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State of the art on measuring driver state and technology-based risk prevention and mitigation
Findings from the i-DREAMS project

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Abstract

Advanced vehicle automation and the incorporation of more digital technologies in the task of driving, bring about new challenges in terms of the operator/vehicle/environment framework, where human factors play a crucial role. This paper attempts to consolidate the state-of-the-art in driver state measuring, as well as the corresponding technologies for risk assessment and mitigation, as part of the i-DREAMS project. Initially, the critical indicators for driver profiling with regards to safety risk are identified and the most prominent task complexity indicators are established. This is followed by linking the aforementioned indicators with efficient technologies for real-time measuring and risk assessment and finally a brief overview of interventions modules is outlined in order to prevent and mitigate collision risk. The results of this review will provide an overall multimodal set of factors and technologies for driver monitoring and risk mitigation, essential for road safety researchers and practitioners worldwide.

Keywords: road safety; driver state measuring; driver state monitoring; literature review; risk prevention

1. Introduction

Nowadays, transportation research and industry worldwide are concerned with advanced vehicle automation and the incorporation of digital technologies in the task of driving. These new technologies bring about new challenges in terms of the operator/vehicle/environment framework and consequently, the area of human factors needs to be further understood and researched. Several factors of driver state have been persistently demonstrated in the literature as critical for safe transport systems. Distraction, in-vehicle or external, remains a serious threat to road safety (Lee et al., 2009). Fatigue and drowsiness are not limited to professional drivers, they emerge as critical risks for all drivers (Zhang et al., 2016). Fitness-to-drive becomes a key question for all operators, with respect to health concerns (e.g. illness, frailty, cognitive state) especially in an ageing yet technologically challenged society (Eby et al., 2008). Extreme emotions, e.g. anxiety, stress, anger have received so far notably less attention (Mesken et al., 2007). Moreover, differences in socio-cultural factors, are still among the main determinants of road risks. At the same time, technology developments make massive and detailed operator performance data easily available (e.g. new in-vehicle sensors that capture detailed driving style and contextual data, increase in the penetration and use of information technologies by drivers, Internet of Things). This creates new opportunities for the detection and design of customised interventions to mitigate the risks, increase awareness and upgrade performance, constantly and dynamically (Toledo et al., 2008; Horrey et al., 2012).

The objective of the i-DREAMS project is to setup a framework for the definition, development, testing and validation of a context-aware 'Safety Tolerance Zone' for driving, within a smart Driver, Vehicle & Environment Assessment and Monitoring System (i-DREAMS). Taking into account, on the one hand, driver background factors and real-time risk indicators, and on the other hand, driving task complexity indicators, a continuous real-time assessment will be made to monitor and determine if a driver is within acceptable boundaries of safe operation (i.e. Safety Tolerance Zone). Moreover, safety-oriented interventions will be developed. Application areas include: new road safety interventions, improved driver well-being and transfer of control between human and vehicle, as well as a more eco-efficient driving style since safer driving implies more eco-friendly behaviour (i.e., so-called 'smart' driving as defined in Young et al., 2011).

One of the initial pillars of the i-DREAMS project is the measurement of risk-related physiological indicators (e.g. fatigue, distraction, stress, etc.), driver-related background factors (age, driving experience, safety attitudes and perceptions, etc.), and driving environment and traffic complexity indicators (e.g. time of day, speed, traffic intensity, presence of vulnerable road users, adverse weather, etc.) to assess driver capacity and task demand in real-time. Existing systems are limited in their capability as mostly kinematic data is typically captured and driver status information is excluded (Mortimer et al., 2018). Car companies are currently researching the incorporation of heart rate measurements, but this is yet to be realised in the near future (Strickland, 2017). Furthermore, the data does not include measures of fatigue or health (but just driver alertness in some cases (Ramasamy et al., 2014) and is incapable of assessing situational complexity – a key requirement to manage the transition of control between human and vehicle in vehicles with Level 3 automation systems (Katrakazas et al., 2015). In the rail environment such systems are rarely used and following recent crashes have attained much higher relevance.

In order to enhance current driver monitoring, as well as propose novel interventions for keeping operators within the boundaries of safe driving, a review of the state-of-the-art in driver state and driver behaviour measuring and technology-based risk prevention and mitigation is needed. This forms the scope of the current paper, which aims at critically reviewing literature of the recent years which reports on measuring task demand during driving, attention and distraction as well as measuring emotions and similar constructs such as arousal or stress. A preview of the work on quantifying fatigue and sleepiness, real-time and post-trip driver behaviour modification methods is provided. Criteria for selecting the most appropriate technologies and techniques and challenges are discussed in the last section of this paper.

2. Review Methodology

This paper reviews and exploits the state of the art on measuring the state of the driver in terms of balance between the given task demands and the driver's available resources to cope with the demands. Fuller's Task-Capability Interface Model (Fuller, 2000) provides the theoretical framework for this endeavour. Since task demands can vary tremendously for different travel modes, this will be done in a multimodal manner for all 'i-DREAMS modes': car, bus, truck and train.

Initially, endogenous factors for monitoring the driver state and exogenous factors for task demand assessment, will be identified. Within this task, variables which influence the level of individual risk in a given traffic situation will systematically be identified. These variables can either be endogenous factors such as distraction, fatigue or cognitive impairment which characterize the driver state (resources) or exogenous factors such as weather, time of day and traffic conditions which can increase the task complexity (demand). The balance of both types of factors is the objective individual risk. The Task-Capability Interface Model serves as a theoretical frame, however, other related models will be reviewed as well, since the suitability might be mode-specific. Furthermore, indicators for factors, identified as relevant for the overall driver state and thus risk level, will be reviewed and compared in a systematic way. As a result, a common set of validated indicators will be synthesised; and these will be combined to assess the individual level of risk of operators.

The next step with regards to the state-of-the-art, will review and - if needed - pre-test state of the art in-vehicle technology to reliably measure relevant endogenous and exogenous factors identified in the previous task. Part of the review is the determination of properties of tools such as smart cameras, on-board diagnostic systems like steering wheel sensors as well as wearables to measure heart rate or skin conductance response. The latter can e.g. serve as indicators for cognitive processes. In order to provide useful information, a list of criteria will be defined to review the state of the art in a systematic manner. Factors such as reliability, non-intrusiveness, acceptability for users etc. will be considered when assessing the technology. Once, the review task is completed, vehicle technologies and applications for safety interventions safety interventions associated with risk prevention and mitigation) will also be identified and assessed as per their efficiency. Existing systems and technologies to inform road users either in real-time or post-trip aiming at enhancing knowledge, attitudes, perception and eventually safety behaviour, will be overviewed.

The assessment of the momentary mental state of the driver is a function of physiological, cognitive as well as affective processes, which influence the cognitive capacity available to safely perform the driving task (task demand) in a given moment. The driver’s mental state and corresponding capacities (cognitive resources) can change moment by moment is considered to be compromised by the (interrelated) factors fatigue and sleepiness, attention and distraction, as well as by emotions, arousal and mood. Those are the factors and related concepts have been considered for the review.

In order to perform a systematic literature review, the search terms were initially identified, then the abstracts and titles were screened as per their relevance, and finally the most relevant papers were overviewed in order to identify the factors and technologies most crucial for driver state and task demand monitoring. With regards to the comparison between studies, focus was given on the underlying constructs (e.g. emotions, distraction types), the indicators used to measure those constructs, the technical equipment, any reported outcome variables, as well as the results and conclusions with respect to the scope of the i-DREAMS project. Literature was searched within popular scientific databases such as Scopus, ScienceDirect and Google Scholar. Examples of key words used per factor, as well as the number of screened and included papers are given on Table 1.

The resulting publications in English language were screened by titles to root out the clearly not relevant ones. Next, abstracts were screened for relevance. At this stage, papers were discarded if the described research for example did not use objective but subjective measures of the constructs of interest or if the measurement method was not reported in enough detail. Furthermore, papers were limited by date (2005 and more recent) for all topics except from task demand, where not enough recent evidence was found, and therefore it was decided to broaden the search horizon from 1990 and onwards.

3. Outcomes and discussion

3.1. Task demand

An initial examination of the eleven studies that have been included in the review demonstrated that the state-of-the-art deals mostly with the effects of road layout, traffic conditions and weather on driver's task demand. On the contrary, not enough evidence on the relation between driver's task complexity and time or location was found. As mentioned before, the included studies are concerned with monitoring the effect of contextual information on task demand and are not involved with the effect of road, traffic, time and weather characteristics on road safety.

Table 1. Key words, screened and included papers per factor analysed

Factor	Key words (without word stem variations)	Screened papers	Included papers
Task Demand	"task demand" AND "driving measures" OR "performance measurements" OR "driver characteristics" OR "driving monitoring" OR "workload" OR "traffic conditions" OR "traffic" OR "weather" OR "road layout" OR "time of day"	413	11
Distraction	"distraction" OR "distracted" OR "inattention" OR "inattentive" AND "driver monitoring" OR "driver measure"	417	32
Emotions	“emotion” OR “affect” OR “arousal” OR “stress” OR “anger”” AND “measure” OR “driver monitoring” OR “workload” OR “physiological” AND “driving” OR “road safety” OR “traffic” OR “driving performance” OR “car”	403	38
Fatigue and sleepiness	“fatigue” OR “sleep” OR “drowsy” OR “alert” OR “monotonous” OR “tired” OR “bored” OR “weariness” OR “time on task” AND “driver monitoring” OR “physiological measure” OR “blink” OR “perclos” OR “yawning” OR “eye movement” AND “ drive” OR “car” OR “professional driver” OR “commercial driver” OR “raffic” OR “road safety”	1,545	187

The effect of context on the driving task, is most frequently measured by psychophysiological indicators and tools such as ECG(Bongiorno et al., 2017; de Waard and Brookhuis, 1991; Marquart et al., 2015; Schwarze et al., 2014; Stojmenova and Sodnik, 2015; Stuiver et al., 2014), tracking measures(Auflick, 2015; Benedetto et al., 2011; Brookhuis and de Waard, 2010; Foy and Chapman, 2018; Marquart et al., 2015; Stojmenova and Sodnik, 2015). Nevertheless, other methods such as EEG(Bongiorno et al., 2017; de Waard and Brookhuis, 1991; Stojmenova and Sodnik, 2015), but vehicle kinematics (Auflick, 2015; de Waard et al., 2008; Foy and Chapman, 2018) skin conductance(Bongiorno et al., 2017; Foy and Chapman, 2018; Stojmenova and Sodnik, 2015) have also proven to be successful for identifying the proportion of additional workload posed on the driver during difficult driving tasks. In order to quantify these effects, researchers mostly conduct a driving simulator experiment, while only two of the eleven studies also tested their research questions on an open-field driving experiment(de Waard and Brookhuis, 1991; Patten et al., 2006).

With regards to the results of the studies, it was observed that there is a decrease in heart rate when traffic is dense under adverse weather (i.e. fog) (Stuiver et al., 2014), which is also evident when transitioning to a motorway from urban traffic (de Waard and Brookhuis, 1991). An increase in heart rate has been documented during lane changing events (de Waard et al., 2008), and when drivers join the urban traffic from a quiet motorway(de Waard and Brookhuis, 1991).Additionally, an increase in HGV vehicle composition was found to increase mental effort on drivers (de Waard et al., 2008). In Marquart et al., (2015), eye blink rates decreases with sharper road curves, as the driving task becomes more demanding. The main disadvantage of the aforementioned studies, was that there are no thresholds given for detecting a significant effect of context on the difficulty level of the driving task.

3.2. Driver State

3.2.1. Distraction

According to (Regan et al., 2008), distraction can be defined as “a diversion of attention away from activities critical for safe driving toward a competing activity”. Following that definition, the review focused on identifying, not the relationship between road safety and distraction, but rather the ways with which distraction can be monitored during trips or experiments. For example, in (Regan et al., 2008) and (Papantoniou et al., 2017) critical driving parameters on distraction are explicitly described. Among those parameters lateral and longitudinal control measurements, surrogate safety measures (e.g. reaction times, gap acceptances) and eye or workload measures are deemed to be the most crucial to identify driver distraction. However, in those two popular studies, the aim is describing the effect of distraction on safety performance parameters, without accurately pointing out the monitoring procedure of distinguishing between attentive and distracted driving.

Overviewing the 32 identified studies on monitoring driver distraction, following the aforementioned focus areas, an observable distinction was that very few papers considered all the major types of distraction (i.e. visual, cognitive and manual) as described in (Costa et al., 2019; Cunningham and Regan, 2018). The majority of the studies (17 out of 32) were concerned solely with visual distraction, probably because of the advances in eye-tracking and camera technologies, while 6 were concerned specifically with cognitive and only 4 with manual distraction. With regards to visual distraction, the phenomenon is usually identified through saccades (Costa et al., 2019), glances and blinks(Bakhit et al., 2018; Costa et al., 2019; Dumitru et al., 2018; Kanaan et al., 2019; Li and Seignez, 2018; Seppelt et al., 2017), or general eye position tracking(Botta et al., 2019; Hammoud et al., 2008). One of the most crucial indicator for detecting distraction and inattention have been found to be PERCLOS (percentage of time that the eyelid covers 80% or more of the pupil) and PERLOOK (percentage of time spent not looking ahead during a certain time interval) with a value of more than 35% indicated distraction in (Costa et al., 2019). Glance duration has also been demonstrated in most of the studies on visual distraction as an important indicator. In (Seppelt et al., 2017) it was found that distracted drivers were identified during near crashes with an average glance duration of 12.39 seconds (s.d. 8.02) and 9.58 seconds (s.d. 5.08) during crashes, when observations were made 10-25 seconds before incidents. In (Botta et al., 2019) 2 seconds was the critical value of glances away of the road, which was also validated in (Kanaan et al., 2019).

Regardless of eye metrics, head position monitoring has also been extensively utilized in order to indetify general distraction scenarios or has been linked with visual and manual distraction. More specifically, in (Huang et al., 2019) a head turn having a duration longer than 5 seconds is considered a precursor of distraction. Similarly in (Hammoud et al., 2008) a head movement of 20 degrees or more to the left or right, has been also linked with distracted driving, which comes in agreement with the thresholds indicated by (Ali and Hassan, 2018).

A different approach was followed in Botta et al., (2019) and McDonald et al., (2019), where driver kinematics were used post-trip to distinguish between distracted and undistracted drivers. Features utilized for that distinction include the standard deviation of lane offset and the steering quartiles (in McDonald et al., 2019) as well as speed, yaw, steering rate values and road geometry (in Botta et al., 2019). However, in both studies no thresholds for detecting distraction are mentioned.

Regarding technologies used to monitor distraction in real-time, most of the studies utilized eye trackers or eye movement encoders (e.g. Botta et al., 2019; Costa et al., 2019; Dumitru et al., 2018; Hammoud et al., 2008), or analysed video and image feeds from cameras (Ali and Hassan, 2018; Hari and Sankaran, 2017; Koohestani et al., 2019; Li and Seignez, 2018). Less frequent approaches include EEG (Costa et al., 2019; Khan and Lee, 2019), hand sensors and magnetic glasses (Huang et al., 2019).

3.2.2. Emotions and stress

Other than the topic of distraction, emotion research has long been neglected in road safety as well as human factor engineering and is only trending since the early 2000s (Jeon, 2017). However, technology aiming at detection of emotions is catching up rapidly. The tools are becoming simpler and more widespread. Eichhorn and Pilgerstorfer (2017) come to the conclusion that drivers experiencing emotions (e.g. anger) while driving are slightly more at risk in traffic, which is supporting the relevance of emotions in the road safety domain.

However, the matter is more complicated than that. First of all, because “emotion”, “arousal”, “mood”, “affect” or “stress” are distinct constructs (although there partly are overlaps) but are often used as one single construct which is seen as complementary and opposite to cognition. And secondly, there is no agreed upon standard definition of “emotions” as a psychological construct. Damasio (2001) sees emotions as the physiological response of the nervous system to a stimulus from inside or outside. This is just a brief physiological reaction whereas “feeling” is the subjective interpretation of that reaction and typically lasts longer. What many researchers agree upon, is that emotions basically have two qualities: valence, which indicates whether an emotion is perceived as positive or negative, and arousal, which indicates how calming or existing the stimulus is perceived (Eichhorn & Pilgerstorfer, 2017). A second prominent school of theories is a categorial approach to emotions as opposed to the aforementioned dimensional one. Ekman (1992, quoted by Balters & Steinert, 2015) proposed a set of categories of distinct emotions which are seen as universally innate and recognized by humans by a person’s facial expression (i.a.). While either of the two approaches can be argued for, it depends on the research question, which is the one to go with.

Table 2 represents counts of reviewed studies which reported on measuring a certain emotions category or qualitative aspect of emotions the one way or another. While (emotional) stress is not an emotion by definition, this construct was included in the search and was most often one of the research topics followed by anxiety or fear and anger, aggression and frustration.

Table 2. Number of studies reviewed per measured emotion or related construct

(Emotional) stress	Anxiety, fear	Anger, frustration, aggression	Various	Arousal, valence	Happiness, euphoria, amusement	Sadness, disappoint-ment
10	8	8	7	6	5	4

Table 2 shows the number of reviewed studies which used a certain measurement method or indicator to determine emotions or similar constructs, respectively. Since the table shows a mere quantification, no conclusion for the applicability in i-DREAMS can be drawn from it. However, a tendency of methods used in recent years becomes apparent. Heart related measures (pulse, heart rate, inter-beat interval etc.) and measures using electrodermal activity (also called skin conductance or galvanic skin response) were used the most often within the 39 reviewed studies. The top four categories are all physiological measures. The first behaviour measure category is ranked fifth. Most of the studies used more than one method to capture the emotion or related construct.

Table 3. Number of studies reviewed per measurement method

Electro-cardio-gram	Electro-dermal activity	Electro-encephalo-gram	Skin temp, infrared cam.	Occular measures	Speech recog-nition	Facial expression	Electro-myogram	Respir-ation
14	13	7	6	5	4	3	3	2

It has to be noted that the vast majority of the 39 studies were conducted within the realm of road safety research, a few in the context of emotion research per se or HMI other than car manufacturing. Furthermore, most of the road safety studies report driving simulator experiments. The experimental laboratory setting of a simulator allows for great flexibility compared to naturalistic driving studies, when it comes to applying measurement equipment. Speech recognition, for example, will not be a useful technique since in a naturalistic setting, participants cannot be encouraged to speak during their drives. At the moment, concrete products to measure emotions and other related constructs are being reviewed.

3.2.3. Fatigue and sleepiness (preliminary results)

It clearly has to be differentiated between 'fatigue' which is tiredness due to mental or physical effort such as driving. In contrast, sleepiness is physiological pressure to fall asleep after e.g. a sleepless night. Fatigue can be overcome by stopping the activity, while sleepiness can be overcome most efficiently by sleeping but can also be influenced by caffeine i.a. (Talbot & Filtness, 2017). The search for publications on fatigue and sleepiness resulted in a high amount of papers (see also table 1). The majority of corresponding research was conducted in cars and in driving simulators. Most reviewed papers measure sleepiness or drowsiness rather than fatigue and the main measures used are electroencephalogram and eye-tracking (PERCLOS, blink rate etc.), but also electro-cardiogram (heart rate variability) and driving behaviour (e.g. lateral lane position, lane deviations, speed, steering wheel movements, braking etc.). As for the other topics, also sleepiness usually is measured through a combination of techniques. Available equipment to measures both fatigue and sleepiness is reviewed in a next step.

3.3. Real-time and post-trip interventions (preliminary results)

With regards to real-time and post-trip interventions, these are usually targeted at psychophysiological measures like heart rate variability, skin conductance, skin temperature, breathing rate, or electroencephalogram. Unobtrusive contactless technologies like audio-visual sensors or eye-tracking might have lower initial hurdles regarding acceptance in cars. A video stream of the driver can be used to extract facial action coding units, which, in combination with voice features can inform an emotion detection system and measures of pupil diameter can be used to assess mental workload. In-vehicle devices, monitors, sound alerts, and smartphones are utilized in order to provide drivers with feedback and enhance road safety as vehicles with a warning system in general led to smaller reaction time if warning messages were delivered in an appropriate timing.

3.4. Post-trip interventions (preliminary results)

As a first step of capturing the state of the art regarding post-trip interventions, currently available systems, applications and schemes have been identified, with a focus on changing driver behaviour by means of gamification. This has been pursued with applications explicitly designed for truck drivers. Within this transport mode, behavioural change techniques are predominantly used to encourage eco driving. Even thought, some of the driver behaviours targeted for this purpose are also safety relevant (e.g. excessive speeding), applications explicitly aiming at improving safe driving behaviour are rather scarce. Therefore, eco driving intervention schemes were taken into consideration, assuming the underlying behavioural change theories are applicable also to the context of safe driving. 19 eco- and safe driving applications have been identified and a standardized survey was sent to the developers to better understand the features and interventions modalities. Furthermore, papers for review were limited by year (varying upon the construct, 2005 e.g. for emotions) to account for the fast developments in this research fields and therefore, to avoid the consideration of outdated information.

3.5. Summary

As it can be understood from the previous section, there is a threefold contribution with regards to the review: i) the critical indicators for driver profiling with regards to safety risk will be identified and the most prominent task complexity indicators will be established, ii) the aforementioned indicators will be linked with the most efficient technologies which are suitable for measuring and assessing these indicators in real-time and iii) interventions modules will be recommended in order to prevent and mitigate collision risk, based on the indicators and measuring technologies.

Special attention needs to be given to cause and effect relationship between risk factors and the safety impact, in order to avoid including indicators which are correlated or repeated. Furthermore, for every indicator there needs to be a clear distinction between its effectiveness for estimating safety level and its utilization or usability in customizing safety interventions. Finally, focus will be given in the transferability of indicators and interventions between cars, buses, trucks and trains, in order to provide an overall multimodal set of factors and technologies for driver monitoring and risk mitigation.

Documented information per paper included: the construct measured and its operational definition, the physiological or behavioural measurement (e.g. electro-cardiogram, gaze behaviour) and corresponding indicators (e.g. heart rate variability, time eyes off road), the used equipment (product or single components) the study design, main findings and positives and negatives in relation to the study but also to the applicability within the i-DREAMS project. This work is currently ongoing. However, in a next step the various measurement methods and tools will be scrutinized in the light of their potential for application within the i-DREAMS platform. Relevant criteria for the assessment and eventual recommendation are:

- Intrusiveness and acceptability
- Reliability and validity
- Costs, availability
- Applicability in naturalistic driving context
- Versatility (potential to capture more than one mental state factor)
- Compatibility with further i-DREAMS equipment
- General advantages and disadvantages

The described work is ongoing and will conclude its work in February 2020.

4. Conclusions and future research directions

Within the i-DREAMS framework, it is assumed that the combination of task complexity (outside factors) and coping capacities (mental state, experience, health, personality etc.) determines level of safety in a given driving situation. While measuring driving task demand factors, imposed on the driver through e.g. traffic density, weather or other drivers – is relatively straightforward, especially quantifying the mental state of a driver and the associated risk is a complex endeavour coming with a lot of aspects to account for. Mental state is a construct that is composed of mainly further constructs. The i-DREAMS project considers the momentary factors attention vs. distraction, emotions, arousal, stress as well as fatigue and sleepiness to be critical factors with the potential to compromise the coping capacity. One of the challenges is the validity of measures, especially when there is no agreed upon definition of a construct like for example emotions and comparability of studies therefore is exacerbated. Then again, the measured constructs are correlated to some extent. To account for those factors, much more research lies ahead.

Some of the reviewed measurement methods seem very promising and have been used in the driving context before. A constraint is that simulator studies – in which many of the reviewed technology has been researched – allow for much more flexibility than a naturalistic driving setting which is planned in i-DREAMS. On the one hand, the equipment in a simulator has to be acquired only once and technical difficulties can be reacted to immediately. On the other hand, gear which demands calibration or supervision by the experimenter is not compatible with the naturalistic driving setting, for example encephalogram, which is frequently used in laboratory settings. Then again, there is more and more novel, non-intrusive equipment manufactured for the driving setting, which will be exciting to explore, such as clothing that enables measuring electro-dermal activity.

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