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APPLYING PASSIVE BRAIN-COMPUTER-INTERFACES IN AUTONOMOUS DRIVING: A CASE OF TAKING OVER CONTROL

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ABSTRACT: This paper communicates the research plan for a dissertation in the field of Passive Brain-Computer Interfaces. The main aim is the detection of a driver's mental state in real time and its use in autonomous driving. One example of this is embedded in the context of driver taking over control of the automated vehicle. A offline experiment in laboratory as well as both an online and offline experiment in a driving simulator will be conducted. This paper proposes an experiment planning as well as materials and methods to be used. The conduction of experiments and data analysis are pending. The outcome of these studies is expected to contribute to the design of the driver-vehicle-interaction in autonomous driving by identifying driver's mental states during mode transition.

INTRODUCTION

In recent years, autonomous driving has become one of the hot topics in research and engineering, which aims at minimizing the workload of drivers and optimizing the traffic situation. However, in most countries the human drivers are still responsible for anything that happens while autonomously driving [1]. Therefore, the autonomous driving systems designed by most research institutes or technology companies at the moment are not fully automated, that is to say, when the system cannot handle some situations or when the automated system is performing some errors, the driver must be able to take over control. For example, driving along a highway could be automated, but once an urgent traffic situation occurs, the driver is required to take over control. When the car drives autonomously, the driver's attention might probably be distracted to secondary tasks other than driving, as a result, a signal given by the system for takeover might be missed, or might surprise the driver. This could be dangerous during driving. Hence, it is of great importance to monitor the driver's mental state during autonomous driving.

Passive Brain-Computer Interfaces (passive BCIs) provide a new perspective on the use of BCI technology and have proven to be one of the most promising approaches for monitoring user's mental state, utilizing real-time brain signal decoding [2]. It could provide valuable information about the users' intentions, situational awareness and emotional states to the technical system. This allows the technical system to better adapt to the user and thus enhances the human-machine interaction performance, leading to neuroadaptive technology [3].

In the context of autonomous driving, passive BCI is considered as a promising method to improve the driver-vehicle interaction. It enables the real-time detection of driver's mental state like fatigue, workload, and degree of relaxation [4], which could provide essential information regarding drivers' state to the car. Combining with other sensor data, the car could adapt to individual aspects of the driver and make decisions accordingly. As passive BCIs do not rely on directed or even conscious actions of the driver [2, 4], the car could gain an additional stream of information about subjective situational interpretation of the driver while in autonomous driving mode. Furthermore, thanks to the improvements on dry electrodes, it is now of great convenience to apply a dry electrodes system in BCI research and its applicability in the context of a running vehicle has also been validated, based on the evaluation of BCI classification accuracy, amplitude and temporal structures of ERPs as well as features in the frequency domain [5].

During autonomous driving, knowing the actual state of the driver and communicating it to the car is crucial, especially in the process of take-over control during autonomous driving. Ensuring that the driver is able to take over control of the automated system properly is one of the major issues in highly automated driving. For example, the detection of whether the driver is in a relaxed state or mentally stressed before takeover, whether the driver fully concentrates on driving or is distracted by other driving-unrelated tasks, and whether the driver is experiencing drowsiness or is totally awake, is relevant information to design a communication from the car to the driver informing the need to take over. Besides, the detection of whether the transmitted signal from the automated system has really been perceived by the driver or was ignored, is also an important issue in autonomous driving. More abstract, from a human factors perspective, it is important that the driver possesses situational awareness [6]. It is important that the car is "aware" about the drivers' situation in order to

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communicate important information in an appropriate and secure way. Based on former studies, drivers tend to show higher drowsiness and less workload with vehicle automation, and more involved with the in-vehicle entertainment, affording less visual attention to the road ahead [7]. Thus in the presented workplan, mental workload, attention, and perception of stimulus will be examined, which are influential factors on driver's situational awareness while driving. They are all recognizable by EEG and their detections could provide helpful information to the vehicle to improve the interaction of driver and vehicle.

Detection of mental workload with EEG has been studied by many researchers (e.g. [8-11]) and some EEG features have been proven to be relevant to mental workload, like ERPs and variation of spectral power in theta and alpha band. However, there are few studies on detection of mental workload in driving, especially in online analysis. Kohlmorgen et al. detected real-time mental workload in drivers operating under real traffic conditions using EEG-based system [12]. They created a system which is able to measure the level of mental workload in real time and mitigate the workload induced by the influx of information from the car's electronic systems, ultimately to detect and avoid stressful situations for drivers. Lei also detected driver's mental workload by EEG in real time and used the result to adapt a secondary task allocated to driver [13]. With the information on driver's mental workload, the system can better know about driver's state before take over and can thus adapt the take over request to it.

Distraction is fatal in driving and found to be one of the main causes for car accidents. Although there are already many physiological methods tracking user's attention (e.g. eye tracking, measuring heart rate), EEG is also an important way to investigate attention, as it could reflect cognitive processing more directly [4]. Many studies (e.g. [14-16]) have found alpha activity as an indicator of attention allocation. Wang et al. [17] also proposed a model to recognize distracted and concentrated EEG epochs with a self-organizing map and found frontal and left motor components relevant to distracted driving. However, there's still less application in online study for driving so far.

ERP could also be used to detect missed stimulus [18]. If a typical ERP sequence is detected, the participant should have responded adequately to the stimulus. If a pending response is not accompanied by an ERP, the participant might have missed to detect the stimulus. In the context of take over control of automated driving, ERP could also be used to detect whether a transmitted request to take over is perceived or missed by the driver, which could provide significant information to the system.

Hypotheses: Mental states like mental workload, attention, and perception of stimulus could be monitored in real time by means of passive BCIs, in driving-like tasks in laboratory as well as in a simulated take-over context in autonomous driving.

MATERALS AND METHODS (IN PLAN)

In the whole experiment process, three studies for detection of mental workload, attention and perception of stimuli will be conducted. In the following parts, I'll present the detailed design for detection of mental workload both in laboratory and in a driving simulator. The experiments for attention and perception of stimuli will soon be developed. The experiment procedure for detection of mental workload is illustrated in Figure 1.

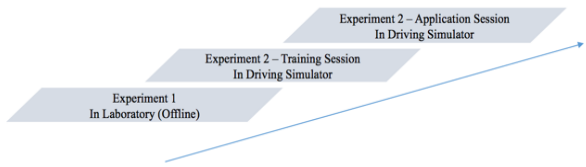

Figure1: Procedure of two experiments for detection of mental workload in laboratory and in driving simulator.

Experiment 1

Laboratory. This experiment will be conducted in a well-controlled laboratory with a screen presenting corresponding task.

Experimental Design. 12 participants will perform two tasks at the same time. The primary task is to monitor an automated system, which might pause at some time point and needs to be controlled by the participants, similar to the context of take-over control in autonomous driving. The Critical Tracking Task [19] will be employed as primary task, which requires the participants to control a bar by pressing the left and right key to bring the bar back to the central line (see Fig. 2). During the monitoring phase, the bar stays in the central automatically and participants need to take action only when a signal for take-over is delivered. Simultaneously, the participants will perform a secondary task – an auditory n-back task [20] – to induce different mental workload levels. A series of numbers will be presented at a time with intervals of 3 second in a randomly ordered sequence. As each new item being presented, participants are required to say out loud the number n items back in the current sequence. For high mental workload level, numbers are two-digit numbers from 10-99 and each time a 3-items-back number should be recalled. For low mental workload level, the numbers are digits from 0-9 and each time one item back. Conductions of different mental workload levels are separated in different blocks and each will be performed 40 times with a counterbalanced sequence (see Fig. 3). Each block lasts 60s and there'll be a brief pause after each block and a longer break after every 20 blocks.

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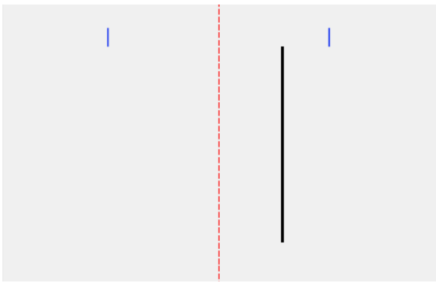

Figure 2: Appearance of Critical Tracking Task. While monitoring, the bar stays always in the central line. From some time point on, it will move away from the central line and participants need to bring it back by pressing the left/right key.

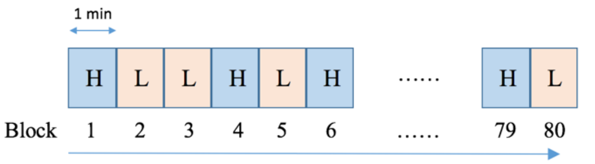

Figure 3: Experiment procedure for two mental workload levels in Experiment 1. H – High mental workload, L – Low mental workload. The sequence of H/L blocks is counterbalanced.

Materials. The data will firstly be collected using a 64 active Ag/AgCl electrodes mounted according to the extended 10–20 system to examine which electrode positions are relevant to the corresponding mental states and to identify the underlying cortical sources. Based on these results, the experiment will be successively conducted with a BrainVision LiveAmp system of a reduced number of dry electrodes.

Analysis. In order to discriminate between different mental workload levels, we'll employ following method to classify two mental workload levels. There are two parts of this analysis method for EEG data: feature extraction and classification. The feature extraction consists of four steps: removal of artifact, bandpass filtering in most discriminative frequency band, spatial filtering, and computing the power spectral in the selected frequency band. Classifiers will be chosen from linear (LDA, rLDA) methods and classification accuracy will be estimated by cross-validation. Furthermore, the performance of primary task including reaction time and deviation of the bar will also be analyzed to investigate the influence of mental workload on take-over performance.

Experiment 2

Driving Simulator. This experiment is based on a high fidelity static driving simulator of the Department of Psychology and Ergonomics at Technical University of Berlin, which consists of steering wheel, gas/brake pedals and other control elements. A driving scenario will be projected in front of the participants and they could also use the side mirrors as well as the rearview mirror. This driving simulator is partly automated with Advanced Driver Assistance Systems such as Adaptive Cruise Control.

Take-over situation. The vehicle is driving automatically on a highway and is going to drive off at the next exit. The driver is engaged in different non-driving tasks and he/she will then be informed of the need to take over control of the vehicle and to drive off the highway.

Experimental Design. In this experiment, there are two sessions, including training session and application session. In both sessions, 12 participants will perform two tasks simultaneously. The primary task is to monitor the automatically driving vehicle in the simulator, and at some time point participants will be informed to take over control of it. At the same time, the participants need to perform secondary tasks. The secondary tasks used to induce different mental workload levels are listening to voice recordings from speeches and answering relevant questions (high mental workload) and listening to some quiet classical music (low mental workload). The procedure of tasks in the training session is the same as in Experiment 1, while each block lasts longer (2 min) and there're be 20 blocks in total. The recorded EEG data in this session will then be trained. In the application session, real-time estimation of driver's mental workload level based on classification trained before will enable the system adapt to the driver and give corresponding information to the driver.

Materials. The data collection will be accomplished using the BrainVision LiveAmp system with active dry electrodes, as stated in Experiment 1.

Analysis. The data collected in training session will be analyzed as stated in Experiment 1. Classifier for distinguishing different mental workload levels will be trained. In the following application session, the best performing classifier will then be applied and the outputs represent estimated level of workload. Corresponding adaptation or feedback will thus be given from the system back to the driver, in order to make take-over more proper and safer.

OUTLOOK

The results obtained from the experiments above will be discussed and conclusions will be formulated. Significant real-time detections of different levels of mental workload, attention as well as perception of stimuli by means of passive BCIs are to be expected, thus providing important information to the vehicle and ensuring the driver-vehicle-interaction more secure and comfortable. It should be confirmed that passive BCIs could be applied in autonomous driving situations to detect drivers' real-time states.

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