Brainwave Controlled Car

1st Yuxiang Ding
Department of Electrical and Computer Engineering
The Ohio State University
Columbus, USA
ding.1335@buckeyemail.osu.edu

2nd Ye Tian
Department of Electrical and Computer Engineering
The Ohio State University
Columbus, USA
tian.977@buckeyemail.osu.edu

***Abstract*—This article introduces the project of controlling the movement of a car based on electroencephalogram detection. This project aims to explore more reliable and convenient control methods for a wider range of people. This project uses OpenBCI 8-channel Cyton Biosensing Board and Ultracortex Mark IV as detection devices, use SVM model to predict the action of brainwave and control a self-made model car. The article will introduce the functions and implementations of each part in detail and explain the key codes.**

***Index Terms*—Electroencephalography, Brain-Computer Interface, Motor Control, Wireless Communication**

I. Introduction

Electroencephalography (EEG) is performed by placing electrodes on the scalp to detect and amplify electrical signals generated by neural activity. EEG has been widely used in clinical settings, particularly for diagnosing epilepsy. Brain-computer interfaces (BCIs) applications utilize EEG signals to enable users to control electronic devices. Overall, these applications are classified into three categories: the medical field, the non-medical field, and the cross-field [1]. Among them, the medical field accounts for approximately 31%, mainly including auxiliary categories (such as brain-controlled prosthetics, intelligent wheelchairs, etc., accounting for 74% of this field), rehabilitation categories (such as limb function training after stroke), and monitoring categories (such as real-time monitoring of patients' emotions or consciousness states). The non-medical field accounts for the largest proportion, at 58%. Its applications are more diverse, mainly including monitoring (accounting for 50% of non-medical research, such as driving fatigue detection and emotion recognition), machine control (17%, such as brain-controlled smart home or robots), entertainment (16%, such as brain-controlled games and music recommendation systems), as well as a small amount of research involving identity authentication and education, etc. The proportion of cross-disciplinary applications is 11%, mainly covering research with both medical and non-medical characteristics, such as brain control systems that have both rehabilitation and gaming functions.

Berger [2] was the first to record human brainwaves using a galvanometer. He identified a rhythmic pattern with a frequency of approximately 8–13 Hz, which he termed the alpha wave. He also discovered beta waves, which are more irregular and associated with focused mental activity. He found that these fluctuations had nothing to do with external stimuli. Even when an animal's heart stops beating and breathing ceases, there is still regular electrical signal activity in its brain. This indicates that the signal is a neural signal rather than caused by blood flow or movement.

This project has achieved the forward and backward movement of the model car controlled by EEG. This application is expected to be applied in the field of traffic driving and may also be applicable to assisted driving for the disabled. By adopting non-invasive brain-computer interface (BCI) technology, users can control external devices merely through thinking, thus eliminating the need for traditional manual methods. For people with disabilities, this application provides a new moving control solution. In addition, this technology can also be applied to assisted driving and safety assurance. EEG is highly suitable for concentration and fatigue detection. Deploying a driver's concentration detection system on the vehicle can alert the driver or activate the intelligent driving function when they are distracted or fatigued. To a certain extent, it can prevent the occurrence of traffic accidents caused by fatigued driving.

This project utilizes the OpenBCI 8-channel Cyton Biosensing Board and the Ultracortex Mark IV headset for EEG signal detection. An SVM model is used to predict brainwave activities and control the customized model car. The following chapters will introduce each component of the system in detail.

II. 2. System Overview

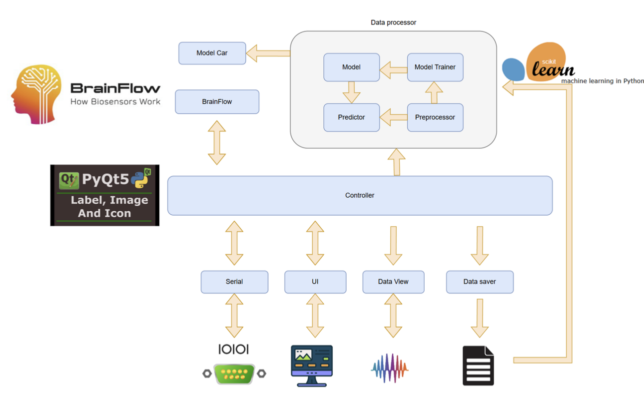

Fig. 1. System flow chart the brainwave-controlled car project.

As shown in Figure 1, the system is divided into three parts. The first part is the EEG detection equipment, which is used to detect EEG signals and convert them into digital signals for transmission to the next stage. The second level is the computer, which serves as the receiving end of the upper level and receives EEG signals. The signal will be filtered here and calculated for the already optimized model. Finally, the brain movements of the subjects will be predicted through the model. The last part is the model car. The trolley, as the final receiving end, receives the action instructions transmitted by the computer and performs the corresponding actions.

III. Hardware Setup

A. EEG detection device

In this project, the EEG detection devices used are Cyton board and Ultracortex Mark IV. As shown in Figure 2(Cyton board) and 3(Ultracortex Mark IV).

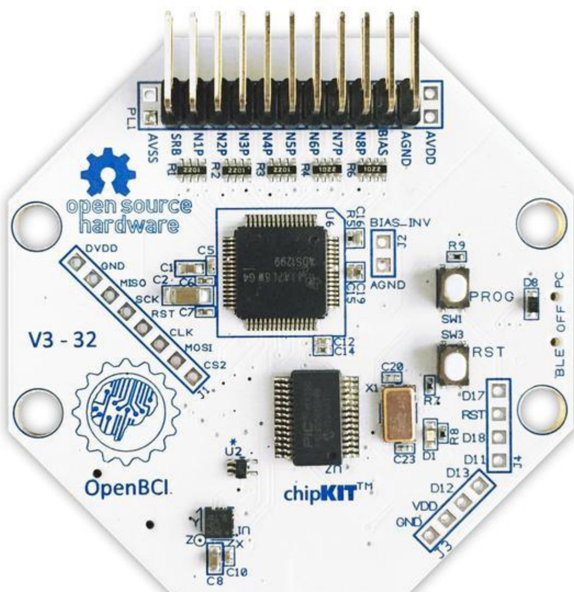

Fig. 2. Cyton Board (Image source: OpenBCI Documentation https://docs.openbci.com/).

Cyton board is an open-source development board developed by OpenBCI, specifically for the research of non-invasive electroencephalogram signals and the development of brain-computer interface applications. This development board offers high-resolution EEG acquisition ranging from 8 to 16 channels and supports the measurement of various bioelectrical signals, such as EMG and ECG. Connect to other devices using a USB dongle. The Ultracortex is an open-source, 3D-printable headset designed to work with the OpenBCI system. This can be used to record brainwave activities.

Table I lists the 8 brainwave detection points selected for this project and the functions of each detection point [3]. These electrode sites have comprehensive uses in multiple aspects such as cognition, emotion, and sensory processing. They are

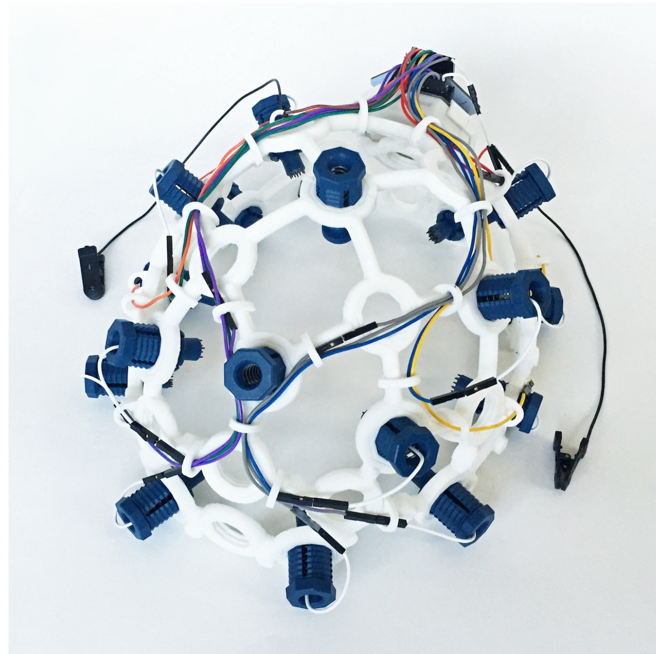

Fig. 3. Ultracortex Mark IV headset (Image source: OpenBCI Documentation https://docs.openbci.com/).

applicable to applications such as brain-computer interfaces, neural feedback, and neuropsychological assessment. Table II shows the correspondence between the detection electrode and the Cyton board pin as well as the channel on the OpenBCI GUI.

TABLE I
Detection Points and Functions

Electrode Position	**Brain Region**	**Function**
FP1 / FP2	Frontal region	Advanced cognitive functions, attention control, and emotion regulation
C3 / C4	Primary somatosensory cortex	Body sensation processing and motor control
P7 / P8	Visual associative cortex	Integration of visual information and spatial perception
O1 / O2	Visual cortex	Basic visual processing

Figure 4 is a picture of the installed EEG headset.

B. Model Car

A self-made model car was used as the final signal receiving end in this project. The materials required for the car are as follows:

- 1 model car kit, including wheels, motors, and other basic structural components.
- 2 3.3V relays
- 1 ESP32 development board
- 1 5V power supply
- Several DuPont lines

Figure 5 shows the circuit schematic diagram of the model car. This is a simplified H-bridge circuit. Relays R1 and R2

TABLE II
THE CORRESPONDENCE BETWEEN PIN AND MONITORING POINTS

GUI Channel	Electrode	Cyton Board Pin
N/A	Ear Clip	Bottom SRB pin (S)
1	FP1	Bottom N1P pin
2	FP2	Bottom N2P pin
3	C3	Bottom N3P pin
4	C4	Bottom N4P pin
5	P7	Bottom N5P pin
6	P8	Bottom N6P pin
7	O1	Bottom N7P pin
8	O2	Bottom N8P pin
N/A	Ear Clip	Bottom BIAS pin

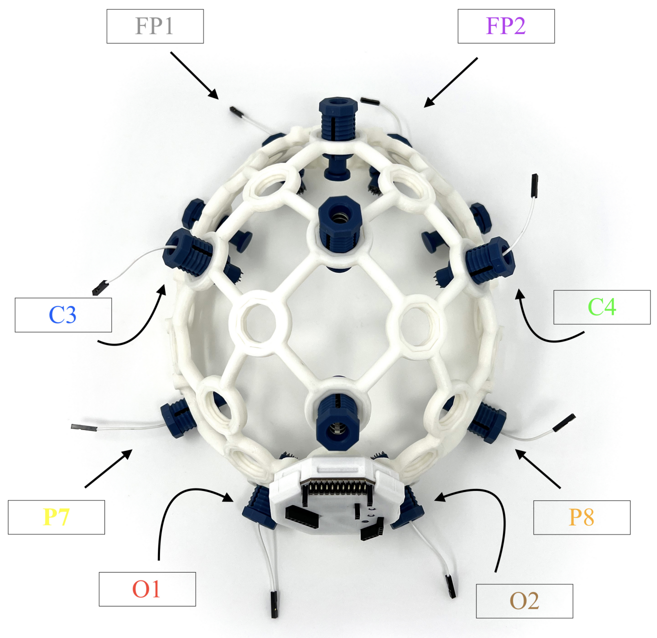

Fig. 4. Installed EEG headset (Image source: OpenBCI Documentation https://docs.openbci.com/).

act as switches, respectively connecting the two ends of the circuit to VDD or VSS. This method can control the flow direction of the current in the motor, thereby controlling the forward and reverse rotation of the motor. Meanwhile, in this circuit, the stopping action requires both ends of the motor to be connected to VDD or VSS simultaneously, which is equivalent to achieving it through an open circuit in the circuit. Suppose the motor rotates forward when the current direction is from 1 to 2 and the relay input is at a high level, then the VDD is connected.

The table showing the relationship between the movement direction of the model car and the relay input is presented in

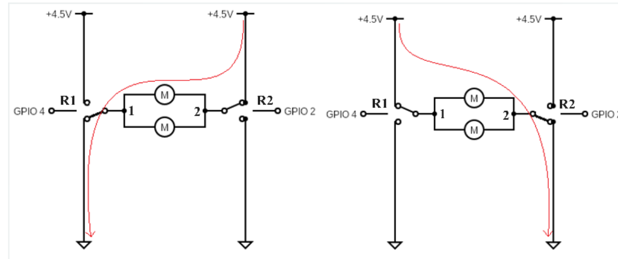

Fig. 5. Model car circuit schematic diagram.

Table III.

TABLE III
INPUT SIGNALS AND ACTIONS OF THE MODEL CAR

R1	R2	Direction
0	0	Stop
0	1	Backward
1	0	Forward
1	1	Stop

The control unit of the model car is implemented by the ESP32 development board. In this design, the GPIO2 and 4 of the development board are connected to the Vin of the relay, and gnd is connected to the VSS of the relay. Meanwhile, a 5V power supply is used to power the development board through the serial port. Figure 3-5 is the model car that was finally assembled.

IV. SOFTWARE DESIGN

A. Training Data Collection

When the training data collection button is pressed, the program will randomly select to collect forward or backward actions and generate action labels. The animation window is opened and data is obtained simultaneously from the EEG headset. The animation will count down for 3 seconds and display ”Keep On Edge” or ”Relax” after the countdown ends to remind the subjects of the emotional changes they need to make next.

Then a two-second prompt animation will be played, during which the user will make corresponding emotional changes. After the time is up, the animation will automatically close, and at the same time, the received data stream will also close. The program will store the action labels and all data streams in the file. The process of training data reception is shown in Figure 6.

The ”Test 10” button is used to make the test program run in a loop 10 times.

B. Test Game

Press ”Test Game” to enter the test game where the small ball collides with the baffle. This function is used to test the accuracy of the model in the early stage and the control ability in actual situations.

When entering the game, the baffle randomly appears on the left or right side of the window and generates a small ball at

Fig. 6. Training data collection Process.

the center of the window. Meanwhile, the computer will start to receive the data stream of the EEG headset and predict the action that the subject is thinking of through the model. The subjects need to wear an EEG headset and try to control the small ball hitting the baffle by using tense or relaxed emotions. When the small ball successfully touches the baffle, the game ends, the window closes and automatically returns to the main page. The sample diagram of the test game is shown in Figure 7.

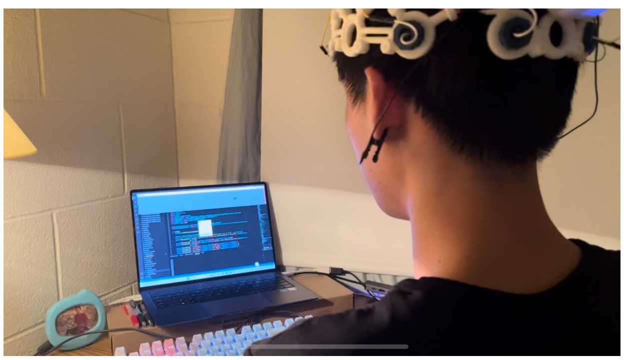

Fig. 7. Test Game Process.

C. *Model Car Controlling*

After pressing the "Model Car" button, enter the car control program. The program will request to connect to the Bluetooth of the model car. Meanwhile, the computer began to receive the data stream from the EEG headset, and the data was calculated by the model to predict the actions in the subjects' minds. Then the car action instructions will be sent to the car via Bluetooth. A "Start/Begin" button will be displayed in the window, through which the stop and start of the car can be controlled.

V. Machine Learning Model

A. *SVM*

Support Vector Machine (SVM) is a supervised learning algorithm that is widely used for binary classification tasks.The theoretic principle of it is to find the optimal hyperplane and separate data points of different categories with the maximum margin.In this project, SVM was selected as the classification model to distinguish between two mental states corresponding to forward and backward movements.

SVM is particularly suitable for this application because it works well with small to medium-sized data sets and can effectively handle high-dimensional feature spaces, which are common in EEG signal analysis. Its ability of creating clear decision boundaries even with limited and potentially noisy data makes it a strong candidate for real-time brain-computer interface (BCI) control tasks. In this project, SVM model can reach about 87% of accuracy to detect the corresponding mental state in real-time tests.

However, SVM also has limitations. It can be sensitive to the choice of kernel functions and hyperparameters, and it may struggle when the dataset contains significant overlap between classes or when the number of samples is very large, leading to increased computational cost. Despite these drawbacks, SVM provides a good balance between classification accuracy and computational efficiency for the needs of this project.

B. *EEGNet*

EEGNet, proposed by Lawhern et al. [4], is a compact convolutional neural network (CNN) architecture specifically designed for EEG-based brain-computer interface (BCI) applications. It features a lightweight structure with depthwise and separable convolutions, enabling efficient learning of both temporal and spatial features from EEG signals while maintaining a low number of parameters.

By completing this project, we firstly select EEGNet as an alternative model to classify motor imagery (MI) tasks, aiming to distinguish different imagined movements such as imagine move one's left leg or arms in brain and the data display left movement, and imagine move one's right leg or arms in brain then the data imply right movement. To make the convolutional neural network suitable for our equipment, we adjust the network parameter by chaning the classes to 2 which was originally 12 and the channels to 8 corresponding to our chosen electrode position which was originally 64, in addition, we also adjust the hyperparameters to reach the best performance as much as possible, and then retraining the model on our collected dataset, we found that the classification accuracy on the motor imagery dataset was relatively low, around 50%. Moreover, when deployed for real-time prediction, the model exhibited noticeable latency at around two seconds, which impaired the system's responsiveness for practical use.

There are several possible factors cause the unsatisfactory performance. Firstly, motor image electroencephalogram (EEG) signals often have a low signal-to-noise ratio and strong inter-agent variability, making it difficult for compact networks such as EEGNet to generalize well under limited training samples. Secondly, compared with classical machine learning methods, deep learning models introduce additional computational overhead, resulting in higher inference latency. These problems indicate that although EEGNet provides an elegant solution for general electroencephalogram (EEG) classification tasks, its application in real-time, small-sample motion image scenes requires careful consideration of model complexity and optimization techniques.

Consequently, the above results have led us to shifted our focus to using Support Vector Machines (SVM) for classification, leveraging tense and relaxed mental states as input features. SVMs are well-suited for small datasets and offer faster inference times, making them more appropriate for our real-time BCI application.

C. Time Domain Signal and Frequency Domain signal Comparison

Time-domain signals indicate how the amplitude of a signal changes over time. In electroencephalogram (EEG) analysis, the raw signals collected from the electrodes are usually recorded as time series, reflecting the direct electrical activity at each electrode site. These signals provide valuable temporal information, but they may be severely affected by noise and may not directly reveal the underlying patterns related to cognitive states.

On the other hand, frequency-domain signals represent the distribution of signal energy across various frequency components. By analyzing the frequency content of electroencephalogram (EEG) signals, it is easier to identify typical brain rhythms, such as α waves(8–13 Hz) and β waves(13–30 Hz), which are usually associated with different mental or cognitive states.

The Fast Fourier Transform (FFT) algorithm is adopted to transform the electroencephalogram (EEG) signals from the time domain to the frequency domain which consist of five waves range from 0.5–50 Hz, they are δ waves(0.5–4 Hz), θ waves(4–8 Hz), α waves(8–13 Hz), β waves(13–30 Hz), γ waves(30–50 Hz). FFT can effectively decomposes time series signals into their constituent frequencies, thereby allowing for spectral analysis of EEG data.

Figure 8 shows the classification accuracy when using raw time domain EEG signals, while Figure 9 shows the classification accuracy after transforming the signals into the frequency domain.

```
KFold Verification Accuracy: 0.4571
KFold Verification Accuracy: 0.5714
KFold Verification Accuracy: 0.5588
KFold Verification Accuracy: 0.4118
KFold Verification Accuracy: 0.4118
Average KFold Verification Accuracy: 0.4822
1/1 [==============================] - 0s 1000us/step - loss: 0.7521 - accuracy: 0.3929
Final testset accuray: 0.3929
```

Fig. 8. Classification accuracy using time domain EEG signals.

It can be seen from the experimental results that the classification accuracy of using time-domain signals which is around 40% is significantly lower than that of using frequency-domain features which have accuracy of 85% in real-time classification tasks. This is mainly because the time-domain signal contains a large amount of irrelevant information and noise, making it difficult for the model to extract meaningful patterns. In contrast, frequency-domain features concentrate signal energy in specific bands related to cognitive activities, providing more discriminative information for classification

```
KFold accuracy: 0.7750
KFold accuracy: 0.8500
KFold accuracy: 0.7750
KFold accuracy: 0.8500
KFold accuracy: 0.8750
Average KFold accuracy: 0.8250
Accuracy on Test Set 1: 0.8333
Accuracy on Test Set : 0.8500
```

Fig. 9. Classification accuracy using frequency domain EEG signals.

tasks. Therefore, converting the electroencephalogram (EEG) signals to the frequency domain has greatly enhanced the model's ability to distinguish different mental states.

D. Spectrogram Analysis of Mental States

By directly observing the EEG spectrum through the OpenBCI GUI (Figure 10), it can be observed that when the subject is in a tense state, the power of the high-frequency band increases significantly compared with the relaxed state. The spectrogram shows clear periodic parts, marked as "tense" and "relaxed", corresponding to the mental states indicated during the recording process.

Specifically, during the tense period, there is a significant enhancement in the frequency band above approximately 15 Hertz, while the low frequency (below 10 Hertz) remains relatively stable in both mental states. This indicates that the characteristic of a tense mental state is elevated β wave and γ wave activities, which are usually associated with increased alertness and muscle tension.

The significant amplitude variation in the high-frequency region makes it easier to distinguish different psychological states when analyzing the characteristics of the frequency domain. Compared with the original time-domain signal, these changes may be masked by noise and baseline fluctuations. The frequency-domain representation concentrates the discriminant information on a specific band, enhancing the separability of the classification task features.

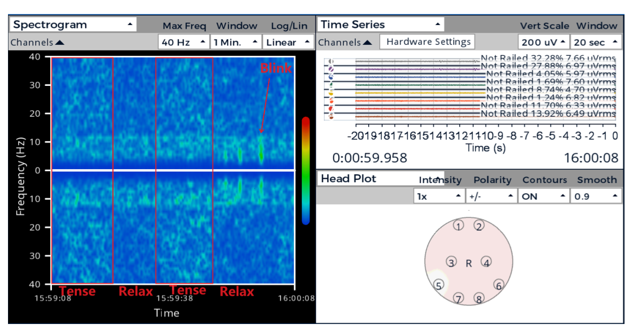

Fig. 10. EEG spectrogram observed through the OpenBCI GUI, showing frequency changes during tense and relaxed mental states.

E. Action Prediction

Based on the observed spectrogram patterns, we found that the mental states of tension and relaxation can be effectively distinguished through their different frequency-domain characteristics. On this basis, the extracted frequency-domain features are used as the input of the well- trained Support Vector Machine (SVM) model to predict the expected actions of the subjects.

In the real-time actions predict process, we create a buffer stack which has the same size as the samples in train and test dataset. Then we extracted data points from the stream flow of the EGG headset once it begun and store these points one by one in sequence into the buffer stack, once the stack is full, we transfer it into frequency signals using FFT algorithm, and input it into SVM model to get an output predict result of either 0 or 1, each indicates an action of move forward or backward. Then the buffer stack was cleared and we begun the next same iteration to output a series of continuous direction.

VI. Car Control Logic

The following is the Arduino pseudo-code of ESP32 in the model car.

Algorithm 1 Car Control Logic for ESP32

```
Setup:
    setupPinMode
    EnableBluetooth

Loop:
if data received from Bluetooth then
    if received 5 consecutive identical values ("forward" or "backward") then
        Change direction
    end if
    if command is Stop then
        Moving ← Not moving
    end if
end if
```

The above pseudo-code shows the general logic of the car. Among them, the mechanism that performs the switch only after receiving the same data for five consecutive times is used for noise reduction and image stabilization. The more times this happens, the less affected by noise and jitter will be. But it will increase the response delay of action switching. In the model prediction stage, there is already a delay of approximately 0.5 seconds. In this step of noise reduction process, the delay should not be set too large; otherwise, it will not be a real-time control system.

VII. Experiments and Results

The subject recruited for this project is a 25-year-old male with normal limb movement ability and no previous experience in brainwave application tests. To establish familiarity and collect sufficient training data, the subject is guided to collect data every day, during which multiple sets of electroencephalogram records were obtained. All the collected data were subsequently summarized and used for model training.

After approximately one month of continuous data collection and iterative model updates, the subjects were able to successfully control the small ball in the board game using only brainwave signals. Initially, the success rate during the game was rather low, mainly due to issues such as unstable EEG signal acquisition, unsuitable helmets, and the subjects' unfamiliarity with mind control tasks. However, through repeated adjustment of the headgear positioning and continuous practice, the performance of the subjects improved significantly. In the later stage of training, the pass rate was close to 100%, and the average time for successfully completing each task was stable at about 4 seconds.

In the upgraded and final experiments involving the control of the model car, we adopt a quite different scheme to show how the subject use brainwave to control the movement of a model car, which is shown in Fig 11. The subjects were asked to face a wall and remain visually unstimulated. The command to move forward or backward is given orally by the assistant beside. Similar to the batting game, the initial success rate is very low, mainly due to inconsistent brainwave patterns and delayed psychological responses. However, with the adjustment of the headwear and adaptation to the control strategy, the performance of the subjects gradually improved.

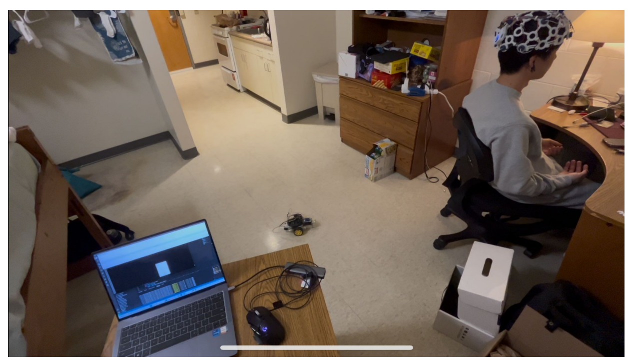

Fig. 11. Final Experiment demonstration of using brain to control car.

Several phenomena were observed in the model car experiment. We noticed that obvious oscillation of the car was occurred during the process of switching the working state. That is to say, when the subject is changing its mental state, the model car will have a performance of oftenly swings between moving forward and backward. Furthermore, as the test duration increases, the severity of switching delay and jitter becomes more obvious. The research also found that maintaining continuous movement in one direction became increasingly challenging over time, as the subjects' ability to maintain a stable mental state weakened with fatigue.

Furthermore, we explored a more autonomous control mode, that is, requiring the subjects to directly observe the model car and control its direction without external language prompts. However, the research found that in this case, the subject encountered significant difficulties. Spectral analysis of electroencephalogram (EEG) signals revealed that visual focus on the model car exacerbated mental stress, making it difficult for the subjects to transition back to the relaxed state required for direction switching. Therefore, the independent visual control of the model car is basically unsuccessful. These findings suggest that brainwave control tasks are highly sensitive to environmental and mental disturbances. Optimal performance requires a quiet and minimally stimulating environment to maximize the subjects' ability to effectively regulate their mental states.

Despite the occurrence of instabilities such as jitter and switching delays during the experiments, we successfully achieved reliable brainwave-based control of the model car under quiet and disturbance-free conditions. This outcome demonstrates that, with appropriate environmental setup and user adaptation, the system can effectively translate mental states into real-world device control. Therefore, the project has successfully met its initial objectives, proving the feasibility of using non-invasive EEG signals for practical, real-time control tasks.

VIII. Discussion

Through the test results, we can find that the system can achieve the goals we preset. But there are also some problems in the system.

A. Delay

In the test, the average time for each state switch was more than one second. The factors causing high latency include: the time for subjects to switch emotions, the sliding window for data collection, the calculation time of the model, and the anti-shake mechanism.

The time it takes for the subjects to switch emotions depends on their individual differences. For some less sensitive people, it may take longer. And the process time for the subjects to change from tension to relaxation of emotions is often longer than that from relaxation to tension. This causes the car to switch from the forward state to the backward state more slowly. And this time will be closely linked to the condition of the subjects on that day, and the degree of fatigue.

For the sliding window of the data stream, since frequency-domain signals are used for prediction, the signals must be within a certain period of time rather than recording a certain moment. If the window time is too short, the prediction accuracy will decrease. If the sliding window is lengthened, the previous data will affect the sum of the overall data, and it will take a longer time to reach the switching threshold after the mood switch. This problem belongs to the same category as the calculation time of the model. We need to look for a model that is more reliable, has a faster computing time and requires fewer samples.

For the fatigue degree, the subjects will gradually become tired after a period of testing. This leads to a decline in reaction ability and the time required for emotional switching will also be longer.

B. Stability

After observation, the stability of this system depends on the following factors: noise interference, the position of the EEG headset and the condition of the subjects.

First, it is about noise interference. The hair of the subjects will interfere with the contact between the electrodes and the scalp. The subject's hair may prevent the electrode from touching the scalp, resulting in poor contact. In severe cases, it may lead to complete signal failure. Apart from the hair, even the slightest movement of the subjects may cause friction between the electrodes and the hair and scalp, generating high-frequency noise. In the algorithm for predicting emotional states, to a large extent, it is necessary to judge the intensity of high-frequency bands, which can easily lead to misjudgment. To solve this solution, we can use a longer claw-shaped electrode so that it can pass through the hair and reach the scalp. And add insulating materials around the electrode to reduce its contact with the hair.

The next one is the position of the EEG headset. There is a significant deviation in the position where the subjects wear the headgear each time. Sometimes, if the subject accidentally moves a little during the test, it might also shift the originally adjusted position of the headset. This leads to the fact that the location of each test may not be the same test point, resulting in inaccurate data. To solve this problem, perhaps a headset made of other materials can be used. For example, elastic fabric, let it wrap around the head. This kind of headset is lighter and can tightly wrap around the head to prevent it from sliding.

At last is the status of subjects. As the test time increases, it becomes more difficult for the testers to maintain their emotions. It makes the jitter get bigger by the increasing of testing time.

C. Subjects Status and electrodes analysis

As mentioned earlier, the mental and physical state of the subject has a significant impact on the stability of the subject. When the subject's state deteriorates, the overall system stability and prediction accuracy also decline progressively. Maintaining a tense mental state for extended periods is physically demanding for the subject, leading to fatigue and decreased mental control over time.

To mitigate potential signal acquisition issues caused by hair interference, we utilized claw-shaped spikey dry electrodes(Figure 12) rather than the flat ones(Figure 13), which are specifically designed to penetrate through hair and establish direct contact with the scalp.

To evaluate the effect of hair length onto the test results, we conducted comparative tests on the same subject before and after a haircut that significantly shortened hair length. In addition, a control experiment was performed to assess whether the application of conductive gel would further improve signal quality. The results indicated that hair length and the use of conductive gel had minimal impact on system performance when claw-shaped electrodes were used.

Fig. 12. Spikey units (Image source: OpenBCI Documentation https://docs.openbci.com/).

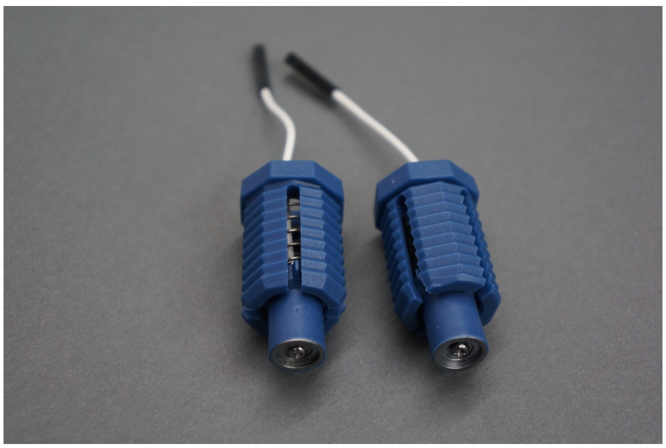

Fig. 13. Flat units (non-spikey) (Image source: OpenBCI Documentation https://docs.openbci.com/).

However, it was observed that the claw-shaped electrodes introduced a new challenge which is long time using can caused discomfort and even pain at the contact points, especially during long testing sessions. This physical discomfort contributed to subject fatigue, which in turn led to unstable EEG signals and degraded system performance over time. These findings suggest that although claw-shaped electrodes effectively address the problem of hair interference, future improvements are necessary to enhance user comfort for prolonged brain–computer interface (BCI) applications.

IX. Conclusion

This project successfully demonstrated the feasibility of using non-invasive EEG signals to control external devices in real time.Through daily data collection, model training, and subject adaptation, we achieved reliable control of both a small ball board game and a model car, meeting the initial objectives of the project.Despite we have encountered challenges such as signal instability, switching delays, and subject fatigue, effective strategies including environmental control and headset adjustments significantly improved system performance.

Overall, this project validates the potential of EEG-based brain–computer interface (BCI) technologies for practical control applications and provides insights into improving system robustness and user comfort for future developments.

Based on the results of this project, several future directions can be proposed to enhance the capabilities and applications of EEG-based control systems.

Firstly, expand mental command categories is a meaningful direction to achieve a fine control on the system, that is to explore more EEG-based commands such as turning, stopping, or speed adjustment to enrich control options.

Secondly, achieving reliable motor imagery control remains a key goal. Future work will focus on improving the system's ability to accurately classify imagined movements, such as hand or foot motions by using more robust and generalize models like EEGNet.

Third, extending the application scope beyond control only for simple model cars is another important direction. By adapting the EEG-based control framework, it is possible to control other assistive devices such as robotic arms or smart home systems, thus exploring broader applications in assistive technology and human–machine interaction. Through these future enhancements, EEG-based brain–computer interface systems have the potential to become more versatile, reliable, and accessible for a wide range of real-world applications.

Last but not least, the project code and implementation details are publicly available at: https://github.com/GoodgoodBoys/EEGProj.git. We are welcome for any We discussion and questions.

References

[1] K. Värbu, A. Chehade, M. S. Akram, and M. A. A. Dewan, "Past, present, and future of EEG-based BCI applications," *Sensors*, vol. 22, no. 9, Article 3331, 2022, doi: 10.3390/s22093331.

[2] Berger, H., "Über das Elektrenkephalogramm des Menschen," European Archives of Psychiatry and Clinical Neuroscience, 1929.

[3] M. Gálvez, "Study of resting-state functional connectivity networks using EEG electrodes position as seed," *Frontiers in Neuroscience*, vol. 12, Art. no. 235, 2018, doi: 10.3389/fnins.2018.00235.

[4] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces," *Journal of Neural Engineering*, vol. 15, no. 5, p. 056013, 2018.