Controlling In-Vehicle Systems with a Commercial EEG Headset: Performance and Cognitive Load

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Abstract

Humans have dreamed for centuries to control their surroundings solely by the power of their minds. These aspirations have been captured by multiple science fiction creations, such as the Neuromancer novel by William Gibson or the Brainstorm cinematic movie, to name just a few. Nowadays, these dreams are slowly becoming reality due to a variety of brain-computer interfaces (BCI) that detect neural activation patterns and support the control of devices by brain signals.

An important field in which BCIs are being successfully integrated is the interaction with vehicular systems. In this paper, we evaluate the performance of BCIs, more specifically a commercial electroencephalographic (EEG) headset in combination with vehicle dashboard systems, and highlight the advantages and limitations of this approach. Further, we investigate the cognitive load that drivers experience when interacting with secondary in-vehicle devices via touch controls or a BCI headset. As in-vehicle systems are increasingly versatile and complex, it becomes vital to capture the level of distraction and errors that controlling these secondary systems might introduce to the primary driving process. Our results suggest that the control with the EEG headset introduces less distraction to the driver, probably as it allows the eyes of the driver to remain focused on the road. Still, the control of the vehicle dashboard by EEG is efficient only for a limited number of functions, after which increasing the number of in-vehicle controls amplifies the detection of false commands.

1998 ACM Subject Classification H.5.2 User Interfaces (D.2.2, H.1.2, I.3.6): Evaluation/ methodology, Input devices and strategies (e.g., mouse, touchscreen)

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1 Introduction

The desire of humans to gain the ability to control everyday actions just by using the power of their mind is old. These ideas became very popular in science fiction literature as well as in movies, like the popular Star Wars series. But in fact, research tries to exploit brain-computer interfaces (BCI) to provide support for motionless interaction. For example, Touch Bionics is offering brain controlled prosthetic arms tailored for amputees, aiming to increase the quality of life for handicapped people. In our related work section we will reveal a more detailed view on research related to the field of BCI.

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Figure 1 Image of a participant while interacting with the driving simulator and the EEG-controlled dashboard.

The focus of our current work however is to use a commercial electroencephalographic (EEG) headset in order to support car drivers in controlling secondary dashboard functions of a vehicle. In our case the Emotiv EPOC headset is used. First and foremost we want to emphasize that the user only controls secondary function of the car by the EEG headset. The testing and evaluation of our approach was done in a safe environment (laboratory experiment and evaluation) since we used a driving simulator and implemented secondary function of the dashboard. Our goal is to find out if the test candidates drive more securely when being able to focus on driving the vehicle itself and not having to manually operate secondary (non-driving essential) functions.

In the following sections we will highlight related work, as well as give a brief description of our setup, the evaluation and our test results.

2 Related Work

One of the most common and well-known fields of application for BCI is to control devices by brain waves. As such, research has intensively focused on measuring and increasing the performance of BCI-based consciously operated systems. In this setting, many medical solutions have been explored that would enable patients with physical disabilities to live a normal life. For example, controlling a wheelchair with the help of EEG devices has been a topic in several research papers. Leeb et al. [8] demonstrated that a tetraplegic patient was able to control the movement of a wheelchair in a virtual environment. In the work of Iturrate et al. [5] a BCI and an autonomous navigation system is used to control a wheelchair. The RIKEN and Toyota Motor Corporation also did research in the field of utilizing brain waves to control a wheelchair in real-time [18]. Stamps and Hamam [12] describe how low-cost BCI devices can be utilized to control prosthetic devices.

Furthermore, the utilization of a commercial headset to control a robotic arm is proposed in the work of Ranky and Adamovich [11]. According to them, after a training period users are able to get used to the control functions and improve the overall performance. Vourvopoulos and Liarokapis compare two commercial EEG headsets in order to control a Lego NXT robot [13].

Controlling vehicles by using BCI also has been subject of research. Zhao et al. [15] did use motor imagery (MI) to control EEG as well as a car in a Virtual Reality (VR) environment. Zhang et al. used a BCI to control an unmanned vehicle [14]. With BrainDriver, a project developed by FU Berlin, Germany, a commercial EEG headset is used along with Laser Range Finder (LRF) and Global Position System (GPS) data to control a car [16]. A quite interesting approach is featured in "Prototype This: Mind Controlled Car" by Discovery Channel [17]. Here, a BCI is used to measure the driver's rage in order to prevent road rage by slowing down the car.

Brain-computer interfaces also have been used to gain knowledge about car drivers to understand what emotional states a driver is experiencing when driving a vehicle. Gugler et al. [20] did monitor attention processes during a monotonous car driving simulation with EEG. The work of Putze et al. [10] and van den Haak et al. [4] utilize BCI to gain knowledge about cognitive workload of drivers during multitasking or under stress.

Osswald and Tscheligi [9] explore the driver distraction when performing secondary tasks during driving. Kyung et al. [7] introduce a wearable in-vehicle device, providing the driver with relevant information and also obtaining the physiological data of the driver.

Relevant to our work is the research of Anderson et al. [1] comparing visualization techniques in terms of cognitive workload by the usage of EEG devices. Cernea et al. [2, 3] also detected facial expressions as well as emotional states during various tasks by using a commercial EEG headset.

3 In-Vehicle Secondary Control Tasks with BCI

Using the previously presented projects as a starting point, our research aims at highlighting the performance of an EEG-based portable BCI headset when used to control in-vehicle secondary, non-vital systems. Additionally, by inspecting the traffic errors of the drivers in multiple circumstances, we hope to capture the influence of such a BCI system on the drivers' cognitive workload, thus further exploring the potential of these devices as in-vehicle interaction systems.

3.1 Design

Driving the vehicle is only one of the many tasks drivers need to focus on. As such, a BCI-powered interaction method could relieve the cognitive workload of the driver and reduce the level of distractions introduced by manually controlling multiple in-vehicle systems. But does EEG-based control have the capacity to reliably execute these commands? To inspect this, we conducted a preliminary study that investigates the performance and accuracy of EEG-based control of in-vehicle devices as well as highlights the error rates for the common tasks drivers have to execute in real-life driving scenarios.

During the experiment, the participants were involved in executing a set of activities that are always or at least sometimes present in everyday driving. The activities were grouped in the following three categories:

- *driving task (highest priority)* – firstly, every driver has to be in control of the vehicle and obey the traffic rules
- *search task (high priority)* – drivers are sometimes involved in search-and-find tasks in the environment surrounding the vehicle (e.g., finding a parking lot, finding a store, etc.)
- *control task (low priority)* – drivers have to interact with the dashboard of the vehicle (in our case via BCI) to activate various devices and vehicle subsystems (e.g., lights, radio, GPS, etc.)

Following this structure, participants were asked to control a vehicle in a simulated environment and obey the traffic rules. Additionally, each driver took part in a set of five search tests, each with duration of five minutes, aimed at simulating a common search scenario that drivers are faced with on a daily basis. Specifically, the tests had the following corresponding search assignments that the drivers had to execute: “Drive around the city, obey the traffic rules, and count the number of X’s you see”, where X would represent the type of objects that needed counting: Pre-Test – the number of red cars; Test 1 – the number of phone booths; Test 2 – the number of vans; Test 3 – the number of grocery stores; and Test 4 – the number of traffic lights. Instead of simply asking the drivers to search for a place, they were instructed to count them in order to allow all drivers to search for the full five minutes, and also in order to eliminate any competitive aspect from the sessions—e.g., if a driver is trying to find a landmark as fast as possible, he might disregard traffic rules or be unable to concentrate on controlling the BCI.

While the five tests were almost identical in terms of driving and search task, they were mainly introduced to capture the differences and particularities of controlling the in-vehicle systems. An initial pre-test was designed to offer a baseline measurement for the driving performance in the virtual environment and the distraction introduced by controlling the dashboard through normal touch-based interaction. For this, the users drove without the EEG headset and completed a search-and-find assignment during which the number of traffic violations was stored. Additionally, as the sessions were recorded, the answers reported by the users at the end of each search test were compared to the actual number of sought objects that appeared on the screen.

In the following tests (Test 1 to Test 4), the users drove the vehicle while wearing the EPOC headset and trying to control the dashboard with their minds. Each test increased the difficulty of the control task by adding commands or increasing their complexity (Figure 4). In order to better quantify the performance of the drivers, the dashboard controls were grouped into Boolean (turn lights on/off, turn heater on/off) and discrete operations (open the left window a bit, turn the volume up to the middle, etc.). In the initial BCI test (Test 1), the users only have to control two Boolean values (e.g. turn lights on/off, turn heater on/off). Test 2 already involved four Boolean controls, while the last two tests involved two Boolean and two discrete commands, respectively, four discrete commands.

For the control task, a supervisor periodically instructed the subjects involved in a test to execute a command on the dashboard (e.g. "turn on the radio"). While drivers are used to execute a command with touch (Test 0), in the case of EEG control the participants had a 10 seconds window to activate the functions via BCI (Test 1 to 4).

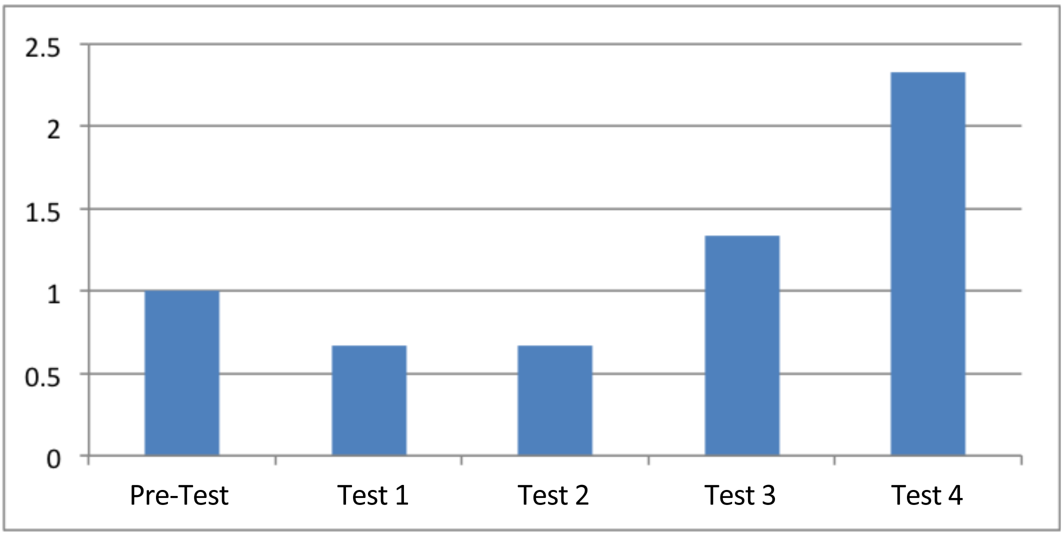

Figure 2 Traffic errors – Average number of traffic violations recorded by the driving simulator for every test.

3.2 Execution

The study was executed on a small sample of 12 participants in order to gather insights about the possibilities of EEG control and inspect the reduction of cognitive load on the drivers. The subjects had to complete an initial questionnaire that reflected an even distribution in terms of gender and age. Furthermore, all participants had a valid driver's license at the time of the experiment and were driving a vehicle on a regular basis.

After the initial questionnaire, the participants took part in an initial training session composed of two parts: getting familiar with the simulator and executing controls with the EPOC neuroheadset. For the simulator training, each user had 30 minutes to drive around and get used to the provided controls and interface. To support a realistic scenario, the controls that needed to be managed included steering, blinkers, direction of movement (forward or reverse), pedals, looking left and right, etc. Note that the virtual environment for the training was different from those used in the experiment, to ensure that no participant would have prior knowledge that would be relevant for the search tasks.

Furthermore, users had up to one hour to learn and train the basics of control with the Emotiv EPOC EEG device. The subjects trained to map various mental activation patterns, such as activating a command when concentrating at a concept or imagining a body movement. This was achieved by employing the EPOC's framework that detects and learns particular mental activations and classifies new activation patterns in existing categories. After training with the BCI, the participants were free to select a set of mental mappings they felt were most efficient and intuitive. These mental patterns were then used to train the EEG system for usage in the experiment.

In terms of the environment, a driving simulator was employed that is commonly used by people preparing for their driving test. The simulator supported traffic rules and was able to detect if a driver violates them. Other features of the simulator included: realistic controls, urban environments with visual and auditory cues, other virtual traffic participants, etc.

Additionally, we implemented a software dashboard to control a set of in-vehicle systems and subsystems. Some of the systems were controlled with Boolean commands (e.g. lights,

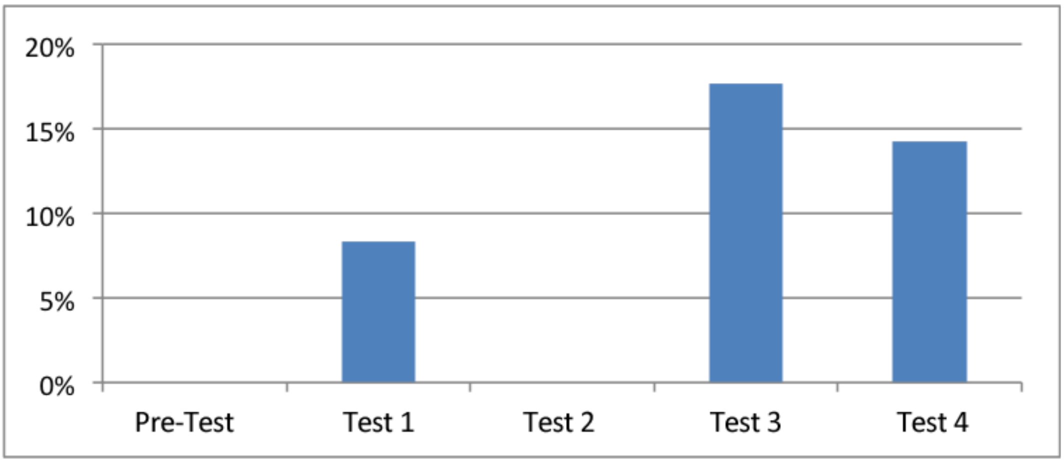

Figure 3 Search task errors – Average percentage of search objects not noticed by the participants during every test.

air-conditioning, seat heaters), while others required a more refined scale of control (radio with volume control, electric windows, etc.). The virtual dashboard could be controlled either through touch by pressing a set of keys or through the EPOC BCI. The dashboard was also conceived to give visual and auditory feedback to the driver about the execution of a certain command.

4 Results and Discussion

Figure 2 highlights the average distribution of traffic violations for each of the five search tasks. One can notice a slight decrease of the errors that the drivers made in traffic in the cases where the EPOC headset was employed for 2-4 simple interaction commands, compared to the touch-based manipulation of the controls. This reduction is relevant, especially when we note that the error rates between the initial training and the baseline search task (Pre-Test) are similar. Also, once discrete commands were considered, the traffic violations increased even passing the baseline level established in the Pre-Test, suggesting that the users had difficulties to execute the different BCI commands. This in turn can be a sign for an increased cognitive load that the execution of multiple complex BCI operations introduces.

The results for the primary search task are highlighted in Figure 3. As the number of search-and-find errors was overall reduced, the results cannot be the based of a thorough analysis. However, we hypothesize that the higher error levels detected for sessions involving discrete control could be again related to an increased cognitive workload.

Furthermore, an element that influences the search task results is the accuracy of the EEG control in each of the sessions (Figure 4). While in the initial tests the control error rates had satisfactory levels, it seems that the error margins increased with the complexity of every session, reaching values of over 40% for Test 4. Such a lack of accuracy can distract and create frustrations for the driver, resulting in higher error rates in the primary tasks. Moreover, we noticed that these control error rates could in some cases be improved with additional training. For the sake of completeness, we would like to mention that no control errors were recorded in the touch-based dashboard interaction (Pre-Test).

Looking at the other side of the coin, Figure 5 highlights the average number of falsely activated commands by the EEG device when the user received no instruction to execute a

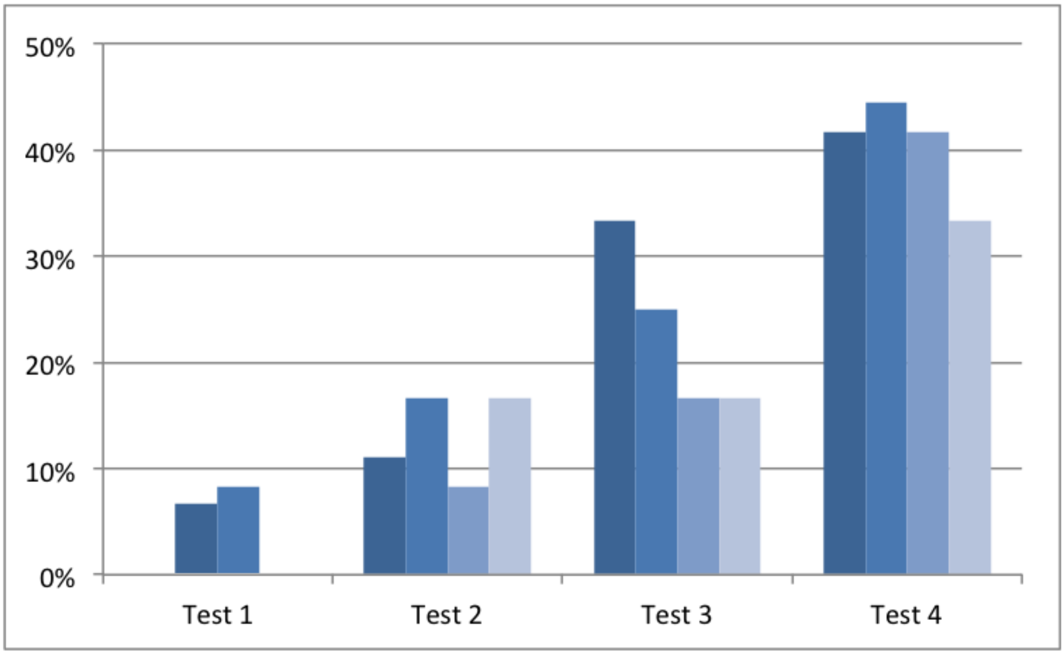

Figure 4 Control errors – Average percentage of not executed EEG-based dashboard commands for every test. The bars in each of the four tests represent: Test 1 – two Boolean commands; Test 2 – four Boolean commands; Test 3 – two Boolean and two discrete commands; Test 4 – four discrete commands.

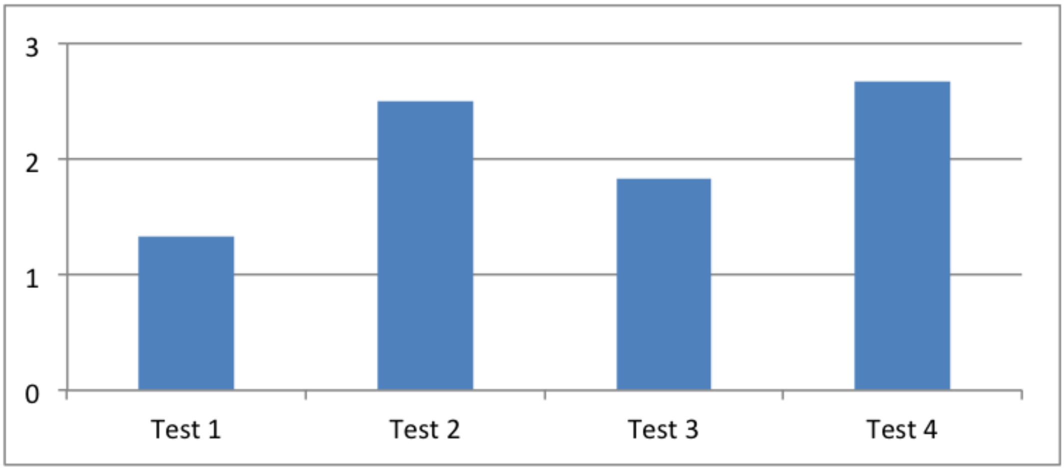

Figure 5 False positives – Average number of false command detections executed by the EEG interface for every test.

function. Considering a number of up to 10 instructions given by the supervisor in every session, the represented error rates can be considered low. Still, in this case, no particular pattern was distinguishable and further research of the topic is planned. Note that Figures 4 and 5 do not include the Pre-Test, as these Figures only reflect information about the EEG-based control, and the BCI headset was not employed in the initial touch-based test.

Besides the previously mentioned experiment, the participants were asked to complete a short questionnaire about their experience with the EEG headset and their impression about the use of BCIs in vehicles. Most users considered the neuroheadset as a viable alternative to touch-based controls, merely suggesting the inconvenient nature of employing non-dry sensors. Also, based on their experiences in the one-hour pre-experiment training, 83% of the participants decided to employ mental mappings that involved mostly imagined body movements (e.g., imagining to move a finger, the eyebrows, the shoulder, etc.) for executing commands.

When looking at in-vehicle usage, 66% of the participants expressed a positive attitude towards using a BCI device with such a functionality. This percentage has the potential to increase, as over 50% of the testers expressed their concern with the current level of accuracy, suggesting that they expect commands to be executed immediately and without repetition, even in the case of non-vital systems (e.g., "I don't want to try this [*turning on the radio*] three times").

5 Future Work

While simulating an environment is a relatively simple and inexpensive solution for many tests, in a next stage of this research we plan to evaluate the EEG headset control with an actual in-car dashboard. This would of course imply the measurement of the EEG headset's performance in control tasks, as well as the comparison of cognitive workload levels when simultaneously driving and accessing the dashboard functionality by touch and by BCI. For the recognition of the cognitive load level we plan to apply the widely accepted NASA Task Load Index (NASA-TLX) [19].

Focusing on a slightly different direction, we plan to investigate the detection of emotional states that the driver and other occupants of the vehicle experience. These states could then be influenced or compensated for by adapting the interior lighting and musical ambience inside the vehicle, making the EGG headset an integral part of a human-vehicle feedback system.

6 Conclusion

As in-vehicle systems become increasingly complex and versatile, it is vital to encourage the development of new interaction metaphors that are suitable for in-vehicle devices and do not representing a distraction to the driver. In this paper, we have investigated the performance and accuracy of EEG-based control of a simulated vehicle dashboard as well as captured traces of effects in-vehicle BCI usage might have on the cognitive workload of the drivers.

Our results suggest that traffic errors—and in a wider sense cognitive load—can be reduced when some interaction with in-vehicle devices is outsourced to BCI systems. At the same time, an increased complexity of the commands controlled through the EEG headset can negatively affect the driver's cognitive load level, manifested in our experiments through higher errors for the traffic and search tasks.

Similarly, in terms of accuracy of the EEG-based control, our findings suggest that the execution error for the BCI commands is within acceptable limits for up to 2-4 simple commands. While this allows for the control of straightforward dashboard elements, the control of complex in-vehicle systems requires further investigation, as accuracy levels decrease when embedding multiple commands that necessitate discretized operations.

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