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Adaptive Automation in Driving: the Effects of Workload Simulation

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Abstract

This study explores the impact of adaptive automation on driving performance. It investigates whether dynamic allocation of control based on physiological measures have an effect on the cognitive demands of people. The research experiments on this using a driving simulator with varying levels of automation and a workload modulating task. Results suggest that adaptive automation can influence driver behaviour, although the effect in not visible in all levels of workload.

1 Introduction

Since the invention of automobiles over a century ago, research has been gone into studying the safety aspect of driving [4]. Many studies have explored different ways to reduce the number of driving accidents, such as implementing seat belts or modifying road designs. However, driving remains a challenging task that demands constant attention and integration of multiple cognitive skills. Drivers often distract themselves with other activities that compete for their cognitive resources [6], which can impair their driving performance and increase the probability of crashes. To overcome this issue car manufacturers are implementing self-driving systems, by automating driving and taking the driver out of the loop this holds the potential to eliminate incidents caused by human error. Nevertheless, this can lead to a different subset of driving incidents.

Examples of automation failure in driving are sensor failure leading to a loss of information, or automation being unable to make a safe and ethical decision due to complexity of the road situation. One challenge of such failures is the loss of human skills and situation awareness, which can impair performance when the automation is unavailable or needs to be overridden. This can result in longer reaction times to hazardous situations and more “unsafe” manoeuvres such as lane deviation [11]. It is thus important for an automated system to both improve on routine system performance and reduce workload while keeping over-reliance and loss of control to a minimum. Lastly Automation must balance the trust that a user has in the system, for over-trusting or under-trusting automation will lead to respectively misuse or disuse of the automated system [8]. Finding an optimal level of (trust in) automation that balances the benefits and costs of automation is a critical task for designing effective and safe automated driving system.

Adaptive Automation is such a technique aimed at optimizing performance by distributing system functions between humans and machines during task execution, considering the environment, task, and operator states. This involves the dynamic allocation of work in real-time to ensure the effectiveness of the system, while also maintaining operator engagement and situation awareness [7]. Different strategies to implement dynamic allocation of automation have been proposed, such as driving models based on a combination of human input and steering dynamics equations [13] or using a driver engagement measure based on physiological indicators such as eye-tracking, heart rate, blood pressure and pupil dilation [1]. Such dynamic allocation strategies based on physiological indicators are also used in (semi) self-driving vehicles.

Changes in these indicators are however not specific to workload or cognitive state [3], This means that any such measurements should not directly be taken as a ground truth for workload and difficulty; nevertheless, they can be used to identify patterns and thus estimate cognitive states [2].

By modulating the difficulty of a concurrent task, we can dynamically automate the simulated driving based on an estimator of workload with a measurement of pupil dilation. In this study, we investigated whether speedometer checks are happening more or less often in case of changing levels of workload. We hypothesized that a lower workload would allow more attentional resources to be allocated to other aspects of driving, such as monitoring speed, while higher workload would demand more attention and reduce speedometer checking frequency.

2 Methods

2.1 Participants

We recruited 32 participants (18 male, 14 female). The participants were aged between 18 and 38 years (M = 23.16, SD = 5), and had normal or corrected-to-normal vision. The participants gave informed consent and received a compensation of 15 euro for their participation. One participant was excluded, this participant showed evidence of not following the instructions properly, further investigation into the performance of this participant showed a significantly lower performance than the average participant indicating a lack of understanding or attention to the task.

2.2 Materials

The experiment was conducted in a driving simulator consisting of a seat, a steering wheel, pedals, and a monitor displaying a virtual environment (figure 1).

The eye-tracking data was gathered using SR Research EyeLink tracking software [12]. The eye-tracking camera was placed in between the monitor and the participant without obstructing the view of the monitor.

During the trial, an automated driving system based on ACT-R was responsible for the driving during automation. This system could take over control of either the steering wheel or both the steering wheel and the accelerator. These take-overs were based on a temporary increase in pupil-dilation, which indicated a high cognitive load for the driver. Once the pupil size changed back to normal the driver was informed on the heads-up display that soon the automation would stop, and the driver had to take over control.

This self-driving mode also controls the other vehicles on the road. The simulation itself does not include physics for road surface and or obstruction, which means that driving into something or driving of the road itself would not change the steering dynamics.

2.3 Task

The participants performed a driving task that involved monitoring and adjusting their speed according to the speed signs. This is a variation on the n-back task, which is a widely used measure of working memory and working memory capacity [10]. The participants in some trials, had to match their speed to the most recent speed sign (0-back condition). In other trials, they had to recall and match the speed sign that was presented 1, 2, 3, or 4 signs earlier (1-back, 2-back, 3-back, or 4-back conditions). The n-back task requires the

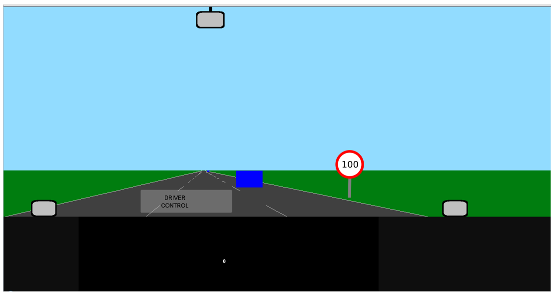

Figure 1: A screenshot of the virtual road we used for our driving experiment. At this point, there are no roadblocks, half trials include these roadblocks on the left lane of the road. In the dashboard the speedometer is visible. Above that, a heads-up display shows the current control state.

participants to keep track of what they have seen or heard before and compare it with what they see or hear now. The higher the number of n, the more difficult the task is. An example of a sequence of speed signs is shown 2.

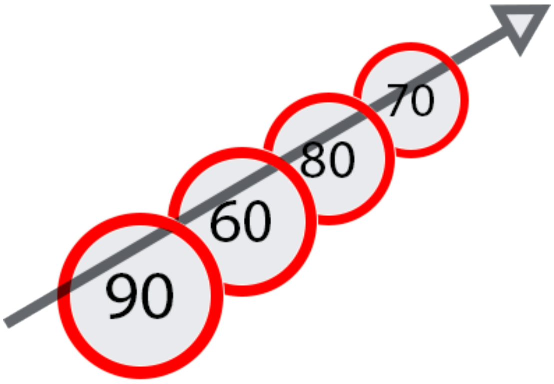

Figure 2: An example of a sequence of speed signs that a driver encounters on a road. The first sign that the driver sees is 90, indicating the current speed. After the driver passes this sign, there is a delay before the next sign appears. If a car has passed these signs the correct speed for the 0, 1, 2, 3 -back trials are respectively: 70, 80, 60, 90. (since no fifth sign appeared yet, the driver is instructed to drive according to the speed of the first sign in a 4-back trial, in this case: 90)

Participants completed the driving session of 80 (+-) minutes, divided into two blocks of 40 minutes each. In each block participants completed a total of 10 trials. Each of the 10 trials consist of a combination of the possible road condition (with or without construction) and the working memory task level. The order at which this combination was presented was randomized for every participant, though the order of the first block was repeated in opposite direction in the second block. Participants were instructed to follow the road and obey to traffic rules. Participants were asked to change their speed in accordance with the combination of n-back level and value of the speed sign. Every 20 seconds a new speed sign was shown on the right side of the road.

2.4 Procedure

Before the experiment, participants were informed about the purpose, procedure, and risks of the study. They were also made aware they could withdraw from the study at any time. The next step involved setting up the eye-tracker which involves calibrated and validated using the supplied software of EyeLink [12]. Before the start of the first trial participants were instructed to get used to the system in the form of a practice session of the driving task with n-back level set to “0”. The participant was asked if they understood the task completely, then the eye tracker was recalibrated and validated, after which a popup message indicated the first “n-back level”. Once the participant acknowledged reading the message, the first trial began. After the first 10 trials the participants were instructed to take a short break. Prior to each trial drift correction of the eye-tracker was performed.

3 Results

3.1 Data analysis

First the collected data was cleaned by removing outliers and filling in missing values The simulator recorded various driving performance indicators, such as speed, lane position and eye-tracking data such as eye-location, eye-fixations and pupil size. These indicators were used to measure the effects of adaptive automation on driver behaviour and attention.

We applied k-means clustering with different values of k and evaluated the quality of the resulting clusters using silhouette scores.

K-means clustering is an unsupervised machine learning technique that partitions a set of data points into a predefined number of clusters based on their similarity [5]. In this analysis, we use k-means clustering to analyse eye-tracking data collected from participants. This data was pre-processed using the software supplied by eyelink[12]. The clustering algorithm assigned each data point to one of the clusters and produced a visual representation of the clusters. Figure 3 shows the resulting clusters, the speedometer cluster was then appointed based on matching coordinates of cluster and speedometer.

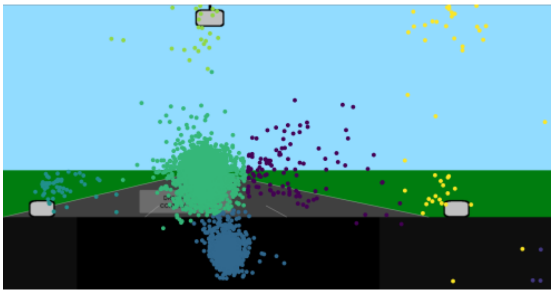

Figure 3: A screenshot depicting the driving scenario with added cluster data. The blue group of points shows the found speedometer cluster.

3.2 Driving performance

3.2.1 Steering reversal rate

Steering reversal rate is often used to measure driving performance on various levels of cognitive and or visual distraction, it is shown that with higher levels of distractions a higher amount of steering reversal rate is found [9]. Figure 4 shows the steering reversal rate for the different values of n-back. Figure 4 shows no clear difference between the reversal rate for these values, A linear mixed effect model comparison with random effects for construction and participant revealed that there was no statistically significant effect on reversal rate by the different n-back values (χ^2=6.87,p$>$ 0.05).

3.2.2 N-back performance

Figure 5 shows the percentage of correct speed driven. From this figure, we see was that the

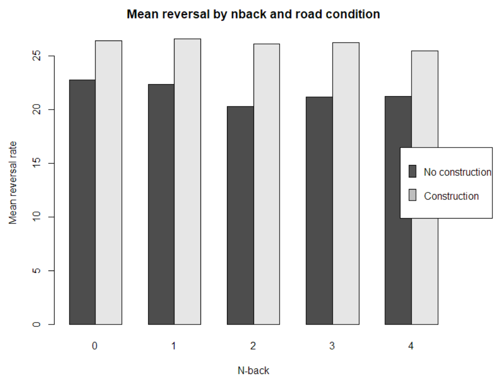

Figure 4: Mean reversal rate per n-back and per construction value

performance was higher in lower n-back trials. This was confirmed using linear mixed effect models (AIC=4947.5, p $<$ .001). This indicates that the modulating the workload based on the n-back task difficulty is successful.

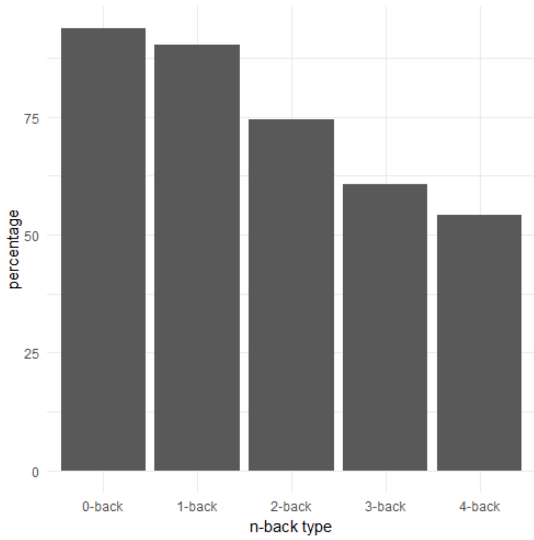

Figure 5: Plot of percentage of correct speeds driven by the participants in a driving simulator task under different n-back levels. The results suggest that the percentage of correct speeds decreases as the n-back level increases, indicating that higher cognitive load impairs driving performance.

3.3 Eye-tracking performance

We computed the proportion of fixations that fell within the speedometer range (figure 7). We then tested whether this proportion varied with the amount of automation during the n-back task using. The linear mixed effect analysis revealed no significant effect of automation percentage on the fixation distribution on both semi-automation and full automation percentage (χ^2 = 0.68, p = 0.4955) (χ^2 = 0.6, p = 0.425). These findings suggest that the amount of automation does not influence the driver's attention to the speedometer. The number of fixations on the speedometer clusters per n-back trials reveals a slight decrease but large standard deviation in speedometer checks for trials with higher n-back value (figure6). This shows that modulating the difficulty of the task results in different behaviour.

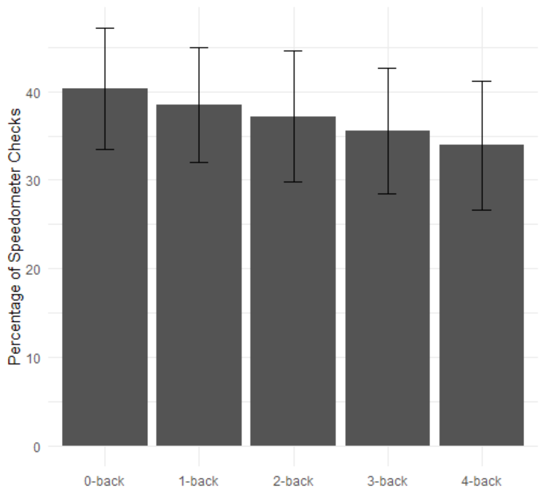

Figure 6: speedometer checks on different levels of n-back.

To investigate whether the interaction between n-back and automation level lead to a significantly different percentage of speedometer checks we fit and compared models with and without the interaction term between automation level and n-back level. This showed a significant effect (χ^2 = 7.08, p ¡ 0.005). These results indicate that while automation itself does not change the behaviour significantly, that the interaction between workload and n-back level leads to a significantly different behaviour in eye fixation.

4 Discussion

The present study investigated the effects of adaptive automation on driving performance. We hypothesized that a lower workload would allow more attentional resources to be allocated to other aspects of driving, such as monitoring speed, while higher workload would demand more attention and reduce speedometer checking frequency. It is shown that the number of fixations on the speedometer increases significantly on higher workload trials.

The aim of the experimental design was to explore how dynamically adjusting the level of automation influences driver's behaviour in terms of monitoring their speedometer. The primary finding of this study was that adaptive automation alone had a no significant impact on driver's engagement with their speedometer; The results do not show a significant change in speedometer checks with changing automation. We see that if we account for the n-back level we do find a significant positive effect for the change in speedometer checks. This shows that in driving with high mental demand, automation does help to overcome some of the cognitive load. Although, the variation in automation effects across different n-back trials may be attributed to various human activities rather than an overall increase in cognitive load.

4.1 Limitations

In this study, we utilized a simulated driving setup, which differs from real-world conditions due to changes in cognitive demands (such as setting up and navigating a route, or a conversation with fellow passengers), and therefore, caution should be exercised when generalizing the results to on-road scenarios. Analyses of the automation further revealed that only a minor part of the driving was done on partial or full automation, this could have impacted the driver's usage of this automation; with increased exposure to automation drivers could potentially allocate more of the freed up cognitive workload to other processes. Future research should study the difference in cog-

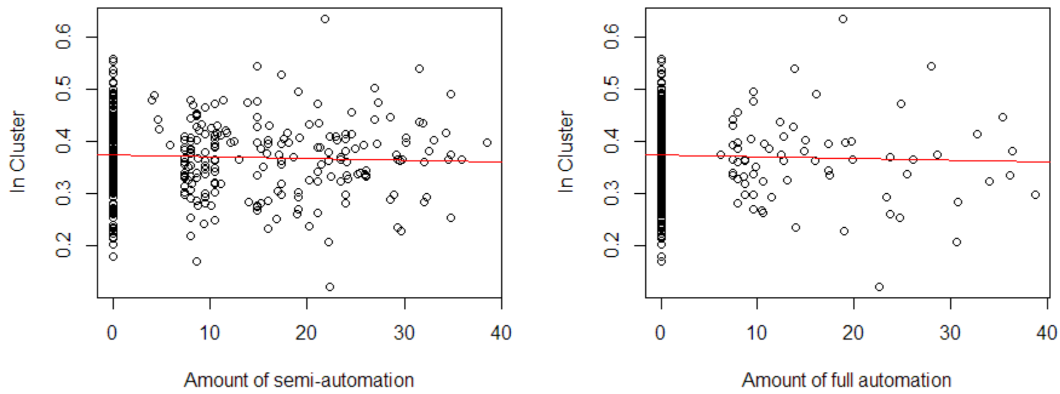

Figure 7: speedometer checks with different amount of automation.

nitive demands while modulating the automation level.

4.2 conclusion

In summary, the research demonstrates that adaptive automation systems, designed to adjust automation levels dynamically, can have a beneficial impact on driver attentiveness and road safety. The results can inform the design and implementation of future automation systems that aim to enhance driver engagement and situational awareness.

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