Experimental Design and Collection of Brain and Respiratory Data for Detection of Driver's Attention

Roman Mouček[1,2], Lukáš Hnojský[1], Lukáš Vařeka[1,2], Tomáš Prokop[1,2] and Petr Brůha[1,2]

[1]Department of Computer Science and Engineering, Faculty of Applied Sciences, University of West Bohemia, Univerzitní 8, Pilsen, Czech Republic

[2]NTIS – New Technologies for the Information Society, Faculty of Applied Sciences, University of West Bohemia, Univerzitní 8, Pilsen, Czech Republic

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Abstract: Attention of drivers is very important for road safety and it is worth observing even in laboratory conditions during a simulated drive. This paper deals with design of an experiment investigating driver's attention, validation of collected data, and first preprocessing and processing steps used within data analysis. Brain activity is considered as a primary biosignal and is measured and analyzed using the techniques and methods of electroencephalography and event related potentials. Respiration is considered as a secondary biosignal that is captured together with brain activity. Validation of collected data using a stacked autoencoder is emphasized as an important step preceding data analysis.

1 INTRODUCTION

Attention of drivers is a very important factor of road safety. Inattentive drivers are dangerous to their surroundings and cause a considerable number of accidents. Since decline of attention, especially during long rides, is natural, it is worthwhile to investigate it even in laboratory conditions during a simulated drive. Results from laboratory experiments can be then used in real environment, e.g. for development of devices maintaining driver's attention or development of autonomous driving systems used at first when the driver is tired or inattentive.

In this paper we follow experiments and studies previously provided by our neuroinformatics research group and published in (Mouček and Řeřicha, 2012), (Mouček and Řondík, 2012), and (Mouček and Košař, 2014). A pilot experiment that is in more detail presented further in this paper partly shares the same assumption as the already published experiments. However, it differs in design and extends it by collecting an additional biosignal - data from respiration, and also by validation of collected data using a stacked autoencoder. Within the presented experiment the experimental design is proposed and the data and metadata suitable for investigation of influence of monotonous drive on driver's attention during simulated drive (a car simulator is used) are collected and evaluated. Then the basic preprocessing and processing steps used within data analysis are described.

When creating the experimental design the methods and techniques of electroencephalography (EEG) and event related potentials (ERP) are used to monitor and analyze brain activity of participating drivers. Event related potentials measures use stimulation techniques to investigate brain responses, so attention of a driver is not only affected by driving on a monotonous track, but also tested and influenced using auditory stimulation in our case. It is considered that the peak latency (peak latency represents a level of driver's attention) of the P3 component (the brain cognitive response described in Section 2) increases in time as the driver is more tired from monotonous drive. However, this component has to be first detected in the collected data. Therefore, the data validation step has to be done. Besides the brain activity the respiratory rate is also captured and its changes (most probably its decrease) are anticipated.

University students in the role of tested subjects participated in the experiment; the captured data were analyzed and partially interpreted observing particular trends in them. Due to an assigned page limit, a more detailed analysis including statistical evaluation and more detailed discussion of the results is not

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provided. Moreover, since we publicly provide the collected data, the analysis can be provided by independent experts. We also realize that the number of subjects participated in the experiment (15 participants) is low for more precise statistical evaluation, but this number seems to be sufficient for a pilot experiment and for the decision about meaningfulness of the used experimental design and usability of the collected data.

The paper is organized as follows. Section 2 gives a short overview of basic principles of the ERP technique and assumptions related to amplitude and latency of P3 component. Then some recent experiments dealing with attention of drivers are briefly presented with respect to the experiments already presented in papers (Mouček and Řeřicha, 2012), (Mouček and Řondík, 2012), and (Mouček and Košař, 2014). The objectives of the proposed experiment are given in Section 3. Section 4 deals with experimental design, used hardware devices and software tools, participants, environment, and course of the experiment. The collected data and metadata are described in Subsection 4.5. The validation of the collected data is provided in Section 5. Sections 6 and 7 describe data preprocessing and processing. Experimental results together with final discussion are provided in Section 8. The last section contains concluding remarks.

2 STATE OF THE ART

This section provides a necessary short description of the ERP technique, the P3 component and the relation of P3 amplitude and P3 latency to attention. Then an assumption dealing with respiratory data is given. Finally, a short overview of EEG/ERP experiments dealing with driver's attention is presented.

Electroencephalography (EEG) and event related potentials (ERP) techniques are used for monitoring brain activity by measuring voltage changes on a scalp surface. ERPs have two advantages compared to classic behavioral methods: they are useful for determining which stage or stages of processing are influenced by a given experimental manipulation (a detailed set of examples is in (Luck et al., 2000)) and they provide an online measure of the processing of stimuli even when there is no behavioral response (Luck, 2005).

The P3 component (also referred to as the P300 component) as one of the event related components (waveforms) depends entirely on the task performed by the subject and is not directly influenced by the physical properties of the stimulus. It is sensitive to a variety of global factors, such as time since the last meal, weather, body temperature, and even day time or the time of year (Luck, 2005). It is not known exactly what the P3 component really means, it is probably related to a process called context updating (Luck, 2005).

However, there are known factors which influence the amplitude and the latency of the P3 component. The P3 component is sensitive to the probability of a target stimulus. P3 amplitude increases when the probability of the target stimulus class decreases or when it is preceded by a greater number of non-target stimuli. P3 amplitude is also larger when the subject pays more attention to the task. However, it is smaller if the subject does not know whether a given stimulus is / is not a target.

P3 latency is associated with stimulus categorization; if stimulus categorization is postponed, P3 latency increases. However, P3 latency does not depend on consequent processes (e.g. response selection). Thus P3 latency can be used to determine if a performed experiment influences the processes of stimulus categorization or processes related to a response (Luck, 2005). More detailed information is available in the literature provided above.

In our case we suppose that stimulus categorization is influenced by driver fatigue that is related to inattention and the time required for low-level sensory processing of incoming stimuli increases with the level of fatigue. We also consider that respiratory rate decreases with the level of fatigue.

When omitting behavioral studies, not many experiments dealing with driver's attention during simulated drive were performed using the techniques of electroencephalography and especially event related potentials.

Suitability of EEG-based techniques is described in (Schier, 2000); drivers' activity during a driving simulation task was recorded. As the result, an increase in alpha activity was interpreted as less attentional activity and a decrease as more attentional activity. EEG data as an effective indicator to evaluate driver fatigue are presented in (Li et al., 2012). The impact of a surrogate Forward Collision Warning System and its reliability according to the driver's attentional state by recording both behavioral and electrophysiological data was presented in (Bueno et al., 2012).

A systematic framework for measuring and understanding cognitive distraction in the automobile was presented in (Strayer et al., 2015). Primary, secondary, subjective, and physiological measures were collected and integrated into a cognitive distraction scale. Simultaneous recording of EEG and eye-tracking for investigating situation awareness and working memory load in distracted driving was introduced in (Ichiki et al., 2015).

The ERP technique was used in (Wester et al., 2008) where the impact of secondary task performance (an auditory oddball task) on a primary driving task (lane keeping) was investigated. The study showed that when performing a simple secondary task during driving, performance of the driving task and this secondary task are both unaffected (Wester et al., 2008).

Amplitude of the P3 component reflecting individual differences of navigation performance in a driving task was investigated in (Bo et al., 2012). Two groups of navigators with good and poor navigation performance participated in a driving task; P3 amplitude was measured while two types of triggers were presented (intersections and street signs). Poor navigators showed larger P3 amplitude than good navigators on the left hemisphere, right hemisphere, the temporal, parietal and occipital sites when intersection triggers were presented, and on the occipital site when street sign triggers were presented, reflecting different levels of mental resource needed to process the spatial information between these two groups.

3 OBJECTIVES OF EXPERIMENT

The presented experiment was designed and conducted to investigate attention of drivers during simulated drive. The assumptions described in Section 2 were considered during designing and performing the experiment and the following objectives were set:

- to construct and implement a monotonous track where a substantial decrease of attention is supposed,
- to use a car simulator located in our neuroinformatics laboratory,
- to capture the brain activity of drivers during a simulated drive,
- to use auditory stimuli during experiment to evaluate brain activity,
- to capture respiration rate together with drivers' brain activity monitoring,
- to perform a pilot experiment on a group of at least ten participants,
- to validate the collected data,
- to annotate, store and made the collected data public,
- to compare the latency of averaged P3 components and evaluate the respiration waveforms to give a preliminary view if the results follow the considerations given in Section 1 and should be further elaborated.

4 DESIGN OF EXPERIMENT

The design of the experiment is a variant on the classic odd-ball paradigm in which presentations of sequences of frequent (non-target) audio/visual stimuli are interrupted by infrequent (target) stimuli. Infrequent stimuli usually elicit a much larger P3 component than frequent stimuli.

Two auditory stimuli were used to elicit the brain activity of the participants:

- non-target stimulus S1 - the sound of car wipers, duration time 900 ms, probability of occurrence p = 0.8,
- target stimulus S2 - the sound of thunder, duration time 900 ms, probability of occurrence p = 0.2,

Both these stimuli were played from the headphones worn by the participants during the whole simulated drive. The participant had to press the button to react to each target stimulus. The response button was located under the steering wheel. Although this response event required some movement from the participant, it did not cause undesired artifacts. The stimulus onset asynchrony (SOA) was set to 3900 ms (it means that the interstimulus interval was 3000 ms). The following rules were applied within the experimental scenario:

- at least two first stimuli are non-targets,
- each target stimulus appears randomly with respect to its probability of occurrence,
- two target stimuli cannot be sequential.

The background sound of drizzling was played from speakers to imitate the real environment. The speakers were located inside the car simulator behind the driver's seat.

The overall length of the experiment was 60 minutes. This length was experimentally verified as a maximum time frame during which the participant did not have difficulties (bad feelings) with an EEG cap placed on his/her head. It was also expected that fatigue would increase approximately after 30 minutes of driving.

The experiment was divided into three driving sessions, each session lasted 15 minutes and was followed by five minutes break. The breaks served both for relaxation of the participant (from driving and watching the simulation scene) and for preventing the participant from familiarity with presented stimuli (habituation to stimuli was thus limited).

4.1 Hardware Equipment

The experiment was performed in the neuoroinformatics laboratory of the University of West Bohemia, Czech Republic that was equipped with all necessary hardware infrastructure for EEG/ERPs and respiratory rate recordings. The experimental car simulator (a front part of a real Skoda Octavia car) was equipped with the Logitech G27 wheel, accelerator, and brake. These were connected to the computer via the USB port.

Three computers were used: the first one for presentation of auditory stimuli, the second one for storing recorded data, and the third one for presentation of the track. The track was projected on the wall in front of the car simulator. V-Amp produced by the Brain Products company was used as an EEG amplifier. It served also as an input of the sensor capturing respiratory rate.

4.2 Software Tools

The stimulation protocol was implemented in the Presentation software tool produced by Neurobehavioral Systems, Inc (Neuro Behavioral Systems, 2014). The sequence of stimuli was generated randomly, but it always contained the same number of target and non-target stimuli. All the sounds (including background drizzling) were recorded using the Audacity software tool and stored in the .wav format. The track was prepared using the World Racing 2 game produced by the Synetic Company (SYNETIC GmbH, 2014). The same track as in (Mouček and Řeřicha, 2012) was used. The BrainVision Recorder (Brain Products, 2014) was used for recording and storing EEG/ERP data and respiration rate. MATLAB, EEGLAB, and ERPLAB software tools were used for processing and analysis of experimental data.

4.3 Recording System

Common EEG caps (the 10-20 system defining locations of scalp electrodes) were used depending on the size of the participants' heads. The reference electrode was placed approximately 0,5 cm - 1 cm above the nose and the ground electrode was placed on the ear. The respiratory rate sensor (produced by the Brain Products company) as well as the EEG cap were connected to the V-Amp amplifier.

4.4 Participants and Course of Experiment

A group of 15 volunteers, university students (thirteen men, two women), aged 21-28, participated in the experiment. The participants got necessary information about the experiment in a written form in advance. Then informed consent was obtained from all of them.

Before starting the experiment, each participant was familiarized with basic behavioral rules during an EEG/ERP experiment (e.g. not to use cosmetic products before the experimental session, or reduce eye blinking and unnecessary movements to decrease the number of artifacts). Then the participant was familiarized with all sounds played during the experiment, with car simulator controls, and with the track. Subsequently the participants were allowed to drive around to get accustomed to the car simulator and simulated drive.

During the experiment the experimenter was controlling data recording and checking the correct behavior of the stimulation program. When the experimental session finished, the participant left the car simulator. Then the experimenter asked him/her to fill in the questionnaire containing questions related to his/her feeling of fatigue during/after the drive.

4.5 Data and Metadata

EEG/ERP data were recorded with the sampling frequency of 1 kHz; no filters were used during data recording. The resulting signal was stored into three files:

- .eeg file containing raw data,
- .vhdr file containing metadata that describe raw data in the related .eeg file,
- .avg file containing the averaged signal around the used stimuli.

All recorded data and collected metadata were stored into the EEG/ERP portal (experiments No. 205-209, 225-236) (EEG/ERP Portal, 2016). These data are publicly available for registered users (registration is free).

5 DATA VALIDATION

The data validation was based on the main objective of P3-based experiments: target and non-target trials are expected to be associated with differently shaped ERP components, especially P2, N2, and

P3 (Blankertz et al., 2011). To validate this objective, dichotomous machine learning was used. If classification of a specific dataset from one subject yields low error rates (defined later), the objective of the odd-ball paradigm is considered to be fulfilled.

The classifier was trained on a randomly selected data subset. The training subset contained 730 ERP trials (described in detail in (Vařeka et al., 2014a)) with equal numbers of targets and non-targets. The trained classifier was subsequently applied to the data of individual subjects.

The Matlab scripts available in (Vařeka et al., 2014b) and using EEGLAB and BCILAB functions were used for the implementation. Feature extraction follows the Windowed Means Method proposed in (Blankertz et al., 2011). This method includes feature extraction: low pass filtering and spatial filtering, and machine learning technique based on one of the deep learning models - stacked autoencoders. Feature extraction was described in detail in (Vařeka et al., 2014a). Machine learning was designed as follows.

The Matlab implementation of stacked autoencoders was used. The parameters (including number of layers, number of neurons in each layer, etc.) were empirically optimized. The experimentation started with two layers, then either new neurons were added into the layer, or a new layer was added until the performance of the classifier stopped increasing.

Finally, the following procedure was used to train the network:

1. The first autoencoder with 100 hidden neurons was trained. The maximum number of training epochs was limited to 500.
2. The second autoencoder with 75 hidden neurons was connected with the first autoencoder to form a 133-100-75-133 neural network, and trained. The maximum number of training epochs was limited to 300.
3. The third autoencoder with 60 hidden neurons was connected with second first autoencoder to form a 133-100-75-60-133 neural network, and trained. The maximum number of training epochs was limited to 200.
4. The fourth autoencoder with 30 hidden neurons was connected with third autoencoder to form a 133-100-75-60-30-133 neural network, and trained. The maximum number of training epochs was limited to 200.

Furthermore, the following parameters were set for the network globally: L2WeightRegularization was set to 0.004, SparsityRegularization was set to 4, and SparsityProportion was set to 0.18.

After the training of each autoencoder, the input feature vectors were encoded using that autoencoder to form input vectors of the next autoencoder.

Using the output of the last autoencoder, softmax supervised classifier was trained with 200 training iterations. Finally, the whole pre-trained 133-100-75-60-30-2 network was fine-tuned using backpropagation.

The learned model was first verified on other P300-based data (Vařeka et al., 2014a). Then, for each subject, error rates depicted by red bars were obtained by applying the classifier in the testing mode. Let us suppose that we have t_p - number of correctly classified targets, t_n - number of correctly classified non-targets, f_p - number of misclassified non-targets, f_n - number of misclassified targets. The error rate was calculated according to Equation 1.

$$ERR = \frac{fp + fn}{tp + tn + fp + fn} \tag{1}$$

As a result, error rates indicate the extent to which the classifier was unable to separate target and non-target single trials. The classification results may slightly differ with each run because of the indeterministic training process.

6 DATA PREPROCESSING

The recorded EEG/ERP data as well as the data obtained from the respiratory sensor were processed using the following workflow:

- Channel selection: The following channels capturing brain data were selected for the initial processing: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, Fz, Cz, and Pz.
- Driving session selection: Data for each driving session were processed separately.
- Data filtering: IIR Butterworth filter (frequency range 0,01 Hz - 20 Hz) was applied to the data.
- Data segmentation: The epochs were extracted from datasets, data corresponding to each target and non-target stimulus were selected in the time interval (-100 ms before the stimulus, 1000 ms after the stimulus) in the area of occurrence of the target or non-target stimulus.
- Application of the filter for automatic artifacts detection: The segmented data exceeding the range (-100 microV, 100 microV) were denoted as possible artifacts and provided for manual inspection.
- Rejection of corrupted data: The data automatically denoted as artifacts were manually inspected

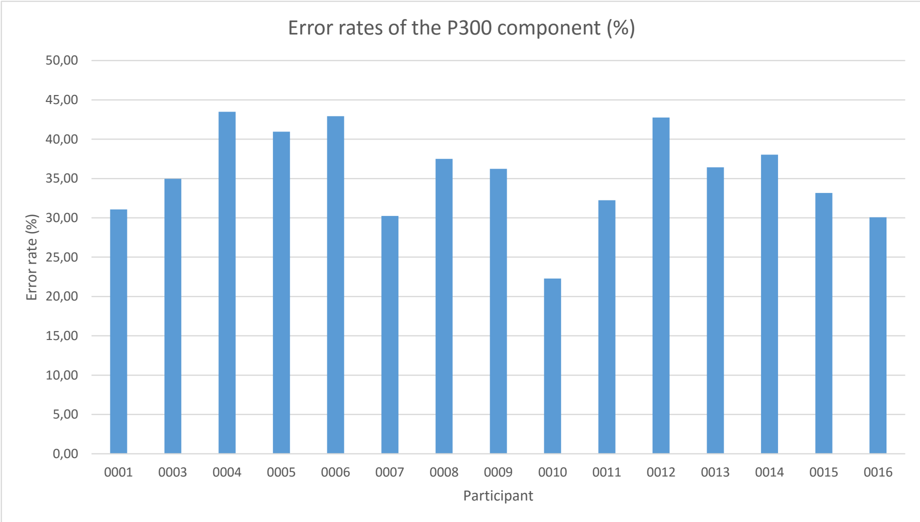

Figure 1: Results of validation. The error rates for each subject are depicted in bars. Higher error rates mean lower amplitudes of P3s and/or more distortion in the EEG/ERP signal.

and most of them rejected. Moreover, each dataset was manually inspected and in case of suspected artifacts the related epochs were rejected. Artifacts were usually caused by eyes blinking, swallowing or movements.

- Baseline correction: The baseline was corrected using the interval (-100ms, 0ms) before occurrence of each target or non-target stimulus.
- Data averaging: The accepted epochs for each participant and each session were averaged and stored separately for target and non-target stimuli.
- The data captured by the respiratory sensor were processed using the following workflow: only the .vhdr file was read, filtering was applied, and the scale for respiration visualization was adjusted.

7 DATA PROCESSING

For the next analysis only the channels P3, P4, Fz, Cz, and Pz (since the occurrence of the P3 component is more significant on these channels) were selected. Then grand averages for each driving session and each participant were computed (separately for target and non-target stimuli). The latency of the P3 component was determined using the technique of peak latency. It is the simplest way to determine the latency of the P3 component when the maximum amplitude in the time frame of possible occurrence of the P3 component is searched for. The P3 component time frame was set to (300 ms, 450 ms) reflecting the expected location of peak latency values occurrence in case of auditory stimulation. Finally, the peak latency was determined manually from computed grand averages.

8 RESULTS AND DISCUSSION

The results from performed experiments are summarized in the figures and tables presented further. The P3 component for the participant 0010 and the values of his/her peak latency for the first driving session and for channels P3, P4, Fz, Cz, and Pz are shown in Figure 2.

It can be seen that the component P3 is clearly identifiable and there is a substantial difference between reaction to target and non-target stimuli. However, the identification of the P3 component was not so evident for all participants. This is shown in Table 1 where peak latencies for selected channels and each driving session are available.

The data collected from participant 0002 were rejected, the resulting values were out of reasonable range, most probably because of technical failure during the measurement. The data from participants 0005, 0006, 0008, and 0009 were also not further interpreted since the N2 component (a repetitive, non-target stimulus elicits N2 deflection that can be thought of as the basic N2 component) had a very high amplitude while the component P3 was not clearly evident (an example for the participant 0006 is available in Figure 3). It can also easily observed that the amplitude of the N2 component decreased in time; the difference in peak amplitudes of this component is

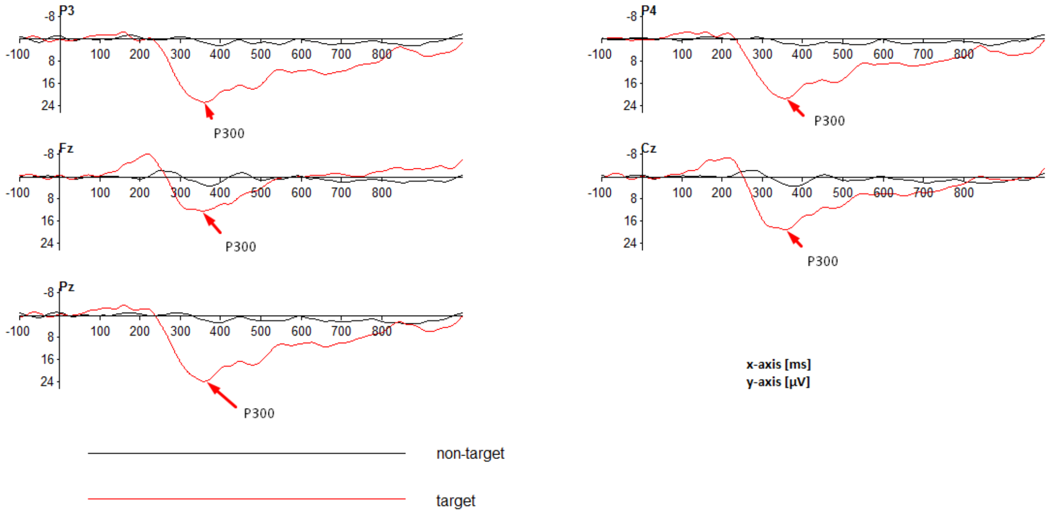

Figure 2: Grand average for participant 0010, the first driving session, channels P3, P4, Fz, Cz, and Pz, peak latency of the P3 component for target and non-target stimuli.

noticeable comparing the waveforms for each driving session. It was probably caused by habituation of participants during the course of the experiment.

However, it does not mean that the data containing high N2 amplitude and low P3 amplitude are incorrect. Since we were unsure with their correct interpretation, they were rejected only for this preliminary analysis. It is reasonably possible that they will be considered for later analysis after reviewing them by another expert in the field. The data from participants 0012 and 0013 were not interpreted because of low amplitude of the P3 component.

It is also evident that peak latencies differ among the participants in average. This is a natural phenomenon that reveals that the cognitive processing of stimuli is different for each individual in the considered time frame. It can be also seen that the average latency for all participants for each selected channel increased as the experiment continued to the next driving sessions.

However, different results we got by computing grand averages for all epochs containing the target stimulus and for all participants. It is not an average of peak latencies as computed above, all waveforms related to the target stimulus within driving sessions were averaged. The resulting waveforms are given in Figure 4. The determined values of peak latency for averaged waveforms are clearly shown in Table 2. It can be seen that grand averages for target stimuli, selected channels and all participants differ between the first and second driving session, while there is no evident difference between the second and third driving session.

The respiration rate was computed for each participant and for each driving session as it can be seen in Table 3. The average respiratory rate decreased in time. Participants 0013 and 0014 had an increased respiratory rate in all driving sessions in general, but it also decreased within the course of the experiment. The values from participants 0002 and 0015 were not captured correctly due to technical difficulties with the sensor.

9 CONCLUSIONS

This paper described the experiment dealing with attention of drivers during a simulated drive. Brain activity and respiratory rate of the participants of the experiment were measured and investigated by using mainly the methods of electroencephalography and event related potentials. Drivers, university students, were stimulated by simple auditory stimuli while driving a car simulator on a monotonous track. The collected data were annotated, stored, preprocessed, validated, and partly analyzed. The peak latency of the P3 component was derived from the data and grand averages for each participant and driving session as well as grand averages for all participants and each driving session were computed.

Experimental results showed that the P3 component had been identified at most participants during all driving sessions. However, some experimental results were not interpreted in this article because of the high amplitude of the N2 component compared to the amplitude of the P3 component. Prolongation of the peak latency of the P3 component was evident in case of most participants and in case of simple averaging of

Table 1: Grand averages for driving sessions, participants and selected channels.

Participant	1st driving session					2nd driving session					3rd driving session				
	Peak latency of P3 component [ms] on channels					Peak latency of P3 component [ms] on channels					Peak latency of P3 component [ms] on channels				
	P3	**P4**	**Fz**	**Cz**	**Pz**	**P3**	**P4**	**Fz**	**Cz**	**Pz**	**P3**	**P4**	**Fz**	**Cz**	**Pz**
0001	423	421	336	410	418	452	450	404	406	486	497	507	402	400	497
0002	rejected because of technical failure														
0003	383	384	382	386	383	390	416	394	399	378	398	431	387	398	346
0004	459	443	422	435	445	464	462	409	456	455	473	476	454	465	469
0005	too high amplitude of N200 component														
0006	too high amplitude of N200 component														
0007	345	334	323	343	341	356	353	357	356	354	357	355	359	358	356
0008	too high amplitude of N200 component														
0009	too high amplitude of N200 component														
0010	361	356	357	357	359	389	389	391	389	389	399	397	394	398	396
0011	317	318	347	305	322	319	311	309	303	327	363	410	307	304	407
0012	Low amplitude of P3 component														
0013	Low amplitude of P3 component														
0014	351	348	358	347	350	399	336	353	337	335	448	359	399	363	365
0015	444	413	404	406	411	428	418	411	415	418	498	505	448	456	449
0016	405	404	392	387	404	418	416	404	406	415	404	389	402	393	399
Avg	**388**	**380**	**369**	**375**	**381**	**402**	**395**	**381**	**385**	**395**	**426**	**425**	**395**	**393**	**409**

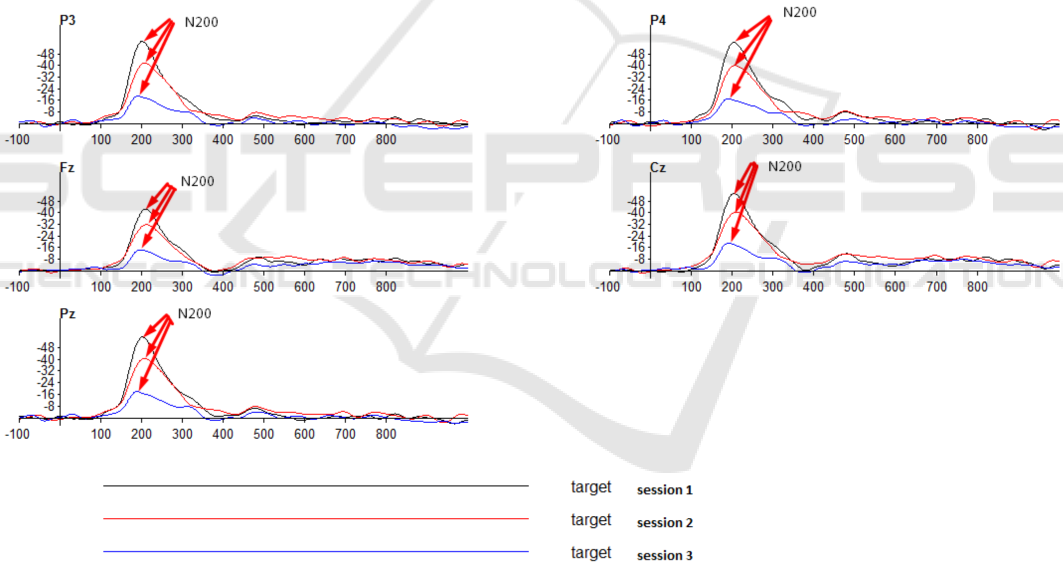

Figure 3: Grand average for the participant 0006, channels P3, P4, Fz, Cz, and Pz, peak latency of the N2 component for target stimulus.

their peak latencies. Despite expectations, prolongation of peak latency in time was not clearly observed when grand averages for all participants were investigated. This prolongation is evident only as a difference between grand averages of the first and second driving sessions. We also supposed that when the driver expected his/her drive to be almost completed (during the third driving session), his/her attention increased. The average respiration rate and respiration rates for most participants showed a decreasing trend during the course of the experiment.

The results in this article were not statistically evaluated. However, the trend of increasing latency and decreasing respiratory rate is clearly visible. The experimental results were naturally affected by different brain reactions of participated drivers and sensibility of captured data to the environmental noise, participants' overall mental conditions, and their movements that caused occurrences of artifacts. Although there was a big effort to eliminate these circumstances by experimental design, setting of experimental conditions, and usage of data preprocessing and process-

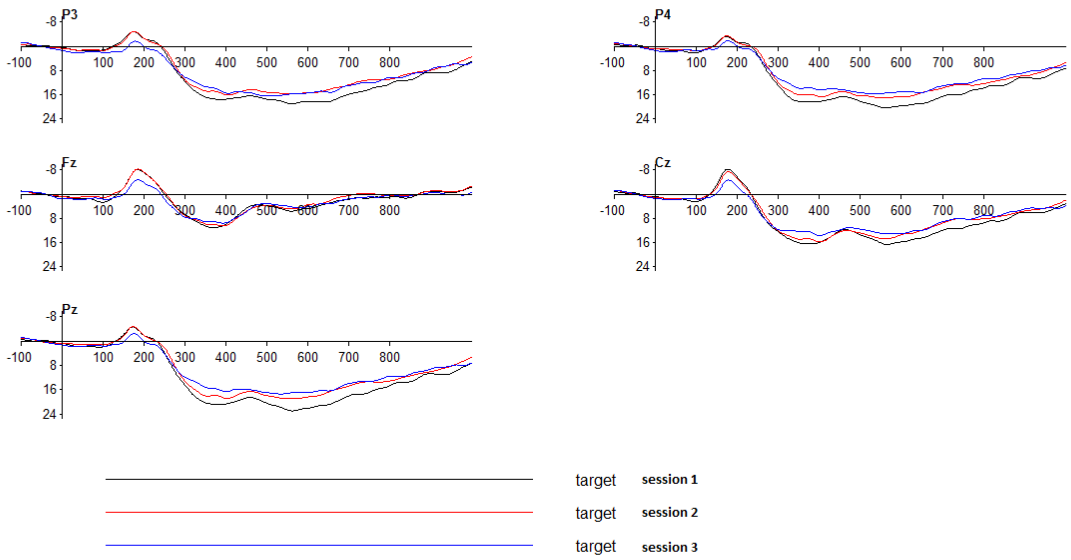

Figure 4: Grand averages for all participants, channels P3, P4, Fz, Cz, and Pz, peak latency of the P3 component for the target stimulus.

Table 2: Grand averages of peak latencies of the P3 component in [ms] for selected channels, target stimulus.

Grand average														
1st driving session					2nd driving session					3rd driving session				
P3	P4	Fz	Cz	Pz	P3	P4	Fz	Cz	Pz	P3	P4	Fz	Cz	Pz
391	391	369	386	389	407	407	395	402	405	406	405	395	402	402

Table 3: Respiration rate for each participant and driving session.

	Respiratory rate		
Participant	**1st driving session**	**2nd driving session**	**3rd driving session**
0001	18	16	16
0002	rejected		
0003	16	15	14
0004	15	14	14
0005	19	18	18
0006	16	16	15
0007	16	15	15
0008	18	17	16
0009	17	17	15
0010	16	15	15
0011	14	13	13
0012	18	18	18
0013	23	22	22
0014	26	25	25
0015	rejected		
0016	16	16	16
Avg	**17,69**	**17,00**	**16,62**

ing methods, they could not be completely removed. That is why we also validated the collected data using the stacked autoencoder.

The observations collected by experimenters from the participants were also summarized. The participants (they filled in the questionnaire) did not report a highly increased level of fatigue after having finished their experiment. Although the participants complained about the tedious ride, the stimulation kept them relatively attentive. One third of participants pointed out that they would like to drive longer without any brake. On the other hand, most participants complained about unpleasant feelings caused by the ground electrode placed on their ear. This feedback have been used for the design of further ongoing experiments.

We believe that by using the results of ongoing research and technological innovations it will possible to capture biosignals more easily in the future. It would facilitate recognition of the human attention level and decrease the number of accidents not only in transport but also during activities that are directly influenced by human attention.

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