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Neural correlates and detection of braking intention under critical situations based on the power spectra of electroencephalography signals

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Dear editor,
Road traffic accidents constitute a problem of serious concern to the society; approximately 1.25 million people are killed and tens of millions of people are injured globally every year[1)]. Statistics have shown that almost 95% of motor vehicle accidents are due to driver behavior to some degree [1]. Furthermore, failing to instantly take the necessary action under emergency situations is one of the major factors causing crashes.

To address these challenges, many studies have proposed various methods. Some methods focus on using different types of external sensors (e.g., lasers and radars) to detect potential crashes and applying some measures to avoid them [2]. In general, these methods have made great progress toward avoiding crashes. However, their current system performance is still limited [3].

To complement these external sensor-based methods, researchers are exploring how to use the behavioral data of drivers under emergency situations to detect their intentions associated with braking [4]. Moreover, some studies have investigated the neural correlates of driver braking response and how to use EEG data to predict driver braking intentions under emergency situations. Haufe et al. [5] used event-related brain potentials (ERPs) to investigate the neural characteristics of driver emergency braking and employed these characteristics to predict emergency braking before behavioral response. Kim et al. [6] proposed a feature combination method, including the readiness potential, event-related desynchronization (ERD), and ERP features, to detect emergency braking under various driving conditions in a driving simulator.

However, the two studies [5, 6] did not explore neutral correlates and the detection of driver's emergency braking intention in the spectral domain. Furthermore, they used AUC as a measure to evaluate the proposed detection methods based on ERP features. However, AUC is suitable for evaluating the ability of a model to discriminate two classes (a classification question) but not suitable for evaluating online continuous detection performance of a detection model over time (a continuous detection question). More specifically, larger values of AUC do not necessarily mean higher online detection accuracy over time.

In this study, to enhance the understanding of the brain activities of driver emergency braking, we employ the power spectra of EEG signals to explore neural correlates used to develop a detection method for investigating driver braking intention under emergency situations. In addition, we evaluate the proposed detection method using its

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1) http://www.who.int/violence_injury_prevention/road_safety_status/en/index.html.

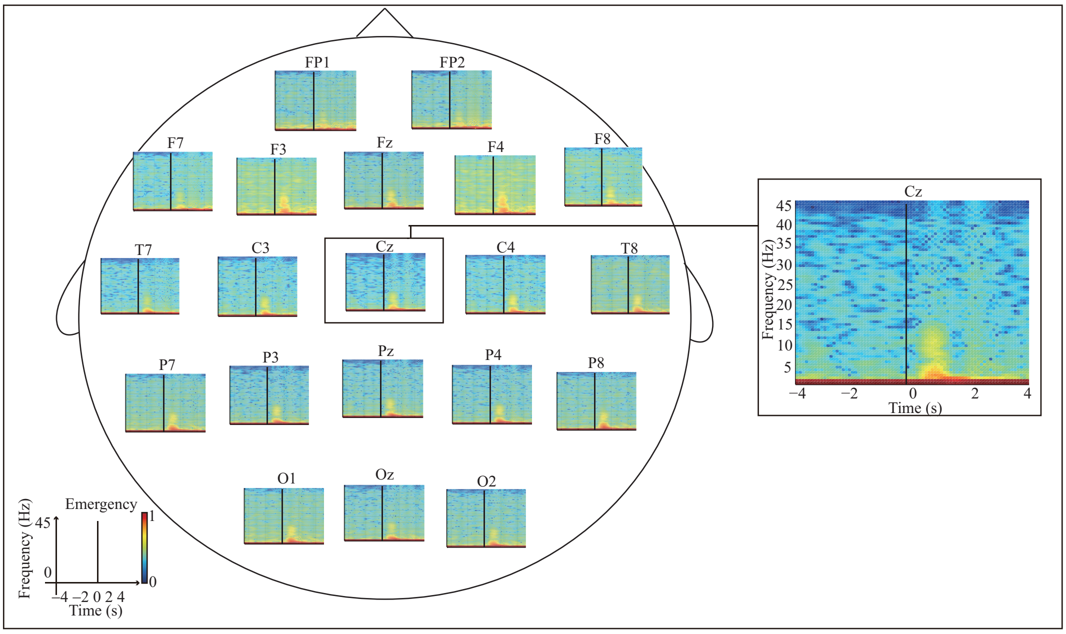

Figure 1 (Color online) Brain signal changes between the normal and emergency situations.

detection accuracy in order to demonstrate the feasibility of using EEG signals to continuously detect the braking intention of drivers under emergency situations.

Data. The EEG data used in our research were taken in the previous study [5]. They were collected using Ag/AgCl electrodes at a sampling rate of 1000 Hz (low cutoff frequency: 0.1 Hz; high cutoff frequency: 250 Hz) from 59 scalp locations in the modified international 10–20 system, with the reference at the nose. The EEG data are available in a public database[2)]. We further downsampled the EEG data to 200 Hz and filtered them using a low-pass filter with a cutoff frequency of 45 Hz.

In a method implemented in the previous study [5], 18 healthy participants performed 3 blocks of a car-following task. Each block contained an average of 108 emergency situations. During driving, a leading vehicle that was controlled by a computer occasionally decelerated, with the braking action accompanied by flashing of brake lights. Participants were asked to immediately execute emergency braking under these situations to avoid a collision. The experiment in the previous study [5] was conducted in accordance with the Declaration of Helsinki.

Neural correlates in spectral amplitude. Figure 1 shows the normalized time-frequency plots of the grand mean EEG data of all subjects at all channels. Emergency situations appeared at a time point of 0 s. The inset shows a magnification of the plot at Cz. These plots show changes in the spectral amplitude of the brain signal under 45 Hz over time from 4 s before to 4 s after the onset of an emergency situation. These brain signal changes are represented as color-coded values (see the color bar) of the spectral amplitudes normalized by the max-min normalization method.

From Figure 1, it can be observed that the amplitudes at some frequencies across frontal, central, parietal, and occipital locations appear to have substantial information about the occurrence of emergency situations. We may use these amplitudes at these frequencies and locations to predict emergency braking.

Detection of braking intention. We employed the frequency features for detecting braking intention. The method comprises three major stages: preprocessing, feature extraction, and classification.

Independent component analysis (ICA) was applied at the preprocessing stage. EEG signals acquired from a single electrode on the scalp contain artifacts caused by blinking of the eye and muscle movement. These artifacts can reduce the quality of the EEG signals. ICA is a popular method for eliminating this problem. ICA can be expressed as follows:

$$Y(t) = WX(t), \tag{1}$$

where $X(t) = [x_1(t), x_2(t), \ldots, x_c(t)]^{\mathrm{T}}$, $x_c(t)$ represents EEG data collected from the Cth channel, $Y(t) = [y_1(t), y_2(t), \ldots, y_c(t)]^{\mathrm{T}}$ represents the independent component (i.e., IC) vector, t is the sampling time point, and W indicates the un-

2) http://bnci-horizon-2020.eu/database/data-sets.

mixing matrix. The power spectra of the filtered EEG signals were calculated using the periodogram method to form the initial feature pool. Wilcoxon rank sum tests were used to determine the frequency points across all channels that were significantly different in terms of power between the normal and emergency driving situations. The results of the statistical test show that the specific frequencies relevant to emergency braking were mainly in the low-frequency range but varied across subjects. We first used the spectral magnitude of frequencies that were significantly different between two situations as an optional feature pool. In addition, we employed sequential forward floating search (SFFS) to determine the optimal features from the optional feature pool [7]. The RLDA was used to build the classification model, which can be expressed as

$$y = w^{\mathrm{T}} x, \tag{2}$$

where x is the feature vector selected by the SFFS and w is a projection vector.

Performance assessment. Pseudo-online testing was conducted to simulate an online procedure in order to evaluate the system performance. The difference between pseudo-online testing and online testing is that the former does not involve feedback and the testing data need to be collected beforehand. For pseudo-online testing, we used a sliding window to compute and output the detection result of every cycle (i.e., every step). More specifically, the sliding window was continuously shifted with a step size.

The system accuracy (SA), hit rate (HR), false alarm rate (FAR), and alarm time were used to evaluate the performance of the proposed system. SA was calculated as $\mathrm{SA} = (1 - \mathrm{FAR} + \mathrm{HR})/2$. HR was defined as the ratio of the number of correct emergency trial hits to the total number of emergency trials. A trial was considered as a correct hit if the output of the detection method was in the emergency braking class within 1500 ms after the onset of an emergency situation. FAR was defined as the ratio of the number of false alarms to the total number of non-emergency commands. The length of time between the onset of an emergency situation and the time when the first emergency braking intention was issued was defined as the alarm time.

Pseudo-online detection result. Pseudo-online detection was conducted with a sliding window of 1500 ms and a step size of 20 ms. The means with standard errors of HR, FAR, SA, and alarm time of the proposed method were $92.8\% \pm 1.8\%$, $5\% \pm 0.5\%$, $93.9\% \pm 0.7\%$, and 474.8 ± 30.5 ms, respectively. The behavioral response time can be measured based on brake pedal deflection, which was also available in the public database [5]. The average behavioral response across all subjects was calculated as 753 ms. The proposed method can generate a braking command 278.2 ms earlier than an average behavioral response scheme, with an average SA of 93.9%.

Conclusion. In this study, we investigated the neural correlates of emergency braking intention in the spectral domain and developed a new method for detecting driver braking intention under emergency situations based on the spectral features of EEG signals. The proposed method can generate a braking command 278.2 ms earlier than an average behavioral response scheme, with an SA accuracy of 93.9%. This study has enriched the understanding of the brain activities of driver's emergency braking intentions, and the proposed detection method could lead to a significant improvement in reducing the risk of pedestrian fatalities. For instance, when a car travels at a velocity of 60 km/h, the risk of pedestrian fatality can be reduced from 18.2% to 9.8% if a braking command is issued 278.2 ms earlier [8].

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