Using a Head-up Display-Based Steady-State Visually Evoked Potential Brain–Computer Interface to Control a Simulated Vehicle

Luzheng Bi, Member, IEEE, Xin-an Fan, Ke Jie, Teng Teng, Hongsheng Ding, and Yili Liu, Member, IEEE

Abstract—In this paper, we propose a new steady-state visually evoked potential (SSVEP) brain–computer interface (BCI) with visual stimuli presented on a windshield via a head-up display, and we apply this BCI in conjunction with an alpha rhythm to control a simulated vehicle with a 14-DOF vehicle dynamics model. A linear discriminant analysis classifier is applied to detect the alpha rhythm, which is used to control the starting and stopping of the vehicle. The classification models of the SSVEP BCI with three commands (i.e., turning left, turning right, and going forward) are built by using a support vector machine with frequency domain features. A real-time brain-controlled simulated vehicle is developed and tested by using four participants to perform a driving task online, including vehicle starting and stopping, lane keeping, avoiding obstacles, and curve negotiation. Experimental results show the feasibility of using the human “mind” alone to control a vehicle, at least for some users.

Index Terms—Brain-controlled vehicle, head-up display (HUD), human–vehicle interaction, steady-state visually evoked potential (SSVEP) brain–computer interface (BCI).

I. INTRODUCTION

USING the human “mind” rather than the limbs to drive a vehicle (such vehicles can be called brain-controlled vehicles) has significant practical values. Such systems may provide a complementary or alternative way for individuals with severe neuromuscular disorders to drive a vehicle to extend their scope of mobility and, thus, improve their quality of life and independence. For the broader driving community, these systems have the potential to facilitate the development of human-centric driver assistance systems to better assist drivers in driving a vehicle [1].

Brain–computer interfaces (BCIs) can establish a direct pathway between the human “mind” and external devices. Owing to its low cost and convenience of use, the EEG has been the most popular signal that is used in developing BCI systems, such as controlling a cursor on the screen [2], [3], selecting letters from a virtual keyboard [4], [5], browsing the Internet [6]–[8], and playing games [9], [10]. Recently, the BCIs that are based on EEG signals have been used to control wheelchairs to help bring mobility back to some severely disabled people [11]–[13].

A more detailed review regarding brain-controlled wheelchairs can be seen in our work in [1]. The EEG signals that are commonly used in developing BCIs include 1) P300 potentials, which are positive potential deflections on the ongoing brain activity signal at a latency of roughly 300 ms after the random occurrence of a desired target stimulus from nontarget stimuli [14]; 2) steady-state visually evoked potentials (SSVEPs), which are visually evoked by a stimulus and are modulated at a fixed frequency and occur as an increase in the EEG activity at the stimulus frequency [15]; and 3) the event-related desynchronizations (ERDs) and the event-related synchronization (ERS), which are induced by performing mental tasks, such as motor imagery, mental arithmetic, or mental rotation [16]. A variety of classifiers have been used to translate EEG signals into an output command, from simple classifiers, such as the linear discriminant analysis (LDA), to nonlinear classifiers, such as support vector machines (SVMs). A more detailed review regarding classifiers can be seen in our work in [1].

Compared with brain-controlled wheelchairs, brain-controlled vehicles have more complicated dynamic characteristics, and they run faster in a more complicated environment. The highest velocities of all existing brain-controlled wheelchairs in a laboratory and in a virtual world are 1 and 1.5 m/s, respectively.

Few studies have explored how to drive a vehicle using EEG signals. Hood et al. [17] used an SSVEP-based BCI with visual stimuli that are developed with light-emitting diodes to control a simulated car to turn left, turn right, and go straight in a driving simulator. They announced that the preliminary experimental results from one subject provided an indication of the feasibility of using EEG signals to drive a vehicle. However, they did not provide the specific experimental results of controlling the simulated vehicle and the specific testing conditions (including the speed of the simulated car and testing scenarios). Furthermore, when they tested the direction control by using the BCI (i.e., turning left and right), the speed control was by the driver via his feet. Rojas et al. [18] applied a commercial BCI product (i.e., the EPOC cap from Emotiv) to control a vehicle as a way to test the feasibility of using brain signals to control a vehicle. The BCI that is embedded in the commercial cap is an ERD/ERS-based BCI, which can issue at most four commands by translating EEG signals. Rojas et al. tested their system by using only one subject to perform lane keeping on a closed...
airfield. The experimental result showed poor steering control (turning left and right) performance, although it only involved a constant speed of 2 m/s. The maximum and standard deviation of the lateral error reached about 10 and 2 m, respectively. Moreover, in their whole testing process, when the vehicle imminently collides or if it is about to leave the free drive zone, the computer instantly stops the vehicle. That is, the vehicle was controlled by the BCI with the intelligence of the vehicle by perceiving the surroundings.

Considering that driverless techniques have been gradually reaching maturity [19], Bi et al. [20] have proposed a HUD-based P300 BCI and applied it for developing a vehicle destination selection system. Users can use the destination selection system to select a desired destination from predefined destinations, and then use an autonomous navigation system to drive a vehicle to reach the desired destination.

Our long-term goal is to develop a brain-controlled vehicle by using a BCI system to select a destination and another BCI system to issue a motion control command when users want or need it. In this paper, we move a step toward this goal by developing a HUD-based SSVEP and by applying it to control a simulated vehicle to demonstrate the feasibility of using the BCI to control a simulated vehicle without any assistance from a driver and the intelligence of the vehicle.

For a brain-controlled vehicle, compared with the control of speed, direction control is more common and important since it is currently only possible for brain-controlled vehicles to travel at a low speed. Thus, in this paper, we investigate how to use the HUD-based SSVEP BCI to control the vehicle direction in conjunction with using an alpha rhythm to control the starting and stopping of the vehicle. The reasons for selecting the SSVEP BCI rather than the P300 and ERD/ERS BCIs to control a vehicle are as follows. First, the P300 BCI needs to take about 4–10 s to issue a command. In contrast, the SSVEP and ERD/ERS BCIs can issue commands at 1 s or even shorter intervals. Thus, the P300 BCI systems are not as suitable to use for issuing motion control commands. Second, the ERD/ERS BCIs require extensive training that may take several weeks (or even longer). Compared with the ERD/ERS BCIs, SSVEP BCIs require minimal training and have stable performance and high accuracy [1]. The potential weakness of the SSVEP BCIs is that they need external stimulation compared with ERD/ERS BCIs.

The remainder of this paper is organized as follows. In Section II, we introduce the methods for developing a HUD-based SSVEP BCI and using it to control simulated vehicles. Section III describes the experiments that were conducted to test the system, whose results are described in Section IV. In Section V, we conclude this paper with a discussion of the current challenges and future research directions.

II. METHODOLOGY

A. Visual Stimuli and Execution Protocol

The SSVEP visual stimuli consisted of two flashing rectangle (5.65 cm × 16.9 cm) checkeredboards, which are displayed on a real windshield (whose top, bottom, left, and right edges are 102, 138, 59, and 59 cm, respectively) of vehicles via a HUD system that we constructed [20], as shown in Fig. 1.

Each checkerboard included a grid of 30 × 10 checkers. The checkerboard pattern needs to reverse colors several times per second to elicit an SSVEP. The left checkerboard reversed its color 12 times each second, generating a stimulation frequency of 12 Hz, whereas the right checkerboard reversed its color 13 times, generating a stimulation frequency of 13 Hz.

When the user wants to control the vehicle to turn left or turn right, he/she needs to focus his/her attention on the corresponding checkerboards (the left and right checkerboards are associated with turning left and right, respectively), and the BCI interprets the EEG signals to infer the stimulus to which the user is attending. When the user wants to control the vehicle to go forward (keep the current heading direction), he/she is required to not attend to any SSVEP stimulus, and the BCI classifies the EEG signals into the going forward command. If the user wants to stop the moving vehicle, the user needs to close his/her eyes until the system outputs a kind of sound when the BCI detects the eye closing from the EEG signals and stops the vehicle. If the user wants to start the vehicle when the vehicle is stopped, he/she also needs to close his/her eyes until the system issues another kind of sound when the BCI detects the eye-closing state from the EEG signals and starts the vehicle.

B. Data Collection

We used a 16-channel amplifier to acquire the EEG signals in ten standard locations (i.e., Fz, Cz, Pz, Oz, P3, P4, P7, P8, O1, and O2), as shown in Fig. 2. The reference potential was the average of the potentials of the left and right ear lobes. The EEG signals were amplified and digitalized with a sampling rate of 1000 Hz and a power-line notch filter to remove the line noise.

C. BCI System of Brain-Controlled Vehicles

The whole BCI system includes two classification models (i.e., Model I for detecting the alpha rhythm and Model II for the SSVEP BCI) and two control models (i.e., the starting/stopping control model and the direction control model). Classification Model I first interprets 4 s of the EEG data (i.e., its time window length is 4 s) with the step size of 0.5 s to detect the alpha rhythm, and if the alpha rhythm is detected, Classification Model I then classifies the EEG data into turning
left, turning right, or going forward commands. The signal flowchart of the whole BCI system is shown in Fig. 3.

1) Alpha Rhythm Detection Model: We applied the ratio of the sum of the powers of the alpha wave (i.e., 8–13 Hz) to the sum of the powers of 0–40 Hz in the power spectrum as features from the EEG data at the ten channels. In other words, we obtained one feature at each channel, with ten features in total. Furthermore, the LDA was used to develop the classifier.

2) Classification Model of the SSVEP BCI: We extracted frequency-domain features using the sums of the powers of the half frequencies ±0.5 Hz, fundamental frequencies ±0.5 Hz, double frequencies ±0.5 Hz, and thrice frequencies ±0.5 Hz of the visual stimuli in the power spectrum of the EEG data from the ten channels. In other words, we obtained eight features at each channel. Thus, we obtained a total of 80 features as follows:

\[ x = [x(1), x(2), \ldots, x(i), \ldots, x(80)]^T \] (1)

where \( x(i) \) is \( i \)th feature.

Since the SSVEP BCI includes three classes (i.e., turning left, turning right, and going forward), it is a multiclass classification, and we adopted the one-versus-rest classification strategy. In other words, we built a single binary classifier per class to distinguish this class from the other two classes. In this paper, we used an SVM with a radial basis function as the kernel function to develop all the binary classifiers as follows:

\[ y_j = \sum_{i=1}^{N_j} w_i^j \exp \left(-g \| x_i^j - x \|^2 \right) + b_j \] (2)

where \( N_j \) is the number of the support vector of the \( j \)th classifier, \( w_i^j \) is the weight of the \( i \)th support vector of the \( j \)th classifier, \( w_i^j \) is the bias of the \( j \)th classifier, and \( x_i^j \) is the \( i \)th support vector of the \( j \)th classifier. We applied the LIBSVM software library developed by Chang and Lin to determine the parameters of each binary classifier [21].

To classify the EEG data, the class that is associated with the maximal score of all binary classifiers was determined as classification result \( R \), i.e.,

\[ R = \arg \max_{j=1,2,3} y_j. \] (3)

3) Control Models: In the brain-controlled vehicle system, there are two control models. One model is the starting/stopping control model that is based on the alpha rhythm as follows:

\[ V(n) = V_0 \times f(n) \begin{cases} f(n) = \sim f(n-1), & \text{if } g(n) = 1 \\ f(n) = f(n-1), & \text{otherwise} \\ f(0) = 0; g(0) = 0; \quad n \geq 1 \end{cases} \] (4)

where \( V_n \) is the speed at the \( n \)th update, \( g(n) \) is the output of Model I, \( g(n) = 1 \) means eye closing, \( g(n) = 0 \) means eye opening, and \( V_0 \) is a positive speed constant and is initially set to 3 m/s.

The other model is the direction control model that is based on the SSVEP, which is defined as

\[ \alpha(n) = \min \{ [\alpha(n-1) + \Delta \alpha \times l(n)], \alpha_{\text{max}} \}, \]

\[ l(n) \in [-1, 0, 1] \quad \Delta \alpha = 10^\circ \]

\[ \alpha(0) = 0^\circ \quad \alpha_{\text{max}} = 100^\circ \quad n \geq 1 \] (5)

where \( \alpha(n) \) is the steering angle at the \( n \)th update; \( l(n) \) is the output of Model II, with \( l(n) = 1 \) for turning left, \( l(n) = -1 \) for turning right, and \( l(n) = 0 \) for going forward; and \( \Delta \alpha \) is a positive angle constant and is initially set to be 10\(^\circ\), which can be adjusted. Furthermore, when the brain-controlled vehicle turns, the speed decreases to 2 m/s.
III. Experiment

A. Subjects

Four participants, with three healthy males and one healthy female (a mean age of 25), voluntarily participated in the experiments and received no monetary compensation. All participants had no history of brain disease, and their visual acuity was normal or normal after adjustments. All the participants had never participated in any experiment of brain-controlled simulated vehicle before the experiment.

B. Experimental Platform

A brain-controlled simulated vehicle has been designed and constructed. It includes three main parts, as shown in Fig. 4. The first main part is the HUD-based SSVEP BCI with the alpha rhythm, which consists of the SSVEP visual stimuli presented on a real windshield via a HUD, the EEG measurement system, and the proposed signal processing and classification module, as described in Section II. Second is the control models that are described in Section II, which include the simulated vehicle with 14-DOF dynamics and the 3-D driving scene. Finally, we have the communication system between the computer supporting control models, the 3-D driving scene, and the virtual vehicle and the other running the EEG acquisition and signal processing module.

C. Experimental Procedures

Before the start of the experiment, we explained the experimental procedures to the participants so that they can become familiar with the experimental protocol. We displayed the visual stimuli on a real windshield via the constructed HUD. The subjects were asked to sit in a seat in front of the windshield, with similar distance of a vehicle driver to the windshield and similar vision angles when driving real vehicles. We adjusted the position, size, and intensity of the visual stimuli, and we set the parameters of the EEG collection system. We properly attached electrodes on the scalp of the subjects. Before the start of data collection, the contact impedance between the scalp and the EEG electrodes was calibrated to be below 10 kΩ.

The experiment includes two parts. The first part is for training the alpha rhythm detection mode and the HUD-based SSVEP BCI model for driving the vehicle, and the second part is for evaluating and testing the brain-controlled vehicle. The participants were given 15 min of break between the two parts of the experiments, and they all began with some minutes of practice.

The first part of the experiment includes three phases. The first phase is for collecting the EEG data that are associated with the turning left and right commands when participants attend to the left and right SSVEP stimuli. The second phase is for collecting the EEG data that are associated with the going forward command when participants do not attend to any stimuli, given the SSVEP stimuli flick all the time. The third phase is for collecting the EEG data that are associated with the starting/stopping command when participants close their eyes.

In the first phase, the participants were required to complete six sessions of attending to the left and right SSVEP stimuli. In each session, the subjects were required to complete four trials with an interval of 10 s between two consecutive trials. In each trial, they respectively attended to the left and right SSVEP visual stimuli for 12 s. In the second phase, the participants were required to complete three sessions of not attending to any stimuli, with each session including eight trials at an interval of 10 s between two consecutive trials. In each trial, they were required not to attend to any stimuli for 12 s, given the SSVEP stimuli flick all the time. In the third phase, the subjects were required to complete three sessions of closing their eyes, with each session including eight trials at an interval of 10 s between two consecutive trials. In each trial, the participants were required to close their eyes for 12 s.

We set the time window length to 4 s and the step size to 0.5 s to extract the EEG epoch as samples. This way, we obtained $408 \times (12 - 4) / 0.5 + 1 \times 6 \times 4$ samples that are associated with the turning left and right commands, $408 \times (12 - 4) / 0.5 + 1 \times 3 \times 8$ samples that are associated with the going forward command, and $408 \times (12 - 4) / 0.5 + 1 \times 3 \times 8$ samples that are associated with the starting/stopping command.

In the second part of the experiment for evaluating and testing the brain-controlled vehicle, we required the participants to control a simulated vehicle using the proposed BCI to travel along the centerline of the lane with two stopped vehicles as obstacles until the vehicle reaches the destination. We required the participants to follow two rules. First, they should try to keep the vehicle inside the boundaries, and once the vehicle crossed the boundary, they should try to go back to the path. Second, when the participants see an obstacle, they need to control the vehicle to avoid it. Ten runs were conducted for each participant. The experiment task scene is shown in Fig. 5.

IV. Results

A. BCI Performance

We randomly selected 204 samples from the collected samples (408) that are associated with eyes closed and 204 samples...
TABLE I  
ACCURACY OF THE ALPHA RHYTHM DETECTION MODEL

<table>
<thead>
<tr>
<th>Subject</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Mean with std. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>98.20%</td>
<td>98.81%</td>
<td>99.10%</td>
<td>78.01%</td>
<td>93.53%±5.18%</td>
</tr>
</tbody>
</table>

Table II shows the accuracy of the SSVEP BCI for the turning left, turning right, and going forward commands. Subject B shows the best performance, with her accuracy ranging from 96.32% to 100%. Furthermore, Subject A shows good performance, with his accuracy ranging from 86.47% to 90.20%.

Fig. 6. Accuracy of the SSVEP BCI over time.

B. Brain-Controlled Simulated Vehicle Performance

We applied the task success rate, the task completion time, the ratio of task completion time to the nominal time, the mean lateral error, the obstacle avoidance success rate, the false stopping rate per kilometer, and the out-of-boundary rate per kilometer as metrics to evaluate the performance of the brain-controlled simulated vehicles. It should be noted that, except for the task success rate, all metrics can be computed only when the vehicle can successfully reach the destination.

The task success rate was calculated as the number of vehicles that successfully reaches the destination over the number of trials that is required to be finished. Note that, when the time taken is greater than the timeout limit, which is set to be twice whereas the accuracy of Subject C is around 70%. However, Subject D has poor performance, with his accuracy ranging from 33.09% to 72.79%; the accuracy of turning left is even less than the chance (33.33%), and the accuracy of turning right is slightly higher than the chance.

It should be noted that the accuracy percentages in Table II were computed without considering the transitions among the turning left, turning right, and going forward commands, which frequently happen during the driving. Moreover, the accuracy during the phase of transitions among the three commands is rather important to driving since the transitions occur when the drivers need to correct the vehicle movement. Thus, we need to analyze the performance of the BCI during the transitions.

In this figure, the $x$ axis represents the time length of the new data in 4 s of window data with a step size of 0.5 s, whereas the $y$ axis represents the accuracy that is gained if the time length of the new data is the same as that of the $x$ axis. We can see that the accuracy across the subjects is almost at the level of chance (33.33%) within 2 s after the transitions start. However, after 2 s, the accuracy of Subjects A and B rises to about 60% by 2.5 s, to more than 75% by 3 s, and to more than 87% by 3.5 s, whereas the accuracy of Subjects B and C hardly increases within 3 s and only rises to less than 50% by 3.5 s.
the nominal time, the trial is stopped and is considered failing to finish the driving task. The nominal time was calculated as the length of the centerline of the lane over the maximum speed. The task completion time was defined as the time taken from the vehicle being started to reaching the destination. The mean lateral error was defined as the mean of the lateral error between the track of the simulated vehicle controlled by the BCI and the average track of the vehicle controlled by a driver via limbs in three runs. The false stopping rate per kilometer was defined as the number of stopping commands that is recognized per kilometer after the vehicle starts and before it reaches the destination.

Table III shows the performance of the brain-controlled simulated vehicle across all participants. In Table III, we can see that Subject D failed to reach the destinations in all the runs. Subject A shows good performance in using the EEG signals to control the simulated vehicle. He not only successfully reached the destinations in all ten runs but he also had a relatively small mean lateral error, a high obstacle avoidance success rate, a low out-of-boundary rate, and no false stopping. Subject B showed 90% task success rate with 94.44% obstacle avoidance rate, and Subject C had 60% task success rate with 100% obstacle avoidance rate. However, both Subjects B and C did not have as good real-time control performance as Subject A. The vehicle that they controlled showed great lateral error, high out-of-boundary rate, and some false stopping times. Fig. 7 shows the comparison between the average track of the simulated vehicle controlled by a driver via limbs and the actual trajectories when the brain-controlled vehicles successfully reach the destination. The black solid line is the average track of the vehicle controlled by a driver via limbs in three runs. The red dashed line is the centerline of the lane. The other lines are the actual trajectories when the brain-controlled vehicles successfully reach the destination.

V. DISCUSSION AND CONCLUSION

In this paper, we have developed a new SSVEP BCI with visual stimuli presented on a real vehicle windshield via a HUD, and we have applied this HUD-based BCI in conjunction with the alpha rhythm to control a simulated vehicle with a 14-DOF vehicle dynamics model. A real-time brain-controlled simulated vehicle was developed and evaluated by using four participants to perform a driving task online, including starting/ stopping the vehicle, lane keeping, avoiding obstacles, and

<table>
<thead>
<tr>
<th>Subject</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task success rate</td>
<td>100%</td>
<td>90.00%</td>
<td>60.00%</td>
<td>0%</td>
</tr>
<tr>
<td>Mean lateral error (m)</td>
<td>3.62</td>
<td>8.46</td>
<td>8.44</td>
<td>-</td>
</tr>
<tr>
<td>Task completion time (s)</td>
<td>361.96</td>
<td>359.99</td>
<td>371.95</td>
<td>-</td>
</tr>
<tr>
<td>Time ratio</td>
<td>1.42</td>
<td>1.27</td>
<td>1.38</td>
<td>-</td>
</tr>
<tr>
<td>Out-of-boundary rate per km</td>
<td>1.57</td>
<td>3.42</td>
<td>3.5</td>
<td>-</td>
</tr>
<tr>
<td>Avoiding obstacle rate</td>
<td>95.00%</td>
<td>94.44%</td>
<td>100.00%</td>
<td>-</td>
</tr>
<tr>
<td>Starting/stoping wrong rate per km</td>
<td>0</td>
<td>0.39</td>
<td>2.8</td>
<td>-</td>
</tr>
<tr>
<td>Average velocity (km/h)</td>
<td>7.62</td>
<td>8.59</td>
<td>8.21</td>
<td>-</td>
</tr>
</tbody>
</table>
The EEG signals and thus affect the BCI system performance. However, it is impossible for some users (e.g., Subject D) to drive the brain-controlled simulated vehicle because the SSVEP BCIs for these users have rather low accuracy. Some studies have shown that existing BCI systems cannot work for all users, which is called by some researchers as the “BCI illiteracy”, when the accuracy is lower than 70% [22]–[24]. This is because some users cannot produce the necessary brain activity patterns for a particular kind of BCI systems. In addition, although some users, such as Subject B, show high accuracy on the SSVEP BCI, they have poor performance in using the BCI to control the simulated vehicle. The main reason for this is that they likely did not learn how to use the BCI to control the vehicle well. It should be noted that all the subjects had never participated in any experiment on brain-controlled simulated vehicles before the formal experiment. As they drive a vehicle using their limbs, more practice should be helpful to improve the performance of the brain-controlled vehicles.

The work that has been reported in this paper moves a step toward developing a brain-controlled vehicle by using a BCI system to select a destination and by using another BCI system to issue a motion control command. However, several challenges need to be addressed, and they open future research opportunities along this direction.

First, the maximum speed of the brain-controlled vehicle is only about 11 km/h, which is too low for a vehicle. In practice, it is desired that the brain-controlled vehicle can travel at a 30–40 km/h speed. Higher speeds require better performance of the BCI (i.e., higher accuracy and shorter time of issuing a command), particularly during transitions among commands, which can be likely dealt with by some new classification methods or by selecting new features that can represent the change of EEG signals during the phase of transitions.

Second, the proposed BCI system cannot currently perform the speed control of brain-controlled simulated vehicles. This problem can be likely handled by adding two additional SSVEP stimuli that represent accelerating and decelerating, respectively. Another possible solution is to develop a hybrid BCI, which combines the SSVEP BCI and another BCI, and to apply two independent EEG signals to control the speed and direction of the vehicle, respectively.

Third, under the constraints of the limited and unstable performance of all existing BCI systems, finding ways to enhance and ensure the overall driving performance is very important. Future potential directions include developing methods to combine the information from the BCI and vehicle intelligence (such as surrounding sensing and path planning), and fusing additional useful information from other sources, such as predicted driver intentions.

Fourth, we have conducted the experiment in a laboratory, where the environmental factors were constant. However, in practice, vehicles are used outdoors, and increased noise can be expected. Real-world driving environments may have significant effects on users’ psychological states, which may affect the EEG signals and thus affect the BCI system performance.

Our future work aims to address the aforementioned issues, including testing the proposed system in a real vehicle in the testing field, improving the performance of the BCI, particularly during the stage of transitions among commands, and finding ways to improve the overall driving performance of brain-controlled vehicles by combining the BCI with other intelligent techniques and other information resources.

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References


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