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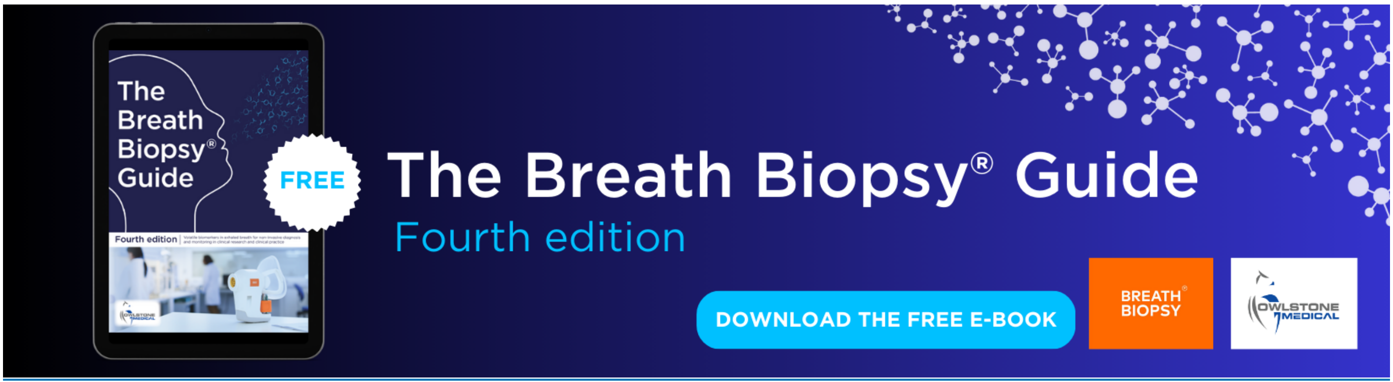

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Electrophysiology-based detection of emergency braking intention in real-world driving

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Abstract

Objective. The fact that all human action is preceded by brain processes partially observable through neuroimaging devices such as electroencephalography (EEG) is currently being explored in a number of applications. A recent study by Haufe *et al* (2011 *J. Neural Eng.* **8** 056001) demonstrates the possibility of performing fast detection of forced emergency brakings during driving based on EEG and electromyography, and discusses the use of such neurotechnology for braking assistance systems. Since the study was conducted in a driving simulator, its significance regarding real-world applicability needs to be assessed. *Approach*. Here, we replicate that experimental paradigm in a real car on a non-public test track. *Main results*. Our results resemble those of the simulator study, both qualitatively (in terms of the neurophysiological phenomena observed and utilized) and quantitatively (in terms of the predictive improvement achievable using electrophysiology in addition to behavioral measures). Moreover, our findings are robust with respect to a temporary secondary auditory task mimicking verbal input from a fellow passenger. *Significance*. Our study serves as a real-world verification of the feasibility of electrophysiology-based detection of emergency braking intention as proposed in Haufe *et al* (2011 *J. Neural Eng.* **8** 056001).

S Online supplementary data available from stacks.iop.org/jne/11/056011/mmedia

Keywords: emergency braking intention detection, real-world driving, electroencephalography, electromyography, mental state monitoring

1. Introduction

Due to advances in measurement technology and algorithm development, the use of neurophysiological measurements has recently been extended from basic neuroscience and clinical practice to what is called 'neurotechnology'. Besides work on brain–computer interfaces (BCIs) aiming to assist severely handicapped (e.g., tetraplegic) persons in managing everyday communication (see, e.g., Wolpaw and Wolpaw (2012), Naci *et al* (2012), Riccio *et al* (2012)), non-medical applications are increasingly explored (see, e.g., Blankertz *et al* 2010 for a review). One goal pursued here is to complement behavioral data with information derived from brain signals based on the consideration that any behavioral action is preceded by mental preparation. Along these lines, the use of neurotechnology in driving assistance systems has recently gained considerable interest. Kohlmorgen *et al* (2007) and Dijksterhuis *et al* (2013) study electroencephalography (EEG) correlates of mental workload during (real-world and simulated, respectively) driving, while Kecklund and Åkerstedt (1993), Schmidt *et al* (2007), Papadelis *et al* (2007), Schmidt *et al* (2009), Simon *et al* (2011) and Sonnleitner *et al* (2012) study fatigue and attention during monotonous real-world driving. Other authors demonstrated the feasibility of brain-operated real-world driving using conventional BCIs paradigms (Göhring *et al* 2013), and the feasibility of predicting steering timings using EEG (Gheorghe *et al* 2013). Another line of research is the detection of anticipatory brain reactions to particular traffic events (Haufe *et al* 2011, Khaliliardali *et al* 2012, Kim *et al* 2014). Haufe *et al* (2011) investigated the use of event-related brain potentials (ERP) in driving/braking assistance systems. The authors showed that the ERP signature characterizing emergency situations is highly informative with respect to distinguishing these situations from normal driving periods in a simulated driving setting. In combination with electromyographic (EMG) signals measuring the muscle tension at the right lower leg, these potentials predicted emergency brakings about 130 ms earlier than corresponding behavioral measures such as gas and brake pedal deflections, which amounts to a reduction in braking distance of 3.6 m at a speed of 100 km h^{-1}.

The study of Haufe *et al* (2011) was conducted in a simulated driving environment, offering a limited degree of realism. Real driving, in contrast, is characterized by a higher diversity of driving situations. Moreover, artifacts and noise are expected to degrade the quality of the measured brain signals in real-world driving settings. To verify the feasibility of electrophysiology (EEG and EMG) based emergency braking intention detection under realistic conditions, it is necessary to conduct additional studies in a more natural environment. Kim *et al* (2014) benchmark the results of Haufe *et al* (2011) with respect to the diversification of driving situations by performing a simulation study, in which the participants were exposed to a rich variety of critical and non-critical traffic situations, and are able to distinguish three different types of emergencies from other traffic situations. Here, we intend to evaluate the robustness of the findings of Haufe *et al* with respect to artifacts and other adverse effects occuring in real driving. To this end, we conducted a study ($N = 20$) replicating the experimental design of Haufe *et al* (2011) in a real car on a non-public test track. The main question we wanted to answer with this study was 'can electrophysiology improve the prediction of emergency situations during real-world driving to a similar degree as during simulated driving?'

2. Methods

The experiment was designed to largely reproduce the protocol used in Haufe *et al* (2011) with the exception that a secondary task was introduced, which had to be performed half of the time. Sonnleitner *et al* (2013) analyze the relationship between EEG alpha spindles and brake reaction times on these data in the presence or absence of the secondary task. While we describe the experimental and data recording procedures relevant to the current study, additional details are therefore found in Sonnleitner *et al* (2013).

2.1. Participants

In total, 25 individuals participated in this study. Five of the resulting datasets had to be excluded from further analysis due to technical problems. Therefore, the sample consisted of 20 participants (22–53 years, mean: 29.0 years, five females). Subjects were recruited from an in-house database, in which volunteers for experiments are listed. Every subject had normal or corrected-to-normal vision, reported normal hearing and had no history of psychiatric or neurological diseases. Participation was voluntary and occurred during working hours. All experimental procedures were conducted in accordance with the ethic guidelines of the declaration of Helsinki. Data were collected anonymously. Informed consent was obtained after the task had been explained. Participants were informed they had the option to end participation in the experiment at any time without any type of penalty. Participants received a gift worth approximately 20 EUR for their participation.

2.2. Experimental setup

The study was conducted on a non-public test track in an unused military training area in Münsingen, Germany.

Car-following task (primary). The primary task was to drive in accordance with official traffic regulations. Participants had to drive three rounds on the test track, one round being 37 km long with distinct variations in road curvature and altitude. The setup consisted of two Mercedes-Benz S-class cars: the lead car was navigated by an investigator and the following car was driven by the participant. Participants were instructed to follow the lead car at a constant distance of approximately 20 m at a maximum speed of 60 km h^{-1}. In order to obtain a reference for the required distance, the participant's car was parked 20 m behind the lead car before the start of the experiment. The investigator initiated emergency braking with an interstimulus interval of 42.5 s–57.5 s (M = 50 s, uniformly distributed jitter) after receiving an acoustic trigger from a laptop, provided that the lead car had a constant velocity of 60 km h^{-1} and adequate separation to the trailing vehicle. Given the lead car's abrupt braking from 60 km h^{-1} to 40 km h^{-1}, the participant was instructed also to brake immediately as soon as the brake light of the lead car flashed, irrespective of the actual distance between cars. After every emergency braking, the investigator accelerated back to 60 km h^{-1} using cruise control.

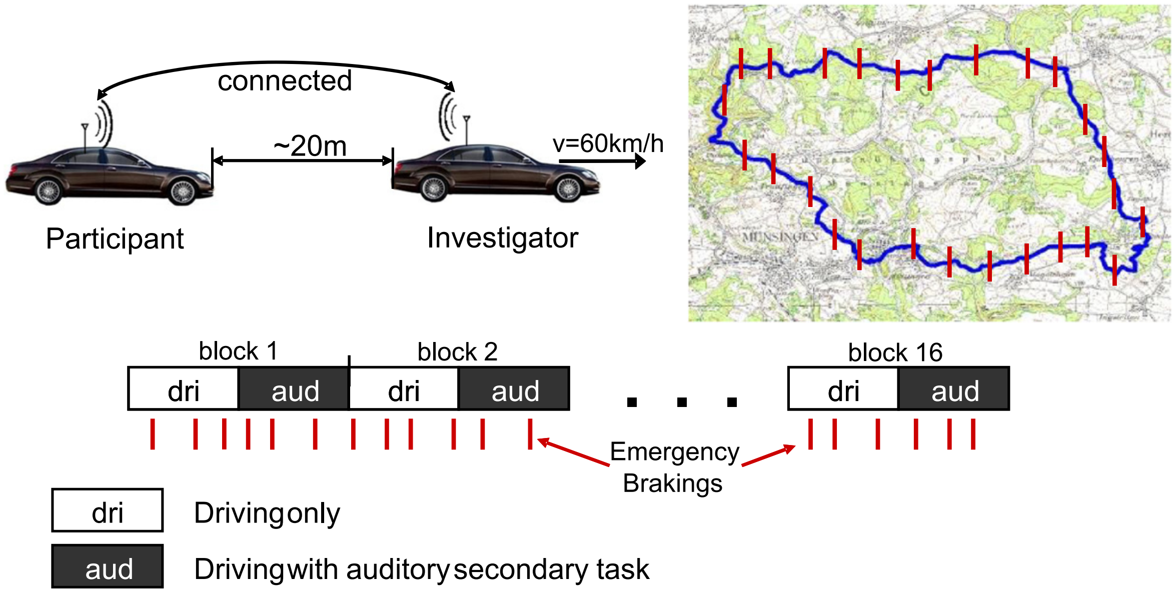

Figure 1. Procedure of the car-following task. The participant followed the investigator in the leading car with 60 km h^{-1} at a distance of approximately 20 m for three rounds on the test track. Alternatingly, participants drove with or without auditory secondary task. Figure courtesy of Sonnleitner *et al* (2013). Reprinted with permission from Elsevier.

Auditory task (secondary). As a temporary secondary task, participants listened to parts of an audio book. They were instructed to alternately detect two frequent German words by pressing a button that was attached to their left index finger with their thumb. The primary car-following task had to be prioritized over the auditory secondary task at all times.

Structure of the experiment. Participants had to drive three rounds on the test track, with short breaks between each round, which occurred after about 40 and 80 min of driving. The experiment consisted of 16 blocks, superimposed on the continuous driving task. In every block, participants drove for 3 min without performing the auditory secondary task and for 3 min with secondary task (see figure 1). The beginning and the end of every 3 min interval was announced verbally. For the whole study, participants had to drive a total of 48 min in both conditions (driving only, driving with auditory secondary task).

2.3. Acquisition of electrophysiological and behavioral data

After agreeing to the study, participants were fitted with a 32-electrode-cap (actiCAP, Brain Products GmbH, Munich). A set of 25 EEG electrodes (F3, Fz, F4, P7, P8, T8, FC3, FC4, C3, Cz, C4, T7, CP3, CP4, FC5, P3, Pz, P4, FC6, O1, O2, Oz, CPz, PO4, PO3) was positioned according to the international 10–20 system. EEG data were recorded relative to FCz, and all impedances were maintained less than 10 k Ω. Muscle activity from the right foot was measured with two electromyography (EMG) electrodes, positioned at the right musculus tibialis anterior and on the right thigh. All data were digitized at 250 Hz with a bandpass filter (low: 0.53 Hz, high: 100 Hz), and a 50 Hz notch filter was applied to remove power line interference.

Gas and brake pedal deflections as well as other technical parameters such as the timings of brakelight flashes were acquired with a sampling rate of 50 Hz through the controller area network bus units of both vehicles, and were synchronized with the EEG and EMG data. The time between the lead car's brake lights flashing and the brake pedal response signal from the trailing car was defined as the brake reaction time.

2.4. Data preprocessing

Statistical analysis was performed using MATLAB (The Mathworks). The EEG data were re-referenced offline to common average. The EMG data were rectified by taking the absolute values. All continuous data (EEG, EMG, gas pedal deflection and brake pedal deflection time series) were segmented into target and non-target intervals. *Targets* were defined as those situations, in which the braking response was given no earlier than 300 ms and no later than 1200 ms after an abrupt braking of the lead vehicle (stimulus onset). A further requirement for a valid target was that the participant had the foot on the gas pedal at the moment of brake light flashing. Targets were obtained by cutting out data from –300 ms to 1200 ms relative to the stimulus onset in all valid target situations. Normal driving (*non-target*) segments were obtained by collecting all data blocks (1500 ms duration, 500 ms equidistant offset) that were at least 3000 ms apart from any stimulus. Baseline correction was performed for the EEG data segment-wise by subtracting the average EEG amplitude in the first 100 ms of the extracted interval. The total numbers of target and non-target segments per subject were $N_t = 134 \pm 17$ and $N_{nt} = 5623 \pm 615$ on average ($\pm$ std), respectively.

2.5. Multivariate classification of single modalities

We also investigated the performance with which emergency braking and normal driving situations could be distinguished based on the single-trial spatio-temporal dynamics of the four available measurement modalities at each stage of the emergency situation. To this end, we constructed additional sets of segments with constant length of 1500 ms. The endpoints of these segments varied in steps of 20 ms from −200 ms to 1180 ms relative to the stimulus onset. Furthermore, separate datasets were created for the four individual modalities EEG, EMG, gas and brake. The target and non-target segments were split into training and test parts, such that the training sets contained only data from the first half of driving and the test sets only data from the second half. The following procedure was performed for each time shift and for each modality. Ten discriminating time intervals were determined heuristically (Blankertz *et al* 2011). EEG electrodes showing strong artifacts on the training data were discarded (Haufe *et al* 2011). For each segment, signals of the remaining electrodes were averaged within the selected time intervals and stacked into feature vectors, which were used to train regularized linear discriminant analysis (RLDA) (Friedman 1989, Duda *et al* 2000) classifiers. For regularization, the automatic shrinkage technique (Ledoit and Wolf 2004, Schäfer 2005, Blankertz *et al* 2011) was adopted. Data from the first half of driving were used for selecting time intervals and for training the RLDA classifiers. The trained discriminant functions were applied to the corresponding test data, and the resulting outputs were used to measure classification performance. We used the area under the receiver-operating characteristics curve (AUC, Fawcett 2006) as a performance measure. Area under the curve (AUC) scores are normalized to the interval [0, 1] where 1 indicates perfect classification, 0 indicates perfect misclassification, and 0.5 is attained for chance-level classification. Grand-average AUC scores were calculated as the arithmetic mean across subjects.

3. Results

We analyzed the data following the procedures in Haufe *et al* (2011). Since certain slight modifications were needed to ensure full comparability of the results of the two studies, we also reanalyzed the data presented in Haufe *et al* (2011).

3.1. Behavioral data and univariate analyses

The grand-average median response time in target situations was 720 ms, and was thus slightly longer compared to the laboratory setting of Haufe *et al* (2011), where it was 665 ms. This slight increase could be attributed to the additional workload introduced by the secondary task to be performed half of the time. The median response time in the driving-only blocks was 676 ms, while it was 740 ms in the blocks in which the auditory task had to be performed, including the announcements. Note that all graphical data presented in this manuscript comprise both real-world driving conditions (driving-only and auditory dual task), while separate data is presented in the supplementary data (section S1), available from stacks.iop.org/jne/11/056011/mmedia.

We computed grand-average stimulus-related behavioral and EMG signals by taking the arithmetic mean of the extracted target segments of all subjects. The resulting curves are depicted in figure 2(A) as thick lines. The corresponding curves obtained in the previous laboratory study are overlaid as thin curves. Note that, unlike in Haufe *et al* (2011), the average of the entire data (not only of data from the second half of driving) is depicted here. Both curves show a striking resemblance, indicating that the real-world experiment induced the same behavioral pattern as the laboratory study. This pattern is characterized by an initial burst of EMG activity, a subsequent drop of the gas pedal deflection, and finally an abrupt increase of the brake pedal deflection.

In analogy to the behavioral and EMG channels, we computed grand-average event-related potential (ERP) curves. These are shown in figure 2(B) for a selection of 11 EEG channels. The corresponding laboratory data are again overlaid as thin curves. To make both curves comparable, the lab data were transformed to common-average reference prior to the re-analysis. Figure 2(C) depicts an alternative representation of the ERP sequences, where average voltages in five subsequent time intervals of 160 ms length are shown as a series of topographical (scalp) maps. Here, the upper panel (thick scalp outlines) depicts real-world data, while the lower panel (thin outlines) depicts the laboratory data of Haufe *et al* (2011).

Figures 2(B) and (C) highlight the similarity of the event-related potentials elicited by forced emergency brakings in both studies. That is, we observe a spatio-temporal ERP complex composed of the identical three subcomponents reported in Haufe *et al* (2011): an early symmetric negative deflection in occipito-temporal areas, a later negativity at central scalp sites and a late positive deflection in centro-parietal areas. As also noted in Haufe *et al* (2011), all of these three ERP components have a clear functional relevance. The early occipital negativity (visual-evoked potential, VEP) can be attributed to low-level processing of the emergency-inducing visual stimulus (the brakelight flashing). Higher-level (semantic) processing of the gravity of the emergency situation is reflected in the later centro-parietal positivity (P300). Finally, the late central negativity (readiness potential, along with other movement-related potentials) reflects the preparation and execution of the braking response performed by the right foot.

3.2. Multivariate classification of single modalities

The grand-average AUC scores attained for single measurement modalities at each stage of emergency braking are depicted in figure 3(A). AUC curves obtained on the present real-world data are drawn as thick lines, while the corresponding curves obtained by Haufe *et al* (2011) in a laboratory setting are drawn as thin lines. As the figure shows, both curves are comparable regarding their shape and timing. For each time point, corresponding AUC scores of both datasets were compared using two-sided Wilcoxon rank sum tests. Note, that the reported results are not corrected for multiple

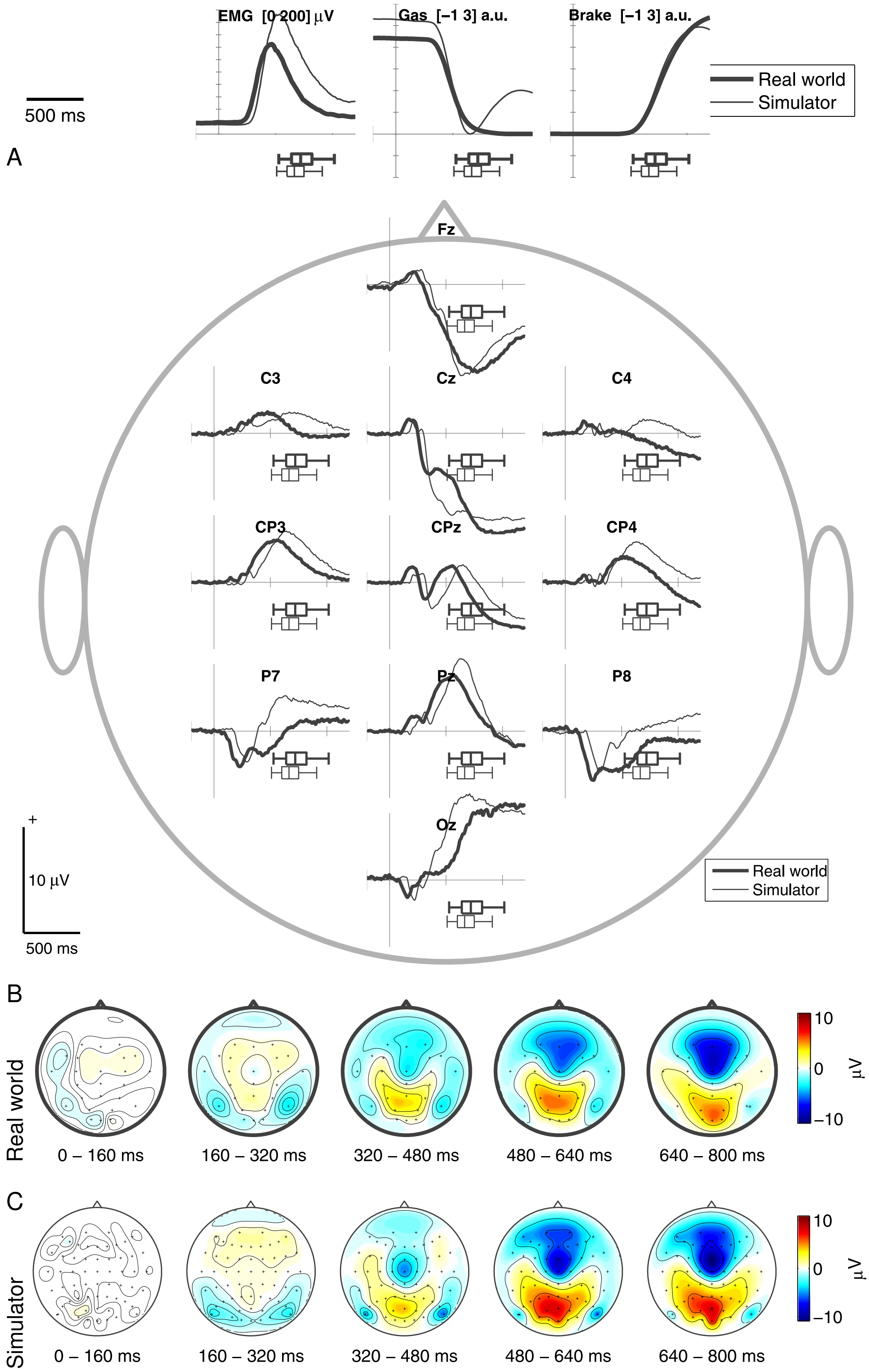

Figure 2. Grand–average stimulus-aligned behavioral and physiological responses to forced emergency braking situations during real-world and laboratory (simulated) driving. The stimulus onset (t = 0 ms) is the time of brakelight flashing of the lead vehicle. (A) Grand–average gas and brake pedal deflections, as well as electromyography (EMG) signals recorded at the right lower leg. (B) Grand–average event-related potential (ERP) curves. (C) Topographical maps of grand–average ERPs in five temporal intervals. In (A) and (B), the distribution of the pooled braking response times in both studies is indicated by two corresponding box plots showing the 5th, 25th, 50th (median), 75th and 95th percentile. Thick lines represent results of the present real-world driving study, while thin lines represent results obtained in the driving simulator study of Haufe *et al* (2011). Similarly, the upper panel of (C) depicts real-world-driving responses, while the lower panel depicts corresponding laboratory data.

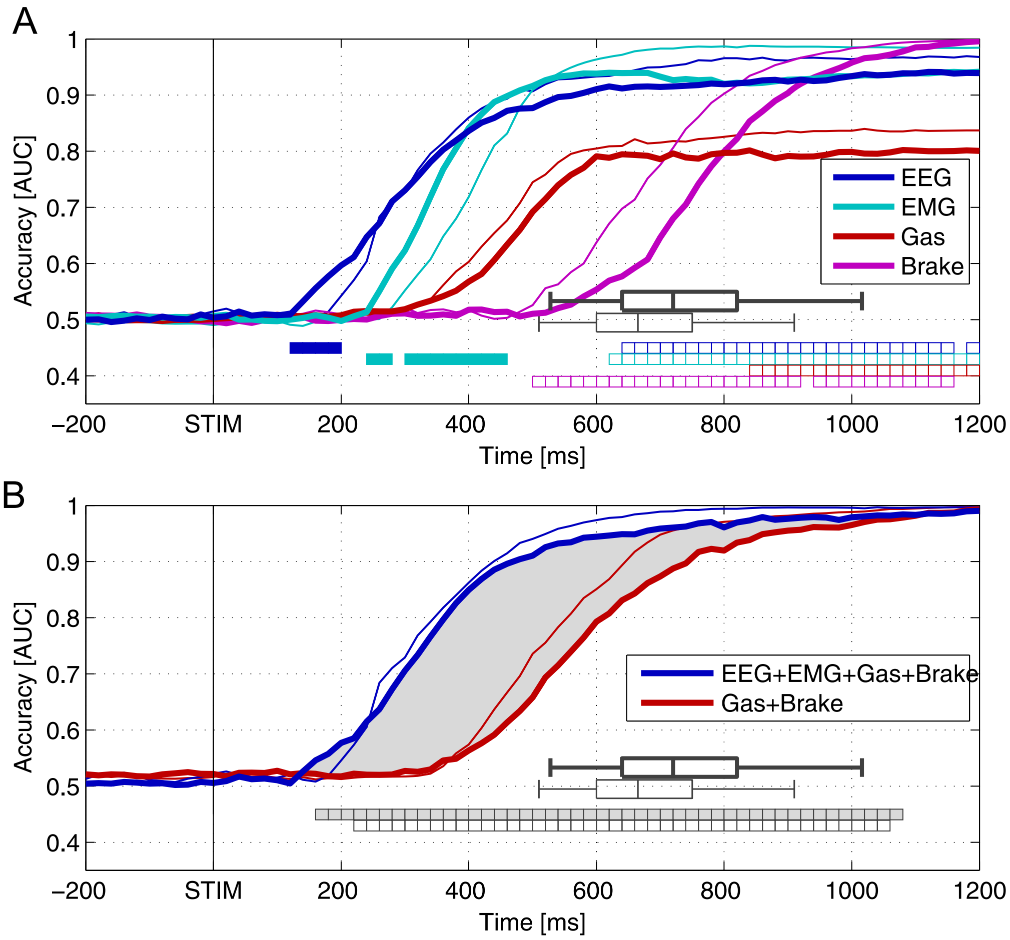

Figure 3. Grand–average area under the curve (AUC) scores calculated from the outputs of linear classifiers that were optimized to distinguish normal driving intervals from stimulus-aligned target intervals representing different stages of emergency braking situations. STIM denotes the onset of braking (brakelight flashing) of the lead vehicle. Thick lines represent results of the present real-world driving study, while thin lines represent results obtained in the driving simulator study of Haufe *et al* (2011). The distribution of pooled braking response times in both datasets is indicated by box plots showing 5th, 25th, 50th (median), 75th and 95th percentile. Classification was based on (spatio-) temporal features observed prior to the decision points. (A) performance of single measurement modalities. Blue: electroencephalography (EEG). Cyan: electromyography (EMG) at the right lower leg. Red: gas pedal deflection. Magenta: brake pedal deflection. Intervals, in which significantly higher accuracy was achieved for the real-world driving data are marked by filled square boxes, while intervals, in which significantly higher accuracy was achieved for the simulated driving data are marked by empty square boxes. (B) performance of combinations of modalities. Blue: EEG+EMG+gas+brake (electrophysiological and behavioral channels). Red: gas+brake (only behavioral channels). The intervals, in which the inclusion of electrophysiological channels significantly improved the classification accuracy are marked as square boxes (no filling for simulated driving, light gray filling for real-world driving).

testing, as we were not interested in an overall result here, but used the statistical tests here just as a robust quantification of the predictive value of different measures over time. The gas and brake modalities generally attained higher grand-average accuracies in the laboratory setting. This difference was significant ($p < 0.05$) between 860 ms and 1200 ms post-stimulus for gas and almost in the entire interval between 520 ms and 1160 ms for brake. The EEG and EMG channels attained higher AUC values in the simulated driving setting compared to the real-world driving setting in the *late* stages of the emergency situations. The difference was significant almost in the entire interval between 660 ms and 1200 ms post-stimulus for EEG and between 640 ms and 1200 ms for EMG. Note in this respect, however, that more EEG channels were available in the laboratory setting than in the real-world driving setting (58 compared to 25, see Haufe *et al* 2011). Interestingly, electrophysiological measures turned out to be more predictive in the real-world driving setting than in the laboratory setting in the *early* stages of emergency braking. This was the case ($p < 0.05$) between 140 ms and 200 ms for EEG despite the lower number of electrodes in the real-world driving setting, and almost in the entire interval between 260 ms and 460 ms for EMG. Significant time points are marked as square boxes in figure 3(A), where filled boxes represent intervals, in which higher accuracy was achieved in the real-world driving setting, while unfilled boxed represent the opposite case (higher accuracy in the laboratory setting).

3.3. Predictive improvement due to electrophysiology

The main goal of the study was to determine whether information contained in electrophysiological channels improves the detection of emergency braking situations in real-world driving to a similar degree as in simulated driving. To investigate this, we repeated the classification analysis described above for the combination of the gas and brake channels, and for the combination of all four modalities. The resulting curves are presented in figure 3(B). Using one-sided paired Wilcoxon signed rank tests, we assessed for every time point post-stimulus, whether the AUC scores obtained for the EEG+EMG+gas+brake modality combination were higher compared to using the only gas+brake. The time intervals, in which this was the case ($p < 0.05$) are marked as square boxes in figure 3(B), where the boxes related to real-world driving are filled with light-gray color. The analysis revealed that the significant intervals were similar for real-world and simulated driving (180 ms to 1080 ms post-stimulus for real-world driving and 240 ms to 1060 ms post-stimulus for simulated driving).

We were also interested in the average time saved by including electrophysiological channels compared to using only behavioral channels. To investigate this issue, Haufe *et al* (2011) constructed two pseudo-online emergency braking detectors, and compared their performance in what one could call a realistic application scenario. They showed that, at constant detection accuracy, the inclusion of EEG and EMG channels led to 130 ms faster detections on average. Here, we took a more straightforward approach to assess this improvement; namely, we calculated the area of the polygons spanned by the AUC curves related to the EEG+EMG+gas +brake and gas+brake modality combinations. This area is marked in light gray for the real-world driving data in figure 3(B). The two endpoints of the polygons were given by the points in which the accuracy scores deviated first and later merged again. These points were $t = 140$ ms (AUC = 0.525) and $t = 1\,000$ ms (AUC = 0.983) for the real-world driving dataset, and ($t = 180$ ms, AUC = 0.516) and ($t = 1\,180$ ms, AUC = 0.997) for the simulated driving dataset. The polygon areas were divided by the difference of the AUC scores at the two polygon endpoints to yield the braking detection time that could be saved using electrophysiology, integrated over all achievable detection accuracies. The average improvement for simulated driving was 200 ms, while for real-world driving it was 237 ms. The analysis was repeated for the driving-only test data and the driving-with-secondary-task-only test data. Notably, the improvement was larger in blocks in which the secondary task had to be performed, and during announcements (253 ms compared to 222 ms in driving-only blocks). See section S1 in the supplementary data for respective AUC curves.

4. Discussion

In the present study, we transfered the experimental design used in Haufe *et al* (2011) to a real-world driving environment. As a primary result, we could replicate the findings of Haufe *et al* (2011). Our univariate analyses of neurophysiological features revealed the same characteristic sequence of event-related potentials and, importantly, the same performance in predicting emergency brakings from the driver's brain signals was achieved. Thus, the expected increased presence of artifacts and environmental noise compared to a laboratory setting was compensated by the data processing, or it was counterbalanced by stronger brain responses due to the more realistic situation. However, we found no evidence for the latter hypothesis, as the amplitudes of the ERPs are not increased in the real-world setting (see figures 2(B), (C)). Moreover, behavioral channels achieved similar class-discriminability in terms of AUC scores.

Note that, as in Haufe *et al* (2011), we here focused on ERP features (that is, 'raw voltages') as predictors for emergency braking events. On the other hand, it is well-known that EEG signals also contain rhythmic activity, which is not phase-locked to any event. The amplitude of brain rhythms has been related to numerous cognitive processes, among them motor preparation and execution. We therefore also assessed the predictive quality of the amplitude of brain oscillations in four standard EEG bands. The results of these analyses, which are presented in section S3 of the supplementary data, indicate that amplitudes of brain rhythms do show patterns specific to emergency braking situations, which are of neurophysiological interest. However, their predictive quality does not come close to the level achieved by ERP or EMG features. Moreover, no improvement is made by including them in addition to those other features. Note however that, using a different way of feature extraction, Kim *et al* (2014) do come to the conclusion that spectral event-related desynchronization features in combination with other EEG-derived features can improve the detection of emergency braking situations slightly compared to using only ERPs.

Apart from the main result of reproducibility, we would like to emphasize two points. First, the average time saved using electrophysiology was even higher for real-world driving than for simulated driving. This appears to be due to a prolonged period of mental processing before the actual braking: while the first EEG and EMG responses triggered by the brakelight flashing occur at the same time in real-world and simulated driving or even earlier during real-world driving (see figures 2(A), (B) and 3(A)), the behavioral responses in the real-world setting are later on average, possibly due to increased workload (see response time statistics). Thus, we conclude that stimulus-related ERP components such as VEP or P300 contribute considerably to a successful classification.

The second point we would like to stress is that our results are robust with respect to the presence of a secondary task, which in our experiment had to be performed half of the time in parallel to the car-following task (see also section S1 in the supplementary data for separate analyses of the dual-task and driving-only conditions). While on one hand increased response times could be observed while driving with secondary task (Sonnleitner *et al* 2013), we also noted the inclusion of electrophysiological signals leading to a larger improvement of the detection performance, backing the above-mentioned hypothesis that early stimulus-related EEG components are a main factor enabling the reliable detection of emergency braking intentions.

5. Conclusion

With this paper, we verified the feasibility of electrophysiology-based emergency braking intention detection as proposed by Haufe *et al* (2011) under real-world driving conditions. In conjunction with Kim *et al* (2014), our work provides further complementary evidence suggesting that an automatic braking assistance system integrating electrophysiology could be adopted in practice. Note, however, that such systems, in order to be practical, may need to adopt a hybrid detection approach, as postulated in Haufe *et al* (2011). Here, physiological and behavioral measures are only used as additional evidence for a system that also takes into account external measures such as distances to obstacles/preceding cars as measured by radar or laser technology.

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