Vehicle Driver Monitoring – Sleepiness and Cognitive load

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Abstract

To prevent road crashes, it is important to understand driver related contributing factors. The overall aim of the Vehicle Driver Monitoring project was to advance the understanding of two such factors; sleepiness and cognitive distraction. The project aimed at finding methods to measure the two states, with focus on physiological measures, and to study their effect on driver behaviour. The data collection was done in several laboratory and driving simulator experiments. Much new knowledge and insights were gained in the project. Significant effects of cognitive load as well as of sleepiness were found in several physiological measures. The results also showed that context, including individual and environmental factors, has a great impact on driver behaviours, measures and driver experiences.

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Preface

This report summarizes the work carried out in the project Vehicle Driver Monitoring (VDM) – An Experimental framework for driver state measurements. The project is a collaborative effort between Volvo Car Corporation (VCC), the Swedish National Road and Transport Research Institute (VTI) and Mälardalen University (MDH). The main objective of the project has been to learn more about the effects of driver sleepiness and cognitive distraction on driver behaviour and physiological responses.

VTI has been responsible for the sleepiness related parts of the project, VCC has been responsible for the parts about cognitive load, and MDH has been responsible for machine learning aspects. Together, we have tried to bring these three concepts together, intrigued by the vision of getting a more comprehensive picture of the driver.

The project started in April 2013 and ended in 2017. We would like to thank Vinnova and the FFI-Vehicle and Traffic Safety Program for funding this research.

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Gothenburg, March 2017

Bo Svanberg

Project leader
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Kvalitetsgranskning

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Summary

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by Emma Nilsson (Volvo Car Corporation), Christer Ahlström (VTI), Shaibal Barua (Mälardalen University), Carina Fors (VTI), Per Lindén (Volvo Car Corporation), Bo Svanberg (Volvo Car Corporation), Shahina Begum (Mälardalen University), Mobyen Uddin Ahmed (Mälardalen University) and Anna Anund (VTI).

To prevent road crashes it is important to understand driver related contributing factors, which have been suggested to be the critical reason in 94 per cent of crashes. The overall aim of the project Vehicle Driver Monitoring has been to advance the understanding of two such factors; sleepiness and cognitive distraction. The project aimed to find methods to measure these two states, with focus on physiological measures, and to study their effect on driver behaviour. Other important questions concerned effects of environmental, inter- and intra-individual factors and if it is possible to detect driver sleepiness and cognitive distraction using machine learning methods.

It is generally believed that sleepiness is easy to measure, but the quantification of sleepiness remains a challenge and a solid physiological measure of sleepiness is yet to be found. Sleepiness and sleep are active dynamic processes, which sometimes only affect local parts of the brain. Taking these temporal and spatial dynamics into account opens up for new ways to measure driver sleepiness, and also helps to gain a deeper understanding of its effects on driver performance.

The effects of cognitive distraction (such as cell phone conversations) on traffic safety are not clear, as different studies reach different conclusions. The recently formulated cognitive control hypothesis suggests that “cognitive load selectively impairs driving subtasks that rely on cognitive control but leaves automatic performance unaffected”. The hypothesis can help to understand the role of cognitive distraction in crash causation. A key difficulty in research on cognitive distraction is that validated ways of measuring it during driving are lacking. Brain activity measures are attractive candidates because of their high face validity. However, since brain activity is difficult to record in real driving, as well as hard to interpret in general, other measures are also relevant to explore.

The data collection was done in laboratory and driving simulator experiments. One sleepiness simulator experiment was performed. It was unique in its design with participants repeating their drives on six occasions, three times during daytime and three times during night-time. Two cognitive distraction simulator experiments were designed to advance the understanding of effects of cognitive distraction in both non-critical and critical driving scenarios. Drivers’ physiological and behavioural responses to sleepiness, cognitive distraction and certain contextual factors were studied. Key results were:

- There was a relationship between lane departures and local sleep in brain regions associated with motor function.
- Self-reported sleepiness level and driver performance differed within an individual when the same experiment was repeated three times in identical settings.
- Darkness was found to be an additive factor in several sleepiness indicators but had no effect on the number of line crossings.
- Professional drivers reported lower levels of sleepiness, even though the more objective indicators indicated that they were actually sleepier than the non-professional drivers.
- Support for the Cognitive Control Hypothesis was found in different traffic scenarios.
- The pupil diameter was the physiological measure with the closest relationship to cognitive load.
• It was demonstrated that while several physiological measures correlated with the level of cognitive load, their similarities and differences at the same time reflected other driver state variations.
• Well established EEG frequency power measures only showed a difference between levels of cognitive load when the driving task was simple.
• A novel combined approach showed better results in mobile EEG artefact handling compared to available state of the art algorithms.
• Automatic sleepiness and cognitive load classifications were improved by the use of contextual and behavioural measures as compared to physiological measures only.

Taken together, the results clearly demonstrate that context (including both individual and environmental factors) has a great impact on driver behaviours, measures and experiences.

From an overall perspective, further research is needed to increase the understanding of the contextual effects and to learn how they can be compensated for. Further research should also continue to focus on how cognitive load and sleepiness affects traffic safety. For example, by continued research on the effects of local sleep, and the dynamic interplay between the driver’s state and the driving task, especially in traffic situations where cognitive control is needed. In addition there is a need to investigate how indicators are influenced by multiple concurrent factors like cognitive load and sleepiness.
Sammanfattning

Driver monitoring – sömnighet och kognitiv belastning

av Emma Nilsson (Volvo Car Corporation), Christer Ahlström (VTI), Shaibal Barua (Mälardalen University), Carina Fors (VTI), Per Lindén (Volvo Car Corporation), Bo Svanberg (Volvo Car Corporation), Shahina Begum (Mälardalen University), Mobyen Uddin Ahmed (Mälardalen University), Anna Anund (VTI)


En vanlig uppfattning är att det är lätt att mäta sömnighet, men att kvantifiera sömnighet är fortfarande en utmaning och det saknas tillförlitliga fysiologiska mått. Sömnighet och sömn är aktiva dynamiska processer som ibland bara påverkar lokala delar av hjärnan. Att ta hänsyn till dessa temporala och spatiala förändringar öppnar upp för nya sätt att mäta sömnighet samtidigt som det ökar förståelsen för sömnighetens effekter på föraren.

Effekterna av kognitiv distraktion (t.ex. i form av ett mobiltelefonsamtal) på trafiksäkerhet är inte tydliga eftersom olika studier kommit fram till olika slutsatser. Den nyligen formulerade hypotesen om kognitiv kontroll (cognitive control hypothesis) säger att kognitiv last enbart påverkar uppgifter under körningen som kräver kognitiv kontroll och lämnar automatiska beteenden opåverkade. Hypotesen kan hjälpa till att förstå vilken roll kognitiv distraktion spelar i uppkomsten av trafikolyckor. En svårighet i forskningen kring kognitiv distraktion är att det saknas validerade sätt att mäta det. Mått baserade på hjärnaktivitet är attraktiva eftersom de har hög ”face validity”. Men eftersom hjärnaktivitet är svår att mäta i verklig körning och även svår att tolka, är också andra mått relevanta att studera.

Datainsamlingen gjordes i flera labb- och körsimulatorexperiment. Experimentet för att studera sömnighet hade en unik design där varje testdeltagare upprepade försöket sex gånger, tre gånger under dagtid och tre gånger under nattetid. Experimenten för kognitiv distraktion var designade för att generera ny kunskap om både kritiska och icke-kritiska körskick. Förarnas reaktioner på trötthet, kognitiv distraktion och kontextuella faktorer studerades både fysiologiskt och beteendemässigt.

Huvudresultaten var:

- Det fanns ett samband mellan linjeöverträdelser och lokal sömn i motorrelaterade områden i hjärnan.
- Förarnas upplevda nivå av sömnighet och deras prestation ändrades med antalet upprepningar av experimentet.
- Mörker gav en additiv effekt på flera indikatorer av sömnighet men hade ingen effekt på antalet linjeöverträdelser.
- Professionella förare rapporterade lägre nivåer av sömnighet, trots att de mer objektiva måtten visade högre nivåer av sömnighet än hos icke-professionella förare.
- Mätningar av pupilldiameter visade större förändringar i olikheter i olika trafiksituationer.
- Även om flera fysiologiska mått korrelerade med kognitiv last, visade deras samtidiga likheter och olikheter att de även reflekterade variationer i andra förartillstånd.
- Väletablerade frekvensbaserade EEG-mått visade bara en effekt av nivåer av kognitiv last när köruppgiften var enkel.
- En metod för artefakthantering av EEG data har utvecklats inom projektet. Resultaten som uppnås med den nya algoritmen är bättre än tillgängliga metoder.
- Resultaten från automatisk klassificering av sömnighet och kognitiv distraktion förbättrades när fysiologiska data kompletterades med miljö- och beteendevariabler.

Sammantaget visar resultaten att kontexten (både individuella faktorer och miljöfaktorer) har stor inverkan på förarbetande, på olika mått och på förarnas upplevelser. Fortsatt forskning behövs för att öka förståelsen av hur kontext inverkar och hur man ska kunna kompensera för kontexten vid mätning av förartillstånd. Fortsatt forskning behövs också om hur sömnighet och kognitiv last påverkar trafiksäkerhet, till exempel genom att studera effekterna av lokal sömn, och det dynamiska samspelet mellan köruppgift och distraktion. Det finns även ett behov att fortsatt undersöka hur flera samtida och samverkande tillstånd, som sömnighet och kognitiv distraktion, påverkar de olika mätten.
1. Introduction

Road traffic injuries are listed as one of the top ten major causes of mortality and morbidity worldwide (WHO, 2013). It is estimated that more than 1.25 million people die as a result of road traffic crashes and some 50 million are injured every year (WHO, 2015).

To prevent road crashes it is important to understand driver related contributing factors, which have been suggested to be the critical reason in 94% of crashes (Singh, 2015). Increased understanding of driver related contributing factors will allow us to customize the vehicle, the infrastructure and the driving environment to human abilities and needs, which in the long run will reduce the number of crashes. Some commonly studied factors are, for example, alcohol, sleepiness, distraction, workload and fatigue. In this project, the focus is on two of these factors, sleepiness and cognitive distraction.

1.1. Driver sleepiness

Sleepiness has been defined as a physiological drive to fall asleep (Dement and Carskadon, 1982), and driver sleepiness is consequently defined as when a driver has to make an effort to remain awake while driving (Anund et al., 2008b).

Driver sleepiness is a condition that cause severe injuries and fatalities (Connor et al., 2002, Horne and Reyner, 1995, Anund et al., 2008a), and it has been estimated that the proportion of accidents that are due to sleepiness is about 10 – 20% (Horne and Reyner, 1999a, Maycock, 1997, Radun and Summala, 2004, Philip et al., 2001). Increased risks have been reported when driving at night or early morning hours (Horne and Reyner, 1995, Stutts et al., 2003, Åkerstedt and Kecklund, 2001), for young drivers (Filtness et al., 2012, Lowden et al., 2009) and shift workers driving home after a night shift (Ftouni et al., 2013, Åkerstedt et al., 2005b). Driving when sleepy impairs driving performance and causes deteriorated lateral and longitudinal control of the vehicle (Philip et al., 2005, Sagaspe et al., 2008, Hallvig et al., 2014b, Van Dongen et al., 2007). With increased levels of sleepiness, these deteriorations become more and more severe and will eventually lead to lane departures (Åkerstedt et al., 2013).

Sleepiness is a result of changes in several factors, and the actual sleepiness level may thus vary as a function of any of these factors. In this project, we aim to learn more about a selection of these factors, and especially how to exploit this new knowledge to design better methods to measure and predict sleepiness. Short introductions to the topics addressed in this project are provided in the following subsections.

1.1.1. Physiological measurements of sleepiness

It is generally believed that it is easy to measure sleepiness. This “fact” probably originates from the widespread usage of polysomnography that is used to assess sleep (not sleepiness) in sleep laboratories across the world. However, a solid physiological measure of sleepiness has yet to be found, and even though much progress has been made in sleep research, the quantification of sleepiness remains a challenge (Mullington, 2011).

Commonly used physiological indicators of driver sleepiness include brain waves (measured via electroencephalography, EEG), blink behaviour (measured via cameras or via electrooculography, EOG), respiration and heart rate (measured via the electrocardiogram, ECG). The brain waves are typically quantified as the total power in the 5 – 9 Hz theta frequency range and/or in the 8 – 14 Hz alpha frequency band. An increase in the theta frequency range has been put forward as a sign of sleep need (Aeschbach et al., 1997, Cajochen et al., 1995) whereas an increase in the alpha band has been found to be a robust indicator of sleepiness in a driving setting (Kecklund and Åkerstedt, 1993, Simon et al., 2011). Blink behaviour is typically quantified in terms of blink durations. Although the effect size is often small, increased blink durations has been found for increasing levels of driver sleepiness.
in essentially all studies were blink duration has been measured (e.g. Schleicher et al., 2008, Åkerstedt et al., 2005a). Heart rate, heart rate variability and respiration are often used as indicators of sleepiness, but there are many confounding factors and the results are often ambiguous.

Sleep research is currently undergoing a paradigm shift. Historically, sleep was thought to be a passive state, but later it was proven to be an active dynamic process (Steriade, 1992). Sleep was also thought to be a global phenomenon, but it has now been found that local regions of the brain “fall asleep” at different times (Krueger and Obal, 1993, Krueger et al., 2008, Krueger and Tononi, 2011). This is referred to as local sleep (Nir et al., 2011). Unlike micro sleep, brief periods of local sleep occur when you are still entirely conscious and functioning (Hung et al., 2013, Vyazovskiy et al., 2011). This may be the reason why sleepiness is so difficult to measure in active individuals – the global EEG is seemingly typical of an awake state even though parts of the brain may be sleeping. If local sleep affects regions that are needed to carry out some task, performance on that task decline substantially.

In VDM, we have investigated if local sleep provides an explanation as to why some sleepy drivers can stay on the road whereas others cannot. The hypothesis is that signs of local sleep can be found in motor related parts of the brain in the lane departure cases, but not in the corresponding matched baseline events.

1.1.2. External factors that influence sleepiness

Both sleep and sleepiness are affected by a variety of internal and external factors. The amount of sleep we obtain generally decreases and becomes more fragmented the older we get. Age is thus an important factor that influence sleepiness. Other factors that affect sleepiness include stress and many medical conditions, especially those that cause discomfort or chronic pain. External factors, such as the surrounding environment, light conditions and what we eat and drink can also affect how sleepy we become. Most driver sleepiness experiments usually handle external factors by controlling for them within the experiment, by excluding these factors with a clever study design, or by just ignoring them.

In VDM, we have investigated the impact of two environmental factors – light conditions (daylight versus darkness) and complexity of the surrounding environment (rural versus suburban). The hypotheses are that darkness will make it harder to stay awake, and so will it be in a monotonous environment compared to a more stimulating environment.

The motivation for choosing these two factors is that they are believed to affect driver sleepiness, but that there is very little research on the topic. For example, it is generally assumed that sleepiness and fatigue are countered by the alerting effect of a more stimulating or demanding environment such as in the city (Horne and Reyner, 1999b). However, there is very little research that actually support this claim. Light exposure in general is a well-known factor that increase the arousal level (Cajochen, 2007, Kaida et al., 2006, Cajochen et al., 2000, Figueiro et al., 2007, Lockley et al., 2006, Ruger et al., 2006). Despite this knowledge, the confounding effect of light conditions is seldom considered in the driver sleepiness literature.

1.1.3. Inter- and intra-individual factors that influence sleepiness

The negative impact of sleep loss on performance show large inter-individual differences, where some individuals are affected more than others (Leproutil et al., 2003, Van Dongen et al., 2003). These large differences between individuals remain also when taking known risk groups into account (Ingre et al., 2006a, Van Dongen et al., 2007). Susceptibility to acute sleep loss has been found to be systematic and trait-like, where the differences clusters on three dimensions: sustained attention performance, cognitive processing capability, and self-evaluation of fatigue and mood (Van Dongen et al., 2004a). It is generally believed that professional drivers can manage quite severe fatigue before routine driving performance is affected (Borghinia et al., 2014). This may be because individuals choosing this
occupation are less susceptible to the effects of sleep loss, and that those who are not, self-select to leave the industry (Howard et al., 2014).

In VDM, we have investigated the impact of sleep deprivation on professional drivers compared to non-professional drivers. The hypothesis is that professional drivers are less susceptible to sleep loss.

Although performance degradations from sleep loss vary between individuals, they have also been found to be stable within individuals (Van Dongen et al., 2004a). Despite this intra-individual robustness, there are many potentially confounding external factors that may cause a severe first-encounter effect. For example, when participating in a driving simulator experiment for the first time, you are likely to be on the edge to perform as well as possible. At the same time, you may be a bit nervous since the driving simulator facilities can be intimidating and overwhelming. On top of that, you have an expert looking over your shoulder, monitoring every move you make. This situation is typical in a research setting, and most often the first encounter is all that is recorded and analysed.

In VDM, each participant carried out the same experiment six times, three times during daytime and three times during night-time, to investigate systematic differences between the repetitions. The hypothesis is that the participants are less susceptible to sleep loss in the first trial.

1.1.4. Prediction of driver sleepiness

Automatic sleepiness assessment based on machine learning is usually based on a multitude of physiological and behavioural signals (e.g. Sahayadhas et al., 2012, Chacon-Murguia and Prieto-Resendiz, 2015, Golz et al., 2010, Lal and Craig, 2001). Numerous signal analysis methods have been used to extract features from these signals (Fourier transform, wavelet transform, principal/independent component analysis, fractal based methods, entropy based methods etc.) and the features have been combined using an abundance of data fusion and machine learning algorithms (neural networks, Kalman filters, support vector machines, decision trees, dynamic clustering etc.). Despite proper employment of cross validation techniques, none of these attempts has provided robust solutions that function across different data sets and different individuals. Our previous attempts (e.g. Sandberg et al., 2011, Ahlstrom et al., 2013) have shown equally promising results, but the developed models are always disappointing since they do not generalize to new data sets.

In VDM, in addition to the physiological information, we have incorporated contextual features with the intent to account for external factors that are known to confound the “classic” sleepiness indicators.

1.2. Cognitive load

Several definitions of cognitive load and cognitive distraction exist. Within the VDM project we consider cognitive load to be the amount of cognitive resources used at a certain time. Cognitive resources refer to neural mechanisms underlying cognitive control (Engström et al., 2013). Cognitive distraction is considered to be the allocation of cognitive resources to other tasks than the primary task (in our case the driving task).

Driver distraction, in the sense of drivers allocating physical and cognitive resources to other tasks than the primary task of driving, is usually viewed as having a detrimental effect on traffic safety. However, while visual distraction (not looking at the road while driving) both intuitively and empirically has a clear coupling to increased crash and near crash risk (Klauer et al., 2006b, Victor et al., 2015) the effects of being cognitively distracted (being engaged in non-visual but working memory loading activities) are less clear, both intuitively and empirically.

The reason why the effect of cognitive distraction on driving is unclear is certainly not because of a lack of debate or theoretical conjecture (Lee and Boyle, 2015). Rather, it’s the result of two different
venues of traffic safety research coming to different conclusions regarding which role cognitive load may play in the development of a critical event in traffic.

One venue is the controlled driving experiments performed in driving simulators and on test tracks. Studies in this venue typically find increased response times to stimuli or critical events when drivers are cognitively loaded (i.e., are being given additional cognitive tasks to perform while driving) (Bruyas and Dumont, 2013, Salvucci and Beltowska, 2008, Strayer et al., 2015). The other venue is the naturalistic driving studies, which started off in larger scale with Virginia Tech Transportation Institute’s 100-car study in 2002, to be followed by many others. In these studies, where normal drivers are unobtrusively monitored during their everyday driving, conflicts and crashes very rarely seems attributable to cognitive load; rather, visual distraction seems to be the key culprit (Victor and Dozza, 2011, Dingus et al., 2006, Klauer et al., 2006a). The formulated cognitive control hypothesis might be able to explain parts of this discrepancy and help to understand the role of cognitive distraction in crash causation (Engström et al., 2017). Engström et al. (2017) also review the sometimes disparate effects found in the two venues in the context of the cognitive control hypothesis.

1.2.1. The cognitive control hypothesis

The cognitive control hypothesis by Engström et al. (2017) says that **cognitive load selectively impairs driving subtasks that rely on cognitive control but leaves automatic performance unaffected**. It thus suggests that to understand the role of cognitive distraction in crash causation, one first has to realise that driving is a largely automatized task. Automatic behaviour in general is effortless and runs without active control or attention by the subject. This is in contrast to controlled behaviour, which requires effort, attention and control by the subject (Schneider and Shiffrin, 1977). To successfully deal with novel tasks, flexible and non-routine behaviours are necessary. This requires employment of cognitive control, which is subsumed primarily by the frontal cortex (Botvinick and Cohen, 2014, Miller and Cohen, 2001). Cognitive control enables overriding previously established automated behaviours which are not relevant for the present task(s), in favour of more task relevant but less frequently executed behaviours.

In other words, by applying cognitive control, a driver can deliberately adapt his/her behaviour to fit the driving situation (Engström et al., 2013). But if a driver engages in a phone conversation or some other non-driving task which requires cognitive control, the driver will be less capable of applying cognitive control to the driving task. Instead, actions under cognitive distraction will to a larger extent be determined by already automatized behaviours (Engström et al., 2013, Engström et al., 2017).

The cognitive control hypothesis thus implies that cognitive distraction will delay a driver response if that response relies on, or is facilitated by, cognitive control. It will however not have any effect on automatized responses.

In VDM, we have tested the cognitive control hypothesis by designing experimental driving scenarios where cognitive control can enhance driving performance, respectively where responses are automatically triggered.

1.2.2. Detection of cognitive load

A key difficulty for research on cognitive distraction is that validated measures of cognitive load during car driving are lacking. In field studies, observable cell phone conversations have often been used to identify increased levels of cognitive load (Victor et al., 2015). However, the actual level of cognitive load during the phone conversation can’t be assessed, and neither can the level of cognitive load in the reference condition (no phone conversation).

In experimental studies, existing measurement techniques can be divided into three categories; self-reports, performance measures, and physiological measures. Self-reports have a high face validity, but either interrupt the driving task or depend on retrospective memory, which is known not to be very
accurate. Performance measures are to some extent able to differentiate between different cognitive load levels, but place severe limitations on the experimental design. Two examples are the ISO standardized Detection Response Task, DRT (ISO 17488, 2016) and the Lane Change Task, LCT (ISO 26022, 2015). DRT differentiates between levels of cognitive load by measuring response times to a randomly occurring stimulus. LCT does so by assessment of lane change performance in a specific simulated driving task. While both are capable differentiating between secondary task-induced cognitive demand levels, neither can be used to measure cognitive load in normal car driving since both change the driving task either by adding a secondary task (DRT) or by changing the driving task itself (LCT). Other performance measures that are typically found to be affected by cognitive distraction are lane keeping, average speed and steering activity (see Engström et al., 2017, for a review). While they don’t interfere with the driver or driving task, lane keeping measures are significantly affected by road geometry, and the direction of changes in average speed are not consistent between studies. Physiological measures enable naturalistic study designs and don’t affect the driving task or cognitive state of the driver. This makes them attractive candidates for measuring cognitive load in car drivers.

1.2.2.1. Physiological measures

The high face validity makes it attractive to measure cognitive load by studying brain activity. With EEG, electrical changes caused by neuronal activity in the outmost part of the brain can be recorded. When studying EEG signals, one often looks at different frequency components within the signals. The origin and function of the different frequencies isn’t fully known, but they have been shown to correlate with different mental characteristics. During increased cognitive load, increases in frontal theta power (4-8 Hz) are typically found (Borghini et al., 2012, Fairclough and Mulder, 2011, Gevins and Smith, 2003, Mitchell et al., 2008) while alpha activity (8-13 Hz) has been demonstrated to decrease in task related brain areas during task execution (Classen et al., 1998).

Apart from a few exceptions, the vast amount of EEG research in highly controlled laboratory experiments is hard to replicate in applied settings such as car driving. Alpha spindles (short bursts of alpha activity) have been successfully measured in driving studies and has been suggested to reflect inhibition of visual information processing (Schrauf et al., 2011, Sonnleitner et al., 2012). Another EEG measure that has been successfully measured in car drivers is the P1 amplitude of the Eye Fixation Related Potential (EFRP). The EFRP is a brain response following eye fixations (Thickbroom et al., 1991). It has a positive wave approximately 80-100 ms after the eye fixation, called P1, whose amplitude is supposed to reflect the depth of visual information processing (Itoh et al., 2006). The P1 amplitude increases during increased visual attention (Takeda et al., 2014, Yagi, 1981) and has in driving studies been shown to depend on the complexity of the environment (Itoh et al., 2006, Wiberg et al., 2015). In cases where cognitive distraction would lead to less visual information processing, that effect can be expected to be visible in the P1 amplitude. The few studies that have looked at the P1 amplitude in car drivers performing cognitively loading tasks have typically found a decreased P1 amplitude, but large variations between tasks exist (Itoh et al., 2006, Takeda et al., 2012), possibly indicating that they have different effects on the visual attention.

Because brain activity is difficult to record in real driving as well as hard to interpret in general, other measures of cognitive load while driving are also sought for. One relatively new option here is tracking the pupil diameter of the driver with an eye tracker. The pupil diameter follow changes in ambient light, but also mental activity and emotions (Laeng et al., 2012). Dilations that are psychologically driven are initiated by the same part of the brain (the locus coreolus) that is also involved in controlling the activation level of the brain (Laeng et al., 2012). Increased cognitive load hence causes an increase in pupil diameter (Recarte et al., 2008).

From eye tracker or EOG data one can also monitor eye movements and eye blinks. Spontaneous eye blinks occur on average 15-20 times per minute and their function is not fully understood. One
function is to lubricate the eye, but that doesn’t require so many blinks. It has been suggested that
during spontaneous eye blinks, attention from external stimuli is released and internal processing
increases (Nakano et al., 2013). This could explain why blink frequency has been shown to increase
during increased cognitive load (Recarte et al., 2008, Savage et al., 2013) when more internal
processing is necessary, and to decrease during increased visual load (Recarte et al., 2008) when the
attention needs to be on external stimuli. Extrapolating from this theory, one might also expect shorter
eye blinks during increased visual load and longer eye blinks during increased cognitive load. Some
support for this conjecture comes from Benedetto et al. (2011).

Gaze behaviour has also been shown to be affected by cognitive distraction. Distracted drivers have an
increased gaze concentration toward the forward roadway (Collet et al., 2010, Savage et al., 2013,
Victor et al., 2005) and a reduced standard deviation of gaze (combined vertical and horizontal
angles).

Numerous studies, including driving studies, have found an increased heart rate (HR) during increased
cognitive load (Bari et al., 2011, Borghini et al., 2012, Brookhuis and de Waard, 2010, Collet et al.,
2010, Meher et al., 2012, Reimer and Meher, 2011). It could possibly be explained by the increased
energy consumption in the brain (Fairclough and Mulder, 2011). It is however not clear if cognitive
load alone (i.e. without the stress or emotions that often comes with it) is enough to cause an increased
HR in car drivers. An increase in HR has been found during increased cognitive load in pilots during
real flights but not in simulated flights (Dussault et al., 2005), supporting this doubt.

Together with increases in HR, decreases in heart rate variability (HRV) are also typically reported.
HRV could possibly be more sensitive to cognitive load (Schrauf et al., 2011, De Ward, 1996) but
requires relatively long time intervals to be reliably assessed. It is hence of limited use in driving,
where potentially critical situations develop and resolve on a much shorter time scale.

Similar to HR, the electrodermal activity (or skin conductance, SC) and respiration rate typically
increase during increased cognitive load (Collet et al., 2010, Grassmann et al., 2016, Meher et al.,
2012, Reimer and Meher, 2011, Wiberg et al., 2015), but, again, it is not clear if cognitive
load alone is enough to induce those changes.

In VDM, we have recorded a number of physiological signals and derived measures which (for
different reasons) have shown to correlate with cognitive load. We have studied the effects of cognitive
distraction, as well as of habituation, driving duration and driving demand, and explored the different
measures’ potentials in assessing cognitive distraction. We have also used machine learning to
automatically detect periods of cognitive distraction.

1.2.3. Contextual environmental factors

Cognitive distraction is not a static state. Rather, there is a dynamic interaction between the driving
task and any cognitively loading secondary task(s). How the driver prioritizes between the tasks, and
how difficult they are perceived to be, will influence both task performance and physiological
responses (due to effects on e.g. stress level and cognitive activity). However, while numerous
physiological studies exist on the effects of different levels of driving demand (Wiberg et al., 2015,
Jahn et al., 2005) and of cognitive distraction (Reimer and Meher, 2011), the interplay between the
two over time has received limited attention.

In VDM, we have designed traffic scenarios, in which our participants have performed cognitively
loading tasks, which consists of both simple driving periods and more demanding periods. This have
enabled us to study how changes in driving demand affect the physiological measures differently
during cognitive distraction.
1.3. Aims and Research questions

The overall aim of the project Vehicle Driver Monitoring (VDM) was to further understand how to monitor drivers and measure driver states during driving. More specifically, the focus was to study physiological variables and their ability to measure and predict sleepiness and cognitive load in drivers.

The main research question was: Can physiological measures, expert judgments and self-ratings be used to measure different levels of cognitive load and sleepiness? The investigation of this rather broad question was operationalised by subdividing it into several sub-research questions. Eventually, these sub-research questions were further refined based on the current state of the art. This is motivated and explained in section 1.1 for driver sleepiness and in section 1.2 for cognitive load.

Q1. Which physiological measures can be used to define levels of cognitive load and/or sleepiness while driving?

Q2. What is the relation between levels of cognitive load and/or sleepiness and levels of impaired driving performance?

Q3. Which factors explain differences within and between individuals in the indicators of cognitive load and/or sleepiness?

Q4. Do contextual factors cause significant differences in indicators of cognitive load and/or sleepiness?

Q5. Is driver state affected by the measuring equipment?

Q6. Is it possible to devise an automatic system for online estimation and/or prediction of cognitive load and sleepiness levels?

This report summarizes all results from the project. Each research question has a chapter of its own, like an executive summary, where the responsible partners briefly describe the main outcomes. Since the intention was to write stand-alone summaries, there may be some overlap in the method descriptions across the chapters. The partners responsible for the work are the authors and contact persons of this work.
2. Q1 – Physiological measures and their ability to measure cognitive load and sleepiness

2.1. EEG analysis of local sleep and its relation to lane departures

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Reference to publication(s):

Introduction

Historically, sleep has been considered a passive state but later it was proven to be an active dynamic process. Until recently, sleep was also thought of as a global phenomenon, but it has now been found that regions of the brain, at the local level of cortical columns and other neuronal assemblies, go silent at different times. This is referred to as local sleep. Unlike micro sleep, brief periods of local sleep may occur when you are still entirely conscious and functioning. If local sleep is present in a brain structure that is currently needed for driving, this will have a negative impact on performance. Local sleep is typically measured with microelectrodes attached directly on the cortex. Such invasive measurements were not feasible here, so instead we estimated local activity by source localization algorithms applied to a scalp EEG. This approach is novel. It is obviously less accurate, and it is not known how reliable source localisation is in this context.

Aim

The primary aim of this research is to investigate if local sleep, measured via source localized EEG recordings, can be related to lane departures.

Method

30 participants drove in an advanced driving simulator at 6 different occasions, 3 during daytime (alert) and 3 during night-time (sleep deprived). Each occasion consisted of three driving sessions (rural daylight scenario, rural darkness scenario and urban daylight scenario). A 30-channel EEG was recorded during the trials, and the source localized brain activity was calculated using standardized low resolution brain electromagnetic tomography. The data were then bandpass-filtered in the 5 – 9 Hz frequency range to focus the analyses to the theta range which is of particular interest when investigating sleepiness after extended wakefulness. Conditional logistic regression with matching was used to test whether increased time-localized EEG theta activity in a brain region increased the risk of having a lane departure.

Results

The results are based on 135 lane departures matched with corresponding non-departures, all from drivers reporting a sleepiness level of KSS = 9. The regression resulted in a model with a significant simultaneous effect of the superior frontal cortex and the precentral cortex on lane departures relative
to non-departures ($Likelihood\ ratio\ test = 25.42, p = 3.023 \cdot 10^{-6}$). Including additional brain regions in the model does not improve its performance. The estimated odds ratio for a lane departure relative to a non-departure was 1.48 in the precentral region and 1.60 in the superior frontal region.

Conclusions
The results indicate increased odds ratios for departures for increased levels of local theta activity in brain regions associated with motor function. The results have to be verified in further experiments for a number of reasons. There is an asymmetry between the left and right hemispheres that we cannot explain, there is possible bias in the results due to multiple comparisons of numerous brain regions and segment sizes, and it is not known how well the results generalise to real road conditions etc.

2.2. Brain connectivity analysis to detect driver sleepiness

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Introduction
Within the brain, each neuron is connected to approximately 10 000 other neurons. These networks of linked neurons govern our thoughts and feelings, and control our actions. The interaction between different networks and regions within the brain is referred to as brain connectivity. It can be assumed that vast changes in information flow will occur in states which include varying levels of attention to the external environment, as known to occur during sleep. To explore this assumption, we examined the brain connectivity in alert versus sleep deprived drivers.

Aim
The primary aim of this research is to investigate if brain connectivity, measured via EEG, can be related to the alertness level of the driver.

Method
30 participants drove in an advanced driving simulator at 6 different occasions, 3 during daytime (alert) and 3 during night-time (sleep deprived). Each occasion consisted of three driving sessions (rural daylight scenario, rural darkness scenario and urban daylight scenario). A 30-channel EEG was recorded during the trials, and the connectivity analyses tried to establish flows of information between these 30 electrodes. Functional connectivity was estimated with the partial coherence method and effective connectivity was estimated with the direct Directed Transfer Function (dDTF). This was done in 30s epochs both in the alpha and in the theta bands. The penalized proportional odds model was used to model the relationship between connectivity and values of the Karolinska sleepiness scale (KSS), which served as a ground truth reference for sleepiness.

Results
The penalized proportional odds model showed poor performance when trying to distinguish three levels of self-rated sleepiness (alert, somewhat sleepy, sleepy), with an accuracy of about 40%. The results were similar in both frequency bands and for both partial coherence and dDTF. Even though
the classification accuracy was rather low, the very low p-values ($p \ll 10^{-4}$) indicate that there really is a relationship between the connectivity estimations and sleepiness.

A few channel combinations appear to be important for sleepiness classification in both the theta and alpha band, and in all three simulated environments. For example, F4 – Fp2 scored high in the proportional odds model in all situations. Figure 1 illustrates channel combinations with high model coefficients.

![Figure 1: Combinations of channels with high coefficients in the model fit when separating](image)

**Conclusions**

Even though the classification results were rather poor, the methodology to use brain connectivity to investigate sleepiness should be investigated further. The results show that connectivity varies a great deal over time. This is obvious given that brain connectivity change due to both internal and external stimuli. Future research should investigate not only the flow between regions but also how this flow varies dynamically over time, thus moving away from analysing isolated events towards analysing sequences of events.

2.3. Effects of cognitive load and traffic environment on EFRP

| Author names (contact person*): | Emma Nilsson**, Per Lindén¹, Bo Svanberg¹ |
| Affiliations: | ¹Volvo Car Corporation. |
| Reference to publication(s): | - |

**Introduction**

Visual information from the traffic environment is critical for safe driving. With eye trackers it is possible to detect what drivers fixate their gaze on. It is however not possible to determine how visually attentive the driver is. Using Eye Fixation Related Potentials (EFRPs), a brain response following eye fixations (Thickbroom et al., 1991), this might become possible. The EFRP has a positive wave approximately 80-100 ms after the eye fixation, called P1, whose amplitude is supposed to reflect the depth of visual information processing (Itoh et al., 2006). The P1 amplitude increases during increased visual attention (Yagi, 1981, Takeda et al., 2014) and has in driving studies been shown to depend on the complexity of the environment (Itoh et al., 2006, Wiberg et al., 2015). In the cases where cognitive distraction would lead to less visual information processing, that effect can be expected to be visible in the P1 amplitude. The few studies that have looked at the P1 amplitude in car drivers performing cognitively loading tasks have typically found a decreased P1 amplitude, but large
variations between tasks exist (Itoh et al., 2006, Takeda et al., 2012), possibly indicating that they have different effects on the visual attention.

**Aim**

The primary aim of this research is to investigate the effect of cognitive load and traffic environment on P1 amplitudes in a simulated rural road environment.

**Method**

72 participants (36 in test series 1 and 36 in test series 2) drove approximately 40 minutes each on a simulated rural road in a moving base driving simulator. The route included three traffic scenarios; an intersection scenario, a hidden exit scenario and an open field scenario. Each scenario was repeated four times. At two of the four open field repetitions in test series 2, and in all four open field repetitions in test series 1, there was an unpredictable side wind present. When driving through the scenarios the participants were either involved in a simple cognitive task (1-back), a more difficult cognitive task (2-back), or were not involved in any task besides driving (No Task). The tasks were one minute long, and the time segment from 10 to 60 seconds after task onset were used in the analysis. The participants in test series 1 did the No Task and 1-back conditions only, while the participants in test series 2 did all three task conditions (but only No Task and 2-back in the open field scenario).

Physiological data, including EEG and EOG was recorded from all participants. EFRPs were derived by averaging the EEG Oz signal, time locked to eye fixation onsets. Saccades that didn’t coincide with eye blinks were automatically detected in the EOG signals. Artefacts were rejected from the Oz signal using the FORCe algorithm (Daly et al., 2015). Oz segments from 0.5 s before to 1 s after fixation onset, with an amplitude range below 150 microV, were extracted for all saccades whose endpoints were within the analysis segment.

P1 amplitudes were normalized using each participant’s individual P1 amplitude (derived from the entire drive). In the statistical analysis only segments with more than 30 saccades were included. The P1 amplitude was calculated as the difference in average EFRP amplitude in the interval 0.02 s before to 0.02 s after that participant’s individual P1 peak time (derived from the entire drive), minus the average EFRP amplitude in the interval 0.5 to 0.1 s prior to fixation onset. Statistical tests were made using SAS Enterprise Guide.

**Results**

To look for effects of the traffic environment on the P1 amplitude the three scenarios were compared in each load case. The open field scenario had a significantly lower P1 amplitude than the intersection scenario in the No Task condition in both test series. The P1 amplitude was also significantly lower in the open field scenario compared to the hidden exit scenario in the 2-back condition. We also extracted two smaller analysis segments from the intersection and hidden exit scenarios. It was an earlier segment of a simpler traffic environment, and a later segment with a more demanding traffic environment (including the intersection respectively the hidden exit). We found no statistically significant difference in P1 amplitude between those analysis segments.

When testing for effects of load (No Task, 1-back, 2-back) on P1 amplitude, we found a statistically significant effect in the hidden exit scenario in test series 2 (2-back had a significantly higher P1 amplitude than 1-back). No other significant effects of load were found.

**Conclusions**

The significant difference in P1 amplitude that was found between the intersection scenario and the open field scenario can be understood in the level of visual attention required in the scenarios. Prior studies have similarly found increased P1 amplitude in more complex environments (Itoh et al., 2006, Wiberg et al., 2015), although they have employed traffic scenarios with larger differences in visual...
complexity. We did however not find any significant differences in P1 amplitudes between the simpler (earlier) and more complex (later) parts of the intersection and hidden exit scenarios. This could indicate that there was no difference in visual attention between those analysis segments. It could however also be that the relatively small number of eye fixations that was detected in these shorter time segments weren’t enough for reliable P1 amplitude estimations.

We also found no consistent effect of cognitive load on the P1 amplitude. This could indicate that the drivers invested enough effort to keep the level of visual attention at an equally high level when performing the cognitively loading tasks as when not doing so. Again, it could also be due to unreliable P1 amplitude estimations. This calls for further investigation.

2.4. Cognitive load level determination using EEG band power analysis.

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**Reference to publication(s):** -

**Introduction**

In the literature, many studies have shown an increased frontal theta power during increased cognitive load in various contexts (Borghini et al., 2012, Fairclough and Mulder, 2011). Also, in numerous cognitive load studies, a decrease in parietal and fronto-central alpha powers are reported when cognitive load increases (Borghini et al., 2012, Fairclough and Mulder, 2011).

There are studies that report that theta oscillations are coupled to memory processes but the topic is not yet fully understood. Alpha oscillations have been more thoroughly investigated and the accumulated evidence suggests that alpha oscillations (parietal, fronto-central) correspond to attentional processes.

The normally used frequency range for the theta band is 4 – 8 Hz and for alpha it is 8 – 13 Hz. However, some studies define these bands in a slightly different way. Also, the alpha peak frequency differs between individuals and is sensitive to e.g. age and gender effects (Bazanova, 2012). Therefore, in this study, analysis of both fixed range band powers and individual band powers were done.

**Aim**

The aim of this study is to investigate whether EEG band power analysis can be used to separate different levels of cognitive load in car drivers. The focus has been on frontal mid-line theta and parietal alpha.

**Method**

33 participants drove approximately 40 minutes each on a simulated rural road in a moving-base driving simulator. Before each drive a 2-minute long resting period took place, where the participants relaxed with closed eyes. The route included three traffic scenarios, namely an intersection scenario, a hidden exit scenario and an open field scenario, which were repeated four times each. When driving through the scenarios the participants were either involved in a simple cognitive task (1-back), a more difficult cognitive task (2-back), or were not involved in any task besides driving (No Task). In the open field scenario, an unpredictable varying side wind from the left was either applied or not. The tasks were one minute long, and the time segment from 10 to 60 seconds after task onset were used in the analysis.
EEG data was recorded and artefacts rejected using the FORCe algorithm (Daly et al., 2015), before analysis. Power spectral densities (PSDs) were calculated for FZ (frontal) and PZ (parietal) electrode positions for each scenario time segment and theta and alpha band powers were determined from each PSD. The theta and alpha band powers were normalized to the total band power, frequency range 5 – 30 Hz.

All 33 participant FZ and PZ PSDs were used for a fixed band analysis. Additionally, after visual inspection of the PSDs for each drive and the corresponding resting period, 18 participants with good signal quality and a pronounced resting alpha peak, were selected for a comparison between fixed and individual band power analysis. The individual power band ranges were based on the individual alpha peak value determined during the resting period (Klimesch, 1999). Three alpha power bands were created, two below the individual alpha peak and one above. The theta band is below the alpha bands. Each band was 2 Hz wide.

To test for effects of scenario (Intersection, Hidden Exit, Open Field and Resting) and cognitive load (No Task, 1-back and 2-back) a mixed model ANOVA was performed for each band power measure. Participant was included as a random factor.

Results

A test to find if band powers differ between the driving scenarios and the resting period was done. Only scenarios where No Task and no side wind applied were included. The test showed significant differences both in theta and in alpha powers. The theta power increased and the alpha power decreased in the driving scenarios compared to the resting period, both at the frontal and parietal electrode positions. This effect can be seen using both fixed and individual frequency ranges. The alpha frequency band above the individual alpha peak gives the strongest response and is therefore used as the individual alpha band power in this study.

There are no significant differences found in band powers between the Intersection and the Hidden Exit scenarios. However, there is an indication that parietal theta power for the Open Field scenario is lower than the other driving scenarios (p = 0.056).

The test for effect of load for the Open Field scenario with no side wind applied showed that frontal (FZ) theta power differs between No Task and 2-back task. This holds for both fixed and individual frequency bands. Using individual frequency bands, there is also a significant increase in parietal (PZ) theta power between No Task and 2-back.

For the other driving scenarios, a lot of statistical test have been done but no consistent results have been found.

Conclusions

Given the above, the answer to whether EEG band power analysis can be used to separate different levels of cognitive load in car drivers cannot fully be answered. For the Open Field scenario (which consists of simpler driving compared to the Intersection and Hidden Exit scenarios) EEG band powers could distinguish between the 2-back load level and the No Task level. However, this was not the case in the other driving scenarios.

Band power analysis could also distinguish between more general high and low demand states. There was a clear difference in theta band power between low demand states (the resting period and the open field wind scenario), and the more visually demanding intersection and hidden exit scenarios. Future studies in this direction are recommended.

As for fixed versus individual band power range analysis, the results were similar for both, but the individual band powers gave better response for the different scenarios.
2.5. Physiological response to cognitive load during simulated driving

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**Affiliations:** 1Volvo Car Corporation.

**Reference to publication(s):** In manuscript

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**Introduction**

A key difficulty for research on cognitive load is that there are today no validated ways of measuring cognitive load during car driving without interfering with the driver or altering the task of driving. While several physiological measures have been shown to correlate with cognitive load in various settings (Brookhuis and de Waard, 2010, Collet et al., 2010, Mehler et al., 2012, Recarte et al., 2008, Reimer and Mehler, 2011), none seem to assess only cognitive load (i.e. respond to cognitive load and nothing else). It could therefore be beneficial to study multiple physiological measures together, to get a better understanding of the mental state of the driver. We measured a number of physiological measures and related them to both cognitive load, task habituation, driving time and driving demand.

**Aim**

The aim is to study the relationship between cognitive load and a number of physiological measures, and to understand some of the factors that explain the response patterns in the different measures.

**Method**

72 participants drove approximately 40 minutes each on a simulated rural road in a moving-base driving simulator. The route included two traffic scenarios, namely an intersection scenario and a hidden exit scenario. Each scenario was repeated four times. When driving through the scenarios the participants were either involved in a simple cognitive task (1-back), a more difficult cognitive task (2-back), or were not involved in any task besides driving (No Task). The tasks were one minute long, and the time segment from 10 to 60 seconds after task onset were used in the analysis.

Physiological data was recorded and a number of physiological measures were derived (listed in table 1). Signals and derived measures were visually inspected and excluded from the analysis if considered unreliable. Participants were included in the analysis if they had had a complete dataset (all four repetitions).

To test for effects of load (No Task, 1-back and 2-back) and repetition (1 to 4), Mixed Model ANOVAs were performed for each scenario and physiological measure. Participant was included as a random factor.
Table 1. Physiological measures included in analysis.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Signal that the measure was derived from</th>
<th>Normalization method</th>
<th>Nr of participants included in hidden exit respectively intersection scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>HR (heart rate)</td>
<td>Chest ECG</td>
<td>The median HR value from the entire drive was subtracted from the HR.</td>
<td>61, 62</td>
</tr>
<tr>
<td>SDRR (standard deviation of RR intervals)</td>
<td>Chest ECG</td>
<td>Not normalized.</td>
<td>61, 62</td>
</tr>
<tr>
<td>PD (pupil diameter)</td>
<td>Camera based Eye Tracker</td>
<td>The median PD value from the entire drive was subtracted from the PD.</td>
<td>35, 39</td>
</tr>
<tr>
<td>SC (skin conductance)</td>
<td>Electrical conductance measured between two fingers</td>
<td>Response size was normalized by dividing the SC signal with the 99th percentile of a low pass filtered SC signal. SC levels were normalized by subtracting the mean SC value -70 to -10 s prior to scenario start.</td>
<td>53, 52</td>
</tr>
<tr>
<td>RR (respiration rate)</td>
<td>RIP</td>
<td>The median RR value from the entire drive was subtracted from the RR.</td>
<td>47, 41</td>
</tr>
<tr>
<td>BR (blink rate)</td>
<td>Vertical EOG</td>
<td>The median BR value from the entire drive was subtracted from the BR.</td>
<td>50, 49</td>
</tr>
<tr>
<td>BD (blink duration)</td>
<td>Vertical EOG</td>
<td>The median BD value from the entire drive was subtracted from the BD.</td>
<td>50, 49</td>
</tr>
</tbody>
</table>

Results

Almost all physiological measures were capable of distinguishing between load and no load conditions. Six of the seven measures showed a significant effect of load in both the intersection and the hidden exit scenarios. The only exception was BD which had a significant effect in the hidden exit scenario only.

However, only PD showed a significant difference between different load conditions (1-back vs 2-back) in both scenarios. PD was also the measure with the smallest overlaps between the load conditions, and the most consistent response patterns between participants. For HR and SC the differences between the load conditions decreased over repetitions. Effects of time on driving task were studied by looking at effects of repetition in the No Task condition. PD and BD were found to have significant effects of repetition in the No Task condition in both scenarios (PD decreased and BD increased), while RR and SDRR had it in one of the scenarios (RR decreased and SDRR increased).

Physiological responses related to the increasing driving demand when approaching and passing the hidden exit respectively the intersection were visible in PD (increasing), SC (increasing), BR (decreasing) and BD (decreasing). In all of them, except from SC, the differences between the load conditions decreased during the increased driving demand. BR was the only measure that had an effect of the increased driving demand that was in the opposite direction of the effect of increased cognitive distraction.
Conclusions

Even though all the physiological measures showed significant effects of cognitive load, a closer look at where the differences lay and how they evolve over the scenarios and repetitions highlights that the different measures reflect different aspects of the participants’ mental state. The measure that best related to the level of cognitive load was PD. HR and SC, measures which are strongly affected by stress, were presumably affected by the relative novelty of the tasks, since their differences between load conditions decreased in later repetitions (unlike the PD responses). PD and BD on the other hand were affected by total driving time, likely reflecting decreased arousal or increased fatigue. Most measures that responded to the increased driving demand, at the same time showed decreased differences between the load conditions (PD, BR and BD). This might reflect either ceiling effects in the specific measures, or in the driver’s level of cognitive load.
3. Q2 – The relation between driver state and levels of impaired driving performance?

3.1. Effects of cognitive load on response time in an unexpected lead vehicle braking scenario

Authors name: Emma Nilsson¹*, Mikael Ljung Aust¹, Johan Engström², Bo Svanberg¹, Per Lindén¹

Affiliations: ¹Volvo Car Corporation, ²Virginia Tech Transportation Institute

Reference to publication(s):

Introduction

The effect of cognitive load on traffic safety and driver response times is not clear. Numerous controlled experiments have demonstrated increased response times during cognitive load and concerns about primarily cell phone usage during driving have been raised (Caird et al., 2008, Strayer et al., 2015). Others argue a protective effect of cell phone conversations, as there are naturalistic studies showing a decreased crash and near crash risk during cell phone conversations (Victor et al., 2015). By looking closer at the driving task itself, some of the disagreements might be resolved. (Engström et al., 2017) formulated the cognitive control hypothesis for the effect of cognitive load on driving performance: Cognitive load selectively impairs driving sub-tasks that rely on cognitive control [i.e. novel or inconsistent tasks] but leaves automatic performance unaffected. Responses to looming (i.e. visually expanding) objects are automatic (Franconeri and Simons, 2003, Náñez, 1988) and should, according to the hypothesis, not be affected by cognitive load. This was tested in an unexpected lead vehicle braking scenario.

Aim

The aim of this research was to test the cognitive control hypothesis in an unexpected lead vehicle braking scenario. The hypothesis predicts no interference of cognitive load, i.e. no effect on brake response times, if the scenario is designed so that the response is triggered by the looming lead vehicle.

Method

50 participants drove in a simulated driving environment consisting of a two-lane rural road with a speed limit of 80 km/h. There was some oncoming traffic and five times during the drive the participants’ car (PC) was overtaken by another vehicle. The fifth time this happened, the overtaking car (OC) suddenly started braking after having passed the PC. The scenario was designed so that the OC, after overtaking the PC, continued to accelerate away from the PC until it suddenly started braking at a set time headway of 1.3 s. When the OC started braking, its speed was instantaneously set to 9 m/s below the speed of the PC, from which it started to decelerate with 0.6 g. Thus, the gap size between the cars started to decrease at the same time the OC started braking and strong looming cues were available from the very beginning of the scenario. Participants were either involved in a simple cognitive task (1-back), a more difficult cognitive task (2-back), or not involved in any task when the OC started braking.

Brake response time was defined as the time from OC deceleration onset to first detectable brake force. Participants who were not looking at, or near, the OC when it started braking were excluded from the analysis.
Results
38 participants were included in the analysis; 10 belonging to the 1-back group, 10 in the 2-back group and 18 in the no task group. A two-sample t-test revealed no statistically significant difference in brake response times between the 1-back group and the 2-back group. The two groups were hence merged to one group; the task group. There was no statistically significant difference between the task group and the no task group.

Conclusions
The present study did not find any effect of cognitive load on brake response time in the lead vehicle braking scenario. The results hence support the cognitive control hypothesis, since the scenario was completely unexpected and the brake response was automatically initiated by the looming cues which appeared as soon as the lead vehicle started to brake.

3.2. Effect of cognitive load on driver behaviour in intersection and hidden exit scenarios

Authors name (contact person *): Emma Nilsson¹, Bo Svanberg¹*, Per Lindén¹
Affiliations: ¹Volvo Car Corporation,
Reference to publication(s): In manuscript

Introduction
To study the effect of cognitive load on driver performance two non-critical driving scenarios were designed in this study, one four-way intersection with an approaching car and one hidden exit with a warning sign. The cognitive control hypothesis (Engström et al., 2017) was used to design the scenarios and to predict the effect of cognitive load. The hypothesis states that Cognitive load selectively impairs driving subtasks that rely on cognitive control but leaves automatic performance unaffected.

The hypothesis implies that drivers with cognitive load would impair their visual search behaviour and the use of cognitive cues in the analysed driving scenarios (the approaching car and the hidden exit warning sign) compared to drivers without cognitive load, since those behaviours require cognitive control.

Aim
The aim of this study was to use two non-critical scenarios to study the effect of cognitive load on driver gaze behaviour and situational adaption.

Method
36 male test participants in each of two studies drove for 40 minutes in an advanced moving-base simulator. The two lane 80 km/h rural road included the two non-critical scenarios repeated four times each. In the intersection scenario, the participants approached and passed a four-way intersection. A car approached the intersection from the right and braked to stop just before the participant passed the intersection. In the hidden exit scenario, the participant passed a hidden exit warning sign, drove through a steep right hand curve and passed the exit that was hidden behind a hedge. In the scenarios, the participants either performed a simple cognitively loading task (1-back), a more demanding cognitively loading task (2-back), or no task (No Task) during 60 s. In study one No Task and 1-back were used and in study two No Task and both 1-back and 2-back. The variables were calculated from 10 to 60 s after the secondary task started. Different eye-trackers were used in the two studies giving different opportunities to calculate the variables. Gaze behaviours were manually coded.
Statistical analyses were done using a mixed model ANOVA. The studies were analysed separately and covered: first glance, last glance and summarized glance time at the approaching car or hidden exit, and average speed.

**Results**

First glance: For the approaching car in the intersection, load had a significant main effect in both studies; in study one for 1-back and in study two only for 2-back compared to No Task. Participants looked later at the approaching car during load. There were no effects of load in the hidden exit scenarios.

Last glance (available in study two): Load had a significant main effect in the hidden exit scenario, both for 1-back and 2-back compared to No Task. No effects were found in the intersection scenario.

Number of glances and summarized glance time (available in study two): The number of glances at the approaching car in the intersection scenario decreased as load increased. The number of occurrences where the driver passed the intersection without looking at the approaching car at all also was 0 for the No Task condition and increased with increased load. For the summarized time that the driver looked at the approaching car or the exit/shrubbery a significant effect of load was found in both scenarios. In the intersection scenario, the summarized glance time at the car was shorter during 2-back and 1-back than in No Task. In the hidden exit scenario, the summarized glance time at the shrubbery/exit was shorter during 2-back.

**Conclusions**

The cognitive control hypothesis predicts that drivers under cognitive load change their non-automatized visual search behaviour and their use of cognitive cues in the driving environment (here the warning sign/memory of the hidden exit and the approaching car in the intersection). The results support the hypothesis by showing that the cognitively loaded drivers looked at the approaching car and hidden exit fewer times, or not at all, compared to drivers without load. Support is also found in the later first glance at the approaching car.

### 3.3. Effects of cognitive load in a side wind scenario

<table>
<thead>
<tr>
<th>Authors name (contact person *):</th>
<th>Mikael Ljung Åst¹, Emma Nilsson¹, Bo Svanberg¹*, Per Lindén¹</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Affiliations:</strong></td>
<td>¹Volvo Car Corporation,</td>
</tr>
<tr>
<td><strong>Reference to publication(s):</strong></td>
<td>In manuscript.</td>
</tr>
</tbody>
</table>

**Introduction**

The cognitive control hypothesis suggests that cognitive load only affects tasks that require cognitive control (i.e. novel or inconsistent ones), but not tasks with automatized responses (Engström et al., 2017). Since lane keeping is extensively practiced, simple and consistently mapped, it can be assumed to be largely automatized for experienced drivers. It should thus only be affected by cognitive load if it becomes so difficult that previous experience becomes insufficient for automatized lane keeping.

Outcome of previous studies of this topic are inconclusive. Medeiros-Ward et al. (2014) found that the standard variation in lane position (SDLP) decreased when drivers were cognitively loaded as long as driving conditions were predictable, but increased when driving conditions were made unpredictable by adding strong cross winds to the driving scenario. On the other hand, He et al. (2014) only found improved lane keeping (decreased SDLP) even when cross winds were added.

This study aimed to replicate Medeiros-Ward et al.’s experiment in a more advanced (i.e. moving base) driving simulator than those used by the two previous studies, who both relied on fixed base
driving simulators. In fixed base simulators automatized lane keeping might be compromised due to the lack of kinaesthetic input.

Besides changes in lane keeping, cognitive load usually also causes steering wheel reversal rate to increase (Östlund et al., 2004). Physiological measures which are sensitive to changes in arousal were also analysed to get a better understanding of how the crosswind affected the drivers.

**Aim**

The aim of this study was to study the effects of cognitive load on driving performance under predictable and un-predictable (strong bursts of side wind) lane keeping conditions by replicating the study by (Medeiros-Ward et al., 2014) in a more advanced simulator.

**Method**

36 male participants drove for 40 minutes on a two lane 80 km/h rural road in an advanced moving-base simulator. The route included an open field scenario repeated four times. An unpredictible side wind occurred at the open field and was active 1 minute and 40 seconds. In the scenario the participants either performed a cognitively loading secondary tasks (2-back), or not (No Task). The side wind was active in two of the four repetitions and 2-back in one repetition with and one without side wind. The 2-back task started 30 s after the wind started and lasted for 60 s. Variables were calculated over the time interval from 10 to 60 s after the task started.

Previous studies have shown that unfiltered SDLP does not converge even after 100 s (Östlund et al., 2005). Since the data segments in this study are 50 s long, the modified SLDP proposed in Östlund et al. (2005) (where lateral position is filtered with a 0.1 Hz cut off, high frequency filter before the calculation) was used. With this filter, SDLP convergences after approximately 10 seconds.

The driving performance variables were mean speed, standard deviation of travel speed, standard deviation of lane position (SDLP) (Östlund et al., 2005) and steering wheel reversal rates (SWRR). The physiological measures were heart rate (HR), heart rate variability (SDRR), pupil diameter (PD), blink rate (BR), blink duration (BD), respiration rate (RR) and skin conductance (SC). The response time and number of missed triggers in 2-back were also analysed. Mixed model ANOVAs were used in the analysis. Load (2-back and No Task) and side wind (Wind and No Wind) were fixed effects and participant was random effect.

**Results**

SDLP increased significantly when drivers were exposed to strong crosswinds. Also, SDLP decreased significantly when under cognitive load (2-back condition). There were however no interaction effects between cognitive load and crosswind.

Both cognitive load and crosswind lead to a significant increase in SWRR, but there were no interaction effects of load and crosswind. All physiological measures, except from BD, had a significant effect of load (HR increased, SDRR decreased, BR increased, PD increased, RR increased, SC increased and BD decreased, although not significantly). None of the measures had a significant effect of crosswind, nor any interaction effects of load and crosswind. There was no significant effect from crosswind on response times in 2-back, nor for the number of missed triggers.

**Conclusions**

The aim here was to test if a crosswind with strong lateral gusts can make lane keeping so difficult that it requires cognitive control for successful performance, i.e. to replicate the findings from Medeiros-Ward et al. (2014) in support of the cognitive control hypothesis. This did not succeed. Instead, lane keeping performance improved under cognitive load, both in the no crosswind and in the strong crosswind condition; the latter being the same outcome as in He et al. (2014).
Furthermore, while arousal as captured by the physiological measures increased significantly under cognitive load (as expected), the crosswind condition had no effect on arousal. The latter was unexpected, since the assumption was that crosswinds would make lane keeping difficult enough to require additional deployment of cognitive control, which should add a further increase in arousal.

The most plausible account for this would be that lane keeping in this study simply was not difficult enough in the crosswind condition to require deployment of cognitive control, despite replicating the crosswind setup from Medeiros-Ward et al. (2014). The underlying reason for this is probably differences in test setup. While previous studies used fixed base simulators, this study utilized a moving base simulator. Participants in the current study therefore had access to an additional modality for sensing lateral vehicle motion and were not solely dependent on visual input, which seems to have been enough to keep lane keeping automatized and thus unaffected by cognitive load, even in the strong crosswind condition.
4. Q3 – Factors explaining differences within and between individuals in the indicators of cognitive load and/or sleepiness

4.1. Are professional drivers less sleepy than non-professional drivers?

**Author names (contact person):** Anna Anund¹, Christer Ahlström¹, Carina Fors¹, Torbjörn Åkerstedt²

**Affiliations:** ¹The Swedish National Road and Transport Research Institute (VTI), ²Clinical Neuroscience, Karolinska Institute.

**Reference to publication(s):**

**Introduction**

There are large differences between individuals in how they are affected by fatigue and little is known about these individual differences. Is it, for example, possible to learn how to drive without decreased performance under high levels of sleepiness? It is generally believed that professional drivers can manage quite severe fatigue before routine driving performance is affected. In addition, there are results indicating that professional drivers can adapt to prolonged night shifts and may be able to learn to drive without decreased performance under high levels of sleepiness. However, very little research has been conducted to compare professionals and non-professionals when controlling for differences in work hours.

**Aim**

The aim was to investigate the development (and effects) of sleepiness on non-professional drivers versus professional drivers who are used to long driving hours.

**Method**

Differences in the development of sleepiness (self-reported, physiological and behavioural) during driving, in an advanced moving-based simulator, was investigated in 11 young professional and 15 non-professional drivers. The study had a within-subject design where daytime and night-time driving was used to manipulate sleepiness. The day sessions were scheduled between 12.30h and 21.15h and the night sessions between 22.00h and 06.15h. On each visit a participant drove 3 times in succession, 2 of them on rural road with a speed limit of 80 km/h and one on suburban road. Here we used the rural road parts. An ANOVA was used to analyse differences in sleepiness and performance between professional and non-professional drivers. The model included factors for time of day (day/night), time on task (1-6 corresponding to minutes 5-10-15-20-25-30), and group (professional / non-professional). Participant was included as a random factor.

**Results**

As expected higher KSS values, longer blink durations, increased number of line crossings, longer reaction times on PVT and more PVT lapses were found during night driving and with increased time on task. With respect to group differences, professional drivers reported significantly lower levels of self-reported sleepiness (KSS) both day and night, had longer blink durations during night-time, more line crossings, and longer reaction times and more lapses on the PVT test during night-time. The professionals drove faster than the non-professional drivers did in general, and both groups reduced their speed during night-time. Looking at how the groups performed under high KSS levels, it was
found that the professionals had longer blink durations and more line crossings than the non-professional drivers. The results give us no reason to believe that professional drivers are more resistant to sleepiness than non-professional drivers in terms of physiology (blink duration) and driving performance (line crossings), but rather in terms of self-reported sleepiness.

**Conclusions**

Professional drivers reported significantly lower sleepiness while driving a simulator than non-professional drivers. However, they also showed longer eye blinks and more line crossings, which both are indicators of sleepiness, and they drove faster. The reason for the discrepancy in the relation between sleepiness indicators and group could be due to more experience of sleepiness while driving among the professional drivers.

4.2. Intra-individual differences in the development of sleepiness

| Author names (contact person*): | Anna Anund¹, Christer Ahlström¹, Carina Fors¹ |
| Affiliations: | ¹The Swedish National Road and Transport Research Institute (VTI) |
| Reference to publication(s): | Article for peer review journal is under preparation. |

**Introduction**

It is well known that there are large differences between individuals in how they are affected by sleepiness. Less is known about differences within an individual. Up to now, most studies take for granted that a driver performing a test represent himself/herself as if there are no differences within an individual from time to time. Whether this is a correct assumption needs further investigation.

**Aim**

The aim of this investigation was to study if drivers’ sleepiness levels and behaviour in expectedly alert and expectedly sleepy conditions varies from time to time when the same experimental procedure is repeated several times. The hypothesis is that there are significant differences within an individual from time to time.

**Method**

In total 26 male drivers visited an advanced moving-base driving simulator. The study had a within-subject design with 6 separate visits: three during day-time and three during night-time. The day-time and night-time driving was used to manipulate sleepiness. The day-time sessions were scheduled between 12.30h and 21.15h and the night-time sessions between 22.00h and 06.15h. On each visit a participant drove 3 times in succession, 2 of them on a rural road with a speed limit of 80 km/h and one on suburban road with a speed limit of 60 km/h. The same procedure was used at each visit.

Differences in the development of self-reported sleepiness (KSS) and number of line crossings were investigated. An ANOVA was used with a model including factors for time of day (day/night), time on task (1-6 corresponding to minutes 5-10-15-20-25-30), visit (1-2-3) and succession (1-2-3). Participant was included as a random factor.

**Results**

Looking into KSS there was a difference between day-time (average KSS 5.0) and night-time (average KSS 7.3) driving ($F_{(df;1,2641)}=2324; p<0.01$), but also between the repetition of the visits; visit 1(KSS 6.0), visit 2 (KSS 6.2) and visit 3 (KSS 6.3) ($F_{(df;2,2643)}=8.635; p<0.01$). As always there were significant effects of time on task and trial order. There was also a significant interaction for time of the day and visit ($F_{(df;2,2642)}=16185; p<0.01$), see Figure 2.
Considering performance, here defined as the number of line crossings (#), there was a significant difference between the total number of line crossings during day-time (# 0.38) and night-time (# 0.56) ($F_{(df\ 1,2641)}=191.3; p<0.01$). Also here there was a difference between the repetition of the visits; visit 1 (# 0.39), visit 2 (# 0.43) and visit 3 (# 0.51) ($F_{(df\ 2,2632)}=59.9; p<0.01$). As usual there was a significant effect of time of task, but in this case not on trial order. There were no significant interactions with visits and the other factors.

![Figure 2. KSS and # line crossings during day-time and night-time for the different visits (1-2-3)](image-url)

**Conclusions**

There is reason to believe that there are differences within an individual in sleepiness levels (KSS) and behaviour in terms of line crossings from time to time even under identical experimental settings. This finding is important trying to understand the validity of results from studies using only one expected alert and one expected fatigued condition.
5. Q4 – Impact of contextual/environmental factors on indicators of
cognitive load and/or sleepiness

5.1. The effect of a suburban versus a rural environment on driver
sleepiness

Introduction

Most driver sleepiness experiments handle external factors (that may or may not affect sleepiness) by simply excluding these factors with a clever study design or by just ignoring them. Since we have very little knowledge about the impact of such factors on sleepiness, we set up a driving simulator experiment to investigate one of these factors – driving on rural roads versus suburban roads. It is generally believed or assumed that sleepiness and fatigue are countered by the alerting effect of a more stimulating or demanding environment such as in the city. However, there is very little research that actually supports this claim.

Aim

The purpose of this research is to investigate the isolated effect of a more demanding traffic environment on subjective, objective and behavioural indicators of sleepiness. This is done by comparing the development of driver sleepiness when driving on a monotonous rural road compared to when driving in a more complex suburban environment.

Method

Thirty drivers were recruited for the experiment. They drove in a rural and in an urban environment with the intention that the two environments would have varying complexities. Both scenarios had a duration of 30 minutes and were driven in a balanced order both in an alert and in a sleep deprived condition. The rural road had a speed limit of 80 km/h whereas the urban road had a speed limit of 60 km/h. To ensure a high degree of experimental control, an advanced moving-base driving simulator was used. Acquired data include vehicle data (speed, lateral position etc.), physiological data (EOG, ECG, EEG, etc.) and subjective sleepiness ratings (KSS).

Results

The difference between the suburban and rural environments was significant for KSS ($F_{(1,1209)} = 13.6$), line crossings ($F_{(1,1211)} = 178.5$), relative speed ($F_{(1,1207)} = 34.7$), large steering corrections ($F_{(1,1211)} = 51.8$) and pedal activity ($F_{(1,1211)} = 51.8$). Relative speed is the actual speed minus the current speed limit. In the suburban environment, the drivers reported 0.2 units higher KSS values, exceeded the speed limit 1.0 km/h less, and experienced 2.5 more line crossings, see Figure 3. The effect of the driving environment on the sleepiness indicators was generally small compared to the effect of sleep deprivation. The impact of the environment on many of the indicators obtained from the vehicle is
however substantial. For example, the peaks in line crossings after 10 minutes and 25 minutes coincide with a more urban setting compared to the surrounding suburban setting. This is also seen in the micro-corrections of the steering wheel angle. Increased pedal activity in the rural setting is due to a larger amount of curves and hills on that road.

Figure 3. The mean values of each indicator computed for each of the six segments (time on task) for daytime versus night-time in the two simulated environments. The speed limit has been subtracted from the measured speed. The error bars represent standard error of mean.

Conclusions

Driver sleepiness has been suggested to be countered by the alerting effect of a more stimulating and demanding environment such as city driving. Our results are rather pointing towards the opposite, with lower sleepiness ratings on the rural road. It may be that the higher number of curves on the rural road forced the driver to remain active while having to continuously correct the course, which in turn may
have been more “alerting” than the simulated suburban road. This result was unexpected, but give rise to a rather interesting theory: There is an additive sleepiness-inducing effect of monotonous environments, but no such thing as a countering/alerting effect of more stimulating environments. Further experiments with a larger variety of highly controlled environments are needed to confirm this hypothesis.

5.2. The effect of daylight versus darkness on driver sleepiness

| Authors name (contact person)*: | Christer Ahlström¹, Anna Anund¹, Carina Fors¹, Torbjörn Åkerstedt² |
| Affiliations: | ¹The Swedish National Road and Transport Research Institute (VTI), ²Clinical Neuroscience, Karolinska Institute. |

Introduction

Most driver sleepiness experiments handle external factors (that may or may not affect sleepiness) by simply excluding these factors with a clever study design or by just ignoring them. Since we have very little knowledge about the impact of such factors on sleepiness, we set up a driving simulator experiment to investigate one of these factors – daylight versus darkness. Given the effects that light conditions have on sleepiness, it is strange that this confounding factor is seldom considered in the driver sleepiness literature.

Aim

In this research, we aim to investigate the effect of light conditions on driver sleepiness. It involved driving the same rural road both in simulated daylight and in simulated darkness, during daytime (alert) and during night-time (sleep deprived). The hypothesis was that higher levels of sleepiness will be reached in simulated darkness compared to daylight.

Method

Thirty drivers were recruited for the experiment. They drove on a rural road both in simulated daylight and in simulated darkness. Both scenarios had a duration of 30 minutes and were driven in a balanced order both in an alert and in a sleep deprived condition. To ensure a high degree of experimental control, an advanced moving-base driving simulator was used. Acquired data include vehicle data (speed, lateral position etc.), physiological data (EOG, ECG, EEG, etc.) and subjective sleepiness ratings (KSS).

Results

The difference between daylight and darkness was significant for KSS, blink duration, EEG theta power, EEG alpha power, lateral position and speed, see Table 2. In simulated darkness, compared to simulated daylight, the drivers reported higher KSS values (0.5 units higher), had longer blink durations (14 ms longer), higher EEG alpha (0.001 V2s higher) and theta content (0.001 V2s higher), and drove slower (0.9 km/h slower) and closer to the centre of the road (5 cm closer). There were no significant two-way interactions.
**Table 2: F-values and degrees of freedom from mixed model ANOVAs for light condition (daylight versus darkness), day/night condition and time on task (0 – 5, 5 – 10, ..., 25 – 30 minutes). Results regarding the interaction between light condition and day/night condition are also included. Participant is included as a random factor. Significant differences at the 0.05 level (0.007 after Bonferroni correction) are marked in grey.**

<table>
<thead>
<tr>
<th>Light/dark</th>
<th>Day/night</th>
<th>Time on task</th>
<th>Participant</th>
<th>Light * Day</th>
<th>Light * Task</th>
<th>Day * Task</th>
</tr>
</thead>
<tbody>
<tr>
<td>KSS</td>
<td>$F(1,1205)=45.7$</td>
<td>$F(5,1205)=957.0$</td>
<td>$F(25,1205)=30.8$</td>
<td>$F(1,1205)=1.4$</td>
<td>$F(5,1205)=0.3$</td>
<td>$F(5,1205)=0.5$</td>
</tr>
<tr>
<td>Blink duration</td>
<td>$F(1,1199)=8.9$</td>
<td>$F(5,1199)=80.4$</td>
<td>$F(25,1199)=12.7$</td>
<td>$F(1,1199)=2.2$</td>
<td>$F(5,1199)=0.3$</td>
<td>$F(5,1199)=2.5$</td>
</tr>
<tr>
<td>EEG theta</td>
<td>$F(1,1130)=7.7$</td>
<td>$F(5,1130)=4.0$</td>
<td>$F(25,1130)=125.0$</td>
<td>$F(1,1130)=0.1$</td>
<td>$F(5,1130)=0.1$</td>
<td>$F(5,1130)=1.2$</td>
</tr>
<tr>
<td>EEG alpha</td>
<td>$F(1,1130)=24.8$</td>
<td>$F(5,1130)=12.2$</td>
<td>$F(25,1130)=120.1$</td>
<td>$F(1,1130)=0.2$</td>
<td>$F(5,1130)=0.4$</td>
<td>$F(5,1130)=1.5$</td>
</tr>
<tr>
<td>Line crossings</td>
<td>$F(1,1205)=0.0$</td>
<td>$F(5,1205)=136.3$</td>
<td>$F(25,1205)=20.8$</td>
<td>$F(1,1205)=0.2$</td>
<td>$F(5,1205)=0.8$</td>
<td>$F(5,1205)=5.4$</td>
</tr>
<tr>
<td>Lateral position</td>
<td>$F(1,1205)=48.6$</td>
<td>$F(5,1205)=6.6$</td>
<td>$F(25,1205)=29.5$</td>
<td>$F(1,1205)=0.7$</td>
<td>$F(5,1205)=4.14$</td>
<td>$F(5,1205)=0.8$</td>
</tr>
<tr>
<td>Speed</td>
<td>$F(1,1205)=22.4$</td>
<td>$F(5,1205)=46.2$</td>
<td>$F(25,1205)=10.3$</td>
<td>$F(1,1205)=7.0$</td>
<td>$F(5,1205)=2.1$</td>
<td>$F(5,1205)=2.2$</td>
</tr>
</tbody>
</table>

**Conclusions**

This study showed that indicators of subjective, behavioural and physiological sleepiness increase with reduced light, except for line crossings. However, effects of night driving are stronger, except for lateral position and EEG theta. Light and time of day did not interact, indicating that light conditions has an additive effect on sleepiness. Thus, light is an important factor to consider in driver sleepiness discussions. Due to the rather low light levels in simulators, the present results should not be generalized to real driving under normal daylight conditions.
5.3. The benefit of including environmental factors in sleepiness classification

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Affiliations: 1Mälardalen University, 2The Swedish National Road and Transport Research Institute (VTI).

Reference to publication(s):

Introduction

Contextual factors such as light conditions and the driving environment influence driver sleepiness (see sections 5.1 and 5.2). For example, it has been suggested that driving in a livelier and more stimulating environment has an alerting effect on the driver.

Aim

The aim of this study is to investigate if it is beneficial to include environmental factors when trying to classify sleepiness.

Method

Data were collected from 30 participants who drove three different scenarios in a moving-base driving simulator: (i) rural road in daylight, (ii) rural road in darkness, and (iii) suburban road in daylight. This contextual information was added as two separate binary features, one for suburban/rural and one for daylight/darkness. Furthermore, a model of sleepiness, the so-called sleep/wake predictor, was added as a third feature. The sleep/wake predictor is based on the time of day, the time since awakening and the duration of prior sleep. Feature selection algorithms LASSO, BSS/WSS (ratio between within-class and between-class) and NCA (neighbourhood component analysis) were applied to identify the relevant features in order to rank the contextual features amongst the EEG based features.

Classification of driver sleepiness was performed with two different classifiers, a support vector machine (SVM) and a k-nearest neighbour (KNN) classifier, with and without these environmental predictors in addition to the EEG based features.

Results

Feature selection showed higher feature weights or coefficients for the contextual features than for the EEG features. It was observed from BSS/WSS that the sleep/wake predictor got a higher weight than the other predictors. With NCA, rural/urban and daylight/darkness predictors obtained the top two scores among all the predictors. However, when using the LASSO algorithm, the contextual predictors were not found to be so important. Much higher classification accuracy was obtained when the three contextual predictors were used, see Table 3.

Table 3. Classification results with and without the contextual information for two different classification algorithms.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>KNN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature set</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EEG</td>
<td>73 %</td>
<td>80 %</td>
</tr>
<tr>
<td>EEG+Context</td>
<td>81 %</td>
<td>85 %</td>
</tr>
<tr>
<td>Sensitivity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EEG</td>
<td>86 %</td>
<td>92 %</td>
</tr>
<tr>
<td>EEG+Context</td>
<td>88 %</td>
<td>91 %</td>
</tr>
<tr>
<td>Specificity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EEG</td>
<td>72 %</td>
<td>79 %</td>
</tr>
<tr>
<td>EEG+Context</td>
<td>76 %</td>
<td>81 %</td>
</tr>
<tr>
<td>Accuracy</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EEG</td>
<td>72 %</td>
<td>79 %</td>
</tr>
<tr>
<td>EEG+Context</td>
<td>76 %</td>
<td>81 %</td>
</tr>
</tbody>
</table>
Conclusions

It has previously been shown that sleepiness classification based on driving behaviour as well as on physiological measures improves when the feature set is augmented with the sleep/wake predictor (Ahlstrom et al., 2013, Sandberg et al., 2011). Here we see that classification accuracy is also improved by adding contextual information. Though feature selection shows higher weights for these factors, further research is required to clarify the full benefit of these factors.
6. Q5 – Impact of the measuring equipment

6.1. Effects of equipment on driver state

<table>
<thead>
<tr>
<th>Authors name:</th>
<th>Bo Svanberg¹, Emma Nilsson¹, Per Lindén¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affiliations:</td>
<td>¹Volvo Car Corporation,</td>
</tr>
<tr>
<td>Reference to publication(s):</td>
<td>None</td>
</tr>
</tbody>
</table>

Introduction

A key difficulty for research on cognitive distraction is that there are today no validated ways of measuring cognitive distraction, or more generally cognitive load, during car driving.

In experimental studies, existing measurement techniques can be divided into three categories; self-reports, performance measures, and physiological measures. Of these, the first two have significant drawbacks. Self-reports either interrupt the driving task or depend on retrospective memory. Well established performance measures changes the experiment design, e.g. the ISO standardized Detection Response Task (DRT) add a secondary task and measures the response times to a randomly occurring stimulus. Other performance measures, e.g. lane keeping and steering activity, are strongly influenced by the traffic environment.

Physiological measures, could potentially enable more naturalistic study designs while not affecting the driving task or cognitive state of the driver. For now the physiological signals are measured using electrodes in contact with the body and that may influence the driver behaviour and state. These effects need to be estimated.

Aim

The aim was to use the participants rating to estimate the effect of the measuring equipment during the drive and the effect on participant state.

Method

72 male participants drove for 40 minutes on a two lane 80 km/h rural road in an advanced moving-base simulator. During the drive the participants performed cognitively loading tasks, an easier one (1-back) and a more difficult one (2-back).

The participants were instrumented with an EEG-cap for measuring brain activity (EEG), four face electrodes for eye movements (EOG), four body electrodes for muscle activity (EMG) and two for heart activity (ECG), a chest strap for respiration (RSP) and two finger electrodes for sweating (GSR). The driver’s gaze behaviour was measured by eye-tracking glasses (half of the participants) or by a system mounted in the vehicle cabin (half of the participants). The driving performance variables were measures from the simulator. For the cognitive task the participants had a response button on the finger.

The participants filled in three questionnaires during their visit: background data (e.g. age), before driving (e.g. state right now) and after driving (e.g. Was it difficult to stay awake during the drive? Were you affected by the equipment?). The rating scale was: one – not at all; two – some; three – moderate; four – rather much and five – extremely much.

Equipment and state ratings with a high share of level one rating, moderate share of two, low on three and no share of level four and five were considered as low total effect. For analysis, the distribution of ratings on the scale steps, factor analysis and correlations between variables were used.
Results

Measuring equipment:

In the study the participants rated the EEG-cap (M = 1.4), face electrodes (M = 1.4), finger electrodes (M = 1.3) and chest strap for respiration (M = 1.3) as having a low effect (M < 1.5) on them. The eye-tracking glasses (M = 2.1), the electrical cord from the electrodes and the cap (M = 1.7) and the task response button (M = 1.7) were rated as having moderate effect on participants.

![Figure 4. Examples of distributions of ratings of effect of equipment items, EEG-cap to the left and eye-tracking glasses to the right.](image)

There was no effect of the response button rating on the cognitive task reaction time.

From the questions on driver states the variables were correlating and could be summarized in effort to stay awake, effort to focus and motion sickness.

The states were all positively correlated with each other. The response button rating did not correlate with any driver state. The rating of the eye-tracking glasses however was significantly correlated with the rating of the effort to stay focused but not the effort to stay awake or motion sickness. The glasses were only used by half of the participants but the ratings of the effort to stay focused did not differ between the two conditions (with and without glasses).

Conclusions

In the study the participants generally rated the equipment as having a low effect on them. There were however three items with somewhat higher ratings, the head mounted eye-tracker glasses, the electrical cord from the EEG-cap and electrodes and the task response button on the right index finger, but the driver states did not seem to be affected by these. Even though there was no effect on driver states the three equipment items named above should be improved in future tests.
7. Q6 – Automatic system for online estimations and predictions of cognitive load and sleepiness levels

7.1. EEG artifacts handling in vehicle driver monitoring

| Author names: | Shaibal Barua, Mobyen Uddin Ahmed, Christer Ahlström, Shahina Begum, and Peter Funk |
| Affiliations: | 1Mälardalen University, 2The Swedish National Road and Transport Research Institute (VTI) |

Introduction

Artifact removal is an essential first step in EEG signal analysis. EEG recordings are often contaminated by artifacts caused by eye movements, muscle activity, cardiac activity, power-line coupling, channel noise etc. In a clinical setting, participants can often be instructed to limit their movements, and artifact removal is usually done by the clinician while interpreting the EEG signals. When acquiring EEG signals in a mobile setting, for example when using a brain-computer interface (BCI), or when acquiring EEG data from a driver in a car, the amount of noise and motion artifacts increases. In such a setting, an automated EEG artifacts handling method is necessary for real-time driver state classification based on the EEG.

Aim

The aim of the study is to investigate and develop an automated method for EEG artifacts handling, where the EEG data is acquired in a mobile setting.

Method

Two sets of EEG recordings were used. The first dataset consisted of 19-channel EEG data recorded from 10 participants (male and female, 18 – 50 years old, no neurological or psychiatric disorders) in a controlled lab environment. The participants performed various ocular and muscle movement activities in a controlled manner. The second dataset consisted of 30-channel EEG data recorded from 30 participants (males, 18 – 25 years old, no sleep disorders) while driving in an advanced moving-base driving simulator.
A novel artifact handling algorithm called ARTE (Automated aRTifacts handling in mobile EEG) was developed. ARTE operates in several steps, starting with a 50Hz notch filter to remove channel noise and 2-second epoch generation. Each epoch is decomposed using the wavelet transform and the approximation coefficients are further decomposed with independent component analysis. Tailored features are engineered from the independent components to identify the artifactual components using Hierarchical clustering and Chauvenet’s criterion. Artifactual components are later handled by applying wavelet de-spiking and wavelet denoising.

**Results**

Quantitative measures such as the signal quality index (SQI), the relative error (RE), the normalized root mean square error (NRMSE), and the mean absolute error (MAE) were estimated to evaluate ARTE. Analyses of variance (ANOVA) was used to compare ARTE with a state-of-the-art method called FORCe. The results showed that SQI values are significantly lower after artifact handling ($F(2,7133) = 1766.79, p < 0.001$), and FORCe provides lower SQI values than ARTE. No significant differences were found between ARTE and FORCe in terms of NRMSE ($F(1,19032) = 0.19, p = 0.66$) and MAE ($F(1,19032) = 1.78, p = 0.18$). Significant differences between ARTE and FORCe were observed in the confounding factors region (NRMSE: $F(3,19032)=63.81, p < 0.001$, MAE: $F(3,19032)=38.39, p < 0.001$) and frequency band (NRMSE: $F(3,19032)=285.4, p < 0.001$, MAE: $F(3,19032)=861.24, p < 0.001$). An expert’s evaluation on overall ratings across all channels showed that 83% of the data are fully affected in the recorded EEG signals (meaning that the entire 60-second segment is contaminated by noise), compared to 37% after artifact handling by FORCe and 30% after applying ARTE.

**Conclusions**

An automated method has been developed for artifacts handling of EEG data acquired in mobile settings. The results show that the algorithm significantly reduce the number of artifacts in the recorded EEG signals. An advantage with ARTE is that it is entirely data driven and does not rely on additional reference signals or manually defined thresholds, making it well suited for use in mobile settings where unforeseen and rare artifacts are commonly encountered.

### 7.2. EEG feature selection

<table>
<thead>
<tr>
<th>Authors name: Shaibal Barua¹*, Mobyen Uddin Ahmed¹, Christer Ahlström², Shahina Begum¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>Affiliations: ¹Mälardalen University, ²The Swedish National Road and Transport Research Institute (VTI).</td>
</tr>
<tr>
<td>Reference to publication(s)</td>
</tr>
</tbody>
</table>

**Introduction**

Using a large number of features increases the volume space and makes available data sparse, and consequently, the performance of a classifier drops. In machine learning it is therefore common practice to apply feature selection algorithms to improve prediction performance, to select more cost-effective predictors, and to better understand the relevant factors related to the target variables.

**Aim**

The aim of the study was to investigate feature selection algorithms for reducing redundant and irrelevant EEG features.
Method

Two sets of 30-channel EEG recordings were used. The first dataset, designed to manipulate cognitive load, consisted of 36 male participants driving for 40 minutes on a two lane 80 km/h rural road in an advanced moving-base simulator. The second dataset, designed to manipulate sleepiness, consisted of 30 young male drivers driving repeatedly for 30 minutes on three different types of roads.

In total, 270 features were extracted for the sleepiness dataset for each KSS observation. For the cognitive load dataset, a total of 570 features were extracted. The features consisted of power spectral densities (PSD) in the alpha, theta, beta, delta, and gamma frequency band from each EEG channel. In addition, four more features were extracted, theta plus alpha by beta, alpha by beta, theta plus alpha by alpha plus beta, and theta by beta. For the cognitive load dataset, 300 additional features were extracted based on entropy and statistical measures from each of the 30 EEG channels.

Several feature selection algorithms were compared, LASSO (least absolute shrinkage and selection operator), BSS/WSS, BIRS and Relief. The algorithms were evaluated based on the performance of the selected feature sets when trying to classify sleepiness/cognitive load in the two datasets with a support vector machine (SVM).

For the sleepiness classification, KSS values divided into 3 groups (Group-1: values between 1 and 5; Group 2: values between 6 and 7; and Group 3: values between 8 and 9) were used as target values. For the cognitive load classification, observations were labelled based on whether an additional task (1-back task) was performed or not.

Results

Table 4 show the results from the sleepiness dataset. The selected features are mainly from the frontal, parietal and occipital channels. For the cognitive load dataset, the results are not as promising. The four algorithms reduced the feature vector to between 40 – 60 features. However, the classification accuracy for the hidden exit and intersection scenario is approximately 66 % and for the side wind scenario the accuracy is about 60 %. When using the full feature set, the classification accuracies for the cognitive load dataset are between 38 % and 49 %.

Table 4. Results from feature selection for the sleepiness dataset.

<table>
<thead>
<tr>
<th>Sleepiness classification</th>
<th>LASSO</th>
<th>BSS/WSS</th>
<th>BIRS</th>
<th>Relief</th>
</tr>
</thead>
<tbody>
<tr>
<td># features</td>
<td>86</td>
<td>46</td>
<td>16</td>
<td>46</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>69 %</td>
<td>82 %</td>
<td>75 %</td>
<td>80 %</td>
</tr>
<tr>
<td>Specificity</td>
<td>87 %</td>
<td>90 %</td>
<td>89 %</td>
<td>90 %</td>
</tr>
<tr>
<td>Accuracy</td>
<td>67 %</td>
<td>78 %</td>
<td>72 %</td>
<td>77 %</td>
</tr>
</tbody>
</table>

Conclusions

The main objective of feature selection is to remove irrelevant features and to improve classification performance. For the sleepiness dataset, a great number of features are reduced, but the classification accuracy is about the same as when the full feature set is used. For the cognitive load dataset, there is also a large reduction in the number of features, this time accompanied by an improvement in classification performance.
7.3. EEG signal analysis for cognitive load classification

| Author names (contact person): Shaibal Barua*, Mobyen Uddin Ahmed1, and Shahina Begum1 |
| Affiliations: 1Mälardalen University. |
| Reference to publication(s): |

Introduction

Understanding cognitive load during driving is important since while driving performing cognitively loading secondary tasks, for example talking over the phone, could affect the primary task, i.e. driving. Electroencephalography (EEG) analysis is an indicative measurement to understand level of activation of the brain to distinct stimuli and response. However, different studies have shown that these level of activation changes could vary depending on the study design and type of cognitive load under scrutiny. Here, despite the variations, machine learning algorithms could detect levels of cognitive load since it learns only from the collected data.

Aim

The objective of this research is to investigate time and frequency domain features obtained from EEG signals to classify cognitive load induced through 1-back task during driving.

Method

30 channels EEG signals were recorded from 36 male participants during driving in a driving simulator, where the environment consisted of three reoccurring scenarios (i.e. hidden exit, intersection and side wind). While driving, the participants performed an auditory 1-back task. During the signal pre-processing step, for each scenario, the first 10 seconds of 60 seconds recording were discarded due to unstable signal recordings. From each EEG channel and each segment 14 EEG features were extracted considering both the time and frequency domain. For the Case-based Reasoning (CBR) classification two separate case libraries were constructed for the time and frequency domain features. Each case in the case library was annotated as 1 if 1-back task was performed during events, otherwise 0. To classify cognitive load, a distance based similarity function (Euclidean) was applied to measure similarities between the cases in the case base and target case.

Results

The evaluation has been performed considering the labelled observations i.e., if the 1-back task is performed or not. During the evaluation, a leave-one-out approach was used for selecting the query cases. The classification results consider 3 scenarios: a) individual scenarios, b) mixed scenarios, and c) mixed scenarios with combined features i.e., frequency and time domain features. As can be seen from Table 5, for all the classifications, the obtained overall accuracy is over 70%. Further, in individual scenarios, classification results for hidden exit are slightly better than intersection and side wind scenarios. In mixed scenarios, using only the frequency domain features provides better result (around 80%) compared to individual scenario. However, using time domain features the result (around 74%) is almost same. Further, in Table 6, in mixed scenarios with combined features the overall accuracy is declined compared to that in other scenarios.
Table 5. Classification accuracy of CBR classifier using leave-one-out validation. Separate classifications have been performed for frequency domain and time domain features.

<table>
<thead>
<tr>
<th>Features</th>
<th>Individual scenario</th>
<th>Mixed scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Intersection</td>
<td>Hidden exit</td>
</tr>
<tr>
<td>Frequency</td>
<td>72%</td>
<td>76%</td>
</tr>
<tr>
<td>Time</td>
<td>76%</td>
<td>77%</td>
</tr>
</tbody>
</table>

Table 6. Classification accuracy of CBR classifier using leave-one-out validation. Frequency domain and time domain features are combined for mixed scenarios.

<table>
<thead>
<tr>
<th>Intersection and Hidden exit</th>
<th>All scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>73%</td>
<td>71%</td>
</tr>
</tbody>
</table>

Conclusions

A possible explanation for the relatively poor results could be that the 1-back task didn’t induce a high enough level of cognitive load for it to be measurable using those EEG features. This should be further investigated using another data set with a more cognitively demanding task (2-back). The visual cue scenarios (i.e. hidden exit and intersection) showed better classification results than the side wind scenario. The reason that the mixed scenario with combined features did not show good results might be since it constructs high dimensional feature vectors, which may fall into the trap of ‘curse-of-dimensionality’.

7.4. Sleepiness classification using physiological signals

Author names (contact person*): Shaibal Barua¹*, Mobyen Uddin Ahmed¹, Christer Ahlström², and Shahina Begum¹

Affiliations: ¹Mälardalen University, ²The Swedish National Road and Transport Research Institute (VTI).

Reference to publication(s):

Introduction

Physiological measures have been used as objective indicators of driver sleepiness. For example, an increase in theta power in the EEG is a sign of sleep need and an increase in alpha power has been found to be a robust indicator of sleepiness in a driving setting. Further, longer blink durations have been associated with increasing levels of sleepiness. By applying machine learning techniques, it may be possible to define levels of sleepiness based on patterns in physiological signals.
Aim
The aim of this study is to develop an algorithm that uses EEG and EOG signals to classify the sleepiness level.

Method
Physiological data were recorded from 30 participants while driving three different scenarios in a driving simulator: a rural scenario in daylight, the same scenario but in darkness, and a suburban scenario in daylight. A number of features were extracted from the recorded EEG and EOG signals, the power spectral density in the alpha, theta, beta, delta, and gamma frequency bands, and blink duration from the vertical EOG. In addition, binary features describing contextual information about the driving scenarios (rural/suburban and daylight/darkness) were also included. Subjective sleepiness ratings were chosen as target labels, using KSS values that were divided into 3 groups (Group-1: values between 1 and 5; Group-2: values between 6 and 7; and Group-3: values between 8 and 9). Sleepiness classification was performed using three different classifiers: k-nearest neighbour (kNN), support vector machine (SVM), and case-based reasoning (CBR). Further, both multiclass and binary class classification were performed.

Results
The results are presented based on (i) 10-fold cross-validation, and (ii) leave-one-out (LOO) validation. The classifiers were optimized based on three slightly different target labels: multiclass classification using KSS Groups 1–3, binary classification excluding KSS Group-2, and binary classification using fuzzy centroid distribution (distributing KSS Group-2 between Group-1 and Group-3 based on the feature values). For 10-fold cross validation kNN and SVM show similar results, whereas CBR perform worse, see Table 7. With leave-one-out validation, all three classifiers showed similar results.

Table 7. Classification accuracy for the three different classifiers using 10-fold cross validation and leave-one-out validation.

<table>
<thead>
<tr>
<th></th>
<th>10-fold</th>
<th></th>
<th>Leave-one-out</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>kNN</td>
<td>SVM</td>
<td>CBR</td>
</tr>
<tr>
<td>Multi-class</td>
<td>77 %</td>
<td>80 %</td>
<td>33 %</td>
</tr>
<tr>
<td>Binary</td>
<td>93 %</td>
<td>94 %</td>
<td>54 %</td>
</tr>
<tr>
<td>Fuzzy centroid</td>
<td>88 %</td>
<td>89 %</td>
<td>52 %</td>
</tr>
</tbody>
</table>

Conclusions
Our experiments show that it is difficult to correctly classify KSS group 2. This is evident from the multi-class results, and particularly from the large increase in performance when shifting to binary classification. This could be either because it is difficult to accurately rate the sleepiness level in the transition phase between awake and severely sleepy, or because the selected features are unable to distinguish these rather subtle differences in sleepiness level. This needs further investigations.
8. Discussion

The VDM project aimed to find methods to measure (focusing on using physiological indicators) two important factors behind vehicle crashes, driver sleepiness and cognitive distraction, and to study their effects on driver behaviour. Based on the research questions, the project findings are discussed below.

8.1. Physiological measures

Several physiological measures have been demonstrated to correlate with sleepiness and/or cognitive load in our studies as well as in other’s (e.g. Brookhuis and de Waard, 2010, Mehler et al., 2012). On a group-level, differences between (at least well separated) levels of sleepiness or cognitive load are highly significant. However, sleepiness and cognitive load are not isolated states. Instead they affect, and are affected by each other as well as by other states such as stress, emotions and arousal. Therefore, physiological responses seen during especially increased cognitive load are often caused by other “state changes”, rather than the increased cognitive activity as such. This was for example seen in heart rate and skin conductance, measures which have shown to correlate with cognitive load in numerous studies (Mehler et al., 2012, Reimer and Mehler, 2011), but whose effect of the cognitive task declined with task repetitions, although the task demand remained.

One way out of this is to try to find more direct measures of the driver state of interest, in our case sleepiness and cognitive load, respectively. This was attempted using EEG measures, but results from primarily lab experiments, i.e. non-applied settings (Gevins and Smith, 2003, Mitchell et al., 2008, Scharinger et al., 2017) proved hard to replicate in a driving context. In the VDM project, expected effects of cognitive load on alpha and theta power was not found when comparing one minute time segments of driving with and without the cognitively loading task. This might seem discouraging, but we have also seen changes in e.g. alpha and theta power related to task responses, as well as to driving manoeuvres. By analysing EEG signals with other methods, which take advantage of their high time resolution, it may be possible to achieve a greater understanding of the dynamic interplay between the driving task and the cognitively loading distraction task. We then need to go from viewing cognitive load as a steady state condition during e.g. a one minute segment of task execution, to look at shorter changes in brain activity from the driving task, the cognitive task, and their interaction. For example, phase shifts in EEG frequencies might reflect cognitive activities (Hanslmayr et al., 2007). This is a relatively unexplored area which requires more research.

Driver sleepiness is a state which changes more slowly and the need for methods with higher time resolution is not as critical. However, if brain connectivity is pursued further, it will be necessary to measure the connectivity per se with high time resolution. In this project physiological measurements have been based on EEG measurements in 30 channels. The results show that under high levels of self-reported sleepiness (KSS 9), local changes in source localised EEG can be seen in the form of increased theta content (5 - 9 Hz) in motor-related parts of the brain. However, increased theta content in motor-related parts of the brain cannot be used as a true value for dangerous sleepiness in general. The procedure should be considered as a means to explain the reason for the line crossing provided that you already know that the driver is sleepy, not as a method for sleepiness detection. Like other physiological indicators, a certain outcome may be due to several different underlying factors. This approach is applicable in test-like situations in simulators and perhaps in field studies, but probably not in naturalistic conditions.

In this project, we only considered brain connectivity on a larger time scale, and were not able to find any clear relationship with sleepiness. A shorter time scale will obviously allow us to investigate brain connectivity dynamically over time, but such an approach will also be more demanding in terms of analysis. A challenging next step would therefore be to quantify the meaning of sequences of connectivity patterns and to see how these patterns vary over time, as a function of the sleepiness level. This is also an unexplored area that needs further research.
Another useful approach might be to focus on measuring changes, caused by e.g. sleepiness or cognitive load, which have actual effects on drivers’ abilities to drive safely. The VDM results suggest that with the P1 amplitude of the eye fixation related potential one might be able to discover changes in drivers’ visual attention (Itoh et al., 2006). Such a measure would facilitate research on the effects of visual attention on driver performance, as well as on what factors influence visual attention. More work is however needed to improve the P1 feature extraction and to validate its relation to visual attention. No effects of cognitive load on the P1 amplitude was found, possibly indicating that the drivers did not compromise their visual attention during task execution.

8.2. Driver state and levels of impaired driving performance

To look for effects of cognitive distraction on driving performance, the cognitive control hypothesis was used (Engström et al., 2017). It states that cognitive load only affects performance in tasks which rely on cognitive control (i.e. inconsistent or novel tasks), but not in tasks with automatized responses. Received results support this hypothesis. Cognitively controlled gaze behaviour, namely looking towards potential, but not salient, threats (a hidden exit and a car approaching from the right) was negatively affected by cognitive load, while automatized brake responses triggered by strong looming cues were unaffected.

Although the cognitive control hypothesis needs further verification in other driving scenarios, as well as other cognitive tasks, the current results help in understanding the effects of cognitive load on driving performance. It is evident that the driving task needs to be taken into careful consideration when interpreting study results, something that is often overlooked. The fact that the effects of cognitive load in controlled experiments and in naturalistic driving studies often differ is most likely (to some extent) explained by this notion. Even though cognitive load increases response times in alert drivers in anticipated events, e.g. repeated lead vehicle braking events and artificial response tasks, as shown in numerous studies (Bruyas and Dumont, 2013, Salvucci and Beldowska, 2008, Strayer et al., 2013, Victor et al., 2015) this effect of cognitive load doesn’t appear to increase the risk of rear end crashes in real life driving (Victor et al., 2015). The automatically triggered response to looming appears to make most drivers (which have their eyes on the road), regardless if they are cognitively loaded or not, brake in time to avoid rear end collisions. This explains the role of cognitive load on the operational level. Whether cognitive load lead to more (unnecessary) critical events, due to reduced abilities to react to cognitive cues in the traffic environment or to plan ahead on the tactical level, deserves further investigation.

Line crossings, here defined as when at least half the vehicle is outside the lane, is a strong indicator of an upcoming crash, especially when combined with high levels of sleepiness. In the VDM studies, several approaches were used to understand when and why driver sleepiness turned out to be a safety critical state. The results indicate a relationship between line crossings at high levels of self-reported sleepiness and increased local theta activity in motor related brain regions. We have also confirmed the previously reported results that the number of line crossings increase exponentially with increasing levels of KSS, but also that line crossings are sensitive to inter and intra individual differences.

8.3. Differences within and between individuals

It is well known that driver sleepiness detection needs to consider individual differences (Ingre et al., 2006b, Van Dongen et al., 2007). However, the reason for this is not fully known. In the VDM project we investigated differences between groups of drivers, in this case professional drivers versus non-professional drivers. The results showed that professional drivers had more line crossings and longer blink durations than non-professional drivers, despite lower KSS ratings. This indicates that it is not possible to learn to drive in a safe manner while being sleepy. We not only found differences between groups of drivers, but also within individuals from time to time even though they were prepared in the same way and drove the same type of scenarios at the same time of the day. Together, these findings
show the importance of contextual information and personalized systems when designing driver support systems. It may also indicate why it is sometimes difficult to generalize results from studies based on only one repetition of the experiment. Whether these results are possible to generalize to real-road settings and to more experienced professionals needs further investigation.

8.4. Contribution of contextual factors

In most driver sleepiness and cognitive load experiments, contextual factors are either excluded (i.e. the study is designed so that the factor doesn’t vary) or ignored. The knowledge about how different contextual factors influence the level of sleepiness and cognitive load is hence limited and deserves further attention. The results from VDM, as well as other studies (Baldwin and Coyne, 2003, Itoh et al., 2006, Stuiver et al., 2014) show that numerous contextual factors have large effects on driver behaviours, experiences and physiological responses. To be able to interpret study results in a larger context, increased knowledge about the influences of different contextual factors is necessary.

One of the factors studied in VDM was the effect of daylight versus darkness on driver sleepiness. It was found that darkness affected physiological responses, as well as experienced sleepiness, in the same direction as sleep deprivation. There was however no main effect on the number of line crossings. Line crossings was shown to correlate with local sleep in motor cortex (section 2.1), and line crossings are often interpreted as crash risk indicator (Fairclough and Graham, 1999, Hallvig et al., 2014a, Otmani et al., 2005, Åkerstedt et al., 2005a). Does this mean that the level of sleepiness, assessed using physiological or driver experience measures have different meanings in a risk perspective depending on if the measures were taken in daylight or darkness? Further research is needed to answer this question.

While the number of line crossings were unaffected by the daylight/darkness, it was affected by the environment (suburban vs. rural driving environment) just as much as by sleep deprivation. Much of the effect is probably due to the surrounding environment and not due to the rural or suburban environments per se, but to details enclosed in these environments. Micro-corrections of the lateral position were affected by the sight distance, the presence of forestry, and the curviness of the road, and this dependence on road geometry and road furniture can also be seen for the number of line crossings. It has been suggested that driver sleepiness is not as common when driving in the city because the more stimulating environment has an alerting effect (Horne and Reyner, 1999a). Our results indicate that a winding rural road that requires continuous micro-corrections to be able to stay in the lane may be even more stimulating than a suburban environment. It will be important to carry out additional experiments with several highly-controlled environments. As a start, it would be important to control the road curvature in a systematic manner.

The cognitive control hypothesis (Engström et al., 2017), which we found support for in our results, states the importance of driving context in the sense of to which extent the driving task is automatized. This implies that results found in a certain context doesn’t necessarily hold if this context changes. For example, while we found no effects of cognitive load on brake response times, the results would most likely have been different if the drivers would have been able to foresee that the car in front could brake. For example, if it would have happened before (Lee et al., 2001, Strayer et al., 2013, Strayer et al., 2003, Engström et al., 2010), or if there would have been some kind of cues in the traffic environment indicating that the car would brake, as in Muttart et al. (2007). Also, the side wind scenario studied in VDM was replicated from a previous study by Medeiros-Ward et al. (2014), although implemented in a different driving simulator (a more advanced moving-base simulator instead of a fixed-base simulator) and in a different traffic environment (rural road driving instead of a three lane highway), and the results were fundamentally different. While Medeiros-Ward et al. (2014) found a reversed effect of cognitive load in the scenario with side wind as compared to without side wind, no such effect was found in our study.
8.5. Automatic system for prediction of driver state

The results from cognitive load classification reached an accuracy of about 80% when distinguishing the 1-back task from no task. Corresponding results from the binary classification of alert versus sleepy drivers reached an accuracy of about 90%. Given the overlapping nature of the features, it would have been interesting to test how the developed cognitive load classifier and sleepiness classifier would perform on a dataset with overlapping driver states. Also, to get a better picture of the mental state as a whole, one can acknowledge that mental states aren’t isolated and classify multiple driver states in the same data set and possibly at the same time. E.g. allow drivers to be classified as both cognitively loaded and stressed at the same time. The results from the physiological responses to the cognitive task speaks in favour of this approach and machine learning methods may be useful if one has large amounts of labelled data to work with.

As mentioned, several studies have found large individual differences in the susceptibility to driver sleepiness (Ingre et al., 2006b, Van Dongen et al., 2004b). When designing systems for driver state monitoring, there are essentially two ways to go. Either the system itself is tailored to a particular individual (given that many cars are now connected to the cloud, this is not as far reaching as it would have been just a year ago), or new indicators that are more robust to individual differences needs to be found.

One of the most prominent results of this project is that contextual information is of great importance. Given a large enough dataset of labelled data, there are no practical difficulties in incorporating contextual information in the machine learning framework. Here, the contextual information was limited to what was included in the scenario design (rural/suburban and daylight/darkness), in combination with the sleep/wake predictor model of sleepiness. Finding the relevant contextual parameters is a greater challenge than accounting for them in the classification algorithm. Another very interesting source of contextual information are the smart watches and fitness wristbands that are gaining popularity. This would not only give access to physiological data in a rather unobtrusive manner, it would also provide data about what the driver is doing when outside the vehicle.

To get most accurate outcomes by using machine learning it is of great importance to ensure the quality of data (Hulse, 2007). The challenge is to ensure the quality of physiological signals acquired in naturalistic and mobile settings. Automated tools for EEG, and other signals’, artifacts handling are thus needed. One such tool was developed within the project.

The sleep/wake predictor, based on time of day, the time since awakening and the duration of prior sleep, has previously been used as an input for sleepiness classification (Sandberg et al., 2011, Ahlstrom et al., 2013), and here it is shown once again how valuable this feature is. The downside of the sleep/wake predictor is that it works great on a population level, but not so well on an individual level. Another limitation is that the predictor does not take time on task into account. This is where machine learning has an important role to play. By adding physiological measures, the idea is to personalize/customize the sleep/wake predictor to the present situation. It would also be interesting to design a cognitive load predictor, based on the continuously changing traffic situation outside the vehicle as well as on the additional tasks carried out by the driver. The minimum required attention framework (Kircher and Ahlstrom, 2016) or the ideas on the dynamics of distraction (Lee, 2014) could be used as a starting point when constructing such a model. Again, machine learning could be used to personalize/customize the model to better fit the current situation and the current driver.

Within VDM, case based reasoning has been the main focus among the machine learning methods. Comparisons have been made against support vector machines and k-nearest neighbour classifiers.
**Limitations**

The studies involved suffers from several limitations. Context have proven to be very important, and we use a simulator. In other words, our context is not real driving, the participants are in a study and we don’t know what results would hold in real driving. Based on this understanding there are several limitations to handle. Most of them were known from the beginning, but we chose to use a simulator in order to have a high degree of control and thus have a better chance to understand more about the driver and his brain. The next step is to see if this is also measurable under real road conditions.

To avoid confounding effects the selected group of participants were a quite homogenous group and we don’t know if the results hold for other groups. In future studies, we also need to include a wider range of participants covering for example females and participants in different ages.

Another limitation is that during the experiments, there were major problems with the equipment, with a consequence that drivers sometimes had to wait for a long time before driving. This for sure decreased their alertness and their performance. The inter individual differences might to some degree be explained by this, however the results do not support that they are for example most sleepy at the first visits when we faced most of the problems. In addition, there is always a risk that participants are influenced by the measuring equipment. When asking them about their experience they did not report that this was a major problem. They only had minor complains about the cables for the EEG and the eye-tracking glasses. In future studies, unobtrusive sensors should be used if possible.
9. Conclusions and further research

Much new knowledge and novel insights have been gained in the VDM project. The key conclusions are that multiple measures (physiological and other) should be evaluated together to estimate driver states, and that context is crucial and has a great impact on driver behaviours, measures and experiences. Context can hence not be disregarded in neither design nor interpretation of studies on driver states such as cognitive load and sleepiness. This was evident in all results.

We found support for the newly formulated Cognitive Control Hypothesis (Engström et al., 2017) in several traffic scenarios. The hypothesis state that cognitive load only has an effect on task behaviours which requires cognitive control (new or inconsistent tasks), but not in tasks with automatized responses (consistent and extensively practiced tasks). We also explored the effects of several different contextual factors on driver sleepiness and found that darkness is an additive factor contributing to effects in several sleepiness indicators but not line crossings, that professional drivers report lower levels of sleepiness even though the more objective indicators indicate that they are actually more sleepy than non-professional drivers, and that there are differences in experienced sleepiness level and driver performance between repeated experimental trials. This show that it is essential to keep track of “other” factors in order to better understand the sleepiness indicators we already have. The results hence emphasize the necessity to take the driving task and overall context into account when discussing effects of cognitive distraction or sleepiness, and to be cautious when generalizing results from one context to another. This should also be kept in mind when designing and evaluating driver support systems, so that they are optimized for the situations where they are most needed.

In our search for physiological measures of cognitive load and sleepiness we made some promising findings and concluded on future paths worth exploring. We found significant effects of cognitive load as well as of sleepiness in several physiological measures. No measure was sensitive to only cognitive load or sleepiness, but different measures were sensitive to different contextual factors (individual and environmental). This is true for physiological as well as behavioural measures. Taking advantage of the measures’ similarities and differences one can hence improve the assessment of the driver state. Based on the results we suggest using physiological measures together with more commonly used behavioural measures in studies, experimental as well as naturalistic, where driver behaviour and/or experience is relevant in order to better interpret results. Using e.g. heart rate, blink duration, pupil diameter and steering wheel reversal rate one can get an understanding of the driver state and how it is affected by the experiment and how it changes over time. The measures usefulness was evident in the study in chapter 3.3 where no effects of an unpredictable side wind could be seen on the driver behaviour. This could be explained by an increased effort invested by the drivers in order to preserve their performance, had it not been for the physiological measures showing that neither the drivers’ arousal level nor cognitive effort changed in the windy condition. Using physiological measures in commercial products is less mature. Besides the obvious requirement of unobtrusive and reliable monitoring, machine learning algorithms should be trained with large amounts of multi-classified data (allowing different driver states to overlap) from several physiological, behavioural and environmental measures.

To measure cognitive load and sleepiness closer to the source, we used EEG measures. In our sleepiness research, we explored the recently discovered phenomenon local sleep and found a relation between local sleep and lane departures. For cognitive load, we used traditional EEG frequency power measures. There are plenty of support for those measures in the literature (from lab experiments in highly controlled and artificial settings), but they turned out to be unsuitable in the more complex car driving setting. Our results indicate that it has to do with the cognitive demand imposed by the driving task, and the fact that cognitive distraction is not a static state, but rather a dynamic interplay between the driving task and the distraction task. Although EEG is not technically available in commercial vehicles in the near future it has unique research possibilities due to its high time resolution. It could
thus help in understanding cognitive distraction and sleepiness and their interplay with the driving task.

Based on the results, the following topics for future research and next steps are proposed:

- To further increase the understanding of contextual factors and how they influence driver behaviours, measures and experiences.

- To further increase the understanding of the effect of cognitive distraction on driving, especially when it comes to the dynamic interaction between driving and the distraction task.

- Further validate the Cognitive Control Hypothesis with other groups of participants, tasks and scenarios. Also define a method to decide to what degree a task is automatized in order to predict the effect of cognitive distraction.

- Implement physiological measures in driver behaviour experiments to improve the possibility to interpret the behavioural changes both during manual and automated driving.

- Perform analyses of EEG signals using the high time resolution to explore the dynamic nature of cognitive distraction.

- Investigate how the flow of information between brain regions (on the electrode level or on the source level) change with increased sleepiness (KSS). The information flow should be analysed with high time resolution, and the relation with sleepiness should be investigated in terms of changed dynamics in the sequences and patterns of information flow.

- Investigate higher frequency bands of the EOG signal to check for tension in the eyes when struggling to stay awake. This will only work in darkness, since sunlight will affect muscle tension. It would also be worth pursuing how patterns and sequences of blinks/eye movements, rather than isolated events such as the blink duration, change with sleepiness.

- To include video based pattern recognition of emotion, stress and/or sleepiness in order to move towards unobtrusive measures and new combined indicators.

- To also look at other driver states that might influence the already identified indicators, such as rest (for automation), motion sickness (for automation), happiness and boredom.

- To investigate how “by-products” of automation, such as more efficient use of time and more travelling, affect driver state.

- Use machine learning to train automatic driver state classifiers based on large amounts of data with multiple concurrent driver states to be able to simultaneously classify several states and also combinations of states.
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