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A Novel Method of Emergency Situation Detection for a Brain-controlled Vehicle by Combining EEG Signals with Surrounding Information

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***Abstract*—In this paper, to address the safety of brain-controlled vehicles under emergency situations, we propose a novel method of emergency situation detection by fusing driver electroencephalography (EEG) signals with surrounding information. We first build a novel EEG-based detection model of driver emergency braking intention. We then recognize emergency situations by fusing the result of the proposed EEG-based intention detection model with that of the obstacle detection model based on surrounding information. The real-time detection system of driver emergency braking intention is implemented on an embedded system, and the driver-and-hardware-in-the-loop-experiment of the proposed detection method of emergency situations is performed. Experimental results show that the proposed method can detect emergency situations with the system accuracy of 94.89%, false alarm rate of 0.05%, and response time of 540 ms. This study has important values in the future development of brain-controlled vehicles, human-centric advanced driver assistant systems, and self-driving vehicles and opens a new avenue on how cognitive neuroscience may be applied to human-machine integration.**

***Index Terms*—EEG, emergency situation, braking intention, brain-controlled vehicles.**

I. Introduction

MANY factors (such as aging and chronic health conditions) have caused the increase in disability rate. Approximate 15% of the world population live with some types of disabilities, and 2-4% of the disabled have significant difficulties in functioning [1]. Living independence has become a severe problem for the disabled people with neuromuscular disorders. Brain-computer interface (BCI) is considered as a solution because it does not depend on users' speech or neuromuscular control. As a cheap and convenient recording method of brain activities, electroencephalography (EEG) has been widely used to develop various BCIs. To improve the mobility of the disabled, EEG-based BCIs have been studied to build brain-controlled wheelchairs [2]-[5] or brain-controlled vehicles [6]-[9]. We have developed an EEG-based destination selection system for the disabled to use intelligent vehicles [8], as shown in Fig. 1. The disabled individuals only need to first choose the desired destination by using such system. Then, the vehicle transports the driver to the desired one.

Fig.1. Brain-controlled vehicle

However, when emergency situations (e.g., unexpected crossings of pedestrians and sudden braking of the leading cars) happen, the safety of brain-controlled vehicles is a big challenge. For current intelligent vehicles, the conventional methods for solving the problem are to use sensor-based obstacle detection systems. In these systems, vehicle-mounted sensors (such as near infrared radiation (NIR) [10], far infrared radiation (FIR) [11], RADAR [12], and LASER scanner [13]) are widely used to detect and track people on road environments for preventing collisions between vehicles and pedestrians. If the information collected by obstacle detection systems indicates that an obstacle exists in front of the traveling vehicle, the vehicle alerts the driver or brakes automatically to avoid a collision.

However, using sensor-based obstacle detection systems to recognize emergency situations has two following weaknesses. One is that these methods can only detect whether there is an obstacle ahead (i.e., 'potential' upcoming dangers) rather than

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'real' dangers. The other is that these methods currently have limitations in system performance because they are strongly affected by environmental factors [14].

Along with another direction of the research, some researchers have adopted behavior or physiological data of a driver to recognize driver braking intention to address the safety challenge under emergency situations [15]-[17]. Since the methods based on behavior data need to use the action of a driver, they are not suitable for brain-controlled driving for the disabled. In this regard of the methods based on physiological signals, Haufe et al. used event-related brain potentials (ERPs) of EEG and electromyography (EMG) signals to detect driver emergency braking intention. Their offline data analysis showed that EEG-based predictions were faster than using EMG signals, and using EMG signals did faster than using behavioral data (e.g., gas and braking pedals) given the same predictive accuracy [15]. The system was further tested offline by using data collected from the real driving [16]. In [17], Kim et al. combined different temporal EEG features to detect braking intention in diverse emergency situations. Their offline data analysis indicated that using the feature combinations performed slightly better than the ERP-based methods in [17]. For brain-controlled driving, Teng et al. have used spectral features of EEG signals to build a detection model of emergency braking intention [18] and further optimized this model [19].

However, using these methods based on recognizing driver braking intention to address emergency situations has three weaknesses. First, an emergency braking intention does not necessarily mean a real emergency situation. Second, currently, the false alarm rate (*FAR*) of these detection methods of driver emergency braking intention is high (especially for brain-controlled driving), which makes it infeasible to apply these methods to practice. For example, the *FAR* of the method developed in [19] is 5.78%. Third, currently, all these braking intention prediction methods (including driving with limbs and brain-controlled driving) mentioned above are only tested in an offline or pseudo-online way since no real-time detection systems are implemented in these studies.

In this paper, to address the safety of brain-controlled vehicles under emergency situations, we propose a novel method of emergency situation detection by fusing driver EEG signals with surrounding information. The contribution of this paper is threefold: 1) it proposes a novel method of emergency situation detection by combining EEG signals with surrounding information for a brain-controlled vehicle; 2) it builds a novel EEG-based detection model of driver emergency braking intention; 3) it implements the proposed detection system of emergency situations in *C* codes on an embedded hardware and tests the effectiveness of the proposed method by using driver-and-hardware-in-the-loop experiments in a driving simulator.

The remainder of this paper is organized as follows. The detection system is shown in Section II. Section III describes the offline and online evaluation of the proposed method. The discussion and conclusion are presented in Section IV.

II. Method

A. System Architecture

The system architecture of the proposed method, as shown in Fig. 2, consists of three major components: 1) intention decoding algorithm, 2) obstacle detection model, and 3) decision rule. The working procedure of the proposed method is as follows. The intention decoding algorithm (IDA) first recognizes driver emergency braking intention by decoding EEG signals acquired from a driver's scalp during driving, while the obstacle detection model (ODM) recognizes obstacles on the road in front of the traveling vehicle by using external sensors. The recognition results of IDA and ODM are then taken as the input of the decision rule, which outputs the final detection result of emergency situations.

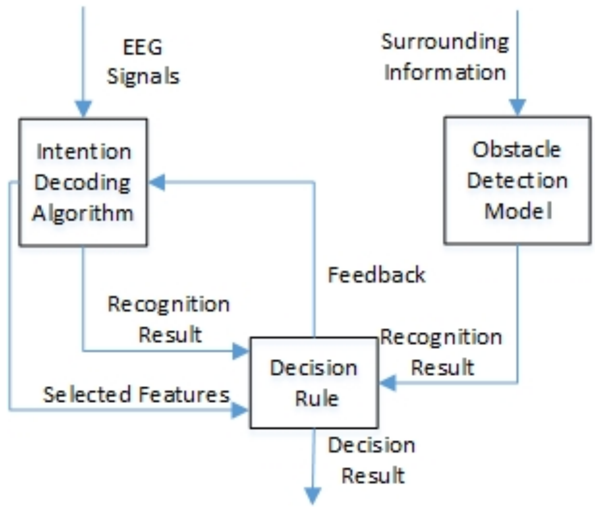

Fig. 2. Architecture of the whole emergency situation detection system

B. IDA

The signal flowchart of the IDA is shown in Fig. 3. The purpose of training procedure was to determine the unmixing matrix of independent component analysis (ICA), the projection matrix of the common spatial pattern (CSP), the labels of extracted feature, and the parameters of regularization linear discriminant analysis (RLDA) classifier.

1) EEG Data

The data that we used for offline and pseudo-online analysis were collected and utilized in [19]. The data can be obtained by accessing http://pan.baidu.com/s/1jILMYGI.

In [19], 12 subjects (10 males and 2 females; aged 20 to 25) participated in the experiment. The experiment was performed in a driving simulator. Three pedestrians, whose locations were randomly designated between 600 m and 2400 m relative to the origin of the road, stood on the right side of the lane. Emergency situations were simulated by using unexpected pedestrian road crossings at the location of 30 m before the traveling vehicle that run at 108km\h. Note that 30 m was set for better stimulating the emergency situations in the driving simulator and is too short and impossible to avoid collisions in the real

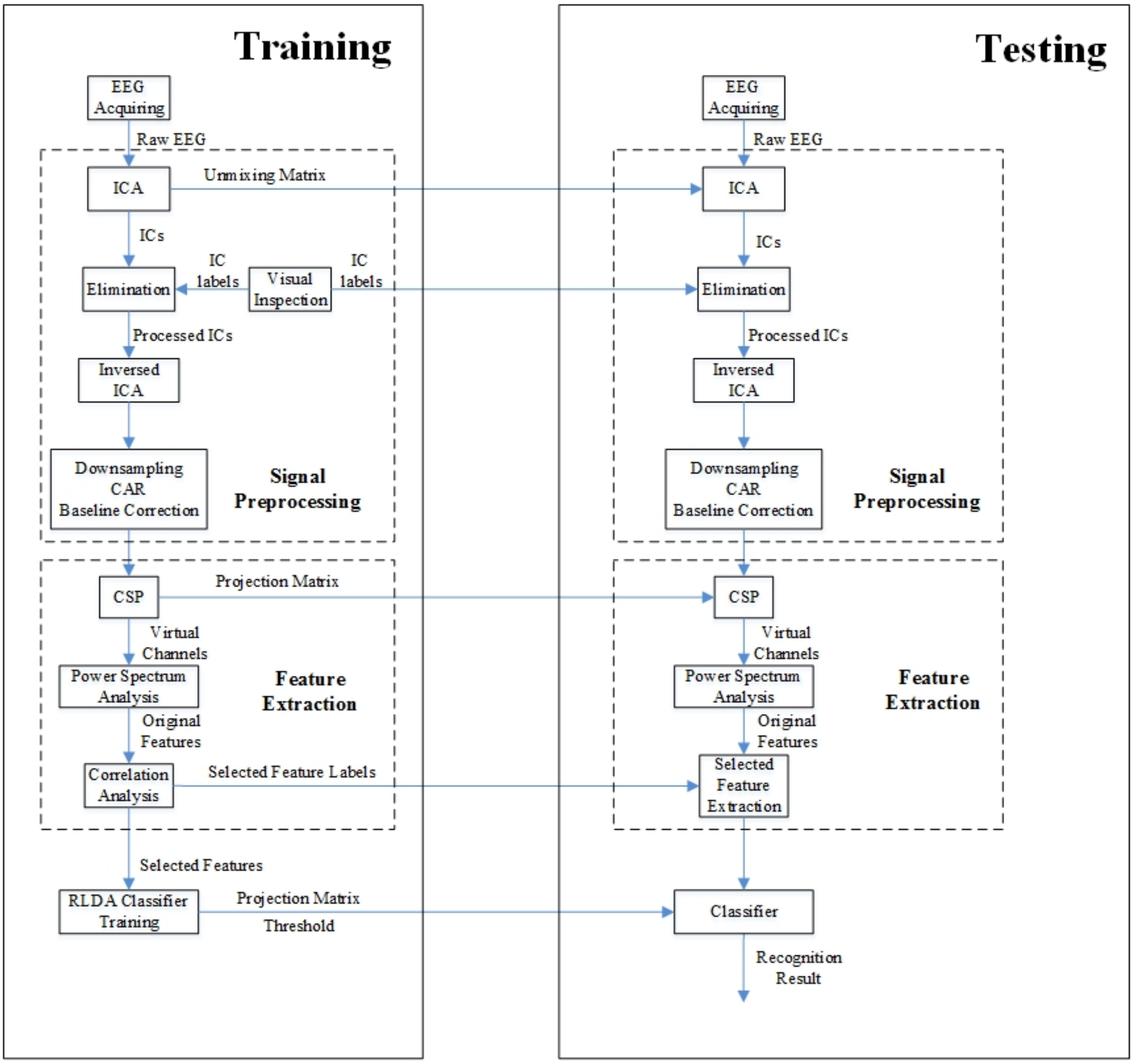

Fig. 3. Flowchart of Intention Decoding Algorithm (IDA)

world. For the normal driving situation, all pedestrians stayed still throughout the entire driving duration. The whole experiment was conducted on two different days separated by several days to avoid the effects of fatigue. Totally, there were thirty trials for normal driving and thirty trials for driving under emergency situations. The two kinds of trials were conducted in a random order. In each trial, participants were asked to perform the 2600-m driving and emergency situations only happened once in every emergency trial. All participants were instructed to sit still in every trial and paid full attention to the virtual traffic scenario. Once they observed pedestrian sudden crossings, they were required to imagine stepping on the braking pedal immediately. Four extra trials were conducted for each participant to measure the response time of the participants. In detail, once the emergency situations happen, the participants need to shift their right feet from the gas pedal to braking pedal as quickly as possible. The response time of the participants was defined as the time interval from the onset of the emergency event to the angle change of braking pedal. The mean response time of 12 subjects was 833.7 ms.

EEG potentials were collected from 16 electrodes (F3, Fz, F4, C3, Cz, C4, T7, T8, P7, P3, Pz, P4, P8, O1, Oz, and O2) based on an international 10-20 system and referenced to the mean of the right and left earlobes. EEG signals were acquired at the sampling rate of 1000 Hz and filtered with a power-line notch filter of 50 Hz and band-pass filter between 0.53 and 60 Hz. All data were given in the mat (MATLAB).

2) Preprocessing

EEG data were first processed by ICA to remove the blinking artifact, which is the major artifact in this experiment. ICA is a kind of blind source separation method, which can be written as

$$Y(t) = W_1 \cdot X(t)\,, \tag{1}$$

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where $X(t) = [x_1(t), x_2(t), \cdots, x_i(t)]^T$, $x_i(t)$ represents the data collected from the ith electrode, $Y(t) = [y_1(t), y_2(t), \cdots, y_i(t)]^T$, $y_i(t)$ represents the ith independent component, and t stands for sampling time point. In this paper, i was equal to be 16 and the unmixing matrix W_1 was determined by infomax algorithm [20]. Visual inspection was carried out by offline analysis based on both the time course and scalp maps of the independent components (ICs). ICs, which abruptly jump and show different temporal and spatial patterns compared to others, were considered to be related to the blinking artifact. We recorded the labels of the ICs most related to the blinking artifact and set the corresponding ICs to be zero in the training and testing procedure. In this paper, the first IC was set to zero, which corresponds to the blinking artifact.

Then, the inversed ICA was applied to ICs to obtain the filtered EEG by

$$X(t) = W_1^{-1} \cdot Y(t) \tag{2}$$

After that, the data were downsampled to 200 Hz. Baseline correction was applied to reduce the drift by using the first 10% sampling points of the current window. The common average reference (CAR) was used to filter the common disturbance among all channels.

3) Feature Extraction and Classification

In feature extraction, CSP was first applied to improve the quality of features. 16 channels were transformed into *m* virtual channels by CSP, which can be written as

$$Z(t) = W_2 \cdot X(t) \tag{3}$$

where $Z(t) = [z(t), z_2(t), \cdots, z_m(t)]^T$, $z_m(t)$ represents the data of the mth virtual channel, and W_2 is the projection matrix.

Then, the original power spectrum features $Z(f)$ were calculated by applying Fast Fourier Transformation (FFT) to $Z(t)$.

After that, we used the correlation analysis to extract the n-dimensional feature vector from the original power spectrum feature vector $Z(f)$, which can be expressed as

$$R(j) = |corr(v_1(j), v_2(j))| \ , \tag{4}$$

where $v_1(j) = [em_j(1), \cdots, em_j(k), no_j(1), \cdots, no_j(l)]^T$, $em_j(k)$ and $no_j(l)$ represent the value of the jth feature of $Z(f)$ in the kth emergency sample and the lth normal sample, respectively. $v_2(j) = [1(1), \cdots, 1(k), -1(1), \cdots, -1(l)]^T$, $1(k)$ and $-1(l)$ represent the class label of $em_j(k)$ and $no_j(l)$, respectively. $R(j)$ represents the absolute value of the correlation coefficient between $v_1(j)$ and $v_2(j)$. Larger value of $R(j)$ means better classification performance. The features associated with the n largest R were extracted as the final features and directly used during the process of testing. That means, the correlation analysis does not need to be applied for testing.

Finally, RLDA was applied to build the classifier, which can be expressed as

$$y = w^T x \ , \tag{5}$$

where x is the input feature vector, y is the output of the classifier, $w = \Sigma'_w / (\mu_1 - \mu_2)$ is the projection matrix, μ_1 and μ_2 represent the mean value of the two class, respectively, and Σ'_w is the regularized within-class scatter matrix, which can be calculated by

$$\Sigma'_w = (1 - \lambda)\Sigma_w + \lambda v I \ , \tag{6}$$

where Σ_w is the within-class scatter matrix, $\lambda \in [0,1]$ is the tuning parameter, I is identity matrix, $v = trace(\Sigma_w)/d$, and d is the dimension of Σ_w. A threshold Tr is set to discriminate the output y. If $y > Tr$, the output of IDA y_{ida} equals 1, corresponding to the emergency braking intention. If y_{ida} equals -1, corresponding to the normal driving.

Note that we used the trial-and-error method to determine the number of the virtual channels m and the dimension n of the final feature vector by manual tuning. The decision criterion was to make the value of the area under curve (AUC) largest for each subject.

C. ODM

In this paper, we did not study how to detect obstacles on the road by using some kinds of sensors. Instead, we used a performance model of sensor-based obstacle detection methods to simulate the detection outcome. That means, we simply emulated a circumstance as if we had an obstacle detection system that had certain imperfect performance characteristics to enable proof of principle in our simulations. We defined that -1 and 1 correspond to the situations where no obstacles exist and situations where some obstacles are in front of the traveling vehicle, respectively. Two command sets Φ_1 and Φ_2, which both consist of M commands, were established, corresponding to the normal driving and emergency situations, respectively. The output y_{odm} of the ODM was generated from those command sets according to the true situation R_0 through the following model.

Model

Define: $R_1 \in \Phi_1, R_2 \in \Phi_2$
$P(R_1 = 1) = \psi_1, \quad P(R_1 = -1) = 1 - \psi_1,$
$P(R_2 = 1) = \psi_2, \quad P(R_2 = -1) = 1 - \psi_2,$

If $R_0 = -1$
$y_{odm} \in \Phi_1$
Else
$y_{odm} \in \Phi_2$
Return y_{odm}

The parameters of the performance model ψ_1 (i.e., false positive rate) and ψ_2 (i.e., detection rate) were set to be 0.8% and 98.41% according to the findings (as are often the case) of [11], respectively.

D. Decision Rule

The decision rule of emergency situations can be expressed as:

$$y_{ida} = 1 \cap y_{odm} = 1. \tag{7}$$

If this rule is satisfied, the driving situation is discriminated as an emergency situation and a braking command is issued immediately; otherwise, the driving situation is discriminated as a normal situation and the vehicle continues traveling.

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Since human brain state changes over time, the performance of the IDA may gradually get worse. Thus, we retrained the classifier online using the adaptive sample set. The adaptive sample set $S_A(t)$ for the tth RLDA retraining can be constructed by

$$S_A(t) = S_O + S_N(t), \quad (8)$$

where S_O represents the original sample set saved offline to train RLDA. S_O was made up of normal and emergency samples. A sample was an n-dimension feature vector that was inputted to the RLDA. S_O was maintained consistent during the test process. $S_N(t)$ represents the new normal sample set added for the tth RLDA retraining. If the IDA and ODM both discriminate the current situation to be a normal situation, this sample will be added to $S_N(t)$. When the number of samples saved in $S_N(t)$ reaches Q (in this paper Q=75), $S_A(t)$ will be used to retrain RLDA (i.e. calculating the new values of the parameters of the RLDA) and $S_N(t)$ will be cleared. The time interval of two consecutive retraining processes was set to be 10 seconds.

E. Performance Assessment

To assess the performance, false alarm rate *(FAR)*, hit rate (*HR*), system accuracy (*SA*), and response time (*RT*) were used. *FAR* was defined as the ratio of issued emergency commands to the total number of commands in the normal driving process. *HR* was defined as the ratio of the number of correct hits to the number of emergency trials. A correct hit means that the braking intention is detected within 1200 ms after emergency situation onset. *RT* was defined as the time length from the occurrence of emergency situations to the first "emergency situation" command issued by the system. *SA* was defined as

$$SA = \frac{(1-FAR)+HR}{2} \quad (9)$$

The proposed detection system was tested in pseudo-online and online ways. Pseudo-online testing was employed to simulate an online procedure to test the system before testing it online in real experiments. It was similar to the online testing, but the testing data were collected in advance. For pseudo-online and online testing, we used a sliding window to compute and output the detection result every cycle (i.e., every step). That is, the sliding window was shifted with a step size continuously.

III. Experiment and Results

A. Pseudo-online Results

1) Parameter Settings

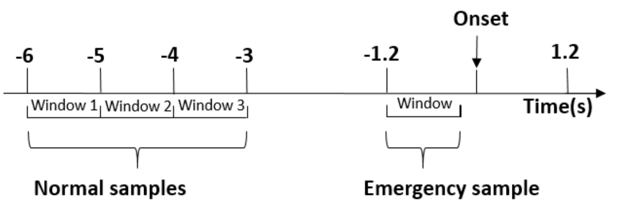

Fig. 4. Extraction of normal samples and emergency samples for training

As shown in Fig. 4, one sample was a data window of 1 s. For each trial, 3 normal samples were extracted between 3 s and 6 s before the onset of emergency situations and one emergency sample was extracted between 1.2 s before and after the onset of emergency. The specific start and end time points of the emergency sample for each subject can be seen in Table I. In this way, 90 normal samples and 30 emergency samples were acquired for each subject.

Offline analysis was conducted to determine the parameters for each subject. We applied a six-fold cross-validation to the samples and calculated the mean AUC of the RLDA classifier across all folds and trials. Parameters that generated the highest AUC were chosen and used in the pseudo-online evaluation. The chosen parameters are shown in TABLE I.

TABLE I
Chosen Parameters for 12 Subjects

Subject	Number of Virtual Channels m	Dimension of Feature Vector n	Start and End Time Point of One Emergency Sample
1	6	100	0.2 s-1.2 s
2	16	100	0.2 s-1.2 s
3	4	50	0.2 s-1.2 s
4	8	10	-0.2 s-0.8s
5	14	50	-0.2 s-0.8s
6	16	20	-0.2 s-0.8s
7	2	30	0.2 s-1.2 s
8	10	40	0 s-1 s
9	2	30	0.2 s-1.2 s
10	12	40	-0.2 s-0.8s
11	16	20	0 s-1 s
12	14	10	-0.2 s-0.8s

Number of virtual channels was chosen from 2 to 16 with the interval of 2. Dimension of feature vector was chosen from 10 to 100 with the interval of 10. Negative start time point of emergency samples means that the time point is before the occurrence of emergency situations and positive value means the time point is after the occurrence of emergency situations.

For the pseudo-online test, six-fold cross-validation was used. In each fold, 25 trials were used for training, and the other trials were used for testing. We conducted the pseudo-online test with the window of 1 s and step of 20 ms.

2) Evaluation Results

We first conducted the pseudo-online test of the braking intention detection method based on the IDA. Fig. 5 shows the final features selected by correlation analysis to train RLDA at all frequencies between 1 and 60 Hz over virtual channels for Subject 10. The black blocks represent the selected features, while the white blocks stand for the remaining features. Then, the proposed method of the emergency situation detection (i.e., the whole system) was tested. Fig. 6 shows the *FAR, HR, SA,* and *RT* of the IDA and whole system. We can see that the means with standard deviations of *FAR, HR, SA, and RT* of the IDA are 2.52%±1.13%, 93.61%±7.51%, 95.55%±3.53%, and 348.92±123.48 ms, respectively, whereas the means with standard deviations of the *FAR, HR, SA, and RT* of the whole system are 0.0172%±0.0070%, 93.89%±5.24%, 96.94%±2.62%, and 498.51±63.51 ms, respectively.

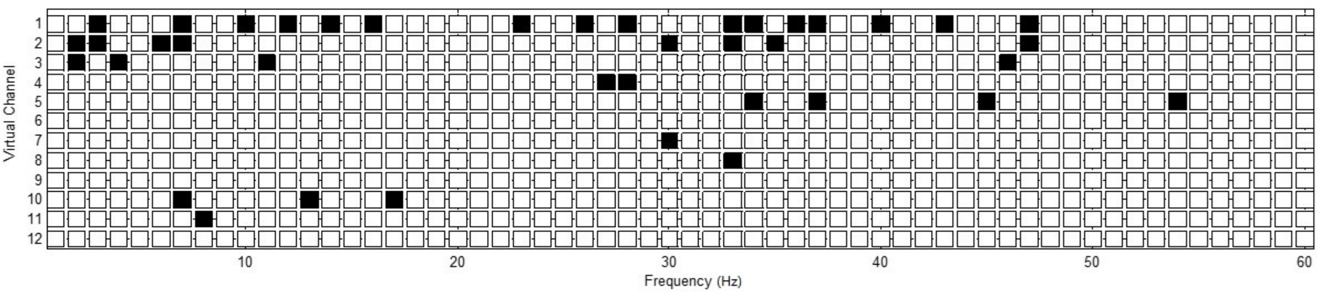

Fig. 5. Selected features by correlation analysis for Subject 10.

Furthermore, we can see that the IDA and whole system both show relatively small variation in the *FAR, HR, and SA* across all subjects. However, they show relatively large variation in *RT*. The comparison in all measures between the proposed methods and benchmark method in [19] is shown in TABLE II.

We can see that, on average, the proposed EEG-based method of emergency braking intention detection reduces the *FAR* from 5.78% to 2.52% and the *RT* from 420 ms to 349 ms, and increases the *SA* from 94.05% to 95.55%, while having the almost same *HR* (93.89% VS 93.61%). If an emergency braking intention meant an emergency situation, compared to the method reported in [19], the proposed method of emergency situation detection would reduce the *FAR* to 0.0172% and improve the *SA* to 96.94%, but increases the *RT* to 499 ms, on average.

Multiple one-way ANOVAs with significance level set to be 0.01 showed that there was significant difference in *FAR* between each of the three methods (all p<0.002). There was no significant difference in *HR* between the benchmark and IDA (p=0.993), benchmark and whole system (p=1), and IDA and whole system (p=0.993). There was no significant difference in *SA* between the benchmark and IDA (p=0.512), benchmark and whole system (p=0.068), and IDA and whole system (p=0.462). The difference in *RT* was significant between the benchmark and IDA (p=0.007), but not significant between benchmark and whole system (p=0.098), and IDA and whole system (p=0.322).

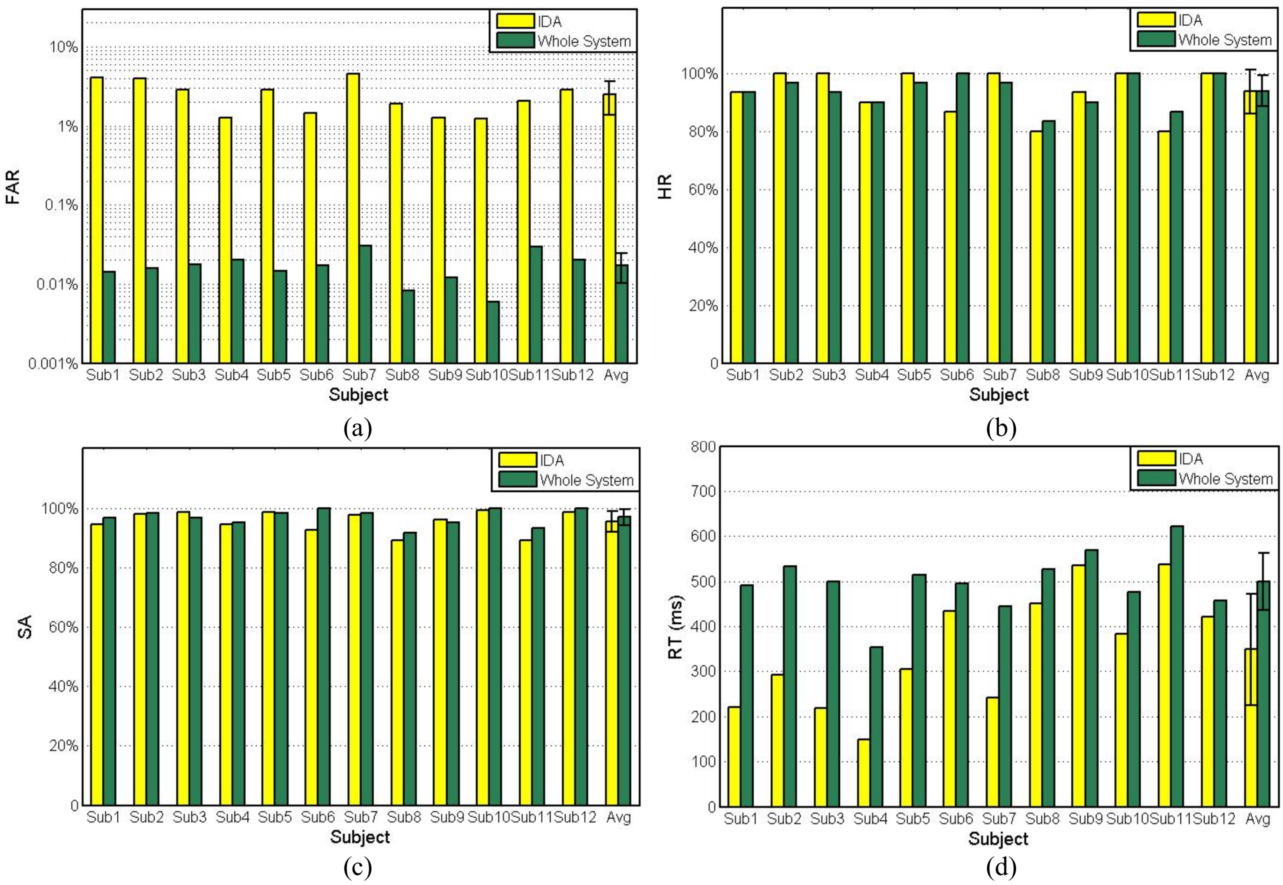

Fig. 6. Evaluation results of pseudo-online test. (a) False alarm rate. (b) Hit rate. (c) System accuracy. (d) Response time.

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TABLE II
COMPARISON OF THE AVERAGE RESULTS ACROSS SUBJECTS AMONG METHODS

	FAR	*HR*	*SA*	*RT* (ms)
Benchmark in [19]	5.78%	93.89%	94.05%	420
IDA	2.52%	93.61%	95.55%	349
Whole System	0.0172%	93.89%	96.94%	499

To show the effect of the performance of the ODM on the performance of the whole system, we tested the performance of the proposed system under the condition of three representative ODMs (i.e., ODM1 with $\psi_1 = 1.5\%$ and $\psi_2 = 95\%$, ODM2 with $\psi_1 = 0.8\%$ and $\psi_2 = 98.41\%$, and ODM3 with $\psi_1 = 0.3\%$ and $\psi_2 = 100\%$). As shown in Fig. 7, it was found that better performance of the ODM can lead to better performance of the proposed system given the performance of the proposed IDA.

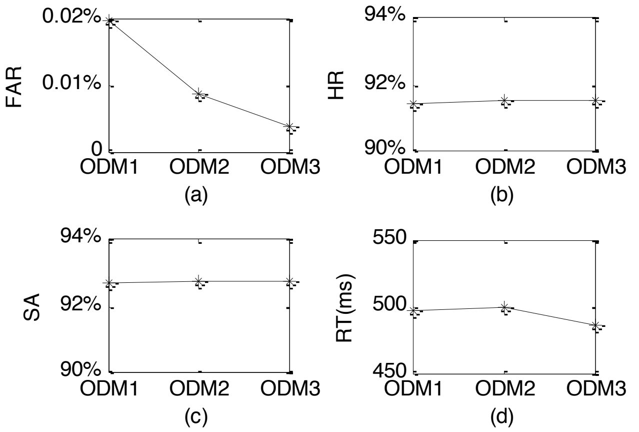

Fig. 7. Performance of whole system with different ODM. (a) False alarm rate. (b) Hit rate. (c) System accuracy. (d) Response time.

B. *Online Experimental Results*

1) *Real-time Detection System implementation*

In order to perform the online experiment, we set up the real-time detection system of emergency braking intention (as shown in Fig. 8, which consists of a digital brain wave measurement system of the SYMTOP company, China, a MinnowBoard-Max-Dual embedded hardware system of Intel company, a driving simulator, and a computer running the virtual vehicle with the driving scene. The embedded hardware system received the collected EEG data and output of the ODM and outputted 10 detection results per second.

2) *Experimental Procedure*

Two male subjects (aged 23 and 26) participated in the online experiment after their models were trained offline using the offline protocol in [19]. The online experimental protocol was reviewed and approved by the local research ethics committee and subjects signed the informed consent forms. In online experiment, 30 trials were conducted in a driving simulator located in a laboratory for each subject using the same simulated path and speed. Three adjacent pedestrians with 1-meter space stood on the right side of the lane. Their positions were randomly designated between 1000 m and 1500 m relative to the origin of the road and unknown to subjects. The emergency situations were simulated by letting one of the pedestrians crossing the road at the position of 60 m in front of the vehicle in every trial. Once the proposed system detects the emergency situation, the vehicle will brake immediately and the current trial will end. One of the scenes of the online experiment is shown in Fig. 9.

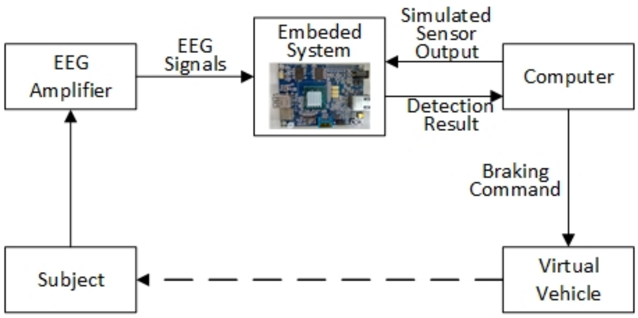

Fig. 8. Structure of real-time detection system

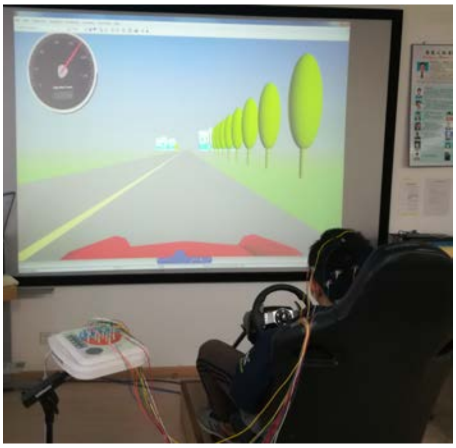

Fig. 9. Online experimental scene

3) *Results*

TABLE III shows the pseudo-online and online testing results of the proposed detection method of emergency situations for the two subjects. We can find that the proposed method shows good online performance with the *FAR* of 0.05%, *HR* of 89.83%, *SA* of close to 95%, and *RT* of 540 ms. However, compared to pseudo-online testing results, online testing results, online testing results in all measures got worse. The main reason for this difference in performance might be that the online task was changed from a “if-and-when” task to “when” task. That means, the certainty of emergency events increase as the task progresses since there were three pedestrians in fixed locations and subjects knew that one of them would step out.

TABLE III PSEUDO-ONLINE AND ONLINE TESTING RESULTS OF THE PROPOSED METHOD OF EMERGENCY SITUATIONS

	FAR	*HR*	*SA*	*RT* (ms)
Pseudo-online	0.028%	96.67%	98.32%	507
Online	0.051%	89.83%	94.89%	540

IV. DISCUSSION AND CONCLUSION

In this paper, we have proposed a novel method of emergency situation detection by combining driver EEG signals with surroundings. We first built a novel EEG-based model to detect driver emergency braking intention and then fused the result of the EEG-based model of emergency braking intention detection with that of the obstacle detection model based on surrounding information to recognize emergency situations. The pseudo-online testing results showed that, compared to the method reported in [19], on average, the proposed EEG-based method of emergency braking intention detection reduced the *FAR* from 5.78% to 2.52%. If an emergency braking intention meant an emergency situation, compared to the method reported in [19], the proposed method of emergency situation detection would reduce the *FAR* to 0.0172%.

Furthermore, we have implemented a real-time detection system of driver emergency braking intention on an embedded hardware and performed the driver-in-the-loop-experiment of the proposed detection method of emergency situations. The online experimental results showed that the proposed method of emergency situation detection can detect emergency situations with the *SA* of 94.89%, *HR* of 89.83%, *FAR* of 0.051%, and *RT* of 540 ms. Compared to the average (833.7 ms) of brake pedal response time of the 12 subjects, the proposed system issued a braking command 293 ms earlier. Furthermore, it had similar response time to that of a typical ODM [21]. This shows the potential of developing such detection system.

This study is important for the future development of brain-controlled and self-driving vehicles in at least two implications. First, it can help address the driving safety under emergency situations by detecting the braking intention of drivers from EEG signals. Second, it provides some new insights into integrating humans with driving automations. For example, the proposed EEG-based emergency intention detection may be expanded to detect other driving intentions or human states. According to these detected intentions or states of humans, self-driving vehicles can adjust their behaviors to make humans possess better user experience.

From a wider perspective, the proposed methods open a new avenue on how to achieve better human-machine integration. For example, the intentions and states of humans can be detected via physiological signals and thus transmitted to machines in a manner that does not depend on overt human behaviors. Machines can use these detected intentions and states as additional information to improve their intelligence and performance.

However, a significant amount of work still needs to be done before such system would be useful in a real vehicle on real roads among real pedestrians and they may open future research opportunities along this direction.

First, given that the hit rate of the ODM was about 98%, the online hit rate of the proposed system was about 90%, which means that it would still hit a minimum of one out of 10 pedestrians. One major reason for the proposed system decreasing the false alarm but not increasing the hit rate is that it was designed to work on the convergent recognition by the IDA and ODM. It is critically important to improve the hit rate of the proposed system since any missing hits can lead to a danger of collision for the real application. One potential solution to increase the hit rate of the system is to redesign the working procedure of the system. For example, since the ODM can detect an obstacle (a possible emergency event) a relatively long time before the real emergency event happens, the ODM can alert humans to make them pay attention to roads, once it detects an obstacle. This would be helpful to decrease the missing rate of the IDA and thus improve the hit rate of the whole system. How to alert humans and how the IDA and ODM are integrated and collaborate need to further be investigated and are potential research avenues to increase the performance of the whole system in this direction.

Another potential solution is to improve the hit rate of the ODM and IDA models by using other advanced techniques. As the development of the sensing, image processing, and machine learning techniques, the hit rate of the ODM should be able to be further increased. Furthermore, the hit rate of the IDA may be improved by using the combination of features from different domains (e. g., temporal, spectral, and spatial domains) of EEG signals and nonlinear classifiers. It can be also improved by combining other physiological information and behavior data with EEG signals.

Second, there are several limitations in the experimental test of the proposed system, which need to be further addressed. The first limitation is that the actual physical properties of the vehicle and road were not emulated completely. The second one is that the uncertainty of the occurrence of emergency events was small. In real-world conditions, greater uncertainty would be present and the performance of the system might be decreased. The third one is that the time length (1.44 minutes) of each trial was short for testing the performance of the proposed system, which involved a method to adapt the EEG classifier to drift over time. Under real-world conditions, one would drive for much longer time and greater drift in the performance of the EEG classifier would likely occur due to the fatigue and attentional drift of humans. The fourth limitation is that we used sudden crossings of pedestrians as emergency situations in a simple driving scenario. However, other emergency situations and more complex driving conditions would exist in real world. These driving conditions (like road type, vehicle speed, and traffic condition) may affect driver braking response and thus influence the performance of the proposed detection system.

Our future work will focus on addressing the limitations mentioned above, including redesigning the integration and collaboration rules of the IDA and ODM, improving the EEG-based method of emergency braking intention prediction by combining other physiological information and behavior data with EEG signals and using nonlinear classifiers, and further

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testing the proposed system by emulating actual physical properties of the vehicle and road, increasing the uncertainty of the occurrence of emergency events, and the length of driving trials.

REFERENCES

[1] *World report on disability*. Accessed on 2011. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs404/en/.

[2] B. Rebsamen *et al*., "A Brain Controlled Wheelchair to Navigate in Familiar Environments," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 6, pp. 590-598, Dec. 2010

[3] J. Long, Y. Li, H. Wang, T. Yu, J. Pan and F. Li, "A Hybrid Brain Computer Interface to Control the Direction and Speed of a Simulated or Real Wheelchair," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 5, pp. 720-729, Sept. 2012.

[4] T. Carlson and J. del R. Millan, "Brain-Controlled Wheelchairs: A Robotic Architecture," in *IEEE Robotics & Automation Magazine*, vol. 20, no. 1, pp. 65-73, March 2013.

[5] Y. Yu *et al*., "Self-Paced Operation of a Wheelchair Based on a Hybrid Brain-Computer Interface Combining Motor Imagery and P300 Potential," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 12, pp. 2516-2526, Dec. 2017.

[6] C. T. Lin, L. W. Ko and T. K. Shen, "Computational intelligent brain computer interaction and its applications on driving cognition," in *IEEE Computational Intelligence Magazine*, vol. 4, no. 4, pp. 32-46, November 2009.

[7] L. Bi, X. Fan, K. Jie, T. Teng, H. Ding and Y. Liu, "Using a Head-up Display-Based Steady-State Visually Evoked Potential Brain–Computer Interface to Control a Simulated Vehicle," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 3, pp. 959-966, June 2014.

[8] X. Fan, L. Bi, T. Teng, H. Ding and Y. Liu, "A Brain–Computer Interface-Based Vehicle Destination Selection System Using P300 and SSVEP Signals," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 1, pp. 274-283, Feb. 2015.

[9] L. Bi, Y. Lu, X. Fan, J. Lian and Y. Liu, "Queuing Network Modeling of Driver EEG Signals-Based Steering Control," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 8, pp. 1117-1124, Aug. 2017.

[10] H. Sun, C. Hua and Y. Luo, "A multi-stage classifier based algorithm of pedestrian detection in night with a near infrared camera in a moving car,"*Image and Graphics (ICIG'04), Third International Conference on*, Hong Kong, China, 2004, pp. 120-123.

[11] P. Hurney, P. Waldron, F. Morgan, E. Jones and M. Glavin, "Night-time pedestrian classification with histograms of oriented gradients-local binary patterns vectors," in *IET Intelligent Transport Systems*, vol. 9, no. 1, pp. 75-85, 2 2015.

[12] M. Heuer, A. Al-Hamadi, A. Rain and M. M. Meinecke, "Detection and tracking approach using an automotive radar to increase active pedestrian safety," *2014 IEEE Intelligent Vehicles Symposium Proceedings*, Dearborn, MI, 2014, pp. 890-893.

[13] B. Kim, B. Choi, S. Park, H. Kim and E. Kim, "Pedestrian/Vehicle Detection Using a 2.5-D Multi-Layer Laser Scanner," in *IEEE Sensors Journal*, vol. 16, no. 2, pp. 400-408, Jan.15, 2016.

[14] F. Li, R. Zhang and F. You, "Fast pedestrian detection and dynamic tracking for intelligent vehicles within V2V cooperative environment," in *IET Image Processing*, vol. 11, no. 10, pp. 833-840, 10 2017.

[15] S. Haufe, M. Treder, M. Gugler, M. Sagebaum, G. Curio, and B. Blankertz, "EEG potentials predict upcoming emergency brakings during simulated driving," *Journal of Neural Engineering.*, vol. 8, no. 5, p. 056001, Jul. 2011.

[16] S. Haufe, J. Kim, I. Kim, A. Sonnleitner, M. Schrauf, G. Curio, and B. Blankertz, "Electrophysiology-based detection of emergency braking intention in real-world driving," *Journal of Neural Engineering.*, vol. 11, no. 5, p. 056011, Aug. 2014.

[17] I. Kim, J. Kim, S. Haufe, and S. Lee, "Detection of braking intention in diverse situations during simulated driving based on EEG feature combination," *Journal of Neural Engineering.*, vol. 12, no. 1, p. 016001, Nov. 2014.

[18] T. Teng, L. Bi and X. Fan, "Using EEG to recognize emergency situations for brain-controlled vehicles," *2015 IEEE Intelligent Vehicles Symposium (IV)*, Seoul, 2015, pp. 1305-1309.

[19] T. Teng, L. Bi and Y. Liu, "EEG-Based Detection of Driver Emergency Braking Intention for Brain-Controlled Vehicles," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 6, pp. 1766-1773, June 2018.

[20] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Comput.*, vol. 7, no. 6, pp. 1129–1159, 1995.

[21] M. Pedersoli, J. Gonzàlez, X. Hu and X. Roca, "Toward Real-Time Pedestrian Detection Based on a Deformable Template Model," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 1, pp. 355-364, Feb. 2014.