Brain-vehicle Interactive Motion Control Based on Improved Queuing Network

Xi Liu*, Ren He

ABSTRACT
Aiming at the blank in the existing brain-controlled vehicle driving, this paper establishes a brain-vehicle interactive motion control model based on improved queuing network, and studies the effects of brain-vehicle interactive motion control proficiency and brain-vehicle interaction related parameters on vehicle driving performance. The results show that with the increasing number of driving tasks, the overall task completion time and lateral deviation of brain-controlled vehicles are significantly reduced, and the out-of-bound rate and false-stop rate are also significantly decreased. It indicates that after a certain period of training and adaptation, the human can gradually master the related skills and control methods of brain-controlled vehicles, and that using electroencephalogram (EEG) signals to control vehicles will see safer and more efficient characteristics. When the control accuracy of the brain over the car is low (55% or so), the track of the car is chaotic at different response time. The longer the response time is, the more difficult for the car to follow the existing trajectory, and the more the steering wheel angle changes. It shows that the longer the interval set for the car to receive EEG signals, the weaker the brain's control over the car, and the greater the offset of the car. As the proficiency of the subjects increases, and the interval of the vehicle receiving EEG signals becomes shorter, the success rate of the vehicle completing the whole driving task becomes greater.

Key Words: EEG, Brain-Vehicle Interaction, Brain-Computer Interface, Improved Queuing Network

Introduction
When human body moves, brain will generate brain signals to be transmitted to various parts of the body via nerve cells and nerve muscle (Wang et al., 2013; Fu et al., 2012). However, many diseases such as muscular dystrophy, amyotrophic lateral sclerosis, paralysis, stroke, and spinal cord nerve injury will all cause neuromuscular damage, so that the signals of the cranial nerves cannot be transmitted (Cincotti et al., 2007; Kaiser et al., 2001; Frolov et al., 2013; Kai and Guan, 2013).

Traditional approaches to repair neural pathways are to enhance the ability of nerve transport to participate in the passageway or to avoid the damaged part in the nerve or muscle passages, but they have limited treatment effects. (Hwang et al., 2009) In recent years, researchers have proposed a new way of communication between the human body and the external environment, namely, the brain-computer interface (BCI) (Arvaneh et al., 2011). The core of BCI is to establish a direct communication path between the brain and the external environment, so that the brain instructions can be transmitted to the external devices through only the established path instead of the neurons and muscles (Rejer, 2015).

The feature extraction of Electroencephalogram (EEG) signals based on brain-computer interface is the core technology in the field of EEG, which “translates” brain
signals into information that are readable to external devices and controlled by the devices through a certain methods (Ang et al., 2011; Ince et al., 2009; Frolov et al., 2013; Abootalebi et al., 2009; Rodríguez-Bermúdez et al., 2013). EEG signals have been widely used in games, auxiliary human movements, military fields, and so on (Choi, 2013).

The traffic driving behavior based on EEG is a new direction of development in recent years. But there are few existing research results (Garcés et al., 2014; Li and Fan, 2006), which mainly focuses on the traffic safety field, such as the recognition of fatigue driving based on EEG signal, the recognition of sleep deprivation based on EEG signal, the testing of reaction time based on EEG signal, and the recognition of brain load level based on EEG signal (Liu and Liang, 2014; Kar et al., 2010; Jap et al., 2011; Chuang et al., 2015; Lin et al., 2010; Lin et al., 2007). However, the research with regard to vehicle driving control (brain-controlled vehicle) using EEG signals and assisting the disabled persons to drive is almost a blank, except that Murata et al. have carried out test on right or left rotation, acceleration, deceleration and other basic operations of the vehicle based on MI-BCI system (Kim et al., 2015; Murata and Yoshida, 2013; Foldes and Taylor, 2013; Lin et al., 2014). Brain-vehicle interaction methods and performance control, setting of brain-car interaction parameters, and others are still the technical problems that need to be solved first.

Aiming at the blank in the existing brain control vehicle driving, this paper establishes a brain-vehicle interactive motion control model based on improved queuing network, and studies the effects of brain-vehicle interactive motion control proficiency and brain-vehicle interaction related parameters on vehicle driving performance. The conclusions may provide some references for the development of brain-controlled vehicles.

Brain-vehicle interactive motion control model based on improved queuing network

Figure 1 is a flow chart showing a driver operating the vehicle under normal circumstances. The driver continuously obtains environmental information from the outside while driving the car. Based on the acquired information, the brain divides the roles and issues the corresponding driving instructions, which are transmitted to the limbs via muscles and neurons to ultimately realize the control of the vehicle.

**Figure 1.** Flow chart of a driver’s routine vehicle operation

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Figure 2 is a driving flow chart of the vehicle with motion control based on brain-vehicle interaction. The driver first makes the expected decision on the control command which is transmitted to the central processor through the brain-computer interface, for the EEG signal recognition and extraction of the features of the EEG signal about the automobile driving intention, so as to finally realize the control of the vehicle. The whole system consists of sensory subsystem, brain-computer interface recognition subsystem, vehicle control subsystem and vehicle dynamics subsystem.

\[ a_s = \frac{2(\Delta E - v \cdot \Delta t)}{t_p^2} \]  

(1)

\[ \Delta E \] is the deviation between the designed vehicle’s driving path and the actual driving path; \( v \) is the driving speed of the vehicle. Let the steering wheel angle variable be \( \Delta \theta_{sw} \), then

\[ \Delta \theta_{sw} = k_p \cdot a_s + k_d \cdot \alpha \]  

(2)

Assuming \( k_p \) and \( k_d \) are the correlation coefficients; \( \alpha \) is the first derivative of \( \alpha \), then \( l \), the driver’s brain decision instruction can be expressed as

\[ l \in \left\{ 0, \Delta \theta_{sw} \in (-10^\circ, 10^\circ) \right\} \]

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(3)

where, \( l=0, 1, -1 \) means that the vehicle is going straight ahead, turning left and right, respectively. The existing methods for the simulation of the vehicle control system based on the BCI mainly includes the result-based simulation and the process-based simulation, as shown in Figure 4. The simulation mode of BCI vehicle control system based on process is selected in this paper.

The lateral control algorithm of vehicle is shown in Formula 4.

\[ a(n) = \begin{cases} 
\min \{a(n-1) + \Delta a, a_{max}\} \\
\max \{a(n-1) - \Delta a, -a_{max}\} \\
an(0) = 0^\circ \quad a_{max} = 10^\circ \quad \Delta a = 10^\circ \quad n \geq 1
\end{cases} \]  

(4)

In the formula, \( a(n) \) is the steering angle of the vehicle in the iteration of step \( n \); the meaning of \( l(n) \) is the same as that in Formula 3, and \( \Delta a \) is constant.

According to the above analysis, the final structure of the brain-vehicle interactive motion control model based on the improved queuing network is shown in Figure 5. In the figure, a dashed line box is the framework for queuing network perception and cognition, which is mainly composed of a plurality of server such as visual input, visual recognition, perception integrator, and function modules such as central fund settlement, signal entry and exit, etc.
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Figure 5. The brain-vehicle interactive motion control model based on the queuing network cognitive system

**Experimental results and analysis of brain-vehicle interactive motion control**

*Experiment design*

Figure 6 shows the distribution position of the EEG signal acquisition cap and electrodes, and the EEG signals of the brain with respect to vehicle control are mainly collected by the blackened electrodes in the diagrams of Fz, Cz, P3, P7, etc.

There are 5 subjects, 3 males and 2 females, with an average age of 25.6 years old, and without any previous serious illness or relevant BCI and brain-testing experiences. The data analysis environment contains Windows64 bit system, 16GB of memory, main frequency of 2.3GHz, and the simulation software, Matlab.

The experiment-specific virtual vehicle system is established, which mainly includes display screen, vehicle model output information, control model, 3D driving environment and data acquisition system. Vehicle model output information includes steering wheel angle, accelerator and brake pedaling strength, sound control early warning module, etc.

The VC ++ SOCKET software is embedded in the BCI platform of brain-vehicle interactive motion control, and the TCP/IP module in Matlab is coupled and connected with the virtual vehicle system. When the subject closes his eyes, the system starts the vehicle by default, then the vehicle goes straight, and the left and right turn are stimulated by watching the corresponding SSVEP, thus the real-time interaction between the brain and the vehicle is finally realized.
The testing process includes the training stage and the testing stage. The former stage is mainly used to help the subjects to familiarize themselves with the relevant steps of the brain-controlled vehicles and the performance of the test system and to use data acquisition system to collect the EEG data when the vehicle goes straight, turns left or right, and starts or stops. During the latter stage, the subject is required to drive the vehicle along the path shown in Figure 7, start and stop the vehicle at the starting and ending point, respectively, and to try to drive the vehicle along the red line in the middle as his capacity allows.

Figure 7. Driving path of brain-controlled vehicle

Analysis on proficiency of brain-vehicle interaction control

First of all, the same subject’s control of the vehicle is analyzed under the condition that he is getting familiar with a certain driving distance. Figure 8 plots the driving trajectories of 3 groups of brain-controlled vehicles, each group containing 5 brain-controlled driving procedures. The driving test of adjacent groups is conducted at an interval of 6 days.

As shown in Figure 8, when the subjects drive the brain-controlled vehicle for the first time, they are relatively unfamiliar with driving, so their driving tracks are messy, and it even occurs that they do not follow the established trajectory. In the second experiment, the proficiency of the subjects gradually improves and the control of the brain over the vehicle is gradually improved. In the third experiment, the 5 brain-control driving processes all basically follow the established driving trajectory, and there is no great deviation on the whole.

Table 1. Comparison of driving-related parameters of the same subject for three groups of brain-controlled driving

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
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</thead>
<tbody>
<tr>
<td>Mission accuracy rate</td>
<td>55%</td>
<td>70%</td>
<td>85%</td>
</tr>
<tr>
<td>Average lateral deviation (m)</td>
<td>9.14</td>
<td>3.88</td>
<td>3.45</td>
</tr>
<tr>
<td>Mission completed time (s)</td>
<td>377.38</td>
<td>302.24</td>
<td>315.11</td>
</tr>
<tr>
<td>Time ratio</td>
<td>1.32</td>
<td>1.21</td>
<td>1.26</td>
</tr>
<tr>
<td>Outbound rate</td>
<td>3.66</td>
<td>1.02</td>
<td>1.53</td>
</tr>
<tr>
<td>Obstacle avoidance success rate</td>
<td>72.93%</td>
<td>100%</td>
<td>98%</td>
</tr>
<tr>
<td>Turn-off rate (times / km)</td>
<td>0.24</td>
<td>0.78</td>
<td>0</td>
</tr>
<tr>
<td>Average speed (km/h)</td>
<td>7.43</td>
<td>9.58</td>
<td>8.17</td>
</tr>
</tbody>
</table>

Figure 8. Comparison of driving trajectories of the same subject for three groups of brain-controlled driving

Table 1 shows the statistics of the task completion rate, driving lateral deviation, out-of-bound rate, average speed and other parameters of the three groups of brain-controlled driving vehicles. As is shown in the table, the task completion rate of the first group of the subjects is only 55%, that of the second group is 70%, and
that of the third group is 85%. The completion time and lateral deviation of the whole task from the first group to the third group are significantly reduced, and the rate of out-of-bounds and false-stop rate also show an obvious decreasing trend. It shows that after a certain period of training and adaptation, the human brain can gradually master the related skills and control methods of brain-controlled vehicles, and that using EEG signals to control vehicles will show safer and more efficient characteristics.

Effects of brain-vehicle interactive parameters on vehicle driving performance

The influences of related parameters of brain-car interaction system on vehicle driving performance are further analyzed. Since the EEG signal can be started at any time, the vehicle is set to respond to the command of the EEG signal and make corresponding changes every 250ms, 500ms, 1000ms, 1500ms, 2000ms and 3000ms. Based on the results of the previous section, it is assumed that the accuracy of the same subject in the first group, the second group and the third group of brain-controlled driving is A1, A2 and A3, respectively. (The accuracy of the previous section is the data obtained at a response time of 100ms), then the accuracy statistics of three groups of simulation tests at different response time is as shown in Table 2.

<table>
<thead>
<tr>
<th>Accuracy</th>
<th>250 ms</th>
<th>500 ms</th>
<th>1000 ms</th>
<th>1500 ms</th>
<th>2000 ms</th>
<th>3000 ms</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>50.37%</td>
<td>54.59%</td>
<td>58.11%</td>
<td>57.26%</td>
<td>54.77%</td>
<td>55.02%</td>
</tr>
<tr>
<td>A2</td>
<td>67.17%</td>
<td>70.24%</td>
<td>71.64%</td>
<td>68.99%</td>
<td>64.92%</td>
<td>73.28%</td>
</tr>
<tr>
<td>A3</td>
<td>86.15%</td>
<td>86.67%</td>
<td>87.26%</td>
<td>84.33%</td>
<td>84.16%</td>
<td>85.97%</td>
</tr>
</tbody>
</table>

As can be seen in the table, the accuracy of the three groups of brain-vehicle interaction simulation tests of the same subject at 6 different response time is basically the same as the actual test results, which verifies the accuracy of the experimental results in the previous section.

Figures 9 and 10 show the driving trajectory and steering wheel angle of vehicle at 4 different response time with an accuracy of A1. As shown in the figure, when the control accuracy of the brain over the car is low (55% or so), the track of the car is chaotic at different response time. The longer the response time is, the more difficult for the car to follow the existing trajectory, and the more the steering wheel angle changes. It shows that the longer the interval set for the car to receive EEG signals, the weaker the brain's control over the car, and the greater the offset of the car.

Figures 11 and 12 respectively show the statistics of the driving trajectory and the steering wheel angle of the vehicle at the response time T = 500 ms with three accuracies. As can be seen from the figure, when the time interval that the vehicle receives the EEG signal is fixed, as the accuracy increases, the vehicle traveling trajectory is closer to the established route, the vehicle offset is smaller, and the time for completing the entire traveling process is less.

Figure 13 shows the success rate of task completion at different response time with three kinds of accuracies. The figure shows that as the proficiency of the subjects increases, and the interval of the vehicle receiving EEG signals becomes shorter, the success rate of the vehicle completing the whole driving task becomes greater.

Figure 14 shows the lateral deviation of vehicles at different response time with three kinds of accuracies. Figure 15 shows the total task completion time at different response time with three kinds of accuracies. As can be seen from the figure, when the driving trajectory accuracy is A1, the influence of different response time on the vehicle lateral deviation and the total time for completing the task is greater; when the accuracy reaches A3, the influences gradually decreases.
Conclusions

Aiming at the blank in the existing brain control vehicle driving, this paper establishes a brain-vehicle interactive motion control model based on improved queuing network, and studies the effects of brain-vehicle interactive motion control proficiency and brain-vehicle interaction related parameters on vehicle driving performance. The following conclusions are drawn.

(1) With the increasing number of driving tasks, the overall task completion time and lateral deviation of brain-controlled vehicles are significantly reduced, and the out-of-bound rate and false-stop rate are also significantly decreased. It indicates that after a certain period of training and adaptation, the human brain can gradually master the related skills and control methods of brain-controlled vehicles, and that using EEG signals to control vehicles will see safer and more efficient characteristics.

(2) When the control accuracy of the brain over the car is low (55% or so), the track of the car is chaotic at different response time. The longer the response time is, the more difficult for the car to follow the existing trajectory, and the more the steering wheel angle changes. It shows...
the longer the interval set for the car to receive EEG signals, the weaker the brain’s control over the car, and the greater the offset of the car. As the proficiency of the subjects increases, and the interval of the vehicle receiving EEG signals becomes shorter, the success rate of the vehicle completing the whole driving task becomes greater.

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