Reducing the impact of vibration-caused artifacts in a brain-computer interface using gyroscope data

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Abstract—**We implemented an artifact prediction method for a saline-pad wireless electroencephalograph equipped with two-axis gyroscope used as a basic brain-computer interface (BCI). The BCI unit serves two purposes in the scope of the project Innotruck. Firstly, it enables remote control of vehicles and other systems over a limited set of trained mental activity. Secondly, it is a source of data for the passive analysis of the operator's mental fitness, which is further integrated into the driver assistance systems. The latter aspect has been the focus of our work. Saline-pad electrodes used in consumer grade electronics are prone to errors stemming from vibrations and sudden head movements. The implemented approach successfully preconditions the signal processing pipeline to take such artifacts into account and reduces the later processing overhead.**

Keywords: brain-computer interface, signal artifacts, driver assistance systems, electroencephalography, saline-pad

I. Introduction

In the scope of the interdisciplinary project Innotruck, hosted through the Institute of Advanced Study of the Technische Universität München, research is done in the areas of automotive human-machine interface (HMI), driver assistance, system architecture and energy management. The long-term focus in the area of HMI is placed on sidestick[1]-based and brain-computer interfaces (BCI) used for the primary vehicle control. Other HMI aspects, such as the touchscreen-based virtual dashboard, are outside of scope of this work.

The choice of a sidestick-based input method for our prototype vehicle, augmented with a wireless brain-computer interface, was made based on multiple factors. The shift to electric vehicles offers a chance for a major in-vehicle information and communications technology (ICT) overhaul with low transition costs for the original equipment manufacturers. ICT requirements of the newly introduced drive train components can be coupled with a more radical change to a data-centric and centralized system architecture, reducing the internal network complexity and accelerating the transition to safe drive-by-wire concepts [1]. The trend of functional integration can be symmetrically extended into the driver interface domain, replacing the old vertical-design paradigm with a new horizontal human-machine interface approach. Sidestick also provides personal mobility to the users with various physical disabilities, which are unable to operate today's physically intensive steering-wheel and pedal-based vehicles.

Brain-computer interfaces are the next step in reducing the physical aspect of the human-computer interaction. Such interfaces might be able to provide optimal control over any information-based system. Solutions which learn and dynamically adapt themselves to the user are still far way. For now, the human is the one who has to adapt and train the classifiers for personalized brainwave activity.

We have used the increased activity in the area of consumer grade BCIs to evaluate the cross-domain technology transfer into the automotive domain. A 14-electrode saline-pad based EEG device has been chosen.

A hidden hypothesis followed throughout the transition from the vertical interfaces towards BCIs is the growing benefit for the driver assistance systems. We assume that the interfaces of the future capture a growing amount of additional data, not related to the primary driving task [2],[3],[4]. This data can be additionally processed in order to make assumptions on the user state and fitness to operate the vehicle. In the next step, we pre-condition the driver assistance systems based on the results of the driver state analysis, effectively reducing the allowed margin of error for lateral and longitudinal vehicle dynamics.

In this work, we focus on the reduction of BCI errors caused by vibrations and sudden head movements which are relatively common during a typical drive. To confirm our method, we have used the data gathered during an experiment with sidestick-operated driving simulator. The participants were wearing the EEG helm throughout the course of the experiment in order to assess their vigilance, which is a topic of another work in the scope of our project.

This paper is organized as follows. In chapter II we explain the experiment setup and the used demonstrator. In chapter III we have a look at the vibration artifacts and lay out the processing method which is used to gain results presented in chapter IV. Finally, we conclude and summarize in chapter V.

II. Experiment Setup

In this chapter a brief overview of the EEG device, driving simulator and the participants' profile is given.

[1] Sidestick is a joystick-based input device placed on the driver's right or the left side.

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A. Electroencephalograph

A 14-channel wireless saline-pad electrode electroencephalograph was used to gather data. The total electrode count is actually 16, but two electrodes are used as reference CMS/DRL. The locations, following the 10-20 standard, are shown on Fig. 1.

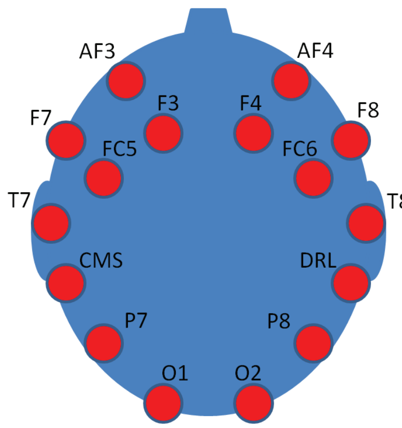

Fig 1. EEG electrode locations

The device performs internal super-sampling of the EEG signal with the frequency of 2 kHz and provides the resulting output signal with the frequency of 128 Hz. Effective sampling resolution is 14 bits, with the least significant bit representing 0.51μV. Dynamic range is 8400mVpp. Digital notch filters are active at 50 and 60 Hz. Signal bandwidth in the range of 0.2-45Hz. The unit is using a 2.4GHz wireless band to connect to the personal computer with a wireless dongle, where further data processing takes place. It is powered by a Li-Polymer battery with a theoretical life of 12 hours.

The EEG helm is equipped with an integrated two-axis gyroscope, originally used for on-screen cursor control through minimal head movements. Various applications have been developed which make use of the gyroscope, since the device is aimed at the consumer and personal computer market. These applications have not been used in this work.

B. Driving Simulator

VIRES Virtual Test Drive (VTD) version 1.1 was used for the data collection, complete with an automobile mock-up, a chassis of a Smart automobile, shown on Fig. 2 and Fig 3. During the data collection, the subjects did not use the steering wheel and pedals, but a sidestick mounted on the right of the driver, at the location of the gear shifter. A simulation of the environment was being shown on a large screen in front of the mockup.

The subjects were seated inside the mockup, wearing the wireless EEG helm which maintained a connection to the data collection computer nearby. The driving simulation itself was running on a desktop computer inside the mockup. A laptop was connected to this computer over the VTD Runtime DataBus (RDB), in order to log the simulation details.

Fig 2. Complete driving simulator setup on the left, personal computer used during helm fitting on the right

Fig 3. Participant with the EEG help inside the driving simulator

C. Participants

A total of 21 participants (18 male, 3 female), all in the possession of a driver's license valid in the European Union, took part in the experiment. Mean age was 26.1; the driving license was possessed for a mean duration of 8.2 years.

The goal of the experiment was determination of subject tiredness, so they were divided into the *normal* and *tired* groups based upon a pre-experiment survey and time of day. This grouping did not have any effect on the correlation between EEG artifacts and gyroscope data, so it is not mentioned in the rest of this work.

Subjects with thick scalp hair took several minutes longer to achieve acceptable signal quality. The typical fitting attempt with direct feedback on signal quality is shown on Fig. 4. Three originally planned participants could not achieve good contact at all and had to forfeit the experiment.

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Fig 4. Fitting of the helm to achieve acceptable signal quality was a trial-and-error process which failed in the case of three participants

III. Vibration Effects and Processing Method

We found that the vibration and movement-related errors have a direct impact on the frontal electrodes, while the impact on the rear electrodes was marginal or insignificant. The assumption is that this is the result of the helm construction and the fitting of the plastic frame carrying the electrodes. We assumed that electrode slippage and the resulting temporary change of signal quality is responsible for the direct correlation between the EEG channel artifacts and gyroscopic extremes. The subset of electrodes which are exposed to the artifacts was limited to the front array containing AF3, AF4, F3, F4, F7, F8 FC5 and FC6. The electrode FC5 has provided erroneous output almost throughout the entire experiment and over most trials and participants. Therefore, it has been completely taken out of the analysis, since the number of complete data sets with this electrode would include less than third of original participant count.

The EEG data was processed in raw form, before being fed to the EEGLAB suite and other post-processing steps. The moving average of the EEG channels had to be constantly re-calculated and taken into account. However, the sudden changes of the moving average in the frontal area were often correlated with the head movements taking place directly before or during the EEG channel change. This is shown on Fig. 5. It is, of course, impossible to always mark the EEG data predictively, since the short term artifacts and/or moving average change can occur in parallel to the actual head movement and electrode slippage. Still, knowing that the mismatch before the previous and actual EEG values on a specific channel stems from a mechanical movement can be used to avoid more complex error processing by taking subsequent signal drift into account.

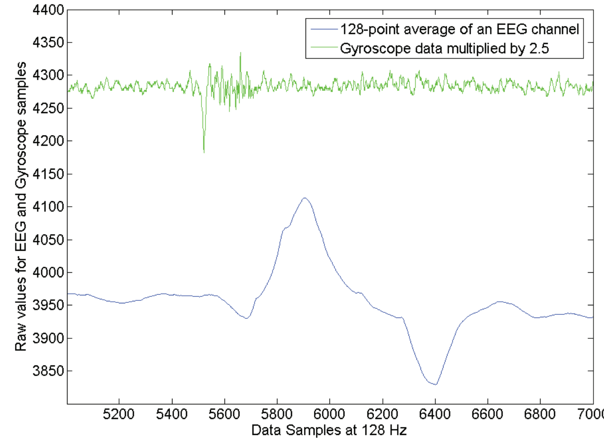

Fig 5. Scaled gyroscopic data and raw EEG data showing how increased gyroscopic Y activity (green) resulted in EEG moving average (blue)

The moving averages of relevant electrode subsets were analyzed together with gyroscopic values in order to tag the moving average changes directly related to mechanical vibrations. All the EEG data was collected during a virtual drive inside the test simulator. The amount of analyzed data per participant was in average 5 minutes, meaning that approximately 100 minutes of data sampled at 128Hz was processed.

It is important to restate that we concentrated on longer-lasting errors in EEG data, where the moving average remained offset for a prolonged period of time. The comparison between long and short term shifts is given on the Fig. 6 and 7 respectively.

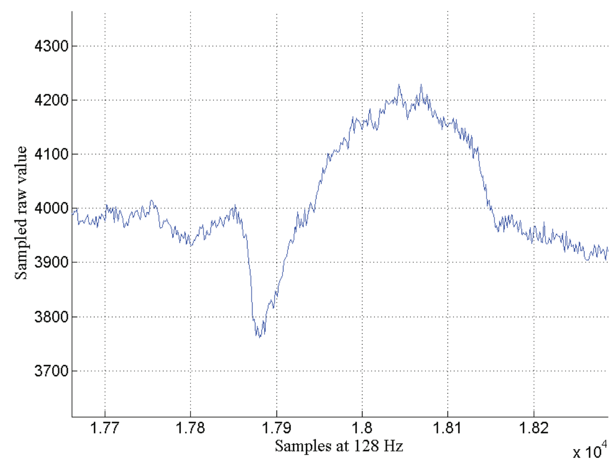

Fig 6. Temporary moving average shift of the EEG data in the timeframe of three seconds

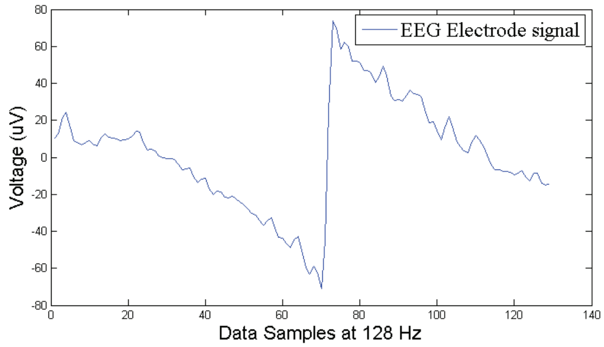

Fig 7. Short-term effect of electrode slippage which stabilized in timeframe of one second

IV. RESULTS

Out of the 21 participants in the original experiment, 10 produced EEG data with moving average artifacts related to gyroscopic data. The shortest description of the results is that the detection is, depending on the subject, either excellent or does not affect artifact removal at all. The data with successful detection contained, on average, more gyroscopic activity, meaning that certain subjects performed stronger head movements during the entire experiment. However, the data from remaining 11 participants with low gyroscopic activity also contained similar EEG artifacts. Either the head movements which are causing them are too weak or there is another source of a different nature which has to be captured by additional experiments. At any rate, the heuristics based on gyroscopic activity increases the chance of capturing known errors, but does not offer a complete and final solution for the artifact detection.

The participants reacted to the saline-pad helm quite well – the mean value of the personal comfort while wearing the helm was 5.375 with standard deviation of 1.2 on the scale of 1 (not comfortable at all) to 7 (very comfortable). Only two participants answered inconclusive to a separate question if the helm was irritating. There were no positive answers to this question and 19 answers were negative.

The results of long-term artifact detection are shown in the table I. Table II shows the effectiveness of detection of the largest artifacts in the EEG data. The results for the detection of largest (amplitude and time-wise) artifacts are much better than of the average ones, hinting that mechanical vibration causes the biggest signal distortion.

TABLE I
EFFECTIVENESS OF THE EEG ARTIFACT DETECTION IN 5-MINUTE SLICES

Subject	Detected Long-Term Artifacts		
	Total Missed	**Total Hit**	**Detection Rate**
1	1	5	83%
2	0	5	100%
3	2	7	78%
4	1	2	67%
5	2	7	77%
6	3	7	70%
7	2	4	67%
8	2	5	71%
9	1	5	83%
10	1	4	80%

TABLE II
EFFECTIVENESS OF LARGEST ARTIFACT DETECTION IN 5-MINUTE SLICES

Subject	Largest Artifacts' Detection Rate
1	100%
2	100%
3	100%
4	50%
5	100%
6	100%
7	67%
8	75%
9	100%
10	67%

V. CONCLUSION

A simple approach for detecting and classifying vibration-caused saline-pad EEG artifacts has been implemented and evaluated. The method managed to tag the artifacts in one half of experimental subjects with very high success rates and with no success at all in the rest. This leads to believe that there are other sources of identical artifacts which should be explored in further experiments. A weaker explanation is the insufficient sensitivity of integrated gyroscope. Further classification of EEG artifacts is necessary, taking both device sensor technology and external factors into account.

ACKNOWLEDGMENT

We would like to thank the International Graduate School of Science and Engineering (IGSSE) as well the Institute of Advanced Study (IAS) of the Technische Universität München for all the support in the organization of our project. Furthermore, we would like to thank fortiss, an Institut der Technischen Universität München, for all the constructive advice and practical support.

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