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Driver Drowsiness Detection System

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Abstract

The drowsiness of a driver remains to be among the main reasons to traffic accidents, although the rapid development of emerging technologies, including Machine Learning and sensors, might have a huge potential in addressing the problem. The aim of this project is to explore the idea of detection and prediction of drowsy driver behaviour in passenger automobile environment. The scope is framed within the development of the conceptual model of the system and definition of the requirements for the proposed solution. The study is focused on available and potential drowsiness measurements and technologies allowing detecting and predicting drowsiness. As the system involves usage of user generated data, considerations on privacy and security are given based on the privacy by design principles.

Chapter 1: Introduction

1.1 Background and motivation

Driver drowsiness is one of the contributing factors to traffic accidents and related injuries as well as death around the world. Drowsiness is a state where the person behind the wheel is sleepy or has fatigue markers; it is a phase between falling asleep and alertness. Since driving is a complex activity, it demands constant information analysis and attentiveness to the environment from the driver.

Driver drowsiness is a well-researched area. However, more real world solutions are needed. One of the challenges in driving an automobile is to subjectively predict the exact time when the person would fall asleep. Therefore, an ample of academic research has been done on the topic, testing and validating different technological solutions that could detect the drowsiness of the driver and produce warnings. Sahayadhas categorised driver drowsiness measurement tactics into three broad categories:

1. Vehicle-based measures – refer to the data obtained from sensors installed in various car components. The most widely used measures include changes in steering wheel movement and standard deviation of lane position. Furthermore, drowsiness can be indicated through calculating variability in driving speed.
2. Behavioural measures – facial movements such as eye blinking rate, yawning along with the head nodding are common signs of the sleepiness.
3. Physiological measures – such as heart rate and electroencephalogram of the person can be used for detection of the drowsiness in early stages with the accuracy.

In order to collect the above mentioned data, variety of technologies can be implemented. However, each of the methods has its own limitations and strengths. Behavioural measures can be hard to detect as well, for instance, the camera of the smartphone might be compellingly accurate on detecting driver fatigue level based on eye-lid openness and head tilt, and however the question of efficiency of the camera in the night with scarce light conditions remains. Therefore, there is a need for hybrid solutions that are able to analyse different types of measurement to have a higher detection accuracy rate.

Looking from the perspective of emerging technologies, implementation of machine learning algorithms for analysis and prediction of drowsy driving promises huge improvements to such systems. The big attention around machine learning and neural networks attracted academic interest into the driving assistance topic. The research area is still young with a few attempts been done so far. Development and implementation of real time devices would also imply lowering the computational complexity of the system. Those might not be sufficient for the model validation considering the heterogeneous base of the drivers. In short, there are on-going researches in the area aiming to come up with the least intrusive and most effective solutions for detection of the drowsy driving with the help of machine learning algorithms.

Despite the technological challenges and general approach to increase the effectiveness in detection and prediction, a huge social issue is generally overlooked in the literature. Data privacy of the applications is a burning concern among the industrial stakeholders, users and privacy organisations. Since designing a service for driver behaviour detection and prediction is reliant upon the personal data of the driver and driver profiling, controversy around the technological need of the data and data privacy arises.

It is arguable whether the ultimate future solution to drowsy driving would be the introduction of autonomous cars onto the roads. SAE International developed a framework with the levels of automation of cars from 0 (No automation) to 5 (Full automation). Many car manufactures are heavily investing in self-driving car technologies and predict cars to be on the road in 2020. However, even if the technologies would be ready by that time for level 5 automation, which totally excludes human driver functionality, there would still be a long way for the cars to be adopted by the mass market. Surprisingly, given by evidence of the ample academic research there are just few implications of drowsy driver detection systems currently in real world.

1.2 Problem formulation

As described above, the area of driver drowsiness detection gained high attention from the researchers over the decade. However, being a well-researched area, there is a limited amount of implementations in the real world. The solutions are mainly available in expensive models of automobiles or do not take into consideration the full spectre of fatigue driving markers. Furthermore, as a complex system might require personal sensitive data, privacy concerns arise. Therefore in this thesis, the main question is formulated as follows:

How can a system that detects and predicts drowsy driving of the driver be designed?

In order to answer the main question, the following sub-questions are formulated:

- What are the current approaches to address the risks and challenges faced in driver drowsiness detection in cars?
- What type of machine learning solutions would best fit to the system?
- How data privacy can be ensured for the driver in drowsiness detection and prediction systems?

The answers to sub-questions will create a base for the analysis and development of conceptual model of the detection and prediction system in in-car environments. The design requirements for the machine learning model will also take data privacy principles into account. The aim of the study is to identify requirements for the drowsy driving detection and prediction systems and eventually contribute to the reduction of traffic accidents.

1.3 Delimitation

Novel endeavours for ubiquitous systems in automobile industry help to connect the car with different sectors and computing networks. In a near future, cars might be connected to road infrastructure, other cars and in-vehicle sensors forming vehicular ad-hoc networks (VANETs). The development of detecting and predicting systems for drowsy driving should take into account all the available context information in order to increase the accuracy. With the availability of vehicular networks, the proposed system might also benefit from Vehicle-to-Infrastructure and Vehicle-to-Vehicle solutions. While it is important to understand the causes of drowsiness of the drivers, there is still a lack of actually implemented systems that could predict and detect drowsiness.

1.4 Concept clarifications

The research topic is related to various definitions that might have a slight difference in scientific terminology, however used as synonyms in everyday life. In order to assure the same interpretation of the main concepts between the reader and the researcher, following clarification is presented: Drowsiness of the driver – also commonly known as a sleep-deprived driving, fatigued driving, tired driving. Despite the fatigue and lack of sleep possibly having different root causes, the symptoms and physiological manifestations are similar.

Chapter 2: Methodology

This chapter presents the methodological approach that was followed for tackling the problem statement described in Section 1.2. To begin with, the project process model is depicted to describe the overall approach to the thesis. Next steps in project initiation, information gathering methods, analysis are given. Furthermore, tools for requirements elicitation and conceptual model depiction are illustrated.

2.1 Preliminary considerations

There are several considerations that led to the methodology construction and defined research strategy. In this section, thoughts regarding viewpoints on process model, system and system engineering definitions and a discussion on incremental approach are given. The first considerations refer to the nature of the process model. The process model can be considered under two different viewpoints: as project management concept for system design development and as the research process. On one hand, the report should reflect the steps undertaken to design the conceptual model. On the other hand, construction of the report is usually organised in a waterfall manner that is different from the agile approach for the system design development. The report creations in compliance with master thesis guidelines can be also considered as a separate project with own pre-defined phases. In order to avoid confusion between descriptions of the process of writing the report and the system design development, they were carefully aligned.

In order to analyse and develop system design, system engineering principles come into play. System engineering emphasises the importance of understatement of user needs and stakeholder's interests. It is defined as a "multidisciplinary application of analytical, mathematical, and scientific principles to formulating, selecting, developing, and maturing a solution that has acceptable risk, satisfies User operational need(s), and minimises development" and life-cycle costs while balancing Stakeholder interests. The decision regarding the type of the process model depends on the specificities of the project and constraints. It should be highlighted, that DDDP systems may rely on various requirements and challenges that are unforeseen in the beginning and emerge in the later phases of the research. There are several benefits to the incremental approach. It is used to assure flexible environment for the development through incorporation of new information gained through feedback loops, for instance from interviews, consultancy and interaction of the users with the system. Incremental approach requires less extensive planning in the early phases of the system design and improves the project from increment to increment.

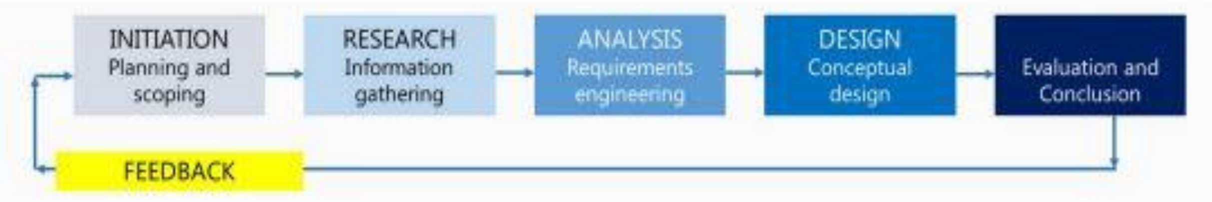


Figure 2.1: The incremental model, inspired by [38].

Having a number of benefits, the drawbacks of this approach address the cost of release of each version. Generation of project versions might be costly in time, allocated mental energy and finance. Another weakness of the incremental model refers to the challenge to incorporate new ideas, when they can be incompatible with the older versions. Therefore, more agile approach to the project was in need. Taking everything into account the project implies parallel process of writing a report and the system design process that is reflected in the process model. Based on the definitions of system and system engineering, main elements of the project should include user demands, stakeholder viewpoints and the risks of the system.

2.2 Process model

To overcome the drawbacks of the incremental model presented in Section 2.1, some of the LeanUX principles were adjusted and involved in the project. In this section, the original LeanUX mind-sets are illustrated and the modifications made for this particular project are communicated. LeanUX is a modern agile methodology used in project management that combines Design Thinking, Lean Start-up and Agile approaches in different phases of the development life-cycle. Originally, the methodology guides teams of up to 10 people through the ideation, prototyping and software development processes, as it is depicted in Figure 2.2.

Figure 2.2: How it all comes together[44].

The flow begins with Design Thinking. This phase is committed to explore new opportunities with an abductive approach with the aim to understand what it is and what could it become when innovative and creative mind is added. In the next phase, Lean Start-up methodology refers to the exploration of opportunities by actions, improving system in a feedback loop. Lean practitioners test their assumptions by building a prototype and learning through the differences between their beliefs of how the system should work and it performs in reality. In the last phase, agile methodology focuses on building elegant software solutions, acknowledging that the changes of the world are rapid and continuous.

Beginning of Table 2.1

LeanUX	Software development life cycle	Master thesis project development life cycle
Design thinking	**From 0 to idea.** Creating vision, framing and desired outcomes in a collaborative design approach with high user involvement [30].	**From 0 to problem statement.** Creating problem statement, project planning and scoping through methodology with a collaboration with the supervisors and collection of background information through the preliminary conversations with the drivers, attendance to the relevant conferences and checking statistics. More focus on: Problem Formulation, Introduction, Background information, Methodology, State of the Art.
Lean StartUp	**Prototyping.** Creating Minimal Viable Products and experimenting. It is important to be in a constant, informal collaboration with the user to receive feedback from each iteration and learn from it [30]. Changes implemented in a small chunks and tested with the user.	**Draft of the project.** Prepare drafts of the project with outlines of all chapters. Depicting the progress in the report in a constant and iterative manner, with small chunks and receiving feedback from the supervisor. Conduction of in-depth interviews with system users. More focus on: State of the Art, Interviews, Secondary Research, Analysis.
Agile	**Software development.** Development in sprints, with the backlog of ideas [30]. Highly iterative and oriented on a constant improvement.	**Working towards the final version of the project.** Continuous development and feedback loop from both supervisors and the users of the system. More focus on: Analysis and Conceptual Design, Evaluation.

The general principle of the LeanUX is being highly user oriented and it highlights the importance of the constant collaboration with users. User-centred design is a product development approach that focuses on the end users of the product. The mind-set of the approach is that the product should suit the suit the user, rather than making the user suits the product.

2.3 Project initiation

Early phases of the project and the prioritisation of stakeholders are described in this section. This phase provides a base for the rest of the project and influences the selection viewpoints of stakeholder classes for the phase dedicated to information gathering. Project initiation typically includes problem identification, where the goals, scope, schedule and budget are formulated. During this step the scopes are perceived as preliminary and changes are possible on the later stages. The list of stakeholders and ranking of them can be arguable and viewed from different perspectives. However, it is vital to create and systematise the list of stakeholders as a discussion point in the early stages of engineering requirements. The drowsiness detection and prediction system development is being created and mediated by various stakeholders, as it is shown in Table 2.2.

Beginning of Table 2.2

Stakeholder Class	Ranking	Rationale
The user – driver	High	Primary stakeholder with the most interaction with the system, interested in satisfaction of their needs.
Regulatory bodies and safety standardisation organisations	High	The likelihood of the proposed solution to be present on the market and be offered to the users is directly dependent on the compliance with regulations and standards.
Society	High	Express concerns on privacy and utility of the proposed system as well as responsible for the public acceptance. Proposal of the system related to the safety of the driver might be useful. However, the collection of personal data needed for design of the DDDP system may raise privacy concerns. Privacy breach can affect number of users, companies and even non-users of the system and raise bigger social and moral questions, as for example in case of the Facebook – Cambridge Analytica data scandal. Therefore it is important to balance the privacy/utility trade-off in the early stages of the development and distil a list of requirements from them.
Automobile companies, similar system manufacturers	Medium	Potential customer of the system and also potential negative stakeholder in case the proposed system will be competing against manufacturer solutions. They interact with the DDDP systems on regular basis and have expertise in the area.
Public institutions, insurance companies	Low	Public institutions might have an interest in decreasing car crashes and promoting safety solutions but they do not interact with the system directly. Insurance companies also might have high interest in the DDDP system as customers, but since they have lower expertise in the domain and the knowledge is important in early stages of system design, the ranking has been set lower compared to the system manufacturers.
Media	Low	Media is a mediator between stakeholders and influence for the public acceptance of the system. However, in the early phases of the concept development of the system, the role of this stakeholder remains limited.

2.4 Information gathering

Information was collected by means of literature review and interviews. Literature review is used to gather information regarding the state of the art in the fields of: drowsiness, measurements and technologies in use, machine learning algorithms, safety and privacy considerations. Research on the state of the art allows capturing the landscape of the existing systems, potential solutions and understanding the problem for making better decisions in later phases. The gathered information is used to derive an essential functionality as well as to identify the missing functionality of the contemporary systems. The problem landscape has been researched through the literature review from online academic papers, white papers and web-pages of service providing companies.

2.5 Analysis

The methodology applied to the research is reliant on the data and information needed to be collected. The gathered information is divided into categories and used for analysis in the following ways:

- Analysis of the current technologies being used in drowsiness detection systems, primarily the study of the types of existing services, candidate technologies and research challenges. Information primarily collected through the literature review.
- Analysis of machine learning algorithms that have high potential for detecting and predicting fatigue marks in driving environment. The analysis relies upon literature review. Analysis of safety and privacy issues in regards of driver behaviour markers collection. The analysis based on gathered information through the review of the literature and relevant EU standardisation activities and initiatives.
- Analysis of the user demands and needs in regards of driver drowsiness detection and prediction system. The analysis based on the review of the nature of drowsiness and user interviews.

2.6 System Design

This section describes the last phase of the project with the goal to create a conceptual design derived from the requirements. The process starts with the creation of scenarios, and then combined findings from analysis requirements list are created. Finally, conceptual design of DDDP in form of diagrams is presented.

2.6.1 Scenarios

Scenarios represent plausible and internally consistent stories that might happen during the interaction with the system. Scenarios are easier to understand rather than being abstract descriptions, and therefore they stimulate the discussions around the system features. Requirement engineers use scenarios to derive system requirements from these discussions.

2.6.2 Requirements

Requirements are based on the analysis and scenarios. Analysis allows the system architecture to be built based on the information gathered through literature review and interviews. Scenarios are used to provoke thought regarding the issues and interaction specificities around the system that could be unforeseen during the analysis. The functional requirements are provided in the form of table with a number, requirement and the rationale behind explaining the importance of it, in order to provide description of the entities and their behaviour to implement in the system architecture.

Chapter 3: State of the Art

In this chapter, the latest developments and potential solutions of driver drowsiness detection and prediction is described. First, we will look into drowsiness nature, measurements and technologies that can enable the system and ways of Driver Drowsiness Detection and Prediction (DDDP). As just the collection of drowsy driving markers might not be enough, we will also explore related machine learning algorithms and academic works. Finally, privacy and safety related issues around DDDP systems are investigated.

3.1 Drowsiness measurements

This chapter is dedicated to the information relevant to understanding drowsiness nature and also for discussion of advantages and disadvantages of modern drowsiness measurements.

3.1.1 Defining Drowsiness

There is no one commonly agreed or unified definition for driver drowsiness. In the literature, drowsiness is usually used interchangeable with the words as “fatigue” and “sleepiness”. There have been no attempts to differentiate these concepts, and term “driver drowsiness” is used to describe a tendency of the driver to fall asleep on the wheel. Fatigue and sleepiness might have different causes; however in driving situation their effects are very similar, as they can decline mental and physical performance of the driver. Drowsiness can be also viewed as a continuous transitional state between being fully awake and sleepy.

Driver drowsiness is a considerable contributor to road accidents. In order to reduce traffic accidents, various countermeasures proposed to prevent sleepiness on the wheel, for instance having a short nap, driving with bright light or consuming caffeine. Drowsiness is a natural process that is influenced by circadian rhythms of the person. Circadian rhythm is a mechanism that regulates sleepiness patterns and effect to the wakefulness of the human. When the person does not get enough of sleep at night the circadian rhythms interferes to the person’s activity and encourages sleepiness behaviour.

3.1.2 Drowsiness markers

Unfortunately, drowsiness cannot be measured directly but has to be approximately calculated on the basis of observable markers. It is important to discover these observable variables or drowsiness markers in order detect the drowsiness process and warn the driver in advance. Driver drowsiness can be detected through observation of following symptoms:

- “Frequent yawning or difficulties keeping your eyes open”.
- “‘Nodding off’ or having trouble keeping your head up”.
- “Inability to remember driving the last few miles”.
- “Missing road signs or turns”.
- “Difficulty maintaining your speed”.
- “Drifting out of your lane”.
- “Different reactions to fight drowsiness, such as deep breaths, shaking head, rubbing eyes, moving body”.
- “Poor concentration or trouble focusing”.

In analysis it is also important to take into account specifics of drowsiness. Researchers pointed that after waking up the cognitive performance of the driver is considerably declined, as the person is prone to misjudgement of the road conditions and making errors in decisions. The analysis can be based on:

- “The driver’s facial and body motion and physiological status (heartbeat, pulse rate)”;
- “The vehicle’s operating condition”;
- “The in-vehicle environment”;
- “The driver’s driving aptitude or behaviour (lane-keeping, speeding, anger, anxiety)”;

- "And a combination of these".

Summarising above-mentioned points, various measures grouped into:

- Subjective measures.
- Vehicle-based measures.
- Behavioural measures.
- Physiological measures.
- Hybrid approach.

3.1.3 Subjective assessment

In many researches subjective assessment mainly executed in form of questionnaires to the driver, or collected through the observations of the experimenter sitting near the driver. Most of the times researchers employed Stanford Sleepiness Scale as well as Karolinska Sleepiness Scale for evaluating subjective sleepiness level. The scales are in general alike, and consist of scale ratings from 1 to 8, and 1 to 9 respectively, describing sleepiness level states from being extremely alert being very sleepy. The SSS, as it can be seen in Figure 3.2, degrees of sleepiness are expressed through adjectives like sleepy, foggy, and awake and used to track overall alertness of the person throughout the day.

Degree of Sleepiness	Scale Rating
Feeling active, vital, alert, or wide awake	1
Functioning at high levels, but not at peak; able to concentrate	2
Awake, but relaxed; responsive but not fully alert	3
Somewhat foggy, let down	4
Foggy; losing interest in remaining awake; slowed down	5
Sleepy, woozy, fighting sleep; prefer to lie down	6
No longer fighting sleep, sleep onset soon; having dream-like thoughts	7
Asleep	X

Figure 3.2: An Introspective Measure of Sleepiness The Stanford Sleepiness Scale (SSS)[32]

Although it might be appealing to recognise the drivers' own perception, subjective assessment results should be interpreted with caution. In case of the questions asked from the driver during the driving process, it is obvious that such interference disturbs drowsiness state and causes additional awareness trigger to the subject, thus decreasing the driver's drowsiness level being measured. Furthermore questionnaires tap into people's attitude that can be different from their actual behaviour. This is a famous problem in research design that highlights the gap between stated and actual behaviour. The obvious solution to tackle with this issue is to use observation methods to identify direct behaviour of the study subject rather than rely on their self-assessment.

3.1.4 Vehicle-based measures

There are various methods have been described in the literature to capture driver drowsiness by means of vehicle-based measures, including lateral lane position on the road and their variables, vehicle heading, steering wheel movements, lane crossing, speed, pressure on acceleration pedal, etc. The increasing drowsiness of the driver and related cognitive fatigue worsen driving performance over the time that can

be tracked through the vehicle movements. Among many measurements lateral lane position and steering wheel variables based on the research carried with drivers are suggested to be useful in predicting drowsiness. Standard deviation of lane position (SDLP) is the widely considered important metric for drowsiness detection in the literature, also referred as lane deviation or lateral position variability. During the long and monotonous driving, driver has been observed to have difficulty to maintain the vehicle in the middle of the right road lane. Fluctuations of the vehicle to the lane position indicate that the driver's alertness decreased, especially after the sleep deprivation episode. Driver's performance deteriorates by time and hence more fluctuations in lane positioning can be observed. The value is usually derived through the lane tracking camera mounted under the car.
Steering wheel movement (SWM): Steering behaviour of the driver besides depending on direct driving tasks and driver's experience also rely upon on the driver's state, e.g. tiredness, laxness and alertness. In fully alertness state, drivers apply small, smooth adjustments in steering to avoid minor road bumps and roadway imperfections by controlling steering wheel. These adjustments can be impaired or altered while the driver's drowsiness state increases or the signs of overreaction for unexpected road conditions typical for drowsiness might be derived. As drivers feel sleepier and hence their reaction time increase, they become less sensitive to the lane deviations and instead of small incremental adjustments, they make bigger steering wheel rotation in order to stay in the middle of the lane. Steering behaviour of the driver can be captured through steering wheel sensor embedded in the car or attached separately.
As it can be seen most used metrics can be correlated or even derived from each other. Lane tracking camera installed under the vehicle is dependent on road conditions and visibility, and thus might be prone to errors when the visibility of the lane is limited. SWM from the other hand does not require installation of additional equipment and can derived directly from the car's board computers.
Vehicle-based measurements are unobtrusive and usually do not require additional accessories and responsibilities from the driver. They use information from sensors already integrated into the car such as accelerometers, steering wheel sensors, cameras recording the road, information available in Controller Area Network (CAN) buses of the modern cars. Being relatively easy to implement these type of measurements are mostly used as industry solutions by car manufacturers and can be find already implemented in novel vehicles. On the other hand, the fundamental challenges for vehicle embedded measurements are that the metrics are dependent on road circumstances. Swift change in vehicle heading or in SWM may reflect alert reaction to the other vehicle presence, as well as lane position change can be caused by bigger road bumps.

3.1.5 Behavioural measures

Changes in circadian processes of the person affects to the visible behavioural changes in body, such as changes in eye pupil diameter, slow eye movements, eye lid closure, yawning, etc. Features derived from eye and head movements are perceived the most promising and attractive for research purposes. Eye and head tracking systems with the use of cameras are non-invasive and in most cases do not require special accessories to purchase. As it was found out in the research, the precision of the systems using smartphone camera to detect eye movements, head position and yawn can be also high, reaching up to 93.37% of drowsiness detection during daylight. However the usage of cameras involves serious issues regarding the privacy of the driver that can cause limited usage of the systems and met opposition from the drivers especially when the camera images are recorded and stored. Another issue is concerned with

the limitations of the camera against sunglasses, head movements, shadows in the face that might cause false positive and false negatives.
Eye movements and eyelid closure can be detected more precise by attaching electrodes placed near eyes of the driver, and calculating electro-oculogram (EoG), in other words, recordings of eye movements. Researchers also suggest harvesting ocular parameters through the use of specially designed eyeglass with embedded high speed camera that can detect eye blinks and moves of eyeball.

3.1.6 Physiological measures

Changes in physiology of the person entering to the drowsiness state occur well in advance and therefore detection and warning of the driver's fatigue can be organised in timely manner. Physiological measures are constantly available and considered as an objective and direct measure to assess persons' functional state. The most popular measures are related to tracing heart rate variability, brain waves and electrical activities of muscles. In most case physiological measures are obtained through attaching electrodes on the driver's body that makes implementation of these types of measures unsuitable for transportation systems.
Heart rate variability (HRV): Cardiac measure can be obtained through electrocardiogram (ECG) by means of attached electrodes on the chest of the person. It is also possible to place electrodes under the driver's seat, making detection of HRV practical from users' perspective and being promising research area. However the measurement is prone to external interference and produce inconsistent results for sleeping attacks.
Brain waves frequencies are measured through electroencephalogram (EEG) that quantifies central nervous system activity and the degree of synchronisation among neurons. Recording EEG typically involves attachment of wet electrodes on the scalp that must remain in contact with the skin, as removal of signal probes result on the loss of the signal. In the more recent research, scholars investigated the usage of dry electrodes that can be comparable to the sensitivity and reliability of wet electrodes. Further investigation in the area could give a rise to invention of head covers with dry electrodes inside suitable for real world driving conditions.

3.1.7 Hybrid approach

Hybrid approach has been seen in the literature suggests combination of various technologies and measurement techniques. Hybrid approach can combine measurements within the same group of measurements. Several researchers highlight the importance of combination different measurements and technologies for increasing performance of the DDDP system. However, in order to develop an efficient drowsiness detection system, the strengths of the various measures should be combined into a hybrid system.

3.2 Recent ML techniques used by measurement types

Vehicle-based measurements represent the most unobtrusive methods for drowsiness detection. These types of methods focus not on the human generated signals, but rather employ data obtained from the car elements that could reflect the alertness state of the operator. The main benefit of the proposed approach is that the random forest classifier does not require extensive pre-processing and also easily trained by the available datasets. The proposed method was compared to PERCLOS for validation purposes and outperformed it. However, due to the usage of the limited data from simulators and absent of contextual

information the results might be hard to generalise. Moreover, the steering angle represents many other factors not related to the drowsiness, such as bumps in the road or inattention of the driver.
Behavioural-based measurements in the most cases rely to SVM. It is the most used technique in the literature. As per authors it is hard to compare different methods since they use various databases, and no standardised benchmarks exist. However the development of deep learning algorithms influenced to the drowsy detection area as well, and promise increase of the effectiveness of the systems.
Another study was dedicated to actually experiment with deep learning and implement CNN to DDDP system. Opposite to the system where features were selected by experts, the researchers employed CNN for detecting underlying complex non-linear feature interaction. Softmax classifier, the activation function commonly used on the last layer for multiclass classification, has been implemented. The solution produced 78% accuracy across subjects; however it can improve with the inclusion of data from head movements.
Physiological features are among the most reliable sources for drowsiness detection and they are widely used in medical settings for sleep deprivation detection. The possibility to analyse and capture correlating changes in the human body can be also used more widely in other fields. Therefore researchers make attempts to harness novel machine learning algorithms for better detection and prediction of sleepiness phases.
EEG signals are "no stationary and present evident dynamic characteristics", and usually approached as a classification problem, to detect whether the driver is drowsy or not. Entropy quantifies the diversity, unpredictability of the data. The higher diversity and it is harder to predict the patterns, the higher the entropy will be. Next, extracted non-linear features from 4 methods were merged. At the same time the researchers also detected eyelid movement, and after extraction of eye blinking features combined them with EEG features. As a last step, extremely learning machine (ELM), the type of feed forward neural networks, was used for classification. Being feed forward, ELM does not require back propagation and therefore computation speed is much higher than neural networks employing back propagation. Preliminary the most popular classificatory in the EEG research was support vector machine (SVM), that is a supervised learning model for binary classification. However as a result this research, ELM outperformed SVM in terms of time spent for analysis and detection accuracy.

3.4 Privacy and Safety

3.4.1 Privacy vs. Utility

The infrastructure for IoT is rapidly developing over the past few years and promise future with new services and business models. IoT devices expand our understating of the physical world, by collecting data and analysing them on the cloud. Service providers need this data for creating new type of analytic functions and learn faster leveraging on the multiple devices rather than rely on one device. We can already imagine the interconnected world where small devices are making everyday life more convenient and productive. However the coin has two sides, where technologies can solve problems but also create ones. From the positive side, IoT technologies allow to collect more fine grained data that can be used for better decision making. Wearable that monitors health indicators help for healthcare professionals to track the progress of the treatment or enforce preventative actions. Real data collection also allows real time decision actions, where more fine grained services can be built upon it, e.g. pricing flexibility will depend on the data from parking sensor indicating precise timing for parking slot usage.

Undoubtedly IoT can enhance the efficiency of systems, for instance by tracking the energy usage, or increase the productivity based on the analysed data.

Unsurprisingly involvement of the big data cause several concerns around it. Besides from data ownership and increasing need for storage capacity, privacy and security are the major concerns of the people worldwide regarding the usage of IoT. The risks of being exposed by compromised devices in a near proximity of the people might be disastrous. The issue regarding the utility and the risk of re-identification of the person attracted research interest in social science. The risk calculated as a likelihood of the matching records to the master data with the re-identification purpose. If the data contains direct identifiers, such as social number, names, id numbers the risk is high. Sensitive data breaches lead to the huge financial and psychosocial losses for individuals and the whole organisations. From the other hand utility depends on the data quantity, it increases the analytic capabilities, improves data quality and likelihood of research replication. Contextual information might enhance our understanding of the physical world, especially with the presence of machine learning algorithms, where hidden patterns derived from the data that have been never thought before. Unfortunately increased utility of the data leads to the increased risk of identification and privacy loss for the individual. Figure 3.8 provides a visual representation on the trade-off between privacy and utility.

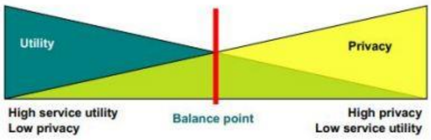


Figure 3.8: Privacy-Utility Trade-off [61]

Finding the right balance in this trade-off is a hot research topic. Following countermeasures for safeguarding user privacy in case of the leakage of information that potentially can be applied to DDDP system have been discussed:

- Differential Privacy is a class of techniques used in large sets of the data that apply probabilistic transformations to each item to prevent individual being identified from the larger set. To illustrate, there are two adjacent databases that differ by just one row. Comparing analytic results obtained separately from each database, the difference is visible and can lead to identification of the user.
- Obfuscation implies data alteration, modification or transformation in a way that it is impossible to carry further research or obtain extra data than it is needed. Usually it is associated with high costs, and remains as an open research question seeking more effective ways to perform obfuscation.
- Cryptography methods are the most prevalent in IoT, referring to the strategy when all data is stored locally in the device and just sends cryptography proofs to the cloud, without sending an actual portion of the data.
- Local IoT services imply full localisation or minimised cloud backend. It is a useful approach for any privacy-preserved IoT application and feasible as IoT devices and local IoT hubs gaining more processing power and increasing storage capacities.
- User controllable privacy refers to most important principles of IoT privacy. The users should be in control of their data, know the purpose and third parties with which the data is shared. Thus the users can make an educated trade-off between the utility and their convenience.

However in order to balance trade-off between the privacy of the driver and employ data power from the video information, new approach is needed. The researchers point that high detailed naturalistic driving databases have been created by research organisations. However due to the identification risks of the drivers, public access to the databases are restricted. The utility of this type of databases are high, as they capture hundreds of drivers in different settings that can be employed by researchers and driving stakeholders to analyse. In order to employ data as well as respect the privacy of the individuals, the researches proposed an algorithm to alter face images. The most of the information is usually contains in the head positioning and the eye movements, therefore they employed face masks over the image, that hides the identity of the driver. Areas near eyes however remained unaltered and available for the analysis. They also deleted background of the image and replicating head positions with the face mask position. Thus the researchers were able to preserve important information and delete or mask identifiable features. Considering various technological approaches to the dilemma between the privacy and utility of the information, the main data stakeholder should not be forgotten. It is the user who actually produces this high valuable data and makes a decision whether to trust the service provider or not. The literature review covered 120 scientific articles related to the privacy of IoT published between 2009 and 2016, revealed that the majority researchers have fundamentalist approach to the problem, express their concerns over the privacy of users, discuss privacy threads or develop analytical frameworks. However, at the same time, most of the solutions seem to imply that the user put efforts to maintain their privacy. They will be motivated to take privacy-preserving precautions, e.g. carefully read user agreements and make thoughtful decisions. However the authors express concerns regarding this way of thinking and encourage future researches to understand the privacy perception of the users and whether they will use organisational and managerial tools to protect their privacy.
The controversy between users' intents to disclose the personal information and the actual behaviour can be seen through the privacy paradox. Privacy paradox refers to the situation when users' express high concern over the privacy of their personal information however provides this type of information for the service when asked. The provision of information highly exceeds over their intention. Privacy paradox is an interesting concept in light of privacy policies and regulations made by governments.
To find a balance in trade-off between the privacy and utility is a complicated issue. As we can see from this section various considerations should be taken into account, including available techniques, interests of stakeholders and user perceptions. One of the solutions to balance interests is an adopting privacy by design approach in the industry. Standardised privacy regulations would help for the industries and developers to implement privacy design approach and adopt the user privacy related philosophy in a straightforward manner, without need to "reinvent the wheel".

3.4.2 Safety Standards

Drowsy driving detection systems belong to the Advanced Driving Assistance Systems and usually consist of electronics and firmware. DDDP is an active safety driving system, and being safety critical demands specific approach throughout the product life-cycle. These types of devices are covered by international safety standards such as IEC 61508 and ISO 26262.
IEC 61508: It is an international standard published by International Electro-technical Commission relevant to each industry in a basic safety standard role. It defines functional safety as "the part of the overall safety that depends on a system or equipment operating correctly in response to its inputs." Systems can be divided into active and passive, where functional safety relies on active systems only.

The standard covers safety life-cycle of the system, and heavily risk and hazard prevention oriented. IEC 61508 conveys following views on the risk:

- Zero risk can never be accomplished; there are always will be risks;
- Safety must be incorporated from the early stages of the project;
- Non-tolerable risks must be decreased.

Thus risks are reduced to the tolerable level by incorporation of safety related functions by using programmable electronic technologies. ISO 61508 is a generic standard that is used for directions; industry and application-based standards should be examined for developing more detailed and related functional safety requirements.

ISO 26262: It is an adaptation of IEC 61508 for automotive industry developed by International Organization for Standardization in 2011. The standard defines functional safety directives for automobile electronic and electrical systems throughout the item development life-cycle, including software development. Same as IEC 61508, the standard is a risk oriented, where the focus is given to the risks and hazardous operations assessment and a development of safety measures to mitigate with risks, e.g. hardware failure. It should be noted that ISO 26262 highlight hazardous as a malfunction of the system for some reasons and within the interaction with the device, and does not take into account external obstacles, e.g. fire, smoke, heat unless they directly cause malfunction of the device. The risks are classified based on Automotive Safety Integrity Level (ASIL) and later used for safety requirements specifications.

ISO 26262 provides a framework for functional safety and can be used for the electronics systems and also for other products. Researchers have developed a framework based on ISO 26262 for risk analysis and mitigation on the conceptual phase of the project that should help to derive safety related functional requirements. They proposed safety goal oriented analysis with the use of diagrams, namely knowledge acquisition in automated specification (KAOS), Goal Structuring Notation (GSN) and scenario–situation matrix (SSM) on the basis of Goal Oriented Requirements Engineering. The goal of KAOS to identify possible hazardous situations and based on safety goal to determine functional safety requirements. GSN is a graphical notation that is used to determine elements and the relationships between elements, arguments and evidences. Scenarios are used to brainstorm the possible hazardous situations and uncover hidden threats of the system.

Chapter 4: Analysis

This chapter presents analysis divided into three sections according to the research sub-question. Each section highlights the arguments and methods for the analysis, presents the answer in a form of proposed solution and derives requirements from them. Later requirements from scenarios and analysis are combined in order to develop a high-level conceptual design of the proposed system.

4.1 Measurements

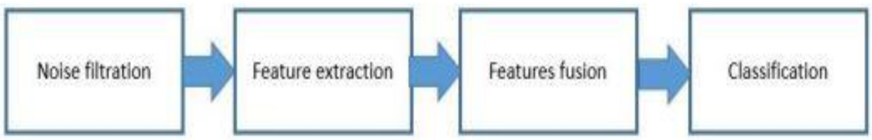
The section is dedicated to the analysis of gathered data to find a solution for the following sub-question “What are the current approaches to address the risks and challenges faced in driver drowsiness detection in cars?” Analysis: Five various measurements employed for detection drowsiness metrics: subjective, vehicle-based, behavioural, physiological and hybrid. Each measurement has own advantages and disadvantages. In order to compare measurements in a normalised way set of criteria that could be relevant for each metrics was chosen. Criteria are formulated based on the information during the

literature review and interviews and defined as following: Reliability, Obtrusiveness and Contact with the body, Technology accessibility.
Being part of Active Safety system per definition in IEC 61508, DDDP ensures functional safety in the vehicle and therefore should be highly reliable. All interviewed experts and users highlighted the importance of good performance of the system so they can rely on the warnings. Therefore, weight for these criteria is set higher compared to others.
Points are represented as a numbers, in order to depict advantages of the measurements relative to each other. The reasoning behind each point relies on the information presented in above mentioned subsections, use cases and empirical data that in general conveyed the same message. Therefore just short examples are given to explain logic behind point distribution. For instance, according to the literature review EEG is a "golden standard" in medicine for drowsiness detection and allows to spot early phases of the sleepiness. Therefore the measurement received the highest point in reliability. Whereas SDLP is influenced by external factors might produces false positives, however it's the most sensitive approach among the vehicle-based measurements and therefore received 1.5 points.
Reliability in this table interpreted as correlation of drowsiness markers yield by particular technology to the driver's fatigue level. Vehicle-based measurements being a reflection of the drowsiness has lower reliability whereas physiological signals carry original information, points were distributed respectfully.
Obtrusiveness, in the table, refers to the noticeability of the system component to the user that might cause irritation or annoyance. Whereas vehicle bases measurements is usually in-built and do not require additional extensive configurations from the user and process in a less obtrusive manner. The need of contact with user's body might cause calibration challenges.
Finally, technology accessibility refers to the ease of obtaining particular hardware for the system development purposes. Dry electrodes for EEG and ECG are novel solutions that are not penetrated in the market. Therefore installation of electrodes would need more research and development focus rather than usage of web camera. Vehicle-based measurements are controlled by the car manufacturers and therefore hard to obtain. Additional software and hardware solutions need to be involved in order to derive these features from the vehicles, therefore the lowest point was given to this type of measurements.
In order to ensure reliability accuracy of the system should be set higher than PERCLOS, DDDP "golden standard", more than 90%. Also, the system should implement IR camera to cope with various lightening conditions. To increase reliability of signal, amplifier for ECG and hardware-based noise filtration should be implemented. In order to decrease obtrusiveness minimum number of electrodes should be in use.

4.2 Machine Learning

This section analyses gathered information to find a solution for the following sub-question "What type of machine learning solutions would best fit to the system?" Analysis: Various machine learning implementations have been discussed in Chapter 3.2. As it can been seen there are numerous approaches in ML for drowsiness detection, where the same measurement type can be assessed based on different logic. The literature review showed abundance of researches on ML implementation in various phases of drowsiness analysis. Generally with the increase of storage capacities, computational power and data amount from IoT sensors there is no doubt that implementation areas of ML algorithms will enhance, including DDDP systems. Data obtained from both behavioural-based measurements and physiological measurements can be represented as a picture. This unlocks possibility of implementation convolutional neural networks examples of which were demonstrated in Chapter 3.2. As it can be seen CNN-based algorithms are in most cases outperformed traditional approaches. Although the algorithm requires high computational costs and high amount of data for training purposes, the performance of the system will rise over the time and hence be more accurate.

Type	Method	ML	Contamination of signal	Noise filtration	Computational cost
Vehicle based	SDLP	Random forest classifier / Dynamic Bayesian Network	high	Need additional sensors	low
	SWM		high		
	Vehicle heading		high		
Behavioral	PERCLOS	SVM /CNN	medium	Need to add additional facial and head movements	medium/high
Phisiological	HRV/ECG	GE SVM	high	Need preprocessing for noise elimination	high
		ELM. CCNN is good.	high		high
	EEG	SVM	high	ICA, entropy, raw signal	high



Proposed ML: Given by the successful results in academic research and potential capabilities CNN-based algorithms will be proposed for hybrid DDDP. Model-based algorithms might be also used for noise filtration and feature extraction.

Requirements: Based on the proposal of implementation of CNN, the system architecture should include components that would allow CNN deployment:

- sensors listed in the proposed technologies,
- a client as a cluster head with the ability to communicate with all the other components,
- Optionally, a server – presumably in the Cloud – for CNN model storage and deployment mechanism.

Data for training the model can be obtained through the usage of open source databases, proprietary databases and databases created by users of the system. Due to the importance of reliability of the system, the response rate of the system should be minimised.

4.3 Data Privacy and System Safety

Given section examines gathered information in order to find a solution for the following sub-question "How data privacy can be ensured for the driver in drowsiness detection and prediction systems?"

Analysis: Undoubtedly, privacy and utility trade-off dilemma is important to consider while providing a service based on data collection and analysis. Users with concerns over the privacy might still underestimate the data they are sharing with services. Uniformed regulation as GDPR supposed to return control to the user over their data; however the service also must include privacy by design principles from the early stages of the project. Therefore for data safety all communications between the system entities should be encrypted. From the safety perspective DDDP being an active safety system do not interact with vital vehicle functions.

Chapter 5: Design

In this chapter, a conceptual design will be presented. Firstly, it will introduce three architectural variations and describe the advantages and disadvantages of each. After that, a suitable variation is carefully chosen. The chosen variation is then described in a more detailed manner using a data flow diagram.

5.1 Architectural design

These sections present three possible variations of the proposed system architecture. The skeleton of this architecture is identical in each case – a server-client architecture depicted in Figure 5.1 – consisting of three groups of elements: (1) sensors, (2) client and (3) server. The variations only differ in the role of the components.

5.1.1 MLaaS approach

Machine learning as a Service approach places the drowsiness detection and prediction logic into a cloud-based service. The client takes the role of a cluster head, communicating with and receiving data from different kinds of sensors. All the data are then forwarded to the machine learning model for processing. The output of the model is the level of drowsiness and a confidence interval for quantifying the uncertainty of the estimation.

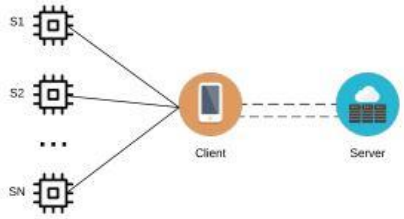


Figure 5.1: High-level system architecture

This approach has one important advantage: it has a simple architecture, following the current conventions in machine learning services. It also allows the system to tap into the vast computational resources of a cloud system.

On the other hand, the disadvantages can be summarised as following:

- All data flow through the client and the network. One of the proposed data sources is an IR video image feed. Videos are expensive in terms of data traffic over the network.
- The other disadvantage of communicating all the data over the internet are the arising privacy issues. The solution would require careful design in terms of security.
- Lastly, the MLaaS approach might increase the system's overall latency, since the data centres might be far from the user. A caching mechanism cannot be considered, either.

5.1.2 Federated learning approach

As opposed to the previously described approach, here, the client is the one performing all the necessary computations. A client in this case might be a performing smartphone, tablet or an integrated system into the car's motherboard. It still communicates with the sensors and consumes all the data they produce.

The machine learning model would be deployed to each client individually. Each client would then continuously improve its own model through further learning. The server would serve the purpose of storing a central model. Each client would over the time continuously propagate its own improvement to the server. It would then aggregate the individual improvement and update the central model. The advantages of this approach are the following:

- the removal of the computational dependency on the server,
- less data to be transmitted (only when propagating the improvements and updating the local learning model),
- Minimised privacy concerns, since all the data are consumed and processed locally and never leave the client. Only data leaving the client are the local improvements to the machine learning model probably in the form of weight adjustments.

The disadvantages of this approach is that it requires a robust and very well performing edge devices – most probably equipped with some sort of specialised neural computer chips such as the ones found in the latest, cutting edge smartphones. These chips may drive the costs of development and production.

5.1.3 Partitioned neural network approach

The following approach can be considered as a combination of the previous two approaches. The computation of the drowsiness detection and prevention system takes place on both the client side and the server side. The neural network itself is divided between the client and the server. The client represents the initial layers of the neural network which serve the purpose of feature-abstraction functions. The client consumes the data stream from the sensors and extracts the features. Those are then propagated to the server, which estimates the level of drowsiness of the driver. It is then sent back to the client who can decide, based on the received data, whether to notify the user at certain thresholds. This approach has the following advantages:

- Allows the utilisation of IoT devices and IoT networks with limited payload sizes, such as Lora or NB-IoT, due to decreased network traffic. The extracted higher-level features are much less space constraint than the raw video feed.
- Allows the utilisation of a part of the MLaaS approach since a part of the computation takes places on the server.
- Minimised privacy concerns, since user-generated data do not leave the client, only the derived features.

As a disadvantage of this approach the development complexity might be considered. Partitioned neural networks are still not very common in production-ready service implementations.

5.2 Data flow

This section describes the data flow of the chosen architectural design depicted in Figure 5.2. The figure depicts four different data inputs: (1) IR Video Image Stream produced by the infra-red sensor, (2) Physiological Data Stream produced by the EEG and ECG sensors, (3) Lane Variability Stream produced by the in-vehicle systems and (4) user feedback generated by the user whenever he sets the sensitivity lower or higher as means of punishing the machine learning model triggering weight adjustments. The first three data streams are consumed by the Drowsiness Marker Extractor function. It extracts the high-level features and propagates them to the Client SDK responsible form communicating with the central service through a defined API. The user feedback is picked up by the User Feedback Listener and it propagates the change in sensitivity to the client SDK. The client SDK communicates the extracted features as well as the change in sensitivity to the central service which then either processes the features and returns the estimated drowsiness level or stores the sensitivity change as a setting in the Sensitivity Store. The client, upon receiving the estimated drowsiness level, propagates the data to the Drowsiness Notification System, which notifies the user about her level of drowsiness in case it reaches a defined threshold and confidence. It is important to note, that while the Central Service and the Sensitivity Store are located on the server side of the architecture, optimally as part of a cloud-based, Machine Learning as a Service, system.

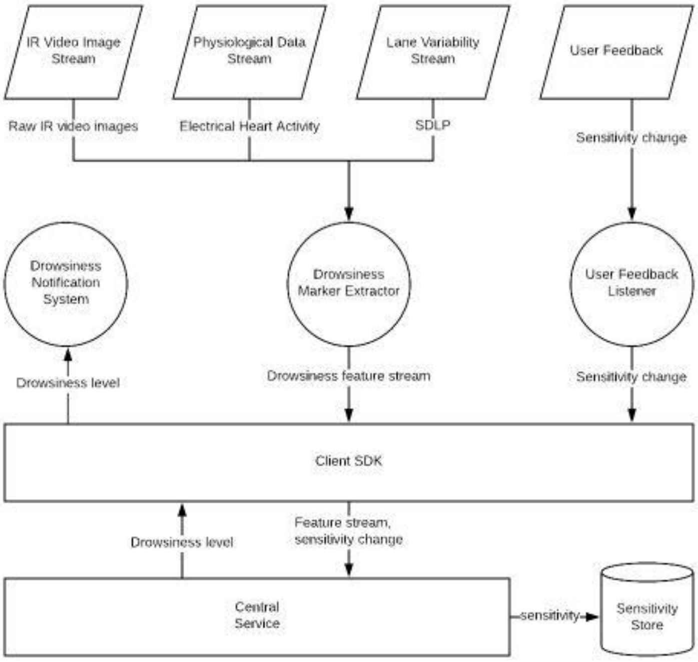


Figure 5.2: Data flow diagram

Chapter 6: Discussions and reflections

The goal of the study was to perform a study of the conceptual design options of driver drowsiness detection and prediction systems as a countermeasure for traffic accidents happening due to drowsiness. The conceptual design and requirements for the system has been developed with a few assumptions regarding the technologies, ML algorithms and privacy regulations. Due to time and resources constraints, certain limitations were set in the project. For the further research and deployment the list of other aspects could be examined.

Cost analysis of the system including hardware and software components would be an important measurement for the system components solution. The trade-off between the cost and utility might influence new design options that could help develop as system in a more affordable way. Furthermore combination and influence of various technologies to each other would be beneficial to study before the development of the system. Proposed conceptual design of the system should be considered as a high-level concept with examples of sensors. However, based on metrics and stakeholder interests combination of the sensors and hence features might vary.

Moreover hence performance of machine learning algorithms depend of the big amounts of data used for training, collection of drowsy driving data would be beneficial for the future related projects.

Consequently, the ways of storing and sharing of these types of databases ensuring privacy of the subject involved in driving would be important.
Validation of the proposed system could be done by dividing database into training set and validation set. Where data would be fed into CNN and the trained model would run validation cycles on the data excluded from training. Moreover cross-validation with the PERCLOS could be initiated. Subjective measurement tools as SSS could employed for additional validation metric.
It should be acknowledged that requirements and conceptual design are in the first iterations and based on the LeanUX approach might be modified further. More detailed requirements list and improved conceptual design can be derived through feedback sessions with experts. Prototypes on the other hand would allow collecting user feedbacks.

Chapter 7: Conclusion

During the project, different technologies related to drowsiness detection and prevention and several machine learning algorithms have been explored and analysed. The analysis of these technologies as well as the expert- and user interviews helped to identify the requirements for the system. Based on the discovered requirements, possible high-level architectural choices have been identified and further examined. The architectural design best fitting the discovered requirements have been chosen as the final conceptual design. The data flow between the lower-level components of the system have been introduced and explained. It can be concluded that based on the chosen conceptual design and the described diagrams, the future development of a functional prototype can be initiated.