver can therefore be written as follows:

$$P([War_t = pertinent]|IR_t, ER_t, IM_t, EM_t, \tau_t^{warning}) =$$

$$\begin{cases} 1 \quad if \begin{cases} ([IR_t = no\,reaction], [ER_t = reaction], ... \\ [IM_t = go], [EM_t = stop], [\tau_t^{warning} = good]) \end{cases} \\ 0 \quad otherwise \end{cases} \tag{5.15}$$

The conditional probability describing the pertinence of warning the driver at time t can be simplified as follows:

$$P(War_t|E_t, I_t, \phi_t) = P(War_t|ER_t, IR_t, EM_t, IM_t, S_t, P_t) \tag{5.16}$$

Pertinence of Automatic Emergency Braking

The estimation of the pertinence of performing automatic emergency braking on the vehicle is done using similar approach as the one described in Chapter 4, Subsection 4.3.3. The state of indicator $\tau_t^{actuation}$ is estimated using parameters a_{min}^{hard} and a_{max}^{hard} manually set with same values as those described in Section 4.3.3. Risk is estimated by comparing the intended vehicle manoeuvre IM_t with the expected one, EM_t. It is considered that if the last solution to avoid an accident is last minute automatic emergency braking, then any sign of driver reaction does not cast doubt on the pertinence of this assistance. Thus, the variables IR_t and ER_t describing respectively the intended and expected driver reactions are not considered.

The probability that it would be pertinent to perform automatic emergency braking can therefore be written as follows:

$$P([Act_t = pertinent]|IM_t, EM_t, \tau_t^{actuation}) = \begin{cases} 1 & if \begin{cases} ([IM_t = go], ... \\ [EM_t = stop], ... \\ [\tau_t^{actuation} = good]) \end{cases} \\ 0 & otherwise \end{cases} \tag{5.17}$$

The conditional probability describing the pertinence of performing automatic emergency braking at time t can be simplified as follows:

$$P(Act_t|E_t, I_t, \phi_t) = P(Act_t|EM_t, IM_t, S_t, P_t) \tag{5.18}$$

Simplified Joint Probability

The joint probability can be simplified as follows:

$$\begin{aligned} P(A_{0:T}, E_{0:T}, I_{0:T}, \phi_{0:T}, Z_{0:T}) = \; & P(A_0, E_0, I_0, \phi_0, Z_0) \cdot \prod_{t=1}^{T} P(EM_t|I_{t-1}, \phi_{t-1}) \cdot P(ER_t|P_{t-1}, S_{t-1}) \\ & \cdot P(IM_t|\phi_{t-1}, I_{t-1}, E_t) \cdot P(IR_t|IR_{t-1}, ER_t) \\ & \cdot P(S_t|P_{t-1}, S_{t-1}, I_t) \cdot P(P_t|P_{t-1}, S_{t-1}) \\ & \cdot P(B_t|IR_t) \cdot P(G_t|IR_t) \\ & \cdot P(Sobs_t|S_t) \cdot P(Pobs_t|P_t) \cdot P(Bobs_t|B_t) \cdot P(Gobs_t|G_t) \\ & \cdot P(Act_t|EM_t, IM_t, S_t, P_t) \cdot P(Adv_t|ER_t, IR_t, EM_t, IM_t, S_t, P_t) \\ & \cdot P(Adv_t|ER_t, IR_t, S_t, P_t) \end{aligned} \tag{5.19}$$

5.3 Experimental Evaluation of the Bayesian Network Framework

5.3.1 Experiment

Purpose

This Section aims to evaluate the performances of the Bayesian model presented in the last Section to estimate for each type of assistance, how much it would be pertinent to assist the driver in case of dangerous situation. The performances are evaluated following the method described in Chapter 4, Subsection 4.5.2, based on the computation of the precision and recall parameters.

The proposed approach aims to take advantage of the manner how drivers usually drive, therefore it was necessary to learn driver patterns. For each driver, training was performed using using a number $n = 15$ runs randomly selected within the dataset storing safe situations. This learned data is used for two purposes within the BN:

- The intended manoeuvre at time t, IM_t, is estimated using personal velocity profiles learnt with Gaussian Processes, presented in Chapter 4, Section 4.4. Those are used to represent the vehicle speed that is expected when the driver intends to stop at the intersection.
- The expected driver reaction at time t, ER_t, is estimated thanks to statistics performed on the acceleration γ that the vehicle usually undergoes when the driver intends to stop. The method is presented in this Chapter in Subsection 5.2.3.

Inferences

The same dataset as the one used in Section 4.5 is used (4 drivers, a total of 260 runs). For each recorded run, the following probabilities were computed through the Bayesian network, using a particle filter running with $N = 400$ particles:

- $P([Act_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t}, Bm_{0:t}, Gm_{0:t})$, the probability that performing automatic emergency braking at time t is pertinent.
- $P([War_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t}, Bm_{0:t}, Gm_{0:t})$, the probability that warning the driver at time t is pertinent.
- $P([Adv_t = \text{pertinent}]|Sm_{0:t}, Pm_{0:t}, Bm_{0:t}, Gm_{0:t})$, the probability that providing the driver with an advice at time t is pertinent.

5.3.2 Qualitative Results

This paragraph aims to show and to explain how the Bayesian network behaves. All details are given in the case of a safe situation, then in the case of a risk situation, and a comparison is finally presented.

5.3.2.1 Safe Situation

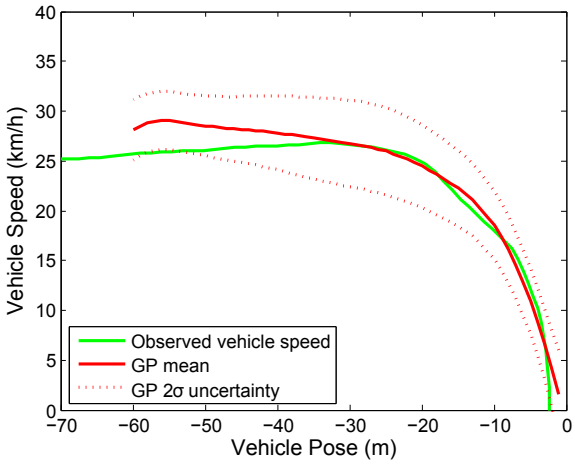
All observed and inferred data in the case of a safe situation are presented in Figure 5.5. Figure 5.5a shows the vehicles speed and Figure 5.5b shows the state of the gas and brake pedals.

Figure 5.5d shows the probabilities related to the driver reaction. The probability that the driver is expected to react $P([ER_t = reaction]|obs)$ starts to increase from $P_t \simeq 40m$ as the vehicle approaches to the intersection. Moreover, the probability that the driver is actually reacting $P([IR_t = reaction|obs)$ also starts to increase from $P_t \simeq 35m$ as the driver starts to release the gas pedal. The state of the gas pedal is shown in Figure 5.5b. The probability $P([IR_t = no\,reaction], [ER_t = reaction]|obs)$ starts to increase a little bit because the driver starts to react a bit later than expected. This probability does not have time to increase till high probabilities, as it decreases to low probabilities as soon as the driver starts pushing the brake pedal.

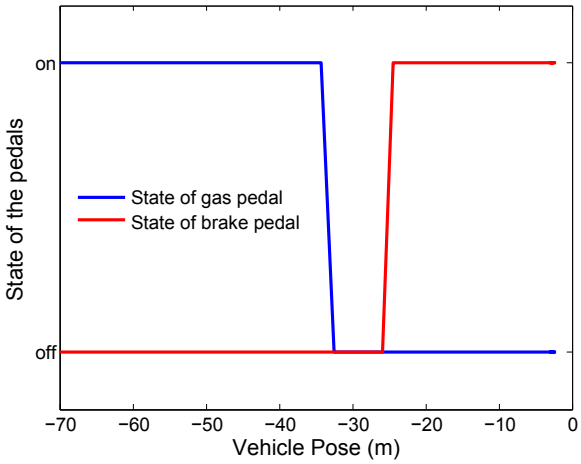
Figure 5.5e shows that the probability that the intended vehicle manoeuvre is not appropriate, $P([IM_t = go], [EM_t = stop]|obs)$, stays low all over the run. This is due to the fact that the vehicle speed matches with the vehicle speed expected when the driver intends to stop. (see Figure 5.5a).

Advice

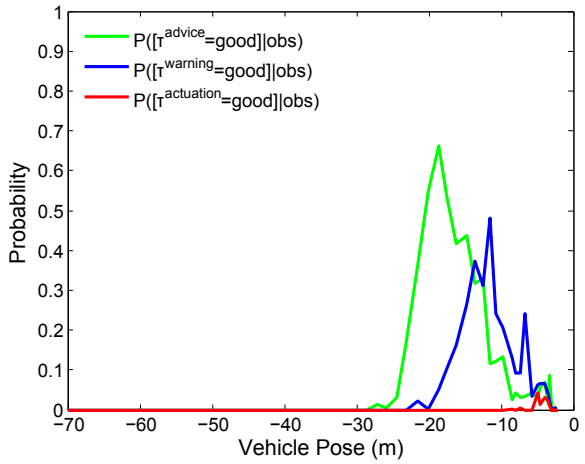
Figure 5.5c shows the probability $P(\tau^{advice} = good)$. It shows a clear peak from $P_t \simeq 25m$ to $P_t \simeq 10m$.



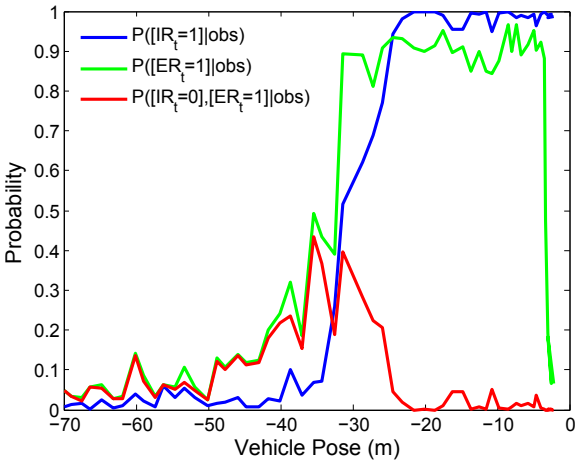
(a) Vehicle speed and learnt velocity profile with respect to the vehicle pose.



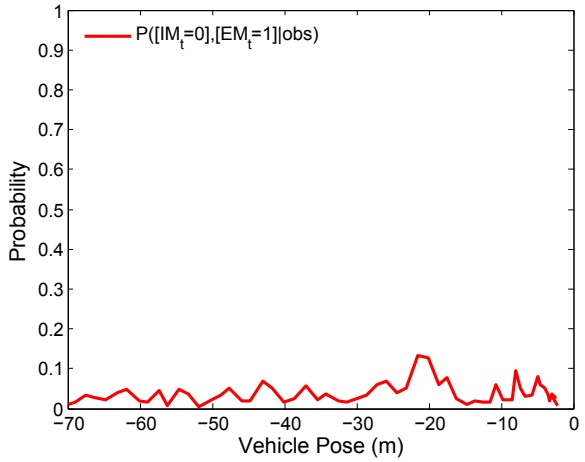
(b) State of the gas and brake pedals with respect to the vehicle pose.



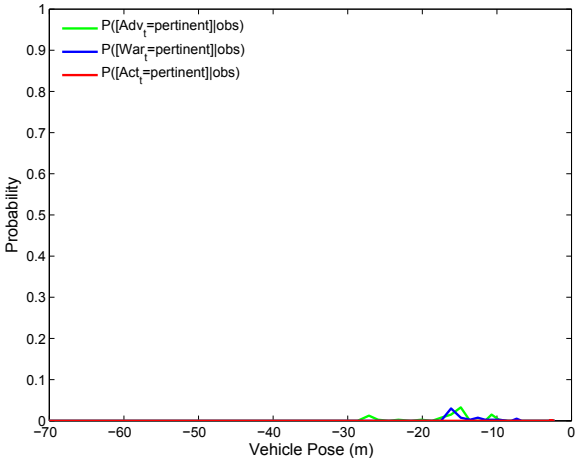
(c) State of indicators $\tau^{assistance}$ with respect to the vehicle pose.



(d) Probabilities related to the driver's reaction with respect to the vehicle pose.



(e) Probabilities related to the vehicle manoeuvre with respect to the vehicle pose.



(f) Probabilities that assistance is pertinent with respect to the vehicle pose.

Figure 5.5: Example of observed and inferred data in the case of a safe situation.

At the same moment, the probability $P([IR_t = no\,reaction], [ER_t = reaction]|obs)$ is low, showing that the driver behaviour is not suspicious.

This means that the two conditions necessary to consider that providing an advice to the driver is pertinent are not satisfied. Figure 5.5f shows that the probability $P([Adv_t = \text{pertinent}]|obs)$ stays low all over the run, meaning that providing the driver with an advice is not pertinent.

Warning

Figure 5.5c shows the probability $P(\tau^{warning} = good)$. It shows a clear peak from $P_t \simeq 20m$ to $P_t \simeq 5m$. In case of inferred risk situation, time and physical constraints would be compatible to warn the driver.

At the same moment the probability $P([IR_t = no\,reaction], [ER_t = reaction]|obs)$ is low, showing that the driver reacts to the situation. Further, the probability $P([IM_t = go], [EM_t = stop]|obs)$ is low as well, showing that the driver has the intention to stop.

This means that the conditions necessary to consider that providing warnings to the driver is pertinent are not satisfied. Figure 5.5f shows that the probability $P([War_t = \text{pertinent}]|obs)$ stays low all over the run, meaning that providing the driver with warnings is not pertinent.

Actuation

Figure 5.6c shows the probability $P(\tau^{actuation} = good)$. It does not show any peak all along the run. In case of inferred risky situation, time and physical constraints would not be compatible to perform automatic emergency braking.

At the same moment the probability $P([IM_t = go], [EM_t = stop]|obs)$ is low, showing that the driver has the intention to stop.

That means that the conditions necessary to consider that performing automatic emergency braking is pertinent are not satisfied. Figure 5.6f shows that the probability $P([Act_t = \text{pertinent}]|obs)$ stays low all over the run, meaning that triggering AEB is not pertinent.

5.3.2.2 Risk Situation

All observed and inferred data in the case of a safe situation are presented in Figure 5.6. Figure 5.6a shows the vehicles speed and Figure 5.6b shows the state of the gas and brake pedals.

Figure 5.6d shows the probabilities related to the driver reaction. The probability that the driver is expected to react $P([ER_t = reaction]|obs)$ starts to increase from $P_t \simeq 50m$ as the vehicle approaches to the intersection. Moreover, the probability that the driver is reacting $P([IR_t = reaction|obs)$ also starts to increase for a very short time because the

driver briefly releases the gas pedal. As soon as he pushes again the pedal (visible in Figure 5.6b), this probability falls to zero. Therefore, the probability $P([IR_t = no\,reaction], [ER_t = reaction]|obs)$ starts to increase from $P_t \simeq 30m$ as the driver does not react as expected.

Figure 5.6e shows the probability that the intended vehicle manoeuvre is not appropriate, $P([IM_t = go], [EM_t = stop]|obs)$. Until $P_t \simeq 25m$, this probability has an average value as the vehicle speed partially matches with the speed that is expected (c.f. Figure 5.6a). However, from $P_t \simeq 25m$, the probability increases to 1 has it is inferred that the driver does not have intention to stop, while he is expected to stop.

Advice

Figure 5.6c shows the probability $P(\tau^{advice} = good)$. It shows a clear peak from $P_t \simeq 30m$ to $P_t \simeq 20m$.

At the same moment the probability $P([IR_t = no\,reaction], [ER_t = reaction]|obs)$ is high, showing that the driver behaviour is suspicious.

This means that the two conditions necessary to consider that providing an advice to the driver is pertinent are satisfied. Figure 5.6f shows that the probability $P([Adv_t = \text{pertinent}]|obs)$ is significant from $P_t \simeq 30m$ and $P_t \simeq 20m$, meaning that it would be pertinent to provide the driver with an advice as long as the vehicle is located from 30 to $20m$ to the intersection.

Warning

Figure 5.6c shows the probability $P(\tau^{warning} = good)$. It shows a clear peak from $P_t \simeq 25m$ to $P_t \simeq 15m$. In case of inferred risk situation, time and physical constraints would be compatible to warn the driver.

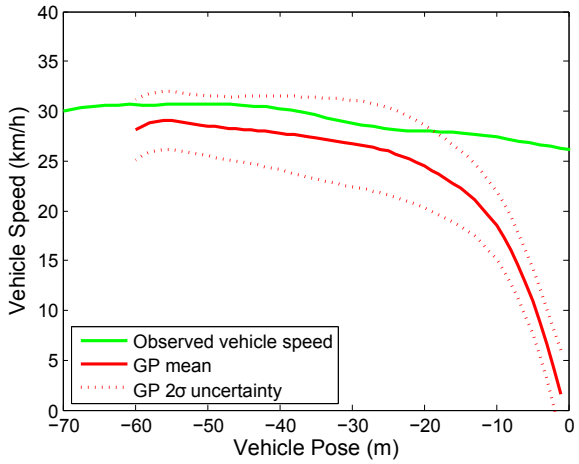
At the same moment the probability $P([IR_t = no\,reaction], [ER_t = reaction]|obs)$ is high, showing that the driver does not show any reaction. Further, the probability $P([IM_t = go], [EM_t = stop]|obs)$ is high, showing that the driver does not have the intention to stop.

This means that the conditions necessary to consider that providing warnings to the driver is pertinent are satisfied. Figure 5.6f shows that the probability $P([War_t = \text{pertinent}]|obs)$ is significant from $P_t \simeq 25m$ and $P_t \simeq 15m$, meaning that it would be pertinent to warn the driver as long as the vehicle is located from 25 to $15m$ to the intersection.

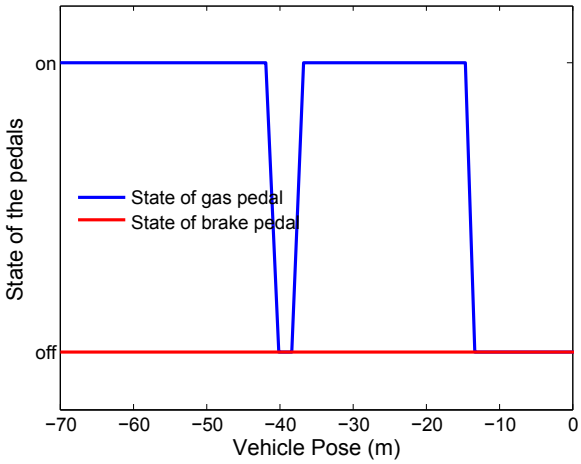
Actuation

Figure 5.6c shows the probability $P(\tau^{actuation} = good)$. It shows a clear peak from $P_t \simeq 15m$ to $P_t \simeq 5m$. In case of inferred risky situation, time and physical constraints would be compatible to perform automatic emergency braking.

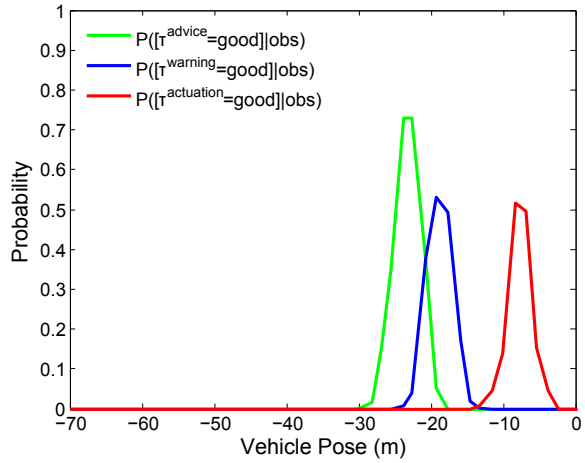
At the same moment the probability $P([IM_t = go], [EM_t = stop]|obs)$ is high, showing that the driver does not have the intention to stop.



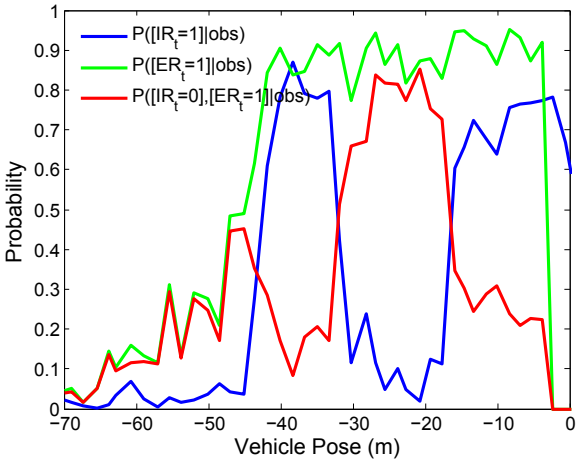
(a) Vehicle speed and learnt velocity profile with respect to the vehicle pose.



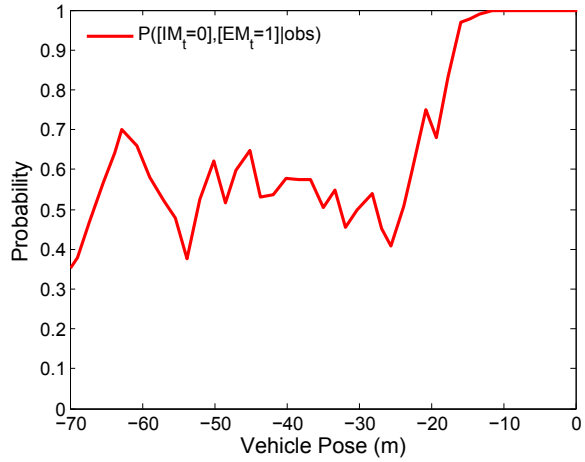
(b) State of the gas and brake pedals with respect to the vehicle pose.



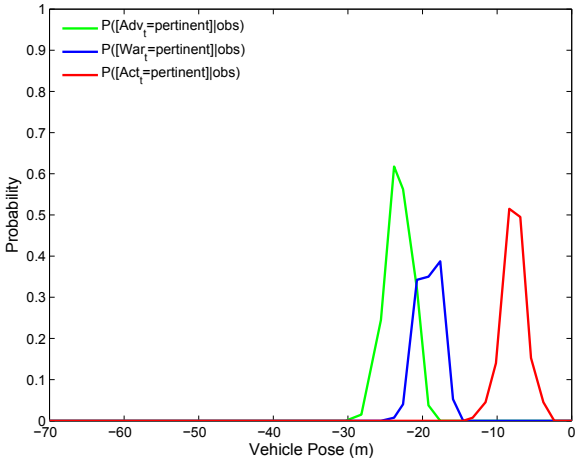
(c) State of indicators $\tau^{assistance}$ with respect to the vehicle pose.



(d) Probabilities related to the driver's reaction with respect to the vehicle pose.



(e) Probabilities related to the vehicle manoeuvre with respect to the vehicle pose.



(f) Probabilities that assistance is pertinent with respect to the vehicle pose.

Figure 5.6: Example of observed and inferred data in the case of a dangerous situation.

That means that the conditions necessary to consider that performing automatic emergency braking is pertinent are satisfied. Figure 5.6f shows that the probability $P([Act_t = \text{pertinent}]|obs)$ is significant from $P_t \simeq 15m$ and $P_t \simeq 5m$, meaning that it would be pertinent to perform AEB as long as the vehicle is located from 15 to $5m$ to the intersection.

5.3.2.3 Summary

The following points can be given as a concise summary of all information presented in the two last subsections:

- In the case of a safe situation, the three probabilities describing the pertinence of the three types of assistance stay very low all over the run.
- In the case of a risky situation, the three probabilities describing the pertinence of the three types of assistance become significant at different times.
- The shape of the probability curves when assistance is inferred as pertinent show a clear peak. It means that in case of risky situations, the BN is able to determine precise time lapses during which assistance can be provided. On the illustrative example shown in Figure 5.6, the width of the inferred curves is smaller than $10m$, which represents a time laps smaller than $1.2s$ as the vehicle moves with a speed of about $30km/h$. Each type of assistance can therefore be provided with relevance and integrity during $1s$ time gaps.

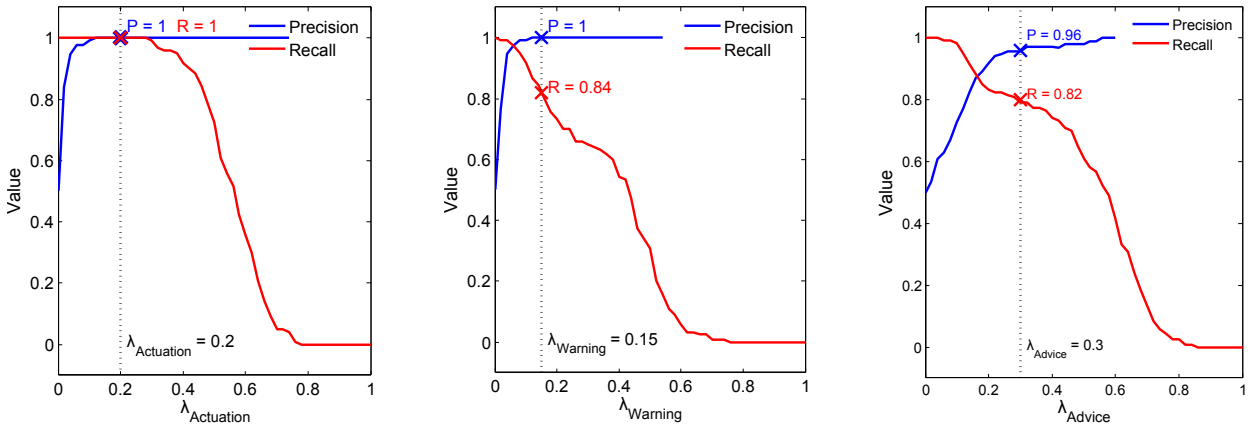
5.3.3 Quantitative Results

5.3.3.1 Performance Evaluation

This paragraph aims to present the performances of the Bayesian model for the classification of safe and risky situations, with the aim to provide the most pertinent assistance between advice, warning and automatic braking. For this purpose, the same method as the one presented in Chapter 4, Subsection 4.5.2 is used. It is based on the computation of the Recall and Precision indicators.

Optimized values of the threshold λ, which represent the sensitivity of the risk assessment had to be found. For this purpose, the Recall and Precision parameters were computed for several values of λ. Figure 5.7 shows the evolution of the Recall and of the Precision with respect to λ. Finally, the following optimized values were determined for all drivers, such as:

- Figure 5.7a shows that there is a large range for which the value of $\lambda_{actuation}$ allows for $Precision(\lambda_{actuation}) = 1$ and $Recall(\lambda_{actuation}) = 1$. Finally $\lambda_{actuation} = 0.2$ was chosen as an average value of this range.
- Figure 5.7b shows that there is no value of $\lambda_{warning}$ that allows for $Precision(\lambda_{warning}) = 1$ and $Recall(\lambda_{warning}) = 1$. However, $\lambda_{warning} = 0.15$ allows for $Precision(\lambda_{warning}) =$

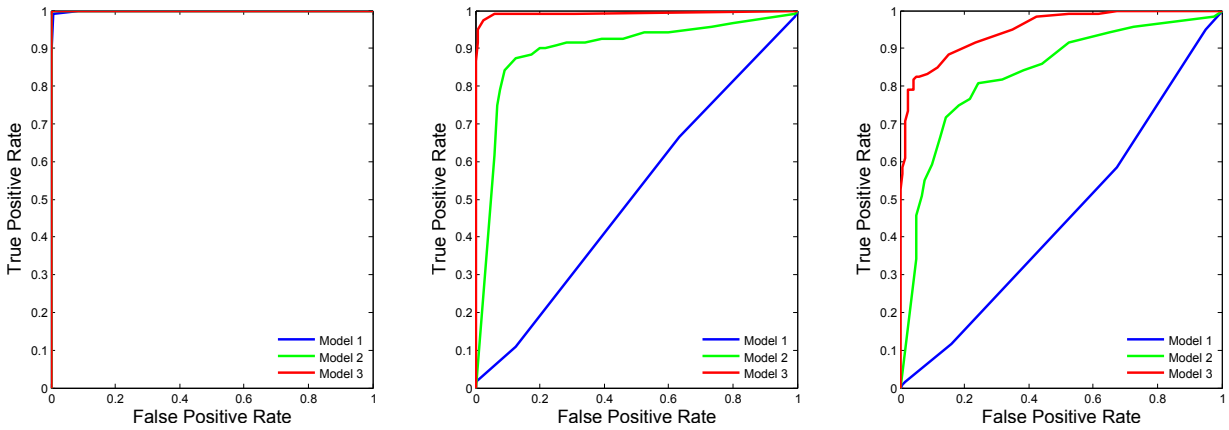


(a) In the case of actuation assistance.

(b) In the case of warning assistance.

(c) In the case of advice assistance.

Figure 5.7: Recall and Precision curves for optimization of threshold $\lambda_{Assistance}$.



(a) For actuation assistance

(b) For warning assistance

(c) For advice assistance

Figure 5.8: ROC curves

1 (i.e. no false alarm) and $Recall(\lambda_{warning}) = 0.84$ (i.e. high detection rate). The value $\lambda_{warning} = 0.15$ was therefore chosen as the optimized value.

– Figure 5.7c shows that there is no value that allows for $Precision(\lambda_{advice}) = 1$. Therefore, a rate of false alarms lower than 5% is allowed. $\lambda_{advice} = 0.3$ allows for $Precision(\lambda_{advice}) = 0.96$ (i.e. 4% of false alarms with the dataset that is used) and $Recall(\lambda_{advice}) = 0.82$ (i.e. high detection rate). The value $\lambda_{advice} = 0.3$ was therefore chosen as the optimized value.

5.3.3.2 Results

Figure 5.8 shows the ROC curves presenting the performances of this model for each of the three types of assistance covered (Automatic Actuation, Warning and Advice). In addition, it shows the ROC curves of the models presented in Chapter 4. For the sake of clarity, the

models are designated as follows:

- *Model 1* designates the original Bayesian network using vehicle state observations and generic velocity profiles, presented in Chapter 4.
- *Model 2* designates the original Bayesian network using vehicle state observations and customized velocity profiles, presented in Chapter 4.
- *Model 3* designates the extended Bayesian network using vehicle state and driver actuations observations plus customized driver profiles. This model is the one described in this Chapter.

It is noticeable that *Model 3* offers better performances than *Model 1* and *2*. It is confirmed by Figure 5.9 that shows the performances of the Bayesian network presented in this Chapter. Finally, Figure 5.10 shows a comparison between the performances of this model and those presented in Chapter 4.

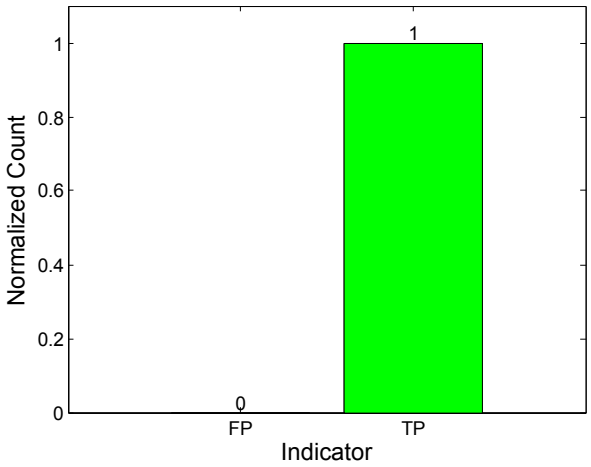
Actuation

Figure 5.9a shows the performances of *Model 3* obtained for the detection of risk situations, leading to the activation of automatic emergency braking. The performances are excellent as the rate of True Positive is at 100% ($TP = 1$), with a rate of False Positive at 0% ($FP = 0$). Figure 5.10a shows that these performances are the same as those obtained for *Model 2*. This was actually expected as the computation of $P(Act_t|E_t, I_t, \phi_t)$ in *Model 3* is performed in the same manner as it is performed in *Model 2*.

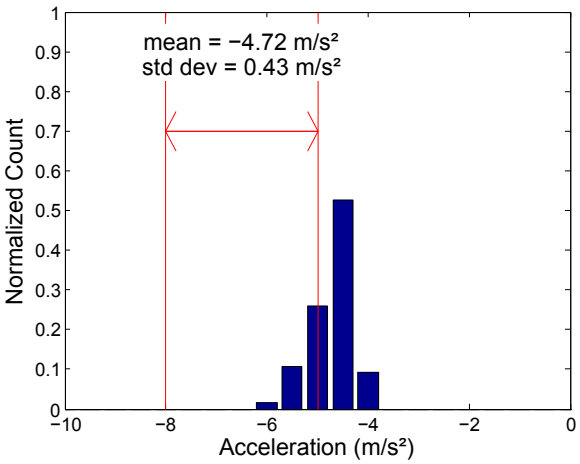
Figure 5.9b shows the repartition of the acceleration that would be necessary to stop on time once decision has been taken to perform automatic emergency braking. The average acceleration is $\gamma = -4.72m/s^2$ with a low standard deviation $\sigma_\gamma = 0.43m/s^2$. It is noticeable that in general, the accelerations that the vehicle would undergo are a bit smoother than those defining the range of emergency deceleration (-5 to $-8m/s^2$, visible in red on the Figure). This light difference can be explained by the low value of the threshold $\lambda_{actuation} = 0.2$ coupled with the significant uncertainty on the vehicle pose. More details were given on this issue in Chapter 4, Section 4.5.4.2 dealing with discussion.

Warning

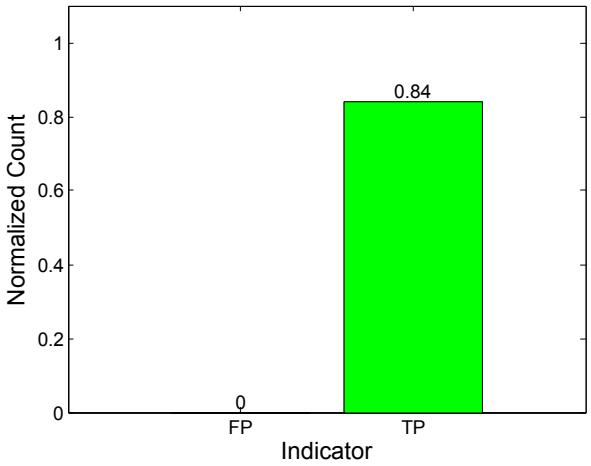
Figure 5.9c shows the performances of *Model 3* obtained for the detection of risk situations, leading to assistance in the form of warnings. The performances are good as the rate of True Positive is at 84% ($TP = 0.84$), with a rate of False Positive at 0% ($FP = 0$). Figure 5.10b shows that these results are better that those obtained with *Model 2* as the rate of True Positive is nearly doubled (46% to 84%). This improvement was favoured by the manner how the pertinence of warning the driver is estimated. That is, in *Model 3* both vehicle state and driver actuations are observed to estimate if the situation is risky, while *Model 2* only observes the vehicle state. The moment at which warning is triggered is the same for both



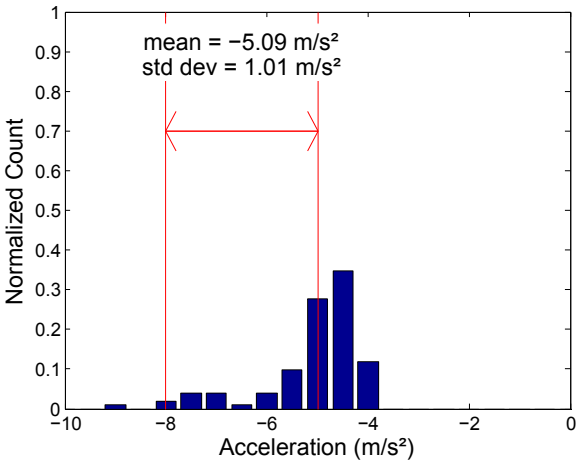
(a) False Positive (FP) and True Positive (TP) rates in the case of automatic actuation assistance.



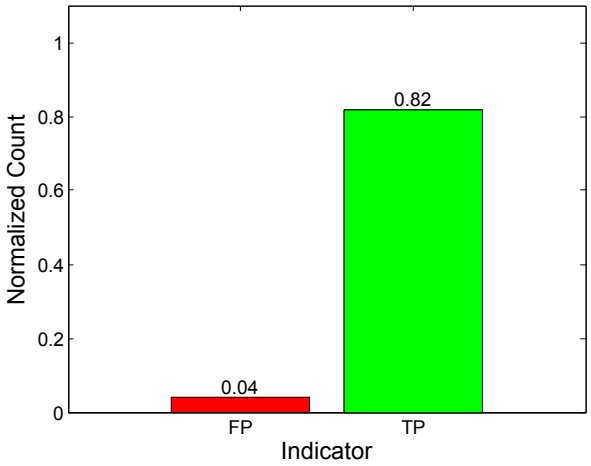
(b) Repartition of acceleration necessary to stop on time in the case of automatic actuation assistance.



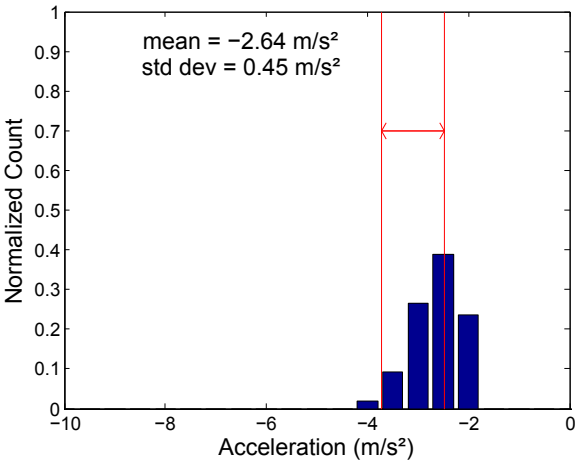
(c) False Positive (FP) and True Positive (TP) rates in the case of warning assistance.



(d) Repartition of acceleration necessary to stop on time in the case of warning assistance.

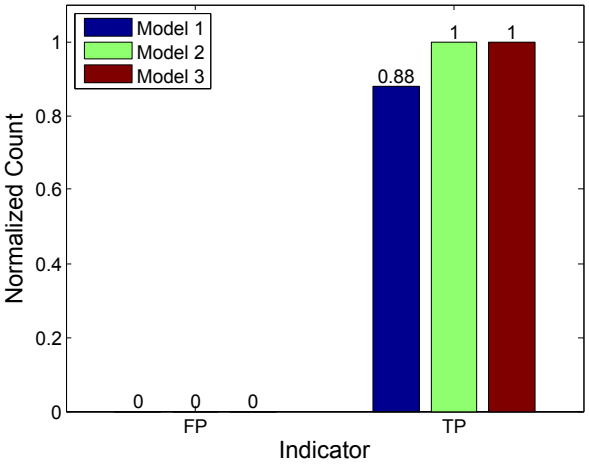


(e) False Positive (FP) and True Positive (TP) rates in the case of advice assistance.

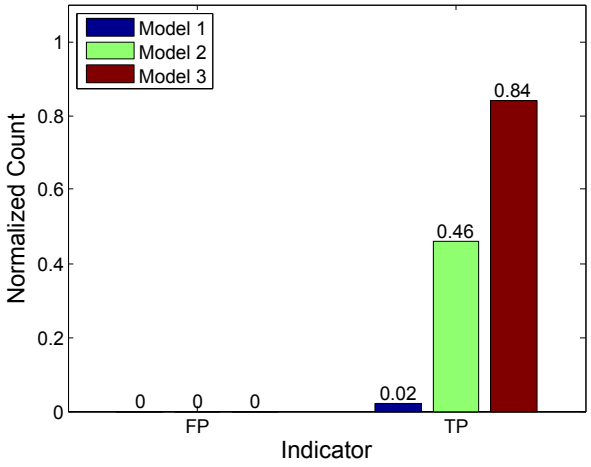


(f) Repartition of acceleration necessary to stop on time in the case of advice assistance.

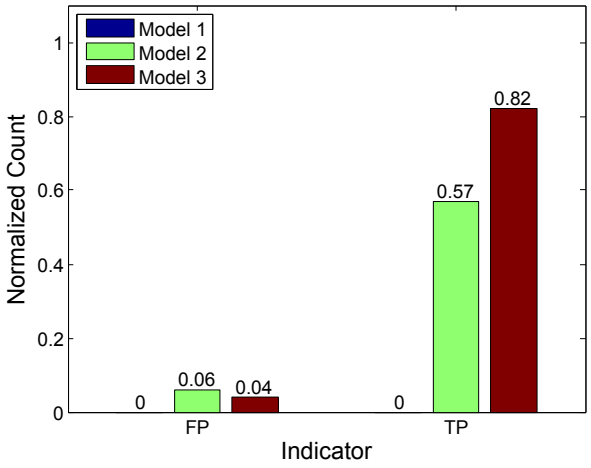
Figure 5.9: Performances of the Bayesian model for the three types of assistance.



(a) In the case of automatic emergency braking assistance.



(b) In the case of warning assistance.



(c) In the case of advice assistance.

Figure 5.10: Comparison between the performances of the three models presented in this thesis.

models, however the observation of the driver actuations allows to improve robustness in the detection of risk situations. This is visible through the evolution of the Precision and Recall indicators. For both models, it is possible to get $Precision = 1$, however *Model 3* allows for a better value of *Recall* than *Model 2*, which is synonym of lower rate of False Alarms ($Recall = 0.46$ for *Model 2*, $Recall = 0.84$ for *Model 3)*.

Figure 5.9d shows the repartition of the acceleration that would be necessary for the driver to stop on time once decision has been taken to warn him. The average acceleration is $\gamma = -5.09m/s^2$ with a standard deviation $\sigma_\gamma = 1.01m/s^2$. In general, the accelerations that the vehicle would undergo are a bit smoother than those defining the range of emergency deceleration (-5 to $-8m/s^2$, visible in red on the Figure). The reasons are the same as those explained above in the case of automatic actuation assistance.

Advice

Figure 5.9e shows the performances of *Model 3* obtained for the detection of risk situations, leading to assistance in the form of advices. The performances are good as the rate of True Positive is at 82% ($TP = 0.82$), with a rate of False Positive at 4% ($FP = 0.04$). Figure 5.10c shows that these results are better that those obtained with *Model 2* as the rate of True Positive gains 25% (57% to 82%). This improvement was favoured by the manner how the pertinence of providing the driver with an advice is estimated. That is, in *Model 3* the driver actuations are observed to estimate if the situation is risky, while *Model 2* observes the vehicle state. When driver actuations are observed, the detection of suspicious behaviours can be done earlier than with the vehicle state, and makes it possible to provide the driver with early advices.

Figure 5.9f shows the repartition of the acceleration that would be necessary for the driver to stop on time once decision has been taken to provide the driver with advices. The average acceleration is $\gamma = -2.64m/s^2$ with a low standard deviation $\sigma_\gamma = 0.45m/s^2$. The expected accelerations interval that is shown in red in the Figure (-2.4 to $-3.7m/s^2$) was determined as the average interval computed with each interval used for each driver. In general, the accelerations that the vehicle would undergo are a bit smoother than those defining the interval used within *Model 3*. The reasons are the same as those explained above in the case of automatic actuation assistance.

5.3.4 Discussion

The results presented in this Section show that observing the driver actuations in addition to the vehicle state has a significant impact on the moment at which risk situations can be detected. As expected, this time shift allows to improve the ability of the Bayesian Network framework to provide assistance in the form of warnings and advices. With the dataset which was used for the evaluation, risk is detected early enough to provide warning assistance in

84% of the cases, without any false alarm. Moreover, risk is detected early enough to provide advice assistance in 82% of the cases, with 4% of false alarms in case of safe situations.

The dataset that was used to compute the performances of the model covers a large number of situations with sometimes hesitant driver behaviours or noisy or incoherent observations. Whilst the qualitative result graphs presented in Chapter show perfect inputs, the quantitative results take into account all the noisy and incoherent inputs. Appendix D shows some results obtained with such inputs. Given the good performances obtained, it is reasonable to claim that the system is robust to noisy and incoherent inputs, especially in the case of Warning and Automated Actuation assistances.

While a more significant dataset would be necessary to ensure the performances of *Model 3*, it is reasonable to believe that an ADAS could take benefits from such a system. Actually, risk is always detected accurately and early enough to make it possible to avoid a probable accident by performing automatic actuation on the vehicle. The other types of assistance, especially advice assistance, aim to avoid situations to become too risky and uncomfortable. As they act as preventive assistance concerned to remain pertinent, it must not be considered as a problem if the system is not able to provide an advice for less than 20% of risk situations.

It was showed that it is theoretically possible to trigger a driving assistance system that would assist the driver in the form of advices. From the point of view of ergonomists, such a system can be considered as a proactive system. To fully evaluate the pertinence and the added value of the system, it would be necessary to make field trials in order to collect the drivers feedback about the pertinence of the provided advices. For this purpose, a Human Machine Interface (HMI) is necessary to provide information to the driver. Existing automotive HMI were not designed for proactive systems, therefore the development of a new HMI is necessary. Nevertheless, developing HMIs for proactive systems remains a challenge for the ergonomics community. That implies further theoretical and methodological researches, however it is not the scope of this thesis.

5.4 Conclusion

This Chapter presented a second extension of the Bayesian Network framework initially presented in [90]. While Chapter 4 aimed to show the benefit of considering individual driver patterns to perform risk assessment, this Chapter aimed to show the benefit of considering the driver actuations as additional observations. The performances of this extended framework for the detection of risk situations and for the pertinence of providing assistance was presented.

The extension of the framework was performed with the hypothesis that driver actuations, as well as the vehicle state, are pertinent indicators to detect risk situations. In that way, the framework presented in Chapter 4 was completed with variables related to the driver actuations and to the driver reaction to the situation. Depending on the type of assistance that is considered, risk can be assessed though the comparison of intended and expected

manoeuvres, or through the comparison of intended and expected reactions. The pertinence of each type of assistance is estimated.

The ability of the extended Bayesian Network framework to detect risk situation early enough to provide each type of assistance was evaluated using dataset recorded in a passenger vehicle. The performances were compared to those obtained with the models tested in Chapter 4, with the aim of evaluating the benefits of considering the driver actuations. The results showed that the performances of the Bayesian Network framework are better when the driver actuations are considered. In the case of automatic emergency actuation assistance, no improvement could be observed as performances already reached 100% of true positive (with 0% of false positive). However, in the case of warning and advice assistance, significant improvements were observed. With the dataset that was used for evaluation, warning and advice assistance could be triggered more than 80% of the time, with a rate of false positive lower than 5% (0% for warning assistance, 4% for advice assistance).

This Chapter showed that, for the chosen case study, risk can theoretically be assessed early enough to trigger early assistance in the form of advices. A perspective for this work is to make the framework work in real time inside a vehicle, in order to collect the feedback of the drivers. These feedbacks will therefore enable to validate whether the time gaps which are used to provide each type of assistance are well selected or not.

Chapter 6

Effect of Preventive Assistance on Other Road Users

Contents

6.1 Introduction

Chapter 3 showed that the cohabitation of road users implies interactions between them. Therefore, the action of a safety ADAS on a vehicle may have consequences on other interacting vehicles. For example, if a vehicle follows another vehicle in which an automated emergency braking is activated, this vehicle will also have to stop to avoid a rear-end collision. Depending on the acceleration that the leading vehicle undergoes, and on other parameters related to the following vehicle, the situation may become uncomfortable and even dangerous.

Last Chapter presented an algorithm which detects whether a manually driven vehicle is likely to be in a risk situation as it is approaching to a stop intersection. This algorithm allows to trigger assistance which could be provided to the driver in the form of advice. It was shown that more than 8 out of 10 times, it allows to detect risk situations early enough to assist the driver with an advice, and thus to allow him to react more comfortably to the situation than with a conventional driving assistance. Thus, it is likely that the situation of other road users interacting with the vehicle will be impacted by this type of assistance.

It is therefore interesting to evaluate how much the integration of such preventive systems in a vehicle can be beneficial for the other road users interacting with it. For this purpose, the results of last Chapter were used, and the approach of two vehicles towards the same stop

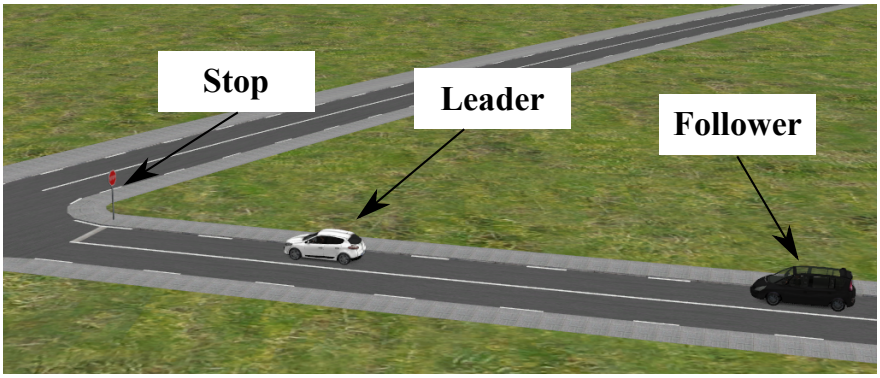


Figure 6.1: Initial conditions. The Leader and the Follower are navigating towards a stop intersection.

intersection was chosen. Simulation was performed to evaluate the benefits on the comfort of the following vehicle when the lead vehicle is provided with an advice instead of a warning.

This Chapter is organized as follows. The manner how the simulation was performed, and how this simulation outputs allowed to generate the results of the experimentation are presented. Then, the results of the experimentation are presented and discussed.

6.2 Experimentation

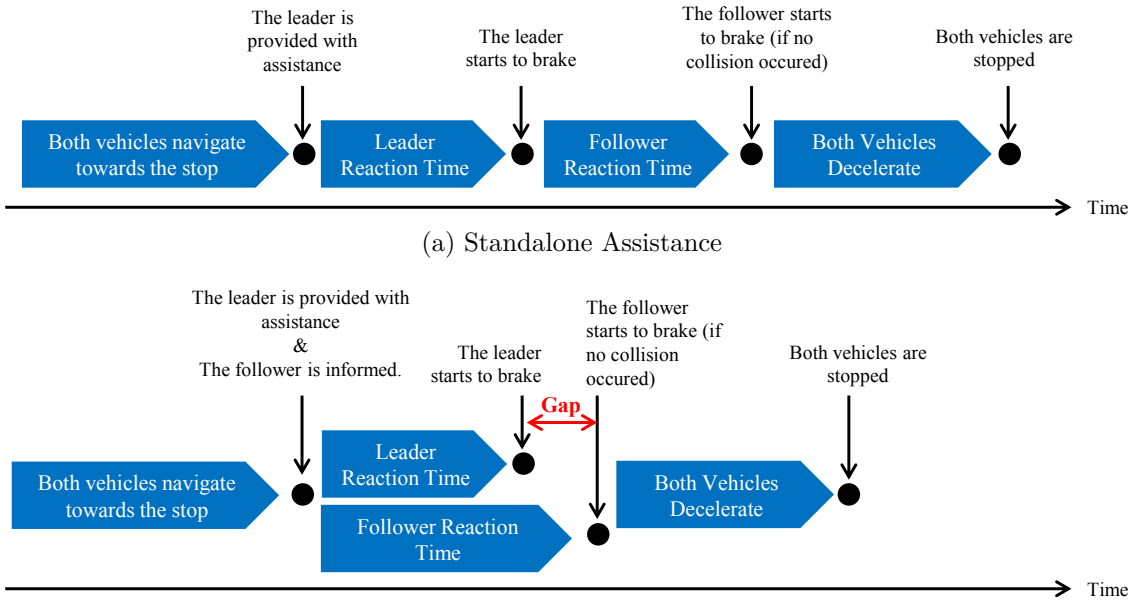
6.2.1 Objectives

The objective of the experimentation that is presented in this Chapter is to evaluate the added value of assistance provided in the form of advice, for other vehicles interacting with the subject vehicle. The case study that is addressed consists of two vehicles, namely the Leader and the Follower which are navigating towards the same stop intersection. These vehicles are navigating in stabilized conditions, that is, with nearly constant speed and interdistance separating both of them. The case study is illustrated by Figure 6.1.

The first assumption is that the Leader is equipped with the risk assessment system presented in Chapter 5. If the driver of this vehicle does not have the intention to stop at the intersection, then the system will provide him with assistance. The driver is then expected to need some time to react (Reaction Time), and to brake in order to stop on time at the intersection level. This deceleration therefore implies that the Follower has to decelerate in order to avoid rear-end collision, and thus to stop behind the Leader.

The worst case is assumed in this Chapter, that is, the driver of the Follower too is not aware of the presence of the stop intersection. After the leader starts to decelerate, the Follower needs some time to understand that it is necessary to stop, and to start to decelerate as well. This sequence of events is illustrated by Figure 6.2a.

The acceleration that the Follower has to undergo depends on 3 major parameters, namely the reaction time of its driver, the time headway between the Leader and the Follower, and



(a) Standalone Assistance

(b) Connected Assistance

Figure 6.2: Time diagrams showing all events occurring when the driver of the lead vehicle is provided with assistance.

the acceleration that the Leader undergoes. Short reaction time and large time headway imply that the driver of the Follower does not have to undergo high deceleration if the Leader starts to brake. On the contrary, long reaction time and low time headway imply that the driver of the Follower may have to undergo high deceleration and even rear-end collision with the Leader if the Leader starts to brake. Moreover, in this scenario implying 2 vehicles, the time passed between the moment at which the Leader is provided with assistance and the moment at which the Follower starts to decelerate corresponds to the sum of the reaction times of both drivers. This time is incompressible in conventional standalone assistance systems.

In Chapter 1, Section 1.3, it is presented that wireless communications between vehicles and infrastructures are subject of intensive research and development. Whilst this technology is difficult to handle, several projects such as Safespot, SCORE@F and more recently SCOOP@F suggest that it will equip future vehicles [126, 127]. In the experiment presented in this Chapter, communication between both vehicles, and thus cooperative assistance was therefore taken into consideration. Figure 6.2b shows the sequence of events which would occur if the algorithm presented in Chapter 5 was used within a cooperative assistant system. When decision is taken to provide the Leader with assistance, the information that it is likely to be about to brake is transmitted to the Follower (the Leader has not yet started to react). Therefore, both drivers react approximately at the same moment, and this allows to shorten the time (called “Gap” on the Figure) during which the Leader decelerates while the Follower is still reacting. Actually, communication has similar effect on the Follower than reducing his reaction time.

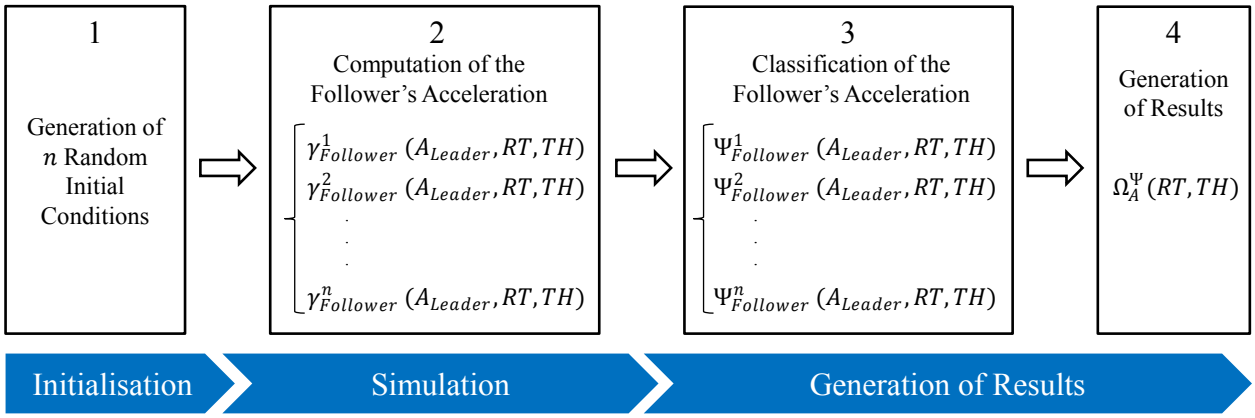


Figure 6.3: Generation of results

The objective of the experimentation is to estimate how much preventive assistance impacts the situation that the Follower has to negotiate, with comparison to curative assistance. The results have to take into consideration the influence of the reaction time of the Follower, and the time headway between both vehicles. Moreover, the experimentation is performed considering a standalone system, and a connected and cooperative system. It was performed by simulation as described in next Section.

6.2.2 Simulation of Vehicle Following and Generation of Results

The aims of the simulation is to estimate how comfortable would be the situation that the Follower would have to handle if the Leader is provided with assistance and thus starts to brake. Figure 6.3 shows the different stages of the experiment: initialisation, simulation and generation of the results. This Section presents these stages in details.

6.2.2.1 Assumptions and Initial Conditions

At initial time, the Leader and the Follower are navigating towards the stop intersection, as shown by Figure 6.1, page 134, and the Leader starts to decelerate. That is, the driver was provided with assistance $A^{Leader} \in \{War, Adv\}$, and his reaction time is passed.

It is assumed that at the moment when the Leader is provided with assistance, both vehicles are navigating in stationary conditions, i.e. with stabilized speeds and interdistance. The Leader is located at pose P_0^{Leader} and is moving at speed S_0^{Leader}. Since the reaction time is passed, the Leader is braking and undergoes acceleration γ_{Leader}. The experimentations presented in Chapter 5 allowed to model γ_{Leader} through a normal distribution $\mathcal{N}(\mu_{\gamma L}, \sigma_{\gamma L})$, with respect to A^{Leader} the type of assistance the driver is provided with. It is therefore assumed that γ_{Leader} follows $\mathcal{N}(\mu_{\gamma L}, \sigma_{\gamma L})$. Further, this parameter is assumed to be constant until the Leader is stopped.

The Follower is located at pose $P_0^{Follower}$ and is moving at speed $S_0^{Follower}$. Since average relative speed between two vehicles can be modelled as a standard normal distribution $\mathcal{N}(0, \sigma_{RS})$ [4], $S_0^{Follower}$ is assumed to follow the normal distribution $\mathcal{N}(S_0^{Leader}, \sigma_{RS})$. Both vehicles are separated by interdistance δ_0, which depends on $S_0^{Follower}$ and the time headway TH between both vehicles. Finally, it is assumed that the Follower has the reaction time RT.

6.2.2.2 Simulation

All simulations were performed considering the motion model and the algorithm that are described below.

Motion Model

Sophisticated microscopic models such as the IDM (Intelligent Driver Model) [155], or the Simulation of Urban MObility model (SUMO) [84] used for simulation purposes were not chosen to model the motion of the vehicles. The first reason is that they are parametric models, and the tuning of the parameters is complex to justify. The second reason is that such models were conceived to simulate traffic flows in nominal conditions, which is not the case for the experiment presented in this Chapter.

Instead, it was chosen to use a more simple motion model. In Chapter 2, Section 2.4.1.1 presented that trajectory prediction can be performed using either dynamic or kinematic motion models. Dynamic motion models require parameters related to vehicles and environment characteristics. The use of such models is not justified here as the experiment does not consider particular vehicles or particular environment conditions. Therefore, it was chosen to use simple kinematic motion models for both vehicles, assuming constant accelerations (CA). The acceleration $\Gamma^n(t)$, the speed $S^n(t)$ and the pose $P^n(t)$ of vehicle n are given by Equation 6.1:

$$\begin{cases} \Gamma^n(t + \Delta t) = \Gamma^n(t) = \gamma^n \\ S^n(t + \Delta t) = \gamma^n \cdot \Delta t + S^n(t) \\ P^n(t + \Delta t) = \frac{\gamma^n}{2} \cdot \Delta t^2 + S^n(t) \cdot \Delta t + P^n(t) \end{cases} \tag{6.1}$$

The interdistance between both vehicles $\delta(t)$ is computed with respect to the position of the vehicles, and l_{Leader} the length of the Leader. It is given by Equation 6.2:

$$\delta(t) = P^{Leader}(t) - P^{Follower}(t) - l_{Leader} \tag{6.2}$$

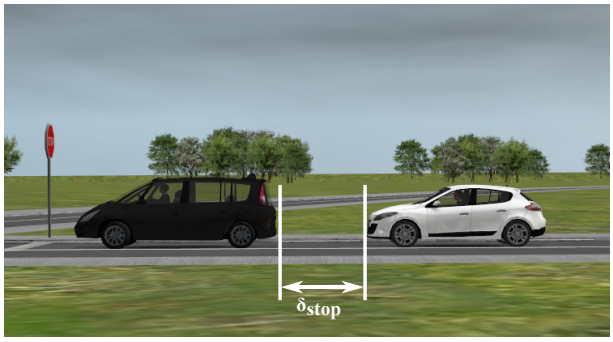


Figure 6.4: Vehicles configuration at the end of the simulation.

The acceleration that the Follower has to undergo to stop on time is computed using Equation 6.3:

$$\gamma_{Follower} = -\frac{(S^{Follower})^2}{2 \cdot D_{Stop}^{Follower}} \tag{6.3}$$

with $S^{Follower}$ the speed of the Follower at the moment at which the it starts to decelerate, and $D_{Stop}^{Follower}$ is the distance from the Follower to the position at which it has to be stopped. This position is defined considering that the Leader is stopped at the stop intersection, and the Follower is stopped behind the Leader with interdistance δ_{Stop}. This is illustrated by Figure 6.4.

Algorithm

Algorithm 6.1, in page 139 presents the successive simulation steps necessary to evaluate whether a rear-end collision occurs between both vehicles, and the necessary average deceleration that the Follower has to undergo to safely stop on time behind the Leader.

After initialization of the variables (lines 2-6), the algorithm runs until collision occurs or until the Follower has stopped behind the Leader (loop starting on line 8). At each time step, the position $P^{Leader}(t)$ and speed $S^{Leader}(t)$ of the Leader are computed. As soon as the speed of the Leader reaches 0, the acceleration γ_{Leader} is set to 0 (line 13-14). The Leader is therefore static until the end of the simulation.

At each time step, the position $P^{Follower}(t)$ and speed $S^{Follower}(t)$ of the Follower are also computed (line 21). In addition, $\delta(t)$ the interdistance between both vehicles is computed (line 22). If RT the reaction time of the driver of the Follower is not passed, then the Follower does not decelerate, i.e. $\gamma_{Follower} = 0$. If RT is passed, then the new value of $\gamma_{Follower}$ is computed (line 19). It is considered that a rear-end collision occurs when $\delta(t) \leq 0$ (line 23). It is considered that the Follower is stopped, and thus the simulation is complete when $S^{Follower}(t) = 0$.

Algorithm 6.1 Algorithm for simulation of vehicle following

Inputs: Distribution of the Leader acceleration $\mathcal{N}(\mu_\gamma, \sigma_\gamma)$, initial Leader speed S_0^{Leader}, initial Leader pose P_0^{Leader}, distribution of relative speed $\mathcal{N}(0, \sigma_{\Delta S})$, timestep Δt, reaction time of the Follower RT, time headway between both vehicles TH.

Outputs: Flag *Collision* indicating whether or not a collision occurred, and $\gamma_{Follower}$ the average Follower deceleration necessary to stop on time if no collision occurred.

Begin
1 /* *Initialization of variables* */
2 Compute $\gamma_{Leader} = \text{rand}(\mathcal{N}(\mu_\gamma, \sigma_\gamma))$
3 Compute $S_0^{Follower} = \text{rand}(\mathcal{N}(S_0^{Leader}, \sigma_{\Delta S}))$
4 Compute $\delta_0 = S_0^{Follower} \times TH$
5 Compute $P_0^{Follower}$ using Equation 6.2
4 Set $\gamma_{Follower} = 0$
6 $Collision = False$
7
8 **While** $(S_{Follower}(t) \neq 0)$ and $(Collision = False)$
9 $t = t + \Delta t$
10
11 /* *Leader* */
12 Compute $S^{Leader}(t)$ and $P^{Leader}(t)$ using Equation 6.1
13 **If** $(S^{Leader}(t) = 0)$
14 Set $\gamma_{Leader} = 0$
15 **End If**
16
17 /* *Follower* */
18 **If** $(time > RT)$
19 Compute $\gamma_{Follower}$ using Equation 6.3
20 **End If**
21 Compute $S^{Follower}(t)$ and $P^{Follower}(t)$ using Equation 6.1
22 Compute $\delta(t)$ using Equation 6.2
23 **If** $(\delta(t) \leq 0)$
24 Return $Collision = True$
25 Return $\gamma_{Follower}$
26 **End If**
27
28 **End While**
29 Return $Collision = False$
30 Return $\gamma_{Follower}$
End

6.2.2.3 Generation of Results

The experiment aims to evaluate the added value on the Follower comfort and safety, of providing the Leader with advice instead of warning. The results were therefore generated twice: once considering that the Leader is provided with warning (i.e. $A^{Leader} = War$), and once considering that the Leader is provided with advice (i.e. $A^{Leader} = Adv$). Moreover, the reaction time of the Follower RT and the time headway TH are critical parameters whose impact is estimated.

In order to cover a large amount of possible situations undergone by the Follower, a large amount of initial conditions have to be considered. For this purpose, n sets of initial parameters $\Phi_0 = \left\{A^{Leader}, P_0^{Leader}, S_0^{Leader}, \gamma_{Leader}, S_0^{Follower}\right\}$ were randomly generated according to Section 6.2.2.1. For each set Φ_0^n, every combination $\{RT \times TH\}$, with $RT \in \{rt_1, rt_2, .., rt_i\}$ seconds and $TH \in \{th_1, th_2, ..., th_j\}$ seconds was considered.

A total of $n \times i \times j$ simulations was performed. Each simulation returned whether a collision occurred, or the value of $\gamma_{Follower}$ if no collision occurred. The situation that the Follower has to undergo $\Psi^n_{Follower}(A^{Leader}, RT, TH)$ is then classified according to the value of $\gamma_{Follower}$, such as:

- $\Psi^n_{Follower}(A^{Leader}, RT, TH) = Moderate$ if $-2.5 \leq \gamma_{Follower} < 0$ m/s^2, i.e. moderate deceleration.
- $\Psi^n_{Follower}(A^{Leader}, RT, TH) = Hard$ if $-8 \leq \gamma_{Follower} < -2.5$ m/s^2, i.e. hard acceleration.
- $\Psi^n_{Follower}(A^{Leader}, RT, TH) = Collision$ if $\gamma_{Follower} < -8$ m/s^2, i.e. it is physically impossible to decelerate hard enough to avoid rear-end collision.

Simulations were performed for the n sets of initial parameters. For each combination $\{A^{Leader} \times RT \times TH\}^n$, $\Psi^n_{Follower}(A^{Leader}, RT, TH)$ is determined.

The results that are computed aim to observe the effect of the 3 parameters A^{Leader}, RT, TH on the value that is attributed to $\Psi_{Follower}$. For this purpose, $\Omega^k_l(RT, TH) \in [0, 1]$ is computed for each combination $\{A_{Leader} \times \Psi_{Follower}\}$ such as:

$$\Omega^k_l(RT, TH) = \frac{\text{nb of occurance}\left\{[\Psi^n_{Follower}(A^{Leader}, RT, TH) = k]|[A^{Leader} = l]\right\}}{n} \quad (6.4)$$

It represents the rate of situations of value $\Psi_{Follower} = k$, given $A_{Leader} = l$, RT and TH among the n initial conditions.

The results are presented in next Section.

6.3 Results and Discussion

6.3.1 Qualitative Results

Parameters

The results which are presented in this Section were generated considering the following parameters:

- The initial speed of the Leader: $S_0^{Leader} = 30$ km/h
- The acceleration that the Leader undergoes (according to Section 5.3.3.2 in Chapter 5):

$$\gamma_{Leader} = \begin{cases} \mathcal{N}(-2.64, 0.45)\,\text{m/s}^2 & \text{if } A_{Leader} = Adv \\ \mathcal{N}(-5.09, 1.01)\,\text{m/s}^2 & \text{if } A_{Leader} = War \end{cases}$$

- The length of the Leader: $l_{Leader} = 4.5$ m
- The initial speed of the Follower: $S_0^{Follower} = \mathcal{N}(30, 3.6)$ km/h
- The interdistance between both vehicles when they are stopped: $\delta_{stop} = 0.5$m
- The number of initial conditions: $n = 500$
- The reaction time $RT = \{0 : 0.1 : 2\}$ seconds (i.e. $i = 21$)
- The time headway $TH = \{0 : 0.1 : 2\}$ seconds (i.e. $j = 21$)

The series of simulations were performed twice: once considering that the Leader is provided with warning assistance, and once considering that the Leader is provided with advice assistance.

The Leader is Provided With Warning

Figure 6.5 presents how warning assistance provided to the Leader impacts the situation of the Follower, with respect to the reaction time of the Follower, and the time headway between the vehicles.

Figure 6.5a shows $\Omega_{Warning}^{Collision}$, that is the rate of situations which result in rear-end collision when the Leader is provided with warning. It is noticeable that collisions happen when the reaction time of the Follower is greater than the time headway ($RT > TH$).

Figure 6.5b shows $\Omega_{Warning}^{Hard}$, that is the rate of situations which result in hard decelerations undergone by the Follower when the Leader is provided with warning. It is noticeable that the Follower has to undergo hard decelerations when its reaction time is approximately of the same order of magnitude as the time headway ($RT \backsimeq TH$).

Figure 6.5c shows $\Omega_{Warning}^{Moderate}$, that is the rate of situations which result in moderate decelerations undergone by the Follower when the Leader is provided with warning. It is noticeable

that the Follower has to undergo moderate decelerations when the time headway is much greater than the reaction time, with a time headway greater than 1.5s ($TH > 1.5$s and $TH > 2RT$).

The Leader is Provided With Advice

Figure 6.6 presents how advice assistance provided to the Leader impacts the situation of the Follower, with respect to the reaction time of the Follower, and the time headway between the vehicles.

Figure 6.6a shows $\Omega^{Collision}_{Advice}$, that is the rate of situations which result in rear-end collision when the Leader is provided with advice. It is noticeable that collisions happen only when the time headway is much lower than the reaction time of the Follower ($TH < 0.5RT$).

Figure 6.6b shows Ω^{Hard}_{Advice}, that is the rate of situations which result in hard decelerations undergone by the Follower when the Leader is provided with advice. It is noticeable that the Follower has to undergo hard decelerations mostly for reaction time greater than 1.5s, and when the reaction time of the Follower is greater than the time headway ($RT > 1.5$s and $RT \backsimeq 1.5TH$).

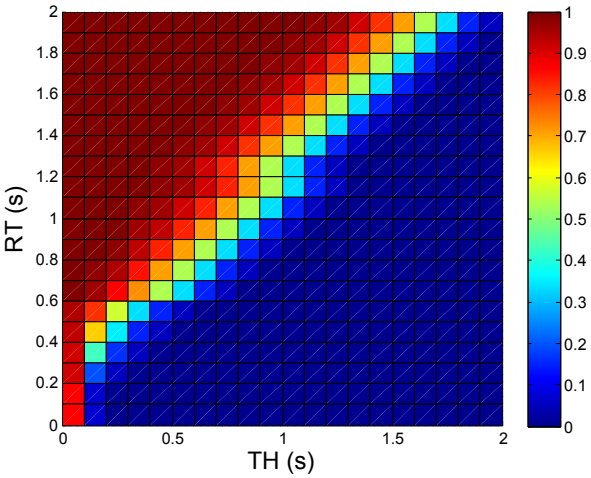
Figure 6.6c shows $\Omega^{Moderate}_{Advice}$, that is the rate of situations which result in moderate decelerations undergone by the Follower when the Leader is provided with advice. It is noticeable that the Follower has to undergo moderate decelerations when the time headway is greater than the reaction time of the Follower ($TH > RT$).

Differences

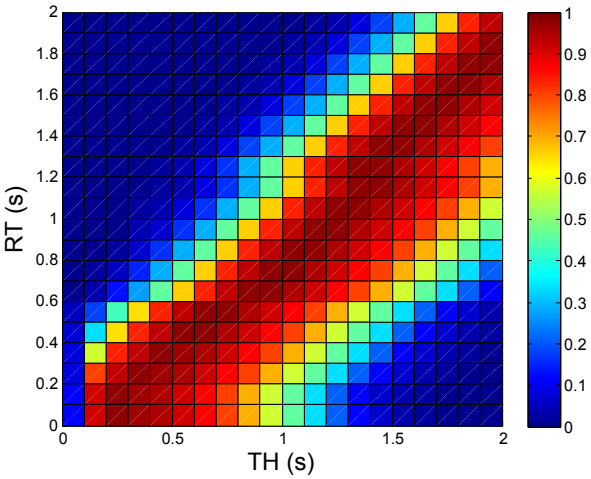
Figure 6.7 highlights how much providing the Leader with advice assistance instead if warning assistance impacts the situation that the Follower has to undergo. It shows the subtraction $\Omega^{\Psi}_{Advice} - \Omega^{\Psi}_{Warning}$. In that way, Figure 6.7a shows the subtraction for $\Psi = Collision$, Figure 6.7b shows the subtraction for $\Psi = Hard$ and Figure 6.7c shows the subtraction for $\Psi = Moderate$.

This shows that providing the Leader with advice assistance instead of warning assistance allows to diminish the risk of rear-end collision, which are replaced by hard decelerations when $RT > 1$s and $RT \simeq 2TH$ (shown by the blue cells on Figure 6.7a and red cells on Figure 6.7b). Further, it allows to favour moderate decelerations to the detriment of hard decelerations for $TH > 0.5$s and $TH \simeq 2RT$ (shown by the blue cells on Figure 6.7b and red cells on Figure 6.7c).

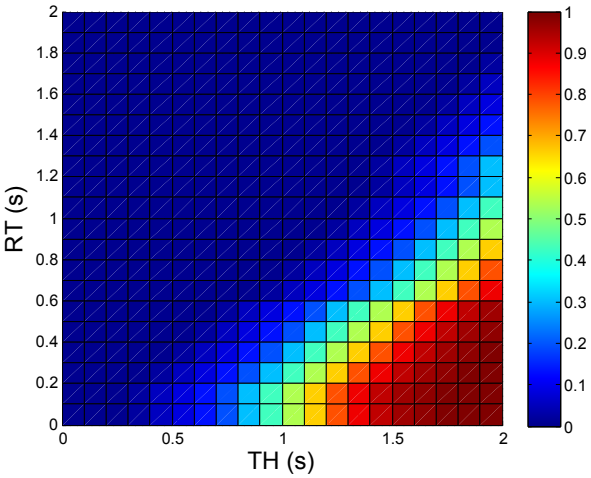
Appendix E shows the same graphs as those shown by Figures 6.5, 6.6 and 6.7, but considering different initial speeds for both vehicles (60km/h and 90km/h). Whilst the influence of the initial speed is noticeable, the graphs show similar results as those presented in this Section.



(a) $\Omega^{Collision}_{Warning}(RT, TH)$

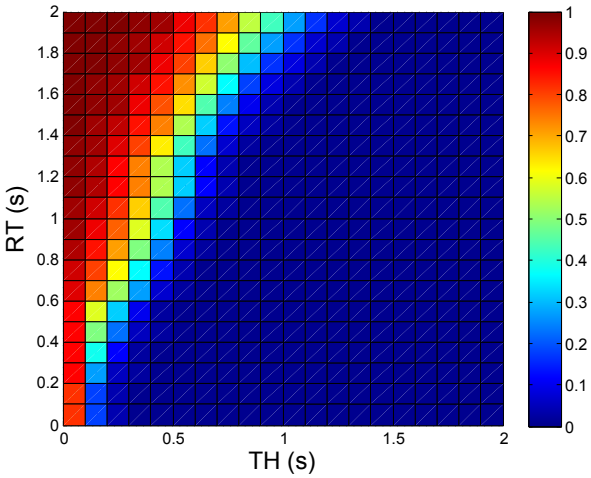


(b) $\Omega^{Hard}_{Warning}(RT, TH)$

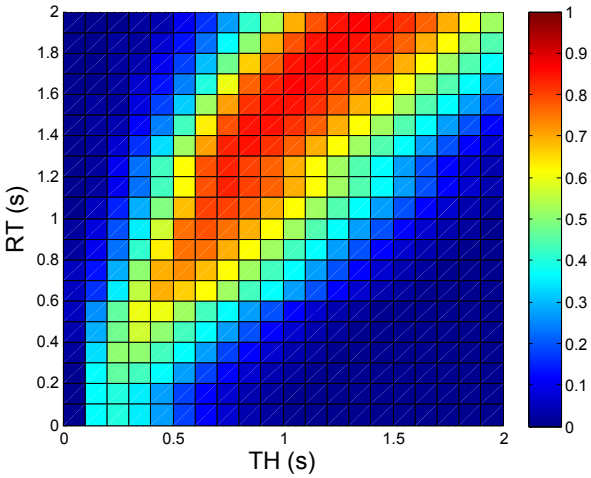


(c) $\Omega^{Moderate}_{Warning}(RT, TH)$

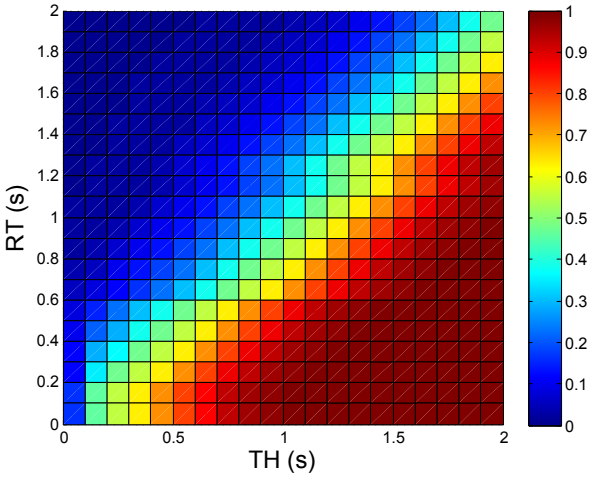
Figure 6.5: Results considering that the Leader is moving at 30 km/h and provided with **Warning** assistance.



(a) $\Omega^{Collision}_{Advice}(RT, TH)$

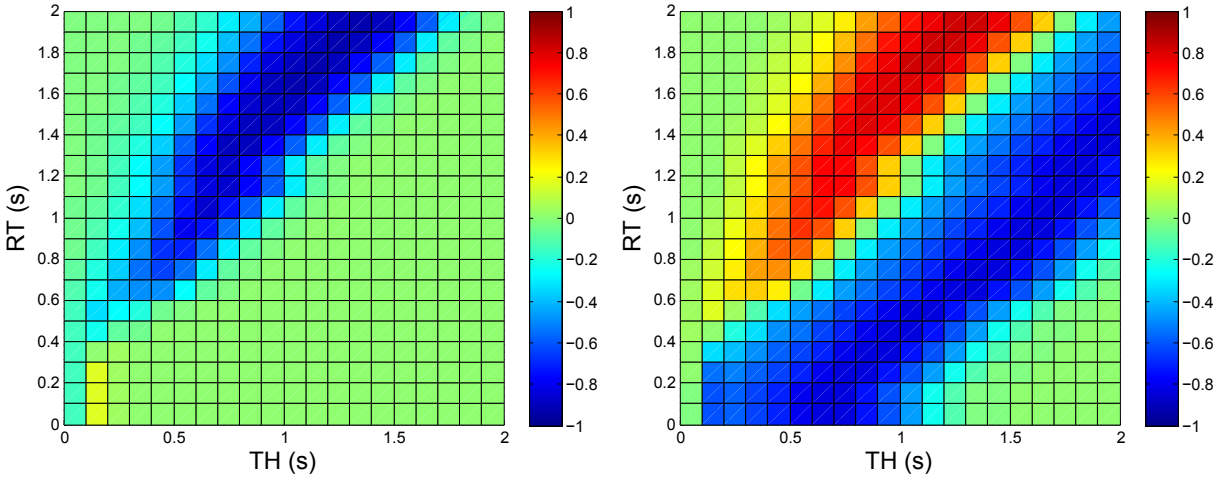


(b) $\Omega^{Hard}_{Advice}(RT, TH)$



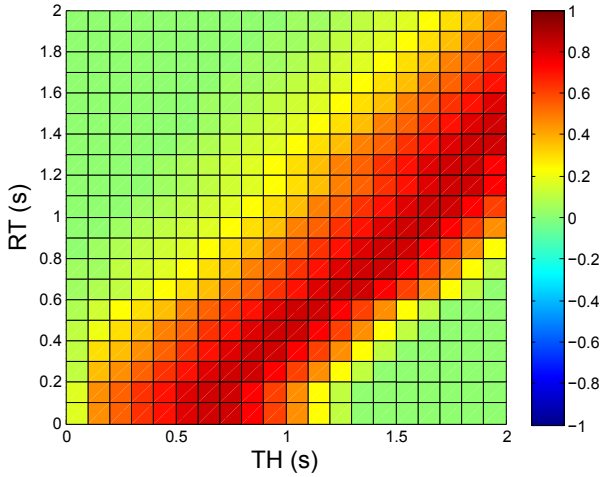
(c) $\Omega^{Moderate}_{Advice}(RT, TH)$

Figure 6.6: Results considering that the Leader is moving at 30 km/h and provided with **Advice** assistance.



(a) $\Omega^{Collision}_{Advice}(RT, TH) - \Omega^{Collision}_{Warning}(RT, TH)$

(b) $\Omega^{Hard}_{Advice}(RT, TH) - \Omega^{Hard}_{Warning}(RT, TH)$



(c) $\Omega^{Moderate}_{Advice}(RT, TH) - \Omega^{Moderate}_{Warning}(RT, TH)$

Figure 6.7: Added values of advice assistance provided to the Leader, for the situation the Follower has to undergo. With Leader initial speed set at 30 km/h.

Table 6.1: Results considering standalone assistance: $RT = 1.5$s and $TH = 1.5$s

Assistance Provided to the Leader	Situation Undergone by the Follower		
	Moderate Decel	Hard Decel	Collision
Advice	47%	53%	0%
Warning	1%	94%	5%

6.3.2 Quantitative Results for Typical Configurations

The results presented in last Section showed that providing the Leader with advice assistance instead of warning assistance has a significant impact on the situation that the Follower has to undergo, depending on the time headway and the reaction time of the driver. Whilst in real time the time headway and the reaction time of the driver are random parameters, it is interesting to analyse the results of the experiment considering typical values for these parameters. This Section aims to discuss these results, considering typical values for RT and TH in the case of standalone assistance and in the case of connected assistance.

Considering Standalone Assistance

In the case of standalone assistance, the Follower is not noticed that the Leader is provided with assistance and thus expected to brake in a short moment. The Follower therefore understands that the Leader is braking only when he reacts after having seen the stop lights.

As mentioned in Chapter 1, the average drivers' reaction time is about $RT = 1.5$s. Further, field experimentations allowed to measure the empirical average time headway $TH = 1.5$s [133]. These values were chosen to generate the results presented in this Section. Table 6.1 presents the rate of each situation undergone by the Follower.

It is noticeable that when the Leader is provided with assistance in the form of advice, the situation of the Follower is more comfortable. Rear-end collision are likely not to happen, and the rate of hard decelerations is almost divided by 2 (from 94% to 53%). Finally, when the Leader is provided with warning, it is likely that the Follower can never undergo moderate deceleration. If the Leader is provided with advice, then the Follower can brake with moderate deceleration almost 50% of the time.

Considering Cooperative Assistance

In the case of connected assistance, as explained in Section 6.2.1 of this Chapter, the Follower is informed that the Leader will probably brake nearly at the moment at which the Leader is provided with assistance. Both drivers therefore react nearly at the same moment.

For this configuration, the time gap defined in Figure 6.2b is defined at 0.5s. This value assumes V2V transmission delays of 100ms [120], and the fact that the reaction time of the Follower is lightly greater than the one of the Leader. This configuration can therefore

Table 6.2: Results considering connected assistance: $RT = 0.5$s and $TH = 1.5$s

Assistance Provided to the Leader	Situation Undergone by the Follower		
	Moderate Decel	Hard Decel	Collision
Advice	99%	1%	0%
Warning	66%	34%	0%

be considered as similar as a standalone assistance configuration, with the reaction time of the Follower set such as $RT = 0.5$s. Note that situations in which the reaction time of the Follower is shorter than the one of the Leader is not considered, because the Follower would probably start to brake before the Leader. The decelerations that the Follower would undergo are therefore likely to be moderate. The time headway is kept similar as the one chosen for the standalone assistance configuration, e.g. $TH = 1.5$s. Table 6.2 presents the rate of each situation undergone by the Follower.

When the Leader is provided with warning assistance, rear-end collisions are not likely to occur, and the Follower may undergo moderate deceleration 2 out of 3 times. This may be considered as rather comfortable situations for the Follower. Nevertheless, providing the Leader with advice assistance allows to make the situations even more comfortable for the Follower as he is likely to undergo moderate decelerations almost every time.

6.3.3 Discussion

The results of the experimentation described in this Chapter show that providing the driver with assistance in the form of advice may have considerable consequences on the comfort and safety of the vehicle which is following. In the case of standalone assistance, and with the parameters which were chosen for the experiment, it would allow to cancel the risk of rear-end collision and to pass from nearly 100% of hard deceleration and 0% of moderate deceleration to nearly 50% of each. In the case of connected assistance, it would allow the Follower to undergo moderate decelerations only. These results allow to confirm that connected assistance, if they are combined with driving assistant systems, can improve the safety but also the comfort of other road users interacting with the subject vehicle. This should motivate further research, and the deployment of cooperative driving assistant systems.

Simulation techniques were used to generate the results. Simulation imply to make several assumptions, therefore the behaviour of the drivers and of vehicles cannot be perfectly modelled. Whilst they allow to estimate how the use of advice assistance in a vehicle may be beneficial for other road users interacting with it, the results which were presented should be confirmed with experiments performed with real drivers and vehicles. Such experimentations would require the development of two HMIs: one HMI for the Follower, and one HMI for the Leader which can be considered as an HMI for a proactive system. As explained in Chapter 5, Section 5.3.4, the development of such an HMI requires further methodological and theoretical research, therefore such an experimentation would require very long

preparation time.

6.4 Conclusion

This Chapter presented an experiment which aimed to show that providing the driver of a vehicle with preventive assistance instead of curative assistance is also beneficial for other road users interacting with this vehicle. The experimentation took into consideration standalone driving assistance, and cooperative assistance.

For this purpose, the algorithm which was presented in Chapter 5 was used. The case study that was chosen for the experimentation consists of two vehicles navigating in the same direction, towards the same stop intersection. The Leader is provided with assistance when he does not have intention to stop at the intersection. Simulation was used to estimate how comfortable the situation of the Follower would be when the Leader is provided with assistance, and therefore brakes to stop at the intersection. Comparisons were done between situations in which the leader is provided with curative assistance (advice) and situations in which he is provided with preventive assistance (warning).

The results show that providing the Leader with advice assistance instead of warning assistance has a significant impact on the situation that the Follower has to undergo. This is the case for both standalone system and cooperative systems. In the case of a standalone system, it is shown that average drivers are likely to be able to undergo moderate decelerations (i.e. to have comfortable reaction) about 50% of the time when the leader is provided with preventive assistance. Moreover, in the case of a cooperative system, it is shown that drivers are likely to undergo moderate decelerations almost 100% of the time.

This Chapter showed, for a chosen case study, that whilst preventive assistance systems are more comfortable than curative systems for the driver of the vehicle in which the system operates, they also allow to make situations more comfortable for the other road users interacting with the vehicle. One major perspective of this work is the implementation in real vehicles of the systems which were simulated, and the analysis of field trials to confirm the results of the experimentation which was presented. An other perspective of this work would be to estimate the impact of such systems in other situations of interaction, such as two vehicles reaching an intersection but navigating in different directions. The constraints imposed by the interactions between both vehicles would be different, as well as the manner how assistance provided in one vehicle has consequences on both vehicles.

Chapter 7

Conclusion

Contents

7.1 Synthesis

The automotive industry is undergoing a revolution with the rapid introduction of intelligent driving assistant systems into the whole range of vehicles, to improve comfort and safety of road users. Whilst these systems proved their effectiveness for the reduction of road accidents, most intervene as a last resort. Within this context, this thesis addressed situation understanding and risk assessment, to make such systems more preventive. The focus of this research was on road intersections where most of accidents occur.

This thesis proposed a framework to identify when situations are likely to become at risk, and thus when is would be relevant to provide the driver with preventive assistance information. The framework was inspired by passengers on board the vehicles who can act like copilots, that is, passengers helping drivers to identify relevant road information and therefore to avoid situations becoming dangerous. The ADAS Copilot paradigm applied in this thesis lead to two major contributions. The first, enhances situation understanding through the contextualisation of perception information via digital maps that enables the identification of the relevant nearby entities to be taken into account. The second contribution results in risk assessment that allows to infer whether or not the driver has taken into consideration the relevant entities into his navigation manoeuvres. The tenet of the approach was based upon the assumption that all drivers are different, thus these need to be taken into account when assessing risk with more accuracy.

Situation understanding was achieved by contextualizing the information returned by the perception sensors, and by including interactions implied by the cohabitation of road users on shared areas. For this purpose, the use of ontologies was proposed. An ontology was

formulated to model a conceptual representation of road users and the constraints imposed by road features and traffic rules. This ontology included the manoeuvres that road users are likely to perform, with respect to the interactions that can occur between road entities. The *a priori* knowledge stored in the ontology is then used as part of a dedicated framework to reason on the perception information together with the one extracted from the digital map. The framework was experimentally tested and validated on a passenger vehicle. It was shown that it allows to identify which road entities should be monitored, and how to implement the monitoring to ensure safe navigation. The resulting information can then be used as guidelines to follow for risk assessment systems.

Risk is estimated by comparing the manoeuvre the driver is expected to perform, with the manoeuvre he is likely to have intention to perform, using a Bayesian Network as introduced in [90]. This thesis considered three types of driving assistance within the same model, namely Automated Emergency Braking, Warning Assistance, and Advice Assistance. The first two are considered as curative as they are activated as a last resort, whilst the third is preventive as it allows the driver to have sufficient time to react comfortably. The three are applied to a vehicle as it approaches a stop line at an intersection. The system was tested on a passenger vehicle using close to production sensors.

The Bayesian model was applied with the available sensors and digital map information, in order to trigger the three types of assistance when risk is inferred. For this purpose, only information about the vehicle state and map information was used. A very important contribution was to introduce the different driver responses into the Bayesian model. Gaussian Processes were used to model the manner how drivers approach stop intersections. Those included uncertainties on sensors and digital maps. A research vehicle was used to collect data sets used to evaluate the ability of the system to trigger each type of assistance, as the driver did not have the intention to stop when arriving to the road intersection. It showed that, whilst performances are improved by incorporating customized driver profiles into the model, the system does not detect risk situations sufficiently early to provide drivers with advice, and thus to allow them to have time to react comfortably.

The Bayesian model was extended to take into consideration the actuation of drivers on the vehicle commands to detect risk situations, in addition to the vehicle state and map information. The assumption made was that every change of vehicle state is the consequence of driver actuation. Thus, by observing how the driver actuates, it would be possible to detect unexpected driver behaviours that affects the vehicle state. The same experimental data was used to evaluate the performances of the model to trigger preventive assistance. The results showed a major performance improvement, favoured by the observation of the driver actuations. For the chosen case study, it was shown that by using customized driver profiles and by observing the driver actuations, it is possible to detect risk situations sufficiently early to trigger preventive assistance, and thus to avoid the situation to become dangerous.

Finally, the evaluation of the benefits brought by preventive assistance on the situation of nearby interacting road users was performed. For this purpose, the approach of two vehicles navigating in the same direction towards the same stop intersection was chosen

as case study. Simulation was done to estimate the impact of assistance triggered by the Bayesian model in the leader vehicle, on the situation that the follower has to undergo to avoid collision. For this purpose, curative and preventive assistance were considered, as well as standalone and connected assistance. The results showed that providing preventive assistance instead of curative assistance to a driver has a major impact on the situation of nearby cohabiting vehicles, as it allows to reduce the deceleration necessary to avoid rear-end collision, and therefore the risk of rear-end collision. Further, these results are emphasised by communications between the vehicles, it allows to reduce the effect of the reaction time of the follower.

7.2 Conclusions

The results obtained in this thesis lead to three major conclusions, which are described below:

1. **Interactions between road entities should be taken into account within the situation understanding process**
   The experimental results showed that, in the contextualization process, it is possible to consider the spatio-temporal relationships which are likely to exist between road entities, within a situation understanding framework. This allows to understand how the subject vehicle interacts with its surroundings, and thus to identify which perceived road entities have impact on its situation. This identification of pertinent entities is performed among all entities returned by perception and digital map data.

2. **Situation understanding should be performed preliminarily to risk assessment**
   The identification of the road entities which interact with the subject vehicle allows to also identify which entities do not interact with it, and thus those which could be ignored to perform risk assessment. Whilst digital maps and perception sensors can provide very rich information about the subject vehicle surroundings, it remains a very complex task to design risk assessment algorithms able to consider all this information at the same time. Preliminary situation understanding as it is presented in this thesis allows to manage the complexity, and computational cost of the risk assessment algorithms by focussing only on a selection of pertinent road entities.

3. **Differences between drivers, and driver actuation should be taken into account for risk assessment**
   The experimental results confirmed two assumptions. The first is that taking into account customized driver patterns within the risk assessment algorithm allows to infer risk situations with more accuracy. The second is that the driver actuation represents very rich information to estimate the driver intention, and to better anticipate risk situations. Combining customized driver patterns and the observation of the driver actuation enables to infer risk situations sufficiently early to trigger preventive assist-

ance, allowing the driver to react more comfortably when he is assisted. The results also showed that such assistance allows to secure the situation of the vehicles interacting with the subject vehicle.

7.3 Perspectives

The results have opened numerous perspectives that are today being applied at Renault in the autonomous vehicles domain and to actuating ADAS. The following sections provide a summary of perspectives for further work based on this research.

7.3.1 Situation Understanding

1. **Ontology Extension for ADAS and Autonomous Driving**
   The ontology that was presented in Chapter 3 allowed to demonstrate the coherence of the approach for situation understanding. In its current state, the ontology only considers road entities which are on the same navigation lane as the subject vehicle. Situation understanding for ADAS, and especially autonomous driving would require to cover more complex road situations. It would therefore be pertinent to extend the ontology to multiple navigation lanes, including lanes converging at road intersections, roundabouts, etc. Further, the list of different types of road entities should be extended, as the list that the current version of ontology stores is limited.
   Such ontology extensions would require significant work. First, it would be necessary to model the immediate road network on which the subject vehicle is navigating. Then, it would be necessary to model the location of the road entities on the road network. Finally, it would be necessary to model the traffic laws and likely interactions between the road entities, as well as the conditions which specify that an entity is relevant for the subject vehicle navigation. Then, the ontology would have to be tested to ensure the coherence of all *a priori* information that is stored, and of all information that reasoning allows to generate. Further, this might need the development of a dedicated method for the creation and the validation of ontologies related to road contexts.
2. **Ontology and Uncertainties**
   One limitation of using ontologies is their inability to easily model uncertainties related to data and object properties. However, considering uncertainties within the conceptual description of road situations would be of great interest. This would allow to consider uncertainties on the state of road entities, on the precision of information extracted from digital maps, on the intentions of the road users, etc. Further, it would enable to take into consideration the fact that road users do not always respect traffic rules. This would imply consequent work to take into account these uncertainties to model interactions between road entities, and thus to estimate the relevance of each perceived road entity for the navigation of the subject vehicle. Whilst the literature

proposes some preliminary works aiming to consider uncertainties within ontologies, these techniques are not mature enough to motivate the development of convenient tools (i.e. reasoners, etc.) to properly reason on such ontologies [43, 173]. These limitations should motivate further research in the domain.

7.3.2 Risk Assessment

1. **Human Machine Interface Development**
   The risk assessment system that was presented in this thesis aims to trigger preventive assistance. The information that is generated has therefore to be used by an HMI to provide information to the driver. The manner how to inform the driver that he is likely to have missed a pertinent road entity is a complex task. The information that has to be provided has to be understood quickly and without effort for the driver. The use of a conventional pictogram or sound alert would probably confuse the driver as they would not allow the driver to identify the road entity he is likely to have missed. Investigations could be done on advices provided by a virtual assistant, or on augmented reality which could precisely describe to the driver the reason why he is assisted. For example, information could be displayed on the windscreen to highlight pertinent road entities.
   Further, preventive driving assistance systems as they are defined in this thesis can be considered as proactive systems. The theory and methodologies to develop HMIs for proactive assistance are not mature yet. Researches, which are in progress to ensure the ergonomics and the user acceptance of such systems, should be carried on [137, 172].

2. **Further Experimentations**
   The system that was presented in this thesis was tested with data recorded in a manually driven passenger vehicle. For this purpose, several acquisition campaigns were necessary. This required significant efforts, to prepare the experimental vehicle, to configure and to make the sensors work, to create the digital map, to hire participants and to carry out the experimentations. However, further experimentations should be performed, to test the algorithm with more participants, to carry out field trials on open roads, to analyse the users experiences and therefore to verify that such systems are relevant and accepted by the users. To perform such experimentations, the development of an HMI is necessary.

3. **Correction of False Map Information**
   Contextual information which is stored in the digital map is one of the major inputs of the risk assessment algorithm. For the experimentation, it was assumed that the information stored in the map was true, however digital maps are often out-of-date and include faults. Using false map information would imply incoherent system behaviours, and users would probably lose confidence in the system. For example, if the map indicates the presence of an intersection that does not exist on the road, a false alarm will occur. On the other hand, if information about an intersection is not stored in

the map, assistance will never be triggered. Map integrity monitoring is therefore of importance when map aided systems operate in a vehicle.
The approach presented in [177] could be used to detect the absence of an intersection in the map. Benefits should be taken from information redundancy which could be obtained from the repetitive journeys of a vehicle, or from a cloud service on which a vehicle fleet is connected. For example, if the vehicles always stop at the same location, and respect velocity profiles which describe the stop at a stop intersection, it is likely that there is a stop intersection at this location. Moreover, perception sensors which might be used as another source of redundancy, would allow to detect traffic signs, or to inform that this is not a intersection that constraints the vehicle to stop.

4. **Extension to Other Situations**
Other road entities than stop intersections may require vehicles to stop, such as pedestrians crossing the road, vehicles stopped in the navigation lane, or whatever static obstacles present on the road. The risk assessment system that was presented in this thesis could be used to estimate whether the driver took the road entity into consideration, and to assist the driver if it is relevant. For this purpose, the obstacles could be considered as virtual stop intersections by the system. However, further research would be necessary to check whether drivers decelerate in the same manner to stop for a stop intersection or for another static object. This may imply to learn a different velocity profiles for each type of object.
The case study that was chosen for this thesis implied that the subject vehicle is always expected to stop at the intersection. It would be pertinent to extend the system to the approach to more complex intersections, such as give way intersections or roundabouts where vehicles may have priority. For this purpose, the use of customized velocity profiles and the observation of the driver actuations should be incorporated in the Bayesian model that was presented in [90]. Further, if it is used within connected vehicles, such a system would probably allow to detect risk situations early enough to provide all involved drivers with preventive assistance.

5. **Use of Driver Monitoring Vision Technologies**
One of the main challenge of this thesis was to push the limits of the data that is available in conventional passenger vehicles, namely CAN, GPS and map data, to infer risk situations. At the beginning of the thesis, driver monitoring vision technologies were not considered because they were not compatible with car manufacturers constraints. This changed recently, since OEMs started to propose new systems satisfying these constraints. These systems offer very rich information about the driver state, and should now be considered as inputs of risk assessment systems. The Bayesian Network that was presented in Chapter 5 should be extended to take into consideration information provided by driver monitoring sensors in order to allow for a better estimation of the driver intention, and therefore of risks.

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Appendix A

Ontology Rules and Axioms

A.1 SWRL Rules

All SWRL rules defined in the ontology presented in Chapter 3 are presented in Table A.1 on pages 170, 171 and 172.

A.2 DL Axioms

The 6 Description Logics Axioms defined in the ontology presented in Chapter 3 are presented in Table A.2 on pages 173.

Table A.1: The 14 SWRL rules edited in the ontology.

#	SWRL Rules	Meaning
1	1 vehicle(?v1) ∧ vehicle(?v2) 2 ∧ distanceToSubjectVehicle(?v1,?d1) 3 ∧ distanceToSubjectVehicle(?v2,?d2) 4 ∧ subtract(?sub,?d2,?d1) 5 ∧ isFollowingParameter(?fParam) 6 ∧ hasValue(?f,?fParam) 7 ∧ lessThan(?sub,?f) 8 → isFollowing(?v2,?v1)	The position *d1* and *d2* of the vehicles *v1* and *v2* are known thanks to the *distanceToSubjectVehicle* parameter. By performing a subtraction (line 4), it is possible to determine the distance *sub* between both vehicles. By comparing this distance with the threshold of the *isFollowingParameter* (line 7), it is determined whether one vehicle is following the other one (line 8).
2	1 vehicle(?v1) 2 ∧ StopIntersection(?stop1) 3 ∧ willReach(?v1,?stop1) 4 → willStop(?v1,?stop1)	The vehicle *v1* will reach the stop intersection *stop1*. This condition means that *v1* will probably stop at *stop1* (line 4).
3	1 vehicle(?v1) 2 ∧ StopIntersection(?stop1) 3 ∧ isToReach(?v1,?stop1) 4 → hasToStop(?v1,?stop1)	The vehicle *v1* is about to reach the stop intersection *stop1*. This condition means that *v1* has to stop at *stop1* (line 4).
4	1 vehicle(?v1) 2 ∧ Infrastructure(?infr1) 3 ∧ isToReach(?v1,?infr1) 4 → hasToDecelarate(?v1,?infr1)	The vehicle *v1* is about to reach the infrastructure *infr1*. This condition means that *v1* has to decelerate at *infr1* (line 4).
5	1 vehicle(?v1) 2 ∧ RoadNetwork(?RN1) 3 ∧ goesTowards(?v1, ?RN1) 4 ∧ isToReachParameter(?param) 5 ∧ hasValue(?param, ?value) 6 ∧ distanceToSubjectVehicle(?RN1, ?d2) 7 ∧ distanceToSubjectVehicle(?RN1, ?d1) 8 ∧ substract(?sub, ?d2, ?d1) 9 ∧ greaterthan(?sub, ?value) 10 → willReach(?v1,?RN1)	The vehicle *v1* goes towards the road network *RN1*. The position of *v1 and RN1* are known through the *distanceToSubjectVehicle* parameters *d1* and *d2* (lines 6 and 7). By substracting *d1* to *d2* (line 8), it is possible to get the distance *sub* between both objects *v1* and *RN1*. If this distance is greater than the *value* that is defined by the *isToReachParameter* (line 5), it means that *v1* will reach *RN1* (line 10).

#	SWRL Rules	Meaning
6	1 vehicle(?v1) ∧ Pedestrian(?p1) 2 ∧ PedestrianCrossing(?pc1) 3 ∧ isClose(?p1,?pc1) 4 ∧ isToReach(?v1, ?p1) 5 ∧ isOnRoad(?p1, ?value) 6 ∧ equal(?value, 0) 7 → hasToDecelarate(?v1,?p1)	The pedestrian *p1* is close to the pedestrian crossing *pc1* (line 3), and is on the road (lines 5&6). The vehicle *v1* that is about to reach *p1* (line 4) has therefore to decelerate (line 7).
7	1 vehicle(?v1) ∧ vehicle(?v2) 2 ∧ Infrastructure(?infr) 3 ∧ hasToDecelerate(?v2, ?infr) 4 ∧ isFollowing(?V1,?v2) 5 → hasToDecelarate(?v1,?v2)	The vehicle *v1* is following the vehicle *v2* (line 4). *v2* has to decelerate at the infrastructure *infr1* (line 3). therefore *v1* has to decelerate behind *v2* (line 5).
8	1 vehicle(?v1) ∧ vehicle(?v2) 2 ∧ Infrastructure(?infr) 3 ∧ hasToStop(?v2, ?infr) 4 ∧ isFollowing(?V1,?v2) 5 → hasToStop(?v1,?v2)	The vehicle *v1* is following the vehicle *v2* (line 4). *v2* has to stop at the infrastructure *infr1* (line 3). therefore *v1* has to stop behind *v2* (line 5).
9	1 vehicle(?v1) 2 ∧ Infrastructure(?infr) 3 ∧ willReach(?v1, ?infr) 4 → willDecelerate(?v1,?infr)	The vehicle *v1* will reach the infrastructure *infr* (line 3). *v1* has therefore to decelerate as it approaches to *infr* (line 4).
10	1 vehicle(?v1) ∧ Pedestrian(?p1) 2 ∧ isToReachParameter(?param) 3 ∧ hasValue(?param, ?value) 4 ∧ distanceToSubjectVehicle(?p1, ?d2) 5 ∧ distanceToSubjectVehicle(?v1, ?d1) 6 ∧ greaterThan(?sub, 0) 7 ∧ lessThan(?sub, ?value) 8 ∧ subtract(?sub, ?d2, ?d1) 9 → isToReach(?v1,?p1)	The pedestrian *p1* is located at a distance *d2* from the subject vehicle (line 4). In addition, the vehicle *v1* is moving at a distance *d1* from the subject vehicle (line 5). By computing the subtraction *sub* between the distances *d2* and *d1* (line 8), the distance between *v1* and *p1 is* known. If this distance is lower than the threshold defined by the *isToReachParameter* (lines 3, 4, 8), then it is considered that *v1* is about to reach *p1* (line 9).

#	SWRL Rules	Meaning
11	1 vehicle(?v1) 2 ∧ RoadNetwork(?RN1) 3 ∧ isToReachParameter(?param) 4 ∧ hasValue(?param, ?value) 5 ∧ distanceToSubjectVehicle(?RN1, ?d2) 6 ∧ distanceToSubjectVehicle(?v1, ?d1) 7 ∧ greaterThan(?sub, 0) 8 ∧ lessThan(?sub, ?value) 9 ∧ subtract(?sub, ?d2, ?d1) 10 → isToReach(?v1,?RN1)	The vehicle *v1* is moving at a distance *d1* from the subject vehicle. The road network entity *RN1* is situated at a the distance *d2* from the subject vehicle. By computing the subtraction *sub* between the distances *d2* and *d1* (line 9), the distance between *v1* and *RN1 is* known. If this value is lower than the value defined by the *isToReachParameter* (line 3 and 8), then it is considered that *v1* is to reach *RN1* (line 10).
12	1 Pedestrian(?p1) 2 ∧ PedestrianCrossing(?pc1) 3 ∧ isCloseParameter(?paramc) 4 ∧ hasValue(?paramc, ?value) 5 ∧ distanceToSubjectVehicle(?p1, ?d1) 6 ∧ distanceToSubjectVehicle(?pc1, ?d2) 7 ∧ subtract(?sub, ?d2, ?d1) 8 ∧ pow(?res, ?sub, 2) 9 ∧ pow(?limit, ?param, 2) 10 ∧ lessThan(?res, ?limit) 11 → isClose(?p1,?pc1)	The pedestrian *p1* is located at a distance *d1* from the subject vehicle (line 5). The pedestrian crossing pc1 is located at a distance *d2* from the subject vehicle (line 6). The distance *sub* between *p1* and *pc1* is computed (line 7). This distance can be negative depending whether *p1* is before, or after *pc1* (from the subject vehicle point of view). SWRL rule do not have the "absolute" operator, therefore *res* is computed as the square of *sub* (line 8). If *res* is lower than to the square of the *isCloseParameter* value *limit,* then if is considered that *p1* is close to *pc1.*
13	1 Pedestrian(?p1) 2 ∧ Vehicle(?v1) 3 ∧ isToReach(?v1, ?p1) 4 ∧ isOnRoad(?p1, ?value) 5 ∧ equal(?value, 1) 6 → hasToStop(?v1,?pc1)	The pedestrian *p1* is situated on the road (line 4 and 5). If the vehicle *v1* is to reach *p1*, then it has to stop before *p1.*
14	1 RoadNetwork(?RN1) 2 ∧ Vehicle(?v1) 3 ∧ distanceToSubjectVehicle(?RN1, ?d2) 4 ∧ distanceToSubjectVehicle(?v1, ?d1) 5 ∧ greaterThan(?d2, ?d1) 6 → goesTowards(?v1,?RN1)	The vehicle *v1* is moving at a distance *d1* from the subject vehicle. The road network *RN1* is situated at a distance *d2* from the subject vehicle. If *d2* is greater than *d1*, it means that *v1* goes towards *RN1.*

Table A.2: The 6 Description Logic Axioms edited in the ontology.

#	DL Axioms	Meaning
1	StopIntersectionAhead $\doteq$ Vehicle $\sqcap \exists$hasToStop $\cdot$ StopIntersection	If an instance of concept *Vehicle* is linked to an instance of concept *StopIntersection* through the object property *hasToStop*, then the instance of concept *Vehicle* is also an instance of the *StopIntersectionAhead* concept.
2	StopIntersectionBefore1Leader $\doteq$ Vehicle $\sqcap$isFollowing $\cdot$ StopIntersectionAhead	If an instance of concept *Vehicle* is linked to an instance of concept *StopIntersectionAhead* through the object property *isFollowing*, then the instance of concept *Vehicle* is also an instance of the *StopIntersectionBefore1Leader* concept.
3	StopIntersectionBeforeSeveralLeaders $\doteq$ Vehicle $\sqcap$ isFollowing$\cdot$ (StopIntersectionBefore1Leader $\sqcup$StopIntersectionBeforeSeveralLeaders)	If an instance of concept *Vehicle* is linked to an instance of concept *StopIntersectionBefore1Leader OR StopIntersectionBeforeSeveralLeaders* through the object property *isFollowing*, then the instance of concept *Vehicle* is also an instance of the *StopIntersectionBeforeSeveralLeaders* concept.
4	PedestrianAhead $\doteq$ Vehicle $\sqcap \exists$hasToDecelerate $\cdot$ Pedestrian	If an instance of concept *Vehicle* is linked to an instance of concept *Pedestrian* through the object property *hasToDecelerate*, then the instance of concept *Vehicle* is also an instance of the *PedestrianAhead* concept.
5	PedestrianBefore1Leader $\doteq$ Vehicle $\sqcap$isFollowing $\cdot$ PedestrianAhead	If an instance of concept *Vehicle* is linked to an instance of concept *PedestrianAhead* through the object property *isFollowing*, then the instance of concept *Vehicle* is also an instance of the *PedestrianBefore1Leader* concept.
6	PedestrianBeforeSeveralLeaders $\doteq$ Vehicle $\sqcap$ isFollowing$\cdot$ (PedestrianBefore1Leader $\sqcup$PedestrianBeforeSeveralLeaders)	If an instance of concept *Vehicle* is linked to an instance of concept *PedestrianBefore1Leader OR PedestrianBeforeSeveralLeaders* through the object property *isFollowing*, then the instance of concept *Vehicle* is also an instance of the *PedestrianBeforeSeveralLeaders* concept.

Appendix B

Gaussian Processes Principles

In recent years, Gaussian Processes (GP) have become widely used by the robotics and machine learning community for regression, classification and prediction problems [130, 139, 13, 31]. The advantage of Gaussian Processes is that they apply simple linear algebra while they are a powerful tool to solve non linear problems.

B.1 Basic Gaussian Processes Principles

Gaussian Processes aim at recovering the functional dependency between two variables x_i and y_i from n observed data points $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{n}$, such as $y_i = f(x_i) + \epsilon_i$. For each observation (x_i, y_i), a random noise ϵ_i exists. It is independent and identically distributed. The data set comprises y_i as the noisy output values at input locations x_i. The Gaussian Process regression consists in learning the predictive Normal distribution $p\left(y^*|x^*, \mathcal{D}\right)$ of a new test output y^* given a new test input x^*.

Training Data

Notations can be simplified by defining the $d \times n$ matrix X which stores all the training inputs $\{x_i\}_{i=1}^{n}$ with d the dimension of x_i. In addition, vector Y of size n which stores all the training inputs $\{y_i\}_{i=1}^{n}$, such as:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ ... \\ ... \\ x_n \end{bmatrix} \quad \text{and} \quad Y = \begin{bmatrix} y_1 \\ y_2 \\ ... \\ ... \\ y_n \end{bmatrix}$$

Mean and Variance

The predictive distribution at the query point x^* is a multivariate Gaussian distribution $N(\mu^*, \Sigma^*)$ based on the training data set $\mathcal{D}$. The mean μ^* is defined as:

$$\mu^* = K^*(K + \sigma_n^2 I)^{-1} Y \tag{B.1}$$

and the variance Σ^* is defined as:

$$\Sigma^* = K^{**}(K + \sigma_n^2 I)^{-1} K^{*T} \tag{B.2}$$

Covariance Function

In these Equations B.1 and B.2, the covariance matrices K, K^* and K^{**} are computed using the covariance function (also called Kernel) $k(.,.)$, such as:

- $K \in \mathbb{R}^{n \times n}$ with $K_{i,j} = k(x_i, x_j)$
- $K^* \in \mathbb{R}^{n^* \times n}$ with $K^*_{i,j} = k(x^*_i, x_j)$
- $K^{**} \in \mathbb{R}$ with $K^{**}_{i,j} = k(x^*_i, x^*_j)$

The covariance function $k(.,.)$ defines the Gaussian Process which may be written as $\mathcal{GP}(0, k(.,.))$. It depends on parameters $\theta = \{\sigma_n, l\}$, commonly called *hyperparameters*, and determined in advance. The parameter σ_n is called the *noise level*, and the parameter l is called the *length scale*.

Several covariance functions exist [130], but the most common is the Squared Exponential given by:

$$k(x_i, x_j) = \sigma_n^2 \exp\left(-\frac{\|x_i - x_j\|^2}{2l^2}\right) \tag{B.3}$$

Hyperparameters

The hyperparameters θ must be tuned to obtain a smooth and reliable regression. This tuning can be considered as the training stage of Gaussian Processes. The most optimized value of θ is given when the probability $p(y|X, \theta)$ is at its greatest. This log marginal likelihood is computed as [130]:

$$\log p(y|X, \theta) = -\frac{1}{2} y^T K_y^{-1} y - \frac{1}{2} \log |K_y| - \frac{n}{2} \log(2\pi) \tag{B.4}$$

with:

- $K_y = K + \sigma_n I$ where I is the identity matrix
- $|.|$ is the matrix determinant

Optimization algorithms have to be used to determine the optimized value of θ. The log marginal likelihood can be locally minimized using a conjugate gradient multivariate optimization algorithm.

Results

An example of results of a basic Gaussian Process regression is presented in Figure B.1a. The hyperparameters θ are optimized, and the curve that describes the mean follows the training samples. However, the variance is under estimated at some points.

B.2 Gaussian Processes with Heteroscedastic Variance

The Gaussian Process model which has been described in the previous section assumes a constant noise level σ_n over the whole process. While this assumption may be justified in most use cases, it may become a problem in other use cases as it may result in a variance Σ^* that is either under or over-estimated (see Figure B.1b). Therefore, in some cases, it may be judicious to use a more flexible noise model.

Update of Mean and Variance

In this way, Gaussian Processes using heteroscedastic noise level were introduced [79]. By heteroscedastic noise level σ_n, it is meant noise level that is input dependent, in comparison with homoscedastic noise level which is not input dependent. Therefore, the constant noise level σ_n is replaced by the input dependent function $r(x)$. Equation B.1 which defines the estimation of mean μ^* becomes:

$$\mu^* = K^* \left(K + \mathbf{R}\right)^{-1} Y \tag{B.5}$$

and Equation B.2 which defines the estimation of variance Σ^* becomes:

$$\Sigma^* = K^{**} + \mathbf{R}^* - K^* \left(K + \mathbf{R}\right)^{-1} K^{*T} \tag{B.6}$$

with:

- $R \in \mathbb{R}^n$ such as $R = \text{diag}(r)$, where $r = \begin{bmatrix} r(x_1) \\ r(x_2) \\ ... \\ ... \\ r(x_n) \end{bmatrix}$

- $R^* \in \mathbb{R}$ such as $R^* = \text{diag}(r^*)$ with $r^* = \begin{bmatrix} r(x_1^*) \\ r(x_2^*) \\ ... \\ ... \\ r(x_n^*) \end{bmatrix}$. R^* is usually learned from training data set $\mathcal{D}$.

Results

An example of results of a heteroscedastic Gaussian Process regression is presented in Figure B.1b. In this version, the curve that describes the mean follows the training samples. Moreover, it is noticeable that the variance increases over the x axis as the noise level parameter $r(x)$ also increases over the x axis. This version of Gaussian Processes solves the problem of variance under/over estimation.

B.3 Gaussian Processes with Noisy Inputs

The Gaussian Process models which have been described in the last sections assume that inputs are noise-free. However, in some applications, the training data set $\mathcal{D}$ may come from observations made with sensors suffering from noise. As a consequence, making the assumption of noise-free inputs may lead to bad performances in the regression process. As a solution, Gaussian Processes which consider noise on inputs have been defined [99].

Noisy Inputs in Gaussian Processes

In standard Gaussian Processes, y is a noisy measurement of the output such as:

$$y = \tilde{y} + \epsilon_y$$

where:

- $\epsilon_y \sim \mathcal{N}(0, \sigma_y^2)$ in the case of homoscedastic Gaussian Processes
- $\epsilon_y \sim \mathcal{N}(0, r(x)^2)$ in the case of heteroscedastic Gaussian Processes

In this version of Gaussian Processes, the inputs are noisy, such as:

$$x = \tilde{x} + \epsilon_x$$

where $\epsilon_x \sim \mathcal{N}(0, \sigma_x^2)$, with the input noise σ_x assumed as constant
The output y as a function of the input x can be written as:

$$y = f(\tilde{x} + \epsilon_x) + \epsilon_y$$

which can be linearized such as (from [99]):

$$y = f(\tilde{x}) + \epsilon_x^T \partial_{\bar{y}} + \epsilon_y \tag{B.7}$$

where $\partial_{\bar{y}}$ is the derivative of the mean of a GP function. To obtain it, a first GP (homoscedastic or heteroscedastic) has to be run to predict the mean and the derivative of the output for each input x_n. The probability of an observation is given by $P(y^*|x^*, \mathcal{D}) \sim \mathcal{N}(f, \sigma_y^2 + \partial_{\bar{y}}^T \Sigma_x \partial_{\bar{y}})$ where $\Sigma_x = \text{diag}(\sigma_x^2)$.

Update of Mean and Variance

Equation B.5 which defines the estimation of mean μ^* becomes:

$$\mu^* = K^* \left(K + R + \mathbf{P}\right)^{-1} Y \tag{B.8}$$

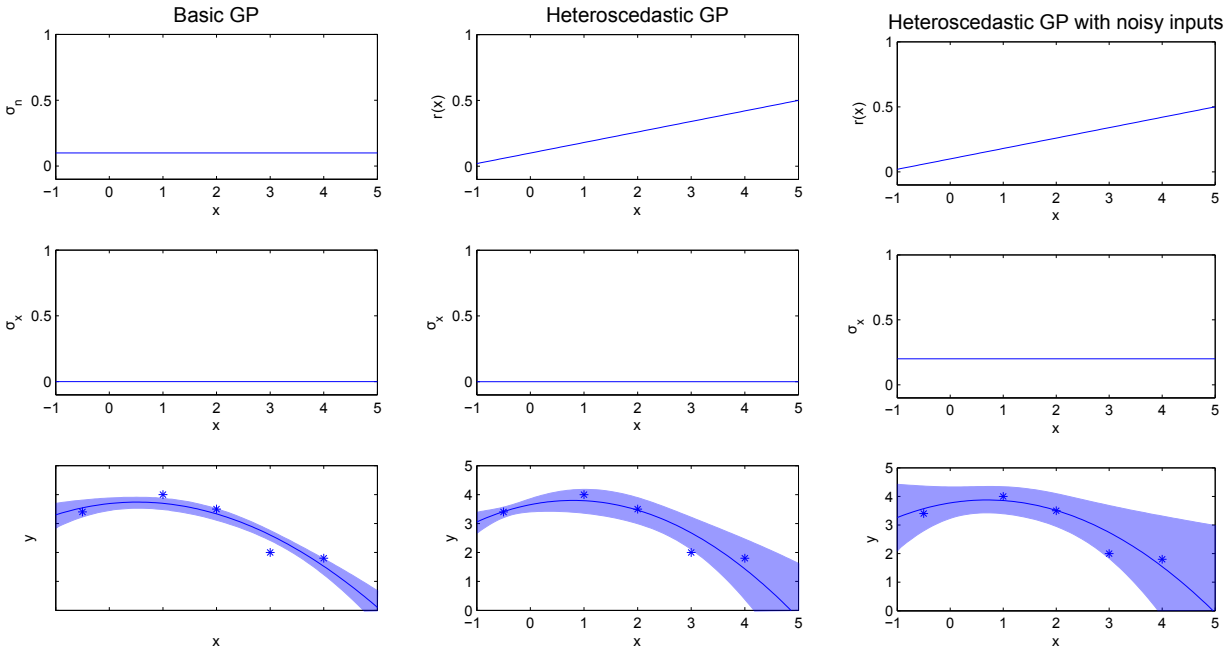
and Equation B.6 which defines the estimation of variance Σ^* becomes:

$$\Sigma^* = K^{**} + R^* - K^* \left(K + R + \mathbf{P}\right)^{-1} K^{*T} \tag{B.9}$$

where $P = \text{diag}(\Delta_{\bar{y}} \Sigma_x \Delta_{\bar{y}}^T)$ and $\Delta_{\bar{y}} = \{\partial_{\bar{y},i}\}_{i=1}^n$.

Results

An example of results of a heteroscedastic Gaussian Process regression which considers noisy inputs is presented in Figure B.1c. In this last version, it is noticeable that the variance is larger over the x axis than the variance of heteroscedastic GP. This is due to the consideration of constant noise on the input (here, $\sigma_x = 0.2$).



(a) Basic Gaussian Processes (b) Heteroscedastic Gaussian Processes (c) Heteroscedastic Gaussian Processes with noisy inputs

Figure B.1: Comparison between the 3 Gaussian Processes models. **On the top line**: value of the noise level σ_n. **In the middle line**: value of noise applied on the input. **On the bottom line**: blue crosses are training data $\mathcal{D}$, the mean μ is represented by the blue line, and the variance Σ is represented by the blue envelope (here, represented by 2σ).

Appendix C

Generic Velocity Profiles

In this thesis, the parametric equation of the true vehicle speed $\mathcal{N}(\mu_S^{stop}, \sigma_S^{stop})$ and $\mathcal{N}(\mu_S^{go}, \sigma_S^{go})$ were based on velocity profiles learned for each driver. However, this approach was compared with the use of generic velocity profiles similar as those used in [90]. This Appendix presents how these generic velocity profiles are computed.

Computation

The likelihood of the true vehicle speed is defined as following a normal distribution such as:

$$P(S_t|\phi_{t-1}, I_{t-1}, I_t) = P(S_t|P_{t-1}, S_{t-1}, I_t) = \begin{cases} \mathcal{N}(\mu_S^{go}, \sigma_S^{go}) & \text{if } I_t = go \\ \mathcal{N}(\mu_S^{stop}, \sigma_S^{stop}) & \text{if } I_t = stop \end{cases} \tag{C.1}$$

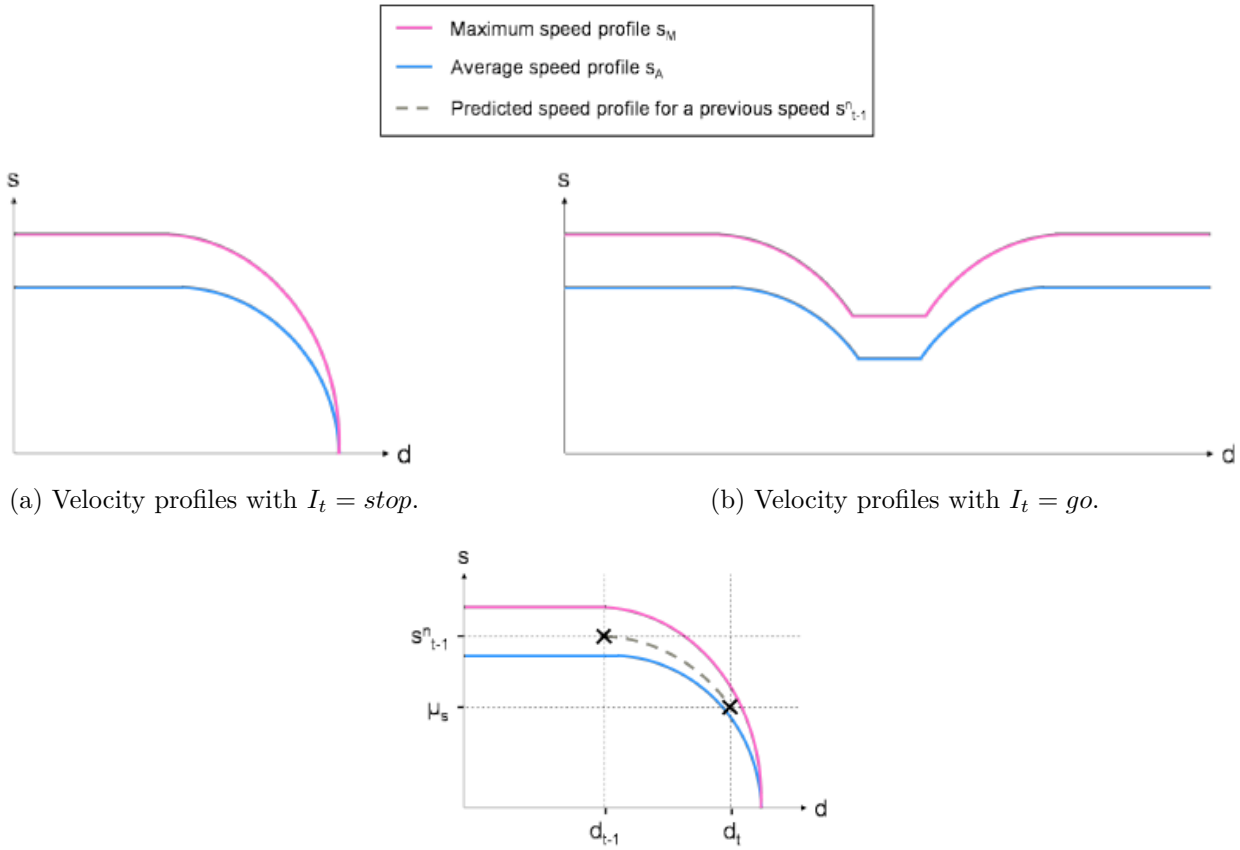
Depending on I_t the intention of the driver, two profiles are generated: $S_A$the average velocity profile and S_M the maximum velocity profile (i.e. the highest speed the vehicle can undergo to perform the expected manoeuvre). Figures C.1a and C.1b present examples of $S_A$and S_M profiles.

Mean

The evolution of the speed of the vehicle is predicted using the following equation:

$$\mu_S(S_{t-1}, P_{t-1}, I_t) = S_A(P_{t-1}) - \frac{S_A(P_{t-1}) - S_M(P_{t-1})}{S_A(P_t) - S_M(P_t)} \times (S_A(P_{t-1}) - S_{t-1}) \tag{C.2}$$

with $S_{t-1}$the vehicle speed at time $t-1$, $P_{t-1}$the vehicle pose at time $t-1$, $I_{t-1}$the driver intention at time t, P_t the prediction of the vehicle pose at time t. Figure C.1c presents a generic velocity profile computed using Equation C.2.



(a) Velocity profiles with $I_t = stop$.

(b) Velocity profiles with $I_t = go$.

(c) Example of profile computed using Equation C.2, with $I_t = stop$.

Figure C.1: Example of generic velocity profiles (Figures from [90]).

Variance

The standard deviation is dynamically set based on the difference between S_A and S_M at position P_t.

Appendix D

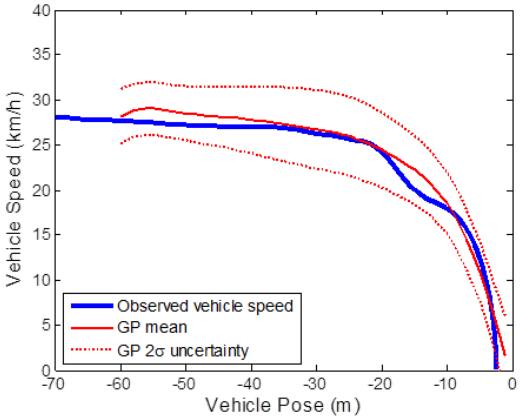
Further Graphs for Chapter 5

D.1 Qualitative Results With Incoherent Pedals State

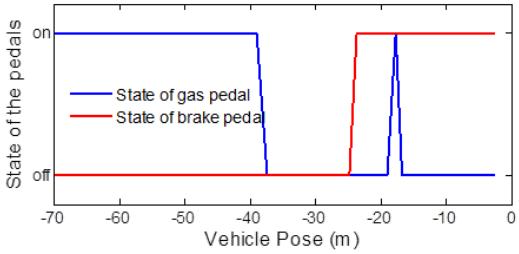
Figure D.1 shows the results with incoherent observed pedal states. At $P = 20m$, the gas pedal is actuated while the brake pedal is already actuated (Figure D.1b). This is not supposed to happen, however Figure D.1f shows that the model is robust to such event.

D.2 Qualitative Results With Hesitant Driver Behaviour

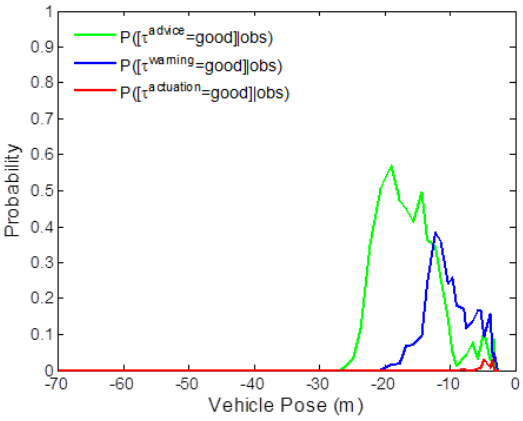
Figure D.2 shows the results obtained with a hesitant driver. Figure D.2b shows the state of the pedals, which fluctuates between *on* and *off*. Figure D.2f shows that the model is robust to such event.



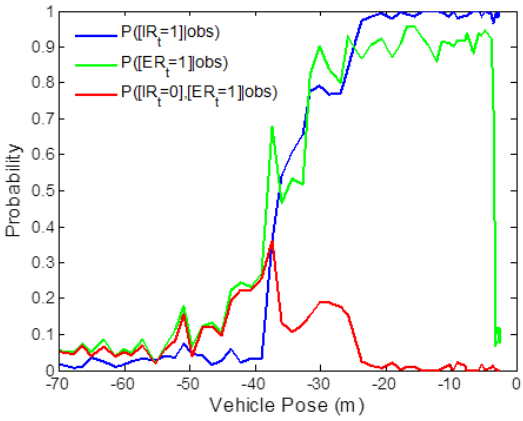
(a) Vehicle speed and learnt velocity profile with respect to the vehicle pose.



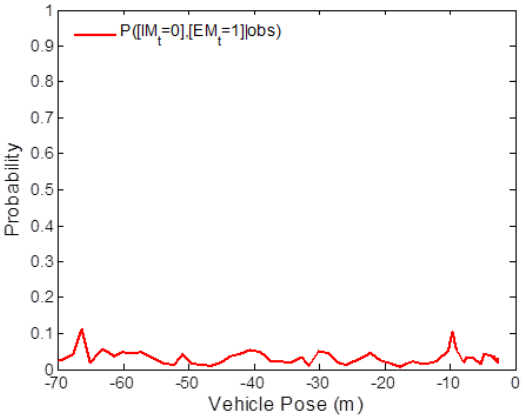
(b) State of the gas and brake pedals with respect to the vehicle pose.



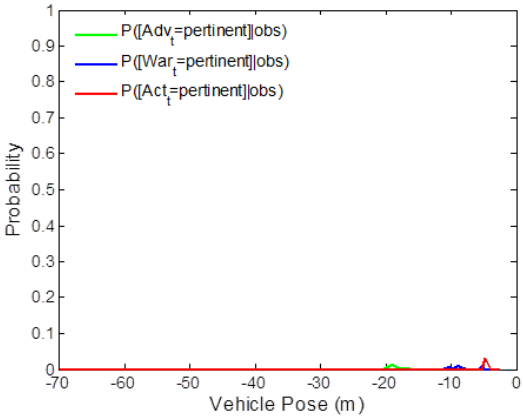
(c) State of indicators $\tau^{assistance}$ with respect to the vehicle pose.



(d) Probabilities related to the driver's reaction with respect to the vehicle pose.

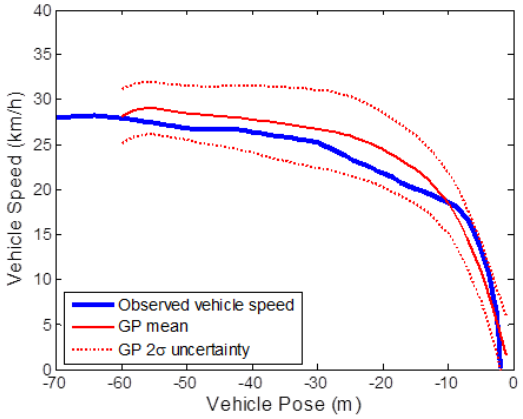


(e) Probabilities related to the vehicle manoeuvre with respect to the vehicle pose.

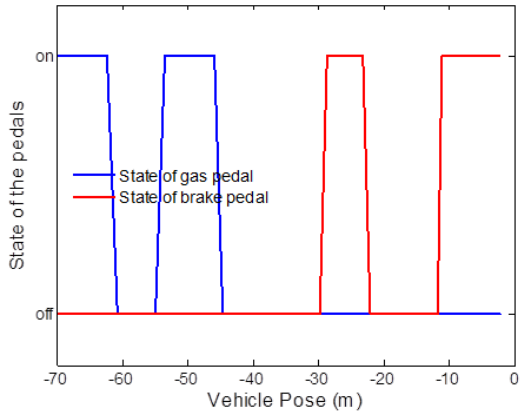


(f) Probabilities that assistance is pertinent with respect to the vehicle pose.

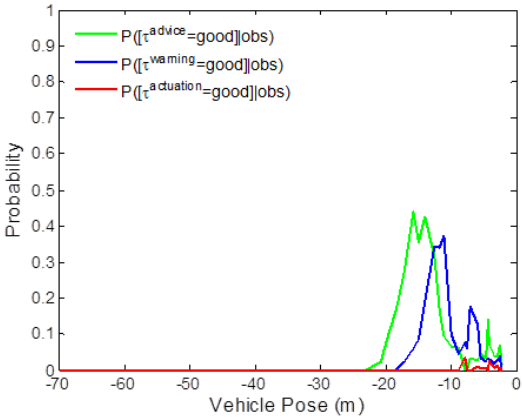
Figure D.1: Example of observed and inferred data in the case of a safe situation with incoherent pedals state.



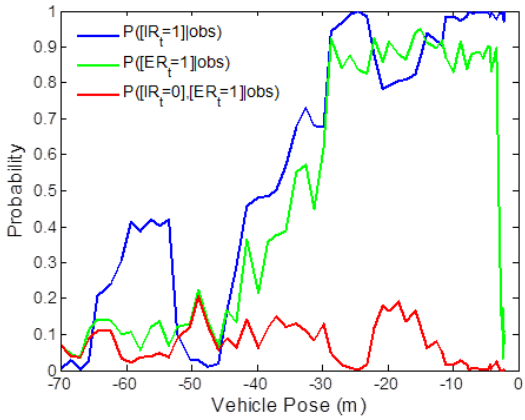
(a) Vehicle speed and learnt velocity profile with respect to the vehicle pose.



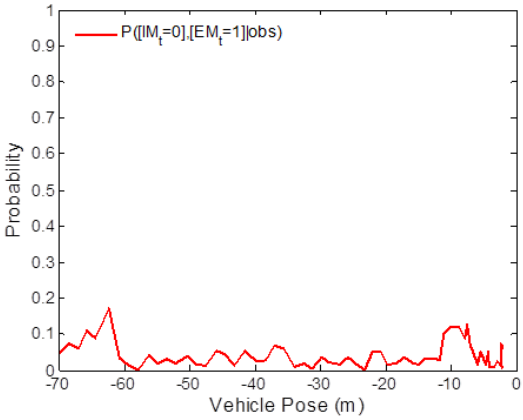
(b) State of the gas and brake pedals with respect to the vehicle pose.



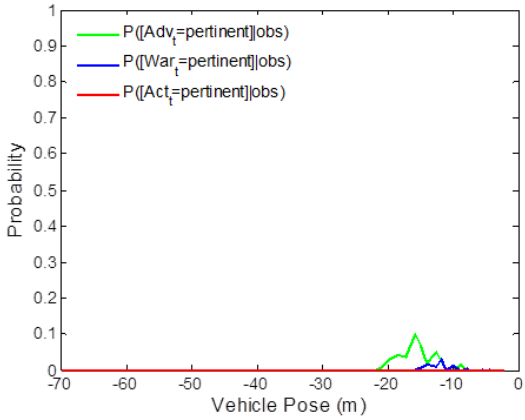
(c) State of indicators $\tau^{assistance}$ with respect to the vehicle pose.



(d) Probabilities related to the driver's reaction with respect to the vehicle pose.



(e) Probabilities related to the vehicle manoeuvre with respect to the vehicle pose.



(f) Probabilities that assistance is pertinent with respect to the vehicle pose.

Figure D.2: Example of observed and inferred data in the case of a safe situation with incoherent pedals state.

Appendix E

Further Graphs for Chapter 6

E.1 Initial Speed at 60km/h

Figure E.1 presents how warning assistance provided to the Leader impacts the situation of the Follower when initial speed is set at 60km/h, with respect to the reaction time of the Follower, and the time headway between the vehicles.

Figure E.2 presents how advice assistance provided to the Leader impacts the situation of the Follower when initial speed is set at 60km/h, with respect to the reaction time of the Follower, and the time headway between the vehicles.

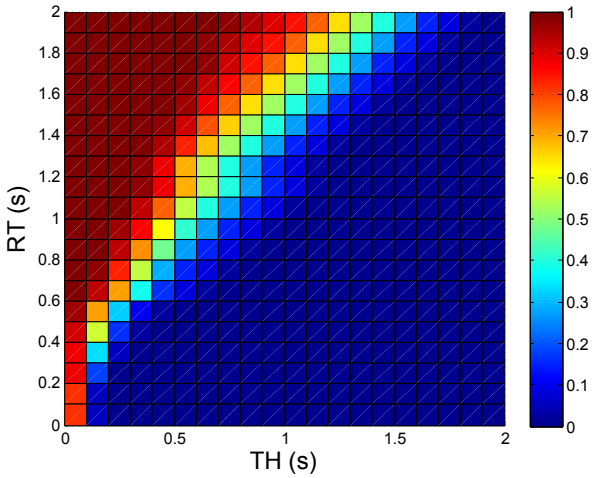
Figure E.3 highlights how much providing the Leader with advice assistance instead if warning assistance impacts the situation that the Follower has to undergo when initial speed is set at 60km/h. It shows the subtraction $\Omega^{\Psi}_{Advice} - \Omega^{\Psi}_{Warning}$.

E.2 Initial Speed at 90km/h

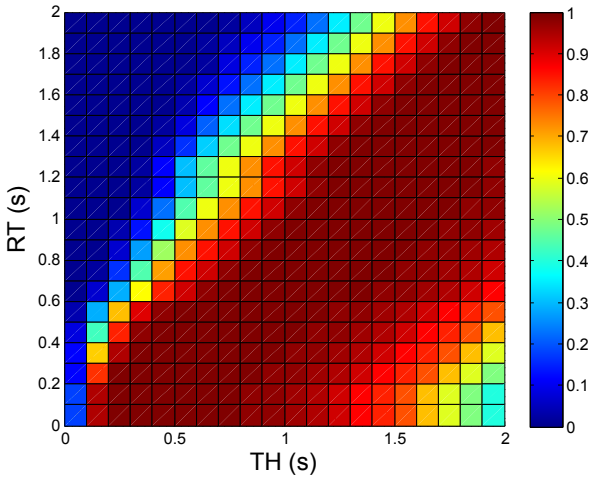
Figure E.4 presents how warning assistance provided to the Leader impacts the situation of the Follower when initial speed is set at 90km/h, with respect to the reaction time of the Follower, and the time headway between the vehicles.

Figure E.5 presents how advice assistance provided to the Leader impacts the situation of the Follower when initial speed is set at 90km/h, with respect to the reaction time of the Follower, and the time headway between the vehicles.

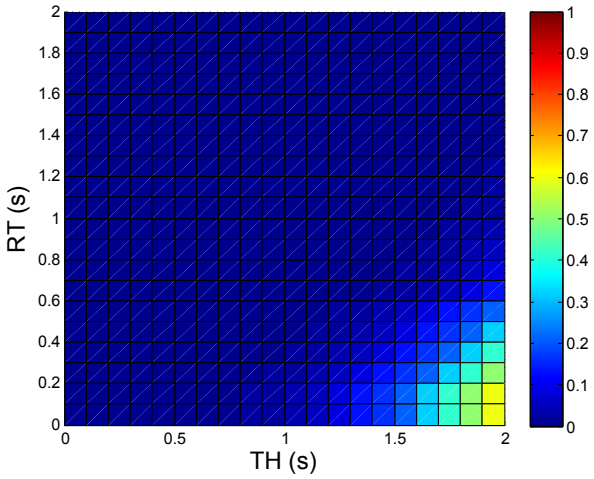
Figure E.6 highlights how much providing the Leader with advice assistance instead if warning assistance impacts the situation that the Follower has to undergo when initial speed is set at 90km/h. It shows the subtraction $\Omega^{\Psi}_{Advice} - \Omega^{\Psi}_{Warning}$.



(a) $\Omega^{Collision}_{Warning}(RT, FT)$

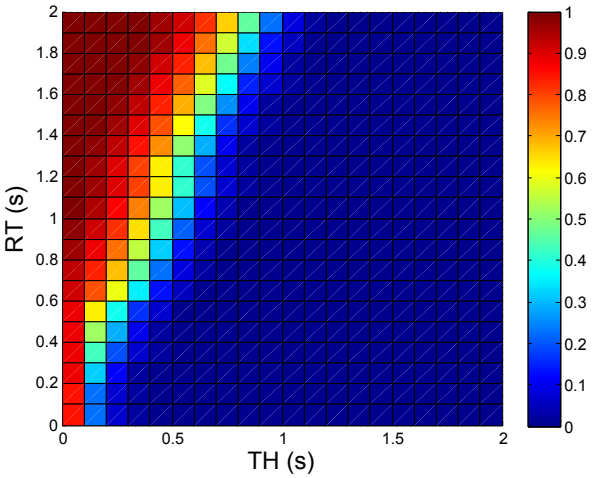


(b) $\Omega^{Hard}_{Warning}(RT, FT)$

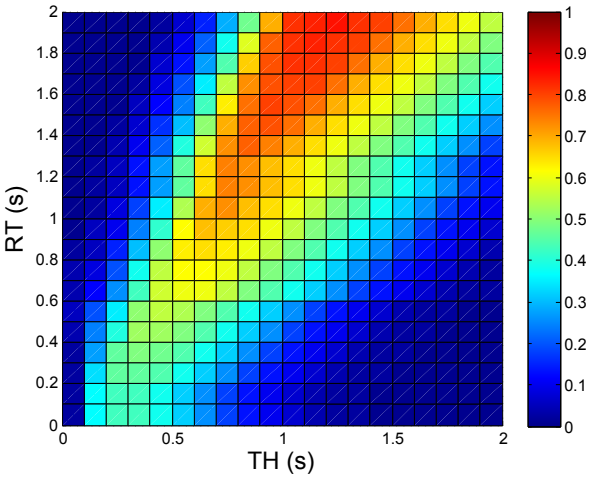


(c) $\Omega^{Moderate}_{Warning}(RT, FT)$

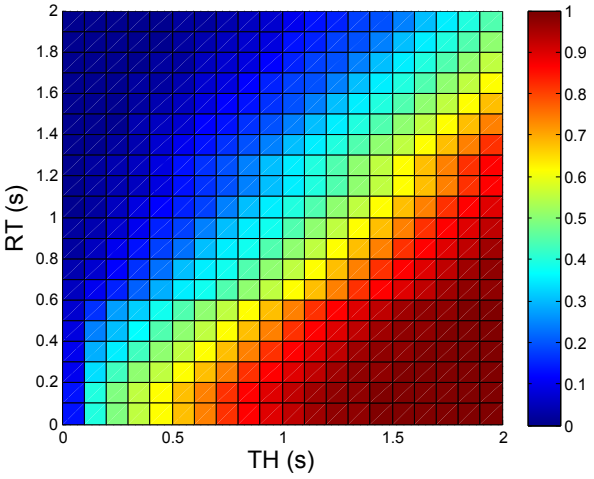
Figure E.1: Results considering that the leader is moving at **60 km/h** and provided with **Warning** assistance.



(a) $\Omega^{Collision}_{Advice}(RT, FT)$

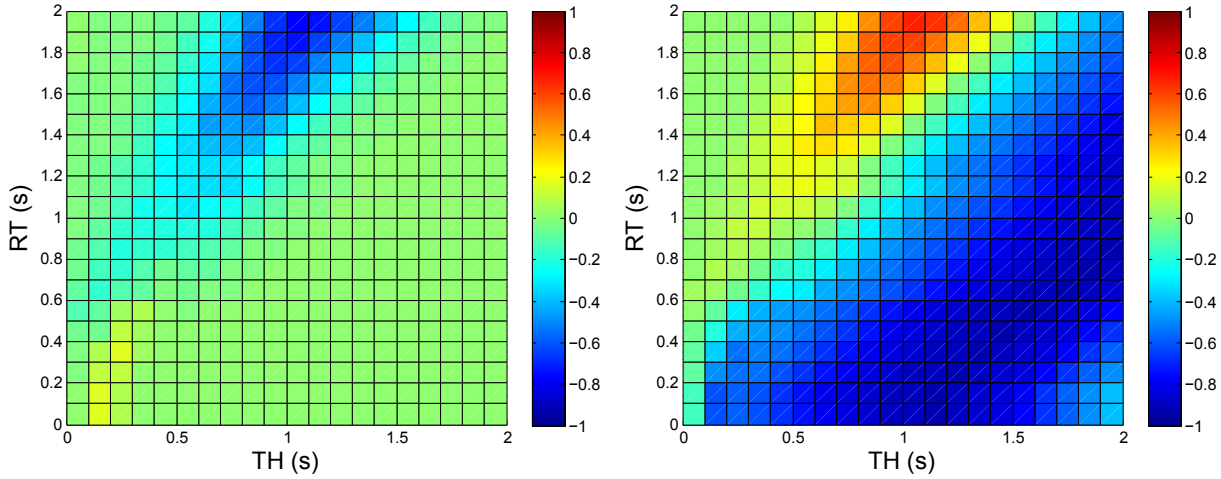


(b) $\Omega^{Hard}_{Advice}(RT, FT)$



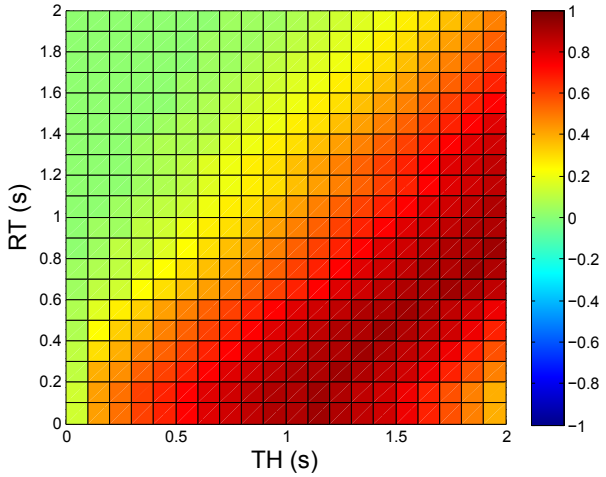
(c) $\Omega^{Moderate}_{Advice}(RT, FT)$

Figure E.2: Results considering that the leader is moving at **60 km/h** and provided with **Advice** assistance.



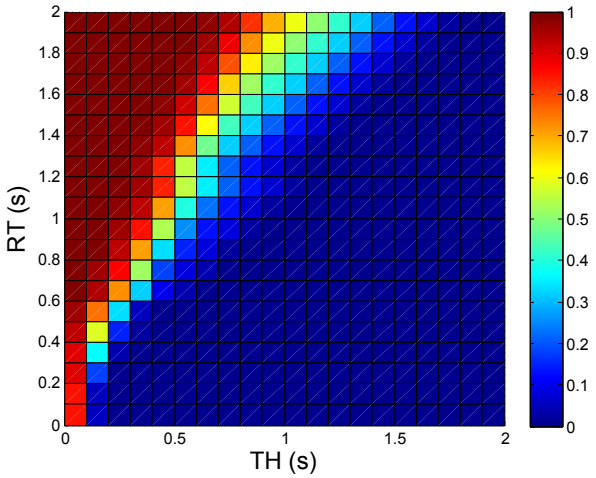
(a) $\Omega^{Collision}_{Advice}(RT, TH) - \Omega^{Collision}_{Warning}(RT, TH)$

(b) $\Omega^{Hard}_{Advice}(RT, TH) - \Omega^{Hard}_{Warning}(RT, TH)$

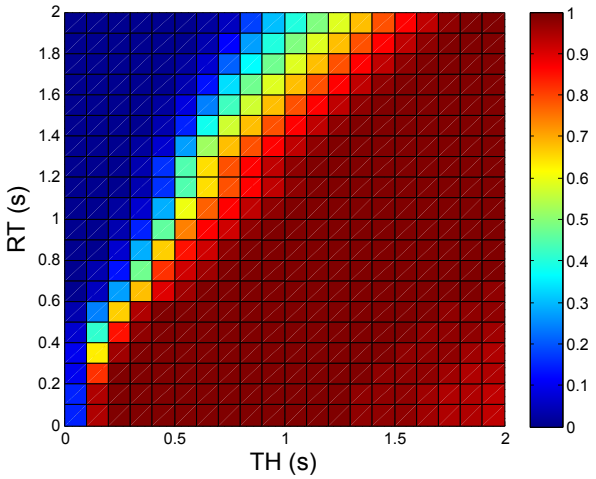


(c) $\Omega^{Moderate}_{Advice}(RT, TH) - \Omega^{Moderate}_{Warning}(RT, TH)$

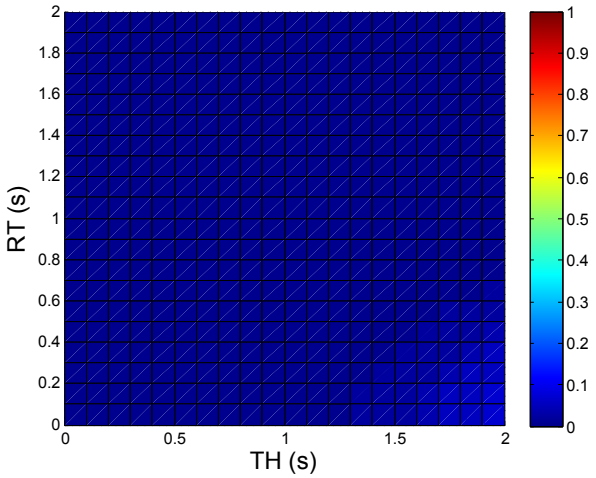
Figure E.3: Added values of advice assistance provided to the Leader, for the situation the Follower has to undergo. With Leader initial speed set at **60 km/h**.



(a) $\Omega^{Collision}_{Warning}(RT, FT)$

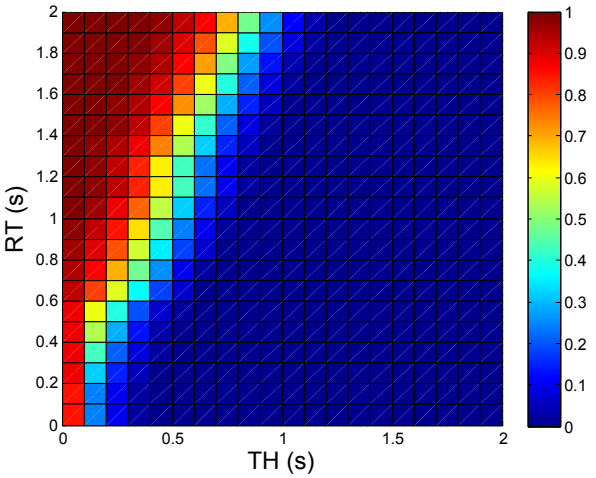


(b) $\Omega^{Hard}_{Warning}(RT, FT)$

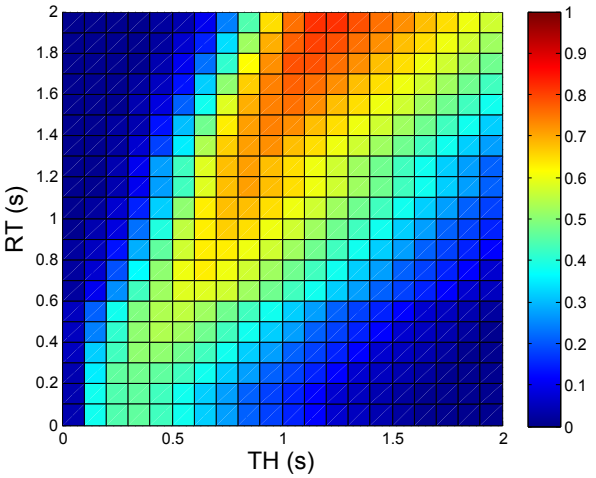


(c) $\Omega^{Moderate}_{Warning}(RT, FT)$

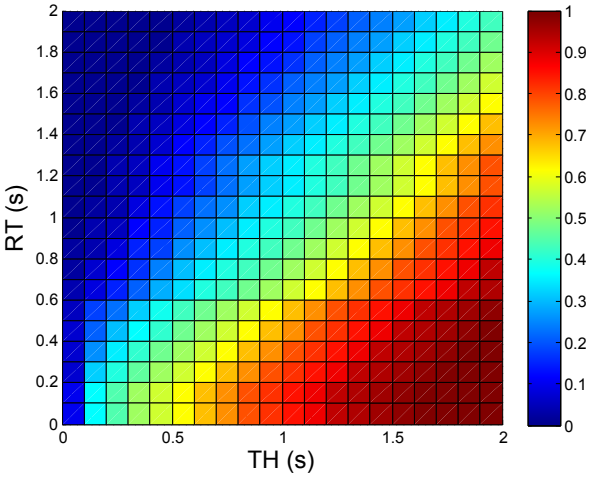
Figure E.4: Results considering that the leader is moving at **90 km/h** and provided with **Warning** assistance.



(a) $\Omega^{Collision}_{Advice}(RT, FT)$

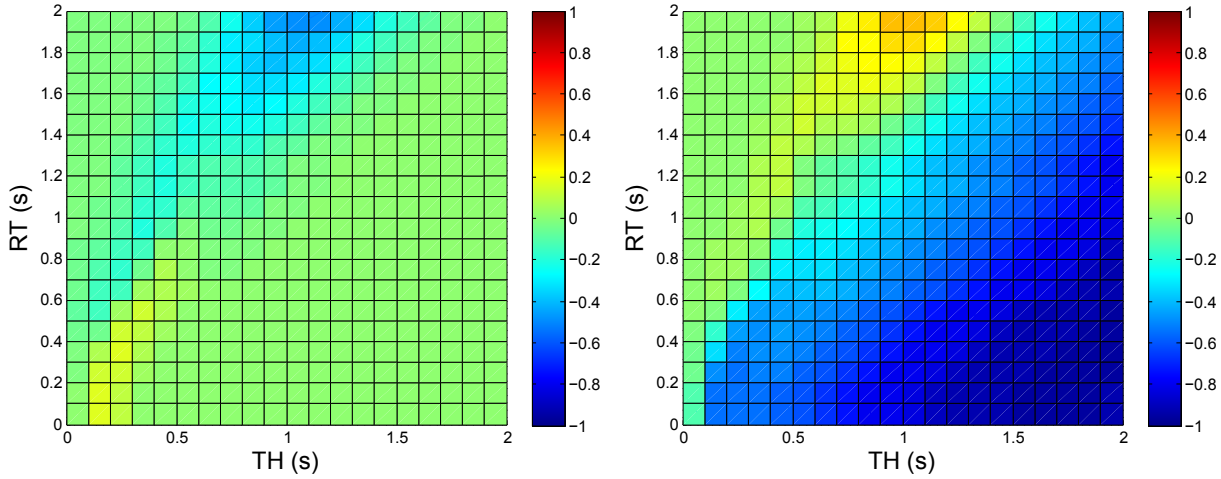


(b) $\Omega^{Hard}_{Advice}(RT, FT)$



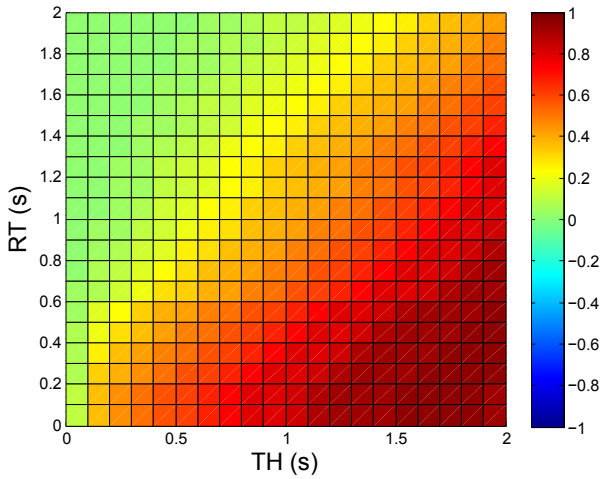
(c) $\Omega^{Moderate}_{Advice}(RT, FT)$

Figure E.5: Results considering that the leader is moving at **90 km/h** and provided with **Advice** assistance.



(a) $\Omega^{Collision}_{Advice}(RT, TH) - \Omega^{Collision}_{Warning}(RT, TH)$

(b) $\Omega^{Hard}_{Advice}(RT, TH) - \Omega^{Hard}_{Warning}(RT, TH)$



(c) $\Omega^{Moderate}_{Advice}(RT, TH) - \Omega^{Moderate}_{Warning}(RT, TH)$

Figure E.6: Added values of advice assistance provided to the Leader, for the situation the Follower has to undergo. With Leader initial speed set at **90 km/h**.

TBS

Terminé BonSoir[1]

[1] With respect to Claudy Faucan.

université PARIS-SACLAY | ÉCOLE DOCTORALE INTERFACES Approches Interdisciplinaires : Fondements, Applications et Innovation

Titre : Compréhension de situation et estimation des risques pour les aides à la conduite préventives

Mots clés : Automobile, aides à la conduite, risque, ontologie, réseau Bayésien, processus Gaussiens

Résumé : Les aides à la conduite dont sont équipés les nouveaux véhicules n'agissent qu'en dernier recours, à cause de leur compréhension de situation limitée. Le but de cette thèse est de considérer les informations contextuelles et la façon dont le conducteur interagit avec l'environnement pour détecter les risques plus tôt que ces systèmes. Les travaux sont répartis en deux phases : la compréhension de situation et l'estimation des risques. La compréhension de situation est réalisée via une ontologie qui permet d'établir les relations spatio-temporelles entre les entités qui sont perçues, et d'identifier lesquelles ont un impact sur la navigation du véhicule. L'estimation des risques est faite par un réseau Bayésien qui prend en compte le contexte, l'état du véhicule, et le conducteur par ses actions et ses individualités qui sont modélisées par des processus Gaussiens. Les résultats montrent qu'il est possible de fournir une assistance plus préventive que des systèmes conventionnels.

Title : Situation understanding and risk assessment for preventive driver assistance

Keywords : Automotive, advanced driving assistant systems, ontology, Bayesian network, Gaussian Processes

Abstract : The driving assistance systems which are embedded in modern vehicles usually suffer from limited situation understanding capabilities, which results in last resort assistance. The purpose of this thesis is to consider contextual information and the manner how the driver interacts with his surroundings, to infer risks earlier than conventional systems. The framework consists of two phases, namely situation understanding and risk assessment. Situation understanding is performed through an ontology. It allows to establish the spatio-temporal relationships between the perceived road entities, and to identify which ones impact the vehicle navigation. Risk assessment is performed by a Bayesian network, which takes into account the context, the vehicle state, the driver's actuations, and the driver's individualities which are modelled through Gaussian Processes. The results show that the framework allows triggering assistance which is more preventive than conventional systems.

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