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A VR-based BCI interactive system for UAV swarm control

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ABSTRACT

The traditional Unmanned Aerial Vehicle (UAV) swarm control mainly adopts the ground station method, which is too fixed, and the interaction is difficult to meet the high dynamic task requirements. There is an urgent need for new interaction methods to integrate the advantages of human thinking in dealing with uncertain problems. Nevertheless, brain-computer interface(BCI) technology is directly controlled by thoughts, one of the most promising next-generation human–computer interaction technologies. Therefore, in this study, we innovatively applied the BCI system based on Virtual Reality (VR) to the group UAV and realized a novel and intelligent group control method, which proposes new ideas and paradigms for the control of swarm UAVs in the future. Specifically, this study takes a quadcopter as an example. A modular and extensible multi-quadcopter system was created, and then a visual stimulation 3D VR scene system with a digital twin function was established. On this basis, the BCI system based on the Stable state visual evoked potential (SSVEP) paradigm was adopted for the swarm control of the quadcopter. The experimental results show that the formation control of multi-quadcopter is successfully realized by the subjects using the proposed VR-based BCI interactive system, with an accuracy rate of 90% and a good performance in information transmission rate. In addition, the immersive VR twin system established one-to-one for EEG signal acquisition allows subjects to have a better experience.

1. Introduce

The brain-computer interface allows the brain to interact directly with the external environment without relying on the peripheral nervous system and muscles as a particular means of information exchange. It has been widely researched and applied in medical rehabilitation, scientific education, and the military [1,2]. On the other hand, UAV technology has made rapid progress in recent years and has been widely adopted in material distribution, aerial photography, mapping, and rescue scenarios. Therefore, many researchers have combined BCI with UAV to create various systems to help quadriplegic patients use brain signals to explore the world and other functions [3–5].

However, most BCI UAV systems only realize the control of a single UAV. For example, Shi et al. [6] integrated monocular vision navigation and decision subsystem to achieve indoor target search for low-speed UAV, Chung et al. [7] utilized the SSVEP method to control UAV. Extensive literature research presents that researchers focus on the application of BCI in combination with a single UAV, while there needs to be more research on cluster UAVs. The UAV swarm is a research hotspot in the field of UAVs at present, and its development concept comes from the collective behavior of natural swarms, such as fish swarms, bird swarms, and bee swarms in nature [8]. Through the local interactions of individuals, these groups form complex swarm systems to accomplish tasks that cannot be accomplished by a single individual [9]. In other words, the swarm UAV system is more robust and flexible and has no difficulty expanding than a single unit. It can also help people to complete new tasks, such as search, exploration, rescue, and pursuit. In addition, the existing UAV cluster control generally adopts the method of the fixed ground station, but integrated intelligent control is the future development direction of swarm control. BCI technology can control objects only through human thoughts, providing a new idea for controlling UAV swarms. Furthermore, future UAV swarms will face more dynamic and complex tasks, especially large-scale swarms or swarm control tasks. For completing these tasks, BCI technology has the advantage of human brain thinking in dealing with uncertain problems. From this, it would make sense to apply BCI technology to UAV swarms.

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As far as the BCI interactive system is concerned, the existing Electroencephalogram (EEG) signal acquisition methods can be roughly divided into invasive and non-invasive [10–12]. Non-invasive is the most commonly implemented BCI scheme because it has no surgical risks and safety hazards. Its paradigm is divided into P300, motor imagery, steady-state visual evoked (SSVEP), and so on [13,14]. SSVEP has the characteristics of fast speed, high accuracy, and a rich instruction set, and it can achieve the output of a large number of instructions in a short time. Thus, in recent years, many researchers have used the SSVEP method to implement the interactive control of the human brain and external devices, such as robotic arms, unmanned vehicles, rehabilitation wheelchairs, and quadcopters [15–19]. Similarly, this study also used SSVEP for EEG signal acquisition. However, SSVEP currently displays visual stimuli through LCD and LED screens. This method has disadvantages such as poor test experience for subjects and inconvenience. Bonkon Koo et al. [20] proposed to use VR instead of panel screens to conduct SSVEP experiments. This VR head-mounted device (HMD) can convert two-dimensional visual stimuli into three-dimensional space and improve the information transmission rate [15,20,21].

In addition, the UAV usually has a long flight distance in the process of group movement, which is limited by the visual distance of the human eye and cannot effectively provide control, while VR can provide infinite scenes and a comfortable user perspective. Hence the VR visual stimulation method was also applied in this study. In particular, we built a virtual scene in the VR system that is the same as the physical environment of the UAV and realized the digital twin during the flight of the brain-controlled UAV cluster. While the subject controls the UAV, the spatial position and posture state of the UAV in the actual environment can be observed. Based on the above, BCI technology, VR technology, and UAV swarm technology will be combined and experimented with in this article, which is dedicated to exploring a novel way of UAV clustering control.

The main contributions of this paper are stated as follows:

1. We propose a VR-based BCI UAV swarm interaction system, which provides a new idea and reference for future UAV swarm control, and expands the application field of the VR-based BCI system.
2. We have constructed a virtual scene combining actual scenes and stimulating targets in order that users can control drone swarms in an immersive manner. Furthermore, this study implements a new stimulus module and intelligent search paradigm for BCI-controlled UAVs, which increases the diversity of UAV swarm formation changes and makes the connection between stimulation patterns and formation changes more closely.

The rest of this paper is presented with the following structure. Section 2 describes in detail the main components and experimental process of the VR-based BCI interactive system. The experimental results and analysis are presented in Section 3. In Section 4, we discuss the advantages and potentials of the VR-based BCI UAV swarm system compared with existing work, and also propose future research work and improvement measures. Section 5 conclude.

2. Methods

2.1. System description

This study uses a quadcopter as an example, and the systems and methods used in this paper can also be applied to UAVs such as fixed-wing, helicopters, parachutes, etc. As shown in Fig. 1, the whole system consists of three subsystems: BCI system, quadcopter swarm system, and twin virtual system. The three subsystems communicate through the UDP protocol to realize data sharing.

In the system architecture shown in Fig. 2, the quadcopter swarm system consists of three quadcopters, an infrared optical motion capture system, and a centralized ground processor. The quadcopter uses optical motion capture technology for positioning with an accuracy of 0.1 mm and realizes the communication between the devices of the system through the wireless network TCP/IP. Furthermore, the quadcopter system adopts MATLAB/ Simulink for algorithm deployment, which has

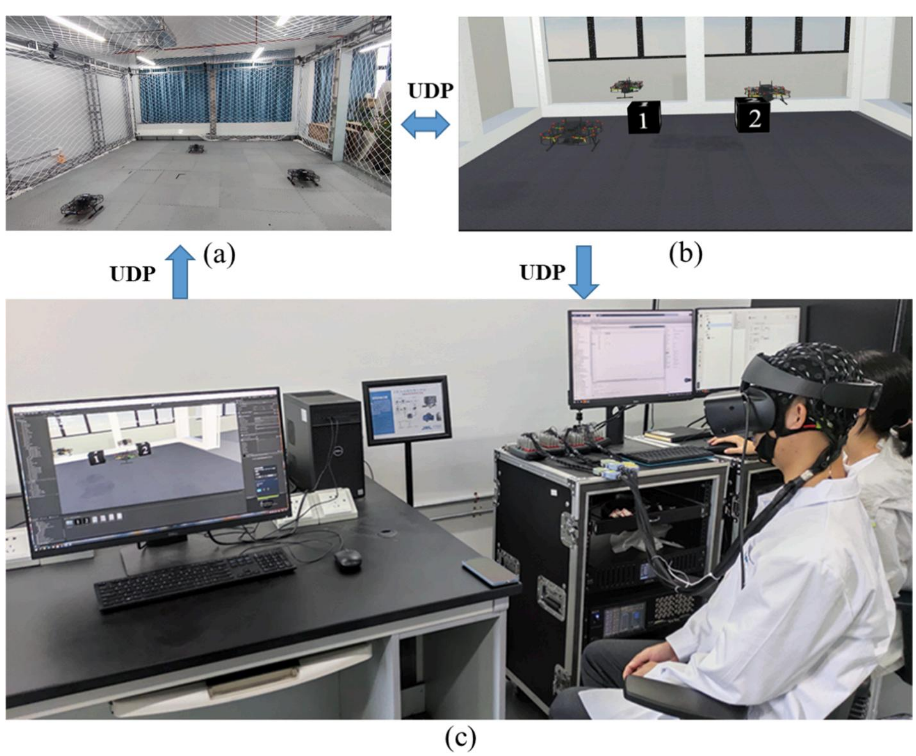

Fig. 1. Experiment system. **a** Quadcopter cluster system, **b** twin virtual system **c** BCI system.

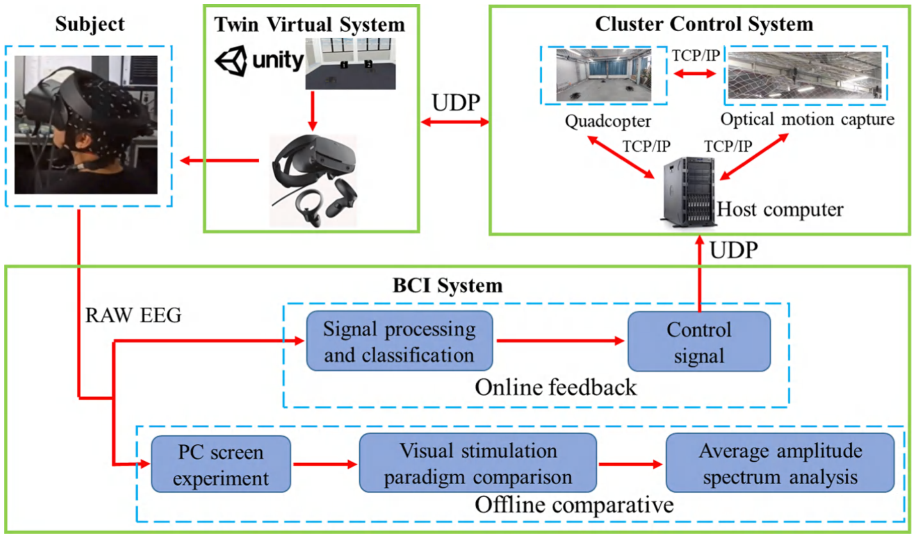

Fig. 2. System architecture.

the characteristics of easy expansion and implementation. The BCI system comprises a 128-channel EEG cap, Tucker-Davis Technologies(TDT) electrophysiological workstation, and a VR head-mounted device (HMD). The model chosen for the VR HMD is the Oculus Rift S, with a refresh rate of 80 Hz. The SSVEP paradigm is implemented by the VR HMD to generate raw EEG signals. The EEG signals are amplified, filtered, feature identified and classified in the online feedback experiments, and sent to the quadcopter cluster system via UDP communication protocol. In the offline comparison experiment, personal computer (PC) screen visual stimulus paradigm comparison and mean amplitude spectral analysis are added to achieve the pre-validation of this study. The digital twin system uses Unity3D software for scene modeling and realizes the mutual transmission of poses and attitudes with the quadcopter swarm system through UDP. Overall, by integrating these subsystems, a quadcopter cluster control system with human will and high-speed computer processing power is constructed.

2.2. BCI system

2.2.1. Subjects

A total of 9 healthy volunteers participated in this study, including eight males and one female aged 25–30, with normal or corrected-to-normal vision. Before the start of the experiment, each subject was trained to memorize the experimental procedure and the contents of each instruction. In addition, subjects were taught theoretical knowledge about SSVEP and visual stimuli considerations. All subjects informed consent to the experimental research, which the relevant laboratory department approved. Subjects conduct experiments in a safe and comfortable environment. In addition, the volunteers slept well before the experiment and maintained good concentration during the experiment.

2.2.2. Experiment process

Experiments in this study include offline comparative experiments and online feedback tests. The offline comparison experiment included the visual stimulation paradigm comparison between VR and traditional personal computer (PC) screen, and the average amplitude spectrum analysis of SSVEP. The offline purpose is to verify the practicability of the VR-based SSVEP system and the rationality of the visual stimulation frequency parameters. Offline means that there is no need to control the quadcopter, only the EEG needs to be processed. The offline comparison process of VR-SSVEP and PC-SSVEP is almost the same. The only difference is in the visual stimulation style, one is a VR head-mounted display, and the other is a PC display. The operation process of the comparative experiment is similar to that of the online test, and the visual stimulation time also lasts for 5 s. Nine volunteers are also invited to conduct the test. For specific procedures, please refer to the content later in this section. In addition, since the visual stimulation frequency and other parameters in this research were determined according to previous studies [22,23], in order to increase the convincingness of the experiment, the average amplitude spectrum of the VR-SSVEP of nine volunteers in the offline experiment was analysis to justify the chosen stimulation frequency.

The online feedback test is the main content of this study, which is divided into three parts. The first part is the quadcopter single navigation experiment. The VR scene contains four visual stimuli styles, as shown in Fig. 3a, which are “forward”, “backward”, “leftward” and “rightward”. They flash at 5, 6, 7, and 8 Hz, respectively. By selectively staring at these four modules in the experiment, the subjects can control the quadcopter to reach any position in the physical space and virtual scene. For the reason that each time a visual stimulus is completed, the quadcopter will move 0.3 m in the specified direction.

The second part is the quadcopter group formation transformation experiment. There are three quadcopters and two visual stimulation styles in the VR scene, as shown in Fig. 3b. The two visual styles “1″ and ”2″ flash cyclically at 5 and 6 Hz, respectively. The formation transformation of the quadcopter swarm was achieved by subjects choosing to fixate on different stimulus modules.

The third part is the quadcopter cluster visual search and formation transformation experiment. On the basis of formation transformation, visual search and new-style visual stimulation modules are innovatively added in this part of the experiment, as shown in Fig. 3c. “A”, “B”, “C”, “D”, and “O” flash cyclically at frequencies of 8, 8.89, 10, 13.33, and 7 Hz, respectively. The flying area of the drone is determined by these five stimulus symbols, such as The multiple five circular regions shown in Fig. 3d. The two formation transformation stimulation modules below are the same as the second part, using the frequency of 5 and 6 Hz to flash. The difference is that a new style is utilized, closer to the shape of the formation change and more closely related. In addition, due to the limitation of site space, the search areas in this experiment overlap, and only two quadcopters are used for the experiment. The following is an example to describe the experimental paradigm of this part: for instance, when the visual search signal “A” is received, the two quadcopters fly to the initial position of the A area, waiting to receive continuous formation change commands. After that, when the area needs to be changed at the end of the formation change, the quadcopter will return to the original position through the “O” stimulation signal and wait for the next area selection signal.

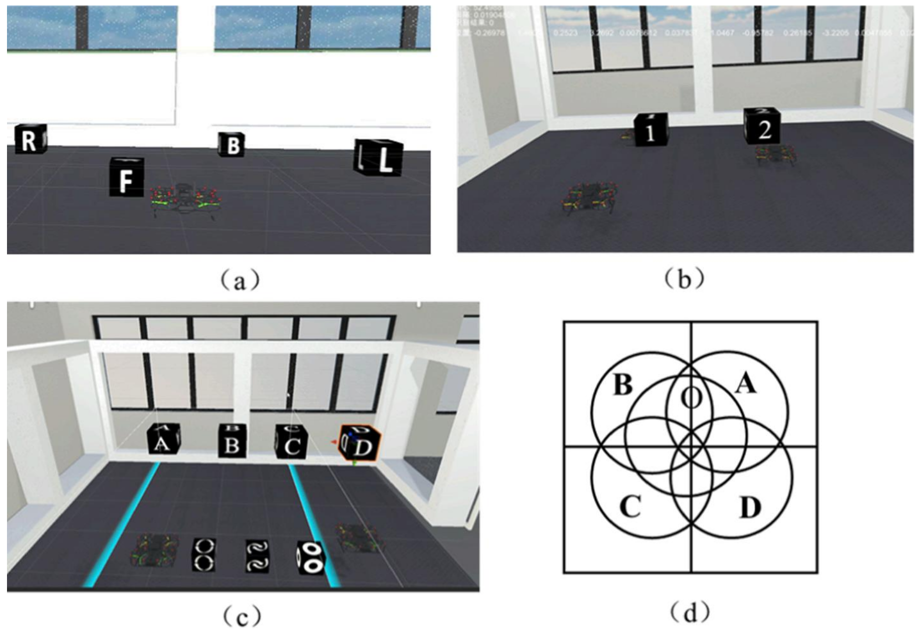

Fig. 3. Visually stimulating scene. **a** Single quadcopter navigation. **b** Three quadcopters change in formation. **c** Two quadcopters search and formation change. **d** Search area selection.

Except for the number of quadcopters and the visual stimulation modules, the single quadcopter experiment and the group control experiment are basically the same. Specifically, according to the experimental specifications, the experimenter is put on an EEG cap and coated with a conductive paste that can reduce skin impedance. The EEG cap and TDT electrophysiology workstation adopted in this study has 128 channels, and the sampling frequency of the equipment is 305HZ. In fact, we use brain electrodes to sample 8 channels of brain vision-related areas for experiments, as shown in Fig. 4, which are O1, O2, PO3, PO4, PO7, PO8, POz, and Oz. The reference electrode and the ground electrode are respectively distributed on the left and right earlobe.

When the impedance value displayed by the electrophysiological workstation is less than the threshold of 5KΩ, the visual stimulation experiment is started. The experimental process is shown in Fig. 5a, there are nine stimulations in each experiment, and stimulation is performed every 9 s. The time of each stimulation is 5 s, and the spare time allows the experimenter to rest to maintain better concentration and can also be used for data processing and transmission in the system. At the same time, the EEG signal data is processed online by MATLAB of the BCI system, and the results are sent to the VR twin system in real-time.

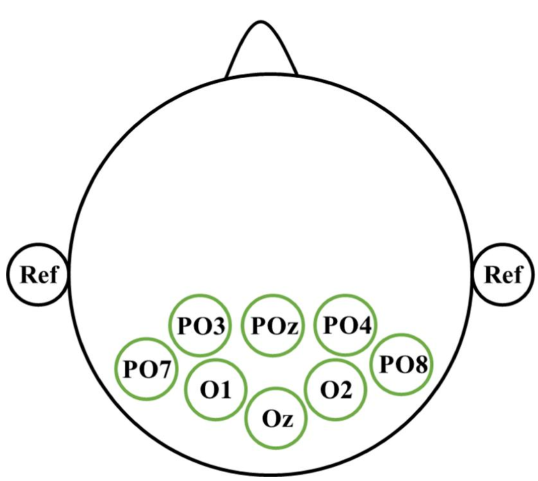

Fig. 4. Location distribution of selected electrodes on the EEG cap.

Finally, after nine stimulations in each experiment, MATLAB records results such as EEG signals and recognition accuracy. In order to reduce the experimental error, each experiment is repeated three times, and a three-minute eye-closed rest is performed after each experiment. In addition, Fig. 5b shows the process of waiting, receiving feedback and responding in the quadcopter cluster system. Due to the time required for EEG data processing and control signal transmission, the response of the physical system has a lag of about 1.5 s.

2.2.3. *Signal processing*

Before SSVEP classification, EEG Data needs to be preprocessed to reduce the negative impact of irrelevant signals on feature extraction and classification accuracy. In this study, preprocessing is mainly performed by filtering. Specifically, TDT software is adopted to perform operations such as high-pass filtering, low-pass filtering, and separation of artifacts, retain EEG data within 0.1–30 HZ, and separate independent components, artifact-related components, and neural activity-related components. Afterward, the components marked as artifacts were removed, and the real EEG data was reorganized.

There are currently many brain-computer interface classification algorithms based on SSEVP, which are mainly divided into classification methods based on deep learning and improved canonical correlation analysis algorithms [24,25]. Although deep neural network classification methods have received much attention in current research. Nonetheless, considering the ease of implementation and stability of the classification algorithm, this study still uses canonical correlation analysis (CCA) to extract and classify EEG signals. The canonical correlation analysis (CCA) algorithm is first introduced by Lin et al. [26] for EEG signal classification based on SSVEP. Since then, CCA has been widely adopted in EEG signal processing due to its advantages of excellent robustness, high accuracy, easy implementation, and small computational requirements [15,27]. The CCA algorithm learns through unsupervised learning and does not need to label the data, which can save a lot of manpower and resources. The calculation process of the CCA algorithm used in this study is shown in Fig. 6.

The number of EEG signal acquisition channels in this study is eight, and the recorded EEG data is set to $X, X \in R^{8\times P}$, P represents the amount of data in each channel. The frequency of the stimulus signal is denoted as $f_m, m = 1, 2, \ldots, M$, M is the number of stimulation frequencies, and the

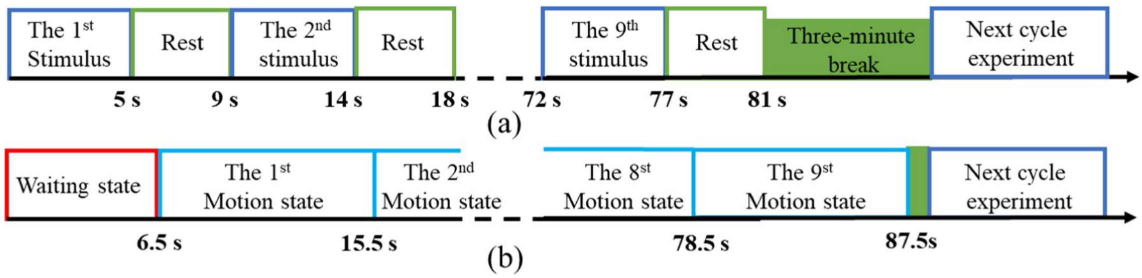

Fig. 5. Experimental procedure **a** Experimental process of visual stimulation. **b** Response process of the quadcopter cluster system.

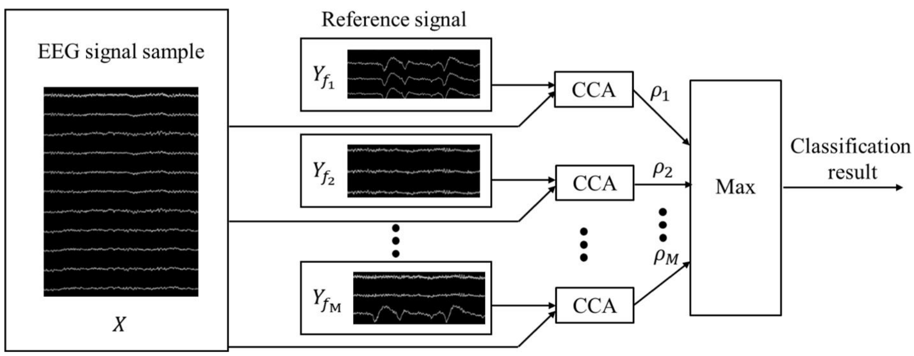

Fig. 6. EEG signal processing method based on CCA.

number of stimulation frequencies in each part in this study is 4, 2, and 7, respectively. The reference signal harmonic function is:

$$Y = \begin{pmatrix} \sin(2\pi f_m \Delta T) \\ \cos(2\pi f_m \Delta T) \\ \vdots \\ \sin(2\pi H f_m \Delta T) \\ \cos(2\pi H f_m \Delta T) \end{pmatrix}, \Delta T = \frac{1}{F}, \frac{2}{F}, \dots, \frac{P}{F} \tag{1}$$

F is the sampling rate, which is 305 Hz. H is the number of harmonics, according to the existing experimental experience [26,28], the selected value is 2. m is the number of stimulation targets, f_m is the stimulation frequency, and P is the number of sampling points. By calculating the maximum correlation coefficient $\rho_m(\rho_m \in R^{2H\times P}, m = 1, 2, ..., M)$ between X and each $Y(Y_m \in R^{2H\times P}, m = 1,2,...,M)$, the target frequency f is obtained as $\underset{f_m}{\mathrm{argmax}}(\rho_m)$.

2.3. Quadcopter swarm system

2.3.1. Quadcopter and its motion control

This research uses Simulink to build a quadcopter swarm system, which has the characteristics of easy portability, automatic code generation, simple compilation and deployment, etc. As shown in Fig. 7, the quadcopter controller is the Pixhawk with an internal IMU, shock absorption system, and data interface. The passive infrared reflective point is installed on the top of the quadcopter and realizes the precise positioning of the quadcopter through the principle of infrared optics, which has the advantages of high precision, low delay, and solid real-time performance. The Raspberry Pi 3B+ is installed above the Pixhawk as the host computer and communicates with the motion capture system and the central console through TCP/IP.

In this study, the quadcopter utilizes the lift generated by four symmetrically installed blades to move in three-dimensional space, which is through the Lagrangian equation to establish the six-degree-of-freedom dynamic model of the quadcopter.

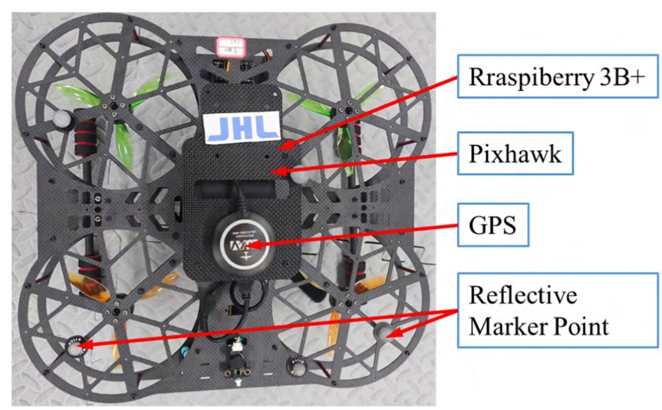

Fig. 7. Quadcopter hardware.

$$\begin{cases} \ddot{x} = [(cos\varphi sin\omega cos\kappa + sin\varphi sin\kappa)U_1]/m \\ \ddot{y} = [(cos\varphi sin\omega cos\kappa - sin\varphi sin\kappa)U_1]/m \\ \ddot{z} = [cos\varphi cos\kappa U_1]/m - g \\ \ddot{\varphi} = [lU_2 + \dot{\omega}\dot{\kappa}(I_y - I_z)]/I_x \\ \ddot{\omega} = [lU_4 + \dot{\varphi}\dot{\kappa}(I_z - I_x)]/I_y \\ \ddot{\kappa} = [U_4 + \dot{\omega}\dot{\varphi}(I_x - I_y)]/I_z \end{cases} \tag{2}$$

Among them, x, y, z is the position coordinate of the quadcopter in the X, Y, Z direction in the inertial coordinate system, φ, ω, κ are the roll, pitch, and yaw angles of the quadcopter, respectively. l and m are the distance from the end of the rotor to the centroid and the mass of the quadcopter, respectively. I_i is the moment of inertia. U_i is the calculated intermediate input, which is determined by the speed of the blade, the lift coefficient and the anti-torque coefficient, etc. [29,30]. After the attitude and position are calculated, the control of the quadcopter is realized by using the linear controller algorithm or the nonlinear controller. These control algorithms include the sliding mode algorithm, back stepping algorithm, self-disturbance rejection control algorithm, and linear quadratic regulator [29,31,32]. Since the high precision of the positioning system in this experiment does not have high requirements on the control algorithm and considering the convenience of engineering implementation, this study uses a cascaded PID linear controller to control the position loop and attitude loop of the quadcopter, as shown in Fig. 8.

2.3.2. Quadcopter formation transformation

There are behaviors such as rounding up, patrolling, and dispersing in biological clusters [33–35]. According to the characteristics of these behaviors, in this study, several formation types such as circular formation, cluster-diffusion and area search are designed, and the formation transformation is realized by means of EEG signals. Actually, the quadcopter needs to ensure a certain height, and the formation transformation is realized by controlling the x, y position of the quadcopter in the world coordinate system. These formations are realized by parametric equations of x, y and time$t$.The circular formation is:

$$\begin{cases} x_i = l\cos(\theta_i + t) \\ y_i = l\sin(\theta_i + t) \end{cases} i = (1, 2) \tag{3}$$

l is the radius of the circular formation, θ_i is the phase angle of the i-th quadcopter.

The aggregation-diffusion formation is adopted by piecewise function, and the quadcopter approaches the center at a constant speed. The area search is achieved through state flow switching, and five stimulus modules bind the location states of multiple drones. The five position states are A, B, C, D, and home position. When the quadcopter group receives the position state signal, it controls the quadcopter to reach the corresponding position state and wait for the formation signal. In the process of formation change, the most complicated task is to make the position x, y of the quadcopter not change greatly in a short time, due to if the position jumps in a short time, the whole system will become uncontrollable. To realize the orderly and smooth formation transformation, the state flow is defined according to the time parameter and fully considering the transformation situation is essential. In this article, multiple state modules are used to realize the state flow design, and multiple simulations and experiments are carried out. Finally, the quadcopter can achieve the effect of smooth formation change. As shown in Fig. 9, it is the x, y position of the No. 1 quadcopter when the formation changes and their values do not change abruptly with time.

2.4. VR digital twins and remote communication

The twin system in this experiment is composed of EEG visual stimulation modules, twin scenes, etc. The subjects observed the quadcopter by wearing the HDM device and received the visual stimulation module to generate corresponding EEG signals. At the same time, the subjects perceive the position and attitude changes of the quadcopter in real time after executing the command so as to make the next reasonable control strategy and command. Specifically, the software used in this paper to realize the digital twin is Unity3D software, and the accurate scene and quadcopter modeling are carried out according to the natural test environment. At the same time, the quadcopter's virtual body can update its entity's position and attitude information in real-time.

In order to realize the data transmission among the subsystems, this paper constructs the remote communication modules and scripts through UDP and TCP protocols. Practically speaking, we mainly interact remotely on three nodes: (1) The MATLAB signal processing program sends a start test command to the twin system through the TCP protocol. After the visual stimulation module in the twin system receives the command, it starts flashing and enters the EEG signal cycle collection process. (2) After the EEG signal analysis is completed, the identified brain control commands are sent to the quadcopter cluster system through the UDP protocol, and the cluster system starts to execute the corresponding action response. (3) The cluster system sends the spatial position information of the quadcopter to the twin system in real-time through the UDP protocol. Then the virtual quadcopter acquires the pose data in real-time and makes corresponding motion feedback to realize the real-time synchronization of the virtual and real quadcopter.

3. Results

In this research, the performance of the brain-controlled quadcopter cluster is evaluated by accuracy and ITR, including offline comparison experiments and online feedback tests. The accuracy rate is one of the

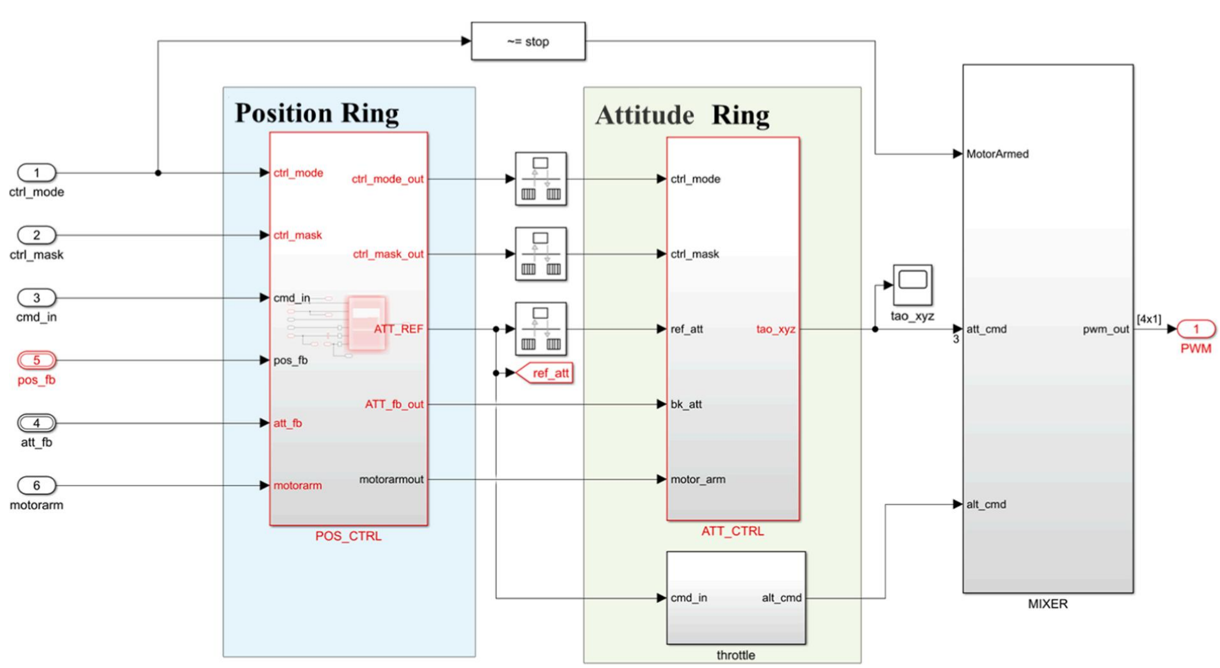

Fig. 8. Simulink model of quadcopter position and attitude control.

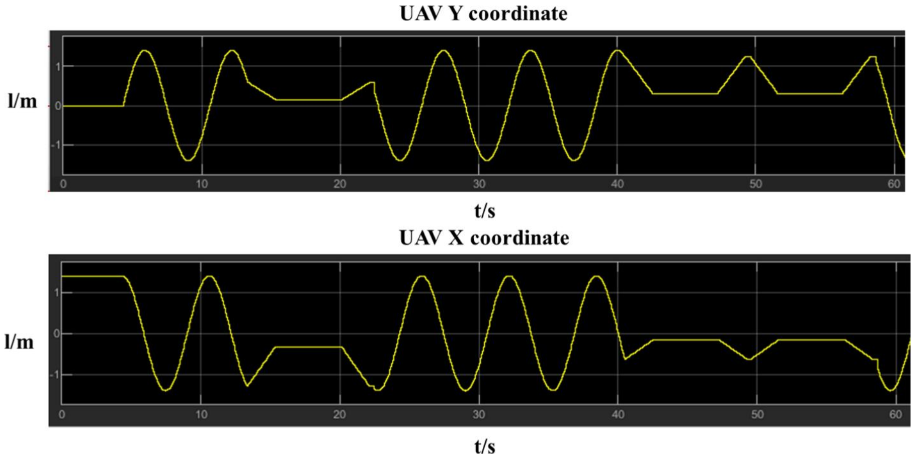

Fig. 9. The x, y coordinates of the No. 1 quadcopter.

most commonly used indicators to measure the performance of human–computer interaction systems. The accuracy rate A_c in this study is the correct rate of the motion of the quadcopter controlled by nine visual stimuli in a single experiment, which can be obtained after each experiment by adding statistical functions to MATLAB.

In addition, the information transfer rate (ITR) is a popular index for evaluating BCI performance, and it is also one of the evaluation methods in this article [36,37]. This indicator comprehensively quantifies the human–computer interaction system by the amount of information transmitted by the system per unit of time. The formula for calculating ITR is as follows:

$$ITR = (\log_2 N_f + A_c \log_2 A_c + (1 - A_c)\log_2(\frac{1 - A_c}{N_f - 1})) \times f_d \tag{4}$$

N_f represents the number of harmonics, which is 2 according to Section 2.2. A_c is the classification accuracy. f_d is the decision rate, which is equal to the time required to output a single command.

In the offline comparison experiment, comparisons of VR and traditional PC visual stimulus paradigms were performed, and the mean amplitude spectra were analyzed. Fig. 10 presents the average recognition accuracy and ITR difference of nine volunteers under the two stimulation paradigms of VR and PC. The experimental results of most volunteers demonstrated that traditional PC screen visual stimuli had a slight advantage in recognition accuracy and ITR compared with VR, similar to the findings of previous researchers, which is likely due to the fact that VR The screen in the glasses is dynamic, and small movements of the 3D visual stimulus target can distract the participants. In addition, there is no significant difference between the results of the PC screen and VR, the gap between the two is within 9%, and the average accuracy rate of VR is basically above 90%. The average ITR is directly proportional to the averageA_c, and the proportional coefficient is relatively large, resulting in a large gap when the difference in A_c is small.

The experimental results of the average amplitude spectrum analysis are shown in Fig. 11. The results indicate that the EEG signal has an obvious peak amplitude at the corresponding stimulation frequency, which is the frequency corresponding to the solid green line in the figure. It can be seen that the stimulation frequencies of 5, 6, 7, 8, 8.89, 10, and 13HZ are reasonable and effective. In general, the results of offline comparison experiments reveal that the VR-based SSVEP system has good performance, it is feasible to apply it to the BCI system, and the selected visual stimulation frequency parameters are reasonable.

In this research, the main part of the experimental content is the online feedback experiment, which can be divided into quadcopter single navigation experiment, quadcopter cluster experiment, and quadcopter cluster visual search experiment. The experimental results are shown in Tables 1, 2, and 3, respectively.

It can be seen from the data in the three tables that the accuracy A_c

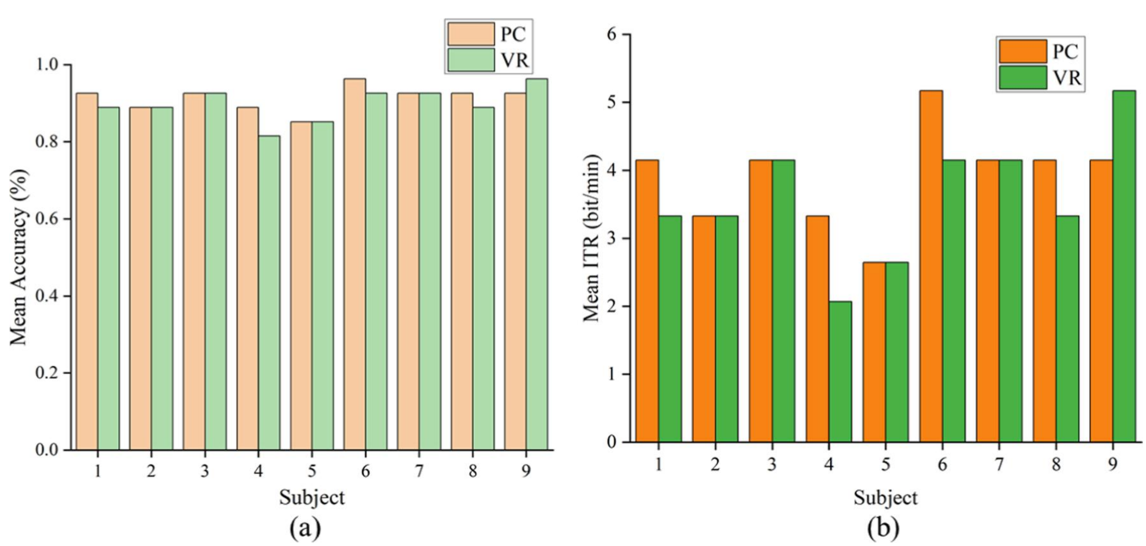

Fig. 10. Offline comparative experiment of VR and traditional PC. **a** Comparison of average accuracy rate of nine subjects. **b** Comparison of information transmission rate of nine subjects.

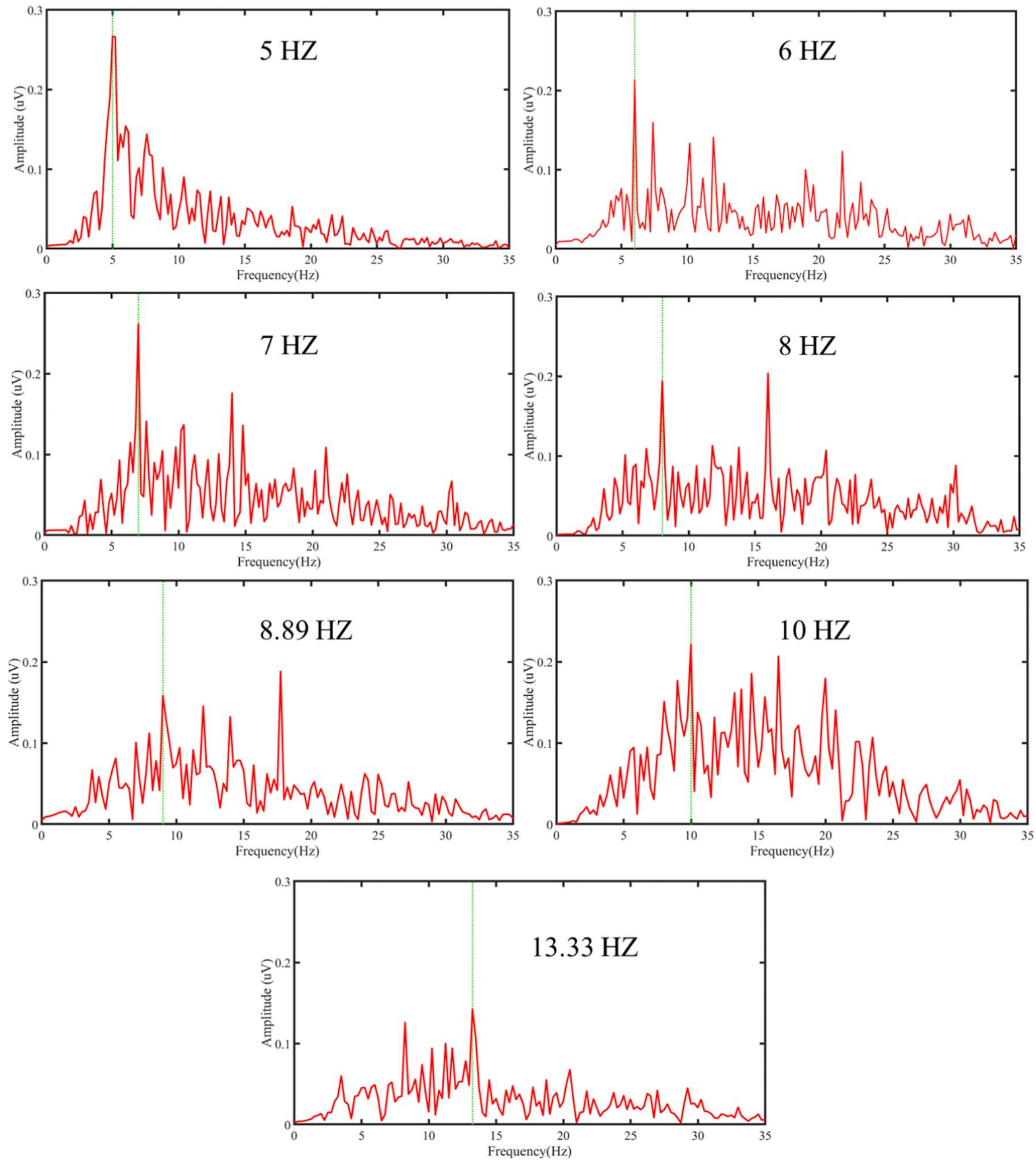

Fig. 11. Average amplitude spectrum of SSVEP of 7 stimulation frequencies selected in the experiment.

Table 1
Single Quadcopter Navigation.

Subject	Results			
	Accuracy(A_c)			Information Transfer Rate(ITR)
	1	2	3	
1	8/9	8/9	9/9	4.148
2	8/9	8/9	8/9	3.330
3	9/9	8/9	8/9	4.1482
4	8/9	9/9	7/9	3.329
5	8/9	8/9	8/9	3.329
6	8/9	8/9	9/9	4.1482
7	9/9	8/9	9/9	5.1695
8	8/9	7/9	8/9	2.6456
9	8/9	9/9	9/9	5.1707
Mean	0.9136	0.9012	0.9259	3.9354

Table 2
Quadcopter cluster formation transformation.

Subject	Results			
	Accuracy(A_c)			Information Transfer Rate(ITR)
	1	2	3	
1	9/9	8/9	8/9	4.1482
2	8/9	8/9	9/9	4.1482
3	7/9	8/9	8/9	2.6456
4	8/9	8/9	8/9	3.3286
5	8/9	9/9	8/9	4.1482
6	8/9	8/9	8/9	3.3286
7	9/9	8/9	9/9	5.1695
8	7/9	8/9	7/9	2.0686
9	9/9	8/9	9/9	5.1695
Mean	0.9012	0.9012	0.9136	3.7950

Table 3
Quadcopter visual search and formation change.

Subject	Results			
	Accuracy(A_c)			Information Transfer Rate(ITR)
	1	2	3	
1	8/9	8/9	9/9	4.1482
2	8/9	8/9	9/9	4.1482
3	8/9	7/9	8/9	2.6456
4	8/9	8/9	8/9	3.3286
5	7/9	8/9	8/9	2.6456
6	8/9	7/9	8/9	2.6456
7	7/9	8/9	8/9	2.6456
8	8/9	8/9	7/9	2.6456
9	8/9	8/9	8/9	3.3286
Mean	0.8642	0.8642	0.9012	3.1313

and information transmission rate ITR of the single quadcopter and multi-quadcopter experiments are close. Whereas the results of the visual search experiment were worse, thanks to the visual search experiment using more types of stimulus frequencies, with a total of seven frequencies, which were more prominent than the four and two frequencies in the previous two experiments. In other words, more visual stimuli occupying the VR field of view will make the classification of EEG signals more complicated. In addition, the results of the nine subjects in this experiment showed some differences. For example, subject No. 7 had good EEG recognition accuracy in the other two parts except in the third part of the experiment. The recognition accuracy of the No. 8 recipient in the three groups of experiments is not very good. This phenomenon is due to individual differences in EEG decoding among different subjects.

In addition, the flight trajectory of the quadcopter was also used to verify the control effect of EEG signals. For the convenience of presentation, the real-time recorded trajectories in the infrared optical motion capture system are utilized, as presented in Fig. 12. Fig. 12a is the navigation control result of a single quadcopter. The quadcopter flies 0.3 m in the specified direction after receiving the EEG signal classification results of “forward”, “backward”, “left” or “right”. From this we can see that the motion trajectory of the quadcopter is not a very uniform straight line, which is caused by positioning error and communication delay. However, by combining the motion trajectory in Fig. 12a and a series of real machine pictures in Fig. 13, we can intuitively see that the navigation control of the quadcopter is realized through EEG.

Fig. 12b and c are the formation transformation and search results of multiple quadcopters, respectively, and the motion trajectories of different colors represent different quadcopters. Similarly, there are also unsmooth phenomena caused by factors such as positioning errors in these motion trajectories. But in general, combined with Fig. 14, it can be observed that the three quadcopters operate in a circular or a cluster formation, and the flight altitude is maintained at about 0.9 m. Similarly, according to Fig. 15, it can be seen that the formation of the two quadcopters changes in different areas according to different instructions, and the operating height of the two quadcopters is also about 0.9 m.

4. Discussion

The purpose of this paper is to use a quadcopter as an example to demonstrate that UAV swarm control can be achieved through a VR-based BCI interactive system. In general, the participant results in this paper show that by wearing VR HMD and a virtual twin environment, users can successfully and efficiently control multiple quadcopters through their thoughts so that the quadcopters can achieve formation transformation in 3D space.

What we want to emphasize is that VR and BCI is a feasible and advanced method to control the quadcopter swarm. The quadcopter operator generally thinks through the brain and then transmits it to the limbs to operate devices such as joysticks to realize the control of the quadcopter. In comparison, BCI can control the quadcopter only by thinking of the brain without extra limb control, which provides a new interactive method for the control of the UAV swarm. Furthermore, quadcopters commonly fly far, and the distance that the human eye can observe is limited. Through VR and virtual scenes, the shortcoming of human eyesight distance can be eliminated. Although in this research, the quadcopter has a small operating space due to the use of motion capture system positioning. Moreover, with the development of quadcopter positioning and VR technology, in the future, the quadcopter camera can be sent back and processed into VR scene images in real-time so that users can comfortably control the quadcopter cluster in an extensive range from the first perspective. In addition, the introduction of VR HMD into SSVEP can not only bring the benefits of immersion to users but also provide more three-dimensional visual stimulation. In particular, the operation scene of the quadcopter’s physical space was reconstructed one-to-one in this study, allowing the experimenter to control the quadcopter cluster in both physical space and virtual space at the same time.

Besides, since this article is a novel cross-field research, there is no identical simulation and experiment for item-by-item comparison, so it can only be compared with experiments of the same type, such as BCI-controlled manipulators, virtual drones, virtual cars, and electric prosthetics, etc. On the one hand, the accuracy rate of 90% in this study is a commendable result, which compares favorably with the results of some existing work on BCI-controlled intelligent robots. For example, Zhou et al. [38] used SSVEP-based BCI to control the VR desktop flight simulator with an operation accuracy of 86.8%. Some researchers applied the same method to achieve an accuracy of 87.50 ± 3.10% for the grasping robot arm [39]. There are also some BCI control studies

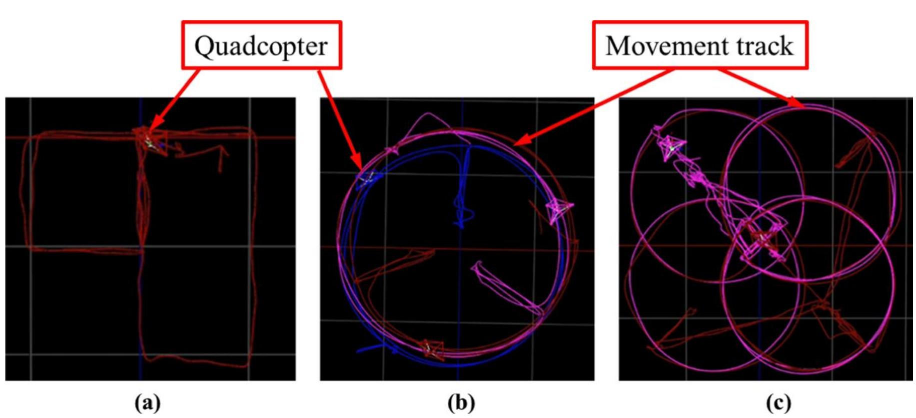

Fig. 12. Trajectory diagram of the quadcopter **a** Single quadcopter. **b** Three quadcopters change in formation. **c** Two quadcopters search and formation change.

Fig. 13. Single quadcopter navigation experiment.

Fig. 14. Three quadcopters change in formation.

[17,40] on virtual unmanned vehicles and other equipment, and the accuracy is slightly lower than 90%. It is worth mentioning that control accuracy is one of the most important elements of an interactive system. Subsequently, the higher accuracy in this study will provide high practical value for future remote control and paralyzed disabled people. On the other hand, clustering and intelligence are essential directions for

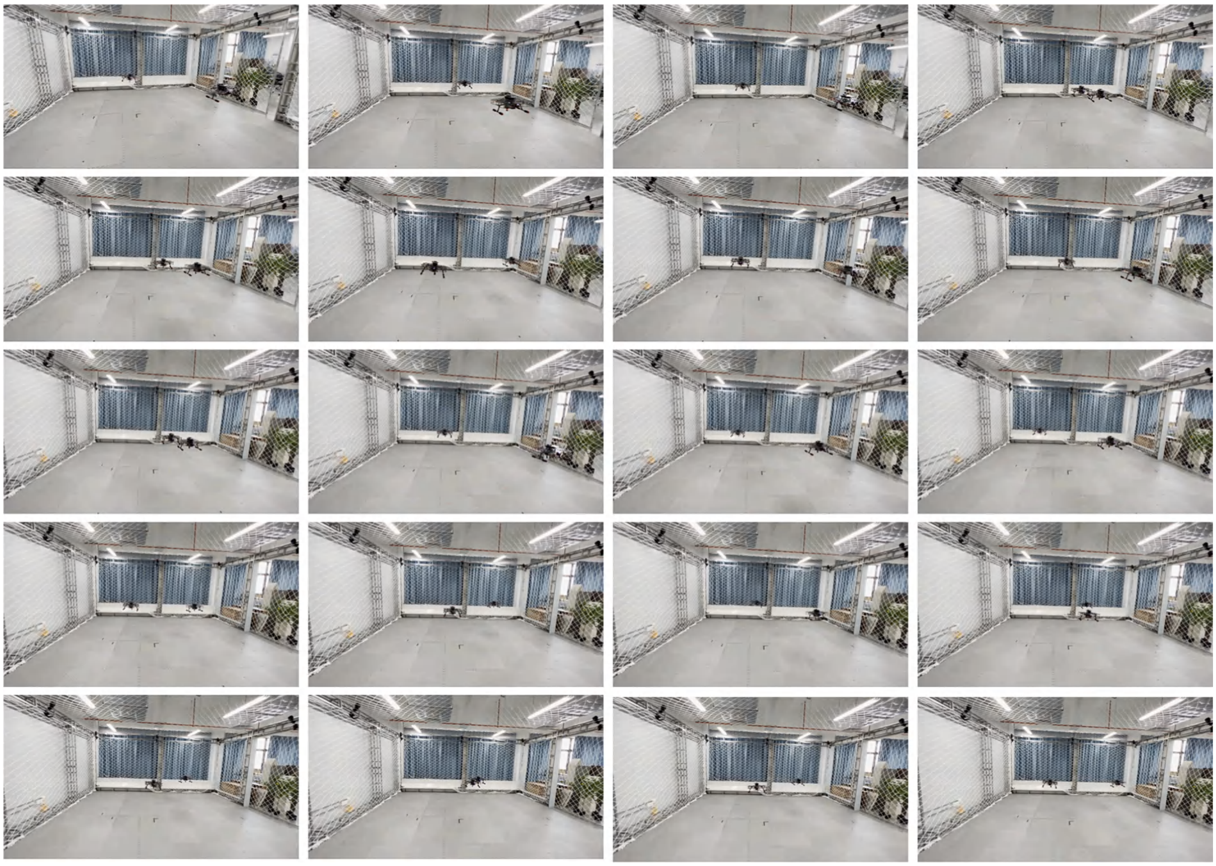

Fig. 15. Two quadcopters search and formation change.

the development of future UAVs. There have been some researchers combining BCI with UAV [6,7,15,41], but most of these studies act on search navigation and algorithm innovation for a single UAV, while the exploration of application to UAV clusters has not yet emerged. This study is dedicated to filling the gap in this area. Although there are some shortcomings in the response rate and cost of the current system. Nevertheless, the proposal of a new way of UAV cluster control is exciting and can improve UAV clustering.

Furthermore, the average information transfer rate of the three groups of online experiments is 3.62 bit/min, which is on the upper side compared to similar work. Meng et al. [15] used BCI to control the virtual quadcopter with an information transmission rate of 4.6bit/min, Yang et al. [18] used EEG signals to assist the driving of virtual vehicle control for hundreds of seconds, and the information transmission rate was low. In fact, if reducing the time of visual stimuli is only an offline process of classifying EEG signals, the ITR could reach 20bit/min. But the whole system of this paper is hugely complex, covering the interaction of the quadcopter hardware, the Unity3D software scene, the MATLAB/Simulink program, and the positioning of the motion capture system. On the other hand, subjects needed 4 s to rest after visual stimulation. For these reasons, the online ITR of the quadcopter cluster control in this exploration is much lower than that of the offline EEG classification. In the long run, there is still much room for improvement in the information transmission rate. In the future, we can improve the accuracy and information transmission rate by improving the EEG signal classification algorithm and optimizing the visual stimulation parameters et al.

Due to site space and time limitations, this paper only adopts two formation methods: circular formation and aggregation-diffusion. However, in the actual quadcopter formation, there are various formations and collaborative arrangements. These quadcopters clustering methods are currently an enormous and novel discipline. This research lays the foundation for the brain-controlled quadcopter cluster. In the future, we will introduce a variety of UAV formation methods, including algorithms based on behavioral methods, virtual structure methods, artificial potential field methods, graph theory methods, and Kalman filtering [42]. By introducing a variety of different UAV formation methods, a more intelligent and practical BCI control drone cluster system can be developed. When the VR/AR HMD is used for visual stimulation, the stimulation parameters, including the size, position of the stimulation module, and the subject's viewing angle, all have an impact on the experimental results [15,20]. These factors have not been studied in this paper, and we will expand this work in the future to improve the response sensitivity and accuracy of EEG. Furthermore, this study adopts an EEG cap and a TDT electrophysiological workstation for EEG signal extraction. Although it has a high recognition accuracy, it also has shortcomings in terms of long deployment time and portability. With the development of current EEG devices, portability and good user experience are attracting more and more attention. In further research, the method in this study will be deployed into a mobile portable EEG device, which will make the whole system more practical.

5. Conclusions

In this study, taking a quadcopter as an example, a system including a VR-based BCI subsystem, quadcopter formation subsystem, and digital twin subsystem is built to realize the control of quadcopter clusters by human will. VR HMD was used for EEG acquisition, and data classification was performed by a typical CCA algorithm. In the quadcopter cluster control, the hardware and program design are adopted through MATLAB/Simulink and optical motion capture system, and the multistate flow module design is utilized to realize the smooth formation transformation of the quadcopter. Furthermore, a digital twin scene is established, and the information exchange of the entire software and hardware system is carried out in real-time through the wireless network. The experimental results indicate that the control accuracy rate of the quadcopter cluster using VR and BCI methods reaches 90%, the subjects have sound experience, and the information transmission rate of the whole experiment has an excellent level. On the whole, the system in this paper confirms the feasibility of BCI and group control integration, improves the intelligence level of the UAV group, and will have application prospects in aerospace, search and rescue, reconnaissance, and helping paralyzed patients.

CRediT authorship contribution statement

Tao Deng: Investigation, Methodology, Software, Data curation, Writing – original draft. **Zhen Huo:** Data curation, Investigation, Software. **Lihua Zhang:** Methodology, Funding acquisition, Resources, Project administration. **Zhiyan Dong:** Methodology, Funding acquisition, Resources, Supervision, Project administration. **Lan Niu:** Formal analysis, Validation, Software. **Xiaoyang Kang:** Resources, Project administration. **Xiuwei Huang:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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