A Robust Drowsiness Detection Method based on Vehicle and Driver Vital Data

Sate of the Art and Research Challenges

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Abstract

Driver drowsiness is one of the main causes of serious and fatal traffic accidents. Current driver assistance systems often use parameters related to driving behavior for detecting drowsiness. However, the ongoing automation of the driving task diminishes the availability of driving behavior parameters, therefore reducing the scope of such detection methods. The driver's role as the sole operator changes; the driver must supplement, supervise or serve as a fallback part of a highly assisted or automated system. Reliably monitoring the driver's state, especially the risk factor drowsiness, becomes more and more important for future automated driver systems. Numerous approaches, utilizing vehicle-based, behavioral and/or physiological based metrics, exist. The first part of the paper is a literature review and summarizes current approaches related to drowsiness modeling and detection within the automotive context. The second part presents the research project and discusses prevailing research questions. Therein, the focus is placed on the utilization of wearables for driver vital data measurements.

1 Motivation

Drowsiness is one of the major reasons for accidents in everyday traffic. The results of a naturalistic driving study of the National Highway Traffic Safety Administration (NHTSA) showed that the risk for being involved in a crash or near-crash is almost four times higher while drowsy. Drowsiness contributes to crashes in the range between 12.2% (Klauer et al., 2005) and 19% (Nabi et al., 2006). Different car manufacturers provide driver assistance systems to counteract the potential risk of drowsiness, for example with a rest recommendation. For assessing drowsiness, current commercial systems mainly focus on the analysis of parameters that are related to the driving behavior and imply drowsiness (Čolić et al., 2014; Mortazavi et al., 2009). In the context of the ongoing automation of the driving task over multiple levels these driving parameters will not be available anymore to a large extent (Schmidt et al., 2016). According to

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the taxonomy provided by the Society of Automotive Engineers (SAE), the automation of the driving task can be summarized in six levels (see Figure 1) (Society of Automotive Engineers (SAE) International, 2014). It can be seen that across different levels of automation the driver's role changes from the sole operator to a fallback part of a very complex system. In this context,

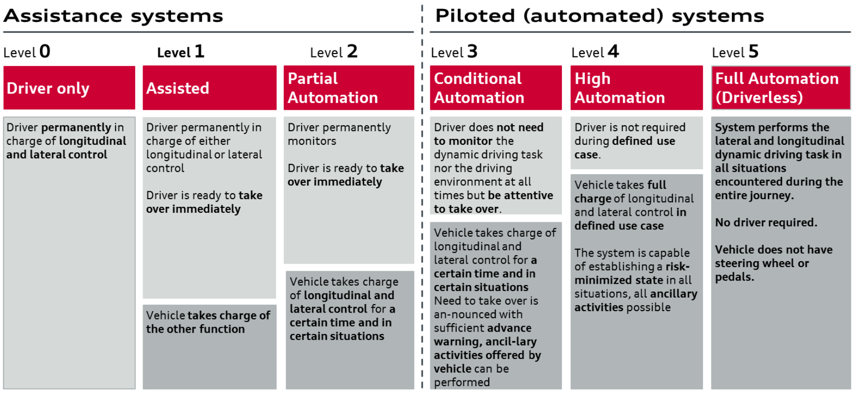

Figure 1: SAE levels for the automation of the driving task (Society of Automotive Engineers (SAE) International, 2014)

the driver's attentional focus towards the driving task and also their alertness might decrease through the monotony of observing (Körber et al., 2015). Nevertheless, in level 2 (partial automation) the driver still has to monitor the driving process and has to be attentive all time to take over when required. Furthermore, in level 3 (conditional automation) there is no need for the driver to monitor but to respond appropriately to a request to take over at any point of time. A relevant topic in this context is whether the driver could control the vehicle after a request in an acceptable take-over-time frame. Therefore, the reliable monitoring and detection of the driver's current state, especially of the risk factor drowsiness, will become a more critical task in the future. Knowing the physiological state of the driver with high reliability potentially provides a parameter that can be used to improve future driver assistance systems and to counteract incoming drowsiness already at an early stage.

The subsequent chapter contains a literature review and gives an introduction in and overview of different methods for drowsiness detection. This is followed by the presentation of the research project where the focus is placed on driver vital data measurements with wearables.

2 Related Work

For the detection of drowsiness in an automotive environment many different approaches and methods have been proposed but no standard exists. As summarized in (Sahayadhas et al., 2012), mainly three groups of measures (vehicle-based, behavioral, physiological) and a series of subjective reference metrics are used for detecting and monitoring drowsiness.

These subjective metrics are considered in studies in order to validate a method or its performance. The self-assessment and personal rating of drowsiness by the drivers is evaluated. They are asked to reveal and rate their perceived drowsiness either verbally or in form of a questionnaire (Sahayadhas et al., 2012). Just to name a few, the best-known subjective measures are the Epworth Sleepiness Scale (ESS), the Multiple Sleep Latency Test (MSLT), the Maintenance of Wakefulness Test (MWT) and the Stanford Sleepiness Scale (SSS) (Čolić et al., 2014). The most common subjective metric, also named in (Čolić et al., 2014), is the Karolinska Sleepiness Scale (KSS) (Akerstedt and Gillberg, 1990). It is represented by a nine-point scale ranging from "extremely alert" to "extremely sleepy". A limitation of subjective measures is the missing potential to record in real-time and to detect very sudden changes in drowsiness, e.g. when KSS is used every 5 minutes. Moreover, asking the drivers to reveal their current drowsiness can also have an activating effect and thus decrease drowsiness (Sahayadhas et al., 2012). In terms of vehicle-based measures for driver drowsiness detection, the driving behavior is investigated. Vehicle-based measures have the advantage to be real-time, continuous, non-intrusive and reliable (Z. Li et al., 2017). These measures include the steering wheel movement (SWM), steering wheel angle (SWA) and the standard deviation of the lane/lateral position (SDLP) (Sahayadhas et al., 2012; Z. Li et al., 2017). But with regard to future automated driving these vehicle-based measures will not be available and useful for drowsiness detection anymore (Schmidt et al., 2016). The second group of measures are the behavioral ones where the focus lies on eye behavior, facial muscle activity/expressions or head movements recorded with a camera. These measures are non-intrusive, but as an example poor light conditions can negatively influence the monitoring depending on the system setup used (Sahayadhas et al., 2012). The third group is represented by physiological measures. The driver's physiological state is analyzed through electroencephalography (EEG), electrocardiography (ECG), electrooculography (EOG) and electromyography (EMG) (Sahayadhas et al., 2012). Due to the sensor mounting directly on or around the driver, the collected data is susceptible to driver movements in most of the cases. Nevertheless, these measurements provide in general a higher accuracy (Z. Li et al., 2017).

In the following, different existing approaches will be presented. Therein, in most cases different types of measurements are combined or compared due to their advantages and limitations (see Table 1). Regarding their real-time character and non-intrusiveness vehicle-based measures would be the optimum, but are no longer available in automated driving. Therefore, alternatives are necessary.

2.1 Drowsiness Detection with a Single Measure

In a very recently published work from Li and colleagues vehicle-based measures in form of SWAs were used for online driver drowsiness detection (Z. Li et al., 2017). Therein, approximate entropy features were extracted of the SWA time series. For obtaining the current drowsiness state a binary decision classifier was used with two drowsiness levels: awake and drowsy. In average for both drowsiness levels 78.01% of detections were right. In another work from Ingre and colleagues the focus was also on vehicle-based measures. Statistical features from SDLP were evolved. The evaluation of their experiment showed that an increase of KSS ratings comes along with an increase of SDLP (meters), but not consistently for all subjects (Ingre et al., 2006).

The facial muscle activity as a parameter of behavioral measures for detecting driver drowsiness was investigated in the work of Assari and Rahmati. They presented a system based on

Measures	Parameters	Advantages	Limitations	Source
Vehicle-based measures	SWM, SWA, SDLP	Real-time, non-intrusive	Not available in automated driving	(Z. Li et al., 2017) (Schmidt et al., 2016)
Behavioral measures	Eye behavior, face muscles, head movements	Non-intrusive	Interpersonal accuracy	(Sahayadhas et al., 2012)
Physiological measures	EEG, ECG, EOG, EMG	Reliable	Intrusive	(Z. Li et al., 2017)
Subjective measures	Questionnaire	Takes personal feeling into account	Not real-time	(Sahayadhas et al., 2012)

Table 1: Advantages and limitations of different types of measures

infrared light because of its independence to different lighting conditions. The eyebrow raising, eye closing and mouth openness over a specific time served as their facial indicators for a beginning drowsiness. The system showed satisfactory results even in the existence of glasses or a beard (Assari and Rahmati, 2011). Lin and colleagues developed a method with PERCLOS (percentage of eye closure time) characteristics by using a cascade classifier based on an Adaboost machine learning algorithm that was trained with labeled eye pictures. The algorithm reached an average accuracy of 85% and showed the robustness of the PERCLOS measures for an in-car and real-time drowsiness detection system (Lin et al., 2015).

In the course of physiological measurements, a change in the heart rate variability was found to be a parameter for commencing drowsiness. In more detail, the variations of the R-R intervals in the heart rate are considered. Therefore, the ratio of low (0.04-0.15 Hz) and high (0.14-0.4Hz) frequencies in the ECG measures is calculated. With an increasing drowsiness, the heart rate and the ratio decrease (Sahayadhas et al., 2012; Patel et al., 2011). In the work of Jung and colleagues driver's health was monitored with a pair of conductive electrodes connected to an embedded ECG sensor and located on the steering wheel. Within a personal area network (PAN) the data is transmitted wirelessly to a PC where the ECG data is analyzed in consideration of heart rate variability (HRV). The results depict that a non-intrusive ECG measurement with sensors on the steering wheel is a promising way to assess driver drowsiness (Jung et al., 2014). Patel and colleagues tested with labeled ECG data HRV in combination with neural networks and reached 90% detection accuracy (Patel et al., 2011).

2.2 Drowsiness Detection with Hybrid Measures

A combination of physiological and behavioral measures was investigated in the following works. Wang and colleagues used EEG features and facial expressions through video moni-

toring for drowsiness detection. Subjective labels were provided by SSS ratings. With Support Vector Machines (SVM) a drowsiness detection model was constructed reaching an accuracy of 88.62% (Wang et al., 2014). Li and Chung proposed a low-power brain-machine-interface (BMI) for measuring EEG data and tracking head movements in form of a self-developed headset. For processing, the data is transferred via Bluetooth Low Energy (BLE) to a smartphone. With an embedded SVM model for binary classification (alert, slightly drowsy) the results are displayed on the smartphone's interface in real-time. 1-minute-videos labeled with Wierwille scale ratings served as a training data set. The BMI system obtained detection accuracies of 82.71% (only EEG data) and 96.24% (EEG data + head movements) (G. Li and Chung, 2015). Three measures for drowsiness detection were compared in a simulator study, namely PERCLOS, ETS (eye-tracking signal) and EEG/EOG in the work of Trutschel and colleagues (Trutschel et al., 2011). For alertness classification Learning Vector Quantization (LVQ) networks were used. On the one hand objective labels were used from measurements of variation of lane deviation and on the other hand subjective labels derived from KSS ratings. Concerning the results, the informational content of drowsiness was clearly higher in ETS and EEG/EOG measurements compared to PERCLOS. Vehicle-based and physiological measures were combined in the work of Hallvig and colleagues. In a real-world driving study the prediction of lane departures from subjective and physiological sleepiness was investigated. Every five minutes the subjective ratings were measured with the KSS. Furthermore, electroencephalography (EEG), electrooculography (EOG) and lane departures (LDs) were tracked continuously. The results showed that the number of unintentional LDs was raised during night driving and that the prediction of LDs is possible with KSS (Hallvig et al., 2014).
The presented literature points out that in rare cases a single measure is applied and sufficient. Hybrid solutions mostly with a machine learning model for classification (see Table 2), are preferred.

Source	Used Features	Classifier	Accuracy	Ground Truth
(Patel et al., 2011)	HRV	Neural Networks	90% (12 subjects)	labeled ECG Data
(Wang et al., 2014)	EEG, Facial Expressions	SVM	88.62% (15 subjects)	SSS labels
(Lin et al., 2015)	PERCLOS	Cascade Classifier, AdaBoost	85% (self-reported)	labeled eye pictures
(G. Li and Chung, 2015)	EEG, Head Movement	SVM	96.24% (6 subjects)	1-minute-videos Wierwille labels
(Z. Li et al., 2017)	SWA	Binary Decision Classifier	78.01% (6 subjects)	1-minute-videos expert labels

Table 2: Comparison of different approaches of related work using a machine learning approach for driver drowsiness classification

3 Research Objectives and Approach

Currently, there is a trend towards fitness tracking and health monitoring. In consumer electronics the use of wearables is established. These kind of systems are developed for tracking biometric information related to the user's activity and fitness over a longer period of time. For example, this information can include the daily number of steps, the heartbeat, the sleep quality or even the consumption of calories. Assuming that every person has or soon will have a smartwatch or a wearable, the recorded data on these devices could be used without the need for additional sensors for the parameterization of advanced driver assistance systems (ADAS). This research project examines whether and how common fitness tracker and smartwatches are suitable for this purpose and what reliability can be achieved with it. The use of driver vital/physiological data measurements with wearables (e.g. fitness tracker, smartwatches) for monitoring and detecting driver drowsiness will be investigated. Furthermore, additional data from in-vehicle sensors, including a driver monitoring camera will be considered. New modeling approaches and detection algorithms will be designed and evaluated along existing mechanisms.

Research Questions

- Which vital measurements are suitable for an accurate and timely detection of driver drowsiness in the context of automated driving?
- Is the accuracy of the vital measurements based on wearable devices sufficient to detect driver drowsiness accurately and timely?
- Which in-vehicle sensors are to be considered to increase the reliability and accuracy of the drowsiness detection system?
- How can driver drowsiness be scaled and modeled accurately and robustly for different stages of automated driving, across different subjects and at best non-intrusively in order to initiate countermeasures proactively?

4 Experimental Setting and Implications

The first step is the collection of data and the investigation of different methods and approaches with multiple wearables and sensors in the framework of driving simulator studies. Various groups of study participants with different psychological and physiological preconditions (e.g. stages of drowsiness: awake, hyper-vigilant, drowsy, sleepy) under different conditions (e.g. night/day driving, partly/fully automated driving) will be tested. The validation of the obtained results will be carried out with reference measuring instruments (e.g. professional medical ECG/EEG measurement) during the studies.

After the completion and evaluation of obtained data from the simulator studies, the focus will be on a reduced setup of the most promising wearables and sensors for drowsiness detection. With the recorded data, different methods and algorithms for drowsiness classification will be

developed. These methods can be based on machine learning models (see Figure 2) or statistical models. In a final real-world driving study, the proposed solution will be validated and its performance evaluated.
The goal of the research project is the development of a reliable and timely monitoring tool for the detection of driver drowsiness based on vehicle and driver vital data measurements. The fusion of different sensors and information sources shall result in an automotive-compatible sensor technology, prototypically integrated in a car and tested in real-world automated driving. Future driver assistance can be improved in consideration of the critical risk factor drowsiness across different automation levels of the driving task.

5 Contribution and Conclusion

Driver drowsiness will be an important issue to investigate in the progressive development of automated driving functions, especially in situations where the driver is expected to take over control from the vehicle. The use of current research and own future studies that refer to different approaches of drowsiness detection research will allow an implementation of a reliable and timely drowsiness detection method for automated driving. Those approaches include different vital and vehicle-based measurements, the assessing of drowsiness across individuals and the real-time detection of drowsiness. A reliable information about the driver's state, in particular drowsiness, can potentially be used to parameterize future ADAS in order to reduce accidents and therefore increase road safety.
As a next step and for future research it will be an important issue to investigate which countermeasures against driver drowsiness are feasible in an automotive environment and suitable for the respective level of automation.

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