Single-trial detection of cognitive processes for increasing traffic safety

Dipl.-Ing. Sebastian Welke
Center of Human-Machine Systems, GRK prometei, Technische Universität Berlin,
Berlin, Germany
PD Dr.-Ing. Thomas Juergensohn
HFC Human-Factors-Consult GmbH,
Berlin, Germany
Prof. Dr.-Ing. Matthias Roetting
Department of Psychology and Ergonomics, Chair of Human-Machine Systems, Technische Universität Berlin,
Berlin, Germany

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ABSTRACT

To increase driver's interaction with vehicles, research interest is growing to develop new approaches that allow for detecting the driver's intention. The extraction of features from electroencephalograph (EEG) data enables establishing a new communication channel by the use of brain signals as additional interaction channel. So far, the applicability of EEG data in the context of driving is strongly limited by the robustness and ambiguity of the chosen features. The major goal of the presented approach is the robust discrimination of EEG patterns preceding intended actions of the driver for predicting upcoming manoeuvres.
A pilot study on a test track containing elements of driver safety trainings was carried out. While driving, the manoeuvres the brain activity (64/32 EEG channels) and data from the car controller area network (CAN) was recorded.
In this paper we present the bottom layer of a classification model for upcoming driver's movements by classifying left against right foot movement as well as left and right obstacle avoidance manoeuvres as sub-classes of the classes hand and feet movements.
This way, we present two ways in which features extracted from EEG can be used: (1) by exploiting event-related potentials of independent components for identifying sources of consolidated neural activity, and (2) to establish the fundamentals of an approach for an EEG-based rapid-response system that can predict the upcoming action of the driver. The latter was done by an offline classification of variances in certain frequency bands of the EEG. Feature validation was implemented by spatial and functional filtering driven by independent components of the corresponding EEG datasets.

INTRODUCTION

The year 2007 saw a number of 335.845 injured and 4949 fatalities as a result of traffic accidents in Germany [1]. In comparison with the last decade, the decreasing number of injured and fatalities indicates that vehicle-safety research has proven to be very effective. Nevertheless, this positive trend suffers from the constant high number of traffic accidents and also from the fact that there are still a high number of fatalities.
To reduce these numbers, a new approach in vehicle safety research is necessary.
One possible approach focused on this context is an absolutely driver-centred point of view. The idea is to use the driver's intention to improve and trigger existing drive-dynamic and driver support systems. Therefore, cognitive processes before an intended action, particularly movement preparations and decisions, can be identified as a possible source for such a trigger-support system.
In this manner the EEG allows associating mental processes with measurable electrical recordings which reflect brain activity and dynamics with a precision in the range of milliseconds. This way, changes in the EEG data could be analyzed that are induced by intended actions (e.g. emergency braking or left/right steering) as well as decision-making processes during driving (Fig. 1). Hence, the major goal is the robust discrimination of EEG patterns correlated to different mental processes in this context. Therefore, a pilot experiment was carried out for analysing EEG signals in a real-world driving scenario with an unforeseen obstacle. Hence, the first research question is whether it is possible to find EEG features which reflect cognitive processes following the popped up obstacle, and second, the possibility to transfer the idea of using this information to discriminate the upcoming driver's action or manoeuvres (Fig.2).

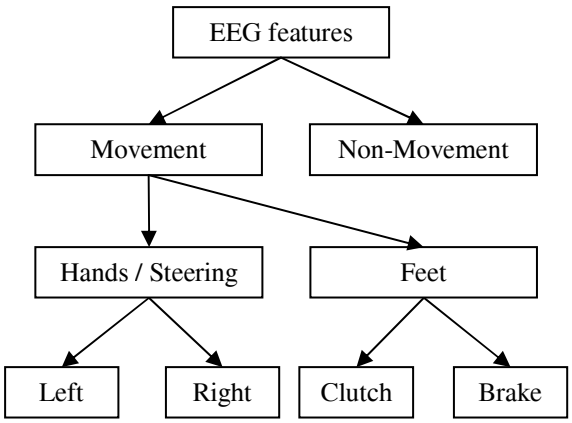

Figure 1. The figure shows a general approach for a hierarchical classification model of upcoming drivers movements based on brain dynamics.

The following section gives an overview of the neuropsychological background of the presented approach. Then we explain the used experimental environment and setting and go on describing the experiment, the data acquisition, and the used methods for analyzing the EEG data. Finally, we show how the findings of the presented experiment can be used for answering the research questions.

Neuropsychological background

In the domain of neuropsychological research, it is well known that aspects of the human information processing, expectation and movement preparation can be examined by means of event-related potentials (ERPs) and event-related desynchronisations (ERD). The potentials not only reflect direct brain activity with a latency and precision in the range of milliseconds, but also allow for a qualitative discrimination of various cognitive processes.

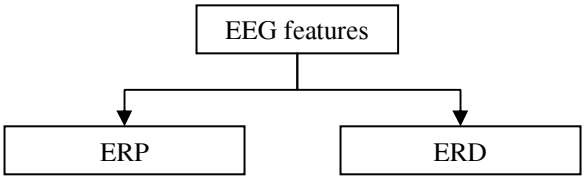

Figure 2. The figure shows a general categorization of EEG features that reflects event-related brain activity.

One category of ERPs is related to a given stimulus and occurs only by averaging EEG data from different trials locked to the given stimulus. The other category is locked to the response of the participant e.g. a keystroke.

Both, the stimulus-locked and the response-locked ERPs can be induced by the processing of e.g. visual, auditory or semantic information and also due preparing motor tasks.

Different neuropsychological consolidated ERPs are suitable as a possible source for projecting the abstract concept of *driver's intention* to features in EEG data. This way, for feature selection the readiness potential or the contingent negative variation (CNV) could be applied.

In the field of response-related ERPs the pre-motor or readiness potential (BP) seems to be a useful ERP for approaching the representation of the driver's movement intention in EEG data. In preparation of motor tasks, this potential precedes the actual execution. Before accomplishing motor tasks, this potential is characterized by a negative shift in the averaged EEG data at the scalp, reflecting the motor preparation.

The CNV is both, stimulus-locked, but also response orientated. This ERP is also known as a potential related to expectancy. This kind of CNV can be induced by a 2-stimuli paradigm. The first stimulus is the request to prepare an action and the second stimulus is the corresponding *go-signal* e.g. for a motor response. Between these two stimuli a negative shift in the averaged EEG data can be observed at the scalp, reflecting the expectation of a task.

To transfer the idea of using these potentials for predicting the upcoming driver's action the extracted information from these potentials has to be related to the upcoming movement. Therefore, the spatial information of the negative shifts induced by BP and CNV could be used to discriminate the upcoming movement.

Different studies figured out that several brain areas contribute to the readiness potential (BP). Activity of the medial-wall motor areas as well as activity of the primary motor cortex MI affect this potential [2,3]. Multi-channel EEG recordings of unilateral finger movements show that this negative shift originates on the frontal lobe in the area of the corresponding motor cortex (homunculus) contra-lateral to the performing hand [4,5]. This spatial information used as feature allows for discriminating EEG recordings towards upcoming left from right hand movements [4,5,6]. The literature does not suggest any information towards comparable characteristics of the CNV. On the other hand, event-related desynchronisation in certain frequency ranges of the EEG also accompanies brain activity.

It is well known from neuroscience that for instance the mu rhythm is induced by idle motor neurons. These neural networks tend to exhibit locally synchronous polarity oscillations which can be observed above the motor cortex. Performance of motor actions causes this synchrony to break down

and as a result, the measured amplitudes in the affected EEG signal spectra drop accordingly. This can be used to infer the laterality of the ongoing motion [7]. This fundamental finding is also known from the occipital area of the human brain. The well known *alpha-block* in the alpha rhythm can be caused by an abruptly opening of the eyes after a period of closed eyes. In the latter condition the neural structures of the occipital brain that are responsible for visual information processing generate these locally synchronous polarity alpha oscillation.
In sum, there are a lot of features in EEG data preceding and accompanying neural processes which allow differentiating between these diverse cognitive processes. The application of methods from the area of statistical machine learning has proven to be very practical and efficient for extracting and classifying EEG features in this kind of research [4,5,6,8].

METHODS

Experiment

The presented pilot experiment was carried out at the ADAC Fahrsicherheitszentrum Berlin-Brandenburg. Participants were requested to repeatedly perform obstacle avoidance manoeuvres when the obstacle (water wall) popped up (Fig. 3, obstacles in red).
The direction of the manoeuvres was self-paced decided by the drivers. With reference to a two-way traffic scenario the participants were required to pass a water gate at the end of the track. The whole experiment lasted one day totally (half day for each participant). The car utilized for this study was a VW Touran from the Chair of HMS, TU Berlin.

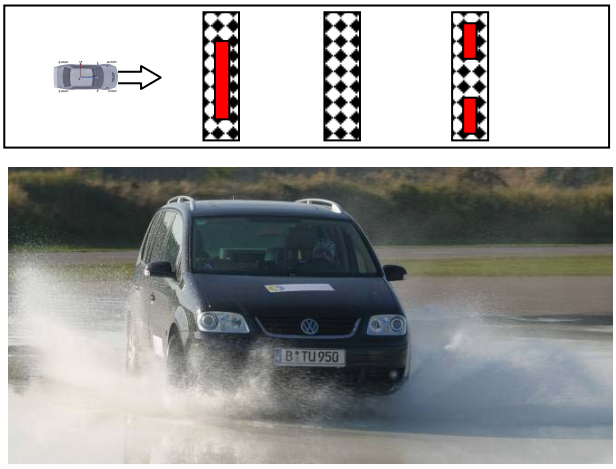

Figure 3. The figure shows the setup and the research car (VW Touran) with participant.

Participants

A female (age 28, participant S) and a male (age 28, participant T) participant took part in this pilot experiment. Both of them are free from neurological/psychiatric disorders.

Data Acquisition

While performing the driving task brain activity was recorded with 62 Ag/AgCl (participant T) and 32 Ag/AgCl (participant S) impedance-optimized electrodes (ActiCap, Brain Products), referenced to a signal measured at the intersection of the frontal and two nasal bones of the skull (Nasion) were no neural activity occurs. This was used as baseline of the electrical measurement. Finally, brain activity was sampled 1000 Hz and wide-band filtered. The horizontal eye-movement of participant T was recorded using the Electrooculogram (EOG).
Data from the car controller area network (CAN) was sampled with 50 Hz and recorded as well as videos (30 fps) of the driver's action and the view through the windshield. All of the data was synchronized by an external sync signal.

Data Pre-processing

For ERP analysis, the EEG data was digitally filtered using a high pass filter (1 Hz) to minimize drifts. In a next step, the recorded data was divided into causal epochs related to the drivers' actions like the steering response (increase of the steering speed [deg/s]) or to slam on the brake or clutch (switch [0 1]). Data epochs were extracted from 5000ms before the driver's response, until 4000ms after the taken action. The average of time range [-5s,-2s] was chosen as baseline. The corresponding baselines were removed from every epoch.
For ERD analysis, data was sub-sampled to 200 Hz and digital filtered between 1 Hz and 90 Hz.

ERD Feature Extraction and Classification

To extract ERD features from the EEG data, the Common Spatial Patterns (CSP) algorithm was used [9]. The rationale behind CSP is to find few, e.g. 4 to 6, linear combinations of EEG channels such that the variance in each trial projected according to these patterns is most discriminative (i.e. differs maximally between two classes). Subsequently, the EEG data for each trial is projected according to each pattern and the logarithmic power spectral density is calculated similar to the above method, yielding 4 to 6 features.
To estimate conservative classification accuracy, features from the EEG data (sub-sampled to 200Hz) were extracted using a moving window with a length

of 150 ms and an overlap of 125ms. The CSP-based feature distributions generated for this window were classified using the Linear Discriminate Analysis (LDA) for each of the time windows [10]. The classification accuracy was computed by using a 10-fold cross-validation (CV) for a comparable number of trials per class. This was implemented for every bin of the Fast-Fourier-Transformation (FFT) with a micro band range (± 2 bins) around each measured band for the CSP computation. Consequently, the resulting plot contains information about the estimated classification accuracy depending on class specific variances for each time window and corresponding frequency range.

Analysis

In the analysis we concentrated on the EEG data obtained where the participants performed the obstacle avoidance manoeuvres. In this manner an ERP and ERD analysis of the EEG data was carried out. EEG recordings involve plenty of influences (artefacts) to the quality of the EEG signal, such as eye movements, muscle noise, cardiac signals and coincidental noise patterns. In this study, two methods, Independent Components Analysis (ICA) and Average Re-reference, were used to improve the data quality for identifying ERP components and for verification of ERD features.
To improve the data quality we used a method to re-reference the data to the average potential across the whole head [11], termed Average Re-reference. Therefore, the average time course of all electrodes was calculated and removed from each electrode.
The ICA decomposes EEG data into temporally independent and spatially fixed components, which account for artefacts, stimulus and response locked events and spontaneous EEG activities. Recently, it has been considered as a powerful tool for EEG components identification and artefacts removal as well as source identification [12, 13, 14, 15, 16, 17].
After calculation of independent components (IC), we followed the following procedure to remove artefacts:

- Rejection of Independent Components (IC) that are related to eye and muscle movement from the neck as well as ICs that reflects the heart beat and
- Rejection of IC-dipoles outside the head.

The following section gives an overview over the ERP analysis for each participant driven by events inferred from the CAN data (i.e. de-clutch) and go on analysing the ICs for each participant separately since this depends on each of the dimensionalities of the recorded EEG. Finally we show the estimated classification accuracy for clutching vs. braking as well as obstacle avoidance to the left vs. right side based on oscillatory features for both participants.

RESULTS

ERP analysis and ICA – participant T

On Figure 4, the EEG signal at electrodes C1, Cz and C2 averaged over all extracted clutch presses (left foot) shows characteristic waveforms. The time range represents the clutching procedure with an onset around 1500 ms before the CAN-bus indicates that the driver has de-clutched (Figure 4, point of origin).
This pre-processed data shows significant components across the central part of the brain with a two-peak maximum at the latency of around 400 ms before and after the foot response (clutch). The same characteristic was observed using the common averaged reference. For taking the brake or steering in both directions no clear ERP could be observed in the raw data.

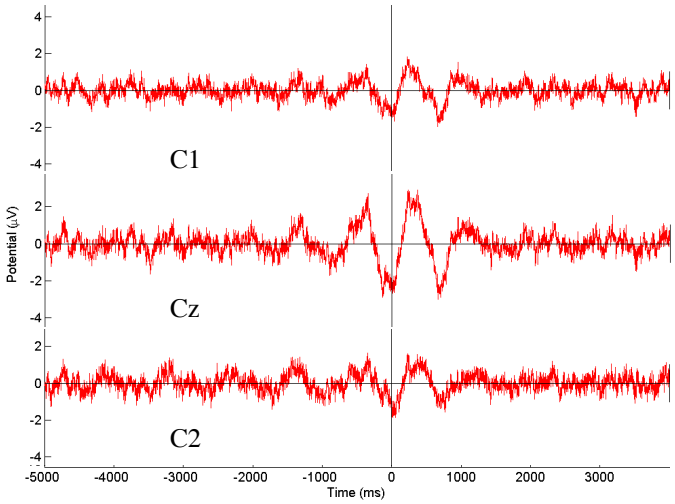

Figure 4. Averaged EEG signal from 244 clutch presses of participant T at electrodes C1, Cz and C2.

Independent Component Analysis

The independent component analysis (ICA) decomposes the EEG into temporally independent and spatially locked components.
These components could either be the result of task events or stimulus, or account for artefacts. Figure 5 shows some of the independent components from the EEG set of participant T.
Figure 5(1) shows an Independent Component which contains noise that is spread over the whole head (this component is missing when the ICA was computed on a common averaged EEG set); while Figure 5 (2 and 3) demonstrates clear ICs which decomposes vertical and horizontal eye-movements.

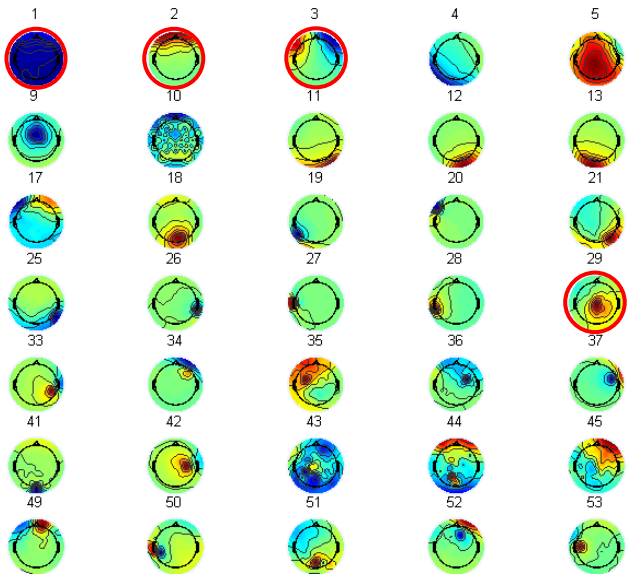

Figure 5. Selected scalp maps of the independent components of the EEG set from participant T.

In contrast Figure 5 (29) shows an IC dipole that seems to contain neural information of the central area of the brain. These components are of particular interest since they should represent only real movement related brain activity (cf. homunculus).

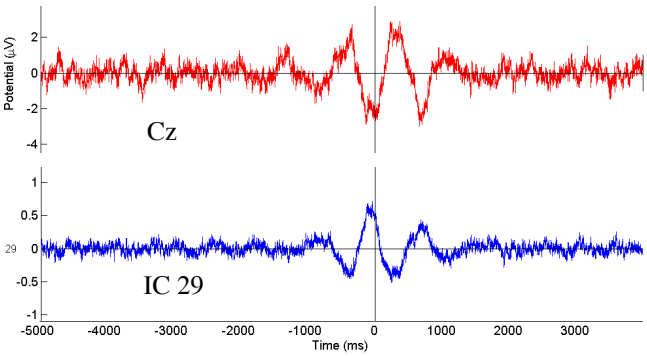

Figure 6. Averaged EEG signal [Cz] and IC 29 activity from 244 clutch presses [T].

Figure 6 shows the IC activity across the time for an extracted epoch determined by slamming the clutch. The IC activity shows a hight correlation to the the observed ERP at electrode Cz (cf. Fig. 4).

The spatial information given in Figure 7 allows for interpreting the source of the observed potential at Cz in comparison to the observed activity of IC 29. The IC 29-based dipole is located in the motor cortex of subject T for the used head model.

To transfer the idea of using spatial information of negative shifts induced by the readiness potential or the location of the IC-based dipole for discriminating the upcoming drivers action, these features have to be class-specific. Otherwise they are not suitable for an EEG-based classification system for upcoming driver's movements.

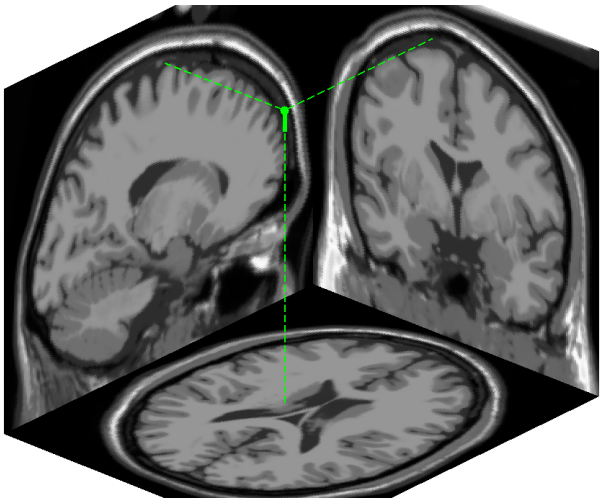

Figure 7. Dipole fitting of IC 29 for a boundary head model with warped electrode positions of participant T.

The spectral properties of the ICs can also be used for selecting brain based components. By exploiting differences in known movement-related EEG spectra it is possible to separate movement related independent components which contain information of activity in the motor cortex. This way, it is well known from the neuropsychological literature that the movement imagination as well as the movement execution is accompanied by variances in the alpha and beta band of the corresponding EEG [6, 8].

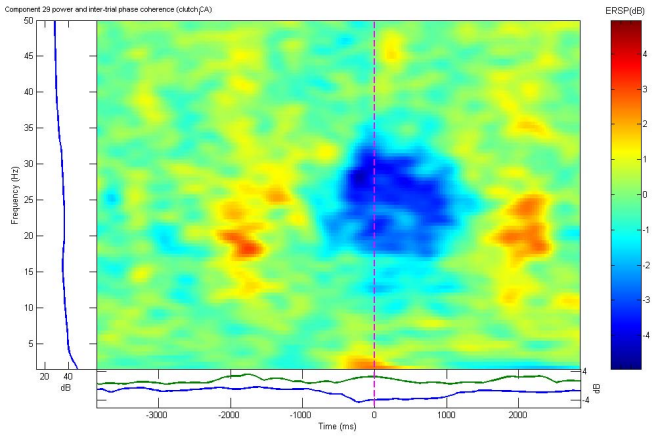

Figure 8. Event-related spectral perturbation of IC 29 (baseline [-5 to -4]) – participant T.

Figure 8 shows the event-related spectral perturbation of the activity in component 29. Here, clear changes in different frequency bands could be observed. Changes in self-contained and characteristic spectral ranges of the EEG spectrum could be used as indicator for a brain based component. Such a component is suitable as carrier of information preceding the driver's movement.

ERP analysis and ICA – participant S

The average of each extracted epoch shows no clear ERP for participants S in the raw EEG data.
In Figure 8 the ICs that are computed for the continuous EEG set of participant S are presented. A clear decomposition of noise and eye-movement could be observed (Fig. 8 1-3).
Figure 9 shows the averaged time course of the activity from component 26 that is also located in the middle of the primary motor cortex. Here, a weak ERP could be observed in the component activity that is comparable to the observed ERP of IC 29 from participant T (see Fig. 6). The dipole fitting of the computed independent components reveals that the decomposition was not so clear like for participant T.

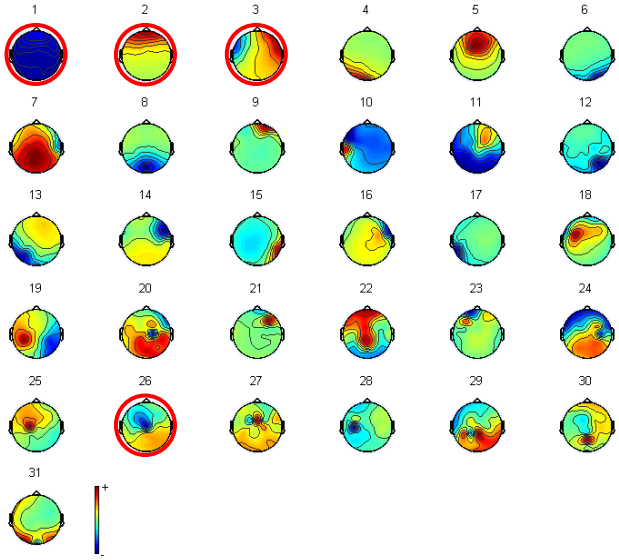

Figure 8. Scalp maps of computed independent components – participant S.

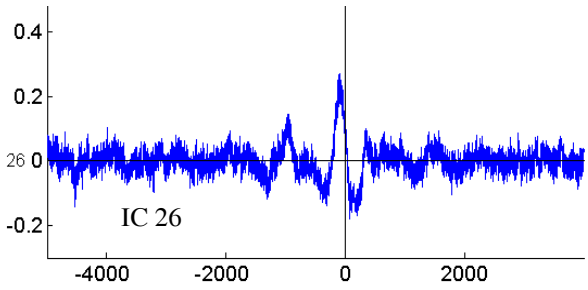

Figure 9. Time course of IC 26 for de-clutching – participant S

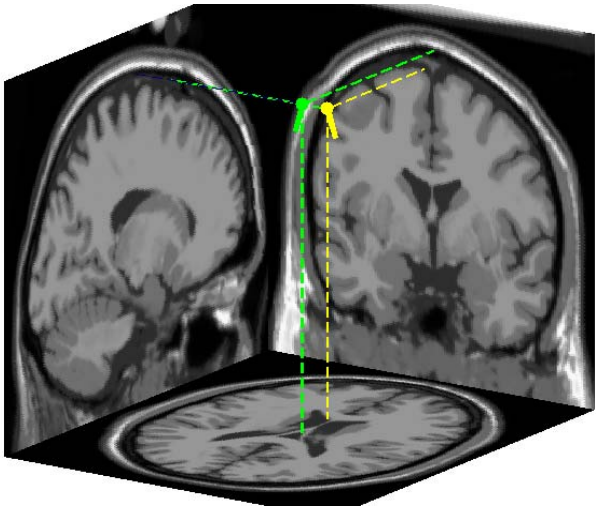

Figure 10. Dipole fitting of IC 26 (green) and IC 30 (yellow) for a boundary head model with warped electrode positions of participant S.

There are two diploes located in the expected area of the motor cortex containing information of this source. No other ERP in the component activity could be observed by averaging epochs based on the driver's responses (clutch, brake and steering).

ERD Classification

One of the central research questions in this research area is whether the analysis and extraction of EEG features is suitable for projecting the driver's intention. Therefore the chosen EEG features have to be related to the cognitive process.
Furthermore, they have to be detectable in single trial conditions. The analysis of the induced ERPs revealed that there are potentials preceding the movement execution.
The extraction and classification of ERD features is an approach for establishing an EEG-based driver support system, too. Of particular interest here is the classification of ERDs between different drivers' movement representations in the EEG data.
To define the class-specificity of the ERDs preceding the driver's action, the classifier output was estimated based on a data-driven approach (see ERD-Feature Extraction and Classification).

According to machine learning methodology, the machine will be trained on the extracted spectral features [18]. Especially in this phase, the EEG data typically consists of underlying cognitive processes but also coincidental noise patterns and artefacts. This additional information has to be removed from the recorded EEG data before the classifier can be trained to stress the neural source of the feature.

Therefore, for participant T, 14 out of 61 and for participant S 18 out of 31 independent components were selected as brain based.
To estimate the ERD-based classification accuracy these *brain* components where re-projected to the EEG data. In a second step the presented data-driven feature extraction was computed. To compare and validate, both the raw EEG set and the re-projected EEG set were used as input for the data-driven feature selection and classification.
Figure 11 (top) and 13 (top) shows the estimated classification accuracy based on variances in certain frequency bands of the EEG spectra preceding the feet movement execution on raw data. The results are going up to more than 75% accuracy around the movement execution. There are also good classification estimations around 500 ms before the movement in different frequency bands. As seen in Figure 5 and 8, the EEG dataset contains a lot of components which have probably no neural source. To validate the data-driven ERD-features, the spatial information of these components was used for functional filtering. All of the components which do not reflect brain activity were rejected. To separate the brain ICs from the artefact ICs the spatial localisation of the IC-based dipole was used as well as the properties of the components.
Figure 11 (bottom) shows that there are very different results from those estimated without the rejection of components that are containing information from eye and muscle movements. For both participants, a new weakly class-specific area in the range of 45Hz to 65Hz at 1500ms before the foot movement becomes evident.
Figure 12 and 14 show the estimated classification accuracy for the left and right obstacle avoidance manoeuvre. Here the exact point in time of the driver's response was inferred from the increase of the steering speed following the unforeseen obstacle (i.e. water wall). The classification of raw data shows for both participants very good results in the beginning of the taken avoidance manoeuvre. Preceding the steering act there are also areas of class-specific variances in the spectra of the data sets. The back-projection of the *brain components* reveals other areas of interest for classification. These areas become evident in the beta band as well as in the gamma band of the EEG data sets.

DISCUSSION

The presented results indicate (1) that there is the possibility to decompose EEG data into independent components representing artefacts caused by the driver's movement and the car environment to some degree and (2) that the presented data-driven approach for feature extraction is highly applicable, but fragile in the presence of coincidental noise patterns and artefacts.

ICA and feature extraction

The main challenge of this approach is that the decomposition of the EEG implies that the neural sources are really independent from each other. This question cannot be answered finally. Also, the residual variance of the dipole fitting indicates that the source identification is not definite in each case. Rejecting components that contain for instance eye-movements could also contain suitable parts of real class-specific brain dynamics.
The results also reveal that an observed ERP in the raw data can be found in independent components. This indicates that the ICA is able to decompose EEG data under very hard experimental conditions. The fact that an ERP for de-clutching can be observed in the components for both of the subjects indicates that there are similar neural processes preceding and accompanying the de-clutch procedure while driving.
Furthermore, the time course of this ERP allows for an extraction of clutch-specific features up to 700ms before the action can be observed in the EEG data. Unfortunately, this feature is only related to the left feet movement and does not allow for a classification of braking against clutching. Furthermore, the observed ERP does not match to any of the expected related motor ERPs. It seems to be a mixture of readiness potentials and CNV. Although, the observed ERP is well located at Cz and the IC also reflects the characteristic of the raw data, the behaviour of this signals could be affected by a haptic process. It could be that the EEG signal is affected by the process of de-clutch and clutch-in or due to a clutch sensor that induces this kind of signal characteristic. But an ERP only reflects the linear parts of the epoched EEG data. More and other information preceding the driver action could be present in the frequency domain.
Regarding the presented classification results, the good classification of brake against clutching implies that these two feet movements are really comparable and only body-side specific. But this comparison suffers from the fact that for breaking a foot movement from the accelerator to the braking pedal precedes the actual braking. The shown classification results are probably affected by this foot movement. This foot movement preceding the actual braking probably affected also the absence of a braking response related ERP.
To validate the classification accuracy, a 10-fold cross-validation was carried out. Nevertheless, the number of trials for the obstacle avoidance manoeuvre was too small for a significant computation of the ability to classify.

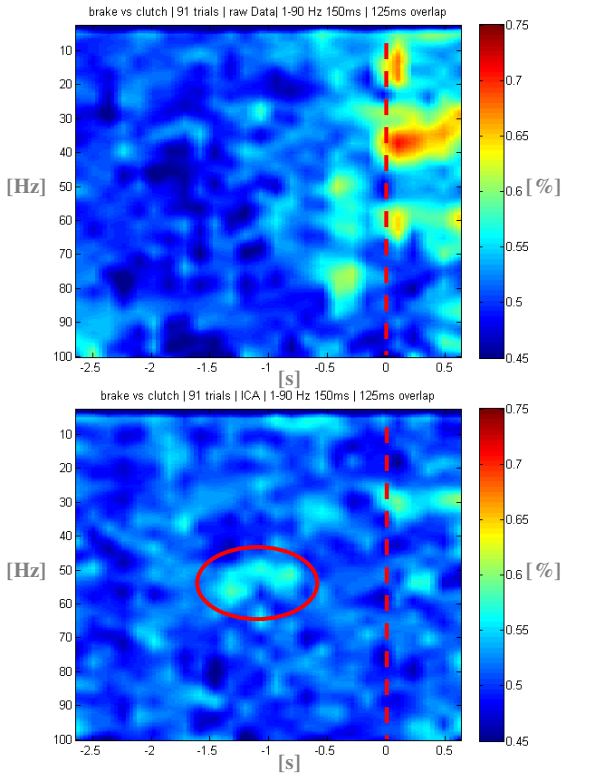

Figure 11. Estimated classification accuracy before using the clutch against brake on EEG raw data (top) and IC-filtered EEG data (bottom) [T].

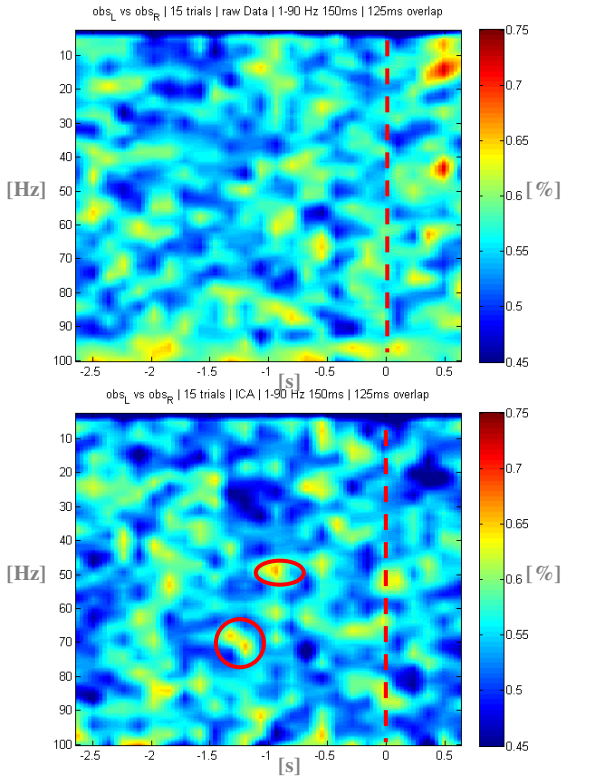

Figure 12. Estimated classification accuracy before the obstacle avoidance to left or right side on EEG raw data (top) and IC-filtered EEG data (bottom) [T].

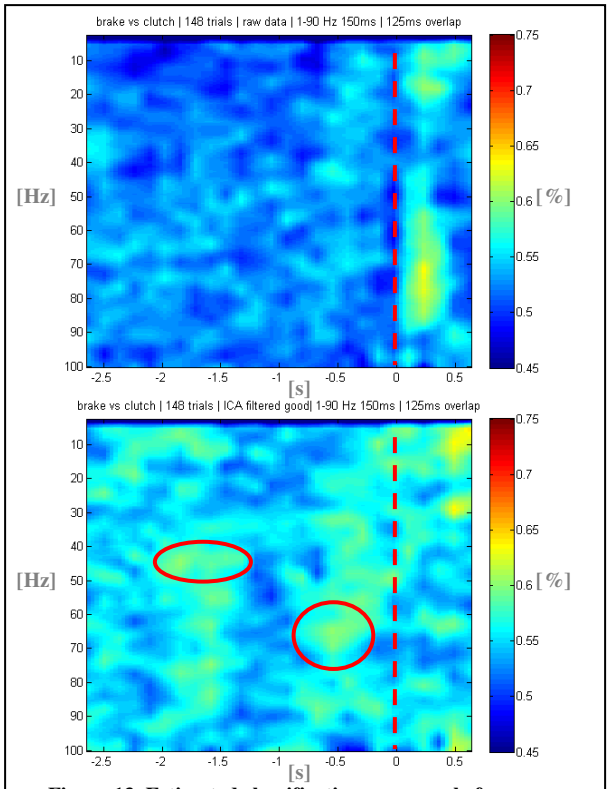

Figure 13. Estimated classification accuracy before using the clutch against brake on EEG raw data (top) and IC- filtered EEG data (bottom) [S].

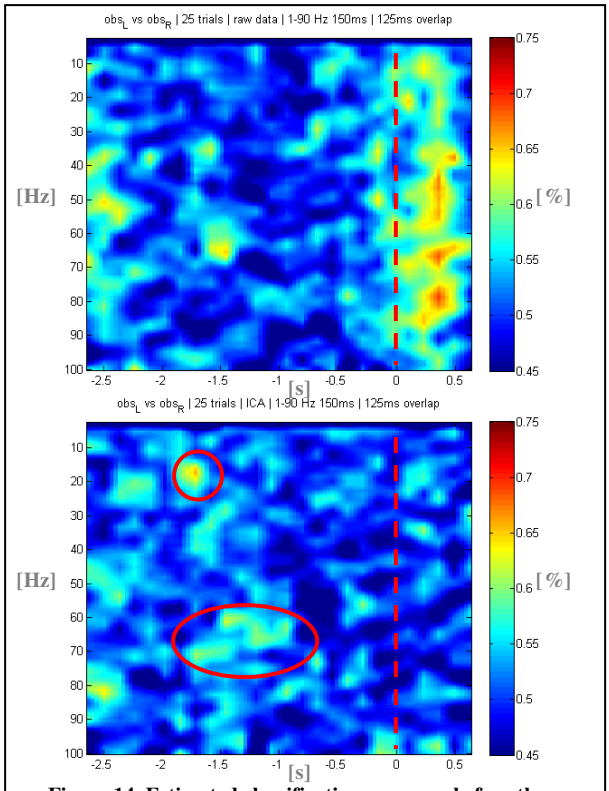

Figure 14. Estimated classification accuracy before the obstacle avoidance to left or right side on EEG raw data (top) and IC-filtered EEG data (bottom) [S].

CONCLUSION

Conclusively, we have presented a pilot study for exploring the electrical brain dynamics (i.e. EEG) preceding intended actions of the driver in a real-world environment. This way, a hierarchical classification scheme was used for predicting the upcoming movement of the driver.

Potential

We have shown that the human brain contains information preceding the movement execution that can be extracted from the EEG and that these features can be used for single trial detestability. We also presented a useful approach for validating these extracted features by decomposing the EEG data into independent components. This way, it is possible to select features which contain information of real brain based EEG representations in single trial conditions.
Hence, the brain as origin of intentions and distributor of information preceding an action has a very high potential to increase traffic safety since data from the cat area network only reflects the driver's action but not the corresponding intention.
We observed a potential in the EEG raw data related to the process of de-clutch and clutch in for participant T. The analysis of the corresponding independent components reveals that one of these components clarifies this ERP to a high degree. This indicates that the ICA was able to separate real brain sources from sources that contain other sources of electrical activity. Furthermore, this kind of analysis enables a better understanding of ERP observations in the EEG since the decomposition of EEG into ICs contains information about the localisation of the source in the brain.
The presented results of an ERD-based classification of upcoming feet movements as well as the direction of obstacle manoeuvres promises a good possibility the extract features from the EEG containing information about the driver's movement intention in these conditions. This additional information can be used in a driver support system i.e. to prepare the braking system

Challenges

To classify different foot movement, the extracted feature has to be definite and class-specific. The observed ERP was only descriptive to the class of left foot movements (clutch). Furthermore it is well known from the neurophysiologic literature that ERPs reflect brain activity in the range of milliseconds but only by averaging a couple of trials. This way, ERPs are not well qualified to predict the upcoming driver's movement in single trial conditions. The ERD representation of brain dynamics is much more applicable. Nevertheless, this estimated classification accuracy indicates that there is class-specific information in the EEG data. The estimated classification accuracy is in fact too imprecise as suitable definite information channel for a driver support system.
To validate these findings this analysis has to be carried out for more subjects. Due to the fact that the number of independent components depends on the dimensionality of the recorded EEG, this study should be carried out with more EEG electrodes. This should affect the decomposition positively and would allow for a better identification of non-artefact affected EEG representations of brain dynamics. Furthermore, to classify the feature distributions only a simple but robust classifier (LDA) was used. Here, a lot of other classifiers (i.e. support vector machines) are also suitable for this kind of classification approach.

ACKNOWLEDGEMENTS

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