Timely Constraints of EEG in Cognitive Distraction and Focus Detection while Driving

Emil Riis Hansen, Mikkel B. Kristensen, Eike Schneiders
Department of Computer Science Aalborg University
Selma Lagerløfs Vej 300, 9220 Aalborg Ø
{erha13, mikris13, eschne13}@student.aau.dk

ABSTRACT

Previous studies have shown that it is possible to distinguish cognitive distraction from cognitive focus using electroencephalography (EEG).However, there is still a lack on research regarding the possibility to distinguish cognitive distraction from cognitive focus over time. We create Animus, a system to distinguish between cognitive distraction and focus of drivers. Using a driving simulator, we collected EEG data from 8 subjects over the course of 2 days with 7 days between. When training and evaluating Animus on data for one day, Animus achieved an average classification accuracy over all subjects of 98.01%. When training on data from day 1, and evaluating on data from day 2, Animus achieved an average accuracy of 77.95%. These results suggest that brain waves are consistent enough over time, for Animus to distinguish between cognitive distraction and focus on future days. To identify the impact of the EEG helmets placement, we performed a second experiment. Two driving sessions were performed, one where the helmet was reattached, and one where it stayed on. Reattachment of the helmet reduced the classification accuracy from 84.06% to 77.11%. This implies that the placement of the EEG helmet impacts the classification accuracy.

Author Keywords

Electroencephalography, Cognitive Distraction, Cognitive Focus

INTRODUCTION

According to the World Health Organization, traffic accidents are a leading cause of death, and the main cause of deaths among people aged 15-29. Worldwide this amounted to 1.4 million deaths due to vehicle crashes in 2016 [19]. Furthermore, it is estimated that 25% of road accidents are due to driver distraction [23]. Driver distraction can broadly be divided into visual, physical and cognitive distraction. Visual distraction occurs when the driver gazes at task unrelated stimuli. Among such stimuli are humans, as well as technology like mobile phones, GPS, and radios. Physical distraction occurs when the driver removes his hands from the steering wheel, in order to interact with his surroundings. Cognitive distraction is a mental state, where even though the drivers gaze is directed towards the road, attention is drawn towards

Figure 1: The driving simulator in use. Simulator setup, 32" main screen, 23" side screens. We used the Thrustmaster T80 steering wheel and pedals.

thoughts unrelated to the task of driving [1]. Distraction can either appear due to external sensory stimuli, like sound or touch, or by internally generated thoughts.

Since approximately 25% of road accidents are due to driver distraction [23], the detection of such is an important field of study. The ability to detect distraction can be used to create in vehicle applications to diminish the number of car crashes due to driver distraction. During this study, we will investigate driver distraction due to cognitive distraction. Cognitive distraction has previously been identified using eye movement, head movement, blink frequency, heart rate, driver temperature at the tip of the nose and EEG [36].

Alizadeh and Dehzangi [1] as well as Sonnleitner et al. [27] have been using EEG data to create systems for the detection of cognitive distraction in drivers. Their systems are trained and evaluated on data measured on the same day. However, to the best of our knowledge, it has not yet been investigated whether EEG data from one day, can be used to create a system for cognitive distraction detection in drivers, which also works on future days. Furthermore, there is a lack of HCI research regarding distraction detection using EEG. An objective approach to detect when a driver is distracted could be used to investigate whether new technologies in the car, demand to much attention, and thereby distract the driver from their primary task. This approach is not limited to technologies regarding driving, but could be extended to other HCI research, such as attention in learning or UX testing.

During this study we will investigate whether EEG signals can be used to distinguish between cognitive distraction and focus, when driving in a driving simulator. Furthermore, we will investigate whether EEG signals are consistent over time, to a degree where cognitive distraction and focus brain waves from one day, can be used to distinguish between cognitive distraction and focus brain waves from a future day. Due to high variability in brain waves between subjects, both research questions will be investigated using a subject dependent system[6].

This paper is structured as follows: We will start by introducing related work within the field. Afterwards we will describe the system we created for measuring and investigating brain waves, using EEG. We then describe the two experiments we conducted, and the results we got from each of them. This is followed by a discussion and limitations and future work. Lastly we conclusion on the study.

RELATED WORK

In order to achieve a better understanding of the research field of cognitive distraction detection while driving, we assessed the literature within the field.

This section will outline the current literature in the field of cognitive distraction. This will include research on distraction detection, how EEG can be used to detect distraction, and how to elicit cognitive distraction and cognitive focus.

Distraction Detection

Current research has a been investigating several approaches on how to identify cognitive distraction. These include vision-based methods, skin temperature, as well as steering angle and driving speed of the car[30, 35, 8]. An additional branch of research is the identification of the effect cognitive distraction has on driving behaviour as well as how to intervene through notifications if cognitive distraction is detected[12, 25, 31, 30]. Lee and Hayes [12] examine different alert strategies for the mitigation of driver distraction. They herein add knowledge to the field of safety critical applications in driving. Dario D. Salvucci [25] uses computational cognitive models to investigate and predict what effect the performance of a secondary task has on a drivers interaction with surrounding vehicles. Such a study can be used in the development of evaluation tools for user interfaces in complex domains. Trbovich and Harbluk [31] investigates how the visual behaviour of a driver changes, while eliciting cognitive distraction by letting the driver interact with a speech based hands-free cell phone system. They find that such distraction sources might contribute to intersection crashes. This contributes to the importance of guidelines and systems for cognitive distraction detection and alleviation while driving. Tchankue et al. [30] create an adaptive prototype in-car communication system to diminish cognitive distraction while driving. They make use of driving speed and steering wheel angle to detect the current distraction level of a driver. This is used to decide when a user should be allowed to receive calls and send text messages. The results show that such a system provide usability and safety benefits while driving, and reduces cognitive distraction. Wesley et al. [35] identify cognitive distraction, by measuring the thermal signature of the face of the driver. They find the changes in thermal signature while cognitive distracted to be measurable. Fridman et al. [8] develop two vision-based methods in order to identify cognitive load while driving. They use video recording of a driver in order to identify the current pupil position. Based on their findings, they conclude that it is possible to identify cognitive load while driving.

Distraction Detection using EEG

Correlations have been found between EEG signals and the distinction of cognitive distraction from focus, which enables the development of an automatic distraction detection systems. Wang et al. [33] create a support vector machine based system using EEG signals, to distinguish cognitive distraction from focus of drivers in a dual task experiment of lane keeping and solving math problems. They achieve 86.2 and 84.5 classification accuracy for driving and math solving respectively. Almahasneh et al. [3] examine how EEG signals change, when a driver is presented with different cognitive secondary tasks. They found that different secondary tasks had different effects on EEG responses, and different locations on the cortex. However, the most affected area during distraction was the right and left frontal cortex region. This suggests that these areas should be investigated, when working with driver cognitive distraction.

Several EEG features have been proposed, in order to distinguish cognitive distraction from focus. Braboszcz and Delorme [7] found an increase in θ and δ frequency bands, and a decrease in α and β frequency bands, during cognitive distraction. Almahasneh et al. [3] found a change in the θ, α and β frequency bands of EEG signals between different cognitive states. Alizadeh and Dehzangi [1] investigate several EEG related features for the distinction of multiple distraction sources while driving. Among others they investigate the higuchi fractal dimension, band power and discrete wavelet transform features. They find discrete wavelet transform to be especially well suited for the distinction of different cognitive states2.

Cognitive Distraction Elicitation

Cognitive distraction is a mental state, where a person is mentally engaged in a secondary task. This can happen when attention is directed towards internal states, such as feelings, thought processes, memories, or during highly over-learned tasks [14, 36]. Cognitive distraction can also be enforced by engaging subjects in a secondary mental task, called elicitation. A multitude of secondary mental tasks have already been studied, with the primary task being driving. Among studied tasks are, using audio books[27], conversations with a passenger, answering of questions[11], speech-to-text, hand-held phone communication[28], mathematical questions [3, 33] and logical decision making [3]. Sonnleitner et al. [27] elicit cognitive distraction by letting participants listen to an audio book while driving, and have them respond every time a specific word is spoken. Jin et al. [11] differentiate between three states of cognitive distraction, high, low and no cognitive distraction. Low cognitive distraction was elicited by having the test subject talk with a researcher. High cognitive distraction was elicited by having the participant answer intelligent test questions given from a researcher. Strayer et al. [28] experiment with eight different distraction tasks in order to identify to what extend they affect the drivers reaction time. In addition to rating the eight different tasks according to most increase in reaction time Strayer et al. used the NASA Task Load Index to rate the eight different tasks according to Workload Rating.

ANIMUS

We created Animus (Latin for "Mind"), a system for measuring EEG signals and distinguishing cognitive distraction from focus. This section will start by describing the hardware used in order to measure EEG data. Afterwards we describe the software components of Animus. The system is illustrated in Figure 3, and will be referenced in this section.

Hardware

EEG is a measure of electrical current from the brain, measured on the scalp of the head. Different regions of the scalp therefore provide information from different parts of the brain. For this study we made use of the OpenBCI Ultracortex Mark IV 3D printed helmet (Mark IV), and the OpenBCI Ganglion biological sensing device[18]. Mark IV can target 35 electrode locations of the 10-20 sensor placement standard. The OpenBCI Ganglion biological sensing device can target 4 locations at a time, has a sampling rate of 200 Hz, and uses ear clips for reference signals. The 200 Hz sampling rate is the upper bound and might be lower during recording. The electrode locations the Mark IV can target, can be seen in Figure 2 as grey and green locations. The reference sensors A1 and A2 are marked as yellow in Figure 2. Almahasneh et al. identified an increase in brain activity in the frontal lobe during distraction [3]. We therefore chose the location F3 and F4, which are part of the right and left frontal lobe respectively, to be part of our sensor locations. C3 and C4 where chosen based on the Ibáñez and Iglesias [10], who identified their importance when it comes to cognitive distractions. Our chosen sensors can be seen in Figure 2 as marked with green.

Software

Animus consist of two components, a illustration of Animus can be seen in Figure 3. Component A, the data measuring component, and component B, the classification component.

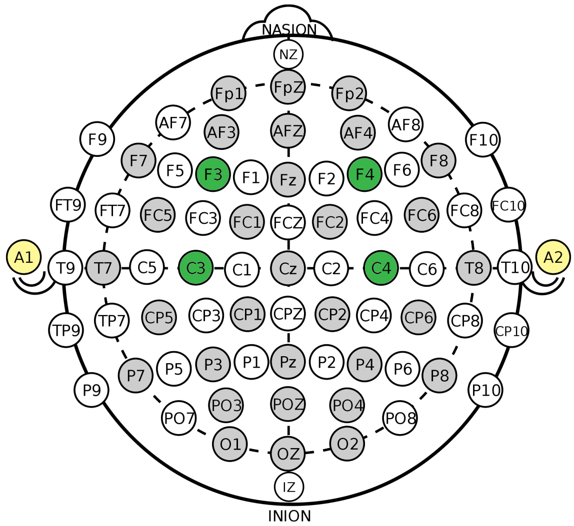

Figure 2: Electrode placement names according to the 10-20 system as depicted on the scalp of a person. **Grey** and **Green** colouring indicates electrode locations which can be targeted by the Mark IV headset. **Green** indicates our chosen sensor locations for measuring of EEG signals. **Yellow** indicates the positioning of the two reference sensors. **White** sensors are part of the 10-20 system but not supported by the Mark IV.

Component A is responsible for the measuring and storing of EEG data, as well as the transformation into the right format for the classification component. Component B starts by cleaning the data, followed by a classification based on the selected features. All elements of Animus will be described here.

Data measuring & storing

The first element of Animus makes use of the Mark IV headset in order to measure EEG data from the four sensors locations, F3, F4, C3, and C4, as illustrated in Figure 2. The data is measured with a sampling rate of up to 200Hz, which is then stored in a database.

The output of this element is a populated database containing measurements for the four sensors.

Segmentation & Splitting

To identify when EEG data can be used to distinguish between driver cognitive distraction and focus, we segment and split the data from the database into multiple splits. We adopted the term data splits from machine learning. Each such split is subject dependent, which means that we never combine data for multiple subjects.

We first segment the raw EEG data for each subject into 2 second time windows[1] with no overlap. A system for driver distraction detection used in safety critical applications, should within small periods of time be able to determine whether a person is cognitively distracted or

Figure 3: Ⓐ: Data Measuring component, the first component of Animus used for measuring and storing EEG signals as well as segmentation and splitting. Ⓑ: Classification component, the second component of Animus used for signal cleaning, feature extraction and selection as well as classification.
① : Raw segmented EEG data splitted into training, validation and evaluation data. ②: Features chosen for each 2 second time windows. ③: n best features chosen by greedy feature selection.

not. We therefore find a 2 second window to be adequate for such applications. The step is used to create several sub sets of data, each with a specific purpose. A split consist of three parts, training data, validation data and evaluation data. The training data is used in order to train a classifier, validation data is used to optimize features, and evaluation data is used to evaluate the performance of the trained classifier[24].

After data segmentation and splitting, the output of component A, which is a segmented split, is used as input for component B of Animus as illustrated with ① in Figure 3.

Cleaning & Feature Extraction

Cleaning is the process of removing noise from data. One form of noise could be externally produced noise like power line interference[32]. In some application areas, predictive models can be trained directly on raw data. This has successfully been done for systems trained on raw EEG data [17]. EEG data does however have a small signal-to-noise ratio, which might lead to a classifier overfitting on the noise in the data[15]. The noise can be reduced by introducing filters for data cleaning, as well as computing features from the EEG time windows, which provide discriminative information for the specific time window. To remove noise we made use of a high-pass filter and a notch filter.

After applied filters, we computed features for each time window. Braboszcz and Delorme [7] found an increase in θ and δ frequency bands, and a decrease in α and β frequency bands, during cognitive distraction. This suggests that band power and band power ratios of an EEG signal, can be used to distinguish cognitive distraction from cognitive focus. We therefore computed the features Higuchi Fractal Dimension, Petrosian Fractal Dimension, Band Power Ratio and Discrete Wavelet Transform. These features have all previously with success been used in the domain of EEG data in the discrimination of different secondary tasks while driving [29, 1, 2, 33]. For the extraction of Higuchi Fractal Dimension, Petrosian Fractal Dimension and the Band Power Ratio features we use the python library PyEEG as described in [5]. For the extraction of Discrete Wavelet Transform features, we use the python library PyWavelets as described in [34]. We used the highpass and notch filter implementations from the Scipy python library.

The output of this element, corresponding to arrow ② in Figure 3, are the features computed for each cleaned time window.

Feature Selection

A classifier needs training data to learn how to distinguish between cognitive distraction and cognitive focus time windows. Training data is in the form of feature vectors. Instead of using all extracted features, one usually selects the n most informative features. This is called feature selection. In Animus n was chosen to be 5. We use a greedy feature selection method, where each individual feature is used to train a classifier on the training data of the split, and validates the classifier using the validation data of the split. We then select the 5 features for which the classifier gave the best classification accuracy on the validation data.

The output of this element, corresponding to arrow ③ in Figure 3, are vectors of the greedily best found n features, one vector for each time window.

Classifier

To understand how well a given split performs, Animus needs to train and evaluate a specific classifier on the training data, and evaluate with the evaluation data. We here chose to make use of a Random Forest Classifier, since it has previously with success been used to distinguish cognitive distraction from focus while driving [1]. Our approach for combining features as well as majority voting was performed, as described by Pioa et al. [21]. We create all possible sets of 3 features from the best found 5 features as extracted in the *feature selection* element. This amounts to 10 sets of features. Animus trains a Random Forest Classifier for each such set, and use a majority voting system on the 10 classifiers to classify each evaluation sample as either being cognitive distraction or focus.

EXPERIMENT A: BETWEEN DAY DISTRACTION AND FOCUS DETECTION

This section will describe experiment A. The goal of this experiment will be to identify to what extend it is possible to distinguish cognitive distraction from focus. Furthermore, we will investigate how consistent brain waves are over the span of 7 days. The experiment consist of 2 driving sessions with approximately 7 days between each session for each test subject.

In order to test the experimental setup, we conducted several pilot tests. Through pilot testing we optimized the driving simulator based on the findings. Among the most important optimizations was the decision to visualize the directional instructions, by displaying arrows on the cars dashboard, instead of the initial audio command. Furthermore, we chose the used cognitive distraction and focus elicitation methods, as described in the "Cognitive Distraction and Focus" section. identified the cognitive distraction elicitation method to be used.

Participants

8 people participated in our experiment (3 females; age between 21 and 55, mean = 31, sd = 13.9). Participants where recruited using social media, banners as well as mouth-to-mouth. All participants were unpaid. The participants have had their drivers license for between 3 to 38 years (mean = 13.1, sd = 14.5), and drive between 2500 to 60000 kilometres per year (mean = 21750, sd = 18704). Five participants had no prior experience with driving simulators or games, the last three had experience with driving games but not driving simulators. All participants were required to have a legal drivers license. The participants were not informed on the purpose of the experiment.

Two additional participants were excluded after the first driving session. One test subject was unable to comply to the given task. One test subject experienced Simulator Adaption Syndrome during the first session and had to cancel the experiment[9]. This left us with a total of eight test subjects for experiment A.

Cognitive Distraction and Focus

Within the field of cognitive distraction elicitation while driving, a multitude of methods have been proposed. Among others are listening to the radio, solving mathematical equations, listening to audio books and the usage of hand-held devices[28, 27, 33]. When it comes to the elicitation of cognitive focus, a broader consensus exists. Jin et al. [11] propose the use of no secondary task. Lin et al. [14] come to the conclusion that deprivation of sensory stimuli while driving increases the likelihood of the driver to lose focus from the road.

We used approaches presented by Lin et al. [14] and Sonnleitner et al. [27] for the elicitation of Cognitive Focus (Focus) and Cognitive Distraction (Distraction) respectively.

Based on Lin et al. findings, we designed our driving simulator environment in order to increase the amount of sensory stimulus, and thereby increasing the demand for focus on the road. For the elicitation of Focus, we designed a driving environment, see Figure 4, which both contained city environment, with a speed limit of 50 km/h, as well as country road, with a speed limit of 80 km/h. Several AI cars occupied the environment in order to bring dynamic elements into the road network. This was further increased by adding traffic lights, see red squares in Figure 4, with dynamically changing light signals. The randomly generated directional arrows, appearing before an intersection, further increased the necessity for focus on the task of driving.

The same environment was used in order to elicit Distraction. Just like Sonnleitner et al. [27], we also make use of the audio book "Seven years in Tibet". We use an identical approach by asking the test subjects to press a button on the steering wheel when the word "og" (engl. "and") was mentioned. This setup had the intention to divide the test subjects focus between the driving task and the audio book, and thereby elicit Distraction.

Driving Simulator

In order to measure EEG data as well as performance metrics, for Distraction and Focus, we chose to develop a driving simulator which was used in a lab study. For ethical/safety reasons we could not conduct a field study[4]. The driving simulator was build using Unity's driving modules as well as pre-existing 3D assets. The reason why we chose to build a driving simulator, instead of using already existing ones or using driving games was threefold.

1) By building the driving simulator, we had the possibility to fully automate the collection of driving performance metrics. The measured driving performance metrics where deviations from the allowed speed limit as well as off road driving. When drivers where leaving their traffic lane a warning notification would appear in order to notify them about their deviation from the driving lane. This was done due to the lack of tactile feedback a real car would give the driver. 2) In addition to the data logging, our own implementation gives the possibility for random route generation at runtime. A random directional arrow is generated, see Figure 1 , when closing in on a intersection. On completion of the turn the arrow automatically disappears. 3) Furthermore, our own implementation supports the use of multiple external monitors in order to support side window view, as illustrated in Figure 1.

Existing driving simulators had limitations in terms of steering wheel support, micromanagement of the environment and functionality, as well as performance metric logging. Driving games where discarded due to the lack of control over the environment, AI-behaviour as well as lack of core functionality like route generation or performance metric logging.

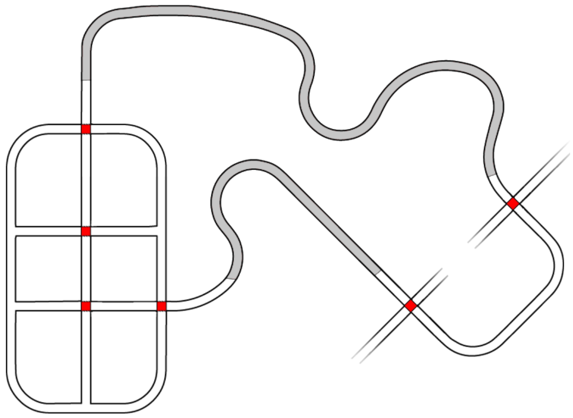

Figure 4: Road network of the driving simulator, **Red:** traffic lights.

Data Splits

In order to understand in what situations EEG data can be used to determine when a driver is distracted or focused, we analysed different parts of the data measured using the Ⓐ Data Measuring component of Animus, as illustrated in Figure 3. We call each such part of the data a split. A split always consist of three data partitions, training, validation, and evaluation data. The partitions are used in the training, feature selection and evaluation of a classifier. The classifier will then give a classification accuracy, indicating how well Animus was able to distinguish Distraction from Focus, based on the given split. This allows us to create multiple splits, to understand in what situations EEG data can be used to distinguish when a driver is driving in the condition Distraction or Focus. Based on the EEG data collected, we created three splits.

Given Distraction and Focus data from a driver, measured over a single day, we want to know if Animus can distinguish between unseen EEG data from the same day and driver. We call this split Within Session. To see whether the results obtained from Animus on split Within Session can be repeated, we create split Within Session Repeated. The Within Session and Within Session Repeated split are partitioned into 50% training, 20% validation and 30% evaluation data.

Animus will only be useful in a real car, if it can distinguish between unseen EEG data from days which Animus has not previously seen any data. To understand if this is possible, we create the split Between Days. Here we trained on data from the first day, and evaluated on the unseen data from the second day. For Between Days the data from the first day is split 70% training and 30% validation data. Day 2 is used for evaluation data.

Procedure

All studies were performed in the usability lab located in Cassiopeia at Aalborg University. Before driving sessions, subjects were presented with the same introductory text, explaining what was going to happen during the experiment. This was to ensure all participants received the same information prior to the experiment. Following this, the test subject was asked to turn off his phone, which was removed from the test room. Participants were asked to drive within Danish traffic regulations. After read introductory text, the subject had time to ask questions. The Mark IV was then attached to the participant, which then had the possibility to familiarize themselves with the driving simulator. No data was collected during this phase. During driving sessions, both the screen as well as driving performances were recorded.

Subjects now had to drive in two conditions, Distraction and Focus. In condition Focus, test participants were asked to drive in an environment containing both city and rural streets. Such an environment elicits cognitive focus on the driving task [13, 16]. While driving, randomly generated turn signals, were presented to the driver when approaching an intersection. The participants would then over the cause of 15 minutes drive in the simulator, from which all data was regarded as cognitive focus. In addition to the aforementioned performance metrics, a log entry was made, each time a participant got a new turn signal from the system, as well as an entry after the direction had been followed.

In condition Distraction, a secondary task was added, to elicit Distraction. Participants listened to the audio book "Syv år i Tibet" (Seven Years in Tibet), and were instructed to push a button, each time they heard the word "og" (engl. "and") [27]. Each time the button was pushed, a log entry was made. All data collected from this condition, was regarded as cognitive distraction. Again log entries based on directions were created, as in the previous condition.

Between the two test conditions test subject would have a break. After the second driving condition a semi structured interview was conducted.

To minimize ordering effects, participants were asked to drive condition Distraction and Focus in a perfectly counterbalanced measure design[26]. After both conditions had been driven we waited for approximately 7 days before the experiment was performed again.

Data Analysis

In this section we will describe how we derived driver performance metrics from the automatically generated log files. As mentioned we automatically logged information about off road driving and deviations from the allowed speed limit. From this, as well as the video analysis, we derived information on the eleven performance metrics displayed in Table 2. When leaving the road we logged both the time for exiting as well as re-entering of the traffic lane. From this data we could derive the total number, total time, and the average time off road. For each frame of the simulation the current deviation from the allowed speed was logged. This made it possible to derive the amount, the total time, as well as the average time for each occurrence of speeding. In order to be considered speeding, a threshold of 3 km/h was defined[22]. This means that only driving above 53 km/h, in city, and above 83 km/h, outside of city, was considered speeding. This is in regulation with the danish traffic law. The average country road speed was taken as a measure, in order to compare average speed on the grey stretch, as illustrated in Figure 4. Since the test subjects were instructed to drive the allowed speed, we consider an average speed closer to the speed limit as better. The last four performance metrics, as listed in Table 2, was derived using video analysis.

Results

This section will present three types of results achieved during Experiment A. These will be classification accuracies created by Animusindicating when EEG data can be used to distinguish between Distraction and Focus, driving performance metrics, and qualitative statements collected from the post session user interviews.

Classification Accuracy

After Animus is trained a number of evaluation time windows are evaluated, the amount depends on the chosen split and is illustrated in Table 1. Each evaluation time window is classified as either Distraction or Focus. The classification accuracy for all splits, as well as the combination of Within Session and Within Session Repeated, called Within Session Combined, are presented in Table 1.

The split Within Session is designed to investigate if Distraction and Focus are distinguishable, if the training, validation and evaluation data comes from the same session. We measured in total 7198 time windows of EEG data during the two 15 minute conditions. The evaluation set, which is 30% of the total amount of time windows, contains 2173 time windows. We found that Animus with a mean accuracy of 97.70% (SD = 2.39, 2123 correctly classified time windows) over all subjects was able to distinguish the conditions Distraction from Focus, when trained and evaluated on data from the same day. This means that we can train a subject dependent system on 2 second Distraction and Focus EEG windows from one day, and use the system on the same day, to determine with an accuracy of 97.70% on any 2 seconds of driving, whether the driver was driving in the condition Distraction or Focus. Training and evaluating Animus on EEG data from session one, we achieved classification accuracies for the individual subjects varying from 93.07% to 100%.

To see whether the results from Within Session session can be repeated, we performed the Within Session Repeated split as presented in the "Data Analysis" section. The only difference betweenWithin Session and Within Session Repeated is, that Within Session Repeated uses data from session two, which was performed one week after session one. Animuswas able to distinguish Distraction from Focus with an accuracy of 98.32% (SD = 2.23%, 2163 correctly classified time windows). We achieve classification accuracies varying from 93.45% to 100% over all participants, which indicates that the results from Within Session can be repeated. The combination of Within Session and Within Session Repeated, called Within Session Combined, achieved 98.01% average classification accuracy over all test subjects.

To test whether Distraction and Focus can be distinguished over time, where we train on data from one day an evaluate on data from another day, the Between Days split was developed. The total amount of time windows across all test subjects, collected during both 30 minute sessions, is 14485. The amount of evaluation time windows is 7287 across all test subjects. When training and validating on session 1, and evaluating on session 2, Animusachieves a mean accuracy of 77.95% (SD = 9.74, 5680 correctly classified time windows) The accuracy varied between 69.70% and 98.57% for the individual test subjects. These results indicate that the generalizability of Distraction and Focus varies from person to person.

Driving Performance

We automatically collected several driver performance metrics. This gave us the possibility to investigate driver performance in different conditions while driving. We collected driver performance metrics in order to identify 11 different metrics. These are listed in Table 2.

During the video analysis the amount of missed directional arrows, ignored red lights and stop lines were tracked. If more than 5% of all arrows received was ignored the test subject was excluded from the experiment.

The results shown in Table 2 imply that the overall driving performance in regards to the listed metrics are better during the Focus scenario. Nearly all values are improved, as marked in green and grey. The only three exceptions, as marked in red, are the metrics related to speeding.

We observed that the average total speeding time across both sessions for all test subjects was 16.84% longer in the Focus condition compared to the Distraction condition. A possible explanation for this observation could be that test subjects slowed down in order to be able to direct focus on the audio book.

For the two grey areas, the improvements are not expressible in a percent value since the amount of collisions produced and percent stop lines ignored was 0 in the Focus scenario. This is a performance increase by comparison to the Distraction where each test subject on average ignored 1.59% of all stop lines. On average each test subject produced 0.13 car collisions, as each test subject drove twice in the Distraction condition.

We can conclude that test subjects began to drive slower while driving in the Distraction condition. Furthermore, on all non speeding related metrics, we could observe a

Exp.	Split	Mean accuracy (SD)	Evaluation time windows	Correct classified time windows
A	Within Session (*N=8*)	97.70 % (2.39)	2173	2123
	Within Session Repeated (*N=8*)	98.32 % (2.30)	2200	2163
	Within Session Combined (*N=8*)	98.01 % (2.30)	4363	4286
	Between Days (*N=8*)	77.95 % (9.74)	7287	5680
B	Dynamic (*N=2*)	77.11 % (7.83)	586	452
	Static (*N=2*)	84.06 % (3.85)	595	500

Table 1: Mean accuracy and standard deviation for all subjects for the different splits performed. Within Session Combined is the combination of Within Session and Within Session Repeated.

	Average		Difference
Scenario	**CD**	**CF**	%
Total times off road (#)	40.81	38.31	6.13
Total off road time (sec)	47.84	37.49	21.64
Avg. off road time (sec)	1.15	0.97	15.15
Total times speeding (#)	8.44	9.44	-11.85
Total speeding time (sec)	19.64	22.94	-16.84
Avg. speeding time (sec)	2.38	2.55	-6.99
Avg. country road speed (km/h)	62.70	65.56	-4.56
Red lights ignored (%)	1.90	1.58	17.19
Stop lines ignored (%)	0.69	0.00	-
Arrows ignored (%)	0.51	0.18	64.79
Caused collisions (#)	0.06	0.00	-

Table 2: Performance metrics average for Distraction, Focus and the % difference between them. **Green:** Better performance while focused. **Red:** Worse performance while focused. **Grey:** Not expressible in percentage.

better performance in the Focus condition. This could be related to the divided attention.

Qualitative Results

The results presented in the Table 2 where complemented by the follow up interviews. Test subject 1 stated *"It was a lot harder with the audio book to drive according to traffic regulations!"*, Test subject 3 said *"...it was significantly harder with the audiobook in the first five minutes of driving..."*.

We observed that the average total speeding time across both sessions for all test subjects was 16% longer in the Focus scenario compared to the Distraction scenario. A possible explanation for this observation could be that test subjects slowed down in order to be able to direct focus on the audio book. This hypothesis was supported by test subject 4 who said *"...I observed that as soon as I started paying attention to the word **and**, I began to drive a lot slower since I was focusing on something entirely different..."*. Tests subjects 5 commented that *"...in the session with the audio book, it was harder to abide to traffic regulations since you also had to focus on clicking the button when told to..."*.

EXPERIMENT B: HELMET PLACEMENT

This section will describe experiment B. Experiment B was performed based on the results identified on the data collected for the three splits Within Session, Within Session Repeated and Between Days. Experiment B was performed in order to investigate the impact of small deviations in the placement of the EEG helmet between session. The outcome of this can not be used in order to conclude a concrete finding, because of the small amount of participants, but it might indicate a tendency in the impact of consistency of the helmets positioning on the classification accuracy.

Experiment B makes use of the same conditions, Distraction and Focus, as well as the same driving simulator as described in Section "Experiment A: Between Day Distraction and Focus Detection".

Participants

This experiment had 2 test subjects, one female of age 23 and one male of age 26. Participants where recruited using mouth-to-mouth. Both participants where unpaid and have had drivers license for 5 and 8 years and drive 30000 and 1000 kilometres per year respectively.

Data Splits

In order to identify the impact of the Mark IV positioning between the individual sessions, we developed two new data splits. These are called Static and Dynamic. Both splits consist of two sessions, each having 2 conditions. Between each session there was a short break of 1 minute. In the Dynamic split, the Mark IV was removed and directly reattached between the two sessions, whereas the Mark IV was not removed between sessions for the Static split. Both splits are separated into 70% training and 30% validation data from the first session, and the second session represents the evaluation data.

Procedure

Just as in experiment A, the test subject was read an introductory text and the Mark IV was applied in the same fashion as in experiment A. The same driving simulator and elicitation method for the conditions Distraction and Focus, as described in experiment A, was used.

After the Mark IV was attached, the test subject had the possibility to familiarize themselves with the driving simulator during a test drive. Afterwards the first of the two Static sessions began. Here the subject would drive for 5 minutes in the Focus condition directly followed by 5 minutes driving in Distraction. These 10 minutes where followed by a short break of 1 minute, the Mark IV stayed on during the Static split, before Static session two began. Again the test subject would drive 5 minutes in Focus followed by 5 minutes Distraction, and the Mark IV was removed.

The first of the two Dynamic sessions was preceded by an extended break of 30 minutes. Following this the test subject would get the Mark IV reattached. The first session, consisting of 5 minutes Focus followed by 5 minutes Distraction, was driven, and the helmet was removed. Afterwards the Mark IV would get reattached and another session with the two conditions, 5 minutes Focus followed by 5 minutes Distraction, was driven.

Results

This section will describe the classification accuracy achieved for the two splits Static and Dynamic as described in Section "Experiment B: Helmet Placement". The classification accuracy can be seen in Table 1.

Since it is almost impossible to place the Mark IV EEG helmet exactly the same across sessions, we conducted experiment B to investigate what impact the consistent placement of the helmet has on the results of Between Days. Experiment B makes use of two splits, Static and Dynamic. In the Static split the helmet was not removed, there the total amount of time windows was 1201 and the number of evaluation windows was 595. Animus achieved a classification accuracy of 84.06% (500 correctly classified time windows). For Dynamic, the Mark IV is removed and reattached between sessions. Dynamic makes use of 586 evaluation. The classification accuracy Animus achieved was 77.11% (452 correctly classified time windows). The difference in classification accuracy between Static and Dynamic corresponds to 6.95 percent points which indicates that the small change in placement of the helmet in between the two splits, has a measurable impact on the classification results.

DISCUSSION

According to the World Health Organization, the number of deaths related to road accidents in the year 2016 amounts to 1.4 million[20]. Since it is estimated that 25% of road accidents are due to driver distraction [23], the ability to identify driver distraction is an important field of study. In order to identify driver distraction and focus, we developed two conditions referred to as Distraction and Focus. We developed Animus which makes use of EEG data collected during the two experiments. Animus achieved 98.01% classification accuracy for Within Session Combined, which shows that the distinction of Distraction and Focus is possible. Furthermore, Animus achieved 77.95% classification accuracy when evaluated on data from a different day than the training data. Through the second experiment we could see implications for the relevance of the EEG helmets placement, here the classification accuracy dropped from 84.06% to 77.11% when the helmet was removed between collection of training and evaluation data. These results point to several conclusions. 1) A system like Animus can be used to distinguish the two conditions Distraction and Focus, if the data for training and evaluation is collected on the same day, 2) if data is collected on different days, there still exists information within the data, which can be used to distinguish Distraction from Focus, and 3) when collecting data on different occasions, it is important to consider the effect an inconsistent placement of the EEG helmet can have.

Classification Accuracy

Wang et al. [33] developed a system in order to distinguish if a driver is focused on a given mathematical task or on lane changing. They achieve 84.5% and 86.2% classification accuracy for mathematical task solving and driving task respectively. These results are based on EEG data, measured during four different sessions. A possible explanation for the lower results compared to our single day classifications, where Animus achieved 98.01%, could be the fact that they drove 4 different sessions on one day. Our test subjects drove a single session where both training and evaluation data was measured. When we drove 4 times during one day, represented using the Static split, we achieve 84.06% classification accuracy which supports Wang et al. findings.

Sonnleitner et al. [27] collect 16 data sets for the driving task as well as 16 data sets for the distraction task. They performed a 32-fold cross validation. They achieved a classification accuracy of approximately 92%. The experiment performed corresponds to the presented Within Session combined split. Animus achieved 98.01% accuracy which is an improvement, compared to Sonnleitner et al., of approximately 6 percent points.

Alizadeh and Dehzangi [1] measure EEG data based on 7 different driving tasks. Using the measured data they perform a 10-fold cross validation and achieve an average accuracy of 98.99%.

To the best of our knowledge, no HCI research exists on the generalizability of a system for classification on future EEG data. To extend upon existing research, we developed the Between Days split. We achieved 77.95%, which indicates that the evaluation on future unseen data to some extend is possible, although this is no trivial task.

Elicitation approaches

A problem when it comes to cognitive distraction elicitation is, that no consensus exists within the HCI community on which method to use. Based on Sonnleitner et al. [27] we chose to make use of an audio book in order to elicit cognitive distraction.

When looking at the results achieved by Alizadeh and Dehzangi [1], a distinction of 7 different distraction methods is achievable. Alizadeh and Dehzangi achieved 98.99% classification accuracy, which indicates that the difference in brain waves, between any of these is significant enough to be distinguished. This could have the consequence, that a distraction form other than the used audio book, would not be recognized by the Animus. In order to identify the robustness of a system like Animus, when it comes to its ability to identify alternative cognitive distractions, is left for future work.

Since we use the elicitation approach presented by Sonnleitner et al. [27], we do not have conclusive knowledge of how well the system would work in a field study, without the artificial elicitation of the distraction condition. Using our two conditions, Distraction and Focus, we assumed that the test subject was continuously cognitive distracted or focused. In reality this is likely not going to be the case, since the transition between distraction and focus might by a rapidly changing.

LIMITATIONS AND FUTURE WORK

For this study we conducted two independent experiments. "Experiment B: Helmet Placement" was performed in order to identify to what extend the Mark IV placements has an effect on the Animus' classification accuracy. A limitation during this experiment is the low participant number. Our results where derived from driving sessions using two test subjects, and indicate that the helmets placement indeed has an impact on the Animus' classification accuracy. It is left for future work to expand on this in order to achieve conclusive data on this issue.

When measuring data for Distraction and Focus, we designed elicitation methods as described in the "Cognitive Distraction and Focus" section. The limitation is the assumption that driving in the Distraction and Focus condition exclusively elicits cognitive distraction and focus respectively. Our results are build on this assumption. This means that a test subject driving in the Distraction condition actually gets cognitive distracted, from the task of driving, by the audio book. Identification and experimentation of additional elicitation approaches is left for future work.

CONCLUSION

During this study we investigated the possibility to use EEG signals in order to distinguish when a driver is cognitive distracted or focused. In order to measure EEG data, we developed a driving simulator which was used in two experiments, A and B, using 8 and 2 test subjects respectively. During the driving sessions we tried to elicit cognitive distraction and focus. We developed the two conditions Distraction and Focus, in order to measure EEG data for later classification. Using Machine Intelligence principles, such as filtering and feature selection, we developed a system, called Animus, which used the measured data to train and evaluate a classifier for the distinction of Distraction from Focus. Based on the data measured Animus achieved the following three results.

1) The distinction between Distraction and Focus is possible, if both the training as well as the evaluation data is measured during the same session. These results are repeatable, which was demonstrated by repeating the data collection on a second session. Animus achieved the classification accuracies of 97.70% and 98.32% for session 1 and session 2 respectively.

2) When using evaluation data measured during a different session than the training data, the distinction between Distraction and Focus is, to some extend, still possible. We here achieve a classification accuracy of 77.95%, which shows a performance drop of 20.06 percent points compared to the 98.01% achieved using data only from one day.

3) Lastly, we found indications for the relevance of a consistent placement of the Mark IV used. Here we could see that the removal and reattachment of the helmet between the collection of training and evaluation data, lead to a classification accuracy drop from 84.06% to 77.11%. The 84.06% percent was achieved using two sessions on the same day, without removing the Mark IV. This indicates the relevance of a consistent Mark IV placement.

ACKNOWLEDGEMENT

We would like to thank our experiment participants for their time. Furthermore, we would like to thank our supervisor for supervision during the development of this study.

REFERENCES

1. Vahid Alizadeh and Omid Dehzangi. 2016. The impact of secondary tasks on drivers during naturalistic driving: Analysis of EEG dynamics. In *Intelligent Transportation Systems (ITSC), 2016 IEEE 19th International Conference on*. IEEE, 2493–2499.
2. Hossam Almahasneh, Weng-Tink Chooi, Nidal Kamel, and Aamir Saeed Malik. 2014a. Deep in thought while driving: An EEG study on drivers' cognitive distraction. *Transportation research part F: traffic psychology and behaviour* 26 (2014), 218–226.
3. H. S. Almahasneh, N. Kamel, A. S. Malik, N. Wlater, and Weng Tink Chooi. 2014b. EEG based driver cognitive distraction assessment. In *2014 5th International Conference on Intelligent and Advanced Systems (ICIAS)*. 1–4.
4. Kenneth Majlund Bach, Mads Gregers Jæger, Mikael B Skov, and Nils Gram Thomassen. 2009. Interacting with in-vehicle systems: understanding, measuring, and evaluating attention. In *Proceedings of the 23rd British HCI Group Annual Conference on People and Computers: Celebrating People and Technology*. British Computer Society, 453–462.

5. Forrest Sheng Bao, Xin Liu, and Christina Zhang. 2011. PyEEG: an open source python module for EEG/MEG feature extraction. *Computational intelligence and neuroscience* 2011 (2011).
6. Lachezar Bozhkov, Petia Georgieva, Isabel Santos, Ana Pereira, and Carlos Silva. 2015. EEG-based Subject Independent Affective Computing Models. *Procedia Computer Science* 53 (2015), 375 – 382. DOI:http://dx.doi.org/10.1016/j.procs.2015.07.314 INNS Conference on Big Data 2015 Program San Francisco, CA, USA 8-10 August 2015.
7. Claire Braboszcz and Arnaud Delorme. 2011. Lost in thoughts: neural markers of low alertness during mind wandering. *Neuroimage* 54, 4 (2011), 3040–3047.
8. L. Fridman, Lex Fridman, Bryan Reimer, Bruce Mehler, and William T. Freeman. 2018. Cognitive Load Estimation in the Wild. (2018), 1–9. DOI: http://dx.doi.org/10.1145/3173574.3174226
9. Germán Gálvez-García, Javier Albayay, Lucio Rehbein, and Francisco Tornay. 2017. Mitigating Simulator Adaptation Syndrome by means of tactile stimulation. *Applied Ergonomics* 58 (2017), 13 – 17. DOI:http://dx.doi.org/10.1016/j.apergo.2016.05.004
10. AJ Ibáñez-Molina and S Iglesias-Parro. 2014. Fractal characterization of internally and externally generated conscious experiences. *Brain and cognition* 87 (2014), 69–75.
11. Lisheng Jin, Qingning Niu, Haijing Hou, Huacai Xian, Yali Wang, and Dongdong Shi. 2012. Driver cognitive distraction detection using driving performance measures. *Discrete Dynamics in Nature and Society* 2012 (2012).
12. John D Lee, Joshua D Hoffman, and Elizabeth Hayes. 2004. Collision warning design to mitigate driver distraction. In *Proceedings of the SIGCHI Conference on Human factors in Computing Systems*. ACM, 65–72.
13. C. T. Lin, S. A. Chen, L. W. Ko, and Y. K. Wang. 2011. EEG-based brain dynamics of driving distraction. In *The 2011 International Joint Conference on Neural Networks*. 1497–1500.
14. Chin-Teng Lin, Chun-Hsiang Chuang, Scott Kerick, Tim Mullen, Tzyy-Ping Jung, Li-Wei Ko, Shi-An Chen, Jung-Tai King, and Kaleb McDowell. 2016. Mind-wandering tends to occur under low perceptual demands during driving. *Scientific reports* 6 (2016), 21353.
15. S. Marcel and J. D. R. Millan. 2007. Person Authentication Using Brainwaves (EEG) and Maximum A Posteriori Model Adaptation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 29, 4 (April 2007), 743–752. DOI: http://dx.doi.org/10.1109/TPAMI.2007.1012
16. Malia F Mason, Michael I Norton, John D Van Horn, Daniel M Wegner, Scott T Grafton, and C Neil Macrae. 2007. Wandering minds: the default network and stimulus-independent thought. *Science* 315, 5810 (2007), 393–395.
17. Maryam Mustafa, Stefan Guthe, Jan-Philipp Tauscher, Michael Goesele, and Marcus Magnor. 2017. How Human Am I?: EEG-based Evaluation of Virtual Characters. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 5098–5108.
18. OpenBCI. 2017. Open Source Brain-Computer Interfaces. (2017).
19. World Health Organization. 2015. *Global status report on road safety 2015*. World Health Organization.
20. World Health Organization. 2018. World Health Organization: Top 10 causes of death. http://www.who.int/gho/mortality_burden_disease/causes_death/top_10/en/. (2018). Accessed: 2018-7-4.
21. Yongjun Piao, Minghao Piao, Cheng Hao Jin, Ho Sun Shon, Ji-Moon Chung, Buhyun Hwang, and Keun Ho Ryu. 2015. A New Ensemble Method with Feature Space Partitioning for High-Dimensional Data Classification. (2015). DOI: http://dx.doi.org/10.1155/2015/590678
22. Politi. 2006. Oftest stillede spørgsmål om ATK. (2006).
23. Thomas A Ranney, Elizabeth Mazzae, Riley Garrott, and Michael J Goodman. 2000. NHTSA driver distraction research: Past, present, and future. In *Driver distraction internet forum*, Vol. 2000.
24. Z Reitermanova. 2010. Data splitting. In *WDS*, Vol. 10. 31–36.
25. Dario D Salvucci. 2013. Distraction beyond the driver: predicting the effects of in-vehicle interaction on surrounding traffic. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3131–3134.
26. Martyn Shuttleworth. 2009. Counterbalanced Measures Design. (2009). explorable.com/counterbalanced-measures-design
27. Andreas Sonnleitner, Matthias Sebastian Treder, Michael Simon, Sven Willmann, Arne Ewald, Axel Buchner, and Michael Schrauf. 2014. EEG alpha spindles and prolonged brake reaction times during auditory distraction in an on-road driving study. *Accident Analysis & Prevention* 62 (2014), 110–118.
28. David L Strayer, Jonna Turrill, Joel M Cooper, James R Coleman, Nathan Medeiros-Ward, and Francesco Biondi. 2015. Assessing cognitive distraction in the automobile. *Human factors* 57, 8 (2015), 1300–1324.

29. Abdulhamit Subasi. 2005. Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients. *Expert systems with applications* 28, 4 (2005), 701–711.

30. Patrick Tchankue, Janet Wesson, and Dieter Vogts. 2011. The impact of an adaptive user interface on reducing driver distraction. In *Proceedings of the 3rd International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. ACM, 87–94.

31. Patricia Trbovich and Joanne L Harbluk. 2003. Cell phone communication and driver visual behavior: The impact of cognitive distraction. In *CHI'03 extended abstracts on Human factors in computing systems*. ACM, 728–729.

32. Ali Bulent Usakli. 2010. Improvement of eeg signal acquisition: An electrical aspect for state of the art of front end. *Computational intelligence and neuroscience* 2010 (2010), 12.

33. Yu-Kai Wang, Tzyy-Ping Jung, and Chin-Teng Lin. 2015. EEG-based attention tracking during distracted driving. *IEEE transactions on neural systems and rehabilitation engineering* 23, 6 (2015), 1085–1094.

34. F Wasilewski and others. 2010. PyWavelets-Wavelet Transforms in Python. (2010).

35. Avinash Wesley, Dvijesh Shastri, and Ioannis Pavlidis. 2010. A novel method to monitor driver's distractions. In *CHI'10 Extended Abstracts on Human Factors in Computing Systems*. ACM, 4273–4278.

36. Matthew R Yanko and Thomas M Spalek. 2014. Driving with the wandering mind: the effect that mind-wandering has on driving performance. *Human factors* 56, 2 (2014), 260–269.