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Prediction of Upcoming Emergency Reactions During Simulated Driving Based on ERP

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Abstract. We present an emergency braking assistance system, which is capable of detecting the driver's braking intention in more general emergency situations compared to a previous study [Haufe et al., 2011]. Precisely, the system is applied to three kinds of realistic emergency situation instead of only one. We found a significant positive event-related potential (ERP) deflection for all three kinds of emergency reaction about 300ms post-stimulus in parietal regions. Moreover, the result shows that electroencephalography (EEG)-based prediction of emergency reactions is faster than behavioural responses such as electromyography (EMG) or brake/gas pedal deflections, even though the maximal achievable accuracy of EEG-based prediction is lower compared to other modalities.

Keywords: EEG, ERP, Emergency Braking, Neuro-driving, BCI

1. Introduction

Prediction of upcoming emergency reactions is important for preventing traffic accidents. If a braking assistance system can predict the driver's intention prior to the behavioral response, this information can be used to apply safety measures in time and thereby to mitigate the impact of traffic accidents or even to avoid accidents. Conventionally, external sensors such as laser or ultrasonic sensors have been used to predict upcoming collisions. Recently, it has been proposed to additionally monitor the driver's mental state based on electroencephalography (EEG) [Haufe et al., 2011], [Papadelis et al., 2007]. In particular, an existing study revealed that an EEG-based assistance system can detect emergency braking 130 ms earlier than a system relying only on behavioural responses. In the present study, the prediction performance of such a system is investigated under more general circumstances in order to overcome the lack of generality caused by the fact that only one specific type of emergency situation was considered in [Haufe et al., 2011]. We find that the event-related potential (ERP) signatures evoked by three different types of emergency stimuli are similar to those described in [Haufe et al., 2011]. Classification analysis moreover indicates that it is possible to detect the various kinds of emergency situations prior to actual braking based on EEG.

2. Material and Methods

2.1. Material

The driving simulator was composed of three 42 " wide screens, a steering wheel, an accelerator and a brake pedal, and a seat. The simulator software was developed using the Unity 3D engine (unity3d.com), which is highly customizable and offers an excellent degree of realism. In the virtual environment, there were three driving lanes, and two virtual vehicles besides the subject's vehicle.

2.2. Methods

2.2.1 Experimental Paradigm

Five healthy subjects (male and right-handed, age 26.2 ± 1.64 years) participated in this study. The subjects' task was to drive a virtual vehicle using the steering wheel and accelerator/brake pedals. They were instructed to follow a lead vehicle within the desired distance mainly on the middle lane. In case of an imminent crash, the participant was instructed to perform immediate braking. The following three types of emergency situation were artificially induced at random intervals.

The brake stimulus The lead vehicle abruptly decelerates.

The cutting-in stimulus A vehicle from the neighboring lane abruptly changes to the subject's lane in the front of subject's vehicle.

The pedestrian stimulus A pedestrian appears quickly in front of the subject's vehicle.

2.2.2 Data Analysis

Target segments were defined from -300ms before each stimulus onset to 1200 ms after each stimulus onset. Non-target segments were extracted by moving a window over the entire recording. Baseline correction of EEG data was computed by subtracting the mean amplitude in the first 100 ms of the window. The class-discriminability using optimized combinations of spatio-temporal features was investigated using shrinkage-RLDA (regularized linear discriminant analysis) classification. The first half of target and non-target epochs was used as training set and the second half was used as test set. The class separability of the RLDA output was assessed using the area under the curve (AUC) [Fawcett, 2006] measure. The AUC is given by

$$U = R - \frac{n_1(n_1+1)}{2}, \quad AUC = \frac{U}{n_1 n_2} \tag{1}$$

where n_1, n_2 are the number of test data for each class (target, non-target) respectively, R is the Wilcoxon rank sum statistics of the classifier outputs on test data, and U is the corresponding Mann-Whitney statistics. The known distributions of R and U provide a non-parametric test for the null hypothesis of zero correlation between classifier output and class label.

3. Results

Fig. 1 shows the grand average AUC classification accuracy scores computed from the outputs of linear classifier for each stimulus as a function of classification time relative to the stimulus onset. Furthermore, this figure depicts classification accuracy of different modalities, which are EEG, EMG and brake/gas pedal deflection. Fig. 1(a) depicts AUC scores for the brake stimulus, while Fig. 1(b) and Fig. 1(c) show AUC scores for the cutting-in and pedestrian stimuli respectively. The results show that EEG (neurophysiological response) conveys the same information about emergency situations faster than the EMG (physiological response) and the Brake (technical response).

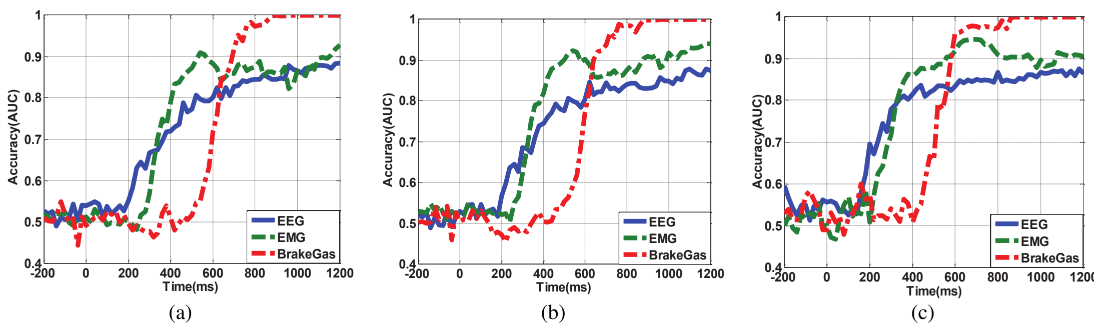

Figure 1: *Grand-average AUC scores computed from the outputs of linear classifier for each stimulus. (a) Brake stimulus. (b) Cutting-in stimulus. (c) Pedestrian stimulus.*

4. Discussion

This study demonstrated the possibility of detecting multiple classes of emergency situations in a diversified simulated driving scenario, extending previous research [Haufe et al., 2011]. While these results are preliminary, we intend to acquire more data and improve our analysis methodology in order to obtain more stable results and decrease the number of false alarms.

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References

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern Recogn Lett*, 27(8):861–874.

Haufe, S., Treder, M. S., Gugler, M. F., Sagebaum, M., Curio, G., and Blankertz, B. (2011). EEG potentials predict upcoming emergency brakings during simulated driving. *J Neural Eng*, 8(5):056001.

Papadelis, C., Chen, Z., Kourtidou-Papadeli, C., Bamidis, P. D., Chouvarda, I., Bekiaris, E., and Maglaveras, N. (2007). Monitoring sleepiness with on-board electrophysiological recordings for preventing sleep-deprived traffic accidents. *Clin Neurophysiol*, 118(9):1906–1922.