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

Luzheng Bi, Senior Member, IEEE, Huikang Wang, Teng Teng, and Cuntai Guan, Fellow, IEEE

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.

Manuscript received March 31, 2018; revised June 23, 2018 and August 29, 2018; accepted on August 30, 2018. This work was supported in part by National Natural Science Foundation of China under Grant 51575048, the Beijing Natural Science Foundation under Grant 4162055, and China Scholarship Council under Grant 201706035010. Corresponding author is Luzheng Bi (e-mail: bhxblz@bit.edu.cn).

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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, Haufler 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.
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

$$Y(t) = W_1 \cdot X(t),$$

(1)
where \( X(t) = [x_1(t), x_2(t), \ldots, x_i(t)]^T \), \( x_i(t) \) represents the data collected from the \( i \)th electrode, \( Y(t) = [y_1(t), y_2(t), \ldots, y_i(t)]^T \), \( y_i(t) \) represents the \( i \)th independent component, and \( t \) stands for sampling time point. In this paper, \( i \) was equal to 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

\[
X(t) = W_1^{-1} \cdot Y(t)
\]  (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

\[
Z(t) = W_2 \cdot X(t)
\]  (3)

where \( Z(t) = [z(t), z_2(t), \ldots, z_m(t)]^T \), \( z_m(t) \) represents the data of the \( m \)th 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

\[
R(j) = |corr(v_1(j), v_2(j))|,
\]  (4)

where \( v_1(j) = [em_1(1), \ldots, em_k(k), no_1(1), \ldots, no_l(l)]^T \), \( em_k(k) \) and \( no_l(l) \) represent the value of the \( j \)th feature of \( Z(f) \) in the \( k \)th emergency sample and the \( l \)th normal sample, respectively. \( v_2(j) = [1(1), \ldots, 1(k), -1(1), \ldots, -1(l)]^T \), \( 1(k) \) and \( -1(l) \) represent the class label of \( em_k(k) \) and \( no_l(l) \), 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

\[
y = w^T x,
\]  (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, \( \mu_1 \) and \( \mu_2 \) represent the mean value of the two class, respectively, and \( \Sigma'_w \) is the regularized within-class scatter matrix, which can be calculated by

\[
\Sigma'_w = (1 - \lambda)\Sigma_w + \lambda \mu_1 \mu_1^T,
\]  (6)

where \( \Sigma_w \) is the within-class scatter matrix, \( \lambda \in [0, 1] \) is the tuning parameter, \( I \) is identity matrix, \( \nu = trace(\Sigma_w) / d \), and \( d \) is the dimension of \( \Sigma_w \). A threshold \( Tr \) is set to discriminate the output \( y \). If \( y > Tr \), the output of \( y \) equals 1, corresponding to the emergency braking intention. If \( y \) 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 \( \Phi_1 \) and \( \Phi_2 \), 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**

<table>
<thead>
<tr>
<th>Define:</th>
<th>( R_1 \in \Phi_1 ), ( R_2 \in \Phi_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( P(R_1 = 1) = \psi_1 ), ( P(R_1 = -1) = 1 - \psi_1 ), ( P(R_2 = 1) = \psi_2 ), ( P(R_2 = -1) = 1 - \psi_2 )</td>
</tr>
</tbody>
</table>

If \( R_0 = -1 \) \( y_{odm} \in \Phi_1 \)

Else \( y_{odm} \in \Phi_2 \)

**Return** \( y_{odm} \)

The parameters of the performance model \( \psi_1 \) (i.e., false positive rate) and \( \psi_2 \) (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:

\[
y_{ida} = 1 \cap y_{odm} = 1.
\]  (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.
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

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 whole system are 0.0172%±0.0070%, 93.89%±5.24%, 96.94%±2.62%, and 498.51±63.51 ms, respectively.
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. 5. Selected features by correlation analysis for Subject 10.

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

### TABLE II

<table>
<thead>
<tr>
<th>Method</th>
<th>FAR</th>
<th>HR</th>
<th>SA</th>
<th>RT (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark in [19]</td>
<td>5.78%</td>
<td>93.89%</td>
<td>94.05%</td>
<td>420</td>
</tr>
<tr>
<td>IDA</td>
<td>2.52%</td>
<td>93.61%</td>
<td>95.55%</td>
<td>349</td>
</tr>
<tr>
<td>Whole System</td>
<td>0.0172%</td>
<td>93.89%</td>
<td>96.94%</td>
<td>499</td>
</tr>
</tbody>
</table>

(b) Hit rate. (c) System accuracy. (d) Response time.

**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.

![Diagram](image-url)
TABLE III PSEUDO-ONLINE AND ONLINE TESTING RESULTS OF THE PROPOSED METHOD OF EMERGENCY SITUATIONS

<table>
<thead>
<tr>
<th></th>
<th>FAR</th>
<th>HR</th>
<th>SA</th>
<th>RT (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pseudo-online</td>
<td>0.028%</td>
<td>96.67%</td>
<td>98.32%</td>
<td>507</td>
</tr>
<tr>
<td>Online</td>
<td>0.051%</td>
<td>89.83%</td>
<td>94.89%</td>
<td>540</td>
</tr>
</tbody>
</table>

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 model of emergency braking intention prediction by combining other physiological information and behavior data with EEG signals and using nonlinear classifiers, and further
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


