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Can EEG Measurements be Used to Estimate the Performance of Taking over Control from an Autonomous Vehicle for Different Levels of Distracted Driving? An Explorative Study

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Can EEG Measurements be Used to Estimate the Performance of Taking over Control from an Autonomous Vehicle for Different Levels of Distracted Driving? An Explorative Study

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ABSTRACT

Driver distraction is a concern for traffic safety. Most research has been focused on validating or quantifying the relationship between eyes-off-road metrics and driving performance without specifically addressing cognitive aspects of distracted driving. The current study explores to what extent electroencephalogram data is a good predictor of how successful a distracted driver will be able to take over control from an autonomous vehicle. Participants were driving a simulated car while being exposed to varying levels of distraction. During the ride at several moments the participants were warned to take over control, after which the control was transferred. Sometimes after taking over the control an immediate break action of the drivers was expected. It turned out that electroencephalogram based data is able to indicate to what extent participants are distracted. However, electroencephalogram based data is not able to estimate driving performance during take over control.

CCS CONCEPTS

• **Human-centered computing**; • **Human computer interaction (HCI)**; • **HCI theory, concepts and models**;

KEYWORDS

electroencephalogram, EEG, distracted driving, transfer of control, automated driving

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1 INTRODUCTION

About 5 to 25% of car crashes can be attributed to driver distraction [1]. Numerous studies indicate negative effects of distracted driving on driving performance [2–6]. When engaging in a secondary task while driving, several types of distraction may occur [7, 8]. Visual distraction is often being referred to as especially dangerous for safe driving, most research and development has been focussed on validating or quantifying the relationship between eyes-off-road metrics and driving performance or crash risk without specifically addressing the cognitive aspects of distracted driving.

As driving a car in a dynamic environment is primarily a mental task [9] additional insights about the relation between distracted driving and driving performance can be gained by also taking cognitive aspects into account rather than only focussing on the visual behaviour of a driver. There is, for example, a well-known relation between human performance and mental workload. Humans have limited mental resources to devote to the execution of tasks [10]. When a driver experiences driving demands that exceed his or her mental capabilities, then he or she can become mentally overloaded and the driving performance will decrease. A decrease in driving performance will increase the likelihood of mistakes when driving [11]. Mental overload is therefore a danger to road safety.

Brain activity changes as mental workload changes, and brain activity measurements can be used to estimate mental workload [12, 13]. Recent research shows that brain activity measurements can be used to estimate different levels of non-driving related task difficulty in automated driving [14]. A technique of measuring brain activity through electrodes is called electroencephalography (EEG) [15]. Increases in task difficulty and mental workload are most often associated with a decrease of alpha band power and an increase of theta band power [16–19].

1.1 Objective and research questions

The study will determine to what extent being distracted will influence the ability to respond quickly and in time when control needs to be taken over by the human driver from an autonomous vehicle on Society of Automotive Engineers (SAE) level 3. It will also determine whether EEG signals are a good indicator of level of distraction. As such the study will demonstrate whether EEG is an indicator of the ability of a human driver to be able to take

Figure 1: Screenshot of automated driving part in the simulated environment.

over control from the automation. The research questions in this explorative study are as follows:

- Do EEG measurements vary as a function of different levels of distracted driving?
- Does the driving performance during take over control in different levels of distracted driving vary as a function of EEG measurements?

The first exploratory hypothesis is that during automated driving there is a difference in EEG patterns between the different conditions of distraction. The second exploratory hypothesis is that the driving performance during take over control varies as a function of the EEG patterns during automated driving (which is prior to that specific take over control).

2 METHODS

2.1 Participants

A total of 23 participants (15 males and 8 females) with an average age of 33 (SD = 12) participated in this study. All participants had a driving license.

2.2 Materials

The simulator consisted of a screen with a resolution of 1600x1200 pixels and Hori Apex racing steer with gas- and brake pedals. The laptop for the secondary task is placed directly next to the screen of the simulator in order to keep head movements to a minimum. The simulator scenarios were built within Unity (version 2019.4.29f1).

2.3 Experiment

This, within-participant design, experiment contains four different scenarios. Each scenario was played within the city limits with medium traffic load. In automated driving (Figure 1) there was no need for driver intervention.

Experiment started with a practice scenario and took around fifteen minutes. During this scenario, the driver encounters stalling vehicles on which he or she had to respond by braking. After the practice scenario, three different scenarios were conducted. Two scenarios contained the snake game (PyGame) as an active secondary non-driving related task (NDT) with two levels of difficulty. Easy snake game (i.e. "NDT") moves 30% faster compared to the harder snake game (i.e. "Hard NDT"). The participant was tasked to execute the secondary task while still avoiding any accidents during the events. In case of game over, the score was reset and the snake game continued. The third scenario contained no NDT and served as a baseline (i.e. "No NDT").

In each scenario, automated driving was engaged with the exception of handling critical events: a stalled car appeared either in front of the vehicle (i.e. correct detection) or in the other lane (i.e. false alarm) and the system conducted a take over request using audio and visual cues (Figure 2).

The driver had to assess the critical event and act accordingly: brake during correct detection and ignore during false alarm. The event ends by engaging automated driving when the car has come to halt or it passes the stalled car. The critical events were repeated so that in each of the three conditions at least six events had occurred. According previous research [20], driver's response will be a second faster after consecutive take overs, which needed to be accounted for by randomising the occurrence of critical events and false alarms. The total experiment (Figure 3) took an hour.

The driver needs time to gain complete control over the vehicle after the automated driving initiated a take over control request (i.e. take over time; TOT). The process of take over control during automated driving is illustrated in Figure 4.

When the vehicle has an initial velocity of 50 km/h and a breaking force of 9 m/s^2, the breaking time is around 1.54 seconds. This results – together with a TOT of 1.5 seconds – in a total time budget of 3.04 seconds for handling critical events.

2.4 Data acquisition and analysis

2.4.1 Performance measures. Time-To-Collision (TTC) was measured as the distance between the two vehicles divided by the speed difference, as the vehicle in front is stalled this simplifies to the following equation:

$$TTC = \frac{distance}{velocity}$$

The reaction time was determined by calculating the time between the audio cue and the first moment the participant started braking.

2.4.2 Electrical encephalogram data. The EEG data is recorded by a TMSi SAGA 32-channel EEG device with a sampling rate of 500 Hz. Low-pass filter (1 Hz) and a notch filter (48 to 52 Hz) are applied using Hamming window. Welch's averaging was used with a window length of 500 datapoints and 0% overlap. The band power is then calculated by averaging the power over the following frequency regions: theta (5-7 Hz), alpha (8-12 Hz), beta (13-30Hz) on respectively Fz, Cz and Pz [21, 22].

2.4.3 Statistical analysis. All analyses were performed with linear mixed-effects model analyses using LME in R (R Core Team, 2017) with participant as random factor. There was no effect of event order on performance and any of the EEG outcome measures, which demonstrates that participants became neither better nor worse in their performance *within* condition. The data was checked for outliers and normality.

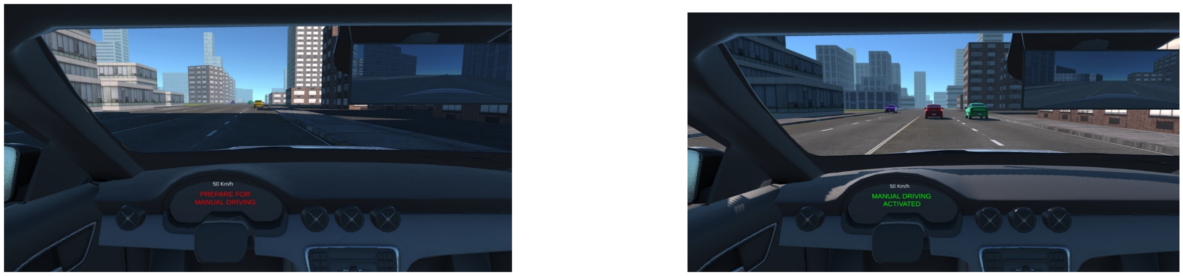

Figure 2: Screenshots of take over request part during a correct detection (stalled car in front of the vehicle).

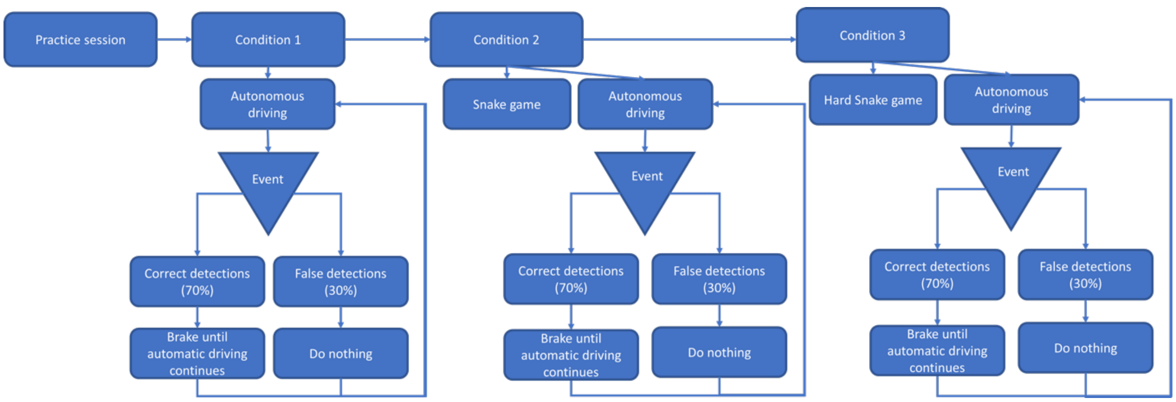

Figure 3: Experiment design with conditions.

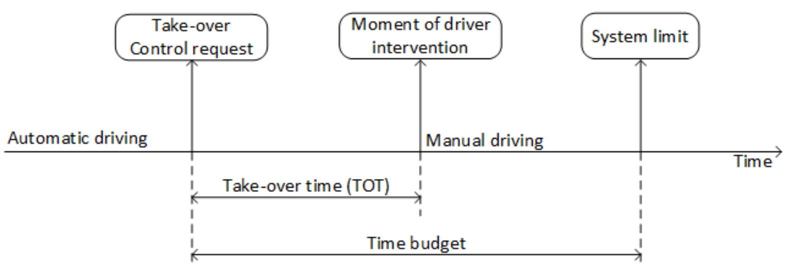

Figure 4: Illustration of the take over control procedure, containing the take over time (TOT) and time budget, derived from Zhang [20].

Table 1: Overview of descriptive statistics (M, SD, CL) of condition on reaction time (with .95 as confidence level)

Condition	M	SD	Lower CL	Upper CL
Hard NDT	1.41	.10	1.21	1.61
NDT	1.34	.10	1.13	1.54
No NDT	1.18	.10	.98	1.39

3 RESULTS

3.1 Effect of condition on performance

The expectation is that the driving performance when distracted is lower than when the driver is paying fully attention to the driving performance without any distraction of a non-driving related task (NDT). To determine if the different conditions affect the driving behaviour, two behavioural outcome measures were analysed, the time-to-collision (TTC) and RT. However, effect of condition on TTC was not statistically significant and therefore left out of further analysis. The mean declarative score on RT is presented in Table 1.

Table 2: Overview of effects $(F, p, \eta_p{}^2)$ of condition on RT.

Performance measurement	F	p	$\eta_p{}^2$
Reaction time (RT)	6.048	.003	.048

Table 3: Overview of effects $(F, p, \eta_p{}^2)$ from condition per outcome measure of brain activity in each time window. Time windows are presented in increasing order with increments of 20 seconds, starting with 10 seconds until 110 seconds.

Outcome	10s		30s		50s		70s		90s		110s	
measurement	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$
Alpha	6.70[b]	.05	7.49[a]	.06	9.65[a]	.08	7.78[a]	.08	5.42[b]	.08	2.60	.07
Theta	4.03[c]	.03	4.36[c]	.04	5.45[b]	.05	2.03	.02	1.85	.03	0.86	.02
Beta	9.16[a]	.07	11.35[a]	.08	11.35[a]	.09	4.41[c]	.04	4.04[c]	.06	1.75	.05

[a] $p < .001$; [b] $p < .01$; [c] $p < .05$

Table 4: Overview of effects $(F, p, \eta_p{}^2)$ from brain activity in each time window on reaction time. Time windows are presented in increasing order with increments of 20 seconds, starting with 10 seconds until 110 seconds.

Outcome	10s		30s		50s		70s		90s		110s	
measurement	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$	F	$\eta_p{}^2$
Alpha	.16	.00	.12	.00	.98	.00	.69	.00	.76	.01	.10	.00
Theta	.17	.00	.00	.00	.39	.00	.01	.00	.06	.00	.27	.00
Beta	.01	.00	.21	.00	1.89	.01	.25	.00	.26	.00	.07	.00

[a] $p < .001$; [b] $p < .01$; [c] $p < .05$

Condition had a significant effect on RT as performance which details $(F, p, \eta_p{}^2)$ are presented in Table 2. Post-hoc analysis indicates that reaction time during the *most* mentally challenging non-driving related task increased significantly with 231 ms when compared to the condition with no distraction.

3.2 Effect of condition on EEG

The outcomes of the effects from condition on each outcome measure of brain activity in each time window prior an event are presented in Table 3. These results show that the alpha, theta and beta band powers in most time windows are statistically significant different for condition. In addition, the effect size (as defined by partial eta squared) is highest within the 50 seconds time window for each band power. These findings may suggest a change in distraction and workload, affecting the electrical activity in the brain, especially within the 50 seconds time window prior an event.

Post-hoc analysis shows that the power in the alpha and beta band powers within the 50s time window is statistically different in baseline condition (No NDT) compared to both NDT conditions. The theta band power is only statistically different in baseline condition compared to Hard NDT. These findings may suggest that alpha and beta band powers are most sensitive to whether the participant is distracted or not, but lack in distinguishing the difficulty of that task. Theta band power appears to be sensitive to whether the participant is performing a relative more difficult task or no task at all.

3.3 Relation between EEG and performance

To determine if driving performance is a function of EEG response, reaction time is investigated for each EEG measure in each time window. The outcomes of the effects from each EEG measure and time window on reaction time are presented in Table 4.

These results show that none of the EEG patterns are related to reaction time. The findings suggest that EEG appears to be unable in explaining the driving performance of an automation initiated take over in terms of driving performance during different conditions of distraction.

4 DISCUSSION AND CONCLUSION

During automated driving (prior to the take over control) there is a difference in the alpha, beta and theta band powers between the different conditions of distraction and most strongly affected within the 50 seconds time window based on effect size. Differences in alpha and beta band powers are related to participants being distracted compared to not being distracted. They are not sensitive to differences in difficulty level of the distracting task. Theta band power is related to performing a relative more difficult non-driving related task compared to no task at all. When *combining* theta and alpha/beta band powers it is possible to determine not only whether the participant is distracted or not, but it also indicates a trend in how mentally challenging that distraction is. However, EEG appears to be unable in explaining the driving performance of an automation initiated take over in terms of reaction time during different conditions of distraction.

For practical reasons, the order of the conditions was not randomized. Therefore, it is possible that boredom increased over the course of the experiment which in turn caused the alpha band powers to get higher as the experiment progressed. However, this seems unlikely since theta band power indicates an opposite effect, namely that participants were being more mentally challenged as the experiment progressed.

4.1 Future research

More insight in the underlying mechanisms of driver behaviour may be gained by actually measuring how drivers aim their visual attention by recording their gaze patterns by means of an eye tracker. It may contribute to settlingthe matter about whether overt or covert attention is applied in order to monitor everything that is relevant for task execution. That insight will eventually answer the question such as how do drivers manage to monitor the traffic and pay attention to the distracting task at the same time. The mental effort that drivers put into the task may be assessed by measuring (psycho)physiological data such as heart rate variability. Applying methodological triangulation by comparing these additional data with the EEG output will make the conclusions stronger. It will also provide additional insight into underlying principles that might explain the behaviour of the participants in the experiment.

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