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Context-Centric Design of Automotive Human-Machine Interfaces

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Abstract

Automotive human-machine interfaces are increasingly relying on situation awareness and context processing in order to improve the safety and user experience. Instead of introducing highly specialized and separated systems, which rely on specific human-machine interfaces tightly connected to the necessary context processing capabilities, this work suggests a bottom-up context-centric approach, designing the entire human-machine interaction around a well-defined context-processing service.

In the first step, the context-centric interface design and all its components are defined.

In the second step, several challenges necessary for successful implementation of the design are identified and dealt with. The biggest challenge is the size and the complexity of the knowledge model, containing all the context-relevant data. In addition, a software platform which implements all the necessary context processing services is proposed.

Two innovative human-machine interfaces and a driving simulator are used to assess the approach. The ability to collect the context-relevant data through the human-machine interface is demonstrated, together with the ability to optimize the context-relevant queries placed by the human-machine interface and driver assistance applications.

Zusammenfassung

Automotive Mensch-Maschine-Schnittstellen setzten zunehmend auf Situationsbewusstsein und Kontextverarbeitung, um ein höheres Maß an Fahrsicherheit und ein verbesseres Nutzererlebnis gewährleisten zu können.

Um die getrennten Insellösungen zu vermeiden, welche eine enge Kopplung zwischen der Mensch-Maschine-Schnittstelle und der Methode zur Kontextverarbeitung aufweisen, schlägt diese Arbeit einen Kontext-zentrischen Ansatz vor. Die gesamte Mensch-Maschine-Schnittstelle wird von unten nach oben auf der Basis eines Dienstes zur Kontextverarbeitung aufgebaut. Darüber hinaus wird die Mensch-Maschine-Schnittstelle eingesetzt um die kontextrelevante Daten über den Fahrer während der Interaktion zu sammeln.

Im ersten Schritt wird das neue Kontext-zentrische Design definiert.

In dem zweiten Schritt werden mehrere Anforderungen für die Implementierung der Strategie identifiziert und gehandhabt. Die hohe Komplexität und die Größe des Wissensmodells bleiben in dieser Hinsicht die größten Herausforderungen. Des Weiteren wird eine Software-Plattform vorgeschlagen, welche die Strategie implementieren und praktisch ausführen kann.

Zwei neuartige Mensch-Maschine-Schnittstellen und ein Fahrsimulator wurden eingesetzt um den Ansatz zu bewerten. Die Möglichkeit der Sammlung und Bewertung kontextrelevanter Daten durch die Mensch-Maschine-Schnittstelle wurde demonstriert. Außerdem wurde die Fähigkeit, kontextrelevante Anfragen zu beschleunigen, demonstriert.

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Chapter 1

Introduction

1.1 Background and Motivation

The current automotive cockpit and its usage model are a natural result of an incremental development of the automobile over the course of one century. It has been shaped by the evolution of both the technology behind the automobile and the goals which the driver wanted to pursue during the drive. The tasks performed by the driver, based upon the current automotive technology, are grouped in three categories: Primary tasks which provide control over the vehicle dynamics, secondary tasks which are important for traffic safety(such as vehicle lighting control and traffic signaling), and tertiary tasks which control the so-called infotainment systems and other non-safety-critical systems. The driver pursues certain goals inside the vehicle, in most cases simply reaching the desired destination with the least amount of discomfort and making the most of the time invested in the drive. As an example, listening to an audiobook might be an important part of this goal. Professional drivers might introduce another goals, one example being driving according to the company rules and guidelines regarding fuel consumption, and can place a different emphasis on other goals, such as using specialized communication and infotainment equipment to stay in contact with the headquarters. All these goals are reached by executing a composite of sub-activities, such as route planing, performing sudden and event-triggered maneuvers, staying alert, having a conversation with passengers or over on-board communication systems, etc. Designing and implementing a system which supports the user in such activities, improves user satisfaction and safety while reaching existing goals and making new goals possible is the mission of the presented work in the area of human-machine interaction.

Several external factors affect the future development of the human-machine interfaces(HMI) inside the cockpit and have to be appropriately taken into account:

1. Increased level of automation
2. Centralization of system architecture
3. Introduction of drive-by-wire systems and alternative steering devices
4. New personal mobility concepts
5. Standardization of infotainment platforms
6. Integration of human-machine interfaces and driver assistance systems

An overview of the external factors is provided in the following.

1.1.1 Increased Level of Automation

As the level of automation of driving-related sub-activities increase, other in-vehicle activities will gain importance, while completely new activities will emerge. Right now, the driving route can be completely plotted by a navigation system, meaning that the driver can focus on following the system's instructions and delegate the high-level strategic routing decisions. Further development of advanced cruise control, lane keeping assistant and related functionality which increases overall vehicle automation slowly removes the driver out of the driving loop. A large number of vehicles supporting fully automatic and autonomous operation, called the CyberCars, have already been built and road-tested in the scope of several European Union's research projects[1, 2]. Vehicle manufactures will most probably introduce several intermediate steps, in which the vehicle occasionally requests the driver to take over the control of the vehicle. This might be necessary in very complex traffic situations, in which the vehicle is unsure about the right course of action, due to the limited sensor technology, connectivity and computing power and due to the large number of other non-autonomous vehicles. Keeping the driver in the loop is also important due to the current legislative framework, taking the Vienna Convention on Road Traffic as an example. It states that the driver always has to exhibit full control over the vehicle, full control being defined as a combination of control over lateral and longitudinal vehicle dynamics[3]. It is imperative that the driver can rapidly assess the situation and perform a safe switch between his current task, such as reading the news using the infotainment system, and the driving task. Otherwise, the operator might find himself in the situation where 99%

of the time is spent in boredom and 1% in panic[4]. To summarize, the intermediate steps will mostly likely be driven by the high technical complexity of autonomous systems, total system cost and legal background.

1.1.2 Centralization of System Architecture

The system architecture inside the road vehicles is currently undergoing centralization and grouping, in order to reduce the complexity stemming from a large number of heterogeneous interconnected electronic control units(ECU). The traditional federated architecture is being more and more replaced by the integrated architecture, a concept from the integrated modular avionics domain[5]. One of the goals of the new approach is to implement new functionality on the software level, similar to the plug-and-play installation of drivers on a desktop computer, avoiding the extensive integration of a physical ECU with every new vehicle function. The complexity is therefore migrated to the software and system architecture level, since a comprehensive vehicle runtime environment has to be able to accommodate appropriate software services and provide real-time guarantees for safety-critical functionality[6, 7, 8, 9]. Similar trend can be observed in the area of human-machine interfaces, through the grouping of human-machine interaction-related functions into heavily integrated modules or architectural frameworks. As an example, an already existing product is the Universal Display and Control Unit(UDCU) developed by Continental Engineering Services. Examples of the replacement of the physical human-machine interface elements by an integrated software solution are the virtual dashboard and the single-screen infotainment systems. Prototypes and complete products have already been introduced by Garmin in the form of the K2 system and Tesla Motors and Rimac Automobili head-unit and touchscreen infotainment systems. Physical integration makes the execution of a uniform human-machine interaction strategy more cost-effective, since it reduces the integration complexity.

1.1.3 Introduction of Drive-by-Wire Systems and Alternative Input Devices

Several drive-by-wire systems are currently being introduced to the market, eliminating the need for a mechanical connection between the driver and the drive train. In their present form, due to the prohibitive cost involved in building a redundant electronic system with an acceptable level of safety, they are limited to niche markets, such as the vehicles for physically impaired drivers. Widespread deployment of drive-by-wire systems could enable drop-in replacement of the current automotive human-machine interfaces with arbitrary physical devices[10]. Even before the initial introduction of drive-by-wire systems, the introduction of mechatronic actuators reduced the amount of physical force necessary to operate a road vehicle. Servo actuators are the simplest example, but the electronic handbrake and automatic gear shifter also reduce the amount of physical effort required from the driver. Even further reduction is present in the aforementioned niche market of vehicles for physically impaired drivers, in the form of joystick-based steering solutions. Examples of certified commercial solutions for a joystick-controlled drive-by-wire systems are the EMC Digidrive II, Hand Pro AS VS 500 JS, Audoadapt AB PVM and Paravan-RAFI Space Drive system [11]. A modification of the Paravan-RAFI system, outfitted with a prototypical sphere-sidestick steering device, was installed in the Innotruck vehicle. Innotruck is the prototype vehicle of the project Diesel Reloaded and will be mentioned throughout this work. One downside of a drive-by-wire system, in the case that appropriate force feedback is not present, is the lack of information feedback from the controlled system. The driver can only feel the dynamics of the controlling element, but not of the controlled system [12]. The lack of system feedback and the solving thereof through force feedback is further discussed in the following chapter.

A maximal reduction of physical engagement is present in the domain of medical devices. There are medical conditions which prevent afflicted patients from using their limbs at all, requiring signal extraction from the motor nerve endings or directly from the brain. The brain-computer interfaces, as the last possible step towards driver intent detection and extraction, are still too unreliable and unpractical for everyday use in road vehicles. At any rate, they can provide a certain level of autonomy and personal mobility and increase the quality of life for users with severe medical conditions. Continuous vehicle steering with such an interface remains a tedious, error-prone and practically impossible task, but making point-to-point decisions, even in a road vehicle, is already feasible [13].

1.1.4 New Personal Mobility Concepts

Car sharing is taking off as major trend in large urban areas and it is assumed that this business model will further benefit through the introduction of hybrid and electric vehicles to the market, as well as through the popularization of combined traffic solutions. Transfer of a personal user profile between different vehicles and different vehicle types can be used as a competitive advantage between different car-sharing service providers. The personal profile can affect different vehicle aspects, from vehicle ambient lighting to infotainment and steering sensitivity. Therefore, the success of such product types could heavily rely on the human-machine interaction concept[14, 15].

1.1.5 Standardization of Infotainment Platforms

In order to keep the pace with the short development cycles present in the domain of consumer electronics, the automotive sector is undergoing several attempts to provide a standardized a common runtime platform for non-safety-critical applications in the automobile. Open Automotive Alliance[1] and GENIVI[2] are the most prominent examples, offering respectively Android and Linux as the underlying operating system. Car Connectivity Consortium[3] offers a different approach, by letting the users bring their own device to the vehicle and attach it over the Mirrorlink protocol. Since Linux-based or pure Linux solutions have a very good hold on in-vehicle infotainment, the virtual dashboard built in the scope of this thesis for the Innotruck has been based on Linux. The jambit HUML MirrorLink® client stack[4] was found to be completely compatible with the Linux-based virtual dashboard in the Innotruck in October 2013.

1.1.6 Integration of Human-Machine Interfaces and Driver Assistance Systems

Driver distraction is a large cause of traffic accidents and the resulting loss of lives, injuries and property damages. Several factors might amplify its significance in the years to come: Information overload from numerous different on-board driver assistance systems, vehicle connectivity, introduction of personal mobile devices without proper integration and infotainment systems for passengers. In this context, distraction can be simply defined as *attention given to a non-driving related activity, typically to the detriment of driving performance* [16]. Existing design principles, such as the European Statement of Principles on the Human-Machine Interaction, often provide vague recommendations regarding the cooperation between human-machine interfaces and driver assistance systems, such as *interfaces and interaction with systems intended to be used in combination by the driver while the vehicle is in motion are consistent and compatible*[17]. This leads to the situation where, as stated by Rogers et al. in their work on adaptive user interfaces, the developers thread the thin line between serving the user's needs and not causing unnecessary safety risk [18].

[1] Open Automotive Alliance: http://www.openautoalliance.net/
[2] GENIVI Alliance: http://www.genivi.org/
[3] Car Connectivity Consortium's Mirrorlink protocol: http://www.mirrorlink.com/
[4] jambit HUML Mirrorlink® Client Stack: http://www.jambit.com/huml

The value proposition of the assistance systems and their integration with the human-machine interfaces therefore lies in the areas of safety, workload reduction and general prestige which goes hand-in-hand with high-tech in-vehicle systems[19]. Since such systems most directly determine driver's experience inside a vehicle, it is important to consider them from a product-oriented point of view. The importance of assistance systems is normally conveyed via the categories of reason(they are well-designed and tested) and fear(they reduce the danger). The category of fun is not conveyed often enough, especially since many assistance systems take away direct control from the user, which might be seen as an overall reduction of driving fun. The user is defined as somebody who needs to be assisted, needs to observed and constantly warned when he leaves the baseline behavioral profile[20]. There is, however, a possibility to communicate and advertise the new assistance systems as a way of augmenting the driver, extending his perceptive abilities and relieving him from the loss of time incurred by the tedious driving task. If the vehicle has to learn the driver's profile, it should do so in a passive and non-invasive manner, without requiring constant driver affirmation and feedback. To summarize, the integration of human-machine interfaces and driver assistance systems has the ability to yield a net benefit in traffic safety and user experience and must be taken into account in the HMI design strategy.

1.1.7 Summary

The challenges stemming from all the identified factors, which are only amplified by their parallel influence on the market, are the physical and logical integration of previously physically and logically separated technical systems. The commands provided by the user no longer have direct effect on a specific and separated vehicle subsystem. As an example, driver's braking intent is interpreted by the anti-blocking systems and the electronic stability program, on the basis of driver input and contextual data relevant to the driving situation, wheels' reaction being one of them. Such interpretation is going to extend throughout all vehicle systems, both on the input path(driver is giving commands) and on the feedback path(the vehicle is presenting information to the driver).

The integration of several physically separated human-machine interface devices into a single and more functional device is driven by technological advancement and integration costs. This will continue to be so in the future, since design flexibility and faster product refresh cycles will have to be introduced to the automotive cockpit. The other aspect of the integration is the logical one, meaning that the more and more physically integrated devices have to execute a joint human-machine interaction strategy. What this means is that they all have to gather pieces of user input, such as eye movement and touchscreen activity, and interpret them at the point where all context-relevant data is known. The same applies for control of the feedback towards the user - all the human-machine interface devices must execute a joint information presentation strategy. The basic elements necessary to execute a joint strategy are, apart from interconnected physical human-machine interfaces, a knowledge model and a reasoning engine capable of correct input interpretation and correct information presentation method. However, the added complexity of context processing should be abstracted from the application space i.e. from the software components which require context-relevant data. The separation has to be achieved through a well-defined interface, based on open standards, in order to assure portability and compatibility with existing in-vehicle technologies. The software components can be simply denoted as human-machine interface and driver assistances applications. They must be able to add their own context interpretation rules and directly contribute to the knowledge model, all over the well-defined interface. Driver state assessment represents the most significant input to the knowledge model, apart from deterministic determination of dangerous driving situations. Therefore, driver state assessment must be able to directly influence the entire existing context description.

To summarize, a context-centric human-machine interaction strategy is needed in order to appropriately leverage all of the factors affecting the future developments in the automotive domain. The physical integration of human-machine interfaces should be followed by a logical one, meaning that there should exist a single input interpretation and decision-making point inside the vehicle's system architecture. Special focus must be placed on context processing and situation-aware human-machine interaction, therefore implementing the basic elements of artificial intelligence inside the vehicle. Indeed, the interaction strategy should provide the user with an intelligent user interface - a term coined for interfaces which are coupled with learning capability, a knowledge model and a reasoning engine. Context-relevant data needs to be collected by observing the driver through the human-machine interface, in a passive, unobtrusive and transparent manner.

The rest of this chapter is organized as follows: the goals of the thesis are presented in section 1.2, the main contributions in the section 1.3 and an overview of the entire thesis is given in section 1.4.

1.2 Goals of this Thesis

There are two goals of this thesis. The first one is the definition of a new human-machine interface design for road vehicles, based around a well-defined context processing service.

The second goal is solving several theoretical and practical issues which arise during the implementation of the design. The term transparent driver assistance is introduced, denoting a driver assistance system which gathers context-relevant driver data through observation of the user input through the human-machine interface. A link between human-machine interface and driver assistance applications and context processing is established, through a proposed software solution called the Probabilistic Application Layer. This goal contains the main scientific contribution of the thesis, while the first goal prepares its conceptual and architectural framework.

1.3 Main Contributions of this Thesis

The three main contributions of this thesis are in the areas of signal processing and exact inference on probabilistic models, directly related to interaction context processing and acquiring context-relevant data through future human-machine interfaces.

Fatigue detection is performed upon the driver, based on the signal input provided by the brain-computer interface in a driving simulator. A secondary part of this contribution is increasing the signal fidelity by removing the vibration artifacts with the help of a gyroscope.

Detection of irregular steering trends is performed, based upon the signal input provided by the side stick in a driving simulator.

Exact inference on a Bayesian knowledge model is extended by quality-of-service requirements, by the means of an optimization criteria which extends the well-known junction tree algorithm.

1.4 Structure of this Thesis

This thesis is composed of 7 chapters.

Chapter 1 gives an overview of the thesis and its purpose.

Chapter 2 provides a broad overview of the current state-of-the-art in the area of human-machine interaction in road vehicles and speculates on several future HMI concepts.

Chapter 3 suggests a context-centric human-machine interface design and presents all its key components and concepts.

Chapter 4 presents the horizontal design of the human-machine interfaces in the Innotruck prototype vehicle, which is a transition step toward the context-centric design.

Chapter 5 focuses on context processing and presents an optimization method for exact inference on Bayesian network used to model the interaction context.

Chapter 6 focuses on collecting context-relevant data through the human-machine interface, showing how the HMI can be used to passively observe the driver.

Chapter 7 concludes with a summary of all the main results and presents future research questions.

Chapter 2

Background: Human-Machine Interaction in Road Vehicles

This chapter introduces the reader with the key concepts of human-machine interaction in road vehicles, while providing an overview of current state-of-the-art research and currently developing commercial solutions. At the end of the chapter, several suggestions for future research are given, with the focus on areas of interest for this thesis.

2.1 Basic Concepts of Human-Machine Interaction

In order to define the basic concepts of human-machine interaction, we start with a much more familiar concept of human-human interaction. In a proposed typical person-to-person interaction, person A and person B converse about a topic T while standing close to each other, like shown in Figure 2.1. They use voice and gestures to communicate and these communication channels have a specific bandwidth at their disposal. This is an intentional and expressive form of communication, made possible by the understanding of human language and meaning of intentional gestures. Another form of communication takes place in parallel to the intentional one and it uses body language, unintentional gestures, prosody, and all the remaining observable unintentional signals. The interpretation of these signals takes place both subconsciously and consciously and it can be, for the most part, learned. Assessing the bandwidth and the amount of actual transferred information is difficult, but the mutual understanding generally increases if a person observes and interprets other persons' body cues and signals. To summarize the example, the emphasis is placed on observing the additional data, superposed on the intentional expressive data, and interpreting this additional data in its context.

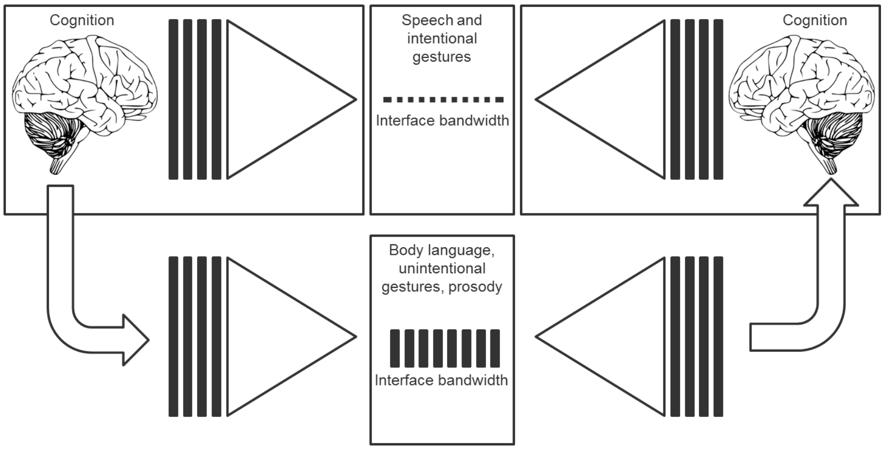

Figure 2.1: Human-human interaction implies a large amount of context processing

The human-human interaction is now compared with the problem at hand i.e. with the interaction between a person and a technical system. The human, further denoted as user, pursues a certain goal and interacts with the system in order to achieve it. The goal might be, for example, entertainment, manipulating a complex technical system in a factory, or traveling to a certain destination. At any rate, inputting signals to the technical system is necessary and it is mostly performed by two methods - by moving various body parts which are connected to(hands on steering wheel) or observed by(cameras focused at the hand gestures) the technical system and by voice control. Sensors and translators translate the user input into raw input data, which the system interprets and reacts to, in according to its context processing and situation awareness abilities. During this process, feedback is given back to the user, to keep him informed about the consequences of his actions and the overall system state. Regarding the feedback, the machine has the option of using all of our senses, most common examples being vision, hearing, force and haptic/touch feedback. The possibilities for improvement therefore lies in three different interaction stages:

1. User input

2. Situation awareness through context processing

3. Feedback output

As shown in the Figure 2.2, human-machine interaction features a certain asymmetry between the interaction participants, due to different modalities used for data input and output. It is possible to improve the user data input and the feedback methods through improvements in sensing and data presentation technology and introducing new human-machine interface devices, such as controlling sticks(joystick, sidestick and similar devices for primary vehicle control). In this work, focus is placed on the third area for improvement - situation awareness through context processing. In addition, focus in placed on user input processing, in order to to extract the additional data which the user unintentionally superposes to the intentional input. This is similar to the example of human-human interaction, in which one person reads body language and picks up the nonverbal cues.

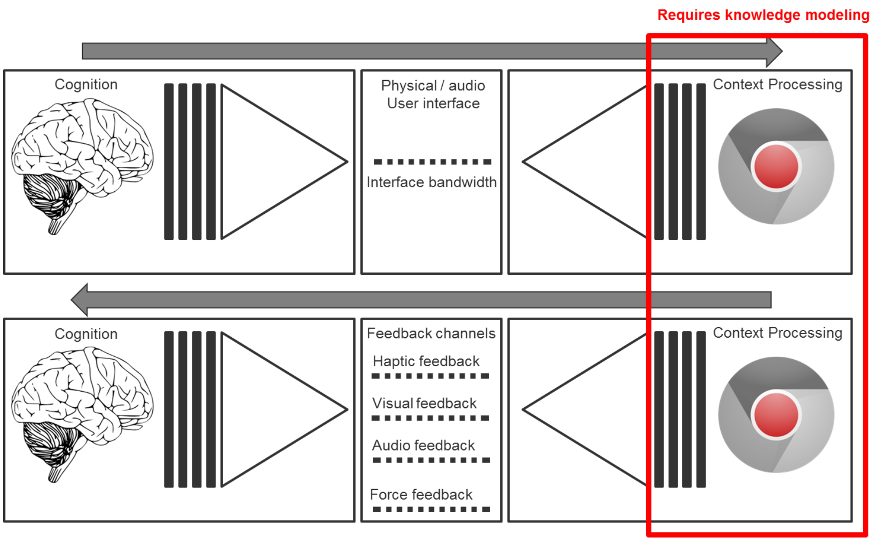

Figure 2.2: Human-machine interaction must implement a significant amount of context processing in order to reach a satisfactory level of situation awareness

In the following, an overview of the historical and current research in all three areas for improvement is presented, ending with an introduction of the contribution provided by this work.

2.2 Integrated and Semi-Autonomous Interfaces for Primary Vehicle Control

An integrated joystick-based solution for vehicle control has been proposed as early as 1962, in a patent issued to General Motors[21]. Even though the integration of multiple degrees of freedom into a single device has many advantages, several disadvantages have been recognized. Most notable are cross-coupling between lateral and longitudinal control and the effect of inertia on the user's body and the controlling stick. Drivers have also experienced increased cross-coupling issues when more than two dimensions have been mapped to the stick. It was therefore suggested to use the additional degrees of freedom only with low speeds and in the cases where additional vehicle maneuverability is needed, or to use a separate steering element for such maneuvers, like a space mouse[22].

The literature in the area of human-machine interfaces contains many comparisons between the horse carriage and the automobile. One reason is the historical development of the automobile, which has effectively replaced the animal-based vehicles. Therefore, many properties of the automobile, such as its power, comfort and steerability, were compared to the ones of the horse and carriage by the automobile manufacturers. Another reason for the comparison, much more interesting for this work, is the common analysis of the benefits of automated technical systems in comparison to manual or animal labor-based systems. An inanimate technical system, built for one specific task and purpose, indeed often has the upper hand over a *biological* solution to the same problem. Even if power, endurance and all the energy-intensive aspects of the comparison are excluded, a technical system can be more humane, easier or cleaner to operate(in the terms of additional processes necessary to maintain the machine) and can release previously bound human and animal resources for more suitable or enjoyable tasks, be it another type of work or leisure. One downside of the technical system is its lack of intelligence. Therefore, it must be overseen and monitored by a qualified human. The monitoring aspect can become repetitive, error-prone and even dangerous, depending on the type of the technical system and the spectrum of dangerous and unpredictable situations which can occur during the operation[23]. Different assistance systems and HMI concepts arise to fill this gap and exactly at this point the literature starts to provide a plethora of comparisons and benchmarks. The main problem remains unchanged - a technical system must acquire task-related intelligence, learning skills and the ability to adapt, requiring different situation awareness and context processing methods, which an animal or a human currently perform far better. An artistic reference to this issue, albeit debatable since the true meaning of the painting remains unknown, is given by Salvador Dali's reaction to Pablo Picasso's Guernica in 1938, through his work *Debris of an Automobile Giving Birth to a Blind Horse Biting a Telephone*, shown in Figure 2.3. This remains the only artistic reference in the scope of this thesis.

The horse reins were, in a sense, high-level instructions which were interpreted and executed by the intelligent animal. Here lies both an advantage and a pitfall, since a direct control of vehicle dynamics is impossible, but a higher level of safety is provided. The automobile commercials at the very dawn of this industry often ventured in this direction and tried to place an accent on the increased level of vehicle control and downplay the increased complexity of driving.

An advertisement from 1905 stated that *"the control of Type XI Autocar brings automobile driving to the simplicity of horse driving. In the rim of the steering wheel, and forming parts of it, are set two grips, one at the right hand, one at the left. These two grips control the throttle and the spark, regulating the speed of the car from 3 to 35 miles an hour."*

Another advertisement from 1903 interestingly claimed that *"the controlling mechanism is simple, strong and instantly responsive to the will of the driver, giving a sense of perfect security."*[23]

Figure 2.3: Salvador Dali: Debris of an Automobile Giving Birth to a Blind Horse Biting a Telephone

The horse metaphor culminated in the projects H-Mode I and II, a cooperation between the Chair for Ergonomics of the Technische Universität München, represented by Prof. Klaus Bengler and Prof. Schieben, and the Institut für Arbeitswissenschaft(IAW) der Rheinisch-Westfälischen Technischen Hochschule(RWTH) Aachen. The projects were funded by the Deutsche Forschungsgemeinschaft(DFG). The goal was to create an intuitive, multi-modal interaction concept for control of highly automated vehicles, taking the interaction with a horse as the inspiration and placing an emphasis on haptic feedback. Visual and acoustic feedback is also used, although its use is kept at a minimal level. Related work by Prof. Frank Glemisch from Deutsches Zentrum für Luft- und Raumfahrt(DLR) emphasizes the importance of human-machine cooperation in the light of the improvements of artificial intelligence and suggests a steering concept which enables control of both land and air vehicles[24, 25]. Indeed, a single device for primary vehicle control can be used for controlling different vehicle types, but more evidence might be needed to support the meaningfulness or practicality of such approach. With a high enough level of automation, the driver(or pilot) could control the vehicle over a very simple interface not related to interfaces for continuous steering, which does not have to have the same physical manifestation for different vehicle types. A comparison is also made with the classical user illusion provided by the graphical user interface of a personal computer, hinting at a need for a similar generalized abstraction layer for different types of vehicles. Comparisons between avionics and automotive technology historically go deeper in related work, starting from x-by-wire comparisons, over the entire redundant system architecture, autopilots/assistance systems and ending with the comparisons of individual physical human-machine interfaces. Such technology transfer between different mobility domains would depend on a multitude of factors, most notable being the underlying business models and the required safety levels with the accompanying legislative measures. Even though HMI components in the avionics sector might provide higher safety and an overall better ergonomic experience, it is important to recognize the different usage profiles and specific ergonomic needs of the automotive sector.

H-Mode experiments inside a driving simulator and with a Stirling Dynamics side stick have shown that the principle of two dimensional control interfaces with position reflective force feedback is a promising concept for cooperative vehicles[26]. As opposed to the force reflective feedback, in which the side stick always attempts to move back to the middle position with a defined spring force, the position reflective force feedback does not allow the user to control the system faster than the controlled actuators can physically move. In other words, position reflective force feedback provides an illusion of a direct physical control of the actuators. It takes the physical force the user is exerting onto the control element as input and positions the control element according to the real physical position of the controlled actuators. The RAFI steering system installed in the Innotruck experimental vehicle and presented later in this thesis features a position reflective force feedback.

Based on a multitude of positive studies on the haptic feedback for vehicle steering[27, 28, 29, 30], following key advantages have been pointed out, focusing on the approach when the feedback is provided directly at the steering element [31]:

1. Feedback is created directly at the element which the user is requested to manipulate

2. A hint on the requested corrective action can be given by automatically performing the first step of the corrective action

3. The bi-directional nature of the haptics enables quick resolution of conflicts between the driver and the automatic system i.e. arbitration

Following upon the horse metaphor, two steering profiles are introduced - tight rein and loose rein. Tight rein appropriately denotes the steering profile in which the driver has direct control over the vehicle dynamics, while loose rein denotes a profile where the vehicle automation takes over, mirroring the instincts and common sense of an intelligent animal. A lane keeping scenario was selected for the experiment, using the haptic feedback with three intensity levels - informing the driver, warning the driver and intervening. Loose rein profile provided more force feedback in all three levels, thereby bringing the vehicle back into the middle of the lane even without the driver intervention. The results showed that both profiles are well-accepted, with the loose rein profile being acknowledged as more useful. Both profiles were found to be easy to learn and more intuitive. Cognitive and physical load and effort were reduced with loose rein profile and both profiles provided an overall better experience than the unsupported manual driving mode[31].

In another H-Mode contribution by Kienle et al., an existing and affordable side stick design has been shown to be resilient to vibrations and forces caused by vehicle dynamics[12].

A study by the Swedish National Road and Transport Research Institute identified following risks in joystick-controlled cars used for drivers with severe disabilities[11]:

1. Time delay in the control system
2. Braking difficult to learn
3. Interference between acceleration/brake and steering

Nevertheless, such vehicles contribute to increased personal freedom and a higher quality of life. In regards to the personal adaption of a joystick steering system, the following possibilities have been identified:

1. Force required to operate the joystick
2. Length of the joystick operating control
3. Size of the working range
4. Control directions for accelerating and braking
5. Progressive function for lateral control

These remarks are comparable to the ones established in H-Mode and were taken into account during the design of Innotruck's cockpit.

The approach suggested by Prof. Gernot Spiegelberg goes one step further than H-Mode and suggests that the entire purpose of the human-machine interface for primary vehicle control consists of the extraction of a quantity called the motion vector from the driver[32]. The motion vector is a classical n-dimensional mathematical vector, with a direction and length, denoting the desired vehicle direction and the amount of throttle/braking which the driver wants to execute at a given moment. It is further suggested that reducing the driver's input to this quantity can reduce the communication load on the vehicle information and communication technology(ICT) architecture, since a relatively small quantity of data is being communicated to other vehicle modules and components. It is assumed that an in-vehicle component called the virtual co-driver can be engineered, with the ability to assess the environment on its own and, combined with the known destination and other context-related data, suggest its own motion vector in any given moment. The comparison of the two motion vectors, the one from the driver and the one from the virtual co-driver, over the course of time, is assumed to be a valuable source of information on the driver mental and physical state. If the driver is found to be in danger(with a high enough probability which makes the decision practically and legally deterministic), the vehicle can start executing the motion vector coming from the virtual co-driver and ignore the motion vector inputted by the driver. Furthermore, it is suggested that the motion vector or a derivation thereof can be extracted through a brain-computer interface, which would result in the ultimate human-machine interface for road vehicles.

Figure 2.4: The motion vector approach assumes that the driver continuously wishes to move the vehicle in a certain direction with a certain speed, analog to moving her/his own body

Even though vehicle movement in a specific direction and with a specific speed is the ultimate result of the driver's interaction with primary vehicle controls, this approach seems to be a rather practical one, focusing on engineering and on the stick as the input device. When using a vehicle with a classical HMI, with a steering wheel and pedals, constructing the motion vector is of course possible, but brings added value only when combined with other assistance systems in the theoretical virtual-co driver, which are yet to be implemented. When driving with a joystick, it is clear that the user input will inherently be translated into a motion vector, so the existence of the motion vector becomes the result of using this specific input device. When operating a brain computer interface, focusing on the heading and the amount of speed/power might be a practical signal-processing choice, but it makes the interaction very tedious for the user, since it requires continuous focusing on the mental production of the motion vector. Looking at the destination and evoking the wish to walk to it might be a better choice, but reading out such activity is, from the engineering point of view, significantly harder than producing a limited set of brain activity like heading and power. It is currently impossible to assess the hypotheses that our body produces an quantity denoted as internal motion vector when we desire to walk to certain point, since the neurological processes involved in path planning and decision making of our brain are still being heavily researched. In the case that the real physical link(perhaps a neural pathway consisting of motor neurons - a vague assumption based on current state of research) between a theoretical brain strategy level and the body execution level were to be found, meaning that a theoretical connection through which the brain strategy level provides simpler instructions to the lower-level execution regions responsible for coordinating our gait were to be identified, it can be assumed that a translator of this data could be constructed, which would indeed extract a meaningful motion vector. Since such neural connections and brain regions originally arose for the purpose of controlling our bodies, it could be speculated that very intricate feedback methods, simulating the responses from our body and other brain regions, would be necessary in order to create a walking illusion which could be utilized for vehicle operation. The question if the drivers would prefer to use their vehicles like they currently use their bodies is far from answering and the entire problem framework might not be suited for the automotive domain, but rather for military, space or other exoskeleton-based vehicles and full body armors.

The advantages of mobility systems which follow the design guidelines of the human body are unclear, since a large-scale benchmark or a comparison with other types of design guidelines has not yet been made. The mechanisms enabling control of our bodies have developed based on a set of constraints which do not have to be followed in the design of technical systems. One of them is the signal latency of the human nerve fiber, which requires redundant and decentralized low-level body control mechanisms. Studying the human body and its functional understanding is, without doubt, extremely important. However, real evidence is necessary to support the potential benefits for the human-machine interaction in road vehicles.

Conduct-by-wire(CbW) is a concept for highly automated vehicles, which also takes the previously presented loose rein profile one step further. The driver does not have to execute the road following task at all, since this is done automatically by the in-vehicle assistance systems. The driver's role is reduced to starting and stopping completely automated maneuvers, using a so-called *maneuver interface*. This interface has to additionally provide the possibility to revert to manual driving, but it is expected that a highly automated vehicle will not require such low-level tasks from driver most of the time. The vehicle can request a maneuver from the driver in case of an unclear traffic situation or a situation in which the planned vehicle trajectory intersects with the one of another vehicle. These event-triggered maneuver requests are also called gates and are virtually placed along the planed vehicle trajectory. If the driver fails to timely produce a decision, the virtual gate stays closed and the vehicle must be immediately brought to a safe stop. The CbW approach proposes a vehicle system architecture built around an automation block, which performs maneuver management and controls the drive train. The automation block receives both sensor data and user input and manages the global and local automatic driving tasks. In this sense, this architectural suggestion presents the current state of the art in research regarding system architectures for transition to autonomous and automatic vehicles[33, 34].

Even though several attempts to create a human-like personal assistant inside a road vehicle have been made, recent research in the area of highly automated vehicles has shown that the interaction concept does not have to be human-like, but human-compatible[35, 36].

To summarize this section, Flemisch et al. propose following transitional automation grades in a vehicle[25]:

1. Manual vehicle control
2. Assisted driving
3. Semi-automated driving
4. Highly-automated driving
5. Fully-automated driving

As the level of automation rises, it is critical to keep the driver in the loop, provide him with an understandable mental model of the automated system and its functional borders. In other words, the user has to understand his current driving situation and the current system mode at all times [37]. Driver state assessment and increasing the driver's trust in automation therefore became major research topics in the recent years.

2.3 Driver Assessment and Trust in Automation

In order to improve the road safety with current and future automated vehicles, it is vital to monitor the driver's physical and mental condition. Since the driver takes the role of the system supervisor in highly automated vehicles, the assessment is vital in order to determine legal responsibility in the case of an accident [38]. This can be done with specialized in-vehicle sensors, or by using the data already provided by the human-machine interfaces. Detecting biosignals would be the best option, since the possible problem would be detected at its biological source and not by indirect observation of its effects on human behavior. An overview of the importance of various biosignals and their reliability for detection of medical emergencies is given in Table 2.1[38].

Table 2.1: Reliability of biosignals for detection of medical emergencies. On the scale from 0 to 3, where 0 denotes complete lack of reliability, while 3 denotes maximal reliability.

Biosignal	Cardio	Epilepsy	Syncope	Sugar shock	Stroke	Sleepiness
Electrocardiogram	2	3	2	1	3	3
Plethysmography	2	3	2	1	3	3
Blood pressure	2	3	2	1	3	3
Electroencephalography	0	2	0	0	2	2
Blood sugar	0	0	0	3	0	3
Skin conductivity	0	0	0	0	0	2
Respiratory rate	1	3	3	1	1	1

Due to their outstanding reliability for detecting a wide range of emergencies, Bartels et al. chose to pursue the sensors focusing on the cardiological biosignals[38]. Since such sensors cannot currently be used as a human-machine interface, the rest of the research is not of relevance for this work, but it is important to point out three identified requirements on the sensor technology for driver assessment:

1. Non-invasive

2. Contactless or with minimal contact
3. Robust against artifacts caused by movement, external forces, environmental lighting and other sources

The approach presented in the following chapters of this thesis focuses on non-invasive and robust sensing technology, which functions as both a human-machine interface and a driver assistance system.

The importance of in-vehicle cameras has been recognized, especially for observing the driver's eyes[38]. The same sensor could be used for gesture recognition or assessing the cognitive load through behavioral cues, during the interaction with the HMI or with the passengers. Even though several setups with Microsoft Kinect sensors and hand/finger gesture recognition were evaluated during the work on this thesis, the camera-based sensors were not in its main focus, were not experimentally evaluated and are not mentioned further on in this work.

Taking a look at devices focused solely on data presentation inside the vehicle, heads-up displays(HUD) represent an excellent solution for information directly related to the driving task. The information is projected in the driver's field of view and can be meaningfully overlaid onto the observed driving environment. The information can be presented in the infinity focus, reducing the time necessary to shift the vision from the road to the presented information. It has been shown that the constant representation of the vehicle's current state with the HUD increases the driver's confidence or his trust in automation, emphasizing its importance in the transitional steps[37]. Necessary steps for a full integration of a HUD from the avionics domain inside the Innotruck experimental vehicle is presented in[39].

Another approach to implementing user-friendly interfaces in semi-autonomous vehicle is the team-based cooperation approach between the human and the vehicle. Humans exhibit inconsistent behavior, may have difficulties in defining own preferences, act in according to their emotions and their efficiency in problem solving is strongly dependent on the problem context. The key to the successful human-machine interaction lies in solving these issues, together with joint consideration of users' psychological, behavioral and cognitive models[40]. Driver characterization is deemed essential for adapting automated systems and a relatively large importance is placed on observing the driver's interaction[41]. Another identified issue arises when using computer agents to guide the behavior of human operators, one example being navigational software in automobiles. Even though the user and the computer agent both want to move from one location to another, the user might want to disregard all the time or energy optimization criteria and act solely on his own preferences, such as interesting landscapes and familiar routes. Therefore, the automated system must be able to learn from its own failed suggestions and balance the objective benefit(such as energy savings) with the user's own preferences. In order to model such interaction, game theory has been utilized and a so-called choice selection process implemented. It is based on the social utility approach, which has been shown to outperform all other approaches while combining models of human behavior with machine learning[42]. Goldman et al. propose defining the human operator and the machine as a team, putting the mutual support, mutual commitment, machine transparency(current system state, behavior and control), user transparency(user state, intent, action) and responsiveness into the focus. The cooperative team-oriented human-machine interaction is demonstrated on the example of a generic full speed range adaptive cruise control system.

The single most related work to this section is the project Adaptive Integrated Driver-Vehicle Interface(AIDE) from the European Union Sixth Framework Program[43]. It placed particular focus on the human-machine interface integration and adaptation in the scope of the automotive HMI. This comprehensive project ran between 2004 and 2008 and produced several results which are essential for this thesis. In particular, the AIDE Sub-Project 3 dealt with developing methodologies and technologies for the design and validation of a highly-integrated driver-vehicle interface. Three vehicles have been chosen as demonstrators: A heavy truck, a luxury car and a city car. The AIDE system was developed as an overall manager of the in-vehicle HMI, which executes AIDE design scenarios. A design scenario is specified through two types of parameters: Application actions and Driver-Vehicle-Environment(DVE) conditions. Application actions are an event started by the user or an application and the DVE conditions are discrete values representing the context or system state[44, 45, 46]. The most relevant elements of the AIDE for this thesis are the DVE Monitoring Modules and Interaction and Communication Assistant(ICA). The ICA is a natural continuation of the work on communication and interaction strategies in automotive adaptive interfaces, which tries to reduce overloading the driver with information or confusing him in dangerous situations[47].

The DVE consists out of following modules:

1. The Traffic and Environment Risk Assessment module
2. The Driver Characteristic module
3. The Driver Availability Estimator

4. The Driver State Degradation

5. The Cockpit Activity Assessment

The two most relevant aspects of the DVE are the analysis of the tasks carried out and the consideration for possible human inadequacies or performance errors. The driver state is represented through three descriptors:

1. Situation awareness

2. Driver state

3. Task demand

The additional static parameters associated to each driver are attitudes/personality and experience/competence. These elements are combined to track the driver's availability, driver's ability and traffic and environment factors.

AIDE work on DVE provides an in-depth analysis and models of driver monitoring methods through the human-machine interface and additional in-vehicle sensors. Most relevant indicators for behavioral adaptation within the driving activity have been defined, reviewed and selected for final implementation.

This work attempts to extend this effort by expanding the AIDE context processing with uncertainty management, management of complex knowledge models and adaptivity between different driver-vehicle-environment models and the appropriate rule sets. In this sense, this work focuses on the theoretical methods behind the context processing in the area of automotive human-machine interaction and their runtime requirements, while AIDE identifies the important model parameters.

2.4 Area for Improvement for further Research and Development

A position paper on the importance of cyber-physical systems from December 2011 by the German National Academy of Science and Engineering(Deutsche Akademie der Technikwissenschaften - ACATECH) points of following focus areas in regards to the human-machine interaction[48]:

1. Intuitive, multimodal, active and passive HMI support(simplified system control)

2. Extending the perceptive capabilities of individuals and groups
3. Recognition and interpretation of human behavior, feelings, needs and intents
4. Detection and evaluation of human and system state and environment
5. Integrated and interactive decision making and executing actions
6. Ability to learn

As stated at the beginning of this chapter, the human-machine interface is currently defined as the part of the technical system which provides the means to capture user input and present the system feedback back to the user. An improvement can be made by improving existing sensors and input devices, introducing new sensing technologies and ergonomic devices, physically integrating existing devices or adding new means of multi-modal feedback and other methods which improve input and output channels from and to the user.

One example of such improvements is reducing the amount of physical force necessary to operate the vehicle. Currently, the user has to translate his wish into the movements of the body parts and has to observe feedback from various devices in order to realize the effect of his actions. Controlling our bodies is natural and it only makes sense to control other machines using the body as the immediate translation level or communication channel. However, the amount of actual force and physical engagement can be reduced, taking the comparison between a steering wheel/pedals/gear shift and a single joystick as an example. Right now, this input method is legal only in vehicles built for drivers with physical disabilities, which cannot operate a classical HMI design. In the next step, currently present only in the medical domain, the physical component of the interface can be fully eliminated, since the HMI can tap into the user's motor nerve endings. As the final step, also currently only present in the medical domain, a brain-computer interface can analyze the brain activity and classify user commands.

Another example builds upon proliferation of monitors/screens and touchscreen-based devices in the vehicle. Having different information appear at different time frames on different locations inside the vehicle can be a source of confusion and driver distraction. Certain safety-relevant information, crucial to primary and secondary vehicle functions, has to be visible at all times. Other, mostly related to infotainment, can be only partially available during the drive and can be kept outside the field of view. This approach groups the screens into the head-unit screen and the infotainment screen, with differing compositions and interaction methods. The head-unit might not be suitable for touchscreen operation, because of fatigue involved in prolonged arm stretching and the dangers of keeping the hand inside the field of view. The infotainment screen, on the other hand, might be used with a combination of specialized input devices and touchscreen, the latter being more attractive to the co-driver. Producing a unified feedback and a unified user experience is obviously easier with a lesser number of configurable devices. This trend might continue driven by the reduction of costs, especially the ones related to integration. A concept virtual dashboard, which both encompasses a head-unit and an infotainment system, has been developed for the Innotruck vehicle [49].

Improvements are also possible in the area of user input preprocessing. Data mining and signal processing of raw input data can be used to extract unintentional data. This is comparable to body language between two persons, and since it is superimposed on the primary input data it is further denoted as **added input data**. For example, user voice might be analyzed for emotion, steering behavior for unusual trends, brain activity for fatigue and camera data processed for gesture control might be additionally processed to analyze head movement, blinking, gaze direction and eye openness.

Transparent learning of driver behavior and unobtrusive improvement of the underlying driver model plays a key role in the acceptance of adaptive human-machine interfaces[18]. The approach is based on gathering data through observing the driver interaction with the HMI over prolonged periods of time or during the interaction with other systems.

Even larger improvements can be made in the area of user input interpretation and situation-aware system responses. All the input channels, together with the conclusions drawn from data mining, should be interpreted together at the same time, in order to understand the user's current wish or even complete goal. Required situation awareness builds upon context processing methods, since decisions have to made based on large amount of current and previously acquired data and knowledge which might be incomplete and inaccurate. When context processing is added to the classically defined human-machine interface, the domain-specific term **intelligent user interfaces** is used. Let us now assess how complex and thorough should the context awareness be and how and in which amount does it bring about an overall improvement of human-machine interaction.

During such interaction, two translation steps can be observed. The first one happens at the user's side, while he translates his ideas to the movements of body parts and interprets the machine's feedback. The other happens at the machine's side, while it is interpreting the physical input being received through what is currently called a HMI and preparing the feedback through various HMI modalities. Throughout these steps, a man-machine interaction has been performed and an understanding has been reached. The interaction was executed with a certain level of mental and physical effort on the user's side and processing and power effort on the machine's side and the interaction had a specific quality in regards to the overall human performance in the task. In the ideal case, the machine would possess artificial intelligence which processes the entire interaction context and it would interact with the user using complete situation awareness. The translation of the original driver wish would be faster and less physically intensive. The feedback would only add to the existing user perceptive abilities and not overlap or overload the user. The development of such future HMI can be further optimized by leveraging solutions from adjacent domains(medical or consumer electronics, as an example) and defining intermediate steps from the current automotive HMI to the long-term vision.

An analysis of the current developments in the area of physical human-machine interfaces reveals several important trends, as shown in Figure 2.5.

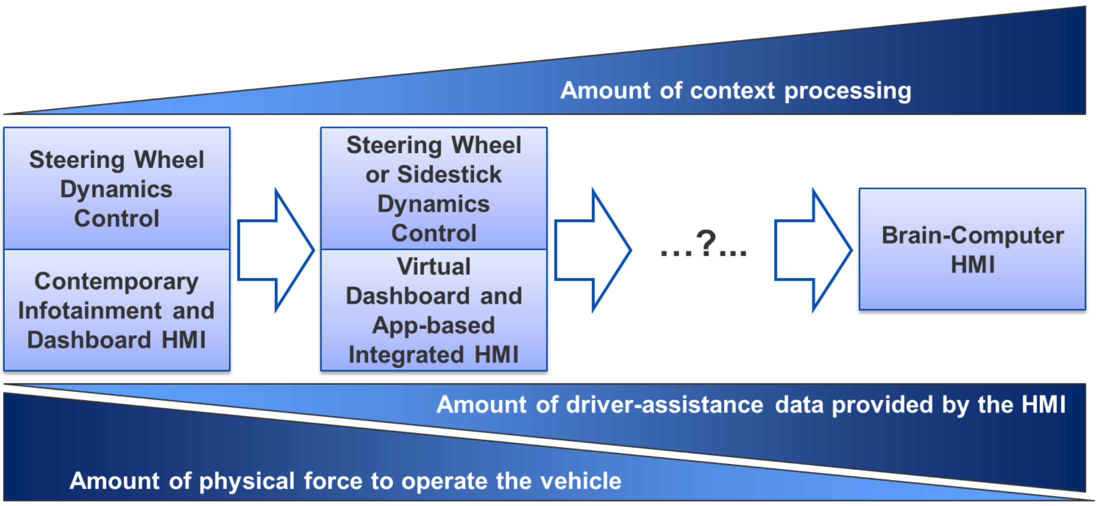

Figure 2.5: Identified trends in the future development of the physical human-machine interfaces

The first building block is therefore a well-designed and well-performing context processing, which enables situation awareness. The Driver-Vehicle-Environment construct, together with its inherent uncertainties, can be modeled with Bayesian networks, as shown in the following chapters. Their exact description, through the rules of conditional probability and associated probability distributions, provides predictability and enables formal testing. The focus is placed on exact inference for the same reasons of predictability and future formal verification. Four specific areas for improvement of Bayesian knowledge models were identified:

1. Exact inference complexity on embedded hardware

2. Separation of conditional dependencies between sensor modalities
3. Dynamic addition and removal of data sources
4. Time constraints for safety relevant functionality

The extension of the junction tree algorithm has been proposed to address all four areas[50]. The details are presented in the following chapters.

The second building block is composed of physical human-machine interface solutions which minimize the physical effort during the interaction and provide a consistent feedback. Two aspects were considered: Control of the vehicle dynamics and the control of all other vehicle functions. For the primary vehicle control, a spherical side stick solution from a project partner RAFI was integrated in the Innotruck vehicle. For the control of all other vehicle functions, a centralized touchscreen-based dashboard was constructed[49]. Furthermore, two HTML5-based applications for the dashboard were developed: An energy management and a parking and maneuver assistance application[51]. In addition to the HTML5 applications, a control panel for the electric vehicles' charging stations is provided in the native dashboard software platform[52].

While new interface types, such as side sticks and brain-computer interfaces, can already be used for vehicle control, we focused on the additional data which they capture by design and which is not related to the primary driving task. We refer to this additional data as "added value" of a specific interface and we attempt to process this data in order to learn more about the driver state. We focused on the electroencephalography-based brain-computer interfaces and have developed a method for robust detection of driver vigilance, which classifies the drivers into two states based on the spectral analysis of the significant independent signal components [53, 54].

2.5 Practical Relevance of the Chosen Research Topic

In order to keep the thesis firmly connected with the activities taking place in the commercial sector, the author participated in several automotive industry conferences and workshops. The goal was to keep the real-life implementation and integration issues in focus, as well as to assess the societal relevance and technical feasibility of the contribution.

To this end, the author participated on a comprehensive industry conference in June 2013[1], with a strong emphasis on industry requirements and with a rather modest representation of the academia. In this sense, the event provided a valuable insight into the international state of the art of the commercial automotive HMI research and development. A participant survey after the event provided the data presented in the following. The main identified drivers of future trends in the HMI development are shown in Figure 2.6.

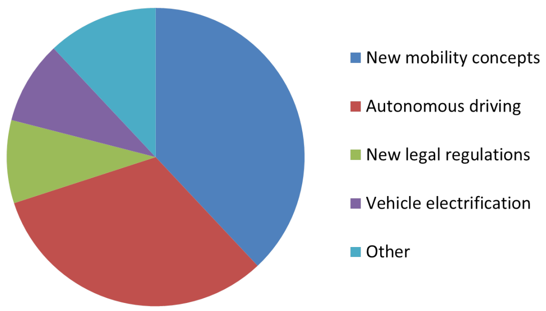

Figure 2.6: Main drivers of future trends in HMI development

The survey also identified thel key HMI challenges and rated them according to their significance. Results are shown in Figure 2.7.

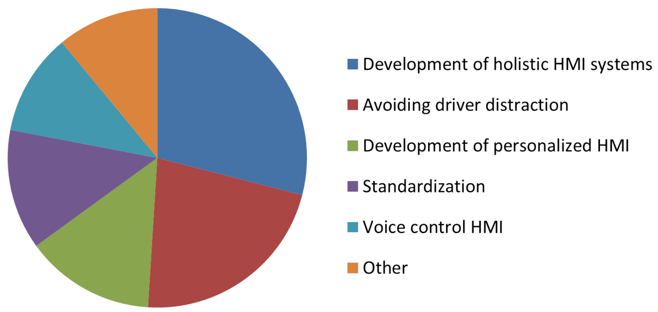

Figure 2.7: Key HMI challenges in upcoming years

Officially recognized key issues were HMI modeling, processing and development, impact of adaptive user interface on reducing driver distraction, autonomous driving and HMI development for better user experience. Head-up displays were recognized as one of the most viable solutions for information presentations. Managing driver workload and managing distraction have become a challenge which has to be addressed through future advanced driver assistance systems. Therefore, the event provided a clear indicator that the future of automotive

[1] we.CONNECT Car HMI Concepts and Systems 2013: http://car-hmi2013.we-conect.com/

human-machine interaction lies in its ability to support the driver and fuse itself with the driver assistance applications. Creating trust between the driver and the autonomous vehicle, a topic already introduced in the previous sections, also took place among the top-rated research and development areas, mostly driven by the demographic shift and the expected customers' fear of system failure. Identification of the new content and the new HMI concepts which will replace the manual driving task has been given top priority, since it is expected that the vehicles will become a valuable content delivery platform. Personalization was recognized as an important customer-binding tool, but the necessary and expected depth of personalization remains an open question. Currently, it is limited so interface skinning, but the additional learning of user habits could have a much bigger impact on overall user experience. Unification of in-vehicle infotainment user interface standards remains, as before, an important open issue, but it is mostly driven by the internal business models and not by the technological advancements.

Main recognized challenges in the area of driver distraction are the need for connectivity over smartphones, aftermarket products, amount of HMI information, actual measurement of the amount of distraction and workload and necessary level of HMI personalization. The recognized HMI technologies which manage distraction are information presentation, personalization of screens, gesture recognition, learning systems and feedback methods. The theoretical impact of an adaptive user interface on reducing driving distraction is through driver workload and distraction estimation, situation-dependent adaptation of the interface and monitoring of the driver. Advanced driver assistance systems of the future will emphasize on connectivity, augmented reality, natural language interfaces and near-field communication with handheld devices.

In the area of voice processing, special consideration has been given to the "always listen" functionality. The driver might not accept the fact that a microphone is always on in their vehicle, since cockpit currently belongs to the private sphere.

Especially relevant to this thesis was the consensus on HMI development for better user experience. Stadardized HMI seems to result in better user experience, with some OEMs seeing the HMI as the core branding asset. HMI should definitely adapt to stress levels of the driver and it should support at least two different strategies for different user groups - map-centric and app-centric. Map-centric approach focuses on presenting only the navigation-relevant data, with geographic references, and is more suitable for user groups above 35 years. Application centric approach focuses on connectivity and seems best suitable for user groups below 25 years. Predictive navigation, taking traffic into account, together with the correct execution of software updates, seem to be the most crucial technical factors which the developers should focus on.

In September 2013, the author visited another automotive industry congress[1], with the emphasis on the needs and current research of the industry and the commercial sector. The industry was mostly represented through HMI segment directors and development managers. Participants were almost exclusively from Europe, even though they represented globally present companies. Prof. Gernot Spiegelberg and the author of this thesis had the honor of moderating the topical session on the Commercial Vehicle HMI, during which following topics received the most attention:

1. HMI for combined traffic - cargo transport and mobility as a service
    (a) What should be personalized and transferred between different vehicle types
    (b) Should infotainment and primary vehicle control device be brought in by the user
    (c) Added value or nice-to-have
2. Challenges of the transition to autonomous vehicles
    (a) New roles of the driver and of the HMI
    (b) New content type and its placement
    (c) Building-up trust between the driver and the vehicle
    (d) Re-taking the vehicle control by demand
3. Wearable or integrated augmented reality devices
    (a) Head-up display or AR glasses
    (b) Cost versus complexity
    (c) Environmental overlay with head movements
    (d) Advantages in distraction detection
4. New devices for primary vehicle control
    (a) Side stick/Joystick devices
    (b) Suitable devices for transition to semi/autonomous decision making

[1] Automotive Cockpit HMI 2013: http://www.cockpit-hmi.com/

   (c) Ergonomic customization by the means of 3D printing

5. Driver distraction

   (a) Who is responsible and who is to blame

   (b) Implementing full control over all devices inside the vehicle

   (c) Tight cooperation with producers of nomadic devices

   Digital instrumentation in the terms of both dashboard and infotainment was voted the most important overall topic for future product development. It is closely followed by vehicle connectivity, driver assistance systems, autonomous vehicles' HMI and measuring distraction with the emphasis of cognitive distraction. This clearly signals that the chosen research topic indeed has a strong connection with the current market needs.

As a conclusion, it can be noted that the topics of interest provided by the automotive sector are well-aligned with the research topics of this thesis.

Chapter 3

Context-Centric Human-Machine Interface Design

Based on the previously introduced areas of interest in HMI research and development, a context-centric design of future automotive human-machine interfaces is proposed. Emphasis was placed on the context-centric design which supports quality-of-service requirements and collecting context-relevant data through the human-machine interface.

3.1 Introduction

In order to handle and capitalize on the already presented driving forces behind the automotive human-machine interaction, a redesign of the human-machine interface is suggested. The design is the blueprint for the implementation of practical engineering solutions and should therefore remain technically realistic, when considering today's automotive technology. The design places interaction context processing in the center, building the necessary software and hardware components around the concept of situation awareness. The goal of this bottom-up approach is to have a unified context manager which all the HMI and ADAS applications can use, instead of offering separated solutions with incompatible interfaces. The applications should passively observe the driver behavior and collect and process the driver input, in order to assess the driver state. The advantage of passive observation is non-intrusiveness, which corresponds to higher application acceptance rate. The results of driver assessment should directly contribute to the overall context description, which is, again, made possible by a unified context manager.

The expected net result of the design visible to the user is the increase of safety and overall driving experience, since more applications can make use of and contribute to the context manager. The commercial sector implementing the design in its products can benefit from the reduction of integration costs through well-defined context processing methods and standardized software interfaces. New applications in the area of driver assistance and human-machine interaction can be developed more effectively, since the complexity of context processing is shifted away from individual applications and devices. The society as a whole benefits through the solving of issues of personal mobility in the face of demographic shift, which requires personalized and learning assistance systems.

3.2 Vertical HMI Design

Current automotive interfaces are built upon a so-called vertical approach, where each physical interface component directly controls a certain vehicle part. Brakes and throttle are, for example, both controlling the longitudinal vehicle dynamics through separated control of two different subsystems. An example is given in Figure 3.1.

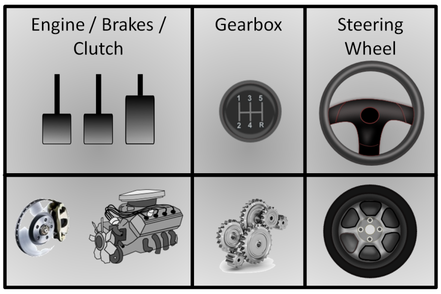

Figure 3.1: Vertical design for primary vehicle functions

The vertical approach encompasses the secondary and tertiary vehicle functions, what can result in very complex dashboards and heterogeneous control elements, as shown in Figure 3.2.

Figure 3.2: Vertical design for secondary and tertiary vehicle functions

There are several issues with this approach. Some of them have already been mentioned in the introduction as a generalized driving force behind the development of HMI, but here we summarize them in the scope of vertical design paradigm.

The vehicle control system is strongly tied to a specific vehicle. A looser coupling, made possible by the addition of a middle interpretation layer between the driver and the actual drive train, would allow for a control system transferable between various vehicles. It would additionally allow creating a shared interpretation level, instead of processing separated interface inputs and outputs. Of course, a drive-by-wire system is necessary in order to implement this kind of vehicle control. Another issue is the physical force and overall physical engagement necessary to operate the vehicle. This can become a problem in elder population or with people who are physically disadvantaged. Seniors should retain their personal mobility in situations where fully autonomous driving is not possible.

Developing assistance systems which span over multiple physical human-machine interfaces and related vehicle subsystems requires a large integration effort, since the devices are physically separated and designed to function as encapsulated systems. In order to maintain a picture of the relevant system states, it is necessary to connect to a large number of different system buses and electronic control units, increasing the system development and integration costs.

In addition, the close coupling between user input devices and vehicle subsystems prevents any form of additional input processing or alternative input interpretation.

Lack of centralized context management prevents creation of a unified interface towards the DVE knowledge model. Safety-critical applications might place completely different quality-of-service requirements on the DVE knowledge model, requiring rapid interpretation of the entire interaction context.

3.3 Horizontal HMI Design

In the horizontal design, which has been proposed as the next HMI design paradigm and has been slowly introduced through physical device integration, all the user input, together with the vehicle and sensor data, flows to one central interpretation point. At this point all the decisions about the next course of action is made, effectively decoupling the actuators from their controlling devices. This approach is illustrated in Figure 3.3.

After the user input has been correctly interpreted, a command is sent to all the actuators which are needed for its execution. In the case of the primary vehicle control, the entire drive train is coordinated from a single decision point. The feedback from the system to the user follows the same analogy - the information from all the devices is collected in a single point,

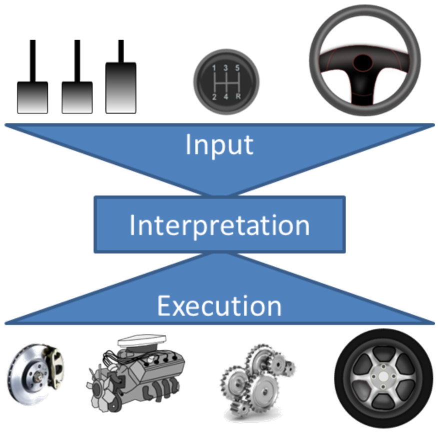

Figure 3.3: Horizontal design for primary vehicle functions

where the decision on the exact presentation strategy is made. Horizontal HMI design has been implemented in the Innotruck vehicle, as demonstrated later in this work.

3.4 Context-Centric Design with Support for Quality-of-Service Requirements

Taking the horizontal design one step further, this thesis introduces the context-centric design, which adds a software component called the context-processing service, which operates at the decision point of the horizontal design. The service abstracts all the context-processing operations from the applications which need to make decisions based on the state of the driver, the vehicle and the environment.

The applications making such decisions, based large amount of context data, require a service which enables placing complex situation relevant questions, such as "is the driver tired?" or "is there direct danger to the driver?". These questions can be modeled as nodes in a probabilistic knowledge model, and asking or querying can be modeled as performing exact inference on the model. The key element of the proposed design is therefore a context processing service, which is placed at disposal of decision making applications. The applications can run on other hardware and software platforms, separated from the service, while placing context-relevant queries with different quality-of-service requirements, as shown in Figure 3.4. It is therefore important to design a standardized interface between the two, which lays down the semantics but does not define the physical or hardware implementation details. This is addressed further on in the next element of the proposed strategy.

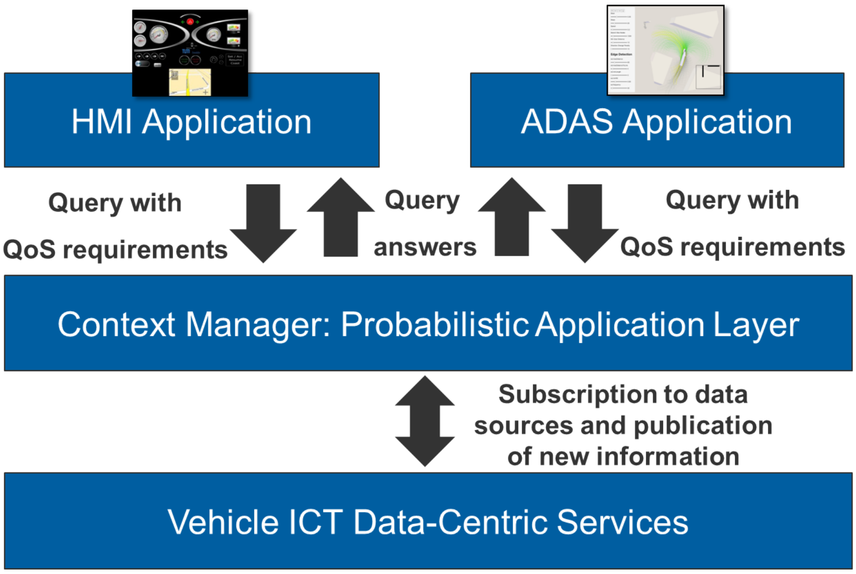

Figure 3.4: Design of a context-centric human-machine interaction, here providing services for two different applications

High integration of human-machine interface and driver assistance assumes that the driver is assisted over the human-machine interface in two directions:

1. From the driver to the system, through passive data processing

2. From the system to the driver, through prioritizing of the information flow, personalizing the interface, force feedback, etc.

Passive data processing is demonstrated in the further chapters, but from the design point of view, the results of the processing appear as new knowledge inside the existing probabilistic knowledge model. The information flow to the driver has to be managed in three steps:

1. Recognition of the current situation and the meaning of information which is to be presented to the driver

2. Rule-based selection of relevant information and its placement in the cockpit

3. Presentation of information on the selected device

Situation recognition can be performed by the main context processing service. The rules can be defined by law or best ergonomic and traffic safety practices. The presentation itself is mostly a technical matter. For the demonstration in the Innotruck vehicle, a virtual dashboard on a touchscreen has been selected.

If multiple agents or applications inside the vehicle try to control the same resource, a form of arbitration is necessary. Arbitration process for the head unit, in the case that more agents try to present data at the same place on the unit's screen, might be completely different from the one for brake control, due to the latter's criticality. This can be solved by design, by disallowing multiple agents for drive train elements and by providing fixed priorities to each agent, or by static mapping when new agent is added or removed.

3.4.1 Open Software Platforms and Standards

In order to technically implement the central context processing service, it is necessary to define its interface towards other software components in the vehicle which require its services. The research activity in the area of decentralized sensor management platforms provided what seems to be the best solution and it is presented in the following.

The requirement to visualize and explain the energy flows inside the Innotruck experimental vehicle was the main cause for the analysis of available sensor management platforms[51]. Some of the requirements placed upon the platform, as specified in[55] were:

1. Plug-and-play capability for data consumers and producers
2. Usage of open standards
3. Flexible onotologies
4. Integration with web-based services

As explained in [51], Software Web Enablement(SWE) from Open Geospatial Consortium satisified all the requirements and was utilized for the underlying sensor management platform.

An overview of the previous work on visualization of energy flow in the Innotruck is provided. The goal of this study was to implement standardized discovery and visualization method for sensor phenomena inside the research vehicle. The visualization had to be platform-independent and correctly scale on devices with various screen sizes and computing performance. This work was performed in the scope of a supervised scientific thesis by Jakob Stoeck.

3.4.1.1 Sensor Management Platforms

A data-centric platform was implemented for the visualization of the energy flow, with rich semantic and at the front of the standardization efforts in the domain. The latter concerns the efforts to facilitate the access to the growing number of Internet-enabled sensing devices scattered through the world. For this purpose, the creation of the semantic sensor web, various standards have been and are being developed. The semantic web, as envisioned by Tim Berners-Lee and described by the W3C Semantic Web Activity, is an evolving extension of the World Wide Web in which the semantics or meaning, of information on the Web is formally defined[56]. Two interconnected solutions came from the side of Open Geospatial Consortium(OGC) and the Institute for Electrical and Electronics Engineers(IEEE).

The IEEE 1451 was developed as a universal transducer protocol standard. It offers a base protocol which provides interoperability between different sensors and sensor networks. The key features are the Transducer Electronic Data Sheets(TEDS). Those descriptions may be deployed in the embedded memory of the sensor or are downloadable as a separate file. They contain calibration and operating data necessary to compute a result in standard SI units and additional sensor metadata to use in the application. The standard specifies templates for the most important types of transducers. The TEDS file from the transducer is communicated over a Network Capable Application Processor(NCAP). Its software and hardware(e.g. RS-232, USB, Bluetooth, etc.) interfaces are standardized in the 1451 standard[57, 51].

OGC has proposed a Sensor Web Enablement(SWE) standard, divided into information model and service model. The main objective of Sensor Web Enablement is to provide a framework of open standards for exploiting Web-connected sensors and sensor systems of all types[58]. The information model provides XML specifications for sensor descriptions, data and streamed data and interface specifications for publishing, managing and subscribing to sensors. It consists of Sensor Model Language Encoding Standard(SensorML), Observations & Measurements(O&M), TransducerML and SWE Common. The first three are XML specifications for sensor descriptions, data and streamed data while the latter is a collection of interfaces for publishing, managing and subscribing to sensors. The SensorML specifies models and XML encoding that provide a framework within which the geometric, dynamic, and observational characteristics of sensors and sensor systems can be defined. The standard defines XML schemas for observations, and for features involved in sampling when making observations. These provide document models for the exchange of information describing observation acts and their results.

The service model consists of four services. The Sensor Alert Service(SAS) can be used for subscribing to alerts in case of a sensor measurement event that fulfills certain user defined criteria. The Sensor Observation Service(SOS) performs requesting, filtering, and retrieving observations and sensor system information. The Sensor Planning Service(SPS) can be used for tasking sensors and setting their measurement parameters. The Web Notification Service(WNS) is, unlike the other three services, not directly sensor related. Instead, it is a utility service which provides asynchronous notification mechanisms between SWE services and clients or other SWE services[51].

The SOS furthermore aggregates readings from live, in-situ and remote sensors. It provides an interface to make sensors and sensor data archives accessible via an interoperable web based interface.

The available resources and vehicle capabilities as seen from the SWE level are described in the so-called catalogue service for the web(CS-W). It contains, among other metadata, descriptions of spatial references and thematic information, enabling different queries by clients searching for specific resources.

An overview of the SWE architecture is provided in the Figure 3.5 [59].

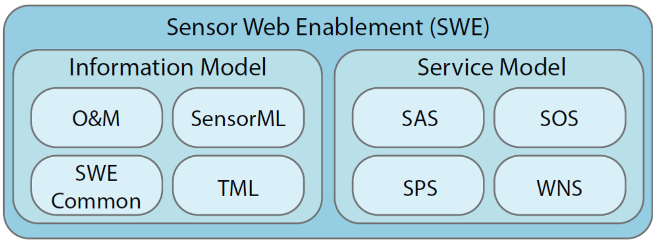

Figure 3.5: Architecture of the Sensor Web Enablement

3.4.1.2 Software Platforms for Proposed Components

The selection of the software platform supporting the virtual dashboard was largely an engineering task, since the main goal was finding a flexible software solution which enables low level hardware control on the one side and an acceptable graphical quality on the other. Nokia/Digia QT C++ Framework was selected, running on top of an OpenSUSE Linux distribution, since it additionally provided easy integration with HTML5 applications running in Webkit. More detail about the applications is found in the following chapters.

This setup enabled easy changes starting from the device driver level(kernel touchscreen driver being one example), all the way to high-level animation management in the graphical user interface.

The alternative platforms used first-hand for implementing smaller software solutions(such as the remote vehicle charging management), were Apple Xcode with objective C in OS X, Microsoft .NET and Visual Studio. Other alternative platforms which were dismissed on the grounds of their prohibitive costs and closeness were Android and FPGA-based solutions.

3.4.2 Further Discussion

In this section, several additional advantages and properties of the context-centric design are presented. What follows is a short summary of remarks collected through numerous discussions with colleagues and industry representatives during the project's lifetime.

An important quality-of-service dimension made possible by the proposed design is the plausibility check of decision making. As an example, the driver could ask the navigational system for an explanation why a sudden route change was performed. The navigational system could follow-up its probability network structure and explain how much importance each branch adds to the final decision. The explanation could go along the lines of "The new route has been selected since the importance of the traffic jam beats the importance of shortest path". Additional questions can be placed, such as "Just how important is the traffic jam?" or "Explain me your entire decision logic". This quality-of-service dimension can be called *provenance* and it can be easily derived from the existing probability networks and the semantic description of their nodes.

However, special consideration has to be made when designing human-like assistance systems. Drivers might develop unrealistic expectations about the system if only limited cognition is present. Perceived user experience might even improve if the system is designed without the additional interaction and conversation options, since the entire system design would remain hidden. Another issue with life-like systems is development of negative personal feelings towards the system, which is perceived as a near-intelligent living entity. This can be imagined as a psychological version of the effect known as uncanny valley. The term denotes a well-known effect in which an almost-human or near-human entity causes fear or another negative emotional response during interaction with humans.

Even though context-centric design enables easy management of user-related data, special care has to be given to presenting the collected data to the user. If the driver feels continuously observed and if he is able to directly see the consequences of his actions on a constantly updated driver model, he might completely change his behavior or feel discomfort during the drive.

3.5 Collecting Context-Relevant Data through the Human-Machine Interface

The context-processing service by itself would not provide a tangible benefit without a method to obtain the relevant context data in the vehicle. The goal of the entire design is to increase safety and add to the vehicle functionality. Therefore, this work proposes using the human-machine interface for collecting the data about the driver, as an addition to the already existing data collection through sensors and vehicle systems. The focus is placed on the driver aspect of the DVE model.

To this end, two methods of collecting the context-relevant data are suggested:

1. Profiling the human performance during the road-following task with the side stick
2. Assessing the driver fatigue during the drive with a brain-computer interface

Both human-machine interfaces, the side stick and the brain-computer interface, are currently not present or at least not widespread in the automotive sector. However, as shown in the last chapter, their usage is spearheaded by the changes in vehicle system architecture, through the shift to a more centralized system design and through the shift to drive-by-wire systems. The side stick was of special interest due to its presence in the Innotruck prototype vehicle. Both interfaces have been proven as a worthy source of driver assessment data, crucial to the driver assistance, which can be directly added to the overall context description. The analysis of the methods used for both interfaces in provided in the following chapters.

3.5.1 An Example of Passive Data Processing Used to Adapt to Driver's Proficiency

A related example of how the knowledge about the driver's proficiency can improve the human-machine interaction is given through the work of Stoeck in the area of aided maneuvering and parking assistance[60]. An assistance application for side stick control of the Innotruck has been developed, in order to overcome the complexity of the new input device(the side stick) exacerbated by the unusual design of the vehicle. The user selects the desired parking position with a simple finger swipe, while the application performs path planning using rapidly exploring random trees. The application additionally helps the driver to follow the optimal path, by providing on-screen suggestions about the next necessary side stick position. The definition of an optimal path leaves plenty of free space to customize it for individual users, since the shortest path might be the one which is the hardest to drive. The implemented heuristic defines a path distance(or path goodness) as a combination of translational and rotational distance. Translational distance is a simple geometrical distance between two points. Rotational distance penalizes paths with large amount of steering. Both distances are weighted and added together to form the total path distance.

$$d_{transl}(p, q) = (q_x - p_x)^2 + (q_y - p_y)^2 \tag{3.1}$$

$$d_{rot}(p, q) = (|q_\theta - p_\theta| + |q_{\theta_1} - p_{\theta_1}|)/\pi \tag{3.2}$$

$$d(p, q) = w_{transl} \times d_{transl}(p, q) + w_{rotat} \times d_{rot}(p, q) \tag{3.3}$$

The approach is very basic, since the rotational distance does not produce expected results in the case of multiple direction changes, but it is trivial to use the heuristic to penalize paths with specific properties, such as driving backwards for prolonged periods of time. In this way, a personalized path heuristic function for maneuver and parking assistance can avoid suggestions which the driver always executes poorly or still cannot execute due to the lack of training. With the vehicle like the Innotruck or a comparable large truck, a very "hard" maneuver suggestion can result in a vehicle position which the driver cannot get out of. Keeping the track of the driver's proficiency and using it to influence assistance system's suggestions is a promising way of increasing driving efficiency and user satisfaction.

Chapter 4

Horizontal Design of Human-Machine Interfaces in the Innotruck

This chapter presents the human-machine interfaces in the Innotruck, which is the vehicle prototype of the project Diesel Reloaded. The work on the vehicle does not constitute a scientific contribution of the thesis, but it is nevertheless very relevant to its topic, since the vehicle embodies the horizontal design of the human-machine interface and therefore represents an important transitional step towards the context-centric design of the human-machine interface. The Innotruck's cockpit features a virtual dashboard and a side stick steering system. The virtual dashboard provides control over the secondary and the tertiary vehicle systems, while the side sticks provide control over the primary systems and enable control of the vehicle dynamics through minimal hand movements.

4.1 Overview of the Cockpit

The Innotruck's cockpit is, by its outer design, similar to the one of a combat jet aircraft. It contains a forward-placed and centered driver's seat and a backward-placed and left-shifted co-driver's seat. A look inside the cockpit is provide in the Figure 4.1. The driver can enter the cockpit through the door located in its back(and leading to the middle segment of the Innotruck) or by opening the cockpit from the outside, using the hydraulic actuators which slide the cockpit open. The driver's seat is equipped with two spherical side sticks, which are presented in the following sections of this chapter. The co-driver's seat follows the same design, but does not feature the side sticks. A large console is installed in front of the driver, containing a large touchscreen and two rear-view mirror screens, also described in the following sections. The console is shown in Figure 4.2 and a look inside its development is provided in the Figure 4.3. The hardware required for the console operation is located in the compartment to the right of the driver. This compartment also houses the electronics which connects the side sticks to the drive-by-wire system.

Figure 4.1: A look into the Innotruck's cockpit from the outside

The outer cockpit design, as well as the design of the entire vehicle, was provided by Prof. Luigi Colani.

4.2 The Virtual Dashboard

In order to control all the vehicle's secondary and tertiary functions, a central console element was designed. The outer design and packaging was primarily chosen to fit the needs of the Innotruck, but the same hardware and software can be reused in any road vehicle. As the next step, integration of a heads-up display unit combined with a smaller console, which can be extended via smartphone, was planned and partially executed during this thesis.

Figure 4.2: A look at the main human-machine interfaces in the Innotruck: The virtual dashboard in the front and the side sticks left and right

Figure 4.3: A view at the driver's workplace during the vehicle's development

4.2.1 Rationale behind the Virtual Dashboard

Virtual dashboard provides many advantages over the classical dashboard with physical elements, most notable being the ability to adapt to different vehicle types, different users and driving situations. Applications can be added and removed with no physical integration effort, by providing them with a limited segment of the display surface and arbitrating between different applications which wish to use the same segment. Full control over the information presentation towards the driver is possible, not only by changing the visual presentation of the information but also through its delaying in the case of information overload or dangerous driving situation. In a truck study with professional truck drivers in a driving simulator, a non-linear(parabolic) relation has already been identified between the complexity level of a specific traffic situation and preferred delay in information presentation to the driver. The average delay(recovery time) was shown to be 3,4 seconds [61]. Rating scale of mental effort(RSME) factor has been used for determining situation complexity [62]. An example of various RSME ratings are given in Table 4.1. The duration of the situation did not have a significant impact on the required driver recovery time.

Table 4.1: Rating scale of mental effort factor for various traffic situations

RSME Factor	Traffic Situation
101,1	Vehicle in front aggressively cutting in
75,5	Tunnel
64,4	Narrow lane
61,7	Taking over maneuver
55,4	Construction site
34,3	Strong braking due to the braking of vehicle in front

Two concepts for the virtual dashboard and the control over the vehicle's secondary and tertiary functions were proposed - a large central console containing a single touchscreen extended with two additional rear-camera displays and a standard consumer-electronics tablet extended with a heads-up display.

The concept with the central console was selected, due to the flexibility in the selection of the hardware platform and the additional connectivity provided by the physical separation of the display unit and the computing unit. The tablet-based solutions at the beginning of the project were significantly underpowered and equipped with low-quality displays. After three years of using the central console, it was finally replaced with a tablet solution, reflecting the change of circumstances on the consumer electronics market. The integration of a heads-up display remains future work and is shortly described later in this chapter.

4.2.2 Central Console Outer design and packaging

An industrial designer Daniel Kocyba was contracted by the Innotruck's technical director, Dr. Marcus Borst, to suggest several console designs. The result is shown in Figure 4.4.

Figure 4.4: Proposed designs of the central console element

Since the outer design of the console had to match the existing design of the Innotruck, provided by Prof. Luigi Colani, the design shown in Figure 4.5 was finally chosen.

Figure 4.5: Chosen design for the central element's outer shell

The location of the element inside the truck is shown in Figure 4.6.

4.2.3 Hardware Platform and the Connection to the Innotruck

The central console contains three LCD screens which are connected to an industrial-grade Intel Atom N510-based embedded HMI computer. The middle LCD is a 15" touchscreen which displays the virtual dashboard. The remaining two LCDs are positioned left and right and are connected to the rear-view cameras. Rear-view camera feed can also be shown on the main LCD. The embedded computer is connected to a vehicle control unit located in the drive train via CAN bus. The vehicle control unit is connected to the Daimler Parametrierbares Sondermodul(a gateway to the vehicle's internal CAN bus) and to the Yamar Powerline Communication Light

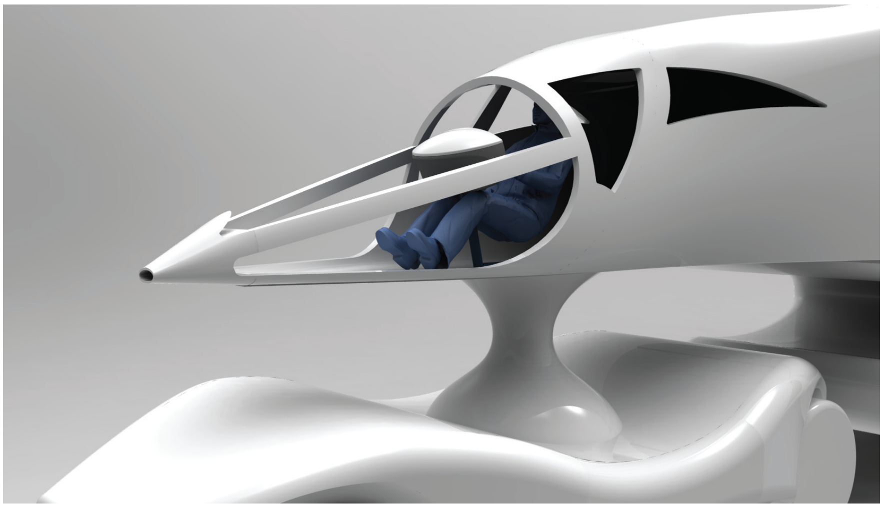

Figure 4.6: Location of the Innotruck's central console in the cockpit

Control System [63, 64]. The VCU is built around the Freescale MC9S12 processor. The layout of the both main and expansion board of the VCU was done by the project's technical director Dr. Marcus Borst and it is shown in Figure 4.7.

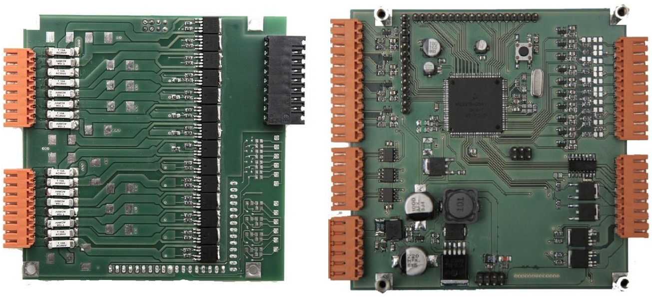

Figure 4.7: The vehicle control unit which serves as a gateway between the central console and the Innotruck

4.2.4 Software Platform

The central console is running on the OpenSUSE Linux distribution, which has been trimmed down for lower boot times. The virtual dashboard is written entirely in Nokia/Digia QT C++ Framework, with the exception of two HTML5-based applications. A screenshot of the dashboard without applications and without camera feed is shown in Figure 4.8. A popular open source solution Navit is used for navigation, together with a GPS sensor which was connected directly to the embedded HMI computer. A port of the open source Xawtv software package was used for displaying and manipulating the rear-view camera feeds.

Figure 4.8: One of the two skins for the virtual dashboard

Energy flow visualization app is shown in Figure 4.9.

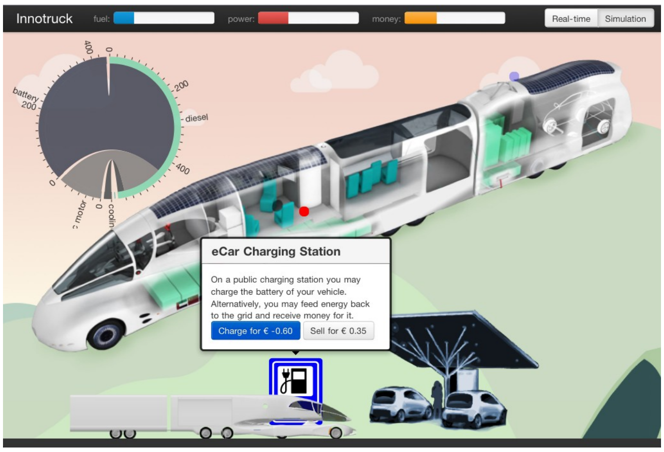

Figure 4.9: Energy flow visualization app for the dashboard running in simulation mode

Maneuver and parking assistance app is shown in Figure 4.10.

4.2.5 Integration of the Heads-Up Display

Even though the planned heads-up display from the avionics domain was not integrated in the scope of the project Diesel Reloaded, preliminary work has shown that it would be a well-suited

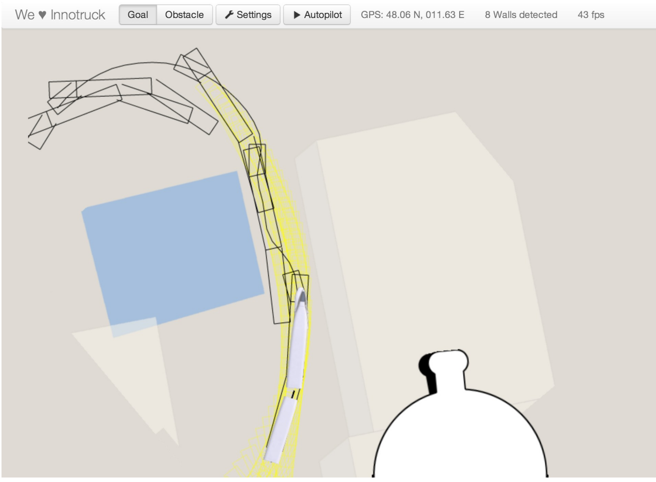

Figure 4.10: Maneuver and parking assistance application for Innotruck, developed by Stoeck[60]

extension to the tablet-based virtual dashboard. Since it is still technically impossible to project the image on the existing curved windshield, the image would be projected on a transparent flat surface in front of the driver. The improvement of the driver's field-of-view is illustrated in Figure 4.11, while the proposed placement inside the cockpit is shown in Figure 4.12.

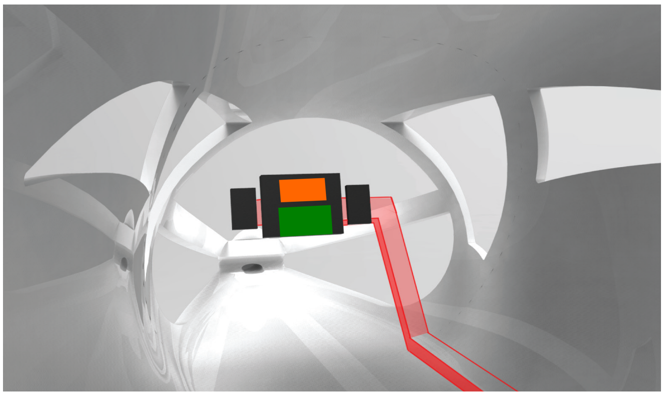

Figure 4.11: Study on replacing the central console with a tablet(green surface) and a heads-up display(orange surface)

4.3 The Side Sticks

The side sticks in the Innotruck were developed by Electrovis®, an engineering office of the company RAFI GmbH & Co. KG. The units are integrated in the armrests of the driver's seat, as shown in Figure 4.13. Steering is performed by rotating the spherical part of the unit left

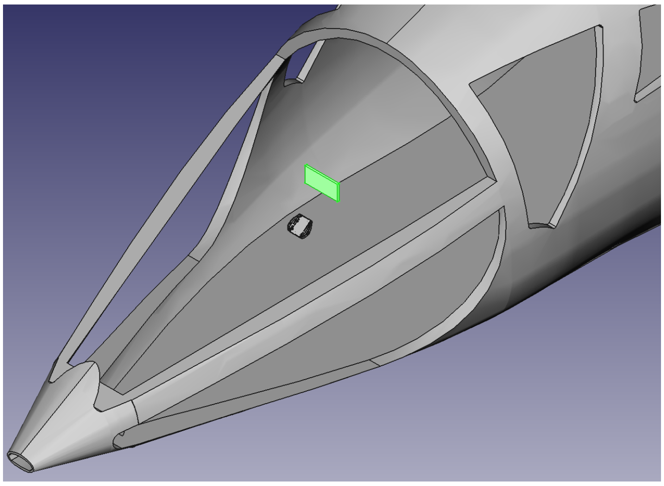

Figure 4.12: Possible placement of the heads-up display in the Innotruck's Cockpit

and right, while the braking and throttle are controlled with two push buttons. Force feedback is used for steering, in order to prevent the driver from moving the side stick faster than the vehicle's wheels can follow. Due to the both redundancy and ergonomics(to accommodate both left and right-handed drivers), two entirely same side stick units are installed in the seat.

A closer look at one of the units is given in Figure 4.14. The entire redundant electronics necessary for operation are located inside the unit's robust casing. The CAN transceivers which connect the side sticks with the drive-by-system are located in the compartment to the right of the driver.

Figure 4.13: The driver's seat with two integrated spherical side sticks

Figure 4.14: One of the two spherical side sticks integrated in the driver's seat

Chapter 5

Context Processing with Quality-of-Service Requirements

In this chapter, a method which enables meeting resource-intensive quality-of-service requirements for interaction context processing is provided. The method is one of the cornerstones of the previously defined context-centric HMI design and presents the first contribution of this thesis. A connection between the human-machine interaction in automobiles and an established probabilistic reasoning method called Bayesian networks is given. Furthermore, the importance of an optimized context processing component, which can provide quality-of-service requirements, is demonstrated. A short introduction to the basic concepts of networks of plausible inference and exact inference methods is provided in the first part of the chapter. In the second part, a method for exact inference optimization with quality-of-service requirements is presented and analyzed. In the third part, the components of the software platform called the probabilistic application layer are proposed. The platform represents a key component of the context-centric HMI design. The goal of this chapter is to provide the reader with a direct connection between the theoretical and practical aspects of the work in the area of context processing.

5.1 Introduction to Context Processing

5.1.1 Interaction Context and Situation Awareness

The human-machine interaction in a current road vehicle can be divided into three categories: active control of the vehicle's dynamics, control of various safety-relevant vehicle functions(e.g.

direction indicators) and, finally, control over the non-safety-relevant infotainment functions[65]. During the interaction with the vehicle throughout all three categories, the driver might inadvertently perform different kinds of errors affecting the vehicle control. Such human errors are partly responsible for 95% of all accidents. Human behavior is the sole responsible cause in 75% of all the cases, showing a clear mismatch between driver skills and situation and task complexity[66]. The work by [67] and [68] suggests further division of driver errors into cognitive, judgment and operation errors, which are mapped onto the corresponding human processes of observation, assessment and action. So-called assisting assessment applications are proposed to resolve this issue. The applications must analyze all the in-vehicle information sources, detect hazardous situations and inform the driver. They should be uniformly present throughout the three human-machine interaction categories, in order to provide a consistent user experience.

Work by Mueller in [69] presents multiple possibilities of restricting the control over the infotainment functions in order to avoid lowered driver performance in vehicle control and the associated safety risks. Rule-based priorization of feedback data is found to be relevant for avoiding driver distraction, but it can only take place after the current driving situation has been correctly assessed. Thus, situation awareness must precede the rule-based approach of optimizing the information feedback towards the driver.

Situation awareness is defined as the perception of environmental elements with respect to time and/or space, the comprehension of their meaning, and the projection of their status after any variable has changed. It can be recognized as an important enabler of autonomous decision making in the field of artificial intelligence. In the case of the human-machine interaction, and drawing a comparison to the human-human interaction, situation awareness additionally has the potential to improve the quality of interaction by following means:

1. The amount of data which has to be exchanged between the human and the machine to perform a specific task or to come to an understanding is reduced

2. The feedback which is provided by the machine can be affected by user workload and relevancy of each piece of information to the current situation

3. Users can be modeled based on the previous and current interactions and an assessment of the mental or physical state or overall proficiency for a given task can be performed

   In this rest of this chapter, a contribution for development of assisting assessment applications in the area of human-machine interaction and driver assistance, as defined by[67], is suggested.

5.1.2 Knowledge Modeling with Bayesian Networks

In order to implement a reasoning method which provides any form of situation awareness, one has to represent all the known data about the driver-vehicle-environment model. When considering related work regarding descriptions of dynamic systems with varying degrees of knowledge uncertainty, with the final purpose of inferring a small and changeable subset of questions regarding to the current situation, several probability frameworks come into consideration. The Bayesian networks(BN) represent joint probabilities of a set of random variables and their conditional independence relation[70]. Dynamic Bayesian networks(DBN) extended on this definition and represent multiple time slices, which are interconnected into a larger single network. The connections can be understood as hidden Markov models. Dynamic Bayesian networks therefore present a generalization of a system for modeling dynamic events[71]. In this work, the dynamic Bayesian networks are not analyzed in detail, since the proposed contribution can be applied to both static and *unrolled* dynamic networks. Unrolling denotes copying of the dynamic Bayesian network several times and connecting the nodes from the previous time slices to the nodes in the following time slices, in order to construct a larger Bayesian network with the same functionality.

Bayesian and Markov networks(MN) are a very popular method of choice for uncertainty management in the field of artificial intelligence. A Bayesian network, represented by an acyclic directed graph, can be converted into the Markov network through moralization and triangulation, as shown later in this chapter. A Markov network is represented by an acyclic hypergraph, which is a chordal undirected graph in which each maximal clique corresponds to an hyperedge[72]. Dynamic Bayesian networks have already been used for intelligent user-assistance systems, to model multimodal sensory observations, changing state of the user and various constraints regarding available resources. The DBN can successfully manage sensor measurement ambiguity, evolution of user's affective states over time and decisions about the user's needs[71]. Compared to neural networks, Bayesian networks provide a method for explicit and a-priori knowledge description. The lack of transparency of a neural network's structure additionally prohibits its dynamic modification during runtime. A combination of a probabilistic knowledge model running in Mathworks Matlab/Simulink on dSpace automotive-grade hardware has already been used in a road vehicle, in order to classify the vehicle maneuver intent, based on data collected from the driver and the vehicle[73].

Situation-aware driver assistance systems have already been implemented with dynamic Bayesian networks in the, for this work very relevant, publication by Rockl[67]. The importance of fusion of human-machine interfaces, machine-machine interfaces and driver assistance systems has been thoroughly analyzed and a model for generating probability of hazards has been presented. Main components of the required architecture are a knowledge broker, utility-based knowledge exchange and a reasoner. The authors recognize that the interaction with the driver can benefit from situational awareness through an intelligent information feedback management. The main contribution is the identification of major architectural components of a situation-aware driver assistance system, with a focus on sensor-based knowledge derivation and vehicle-to-vehicle and vehicle-to-infrastructure connectivity. This thesis, on the other hand, places focus on the management of the knowledge stored in the probability network and efficient and intuitive querying of this knowledge by the applications.

Identified challenges in machine learning for user modeling, according to [74], are the need for large data sets, the need for labeled data, concept drift and computational complexity. The need for large data sets amplifies the issue of computational complexity of inference, and is addressed by the proposed query optimization. The issue of data labeling is delegated to the applications on the one side and the data sources inside the vehicle on the other. The method for semantic labeling is suggested, but the issue is not further addressed by this work. Same can be said for the concept drift, since this issue affects knowledge models which feature non-mutable user attributes. Adding and removing of new knowledge models i.e. probability networks is a task handled by the later proposed software platform called the Probabilistic Application Layer, but the network training and machine learning are out of its scope. Proactive driver assistance with dynamic Bayesian networks has been analyzed by[71], pointing out the problems with erroneous assistance or such assistance which constantly annoys the user by false positives. Setting up correct probability thresholds for proactive assistance would, in the proposed context-centric design, be a task for the higher-level applications, since they use the context-processing service to query the probability of a specific hypothesis.

Bayesian networks are used to model and predict driver's behavior by analyzing the entire driving context in the work of Rakotonirainy[75]. A suggestion to create a high-level Bayesian model containing the vehicle, environment and all the driver information is given, together with the knowledge of the entire system history. Such approach is completely compatible to the driver-vehicle-environment paradigm of AIDE. The work by Cou [76] has shown how Bayesian networks can perform multi-sensor data fusion and emphasized their ability to explicitly model important features, like the sensors' performance. The work done in [77] describes, in another very relevant work on standard platform for sensor fusion, how conditional probability density functions inside a Bayesian network can be used as a standardized output format for all sensors and for the recognition algorithms. The addition of new sensors and recognition algorithms is done by manipulating a limited set of nodes, not affecting the entire system. Calculation performance has, again, been identified as the main disadvantage, partially alleviated by modular network design. In general, related work places large amount of attention on the computational complexity arising from the usage of large Bayesian networks.

Torkkola focuses on driving maneuver classification, as an indirect method of cognitive workload assessment, in order to implement context-aware intelligent driver assistance systems[78]. The classification is performed online with random forests, a method not directly relevant for this thesis. However, the variable importance for each class reveals that a large number of important variables comes directly from the human-machine interface. This provides additional argumentation for using the human-machine interface as a source of context-relevant data.

Inferring the user's affective state and providing correct assistance using visual cues and a dynamic Bayesian network has been throughly analyzed in the work of Li and Ji [71]. Fatigue, nervousness and confusion were recognized, and as a result, support in the form of a warning, information emphasis or information simplification was provided. Areas for improvement have been found in modeling the variability of individual personality, managing complexity of large state space and managing requirements of accuracy. Again, large state space complexity and accuracy of inference on Bayesian networks(through exact inference) are a major topic of this chapter.

Using a priori domain knowledge in order to separate contextual from predictive features in Bayesian networks has been suggested, in order to increase classification and prediction accuracy and to speed up the learning process. Such separation of the network's core, which always performs the same high-level classification, and the context in which the network core is used, could be the first step to an interchangeable Bayesian network format [79]. The software platform suggested at the end of this chapter uses a priori knowledge about the sensor modality and its location on the vehicle(called the modality group) in order to separate the network core functionality from its usage context. This design guideline is presented as a best-practice for handling conditional dependence through hidden external variables and does not constitute the contribution.

Abstract representation of system states has been suggested in order to manage the large state spaces of models based on dynamic Bayesian networks. Relational logic has been successfully employed for abstract state representation, based on logical atoms, which are defined as n-tuples of variables or constants and appropriate relations. An example of such a relation between two variables A and B is in_front_of(A,B), where variables A and B can represent objects detected by vehicle's sensors. An abstract state is therefore a conjunction of logical atoms[80]. Breaking-up the representation model of complex situations is also used in the approach proposed in this work. Any node between the leaf nodes and the query nodes, which is assigned a semantic description, can be interpreted as a deterministic atom of the relational logic.

To summarize on knowledge modeling, a final comparison between Markov and Bayesian networks is given. Even though Bayesian networks can express dependencies which are not representable by Markov networks, the opposite is also the same for non-chordal graphs. Therefore, the class of probabilistic dependencies that can be represented by a Bayesian and Markov network is the class of dependencies which form decomposable models. Their probability distributions have perfect maps in chordal graphs[70].

The Hammersley-Clifford theorem provides the conditions under which a positive probability distribution can be represented as a Markov network. A probability distribution with a positive mass or probability density satisfies one of the Markov properties with respect to an undirected graph G if and only if it is a Gibbs random field, that is, its density can be factorized over the cliques of the graph [81, 82]. The process of moralization, in which the directionality of edges in a Bayesian network is discarded and all unconnected parents are connected by adding new edges, results in a graph with the same factorization property, local Markov property and global Markov property [83].

As the result of this analysis, Bayesian networks have been chosen as the underlying knowledge representation tool.

5.1.3 Basic Concepts behind Bayesian Networks

5.1.3.1 Conditional Probability and Conditional Independence

Let S be defined as set containing all the possible events. The probability measure P quantifies the probability of an event and is defined by:

$$P(A) \geq 0 \tag{5.1}$$

The probability of *any* event happening must be certainty:

$$P(S) = 1 \tag{5.2}$$

The conditional probability of and event A given event B is defined as following:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \tag{5.3}$$

For disjoint events the following rule applies:

$$P(A \cup B) = P(A) + P(B) \tag{5.4}$$

Let A,B and C represent different events. The events A and B are conditionally independent give C if and only if following applies:

$$P(A|C) = P(A|B \cap C) \tag{5.5}$$

which is equivalent to:

$$P(A \cap B|C) = P(A|C) \times P(B|C) \tag{5.6}$$

Let us now introduce the chain rule, which builds upon the definition of conditional probability. An indexed set of N events can be defined as:

$$A_1, \ldots, A_n \tag{5.7}$$

The value of the joint probability of this set is defined as:

$$P(A_n, \ldots, A_1) = \mathrm{P}(A_n|A_{n-1}, \ldots, A_1) \cdot \mathrm{P}(A_{n-1}, \ldots, A_1) \tag{5.8}$$

If this equation is repeated i.e. chained, the result is the following product:

$$P(\cap_{k=1}^{n} A_k) = \prod_{k=1}^{n} \mathrm{P}(A_k \mid \cap_{j=1}^{k-1} A_j) \tag{5.9}$$

The conditional independence between the events A and B implies that once the event C is known, knowing B does not provide any additional information about A.

Knowing the conditional independence between events enables a modular representation of the joint probability and a reduction of representational complexity. This, in turn, enables efficient inference using the variable elimination algorithm, if the correct elimination ordering is chosen. To summarize, assertion of independence reduces the complexity of representing and using the stored knowledge. The efficiency depends on the distributivity of $\times$ over $+$. Time and space complexity of variable elimination is determined by the largest intermediate factor. Finding an ordering to minimize this complexity is an NP-hard problem.

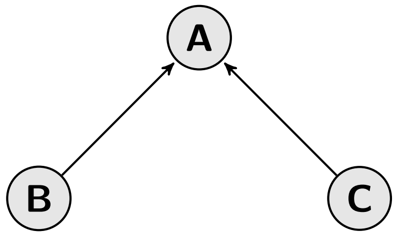

Figure 5.1: Example of a Bayesian network which determines the probability that the driver is tired

5.1.3.2 Encoding Independence in Knowledge Representation

The independence property can be visualized or encoded using graphical models. We differentiate between directed graphical models, which might represent Bayesian networks, and undirected graphical models, which might represent Markov random fields. The structure of a Bayesian network, which express the previously described independence properties, also defines the factorization of the joint probability. In other words, it defines the independence properties using a directed acyclic graph. A simple Bayesian network is shown in Figure 5.1. Let node A denote the fact that the driver is tired. Let node B denote the fact that the current drive lasts very long. Let the node C denote the fact that it is currently very late. The data encoded in its structure tells us that the length of the drive and the current daytime definitely contribute to the driver's tiredness, even though the amount of the contribution is not contained in the structure. The amount in which they contribute to the driver's tiredness is stored in the conditional probability table 5.1.

Table 5.1: Conditional probability table for the Bayesian network example

	B is true C is true	B is true C is false	B is false C is true	B is false C is false
A is true	0.9	0.1	0.1	0.05
A is false	0.1	0.9	0.9	0.95

The factors in an undirected graph, as compared to the directed acyclic graphs of the Bayesian networjs, do not have direct probabilistic interpretations, while the factors in a directed graph represent marginal and conditional densities. Independence in undirected graphs is determined by simple and intuitive graph separation. In direct graphs, independence is determined by a slightly more complicated notion of *d-separation*. D-separation is a relation capturing all forms of independence in a direct graph[70] and it is explained in a very intuitive manner in [84]. A variable A is dependent on variable B given evidence C if and only if there is a *d-connecting path* from A to B, given C. An easy to grasp algorithm which can detect such (in)dependencies in belief networks is the Bayes-Ball algorithm, elaborated in [85].

The previously mentioned moralization procedure is used to convert a directed into an undirected representation, but it does not preserve all the conditional independence properties. All the dependencies stored in an undirected graph are present in the direct graph, but the other way is not true. Some probability densities can only be described by directed graphs and some only with undirected. As an example, Markov graph can represent cyclic dependencies, while a Bayes graph can represent induced dependencies.

5.1.3.3 Inference and Junction Trees

Decision networks have been recognized as an important tool for implementing intelligent user interfaces, but reducing the complexity of user models in order to reduce the computational complexity of exact inference can lead to poor or wrong suggestions. Additional modeling of user interruption or user suggestion cost is necessary, together with user's personality, emotional state and current user activity. When using dynamic Bayesian networks, clique tree algorithms are considered to be particularly suited for exact inference, especially if the observations arrive incrementally and cost of building a clique tree can be amortized over many queries [86, 87].

Exact inference is unfortunately an NP-hard problem, which can be proven by reduction to the 3-Satisfiability(3SAT) problem [88].

Inference can be imagined as an input-output problem, with the input being a vector random variable X, a joint probability density for X, an evidence assignment E and a set of query variables Q. Following this analogy, the output is the conditional density P of query variables Q given evidence E.

Inference on the knowledge stored inside the Bayesian probability network can be performed by exact methods, such as the junction tree algorithm, or approximate methods such as Markov Chain Monte Carlo(MCMC). An overview of MCMC inference is given in [89]. Exact inference was chosen for this work due to the safety-critical nature of tasks in a road vehicle and in order to guarantee that a fully described situation will always be interpreted in the same way, once the network is in place and populated with probability tables. Therefore, this work further concentrates on the junction tree data structure and algorithm. Since exact inference in Bayesian networks has been determined NP-hard, various optimization methods have been developed, which attempt to perform a one-time analysis of the network and optimize inference algorithm on the basis of the a priori structural knowledge. Such analysis might be NP-hard by itself, but it is performed only once, and it provides a long-term reduction of inference complexity. The junction tree algorithm is one of these methods, which constructs a secondary structure on top of the original network, in order to reduce the computational complexity of inference on certain classes of variables by caching intermediate products of variable elimination and enabling parallel execution of different queries. The junction tree is based on tree decomposition, which dates to as early as 1976 and is attributed to Rudolf Halin, but it has been deeply studied in the face of expert systems by Lauritzen and Spiegelhalter [90, 91]. Other names for this secondary structure are join tree, cluster tree and clique tree. The theory behind the junction tree algorithm and junction tree structure is intuitively described in [92], but some key features are repeated here, as an introduction to the proposed contribution.

Nodes in the junction tree are clusters of variables from the original Bayesian network. Edges between the clusters are called separators and are labeled with the intersection of the variable set of the two clusters which they are connecting(structurally connecting but separating in the terms of dependence). Both nodes(clusters) and edges(separators) are associated with a function called belief potential or potential function. Let us denote the cluster belief potentials as ϕ_X and the separator belief potentials as ϕ_X. A potential function maps each instantiation of variables inside a cluster or a separator to a real number, the potential, which is *proportional* to the probability of that instantiation of variables. The potential needs to be normalized in order to become a valid probability value.

The following holds for every cluster and its adjacent separator:

$$\sum_{X \setminus S} \phi_X = \phi_S \tag{5.10}$$

The joint distribution of the original Bayesian network is encoded in the following form:

$$P(S) = \frac{\prod_i \phi_{X_i}}{\prod_j \phi_{S_j}} \tag{5.11}$$

A junction tree T is a tree on graph G constrained by three properties:

1. *Family property*

   The family property states that for each node V in graph G there is a cluster C of tree T which contains the family of V.

2. *Tree property*

   The tree property states that there exists only one path between any pair of clusters in the tree T.

3. *Junction tree property*

   The junction tree property states that or any two clusters A and B of T any for every cluster C on the path between A and B, the following property holds:

$$A \cap B \subseteq C \tag{5.12}$$

A junction tree can be constructed from the Bayesian network in five steps, as explained in [93]:

1. *Moralization*

   In the first step, the original edges in the Bayesian network are made undirected and additional edges are added between the parents of each node.

2. *Triangulation*

   In the second step, edges are added to the graph until it becomes chordal, meaning that every cycle with four and more nodes has a chord - an edge joining two non-adjacent nodes in a cycle.

3. *Construction of the junction graph*

   During the third step, maximal cliques are found and marked as clusters for the next step.

4. *Forming the junction tree*

   In the fourth step, a tree is created by removing the redundant links in the cluster graph from the previous step. Every link between two clusters becomes a separator.

5. *Creating clique potentials*

   In the last steps, every clique is assigned a clique potential - a result of multiplication of all the tables of conditional dependence from the original Bayesian network, which contain all the variables found in the clique.

After the tree has been constructed, it has to be balanced in order to guarantee a global consistency between all the clique potentials. This is performed with the junction tree message passing protocol, explained in the following.

Passing a message from cluster A to the neighboring cluster B over the separator S means marginalizing the probabilities stored in cluster A to the variables contained in the separator S and sending the result of the marginalization to the cluster B. When cluster B receives the marginalized table, it multiplies it with its own tabular probabilities and fully absorbs the knowledge stored in the message.

Let us now define two important functions based upon message passing: Receive(Node X) and Send(Node X).

Algorithm 1 Function Receive(X)

```
for all Children C of X do
  Receive(C)
end for
for all Children C of X do
  Pass message from C to X
end for
```

Algorithm 2 Function Send(X)

```
for all Children C of X do
  Pass message from X to C
end for
for all Children C of X do
  Send(C)
end for
```

Once the junction tree is constructed, following steps are performed in order to achieve global consistency between all clique potentials:

1. One cluster of the junction tree is selected as the root node R
2. The function Receive(R) is called for the root
3. The function Send(R) is called for the root
4. The tree is now balanced

The junction tree has to be re-balanced every time evidence is instantiated, in order to guarantee that each cluster is up to date. Calling the Receive function in the root is further denoted as upward knowledge propagation, while calling the Send function in the root is denoted as downward knowledge propagation.

Most popular message passing algorithms are Shafer-Shenoy, HUGIN and LAZY, further analyzed in [94]. It is important to note that the choice of the algorithm is not directly relevant for the rest of this chapter, since the proposed contribution reduces the total amount of exchanged messages and the total amount of related computations in every case.

To summarize this section, the junction tree exploits conditional independence together with the chain rule, which results in factorized representations of probability densities. This secondary structure, together with the junction tree algorithm, represents, multiplies and marginalizes clique potentials. Variable elimination algorithm can perform inference efficiently in factorized densities. However, variable elimination is query sensitive - different queries have to re-run the entire algorithm. Junction trees, on the other hand, enable simultaneous execution of classes of queries. On a more general note, the algorithm uses the distributivity of multiplication over summation, relying on the properties of a sum-product commutative semiring.

5.1.3.4 Compatible Junction Tree Optimizations

In this section, related work in the form of compatible optimizations of the junction tree algorithm is analyzed. The term compatible denotes that the optimization can be used in conjunction with the one proposed in this thesis, which is further denoted as quality-of-service optimization(QoS) criteria.

The LAZY propagation algorithm by Madsen and Jensen is based on maintaining a multiplicative decomposition of clique and separator potentials and exploiting of barren variables and independence relations induced by evidence[95]. A barren variable is neither evidence nor a target variable and it only has barren descendants[96]. Therefore, such variables have no affect on the posterior probability distribution of the query set. The essence of the LAZY optimization is maintaining a multiplicative decomposition of potentials stored in cliques and separators and delaying their combination for as long as possible. During the LAZY message passing, the internal elimination order is determined on-line on the existing knowledge of barren variables and independence relations invoked by evidence, in order to reduce the amount marginalizations and potential combinations. The rules regarding barren variables and d-separation, based on dynamic evidence and query sets, can be stored as a tertiary look-up structure, parallel to the source Bayesian network and junction tree. This approach is most certainly warranted, since constant checks for d-separation during frequently changing queries incur their own computational complexity. Direct comparison with HUGIN and Shafner-Shenoy on a set of large networks reveal significant reduction of computational complexity, especially with the growing number of evidence variables. Even though LAZY propagation perfectly suits the needs of this thesis and even though adding it to its proposed optimization would not result in any conflicting optimization criteria, it would make the analytical assessment of the contribution heavily dependent on the network structure, mainly on its connectivity. This would make it difficult to demonstrate the general reduction of complexity of evidence upwards and downwards propagation, once the a priori quality-of-service knowledge is provided. Since LAZY augments any given sub-optimal or optimal junction tree built upon a Bayesian network, it would also augment any junction tree constructed with the QoS optimization criteria, but the exact impact has to be measured with the same synthetic tests(Diabetes, KK and ship-ship networks) used to compare against HUGIN and Shafner-Shenoy.

Dynamic jointrees are method for dynamic junction tree reconfiguration, triggered due to a query change[97].QoS criteria also reconfigures the junction tree based on the query changes, but the key difference is that the dynamic jointrees refer to the removal of barren variables(made barren by the new query), while the proposed criteria uses only the query's QoS parameters. The compatible part of the method is reusing the existing computations stored in the tree, after its reconfiguration. All the existing potentials, as well as the messages which are underway, can be reused after marginalization, since local information is not affected by remote cluster changes.

The work on optimization of exact inference of Xia and Prasanna, under the name of Parallel Exact Inference, presents a parallel approach to both junction tree construction and inference[98]. The approach is based on the message-passing paradigm. Optimizing the process of creating a junction tree is fully compatible with the approach presented in this work, up to the point where multiple junction tree alternatives arise. However, even after this point, a message-passing-based search for the optimal alternative tree would be conceptually and technically easy to implement. During inference, the message passing protocol is parallelized and the junction tree is being re-rooted, based on the clique which contains the evidence. As shown later, the QoS criteria is the same as the one used by the Parallel Exact Inference in the case when no alternative junction trees exist, and the only room for optimization lies in re-rooting the junction tree and re-selecting the clusters where the evidence is instantiated.

5.2 Providing Inference Quality-of-Service

As opposed to the previous approaches, this thesis focuses on context processing from the application's point of view. An application needs a context-relevant question answered with a specific quality-of-service requirements, what can result in computationally intensive exact inference. A context processing platform which abstracts the probabilistic model from the application space is proposed. Data sources inside the vehicle, such as sensor inputs and semantic nodes provided by various sub-networks, exist only to generate high-level hypotheses which are correspond to queries from application space. One arising issue is the high query frequency and large knowledge propagation latency inside the probabilistic model. This issue is exacerbated on the automotive-grade hardware, which is traditionally underpowered and cost-oriented. Therefore, it is addressed directly, in the form of a changed optimization criteria for junction tree construction.

Another issue are the structural changes of the probabilistic model during vehicle operation, here denoted as Bayesian network reconfiguration. A structural change can be requested if an application wishes to contribute a new sub-model to the existing probabilistic model. For example, a new Bayesian network for driver fatigue detection can be added, after the vehicle has been retrofitted with a camera observing the driver's eyes. This issue is addressed indirectly, through the proposed context-processing service at the end of this chapter. Tagging the nodes of Bayesian networks with semantic data according to the Open Geospatial Consortium Sensor Web Enablement is proposed, enabling semantic interoperability between different networks.

Since the chosen inference method is exact, the relevant quality-of-service dimensions from the application point of view are query latency(best, worse and average time to answer a query) and highest query frequency(the rate at which the query can be continuously answered). The both are not in a logically expected correlation, since answering a rare and event-triggered query can be performed by a different method(with a differing complexity) than a continuous high-frequency one. In addition, each query has a specific criticality or priority relative to the co-existing queries. The scheduler will always attempt to satisfy the requirements of high-priority queries first, which might result in exclusion(non-scheduling) of low-priority queries. Therefore, another QoS dimension is query schedulability, which might change during runtime if a high-priority query pushes an existing low-priority query out of the schedule. Finally, since different sources provide updates at different rates, final inference result will be based on state of the sources of varying actuality. This might be described as by the difference in the current time and the time the source was updated(absolute actuality) or by the time necessary to reach the next source update(relative actuality). In the rest of this work, focus is placed on reducing the computational complexity of high-frequency queries, in order to meet the requirements of the most computationally intensive applications. A new optimality criteria for the Bayesian network's secondary structure, the junction tree, is suggested, and its effectiveness is demonstrated.

5.2.1 Example of Safety-Critical Quality-of-Service Requirements

In order to understand the impact of latencies when answering safety-critical queries, an example for QoS requirements is given in the following.

Let us assume a query on the probability of a dangerous situation with a frequency of 50Hz. This frequency and its period of 20ms can be seen from two different aspects - as a requirements which has to executed by the on-board embedded hardware and as a value which relates to the vehicle dynamics.

We briefly mention the aspect related to vehicle dynamics and continue to analyze the aspect related to computational complexity throughout the rest of this chapter.

At the speed of 130km/h, the vehicle moves 9,36m between each query, meaning that the lag induced by exact inference directly decides how long the vehicle drives "blindly" that is with the assumption that no significant event happened since the last query was executed. Time-to-collision(TTC) represents the time before the vehicle will impact with another object, person or environment. The border value of TTC represents the time which is necessary in order to reduce the absolute or relative vehicle velocity to zero(in regards to the static or moving object it is colliding with), assuming a constant deceleration of a. Therefore, if the border TTC is reachable with braking deceleration of a, no collision will occur.

$$TTC_{border} = \frac{2|a|}{\Delta v_o} \tag{5.13}$$

In the case the border TTC is not reachable, a collision will occur, with the relative speed between two objects having the value of $\Delta v_{remaining}$.

$$\Delta v_{remaining} = \sqrt{\Delta v_o^2 v - 2 \times |a| \times TTC \times \Delta v_o} \tag{5.14}$$

However, a collision can also be avoided by a lateral evasive maneuver. In the case that the lateral acceleration reaches the maximum value of 1g, assuming the lateral friction coefficient of 1, time to perform the evasive maneuver time-to-evade(TTE) is:

$$TTE = \sqrt{\frac{2 \times (y_{goal} - y_0)}{g}} \tag{5.15}$$

If the vehicle width of 2 m is assumed, together with the assumption that both vehicles are centered i.e. are driving aligned one after another, minimal TTE is 0.6 seconds. Wheel reaction times of 0.1 seconds can be added to compensate for the lag of the vehicle's steering system, making the best-case TTE 0.7 seconds. Average drivers in real-life situations seem to reach values between 1 and 1.6 seconds [99].

5.2.2 Computational Complexity of Elementary Junction Tree Operations

In this section, the complexity of the tree basic operations performed by the junction tree algorithm is analyzed. For simplicity, it is assumed that previously defined operations of message multiplication and table marginalization have the computational complexity equal to the size of the cluster in which they are performed.

The time and space complexity of all operations is exponential in the size of the largest cluster - this quantity is also known as the width of the junction tree.

Storing the clique potential ϕ_A has the complexity of:

$$O(k^{|A|}) \tag{5.16}$$

Performing clique multiplication $\phi_A \times \phi_B$ has the complexity of:

$$O(k^{|A \cup B|}) \tag{5.17}$$

Lastly, performing clique potential marginalization:

$$\sum_{b \in \mathbb{X}_b} \phi_A(a \cup b) \tag{5.18}$$

has the complexity of:

$$O(k^{|A|}) \tag{5.19}$$

The calculation of query complexity can be divided into the upward propagation part and the downward propagation part.

Let us denote the time necessary for upward propagation as t_u and the time necessary for downward propagation as t_d . The highest query frequency supported by the junction tree is therefore:

$$f_{max} = \frac{1}{t_u + t_d} \tag{5.20}$$

In the rest of this chapter, the complexity of executing application queries will be described in FLOPS, since the basic operations on probability density tables are made using floating point precision. For reference, today's average automotive-grade embedded hardware provides between 0.1(platforms for drive train management) and 5(platforms for cockpit applications) MFLOPS.

Even though all the queries might be fully answered after the upward propagation, downwards propagation has to be completed before the next query iteration, in order to have a consistent junction tree structure. If the query set is not fully answered after the upward propagation step(is not contained in the root cluster), partial downwards propagation has to be performed anyway, in order to answer the query. This rule can be relaxed using parallelization of downwards propagation in sub-trees which are "far" from the path used for upwards propagation and synchronizing the both just-in-time. Such relaxation was not performed in the scope of this work.

5.2.3 Proposed Secondary Structure Optimality Criteria

The contribution of this chapter is the QoS-based optimality criteria for constructing the junction trees, which is explained in the following.

The existing procedure for junction tree construction guarantees that the computational complexity of inference is minimized through exploiting tree decomposition. However, this yield optimal results only in the case when no knowledge about the relative frequency of inference on individual variables in known. A query from the application space containing exact quality-of-service requirements adds new knowledge and therefore affects the existing optimality criteria used for junction tree construction. The optimization space or room for improvement are all the valid alternative junction trees gained through the junction tree construction algorithm as well as all the possible placements of the source and query variables in a specific alternative junction tree. Alternative junction trees for a specific Bayesian network exist every time when there are multiple edges(clique separators) of the same size and a free decision can be made during the tree construction.

The query nodes are denoted as $\mathbb{Q}$ while the source nodes are denoted as $\mathbb{S}$. Let us denote the set of valid junction trees as $\mathbb{T}$. Each valid junction tree is assigned a set $\mathbb{T}_p$, containing all possible placements of the root for the message passing algorithm, together with the selection of clusters where the evidence is to be instantiated.

The proposed QoS-based optimality criteria is defined as following:

Once the quality-of-service requirements of all queries are known, such alternative junction tree in the set $\mathbb{T}$ which enables the assignment of set $\mathbb{S}$ containing the instantiated data sources, the assignment of set $\mathbb{Q}$ containing the query variables and the assignment of junction tree root cluster R with minimal computational complexity of upward and downward propagation of most resource-intensive queries should be selected.

In other words, all the configurations of sets $\mathbb{S}$ and $\mathbb{Q}$ in all the alternative junction trees $\mathbb{T}$ should be evaluated for computational complexity requested by the query, additionally taking all the possible junction tree root cluster assignments into account.

For every valid junction tree in $\mathbb{T}$ and for every placement in appropriate $\mathbb{T}_p$, following upward propagation steps are calculated:

1. Reduction of state size of the clusters chosen for evidence instantiation
2. Marginalization over separators and inside cliques
3. Multiplication of clique potentials

The complexity of each operation is defined by the state size of each clique and separator.

Additionally, the advantages of separability induced by the junction tree is taken into account. The goal is the propagate the data induced by the evidence nodes to the query nodes. This task contains a series of serial and parallel steps, as defined by the structure of junction tree and the selected placement in $\mathbb{T}_p$. The exact upwards propagation time is determined by the longest path from the root node to all of the instantiated evidence nodes. The metric i.e. the measurement of length is determined by adding together the three necessary upward propagation steps, parameterized by the size of each cluster or separator. It is assumed that all the branches can be executed in parallel during the execution of the longest path, ignoring the number of supported threads or processes on a specific hardware architecture. For the worst case in the terms of hardware architecture, all the branches can be serialized and summed up, even though this partially defeats the purpose of having a junction tree.

The time needed for downward propagation is, comparable to the upward propagation, the longest path from the root node to all of the leaf nodes. The metric for the path length stays the same, because the same operations are performed in both directions. Since all the nodes have to be visited, no difference in complexity can be expected if the root is located in a leaf node.

The impact of the criteria on the junction tree construction, the concrete reduction of inference complexity and and the practical application of the criteria is analyzed on two Bayesian networks.

The first Bayesian network encodes very basic rules for detecting driver distraction during dangerous turning maneuvers. The second Bayesian network is the standardized INSURANCE network, often used for complexity analysis and benchmarks of probabilistic models and associated algorithms.

5.2.3.1 Optimization Criteria with the Driver Distraction Network

The Driver Distraction Network N encodes following statements:

1. If the vehicle is moving forward at a slow pace, if the wheels are turned left and if the lidar sensor reports an object to the left of the vehicle, the vehicle is on a collision path to the object
2. Analog rule as above for the right turn and the object on the right side of the vehicle
3. If the driver is looking left and has moved his head to the left, he is not paying attention to the right side of the vehicle
4. Analog rule as above for looking right and not paying attention to the left
5. If the driver is not paying attention to the left vehicle side but might drive into an object on the left side, a left-side-collision is expected
6. Analog rule as above for looking right and a collision path on the left
7. If the above defined rules for the left or the right warning are activated, the driver is in a dangerous situation

The last rule seems to incur useless classification which is too abstract to meaningfully react to, but it could be the building block of a higher-order network, which can, for example, precondition passive safety systems regardless of the vehicle direction.

The nodes of N, which describe the probability of the stored statements to be true or false, are described in table 5.2.

Table 5.2: Description and meaning of nodes in the Bayesian network N

Label	Interpretation
A	The driver is currently in a dangerous situation
B	Left-side collision is expected
C	Right-side collision is expected
D	Driver is not paying attention to the left side
E	The vehicle is on the collision path to the object on the left side
F	The vehicle is on the collision path to the object on the right side
G	Driver is not paying attention to the right side
H	The driver is looking right
I	The driver has moved his head to the right
J	The wheels are turned to the left
K	The lidar is reporting an object in front of the vehicle on the left side
L	The vehicle is moving forward
M	The lidar is reporting an object in front of the vehicle on the right side
N	The wheels are turned to the right
O	The driver has moved his head to the right
P	The driver is looking right

The network's structure is shown in Figure 5.2. For the time being, we ignore the tabular conditionals i.e. the conditional probability values assigned to the edges, and focus only on the network's structure.

Another view of the network's structure is given in Figure 5.3. The circular graph layout provides an easier overview of the connectivity and size of the network, especially in comparison to the later analyzed network INSURANCE.

The network N is now translated into a clique network CN, by losing the directionality, performing moralization and triangulation. Lex M algorithm is used for triangulation[100].

The network's structure after moralization is shown in Figure 5.4.

Triangulation is the last step before the identification of maximal cliques takes place, and it results with structure shown in Figure 5.5.

Following maximal cliques are identified after triangulation: BCDE, EJKL, FLMN, ABC, DHI, CEF, CFG, GOP and EFL. The resulting clique network is shown in Figure 5.6.

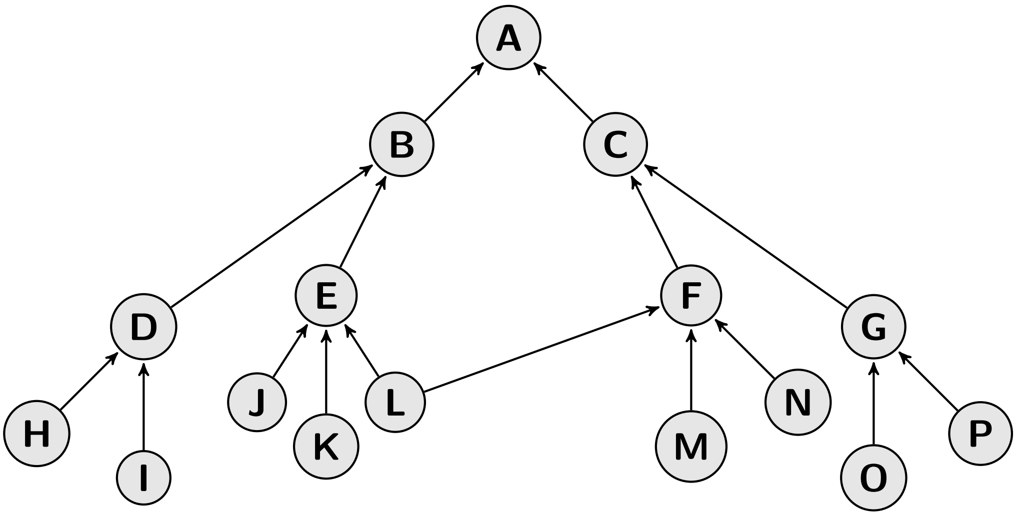

Figure 5.2: Bayesian network N used for detecting driver distraction in dangerous turning maneuvers

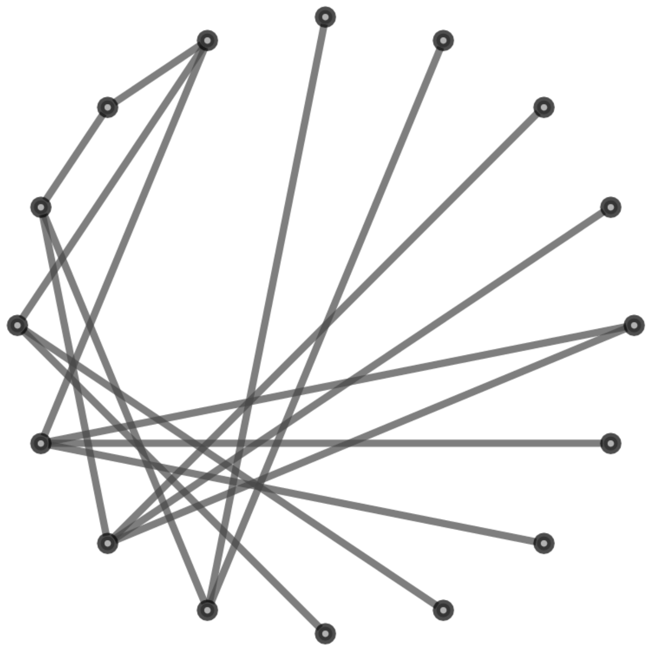

Figure 5.3: Bayesian network N after dropping edge directionality

The clique network CN can be transformed into only one valid junction tree and is therefore used to demonstrate how the choice of the $\mathbb{S}$ and $\mathbb{Q}$ can influence the inference complexity. The resulting junction tree is shown in Figure 5.7.

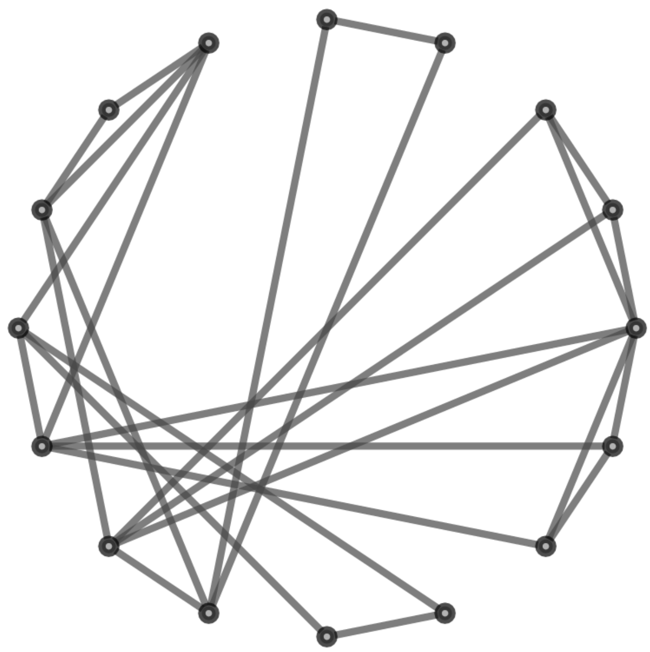

Figure 5.4: Bayesian network N after moralization

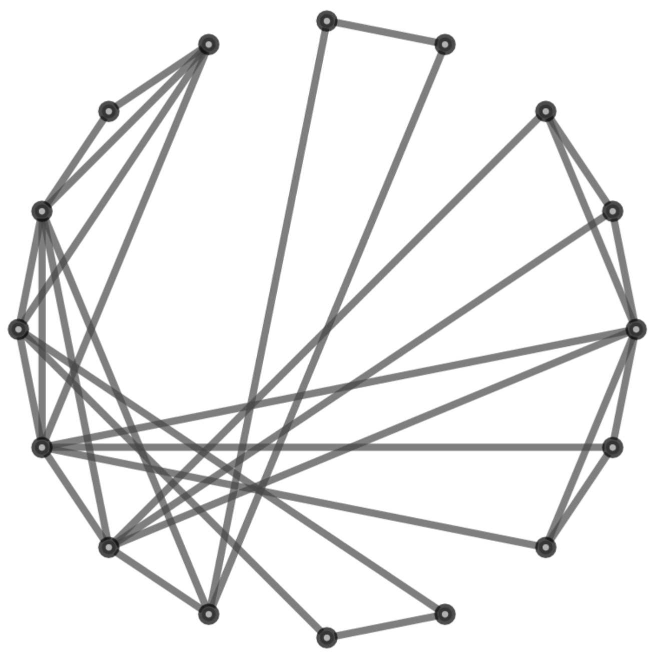

Figure 5.5: Bayesian network N after triangulation

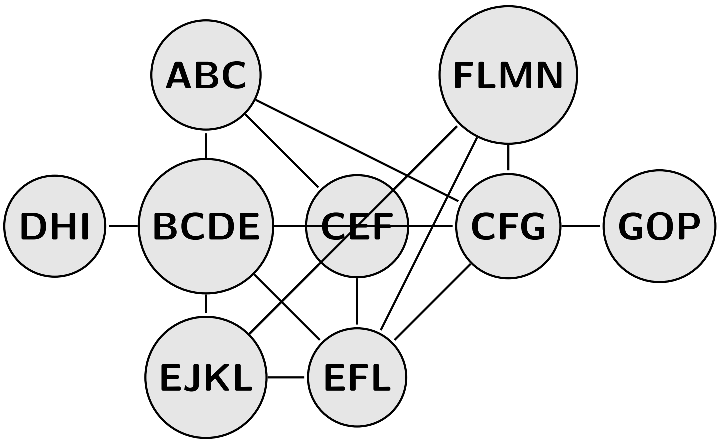

Figure 5.6: Clique network resulting from the network N

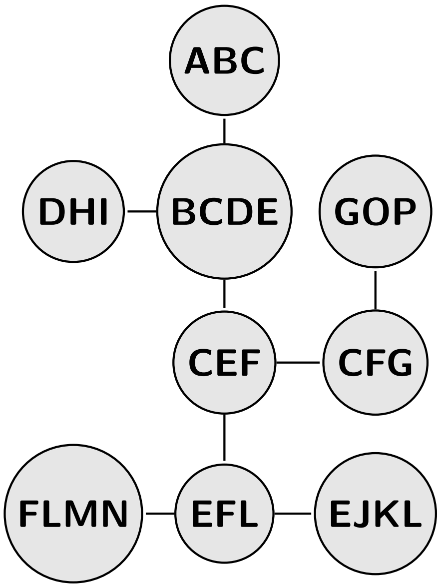

Figure 5.7: Junction tree resulting from the clique network of the converted Bayesian network N

In order to utilize the optimality criteria, a priori knowledge of data sources, application queries and their QoS requirements is necessary.

A query can be answered at a specific frequency if there is at least one node producing new information at this frequency and if the inference computational complexity allows its scheduling.

Let us assume that the lidar measurements(nodes K and M) are the most frequent ones and that they can meet the 50Hz refresh rate requested by the query from the application space.

Since no alternative junction trees exist, the only room for optimization lies in careful selection of sets $\mathbb{S}$ and $\mathbb{Q}$, as well as the root for the message passing protocol. The variables K and M both appear in only one cluster, further reducing the optimization space to root cluster selection. At this point, the QoS optimization criteria becomes equal with the Parallel Exact Inference criteria, since the only further room for optimization lies in parallelization of upwards and downwards propagation.

Let us assume two different junction tree root placements:

1. The root is the cluster ABC, since the variable A is one of the query variables
2. The root is the cluster CEF, since this would reduce the cost of downward propagation through parallel message passing

By choosing to instantiate $\mathbb{S}$ in cliques FLMN and EJKL and $\mathbb{Q}$ in clique ABC and fixing the root at node ABC, the upward propagation has to go through the nodes FLMN/EJKL-EFL-CEF-BCDE-ABC. The operations in the nodes FLMN and EJKL can be done in parallel, due to the junction tree structure. The appropriate complexity c, based on the node size, is:

$$c = 2^3 + 3 \times 2^3 + 2 \times 2^3 + 2 \times 2^4 + 2^3 \tag{5.21}$$

what can be approximated by 2^6.

Taking the previously established 50Hz query rate as an example, the real complexity amounts to 50×2^6 operations per second. Since every basic operation includes floating points, this means that this query requires a constant 3.2 kFLOPS. Since the junction tree root is located in a leaf node, the complexity of the downwards propagation is the same, meaning that it also requires a constant 3.2 kFLOPS. In total, this query incurs a computational load of 6.4 kFLOPS.

Let us now repeat the same calculation with the junction tree re-rooted in node CEF.

By choosing to instantiate $\mathbb{S}$ in cliques FLMN and EJKL and $\mathbb{Q}$ in clique ABC and fixing the root at node CEF, the upward propagation has to go through the nodes FLMN/EJKL-EFL-CEF. The operations in the nodes FLMN and EJKL can be done in parallel, due to the junction tree structure. The appropriate complexity c, based on the node size, is:

$$c = 2^3 + 3 \times 2^3 + 2^3 \tag{5.22}$$

what can be approximated by 2^5.

Taking the previously established 50Hz query rate as an example, the real complexity amounts to 50×2^5 operations per second. Since every basic operation includes floating points, this means that this query requires a constant 1.6 kFLOPS.

The complexity of the downward propagation is dependent on the largest distance from the root node to the every leaf node. This is the path CEF-BCDE-ABC/DHI. The operations in the nodes ABC and DHI can be done in parallel, due to the junction tree structure. The appropriate complexity c, based on the node size, is:

$$c = 3 \times 2^3 + 3 \times 2^4 + 2^3 + 2 \times 2^3 \tag{5.23}$$

what can be approximated by 2^6.

Taking the previously established 50Hz query rate as an example, the real complexity amounts to 50×2^6 operations per second. Since every basic operation includes floating points, this means that this query requires a constant 3.2 kFLOPS. In total, this query incurs a computational load of 4.8 kFLOPS.

To summarize, the re-rooting operation, as the only available optimization measure in a relatively small network with 16 nodes, yielded a complexity reduction of 25%.

5.2.3.2 Optimization Criteria on the INSURANCE Bayesian Network

In order to provide a more standardized and comparable analysis of the optimization criteria, the INSURANCE network was chosen[101]. Its properties are given in Table 5.3.

Table 5.3: Properties of the INSURANCE network

Property	Value
Number of nodes	27
Number of arcs	52
Number of parameters	984
Average Markov blanket size	5.19
Average degree	3.85
Maximum in-degree	3

A graphical explanation of the INSURANCE network is given in Figure 5.8.

A short overview on the construction of the secondary structure, the junction tree, is provided. The construction follows the previously described rules up to the point where the junction

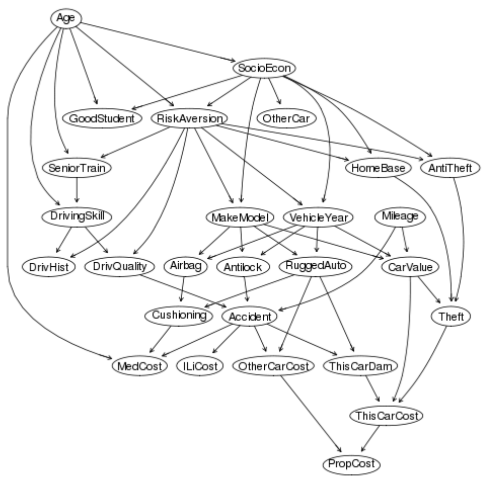

Figure 5.8: INSURANCE Bayesian network(Image copyright by Marco Scutari, University College London)

tree is constructed on top of the clique network. As before, the junction tree has to contain the maximal cliques, since this is one of the existing optimality criteria.

In the first step, the edge directionality is dropped, yielding the network shown in Figure 5.9.

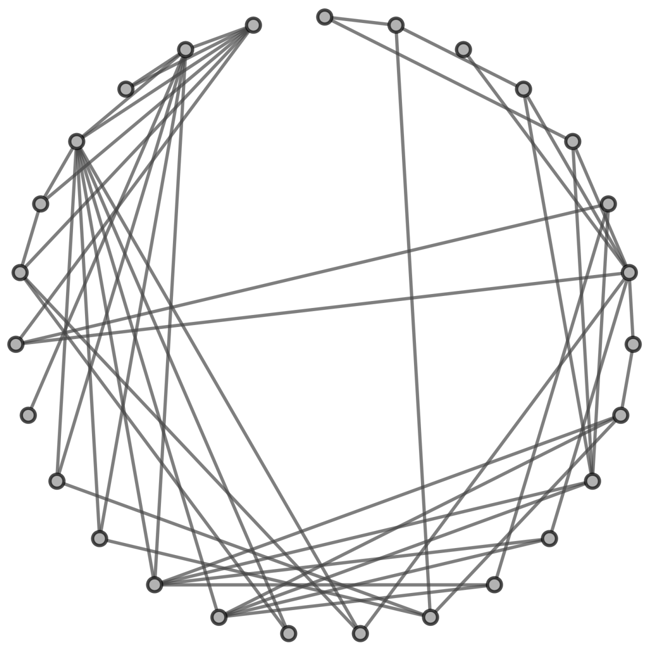

Figure 5.9: INSURANCE Bayesian network after dropping the edge directionality

After moralization, the network takes the form shown in Figure 5.10.

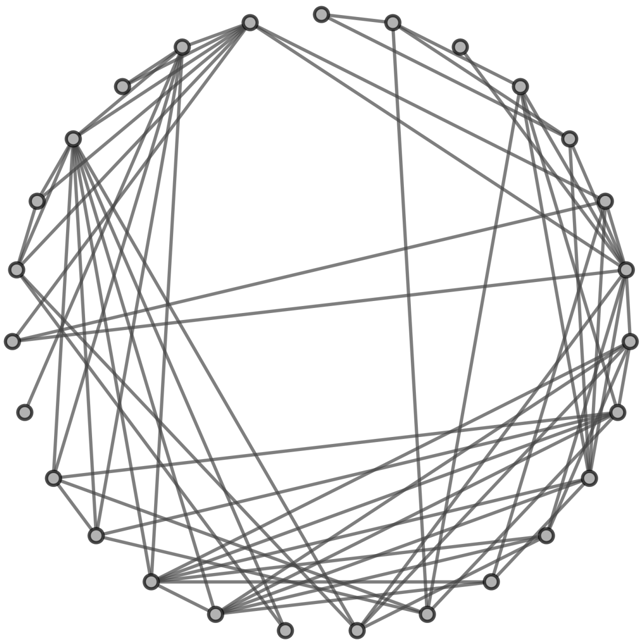

Figure 5.10: INSURANCE Bayesian network after moralization

Triangulation adds even more edges, shown in Figure 5.11

After determining the maximal cliques, the construction of the junction tree is brought to the point where alternative solutions exist, as represented in Figure 5.12. The maximal cliques are in the Table 5.4.

The INSURANCE network provides 224 alternative configurations and the choice can drastically impact the ability to meet the QoS requirements. The alternative configurations arise when following the principle of maximal weight spanning tree(for maximal separator mass). If we added the best-practice principle of choosing the lowest separator weight if the separator mass is the same, the optimal solution might be lost, since this principle does not take the QoS requirements into account. Therefore, the principle of reducing the separator mass is not considered in the suggested optimization criteria. This is the only difference from the current best-practice for junction tree construction and is not crucial for the success of the criteria.

For the analysis of the importance of correct placement of query and source variables, let us select a junction tree configuration shown in Figure 5.13. Let us place the variable Age(Node 1) in $\mathbb{S}$ and the variable ILiCost(Node 23) in $\mathbb{Q}$.

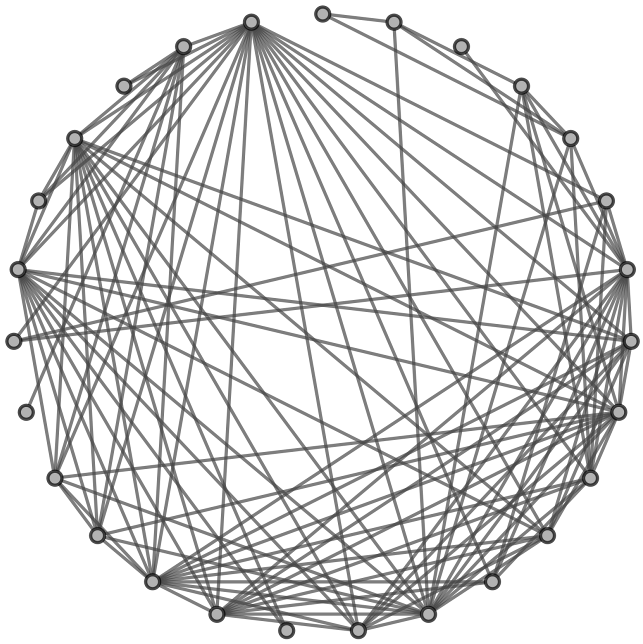

Figure 5.11: INSURANCE Bayesian network after triangulation

By choosing to instantiate $\mathbb{S}$ in clique G and $\mathbb{Q}$ in clique X4(this is the only compatible clique) and fixing the root at node X4, the upward propagation has to go through the nodes G-A-B-J-K-X4. The appropriate complexity c, based on the node size, is:

$$c = 2^8 + 2 \times 2^{10} + 2 \times 2^9 + 2 \times 2^5 + 2 \times 2^5 + 2 \times 2^2 \tag{5.24}$$

what can be approximated by 2^{11}.

Taking the previously established 50Hz query rate as an example, the real complexity amounts to 50×2^{11} operations per second. Since every basic operation includes floating points, this means that this query requires a constant 0.1 MFLOPS.

By choosing to instantiate $\mathbb{S}$ in clique I and $\mathbb{Q}$ in clique X4(this is the only compatible clique) and fixing the root at node X4, the upward propagation has to go through the nodes I-X4. The appropriate complexity c, based on the node size, is:

$$c = 2^4 + 2 \times 2^2 \tag{5.25}$$

what can be approximated by 2^4 or 0.8 kFLOPS.

Table 5.4: Maximal cliques of the INSURANCE network

Clique label	Nodes in the clique
A	1,4,9,10,11,12,14,16,18,21
B	1,10,11,12,14,16,18,20,21
C	1,10,11,17,18,20,21
D	1,10,11,15,17,20
E	1,2,4,7,8,9,11
F	1,2,4,6,9
G	1,4,7,8,9,11,18,21
H	1,15,17,19,20
I	1,19,20,22
J	17,18,20,21,25
K	17,20,21,24,25
L	21,24,25,26
M	24,26,27
X1	4,9,13
X2	1,2,3
X3	2,5
X4	20,23

The first assignment yields a complexity reduction of upward propagation by the order of magnitude of 2^7.

There is no significant difference between the complexity of downward propagation, since the junction tree alternatives of INSURANCE do not change the three structure drastically and since the root has been fixed to the cluster containing the query variables.

For the next analysis, a second INSURANCE junction tree shown in Figure 5.14 is proposed.

The only difference with the previous tree is that the clique X4 has been attached to clique I.

Let us place the variable Age(Node 1) in $\mathbb{S}$ and the variable ILiCost(Node 23) in $\mathbb{Q}$. This time, the placement stays the same, while the two trees are compared to each other.

The first tree requires the upward propagation to go through the nodes B-J-K-X4.

The appropriate complexity c, based on the node size, is:

$$c = 2^9 + 2 \times 2^5 + 2 \times 2^5 + 2 \times 2^2 \tag{5.26}$$

what can be approximated by 2^9 or 25 kFLOPS at 50 Hz.

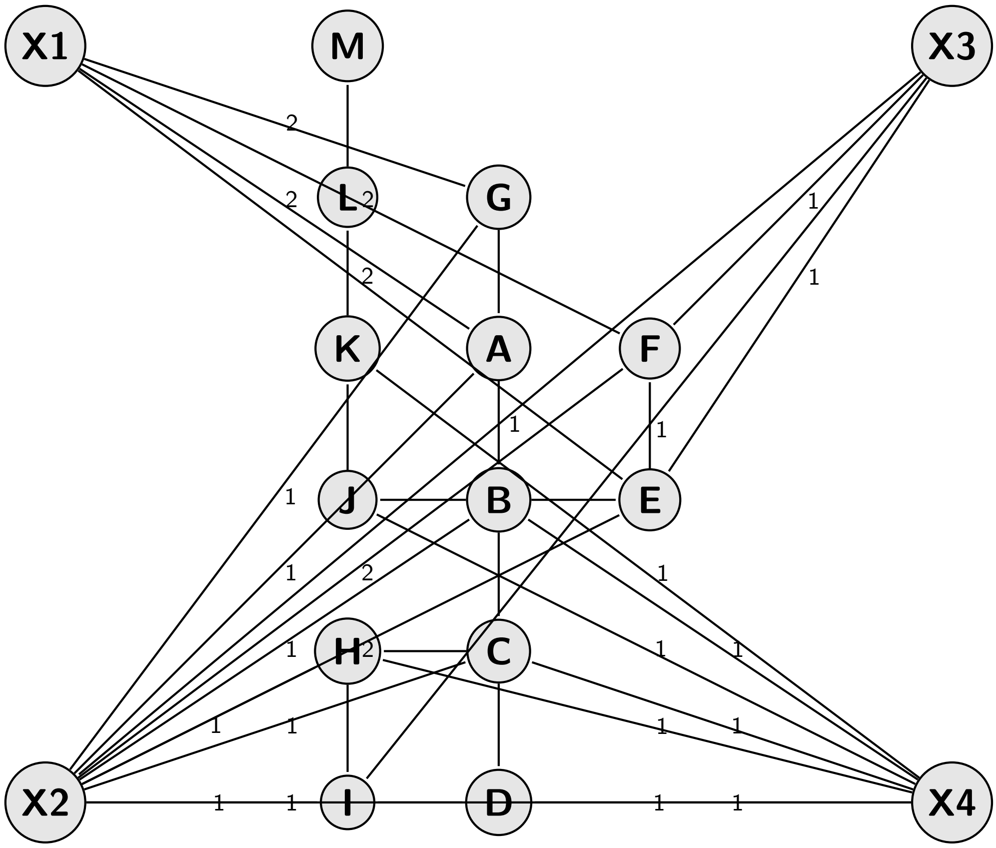

Figure 5.12: Alternative junction trees of the INSURANCE network

The second tree requires the upward propagation to go through the nodes I-X4.

The appropriate complexity c, based on the node size, is:

$$c = 2^4 + 2 \times 2^2 \tag{5.27}$$

what can be approximated by 2^4 or 0.8 kFLOPS at 50 Hz.

By choosing the second junction tree, the complexity for upward propagation is therefore reduced by the factor of 2^5.

To summarize the analysis of the INSURANCE network, it can be noted that the QoS optimization criteria greatly profits from larger node count, but it can be assumed that connectivity has an even greater impact on the size of the optimization space. Apart from the properties of the initial Bayesian network, the complexity of the application query also directly influences the size of the optimization space. A query which depends on a large number of data sources adds all the possible combinations of source instantiation clusters to the optimization space.

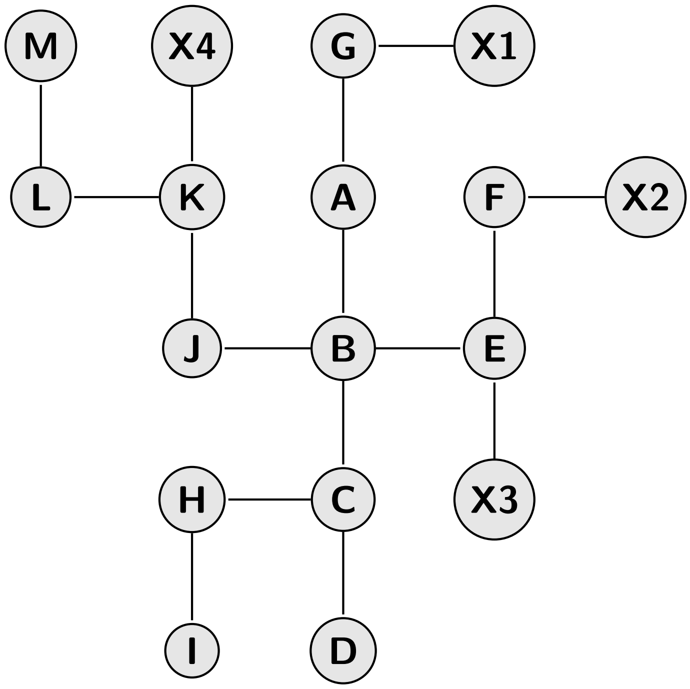

Figure 5.13: A valid junction tree configuration of INSURANCE chosen for assignment analysis

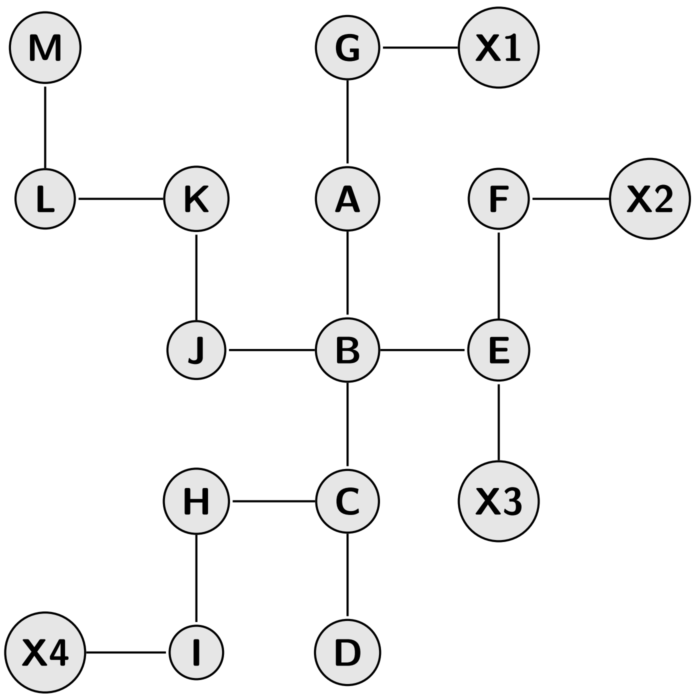

Figure 5.14: A valid junction tree configuration of INSURANCE chosen for tree selection analysis

5.2.3.3 Conclusion and Future Work

It can be concluded that the optimization criteria which takes the quality-of-service requirements into account yields a significant reduction of computational complexity for most resource-intensive queries. Additional space for optimization is present, since the medium-intensive queries might suffer through such favoring of the resource-intensive queries. The optimization criteria presented here is not flexible enough to find a global optimum in regards to the entire query set, but specifically caters to the most resource intensive queries. The added computational cost of catering to medium-intensive queries has to be compared to the benefit, since the speedup might be negligible. Junction trees inherently parallelize all the calculations which are being performed during the knowledge models' operation. Parallelization can be further analyzed in regards to the specific runtime environments and hardware platforms and in regards to optimizing the medium-intensive queries.

Another topic for future work is the analysis of the growth of the complexity of the optimization space search compared to the growth of the underlying Bayesian network. Optimizing the queries is, of course, increasingly complex in growing Bayesian networks. It can be expected that the optimization gains grow even faster, but a benchmark on commonly used networks is necessary to assess the ratio between the one-time computational cost and long-term benefit for a specific query.

Knowledge exchange between vehicles, on the basis of semantically described Bayesian networks, is yet another exciting area for future research. A fleet of vehicles operating in a specific geographical and cultural region might profit from tuning their existing networks through knowledge trading. The top-level intelligent transport system might decide to redesign a specific network deployed in all supervised vehicles, if the field trials show that there is room for improvement. Stored user profiles could also be exchanged between different vehicle types.

With the main concepts and benefits of the optimization criteria explained, a software architecture which connects high-level applications with low-level context processing is proposed in the following section.

5.3 Proposed Software Platform

In this section, the components of a software solution which delegates context processing away from the application space is proposed. Even though it does not add to the contribution, the section tries to bridge the gap between the theory presented in the previous sections and a practical human-machine interface. In addition, some best practices are suggested for implementation, in order to avoid the common pitfalls of modeling the conditional independence.

5.3.1 Introduction

The software solution proposed in the previous section builds upon Bayesian networks for knowledge representation and extends the junction tree algorithm in order to increase the performance of exact inference. This is one of the enabling methods for providing strict time guarantees on exact inference, which is of benefit for the driver assistance systems. In this section, a software service is suggested, which enables the human-machine interface and driver assistance applications to place complex queries, while being context-processing-agnostic themselves. The chosen name for the service is the Probabilistic Application Layer(PAL), denoting the created separation layer between probabilistic reasoning and high-level application space.

As stated before, the HMI and ADAS applications must be able to place context-related queries with specific quality-of-service(QoS) requirements. The QoS requirements might define the allowed worst-case update frequencies / latencies for query answering. This might be relevant to the ADAS applications operating with safety-critical queries, such as the ones related to pre-conditioning of the passive safety systems in a case of a known time-to-crash.

An example of such continuous and safety-relevant ADAS application query might be "Is the frontal crash imminent?", which has to be incorporated as a hypothesis into the Bayesian knowledge model. Such hypothesis has to be continuously inferred and the result of inference has to be delivered to the application in a timely manner, in order to be of practical help to the traffic safety. In the rest of this section, the terms "query" and "hypothesis" are often interchanged, when describing the questions placed by the applications to PAL. The reason for this interchanging of terms is that an initial query, placed by an application, transforms into a node called hypothesis node once it becomes a part of the inference network. The hypothesis node can take a value between 0(the answer to the question is 100% false) and 1(the answer to the question is 100% true). To recap, when a query gets added to PAL, it becomes a hypothesis which is assigned a certain probability of being true.

From this point on and for brevity, the set all the Bayesian networks as well as the isolated nodes in the vehicle are referred to as the main knowledge model.

The sensor nodes or sensor sources should internally be organized into so-called modality groups, based upon the conditional independence which is known beforehand due to the same or similar sensor technology and the similar location/placement on the vehicle. As an example, a pair of feature extraction networks based on camera data might be affected by sunlight or another shared hidden variable. Even though this dependence is not captured as a dependency inside the individual feature extraction network(as it is not be important for its operation), a higher-level network can use the semantic description of nodes to take common hidden variables into account.

In order to provide semantic interoperability between different Bayesian networks, semantic data has to attached to the networks as whole and to the nodes which the network designers deem for significant. As an example, a feature extraction network might contain a large number of levels which have little to none significance for the network user, be it an application or another Bayesian network. However, if the top-level nodes contains a clear conclusion about the feature of interest, for example a recognized object class, it should be expanded with semantic data, in order to make this data available to applications and other networks.

It might often be the case that a vehicle sensor or subsystem adds one or more nodes to the main knowledge model, without any additional network structure. An example might be a node added by the ultrasound sensor, denoting the probability that an object has been placed directly in front of the sensor. Such nodes must be expanded with semantic data, since they are otherwise useless in the main knowledge model. As an implementation suggestion, every new sensor-based data source should be ordered into a modality group. A modality group determines the sensor's technology and location on the vehicle, but it can be expanded by any number of outside factors which can cause conditional dependency between otherwise independent source nodes. In addition, a specification sheet of every sensor should be included. Each sensor has a specific probability of detecting an object in its field of view. This probability depends on a set of known parameters, such as the angle and distance of the object being sensed. On the higher level, however, more data is known in the system, such as weather conditions and time of day, and this data can be used to further modify the plausibility of a sensor measurement. In essence, this type of reasoning is similar to the previously described modal grouping, but it focuses on the plausibility of inferred knowledge and not on eliminating the cross-dependence between different sources.

Proposed software components of PAL are shown in Figure 5.15 and are explained in the following.

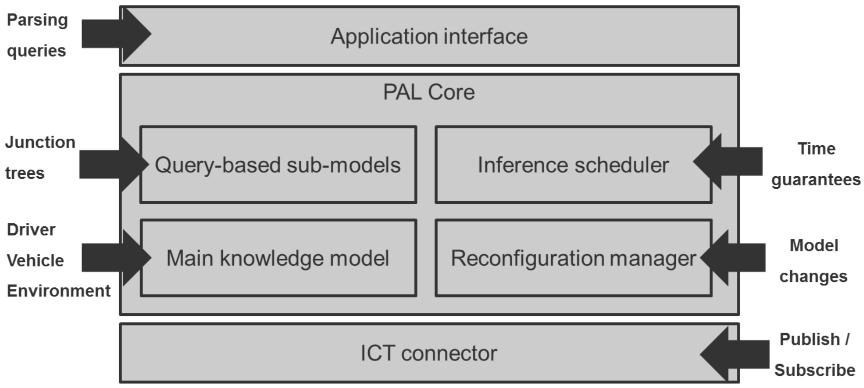

Figure 5.15: Proposed components of the probabilistic application layer

5.3.2 Application Interface

The interface towards the application space is based on XML and heavily leaned on a standard used for semantic sensor web - Open Geospatial Consortium(OGC) Sensor Web Enablement(SWE). An application can request the currently active set of hypotheses(i.e. the queries which the PAL is already answering), the potential set of hypotheses(all the queries which the PAL knows how to answer), suggest new methods of combining data(new Bayesian networks) and insert a single node which is a data source with semantic description. As mentioned before, it can also request an answer from PAL with a quality-of-service requirements.

5.3.3 Main Knowledge Model

The main knowledge model contains all the Bayesian networks and separate data sources inside the vehicle. The nodes can be divided into the following three layers, as shown in Figure 5.16:

1. Hypothesis Layer
2. Feature Extraction Layer
3. Modality Groups

The hypothesis layer(HL), as mentioned before, contains all the to-be-answered queries placed by HMI and ADAS applications. Answering the queries is the sole purpose of PAL, so the entire underlying structure exists in order to enable exact inference on these nodes. Of course, an application can query any node which has semantic data attached to it. It is however expected that the top-level result of each Bayesian network will be of highest importance to the applications.

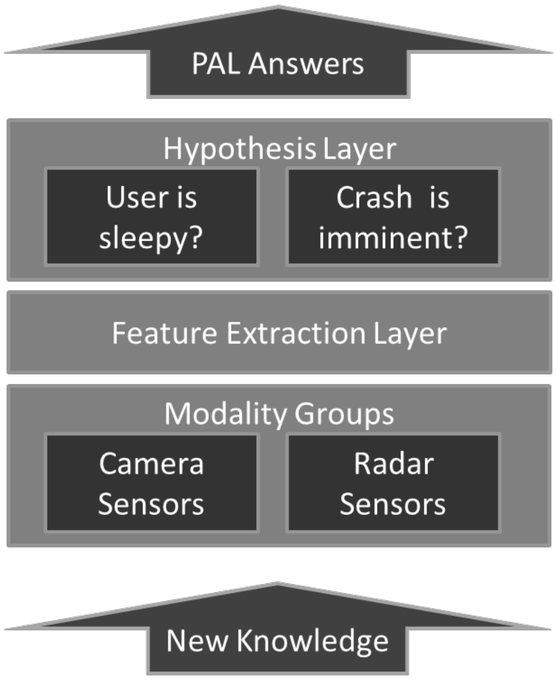

Figure 5.16: Data flow through the main knowledge model

Feature extraction layer(FEL) layer contains all the Bayesian networks inside the vehicle, which exist to reason on the meaning of the values in the low-level data sources. An example is a network for driver assessment based on camera data, or a network which stores driver's personal profile for infotainment system. This layer can be interpreted as a set of different object classification networks which are fed by underlying data sources.

Newly acquired knowledge from the vehicle ICT architecture enters the PAL(preferably) through the modality groups(MG) layer and propagates towards the hypotheses. This layer contains all the data source nodes, grouped into clusters according to their a priori assumed conditional dependence. For example, all the data sources which are stemming from camera systems would be grouped into the visual sensor group. The term modality is used here exclusively to denote a common sensor modality. Since the inference is performed on the junction tree query-specific sub-models, this grouping inside the Bayesian networks only becomes relevant if more nodes from a same group gets included into a junction tree sub-model.

5.3.4 Query-Based Sub-Models

One of the main tasks of PAL is to optimize the application queries i.e. to reduce the involved computational complexity of exact inference on large probability networks. If there are, however, no applications placing queries on the inference engine, the Bayesian networks in the main knowledge model remain the sole knowledge representation inside PAL. Only after the first query is placed(and the hypothesis layer contains at least one node) does the PAL construct a query-based sub-model in order to optimize the inference.

This component therefore contains the junction trees which were constructed using the optimality criteria presented early in this chapter.

5.3.5 Inference Scheduler

The hypothesis layer can contain application queries with different criticality. The driver assistance applications might perform time-critical inference, while the human-machine interface applications might be interested in periodical updates about the driver's assessed fatigue level. Multiple factors determine the time required to perform the exact inference, assuming equal processing power:

1. Data update rate bounded by the vehicle ICT architecture

2. Time to perform the knowledge propagation and normalization of the junction tree

3. Time to perform variable elimination in the cluster of interest in the junction tree

Even though the previously introduced optimization criteria tries to minimize the computational complexity of resource-intensive queries, such queries might not be relevant to the driving safety or they might jeopardize the execution of the queries relevant to driving safety. An example is a human-machine interface application which requires a rapid refresh rate in order to provide smooth animation of a sensor reading on the screen. This query might be so resource-intensive that it prevents parallel execution of another, safety-critical, query. In this case, a priority based scheduling of queries is necessary, with earliest deadline first within the same priority level.

5.3.6 Reconfiguration Manager

Apart from the continuous updating of the knowledge inside the PAL, it is possible to dynamically add or remove a certain data source, hypothesis or the in-between located feature extraction networks. The adding process has two steps: Semantic identification(what exactly is being added and how can it be used?) and performing structural changes on the main knowledge model. Adding of a new element can be rejected, if it conflicts with the quality-of-service requirements of the existing queries.

5.3.7 ICT Connector

This component is responsible for fetching the data from the vehicle ICT architecture and pushing it into the PAL. It contains the connections between the lowest layer of nodes in modality groups and real data sources inside the vehicle.

Chapter 6

Collecting Context-Relevant Data through the HMI

In this chapter, two methods for collecting of interaction context-relevant data through the human-machine interface are demonstrated. Specifically, two signal processing methods for driver assessment through two different human-machine interfaces are evaluated. The human-machine interfaces in question are a side stick and a brain-computer interface. In addition, a method for reducing the number of vibration artifacts collected with the brain-computer interface is presented. The goal of this chapter is to demonstrate how the new human-machine interfaces can contribute to the interaction context in a way which directly increases driving safety. This approach further emphasizes the importance of the context-processing platform introduced in the previous chapter, since the collected data has to be made available to the driver assistance applications. The signal processing methods represent the remaining two contributions of this thesis. They are evaluated experimentally in a driving simulator.

6.1 Introduction to the Driving Simulator

In order to perform data acquisition for driver assistance, an existing Vires Virtual Test Drive simulator was modified, complete with a vehicle mock-up, shown in Figure 6.1. Software version 1.1 was used throughout all experiments. The simulator has been outfitted with a simple side stick on the right of the driver and an EEG-based brain-computer interface. It is shown in Figure 6.2 during one of the experiment runs. Side stick and EEG data have been collected separately or together, depending on the experiment, and analyzed during test drives in the virtual environment. The side stick did not provide force feedback. A simulation of the driving

Figure 6.1: VIRES Virtual Test Drive driving simulator with vehicle mockup

environment was shown on a large screen in front of the vehicle. Only one screen was present, hence the possible lack of driver immersion might have affected the results. Furthermore, the simulator was not equipped to provide lateral and longitudinal forces normally experienced during a real test drive. This could have also reflected negatively on the data, but has to be cross-checked with either a more advanced simulator or a test drive. Simulated vehicle dynamics were those of a typical personal automobile.

6.2 Introduction to the Brain-Computer Interface

The Emotiv EPOC EEG wireless brain-computer interface shown in Figure 6.3 was used for data collection. It is a low-cost consumer electronics 14-channel wireless EEG helm. The provided electrodes, after the 10-20 standard, are AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1 and O2. Figure 6.4 illustrates the exact electrode location.

The device performs internal super-sampling of the EEG signal with the frequency of 2 kHz and provides the resulting output signal with the frequency of 128 Hz. Effective sampling resolution is 14 bits, with the least significant bit representing 0.51 μ V. Dynamic range is 8400mVpp. Digital notch filters are active at 50 and 60 Hz. Signal bandwidth in the range of

Figure 6.2: A participant with fitted Emotive EPOC wireless EEG helm inside the driving simulator

Figure 6.3: Emotiv EPOC helm used during the experiments(Image Copyright Emotiv Systems)

0.2 - 45 Hz. The helm is using a 2.4 GHz wireless band to connect to the personal computer with a wireless dongle, where further data processing takes place. It is powered by a Li-Polymer battery with a theoretical life of 12 hours. Electrodes are of modular design and are equipped

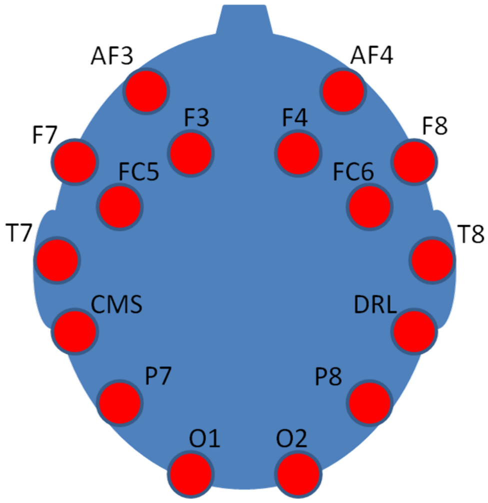

Figure 6.4: Electrode locations as provided by the EEG helm

with saline sensor pads.

The device rated best in terms of usability in the middle price segment in a study done in 2010, what was one of the prime reasons for its selection [102].

6.3 Human Performance Profiling for Sidestick-Based Interface

6.3.1 Abstract

We have established a metric for measuring human performance while operating a side stick-controlled car and have used it in conjunction with a known environment type to identify unusual steering trends. We focused on the analysis of the vehicle's offset from the lane center in the time domain and identified a set of this signal's features shared by all test drivers. The distribution of these features identifies a specific driving environment type and represents the main element of the proposed metric. We assumed that the driver performance, while operating a side stick-controlled car, is determined by the environment type on the one side and the driver's own mental state on the other. The goal is to detect the mis-match of the assumed driving environment, resulting from the introduced metric, and a ground truth about the actual environmental type, which can be obtained through map and GPS data, in order to identify unusual steering trend possibly caused by a change in driver fitness to operate the road

vehicle.

Classification of drivers based on their driving style has already been proven to be useful in improving the acceptance of driver assistance systems. The anticipatory energy saving assistant(ANESA) is an assistance system which hints the driver to start coasting, in the case of an upcoming speed limit [103]. The hints are more useful if adapted to the personal driving style. It has been shown that a set of five driving styles can be identified in four different scenes/environment profiles[104]. Bayesian inference with maximum-likelihood hypothesis was used for driver classification. It is important to note the combination of driver personal style with the environmental profile, since the same approach was used in the experiment described in the following.

6.3.2 Introduction

The most recent basic guidelines for the considerations on the driving context data were provided by the already mentioned AIDE project. The main identified context features were:

- Goal of the current voyage as provided by the navigational system
- Basic traffic information extended with car-to-infrastructure and car-to-car communication
- Assessment of driver's current state, both mental and physical
- Assessment of vehicle's current state

This work represents the effort to indirectly assess the driver's current mental state, by measuring his driving performance when operating a side stick controlled vehicle. The optimal input device for the primary driving task in road vehicles is a very debatable subject. In the scope of the project Diesel Reloaded, side stick has been proposed as the future method for continuous vehicle steering in the automotive domain. As compared to a central stick, where the input device is located between the driver's or pilot's legs, a side stick is located to the left or to the right(or both) of the driver. One advantage is the integration of longitudinal and lateral vehicle dynamics' control in one single physical device, saving space and reducing the amount of physical force necessary to operate the vehicle. Another advantage is accessibility, since the device can be operated by people with a wide range of physical impediments. However, one of the key assumptions for the wide-scale acceptance of side stick controlled vehicles is a reliable and affordable drive-by-wire system. Therefore, the acceptance of the new input device might not only be a question of ergonomics, but also of engineering and regulatory changes taking place in other vehicle subsystems. Vehicle information and communication architecture is one of the key enabling technologies for innovation in the area of human-machine interaction and driver assistance[6].

In this work, we propose analyzing the performance of the lane keeping task as the primary factor describing the successful performance of the overall driving task. A blind signal analysis of the vehicle's offset from the lane center over the course of time is performed. The input signal is therefore a time series of vehicle's lane offset. The goal is to find a lane offset-based metric which describes the driver's performance in a specific environment. The focus is on the definition and the validation of the metric through experimental data in a driving simulator. Once the driver performance in a specific environment is sufficiently described by the metric, we assume than any sudden change in this description directly relates to a new and unusual steering trend in a specific environment. The fact that the driver suddenly altered his driving performance is therefore directly attributed to the change in its mental or physical state. This result can be used as an input for other driver assistance systems. One of the issues is the absence of directly related research, since the lane following task has mostly been analyzed from the driver intention, collision avoidance or autonomous driving point of view. The assessment of the driver performance for side stick controlled vehicles seems to be a novel research domain, what is not surprising, considering the non-existent market share of such vehicles. Nevertheless, the more general task of target following with a side stick represents a very interesting field of research for different vehicle types.

6.3.3 Method

In this section, we describe the method used to obtain the metric for the driver's performance. Based on the previous work in the partially related area of driver steering prediction, we opted for an approach which reduces the driving task to a lane following task, in which the driver uses his previous knowledge, current state and future predictions to keep the vehicle from leaving the road margins[105]. We assume that a perfect lane detection exists and that it provides the lateral vehicle offset from the middle of the lane. The lateral offset was taken as the sole input of the algorithm. The driver's side stick input directly changes the lane offset, but the key difference between analyzing the side stick input and the lane offset is the suppression of the influence of the road profile. A driver following a very dynamic road at high speeds produces a relatively large amount of lateral side stick activity, but if he still manages to follow the road

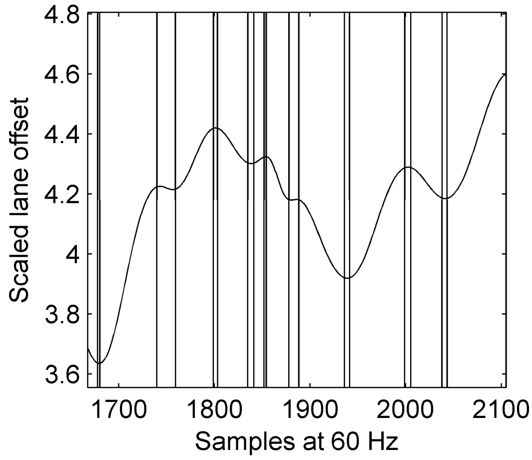

Figure 6.5: Trigger set contains points in which signal started to rapidly change, here denoted with vertical lines.

profile accurately, the activity of the lane offset will be reduced to under- and over-steering. Driver's input for the longitudinal vehicle control, i.e. throttle and brake, is only used as an additional external parameter in the further analysis.

Let the time series offset(n) represent the lateral vehicle offset from the middle of the lane in any given sampled step n. Let δ(n) be the first differential of the function offset(n). The set Δ_0 can be defined as:

$$\Delta_0 := \{\delta_x \in \Delta \mid |\delta_x| < \epsilon_0\}. \tag{6.1}$$

meaning that Δ_0 contains the segments of δ(n) where the lane offset signal underwent a trend change with a magnitude described by ϵ_0. Δ_0 is a set of subsegments of δ(n) of various lengths, in which the differential fell beneath the ϵ_0. Let us now define a trigger set $\mathbb{T}$ as a set containing the first and the last element of every subsegment in Δ_0 . In a case of a subsegment which is one point wide, meaning that the first and the last element are the same, the trigger set $\mathbb{T}$ includes it only once. An example of the trigger set is given in Figure 6.5.

In the next step, we generate an alternative description of the trigger set, based on average number of the triggers in a fixed time window(trigger density). Inside of a larger time window, we iterate a smaller N-points time window, in which the number of triggers is counted and the density is determined. The final counter value or, the trigger density, is added to an appropriate bin. As an example, an N-point window containing four triggers increases the counter value of the bin number four by one. After the entire larger window has been processed, it is fully described by the final value of all the bins. The procedure is analog to generating a signal histogram. Our hypothesis is that for a fixed side stick sensitivity and a fixed side stick sampling rate, a fixed number of bins will take on a typical average value for a specific driver and environment. The shapes of the bins' values and their relation to each other might also prove advantageous in the driver performance assessment. We propose that each environment will impose(or require) a specific behavior of the road offset signal, which the driver has to execute to the best of her/his abilities and which we try to capture with the proposed metric. The static values of the bins as well as the perturbations between the bins should behave in a same manner for the same environment and for the same driver. Such perturbations can also be imagined as spectral shifts of the road offset in the frequency domain, even though we did not engage in spectral analysis of the side stick input in the scope of this work.

6.3.3.1 Trivial Solutions

There are several trivial ways of identifying the environment based on the lateral component of the side stick input. As an example, long and extreme turning maneuvers will signify an urban environment. As another example, the average number of triggers in the side stick signal can trivially differentiate between inside and outside of city. The problem with such rough approaches is that they do not provide any possibility of further analysis, since most of the useful data is discarded. It is, however, possible that a large number of completely different and environment-specific signal processing solutions can be combined and weighted to provide a better result than the uniform procedure presented in this work. This remains a topic for future research and analysis.

6.3.4 Experiment Design

A total of 23 participants, all in possession of a valid driver's license inside the European Union, took part in the experiment(19 male and 4 female). Mean age was 26.48, minimal 18 and maximal 36 years. A pre-experiment survey was filled out in order to determine possible alcohol or caffeine intake. The Virtual Test Drive(VTD) software from the company VIRES was used for the data collection. It was integrated into an automobile mock-up, a complete chassis of a Smart automobile, presented at the beginning of this chapter. A side stick was mounted on the right of the driver, at the location usually taken by the gear shift.

The experiment started with a target following game which was played with the side stick inside the vehicle simulator. The goal was to learn the sensitivity and the behavior of the side

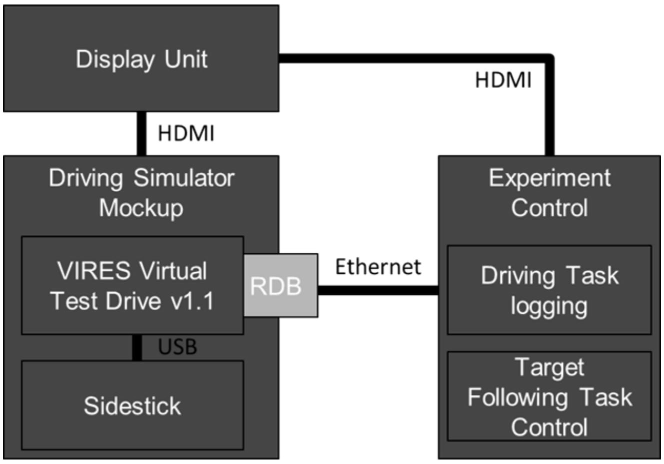

Figure 6.6: Data flow between software and hardware components in the driving simulator

stick prior to the driving phase. Even though the side stick is almost completely absent from the current road vehicles, all the participants possessed experience of using a common joystick, which lessened the learning curve. The participants were required to keep an object shaped as a circle in the middle of a large moving rectangular target for as long as possible. Penalty points were gathered when the circle failed to keep up with the rectangle. A randomly generated target following scenario was executed in each 30-second run. The game lasted no more than 3 minutes.

In the next step, the driving simulation was started. This step consisted of a new learning phase and, finally, the real driving phase. The learning phase lasted no more than 5 minutes. Participants were able to explore the simulation and further increase their grip on the side stick skills. In the second phase, all the participants started from the same position inside the simulated world and the data was collected using the Virtual Test Drive Runtime Data Bus interface shown in Figure 6.6. The participants started the drive on the out-skirts of a virtual city and proceeded to drive towards and finally into the city, continuing on the city roads. Most of the participants chose to take the same route out of the city and back to the original starting position, but this was not strictly required in order to complete this phase. The real driving phase lasted around 7 minutes.

6.3.5 Preprocessing Collected Data

The lane offset data collected in the experiment had to be pre-processed before being forwarded to the previously described method. Additionally, the window sizes and the ϵ_0 had to be defined.

All of these values are directly dependent on the side stick device and had to be manually derived from the data.

A value of 15-seconds has been chosen for the previously defined larger sliding window, while the smaller sliding window was fixed to 200-points(about three seconds). This has been chosen by a brute force analysis of the impact different window sizes have on the observed features and remains in direct connection with the side stick sensitivity and sample rate. These parameters and their further refinement remain an open question and were not covered further the scope of this work. Automatic derivation of parameters would, of course, be the only practical solution if the method was to be applied to fleets of different vehicles.

A value of ϵ_0 of 0.3 was chosen on the same terms, through manual data analysis.

In order to eliminate the bouncing artifacts of the collected lane offset signal, present when the side stick is switching from one discrete position to another, , we iterate a 3-phase 15-point moving average smoothing over the signal. The artifacts removed are rapid oscillations around a stable or steadily transient(ramp) side stick position. They can be removed with a low-pass frequency filter, but the result has proven to be generally worse during the experiment: As the smoothing effect approaches the level of a simple average smoothing, the filter progressively removes more of the important signal features. Therefore, the artifacts were removed by simple averaging in the time domain.

6.3.6 Results

After applying the binning procedure, two bins started to contain relatively large and stable signal features which stayed similar for all participants. These bins were bin number 4 and bin number 5, which count the number of 200-point windows containing respectively 4 and 5 triggers in larger 15-second time window. Lower bins have not been deemed useful for classification and started to fill bottom-up only during long steering maneuvers. The bins higher than 5 were almost always empty and would appear only in the most erratic and non-realistic dangerous driving situations, when the participants opted for a short chase through the streets(even though they were advised not to beforehand). The emerging signal features in bins 4 and 5 differed in two ways throughout the course of every experiment run.

The first difference was the relative difference of the same bin value between different environments. Driving inside the city, as well as driving outside the city as higher speeds, trivially raised the value of bins 4 and 5 throughout all test subjects. In addition, any sudden increase in speed(an external variable which was monitored separately) was intuitively countered with

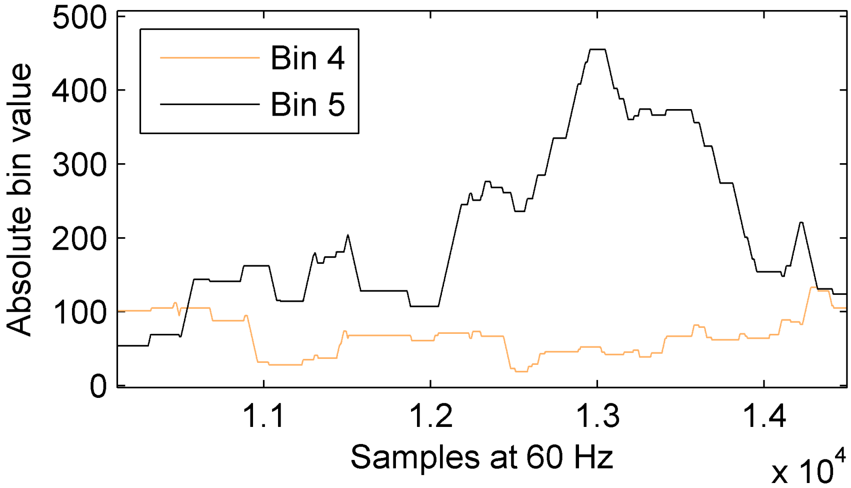

Figure 6.7: Sub-type F0 represents a rise in the value of bin 5 not followed by the rise of bin 4

over-steering in the following curves, which would create significant spikes in the bin 5. This type of differences was only marginally useful for classifying environments, since the average value can drift through a large value range inside the same environment without being classified as another environment, but still denoting a change in driver performance. In other words, too much data about the driver performance is discarded by only focusing on the values of bins. This is, therefore, a version of the previously mentioned trivial solutions.

The second type of differences focuses on the shapes of the bins 4 and 5 and their mutual ratio. This has proven to be the most valuable approach and it mostly tied to the surges in value of the bins 4 and 5. There were four identified sub-types, presented in Figure 6.8, Figure 6.9, Figure 6.10 and Figure 6.10 which are further denoted as F0, F1, F2 and SW.

The SW sub-type represents a switch of absolute values between the bins 4 and 5 and was mostly observed on the borders of two environments and during a change of driving style inside a certain environment. The F0 sub-type represents a surge of bin 5 which is not followed by the bin 4. The F1 sub-type represents a surge of bin 5 which is moderately followed by the bin 4. The F2 sub-type represents a surge of bin 5 followed by a same or similar surge by the bin 4.

Figure 6.11 demonstrates the appearance of the sub-types during a drive in which the participant first drove outside the city(F2), than inside the city(F1) and then began to leave the city and drive outwards to the starting position(SW).

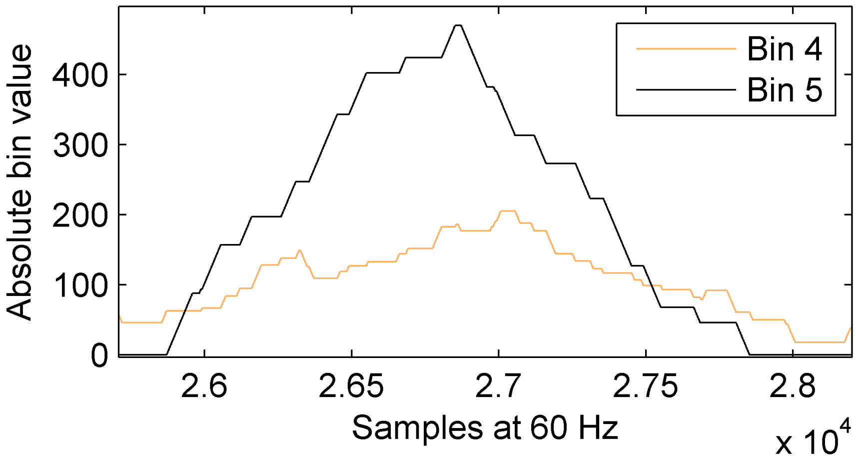

Figure 6.8: Sub-type F1 represents a rise in the value of bin 5 moderately followed by the rise of bin 4

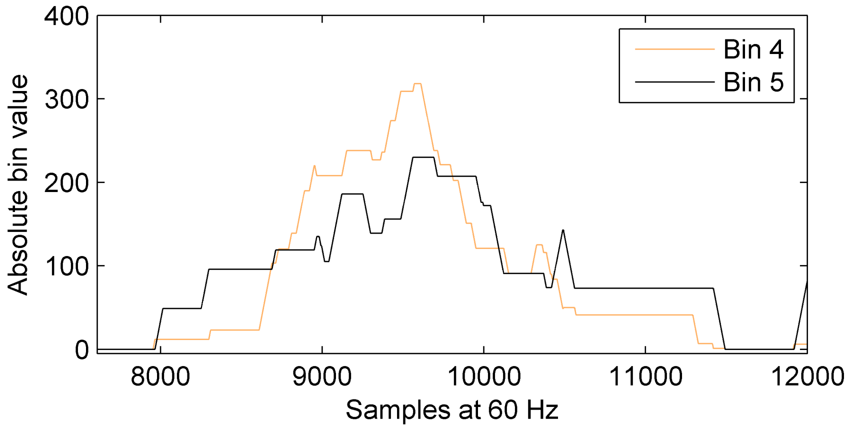

Figure 6.9: Sub-type F2 represents a rise in the value of bin 5 completely followed by the rise of bin 4

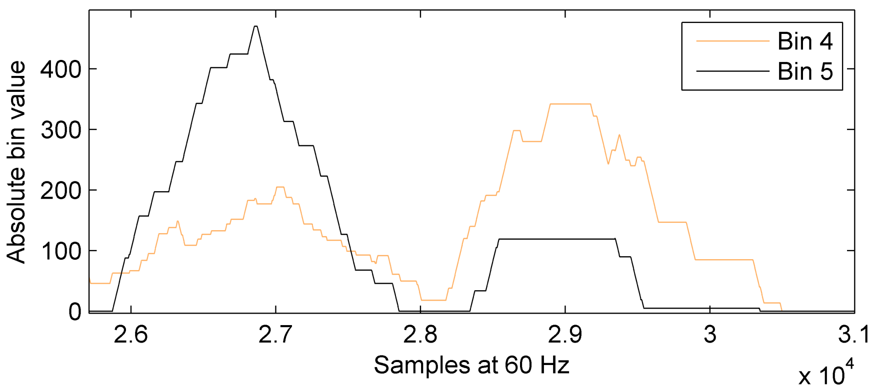

Figure 6.10: Sub-type SW represents a switch between the values of the bin 4 and bin 5

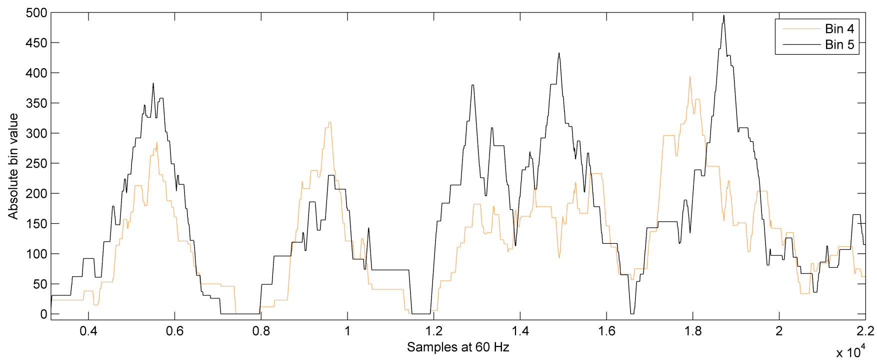

Figure 6.11: Typical form of the bin 4 and bin 5 during the drive

The Table 6.1 demonstrates the occurrence of sub-types in different environments for different drivers.

The relatively large amount of collected data(160 minutes of driving sampled at 60 Hz) resulted in a relatively low amount of detected sub-types, due to their size(some are formed over a period of 60 seconds) and due to the presence of other signal forms, which could have not been classified. Nevertheless, the data clearly shows a correlation between the environment type and the signal features based on the proposed metric.

6.3.7 Conclusion

A metric for measuring driver performance for a side stick-operated road vehicle was proposed. The driving task was first reduced to lane following task, taking the lane offset as the main element of the metric. Binning of the average number of trend changes inside the road offset

Table 6.1: Occurance of sub-types for different environments

Environment	SW	F0	F1	F2
Inside the City	3	3	67	14
Transition between environments	18	0	4	2
Outside the City	1	0	13	29

signal produced several emerging signal features, which can be used for classification of the driving environment. The assumption is that each environment requires a specific performance of the lane keeping task. In this sense, we have identified the signal features which directly correlate with the performance of the driver.

Future work involves classifying additional environment types and comparison with other side stick devices, with their own sensitivity and sampling rates. Additionally, we will compare how the metric fares in more generic target following tasks, side stick still being the main input method.

6.4 Reducing the Impact of Vibration-Caused Artifacts in a Brain-Computer Interface using Gyroscope Data

6.4.1 Abstract

An artifact prediction method for a saline-pad wireless electroencephalograph was implemented. The device is equipped with two-axis gyroscope and used as a brain-computer interface(BCI). The BCI unit serves two purposes. Firstly, it enables remote control of vehicles and other systems over a limited set of trained mental activity. Secondly, it is a source of data for the passive analysis of the operator's mental fitness, which is further integrated into the driver assistance systems. The latter aspect has been the focus of this work. Saline-pad electrodes used in consumer grade electronics are prone to errors stemming from vibrations and sudden head movements. The implemented approach successfully preconditions the signal processing pipeline to take such artifacts into account and reduces the later processing overhead when determining the driver's fitness to operate the vehicle.

6.4.2 Introduction

In this work, we focus on the reduction of BCI errors caused by vibrations and sudden head movements which are relatively common during a typical drive. To confirm our method, we have used the data gathered during an experiment with side stick-operated driving simulator. The participants were wearing the EEG helm throughout the course of the experiment in order to assess their vigilance, which is a topic of another chapter of this thesis. Fitting of the helm is shown in Figure 6.12. As a side note, subjects with thick scalp hair took several minutes longer to achieve acceptable signal quality. Even when such issues are taken into account, the saline-pad electrodes currently remain the easiest solution for rapid fitting of EEG helms with(borderline) acceptable signal quality.

The EEG helm is equipped with an integrated two-axis gyroscope, originally used for on-screen cursor control with minimal head movements. Various applications have been developed which make use of the gyroscope, since the device is aimed at the consumer electronics and personal computer market. These applications have not been used in this work. The gyroscope data was extracted using the device's application programming interface, provided in the scope of the research development kit.

Figure 6.12: Fitting of the helm to achieve acceptable signal quality was a trial-and-error process which failed in the case of three participants

6.4.3 Vibration Effects and Processing Method

The vibration and movement-related errors have a direct impact on the frontal electrodes, while the impact on the rear electrodes was marginal or insignificant. The assumption is that this is the result of the helm construction and the fitting of the plastic frame carrying the electrodes. We assumed that electrode slippage and the resulting temporary change of signal quality is responsible for the direct correlation between the EEG channel artifacts and gyroscopic extremes. The subset of electrodes which are exposed to the artifacts was limited to the front array containing AF3, AF4, F3, F4, F7, F8 FC5 and FC6. The electrode FC5 has provided erroneous output almost throughout the entire experiment and over most trials and participants. Therefore, it has been completely taken out of the analysis, since the number of complete data sets with this electrode would include less than third of original participant count.

The EEG data was processed in raw form, before being fed to the signal processing pipeline presented later in this chapter. The moving average of the EEG channels had to be constantly recalculated and taken into account. However, the sudden changes of the moving average in the frontal area were often correlated with the head movements taking place directly before or during the EEG channel change. This is shown in Figure 6.13. It is, of course, impossible to always mark the EEG data predictively, since the short term artifacts and/or moving average change can occur in parallel to the actual head movement and electrode slippage. Still, knowing that the mismatch before the previous and actual EEG values on a specific channel stems from a mechanical movement can be used to avoid more complex error processing, by taking subsequent signal drift into account.

The moving averages of relevant electrode subsets were analyzed together with gyroscopic values in order to tag the moving average changes directly related to mechanical vibrations. All the EEG data was collected during the virtual drives inside the test simulator. The amount of analyzed data per participant was 5 minutes in average, meaning that approximately 100 minutes of data sampled at 128Hz was processed. It is important to restate that we concentrated on longer-lasting errors in EEG data, where the moving average remained offset for a prolonged period of time. The comparison between long and short term shifts is given in the Figure 6.14 and Figure 6.15. The figure showing the short-term shift is additionally affected by an API software glitch, through which the sign bit flipped after reaching its maximal positive value(signed/unsigned mismatch). The glitch had no effect on the experiment.

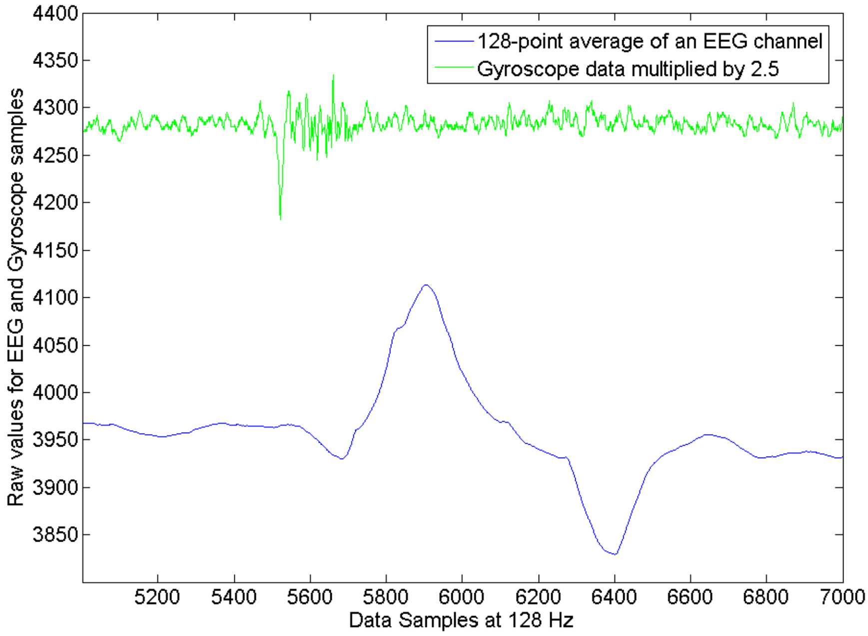

Figure 6.13: Scaled gyroscopic data and raw EEG data showing how increased gyroscopic Y activity(green) resulted in moving EEG average(blue)

6.4.4 Results

Out of the 21 participants in the original experiment, 10 produced EEG data with moving average artifacts related to gyroscopic data. The shortest description of the results is that the detection is, depending on the subject, either excellent or does not improve artifact removal at all. The data with successful detection contained, on average, more gyroscopic activity, meaning that certain subjects performed stronger head movements during the entire experiment. This might be a subjective driver habit, but it can be expected that driving in real-life conditions would feature an even increased number of strong and rapid head movements. However, the data from remaining 11 participants with low gyroscopic activity also contained similar EEG artifacts. Either the head movements which are causing them are too weak to detect with the present gyroscope(less likely), or there is a completely different source of artifacts which has to be captured by additional experiments. At any rate, the heuristics based on gyroscopic activity increases the chance of capturing known errors, but does not offer a complete and final solution for the overall artifact detection. The participants reacted to the saline-pad helm quite well - the mean value of the personal comfort while wearing the helm was 5.375 with standard

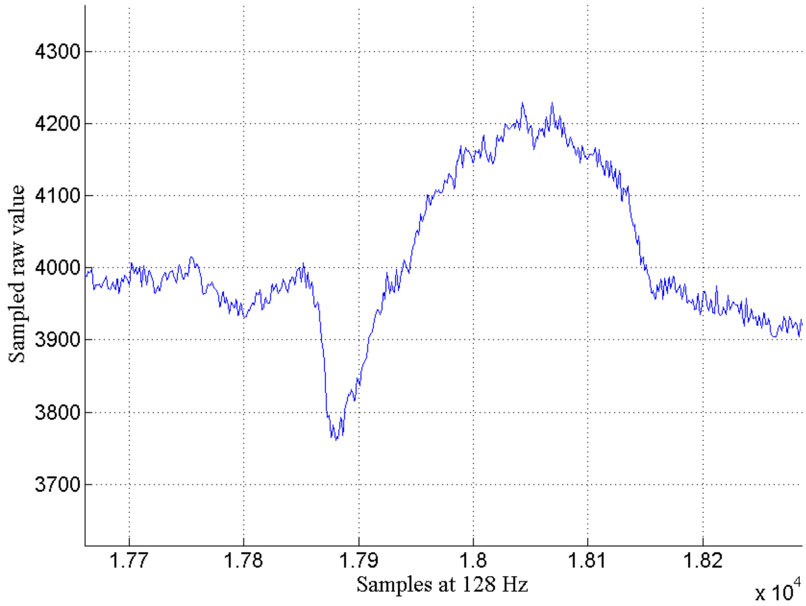

Figure 6.14: Long-term signal artifact which lasts several seconds before stabilizing

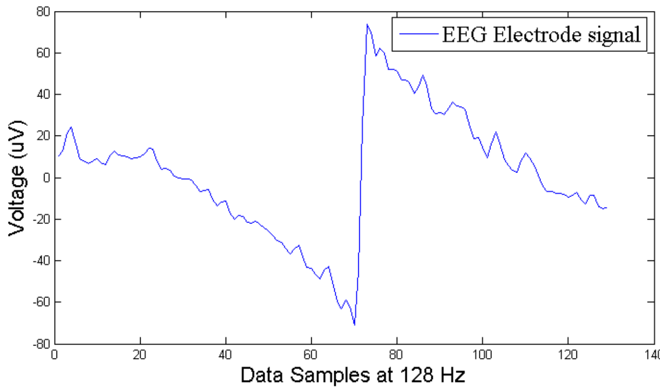

Figure 6.15: Short-term effect of electrode slippage which stabilized in timeframe of one second

deviation of 1.2 on the scale of 1(not comfortable at all) to 7(very comfortable). Only two participants answered inconclusive to a separate question if the helm was irritating. There were no positive answers to this question and 19 answers were negative.

The results of long-term artifact detection are shown in the Table 6.2. Table 6.3 shows the effectiveness of detection of the largest artifacts in the EEG data. The results for the detection of largest(amplitude and time-wise) artifacts are much better than that of the average ones,

Table 6.2: Effectiveness of the EEG vibration artifact detection in 5-minute slices

Subject	Total missed	Total hit	Detection rate
1	1	5	83%
2	0	5	100%
3	2	7	78%
4	1	2	67%
5	2	7	77%
6	3	7	70%
7	2	4	67%
8	2	5	71%
9	1	5	83%
10	1	4	80%

Table 6.3: Effectiveness of largest vibration artifact detection in 5-minute slices

Subject	Detection rate
1	100%
2	100%
3	100%
4	50%
5	100%
6	100%
7	67%
8	75%
9	100%
10	67%

hinting that mechanical vibration causes the biggest overall signal distortion.

6.4.5 Conclusion

A simple approach for detecting and classifying vibration-caused saline-pad EEG artifacts has been implemented and evaluated. The method managed to tag the artifacts in one half of experimental subjects with very high success rates and with no success at all in the rest. This leads to believe that there are other sources of identical artifacts which should be explored in further experiments. A weaker explanation is the insufficient sensitivity of integrated gyroscope. Further classification of EEG artifacts is necessary, taking both device sensor technology and external factors into account.

6.5 A Robust Driver Assessment Method for the Brain-Computer Interface

6.5.1 Abstract

Brain-computer interfaces(BCI) are a valuable proposition for the long-term vision of the automotive human-machine interfaces and for increasing the personal mobility of users with physical disabilities. In this work, we do not attempt to improve the vehicle control through a BCI. Instead, we focus on assessing the driver's fatigue using a non-invasive BCI technology, a mobile electroencephalograph(EEG). Non-invasive EEG-based approaches for driver assessment often rely on the independent components analysis(ICA) and measure the relative power of specific EEG frequency bands. In the case of wireless and mobile EEG devices, especially outside the domain of medical-grade electronics, a higher number of artifacts and lower channel count can be expected. Main priorities for such devices are ergonomics and usability, with signal quality and robustness on the second place. Such devices significantly simplify experiment design and data collection in automobile simulators and real test-drives. This work presents a robust two-step EEG signal processing method for driver assessment for a consumer-grade EEG BCI, which collects artifact-rich data using a limited number of low-quality saline-pad electrodes. We demonstrate that a reliable assessment of driver state in such conditions is possible, if the independent component analysis is extended through an expert system-based assessment of reliable signal components in a specific region-of-interest on the brain surface. The method additionally eliminates the need for manual artifact removal. We show that the lower sensor count, lower sensor quality and mechanical vibrations can be offset through additional signal processing. We additionally show that the data collected by the BCI provides additional value to the driver assistance, meaning that BCIs can serve both as a human-machine interface and a driver assistance system.

6.5.2 Introduction

The societal impact of a successful and non-intrusive method of reducing the losses in lives and property in traffic accidents is without any doubt large. Depending on the type of the human-machine interface(HMI) used for the primary vehicle control, various methods can be utilized to assess the driver state. In the scope of the automotive research project "Diesel Reloaded", the brain-computer interface(BCI) is being analyzed as one of the future automotive HMI solutions. Such interfaces have already been used in semi-autonomous and direct vehicle control [13]. Furthermore, BCI provides personal mobility to physically impeded users, which are not able to operate a standard vehicle equipped with steering wheel and pedals. Even though specific custom-made physical interfaces, one example being miniaturized joysticks, can be used to operate vehicles with only one hand and minimal physical exertion, the BCIs go one step further and read out user's commands directly at the source. Further development of BCI feedback methods can be expected in the future, but current users have to make do with traditional feedback channels through human senses. It is not our goal to compare the user experience and ergonomics of the current physical interfaces and the BCI. Drivers might wish to use their vehicles in the same way they use their bodies and might insist on haptic feedback, but monitoring of their mental state and the level of fatigue will remain of high importance for driving safety.

Research by Jeong et al. has shown that there is a significant difference in brain activity between real and simulated driving, when using positron emission tomography(PET) [106]. Perceptive and visuomotor components can be analyzed during a simulation, but emotional and autonomic responses have to analyzed with real driving and with all the real driving risks present. To avoid this shortcoming of every driving simulator, this thesis focused on the neural correlates of fatigue which are not specific to driving. It is interesting to note that a comparison of passive and active driving was also performed by Jeong et al. No significant difference was found between the brain activity of he driver and one of a passive co-driver, which was requested to keep the eyes on the road at all times. The only difference was in the sensorimotor area, which authors contribute to limited muscle contraction which the driver has to perform during the drive. Electroencephalography is only mentioned in regards to its low spatial resolution, but it remains one of the few technologies which can be implemented in a road vehicle with low costs and low integration effort.

A brain-computer interface should provide a clearer insight into the operator's state when used as human-machine interface, because it additionally captures brain activity not related to the primary task of vehicle control. Lal and Craig concluded that monitoring EEG may indeed be the most promising method for fatigue detection [107]. Current state of spectral analysis suggests that ratios between the alpha, beta and theta frequency bands can yield acceptable driver classification [108]. The currently established methods are however of little use for on-line assessment of driver state with low-cost consumer-grade EEG input devices in automotive conditions, especially if the user keeps changing head position due to external forces and short glances. We present a two-step method called based on region-of-interest independent component selection for spectral analysis, abbreviated as RISSA for brevity in the rest of the document.

6.5.2.1 Participants

A total of 21 participants(18 male, 3 female), all in the possession of a driver's license valid in the European Union, took part in the experiment. Mean age was 26.1 and the driving license was possessed for a mean duration of 8.2 years. All the participants fall into two groups - the normal, which consists of 14 well rested subjects performing the experiment well before 19:00h and the negative which consisted of 7 tired participants performing after 19:00h. The subject tiredness was additionally determined through a pre-experiment survey, in which the subjects were asked to provide objective and subjective data regarding their current overall fitness and fitness to operate a vehicle. Personal average sleep time was also compared to the duration of the last sleep. Energy drinks, coffee and similar stimulants were taken into account in the survey.

6.5.2.2 Experiment Course

The entire experiment lasted approximately one hour per participant. At the beginning, the participants were requested to sit in front of a personal computer wearing the EEG helm and try to relax as much as possible for a full minute. They could observe their own EEG activity on the screen during this time. It was not allowed to touch the helm, close the eyes or engage in any form of deep relaxation. Second phase of the experiment took place in the driving simulator. A simple target following task, not related to driving, was performed with the joystick for 5 minutes. The goal was learning the sensitivity of the device before the driving phase. Third phase continued inside the simulator, starting with a test drive through a virtual city. After not less than 5 minutes of additional training, the simulation was reset and a 10-minute long data collection was started.

6.5.3 Signal and Artifact Properties

Current approaches for driver state assessment often rely on medical-grade EEG devices with a larger electrode count. The electrodes are often gel based and remain fixed on the scalp. Minor head movement is only partially detrimental to the signal quality. In addition, the electrodes are precisely mounted on the scalp according to the 10-20 standard. Usage of a helm with a reduced set of saline pad electrodes, which are relatively equally spaced between each other due to the fixed mounting frame, introduces a different set of challenges. The wireless EEG helm is flexible and enables easy fitting, but the electrodes cannot be positioned individually and independently, since they are a part of one rigid unit. We have observed two types of typical sensor slippage types during the practical work with the EEG helm. The first is an instantaneous contact loss, which is immediately reestablished, which can be called a ”shock” artifact. It is characterized by a sudden decrease of measured voltage, a very fast signal jump and a continuation of the decrease until pre-shock signal state is reached. The artifact is usually contained in the time frame of one second. Another type of slippage manifests as a sudden shift in moving average, which can last for several seconds. These appeared with the subjects with very thick layers of hair directly underneath the electrodes and during strong mechanical vibrations. The upcoming shift in moving average can be partially detected in advance, using the gyroscope built inside the helm which detects problematic types of mechanical vibration [53]. Vibrations are the largest issue with the used EEG helm. We did not detect electromagnetic interference caused by other electrical devices inside the vehicle. In our case, such devices would be the power electronics and computers running the simulation and located inside the chassis. In a real automobile, these would be infotainment and comfort systems. Such interference could be identified in advance, in the moment when the user requests a certain functionality to be activated, if a connection to underlying vehicle system architecture or all provided human-machine interfaces is present. Finally, we observed cases of a single electrode permanently not having optimal contact with the scalp. In the worst case, this manifests itself in a signal with no extreme values or extreme slew rates, but neither time-domain samples nor the signal's spectrum have a biological background. Such data channels can be completely mapped out the collected data for the entire duration of the experiment. Other artifacts stemming from external sources(such as AC frequency) and various muscle and eye activity are dealt with in the scope of ICA decomposition.

6.5.4 Proposed Processing Method

Our proposed approach consists of a pre-experiment preparation phase and an on-line phase which takes place during the data collection.

6.5.4.1 Preparation Phase

Let us define a region of interest(ROI) on the brain surface, in which a well-defined set of rules regarding to mapping of brainwave frequency bands and their ratios to driver state exists. In the rest of this document we refer to this set of rules, which is derived from the biological effects of brainwave activity, the biological context table(BCT). It is necessary for the entire ROI to be invariant to the same BCT, which implies that all the relevant frequency bands can be detected throughout the ROI. There can be an arbitrary amount of ROIs with corresponding BCTs on the scalp. In regards to the EEG device capturing the data, they should be weighted by the a priori reliability, based on actual electrode position and density. For the purposes of this work, we have defined one ROI and its BCT in the preparation phase. The focus of this work is placed on the on-line phase and selecting a reliable independent component inside the ROI. For our experiment, the ROI was set to the frontal and central cortex lobe, mostly due to the higher electrode density for the provided EEG device in this area. Figure 6.16 shows two independent components in this ROI and presents the building blocks of the signal processing pipeline explained in the following section.

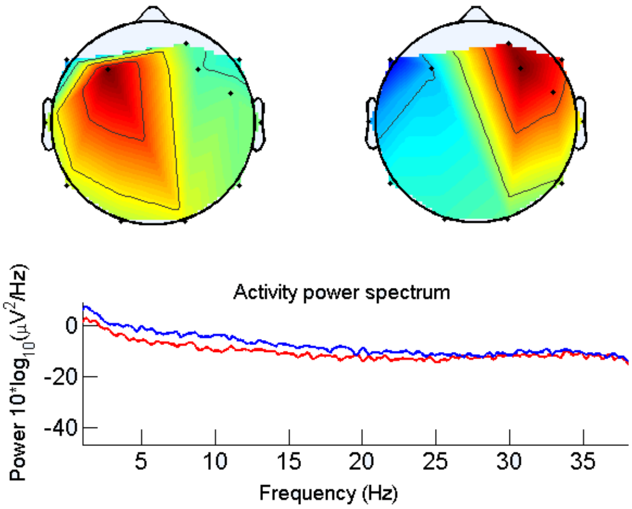

Figure 6.16: Comparison of power spectrum differences for two ICA components in one ROI

6.5.4.2 On-line Phase

Once the ROI and the appropriate BCT are fixed, we connect the following blocks into the signal processing pipeline, illustrated in Figure 6.17:

1. Simple artifact removal in raw data

2. Independent component analysis on the entire scalp

3. Selection of reliable independent component in a ROI

4. Spectral analysis of reliable independent component

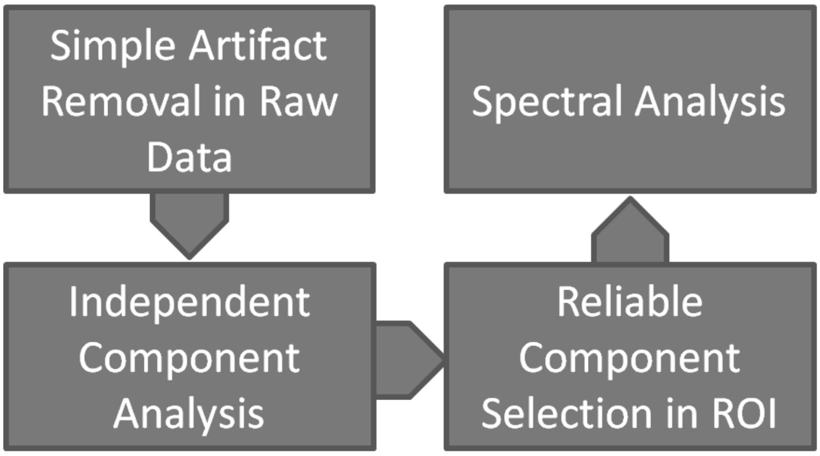

Figure 6.17: Basic blocks of the signal processing pipeline of the algorithm's on-line phase

The simple artifact removal in step 1 relies on the straightforward detection of signal properties already described in this work and is not explained further on. In the rest of this section, we briefly touch the well-known methods which were incorporated as-is into our pipeline(such as ICA), and go into detail when describing custom building blocks.

6.5.4.3 Independent Component Analysis

Let the vector

$$s = \{s_1(t), s_2(t) \dots s_n(t)\} \tag{6.2}$$

contain N independent source signals. Let the vector

$$x = \{x_1(t), x_2(t) \dots x_n(t)\} \tag{6.3}$$

contain N linear mixtures, which are the result of multiplying the vector of source activity EEG waveforms s by an unknown square matrix A which performed the mixing process, that is

$$x = As \tag{6.4}$$

The goal is to find the filter which performs the inverse mixing process and enables extraction of the vector u which is a scaled and reordered version of the original vector s. Therefore, it is necessary to find a square matrix W which inverts the mixing the process and produces u

$$u = Wx \tag{6.5}$$

The main difference between principal component analysis(PCA) and the independent component analysis arises in the assumptions on the nature of differences between s and x. PCA assumes that the data sources are uncorrelated, while ICA has a stronger assumption of statistical independence [109]. PCA has been successfully used in the same context of EEG power spectrum analysis [110]).The consequence of statistical independence is the factorization of the multivariate probability density function fu(u). The extended infomax algorithm based on a neural network and proposed by Bell and Sejnowski is used to find the vector u [111]. The joint entropy H(y) of the output of a neural processor is maximized in order to minimize the mutual information among the output components yi=g(ui) where g(ui) is invertible bounded nonlinearity. The algorithm separates sources with both supergaussian and subgaussian distributions. In this work, the number of independent components has been set to the number of active EEG channels per experiment. This was not always the total number of electrodes, due to the rejection of bad EEG channels.

6.5.4.4 Selection of Reliable Independent Components in a ROI

The ICA components in ROI are evaluated with an expert-based belief network, which provides a measure of so-called goodness for every independent component. We always selected the component with the maximal goodness for the next step, the spectral analysis. Main contributing factors to the component goodness are:

1. Number of electrodes in the vicinity of the component
2. Simple artifacts' amount from the electrodes near to the component
3. Dipole properties of the independent component
4. Spread of the component over the frontal areas prone to facial muscle artifacts

Most of the factors were derived from the existing and well-defined rules for manual component identification when using ICA with common signal toolboxes, such as EEGLAB from the Swartz Center for Computational Neuroscience. A Bayes belief network N contain the contributing factors is shown in the figure 6.18. This network can be extended in the scope of future work to take as many factors into account as possible. Using the built-in gyroscopic sensors for detection of head movement and correlating these movements to a map of electrodes with different sensitivity to different kinds of head motion is a good example. The inference complexity is not an issue, since the network size is negligible. For the future expansion, we suggest using the more performing exact-inference method called the junction tree in this step, since we assume that the number or rules and the resulting network will rapidly grow. The goal is to keep the method online while running on embedded hardware. This suggestion does not constitute a part of the scientific contribution of this work, but rather represents a method for the efficient implementation of RISSA. Previously introduced region of interest(ROI) can contain multiple instances of spatially localized ICA components. The independent component with the largest goodness is selected for the analysis. To recap, frontal and central cortex area was chosen as the region-of-interest, due to the highest electrode density.

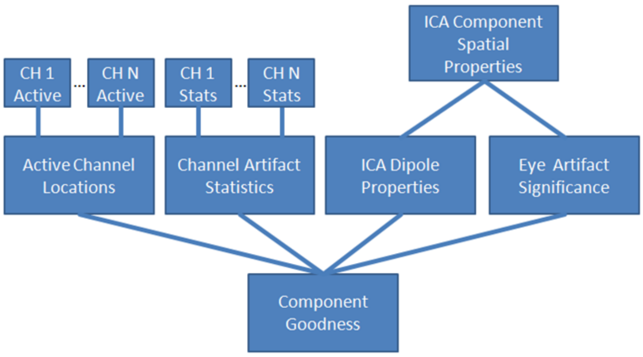

Figure 6.18: Belief network used for component evaluation

6.5.4.5 Spectral Analysis of the Reliable Component in a ROI

Our spectral analysis relies on the set of rules inside the previously defined biological context table(BCT). Cao et al., in their work on EEG-based vigilance analysis, found that the band power of θ, α and β waves reflect the difference in driver vigilance in different ways, based on the observed cortical area [108]. In the central cortex, the θ band was stronger in the sleepy state. In the frontal cortex, the β band was weaker in the sleepy state. The α band was only significant for classification in the occipital and parietal cortex. However, we have found a significant difference in the frontal and central cortex activity by measuring the ratio β / (θ + α), where α contains both slow and fast alpha waves . Due to the large number of artifacts at

Table 6.4: Accuracy of the independent component selection in the region of interest

ICA Components in ROI	Default Activity	Driving
Mean numer of alternatives	4.14	4.26
First choice selection rate	93%	91%
Second choice selection rate	100%	100%

frequencies lower than 4 Hz,analyzing the δ band was avoided, even though it was found to be significant for the frontal cortex. As the end result, our BCT for the ROI of interest was set to the ratio β / ($\theta + \alpha$).

6.5.5 Results

A single 30-second long sample was taken in the default state, while the user was not performing any activity. Six 30-second long samples were taken in the second phase in the driving simulator, while the user was driving through the virtual city. With this data, we benchmarked two aspects of our signal processing method. Firstly, the effectiveness of the belief network used for component selection was evaluated, in comparison to the choices made by manual data inspection. These results are shown in the Table 6.4.

We can observe that the ICA mapped an average of 4 components inside our region of interest during both phases. The method correctly identified the most suitable component with the accuracy larger than 90% in both phases. The second choice selection rate describes how often the best component received the second best goodness i.e. how often the method made a mistake of placing the correct component on the second best place. It is clear that when the method fails to select the very best component(>10% of the cases), it always places that component on the second place. The difference between the two after spectral analysis is often minimal, so this does not affect the following part of result analysis. Secondly, we analyzed the actual difference between the fatigue assessments of the two driver groups as provided by the BCT in the defined ROI. Each group received a scalar value of the frequency band ratio. A two-sample t-test has been performed on the ratios for both test groups. As the result, the null hypothesis has been rejected with the significance level of 5%, meaning that the two groups do exhibit a statistically significant difference. These results are presented in the Table 6.5.

The collected data summarized in both tables confirms that the independent components are being correctly identified and that the BCT in the selected ROI correctly identified the

Table 6.5: Differences in ratio β / ($\theta + \alpha$) between two driver groups

Experiment phase	Normal test group	Negative test group
Default brainwave activity	0.8898	0.7185
Driving in the simulator	0.8292	0.7027

driver state during our experiment. As a result, we claim that the RISSA approach is robust enough to justify further development and experiments in real-life conditions.

6.5.6 Conclusion and Future Work

We have demonstrated how consumer-grade BCIs can be deployed in automobiles to assess the driver fatigue. The issues of low-quality electrodes and low electrode count were alleviated with additional signal processing effort. Our contribution has both increased the robustness of the established methods for EEG signal processing and extended the usefulness of consumer electronics BCI devices in the automotive area for the purpose of driver state detection. One important question is how the resulting driver assessment can be meaningfully used for increasing traffic safety. We suggest a practical approach based on influencing the driver state through infotainment and/or comfort systems, in an attempt to bring the driver back into an alerted and wake state. One option, already made possible in our experiment vehicle, is manipulating the ambient lighting of the driver's workspace. Sudden change of ambient color or a shift to daytime color temperatures can affect the driver wakefulness. Another option is alerting the driver with visual and audio cues, some of which require user interaction. An example is given in Figure 6.19.

Figure 6.19: The EEG helm can be comfortably worn while the prototype vehicle is driven with conventional human-machine interfaces(Image by Juan Jose Gonzalez Herrero)

Chapter 7

Conclusion

This work presents a context-centric approach for designing automotive human-machine interfaces and presents three contributions to context-aware interaction:

1. Extension of exact inference methods for Bayesian interaction context descriptions through quality-of-service requirements

2. Driver fatigue detection with a brain-computer interface

3. Detection of unusual steering trends with a side stick

A software platform called the Probabilistic Application Layer is proposed, which separates the application space from context management.

The quality-of-service optimization criteria for exact inference was evaluated through its direct reduction of inference's computational complexity. A driving simulator was used to evaluate the contributions which are based on signal processing.

This work provides an overview of the importance of the intelligent human-machine interfaces and provides an incremental improvement to the underlying context processing and signal processing methods.

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