• **Review** •

Navigation in virtual and real environment using brain computer interface：a progress report

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Abstract Brain Computer Interface (BCI) provides the possibility of bypassing the peripheral nervous system and directly communicating with surrounding devices. The navigation technology using BCI has gone through the process of exploring the prototype paradigm in the virtual environment to accurately completing the locomotion intention of the operator in the form of a powered wheelchair or mobile robot in the real environment. This paper gives a brief overview of BCI navigation applications that have been used in both real and virtual environments in the past 20 years. Horizontal comparison is conducted between various paradigms applied to BCI and their unique signal processing methods. In view of the shift in control mode from synchronous to asynchronous, the development trend of navigation applications in the virtual environment is also reviewed. The contradiction between high-level commands and low-level commands is introduced as the main line to review the two major applications of BCI navigation in the real environment: mobile robot and Unmanned Aerial Vehicles. Finally, toward the popularization of BCI navigation applications to scenarios outside the laboratory, research challenges including human factors in navigation application interaction design and the feasibility of hybrid BCI for BCI navigation are discussed in detail.

Keywords brain computer interface; virtual reality; human computer interface; navigation; motor imagery; steady state visual evoked potential;

1 Introduction

As an emerging technology, Brain-Computer Interface (BCI) can directly convert human intentions into control instructions without the involvement of the peripheral nervous system, thus effectively facilitating the patient's real life by providing interaction tools which they may not be able to utilize due to their lack of motor functions.

Patients suffering from such diseases as amyotrophic lateral sclerosis (ALS), cerebral palsy, muscular dystrophies, brainstem stroke, multiple sclerosis, etc. cannot use normal facilities to drive assisted vehicles (such as wheelchairs). BCI provides these patients with impaired motor function the ability to interact with assistive devices in an effective and self-paced way. Starting from the study of the principle prototype in a virtual environment, different BCI paradigms have been studied to help these patients regain the ability of moving freely with the help of different degrees of automation system. These BCI-based navigation applications combining multiple BCI paradigms and hierarchical command systems have unique functions and specific application scenarios based on the characteristics of the BCI paradigm used.

Brain-computer interface includes invasive brain-computer interface (EcoG, LFP) and non-invasive brain-computer interface (EEG、MEG、fNIRS、fMRI、PET). The possible risk of infection due to clinical surgery makes invasive brain-computer interface such as EcoG, LFP unlikely to provide means of signal acquisition for controlling actuators outside the lab. Meanwhile, limited by the request of relatively low-cost and fast processing speed for embedded devices of the actuator, MEG and fMRI are not suitable for the control of electric wheelchairs or robots, and the low time resolution of fNIRS is not capable of making the robot perform actions that meet the task conditions. For the above reasons, we only discuss EEG-BCI for navigation in both virtual and real environments in this progress report.

We collected over one hundred articles from Web of Science database using keyword "("Brain Computer Interface" OR "BCI" OR "BMI")AND("virtual reality" OR "VR") AND ("Navigation"). The contribution of this review is two-fold. First, we present a in-depth review about BCI navigation system regarding its signal acquisition devices, feature extraction and classification methods as well as control modes, providing comprehensive material for BCI navigation system designers. Second, we discuss several issues concerning the current trends and challenges of BCI navigation system, namely the use of hybrid BCI, human factors involved in system configuration, paving the way towards more intelligent and human-centered brain-controlled actuators.

The rest of this report is organized as follows, section 2 briefly introduces the paradigm, acquisition equipment, feature extraction and classification method, user interface and control mode of the BCI system used in navigation applications. Section 3 introduces three typical applications of BCI navigation, which are navigation in virtual environment, navigation of brain-actuated robot, and navigation of Unmanned Aerial Vehicles. Section 4 analyzes the development trend of the existing BCI navigation system and summarizes the existing problems. Section 5 summarizes the whole paper.

2 Brain Computer Interface System for Navigation

Figure 1 shows a block diagram of a navigation application based on a brain-computer interface. The signal processing unit receives the user's brain signal collected by the acquisition device and outputs the control signal. The actuator in the control unit receives the control signal and forms the command with the help of the autonomous navigation system, then returns the command to the user interface through the feedback unit to form a closed-loop control. The paradigm specifies what cognitive tasks users use to interact with the BCI user interface. This progress report will briefly review the acquisition equipment, experimental protocol and signal processing method for each paradigm used in navigation application.

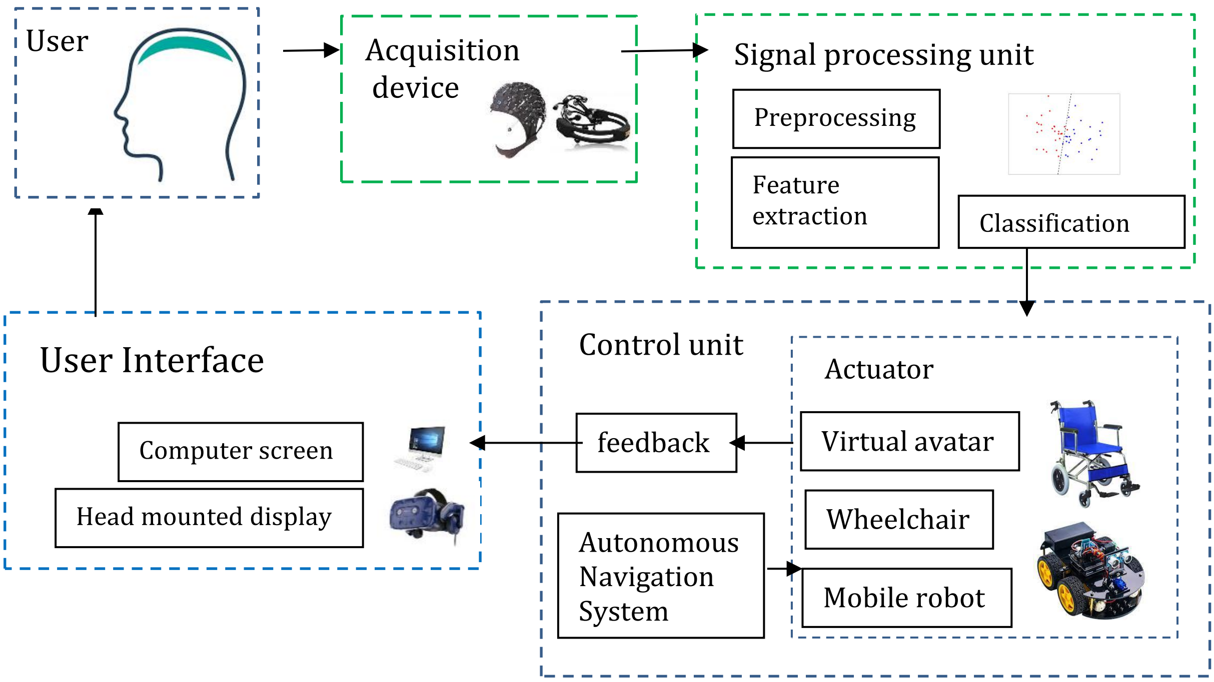

Figure 1 The block diagram of brain-controlled navigation device defined by four components, i.e. acquisition device, signal processing unit, control unit and user interface.

2.1 Brain Signal Acquisition and Processing

2.1.1 Acquisition Devices

Due to the poor spatial resolution of EEG signals, conductive paste must be applied and professional level amplifier must be adopted to ensure signal quality. At the same time, some applications use commercial-grade EEG acquisition equipment, such as Emotive EPOC. Compared to wet electrode, the signal-to-noise ratio of the dry electrode is relatively low due to its high input impedance[1]. The cost of these equipment is low, but they are only suitable for algorithms that do not require high signal quality and simple classification algorithms, such as SSVEP. In fact, Ref[2] and [3] point out that SSVEP BCI systems only need one or two channels of EEG signal for feature extraction and intention decoding.

Table 1 Different acquisition devices used in BCI navigation applications

Acquisition Devices	Typical products
Wet electrode EEG cap	BioSemi EEG cap[4], gTec[5-14], Biopac MP150[15], ADInstrument[16], Compumedic[17],[18], [19],actiCHamp[20,21], BIOPAC[22], g.MOBIlab+[23],
Dry electrode EEG device	Emotive EPOC[24-27],

2.1.2 Feature Extraction and Classification Methods

The SMR-based paradigm usually uses the frequency band energy in the frequency domain feature as a distinguishing feature[4,16]. The extraction of sensorimotor features mainly consists of two parts: band-pass filtering and spatial filtering.spatial filter can effectively search for feature spaces that replaces Sensor domain data, which contains sufficient discriminative information. Typical spatial filtering methods include neurological-based knowledge-driven methods[28,29] and data-driven methods[30]. In order to increase the resolution of features, some feature selection methods[4]are developed. Common Spatial Pattern is a feature extraction algorithm used in the motor imagery paradigm, which can maximize the variance difference between the features of the two types of signals after spatial filtering. It is also widely used in navigation applications[6,31-33].

The P300-based paradigm usually directly uses the original signal for feature extraction because the features of the P300 signal often exist in the time domain. Similar to the SMR-based paradigm, the SSVEP-based paradigm also uses frequency domain features. The commonly used feature extraction algorithm is CCA[18], and the reference signal frequency with the largest correlation coefficient with the current signal is selected as the classification output. Classifiers usually use simple linear classifiers such as LDA[6,21,34], SVM[15,31,35], as well as complex non-linear classifiers such as neural networks[16].

The features of P300 are mainly represented using time domain features. The features of SSVEP mainly exist with frequency domains, and the classification algorithm distinguishes different categories of signals by calculating the correlation coefficients of EEG and specific frequency bands.

Early applications typically use simple classifiers. According to the decision boundary of the classifier, it can be divided into linear classifier and non-linear classifier. The former includes LDA, SVM, while the latter consists of several types including neural networks, hidden markov models and Bayes quadratic classifiers.

The major challenge EEG classifier face is to generalize over multiple subjects. In the past ten years, a variety of algorithms have been developed to solve the inter-subject variation problem. transfer learning solve the covariance-shift problem by transforming the features of the target domain and the feature of the source domain to a invariant feature space. The regularization method restrict the complexity of the classifier to avoid over fitting caused by minimizing empirical risks alone. Adaptive classifier[36] update the classifier parameters in real using the data from target subject, solving the issue of inter-session variation and inter-subject variation simultaneously which proved to be significantly better than static classifiers[37]. At the same time, end-to-end matrix classifier[38] is also widely tried as well as deep learning methods[39-41]. Matrix Classifier uses Riemain Geometry theory to classify the stream of the signal's covariance matrix, and reaches the State-of-the-art effect on multiple tasks. CNN network based on deep learning is also used in a variety of paradigms, although its performance remain sub-optimal due to lack of sufficient data[37].

2.2 Paradigms of Brain Computer Interface

2.2.1 Sensorimotor Rhythm

The imagery movement of specific body parts can modulate the amplitude of the sensorimotor rhythms (SMR). SMR paradigm based on this phenomenon enables subjects to output one of several (usually four or fewer) predefined commands at a pace they can control. This paradigm is usually divided into training phase and online phase. In the training phase, the subjects were asked to perform a motor imagery task for a period of time based on visual or sound cues, usually involving only a certain part without specific actions. A decoder was trained using the previously collected training data of the subjects. The decoder is then used in the online phase to determine the type of motor imagery task currently being performed by the subject given a segment of EEG signal.

There are two advantages of using the SMR-based BCI to control the movement of virtual characters or physical machines. The first advantage is that the interaction is intuitive. Human movement in real environment has the characteristics of autonomous control, and the paradigm of stimulus-evoked response control cannot achieve real self-paced control due to its time-locked nature. This will cause users to respond to commands more frequently when they need to maintain motion control. There is also a lack of corresponding real-time control mechanisms in stimulus-evoked paradigms where there is a need for rapid response. SMR-based paradigm with robust signal processing method can make up for these shortcomings. At the same time, since the movement of the human body in the environment always involves the movement of the limbs, the use of imaginary movement to control is also intuitive and easy to remember for the user.

Another advantage of the SMR paradigm is related to navigation applications. Although the P300 or SSVEP paradigm usually has higher signal decoding accuracy[42,43], they often require the user to stare at the user interface screen during the entire process of inputting instructions. This process easily leads the user to visual fatigue and limits the user's ability to perform multitasking while conducting navigation.

One of the biggest challenges facing the SMR paradigm is the sub-optimal signal decoding method, which results in the lack of controlling dimension. Due to EEG's poor spatial resolution and extremely low signal-to-noise ratio, even the most advanced signal processing algorithms can only output less than five control signals with only decent accuracy. Since it is currently impossible to obtain a higher signal-to-noise ratio signal with non-intrusive equipment, more sophisticated and robust signal analysis methods should be developed to improve the accuracy of SMR signal classification. As for the problem of limited control dimensions, controlling cursor movement and selection can effectively expand the number of control commands at the cost of introducing more unnecessary intermediate steps.

Different subjects will produce personalized EEG features for different motor imagery tasks, which leads to a serious inter-subject variability problem[42]. In recent years, researchers have proposed a variety of methods to solve the covariance shift phenomenon caused by this problem. Transfer learning [44] is used to constrain the features of the subjects to the same invariant feature plane (domain generalization), or use the data of the target domain to improve the classifier performance trained with the data of the source domain (domain adaptation). Adaptive classifier[45] solves the problem of the difference between the training stage and the testing stage by repeatedly updating the classifier parameters with the data of the target subjects in the testing stage.

2.2.2 Steady State Visual Evoked Potential(SSVEP)

SSVEP is a visual-evoked potential elicited by a fixed-frequency visual stimulus. It contains sinusoidal-like waveform whose frequencies are the same as the fundamental and harmonic frequencies of the visual stimulus. By identifying this component, the area of the screen which the user is currently looking at can be decoded from the EEG signal. The user interface usually contains multiple blocks of blinking patterns, each representing a distinct option predefined by the experimental protocol. The option menu can be combined with multiple media presentations, such as LCD screens, LED lights, HMD, etc. Figure 2 shows the application of SSVEP induced by flicker stimulation independent of the computer screen.

One of the advantages of SSVEP-based BCI is its relatively high information transfer rate (ITR)[3] compared to spontaneous signals. According to Ref. [1], locomotion applications of BCI requires less ITR than neuroprosthesis applications.

In early days of BCI development, LCD screen and even CRT screen are used in the user interface subunit. Later LED flicker[46] was proved to have a larger frequency amplitude than LCD and CRT when evoking brain signals, especially in the lower bands of frequency.

Ref. [47] concluded that SSVEP-based BCI systems are the most practical and least resource expensive approach for a BCI controlled wheelchair system. The reasons include low signal-to-noise ratio and low channel number requirements of acquisition equipment, easy-to-implement signal processing methods and high information transmission rate, etc.

One of the challenges faced by SSVEP is the occupation of stimulus patterns that block the visual field. In recent years, the proposal of minimum asymmetric visual evoked potentials[48] alleviates this problem. At the same time, the use of more advanced information coding makes it possible to improve the ITR of SSVEP. By referring to the tiny stimulation placed on the lateral side outside the fovea vision, combined with the space code division multiple access scheme coding command output, the problem of occluding visual field is solved, and the ITR of the whole system is improved by improving the accuracy and the number of instructions.

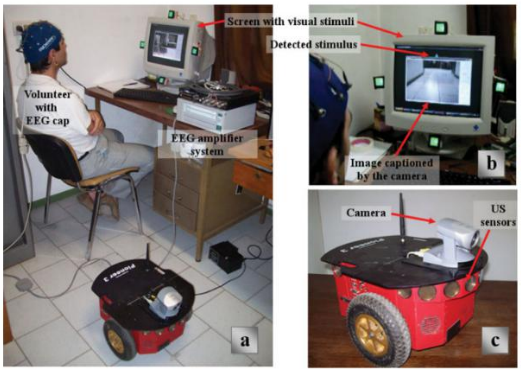

Figure 2 The SSVEP user interface used in [49] to navigate a mobile robot with frontal camera

2.2.3 P300

Similar to the SSVEP paradigm, the P300 paradigm also requires subject to focus his/her visual attention on the visual representation of the options which they want to choose. Since its first appearance in Ref. [50], the P300 paradigm has been widely used in BCI-based communication applications such as the P300 speller because it is capable of providing more control commands than SMR-based paradigms and does not require additional training. Since this paradigm was originally used for communication purposes, the number of commands which P300-based system provides are adequate for locomotion applications that use high-level commands (see section 4.2.2).

In P300-based navigation applications, the paradigm that provides low-level instructions provides users with specific options for controlling the movement of the actuator, and outputs real-time control instructions by decoding the user's visual attention points as shown in Figure 3a. The paradigm that provides high-level instructions presents spatial information to the user through real-time video or a 3-dimensional map established using SLAM, and provides the user with a 3-dimensional location in the scene that is likely to be regarded as a destination by the user as an option. By selecting these target points, the actuator moves to the target area with the help of the autonomous navigation system as shown in Figure 3b.

One problem common with event-related potential based control signal is that it requires the subjects to allocate part of their visual attention to the visual stimuli of the user interface, which results in a heavier workload and easily makes them exhausted. Another disadvantage comes from hardware: more control commands correspond to shorter stimulation frequency intervals. In the specific hardware implementation, the actual refresh rate of the visual feedback of the user interface may be unstable, which brings potential risks to the accuracy of signal decoding algorithm.

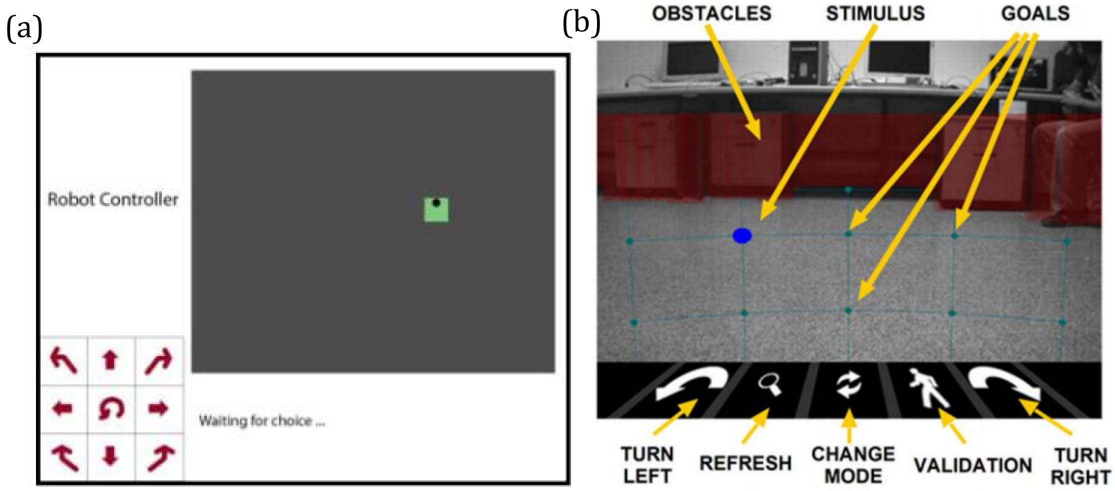

Figure 3 Two different user interface of SSVEP-based navigation system. a) The panel for low-level command for a SSVEP-based application [51] . b) high-level command user interface in P300 navigation system[52].

2.3 Control Modes for Navigation

According to the input data's processing modality, BCI systems for navigation can be classified as synchronous or asynchronous [1].

2.3.1 Synchronous Control

Early navigation applications based on brain-computer interfaces used a synchronous approach. In the synchronous control mode, the user performs cognitive tasks within a fixed period of time according to the prompts of the system such as imagining body movements or looking at the location of the options that they want to select.

Since the visual stimulus that induces the control signal cannot be controlled by the user in a self-paced manner, BCI based on the P300 and SSVEP paradigms is generally considered to be synchronous. In the application shown in Figure 4c, the map of the space where the user is located is simplified and presented to the user. By taking elements at specific locations in the plane as visual options in the P300 paradigm and making them flash in a certain sequence, the user selects the location in the plane to output his/her movement intention and controls the avatar to move to the target area. This control method has the advantage of direct and rapid movement, but it is more suitable for known environments, and at the same time the degree of modification is not high. The application shown in Figure 4d uses the P300 interface, which enables users to flexibly control every movement of the virtual character using low-level instructions, which enhances the applicability to unknown scenes.

The SMR paradigm is generally considered to be asynchronous. However, early part of the SMR paradigm followed a certain time sequence, that is, users can only use EEG to generate control signals within a specified time range, and the time interval is specified by the experimenter. Such applications include the application shown in Figure 4a. Participants use a type of motion imagination in the immersive

CAVE system to control the forward and backward of the virtual character's perspective. In order to increase the dimensionality of control, the application shown in Figure 4b allows the user to use EEG signals to control the virtual rotating pointer to select multiple movement instructions, so that the SMR BCI can be effectively used under the limitation of sub-optimal signal classification accuracy.

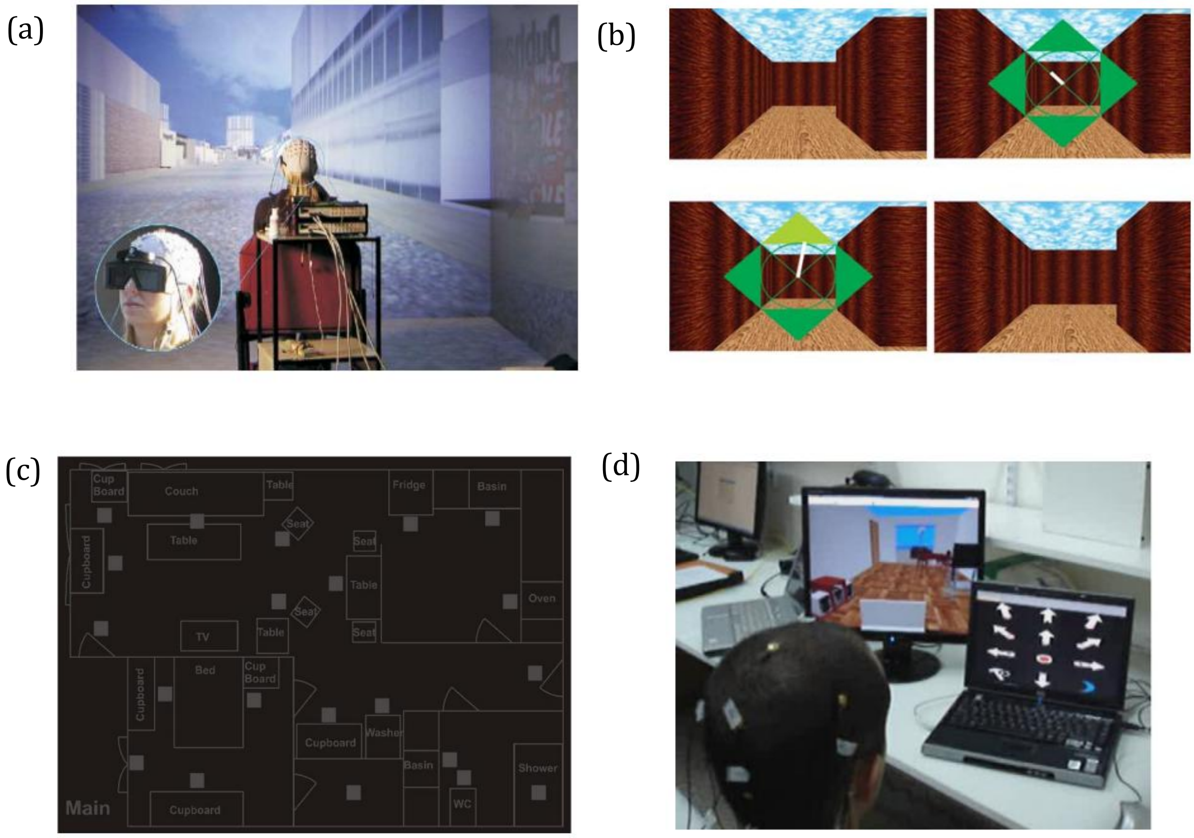

Figure 4 Four classic synchronous navigation system. a) user using motor imagery to move forward in a virtual environment[13] b)virtual pointer to select from four commands using one-class motor imagery[53] c) using P300 to give high-level command of target destination[54] d)using P300 to give low-level command of avatar movement[55]

2.3.2 Asynchronous Control

The synchronous control mode allows users to output control commands only at specific time points, which may not be able to provide a valid response speed in some complex situations. The time interval of subsequent command is limited by the length of the EEG signal required by the classification algorithm. To solve this problem, asynchronous control was proposed, in which the EEG signal is continuously decoded in real time to enable the user to control the navigation in a self-paced manner.

In order to realize asynchronous control, the detection of Non-Control (NC)/Intention Control (IC) status must be implemented. In the NC state, the user's EEG signal will not be used to output the estimated user's current mental state until the system detects the user's IC state.

SMR paradigm is more suitable for asynchronous mode due to its endogenous origin. As mentioned earlier, the signal classification accuracy of BCI based on SMR paradigm is not satisfactory, especially in the case of multiple classifications. If the task of resolving the IC/NC status is forcibly added to the classifier, the accuracy of the classifier is likely to degrade. In order to solve this problem, a hierarchical structure is usually adopted. As shown in Figure 5a, one-class motor imagery classification control signals is combined with the cue action of the actuator to achieve the control dimension of 4 types of control signals. The control method shown in Figure 5b uses the joint output of the classifiers of the three imaginary movements as inputs for different mental states in the IC state and for judging whether the system is currently in the IC state. The methods shown in Figure 5c and Figure 5d controls the translation and rotation of the virtual pointer through the continuous output value of one-class motor imagery signal to separately switch the NC/IC state and different output commands.

Currently motor imagery is the most widely used in asynchronous control due to its endogenous origin. Sub-optimal classification accuracy and inter-subject variability issue is the main obstacle to the successful implementation of MI-based asynchronous control. To address these issues, a variety of transfer learning methods are presented[56,57] to solve problem. At the same time, the control dimension of asynchronous control method is also improved by the use of more complex paradigms, e.g. the Sequential Motor Imagery[32].

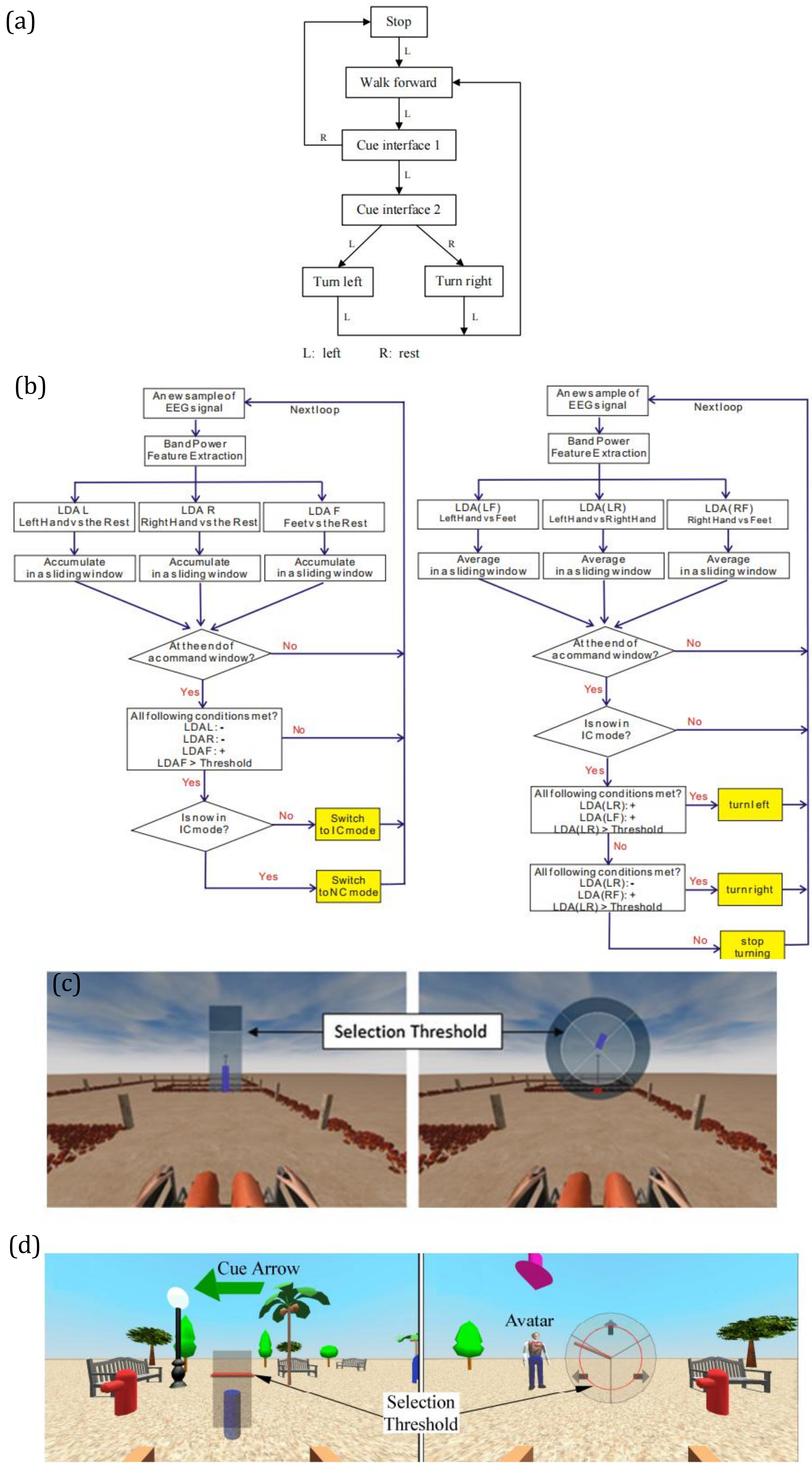
(a)
Stop
L
Walk forward
L
R
Cue interface 1
L
Cue interface 2
L
R
Turn left
Turn right
L
L
L: left R: rest
(b)
A new sample of EEG signal
Next loop
Band Power Feature Extraction
LDA L Left Hand vs the Rest
LDA R Right Hand vs the Rest
LDA F Feet vs the Rest
Accumulate in a sliding window
Accumulate in a sliding window
Accumulate in a sliding window
At the end of a command window?
No
Yes
All following conditions met? LDAL: - LDAR: - LDAF: + LDAF > Threshold
No
Yes
Is now in IC mode?
No
Switch to IC mode
Yes
Switch to NC mode
A new sample of EEG signal
Next loop
Band Power Feature Extraction
LDA(LF) Left Hand vs Feet
LDA(LR) Left Hand vs Right Hand
LDA(RF) Right Hand vs Feet
Average in a sliding window
Average in a sliding window
Average in a sliding window
At the end of a command window?
No
Yes
Is now in IC mode?
No
Yes
All following conditions met? LDA(LR): + LDA(LF): + LDA(LR) > Threshold
Yes
turn left
No
All following conditions met? LDA(LR): - LDA(RF): + LDA(LR) > Threshold
Yes
turn right
No
stop turning
(c)
Selection Threshold
(d)
Cue Arrow
Avatar
Selection Threshold

Figure 5 Four different control strategy of SMR-based BCI navigation system a)The control strategy used in Ref. [19] to expand the output of one motor imagery task to four command b) Control diagram of Ref. [58] to achieve asynchronous control using 3-class motor imagery c,d)virtual selection pointer to switch between NC/IC mode [21,59]

2.4 User interface

The design of user interface for brain-controlled navigation system should depend on specific application requirements. For instance, when designing application such as brain-actuated electric wheelchair, the safety of the driver must be ensured. In order to achieve this goal, BCI systems that provide high-level commands must integrate surrounding environmental information into the user interface or implicitly embody environmental perception in the movement options provided to users.

The visual feedback can be provided to users through real-time video streaming or reconstructed 3D environmental images. In the application shown in Figure 6a, the environment information is reconstructed and combined with the provided movement options to the user and updated in real time following the movement of the user's perspective. In the application shown in Figure 6b, the physical location that can be reached is spatially registered on the video stream in real time. The user navigates the electric wheelchair to the target location by gazing at the corresponding blue point in the video.

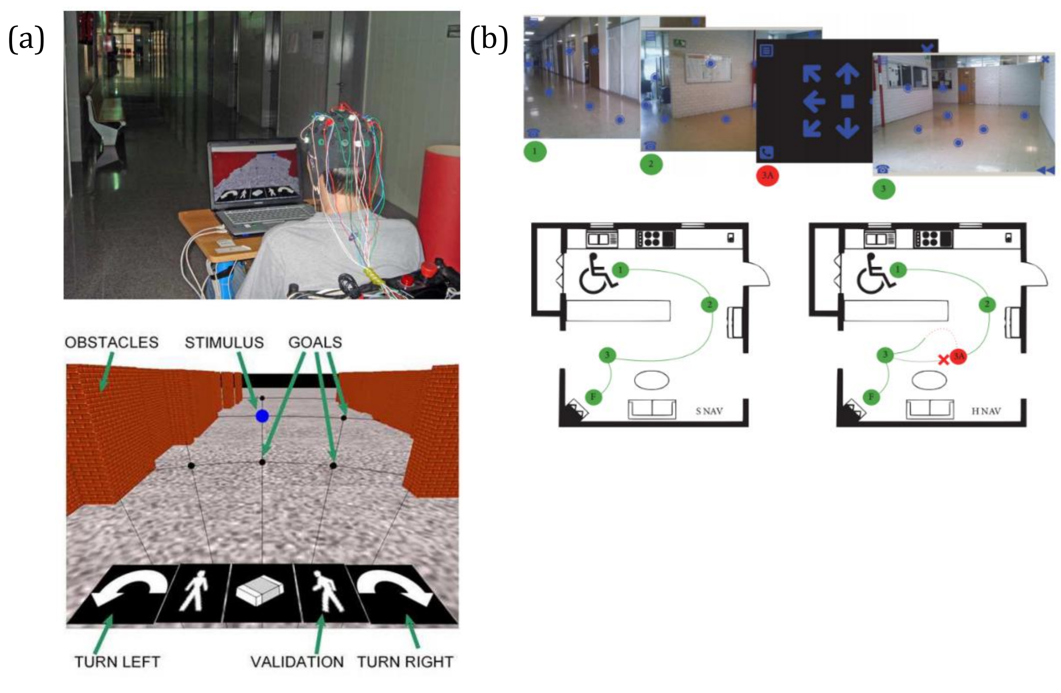

Figure 6 Different user interface of P300-based BCI navigation system a) P300 user interface of reconstructed 3D environment model [5] b) P300 user interface of real-time video stream [5]

3 Typical Applications

BCI-based navigation was first applied in a virtual environment. Early applications are limited by the real-time processing capabilities of the equipment and can only use simple signal processing methods, so they only have the ability to output a small number of control signal types. The user controls the movement of the avatar via BCI, and gets feedback through changes in the virtual environment. With the development of BCI technology, the ITR of the BCI system continues to improve, and it becomes possible to use BCI to control devices in the real world. This chapter will first introduce BCI navigation in virtual environment, then review two major application of BCI navigation in real world, namely navigation of brain-actuated robot and navigation of unmanned aerial vehicles.

3.1 Navigation in Virtual Environment

The feedback based on virtual environment provides users with more realistic visual, auditory and tactile information, thus speeds up the learning process of BCI usage. Pfurtscheller et.al [13] used the motor imagery brain computer interface to control the virtual character navigating in a virtual apartment. The experiment used the CAVE system to build a VR environment. Before entering the VR environment, user received additional training according to the standard Graz-BCI paradigm, users were asked to walk to the end of the route on a one-dimensional trajectory. In addition, the experiment found that compared to PC stimulation presentation, the virtual environment did not significantly improve the user's performance. The author speculates that the reason is the distraction effect of excessive visual stimulation. Robert et.al [60] designed a cue-based BCI paradigm. Ten naïve BCI users can move freely in the virtual apartment after 3 sessions of training. When the subjects reached any node, they carried out appropriate motor imagery task to determine the path that they would go through.

Different from Ref. [13], Friedman et.al [61] adds a dimension to the movement of the avatar controlled by the subject in the CAVE virtual environment. Participants rotate in the virtual bar room by imagining left and right hand movement. In the virtual street, they can control the movement back and forth by imagining foot and hand movement. It can be seen from the analysis of questionnaire after the experiment that different subjects' feelings about presence are inconsistent, while the presence of different tasks differs insignificantly.

The emerging of more reliable decoding algorithms and new interactions can help the improvement of the capabilities of existing brain-computer interface systems. Vourvopoulos et.al [10] proposed a BCI-VR system using multimodal interaction methods. Participants were asked to drive a boat across a series of designated locations on the lake in a virtual environment. Every time a goal is reached the subject gets a certain score and the goal is to get as many scores as possible. Participants used left and right hand motor imagery to control the direction of the hull with a self-paced manner. In the training phase, visual feedback and vibrotactile were used to instruct the user to imagine the action currently.

Comparing to BCI navigation in real environment, the virtual environment can prevent the navigation application from making actions endangering user safety because the subjects are not familiar with BCI operation or system misclassification. The use of motion imagination BCI in the virtual environment can promote the excitation of user's motion related brain regions[62], so as to promote motion rehabilitation. The underlying mechanism is that motor imagination and motor execution have similar neural representation regions and dynamic mechanisms[63].

Table 2 Different BCI navigation applications in virtual environment

	paradigm	preprocess	feature extraction	classifier	feedback	mode
[64]	SMR	0.1-100Hz	band power	threshold	avatar movement	asynchronous
[65]	P300				change of item state	synchronous
[14]	SMR	0.5-30Hz	logarithmic band-power	LDA	avatar rotation	synchronous
[66]	SMR	8-12Hz	band power	threshold	avatar rotation	asynchronous
[12]	SMR	0.5-30Hz	logarithmic band-power	LDA	subject forward, stop or backward	synchronous
[61]	SMR	0.5-30Hz	logarithmic band-power	LDA	subject forward, stop or backward	synchronous
[60]	SMR					synchronous
[11]	SMR	8-30Hz	band power	LDA	single back-projected stereoscopic wall with subject wearing shutter glasses	synchronous
	SMR	0.1-100Hz	logarithmic band-power	LDA		asynchronous （classifier threshold）
[67]	SMR	0.5-30Hz	logarithmic band-power	threshold	subject forward, stop or backward	asynchronous （classifier threshold）
[68]	SMR					asynchronous
[58]	SMR		band power	LDA		asynchronous
[69]	SMR	8-30Hz	CSP	SVM	avator movement	synchronous
[70]	SMR	6-36Hz	band power with feature selection Distinction sensitive learning vector quantization	LDA		asynchronous
[53]	SMR		bandpower	LDA		synchronous
Other works using SMR				[4],[6],[10],[16],[17],[19],[20] ,[21],[25],[27],[31],[32],[71],[72],[73],[74],[75],[76]		
Other works using SSVEP				[18],[23],[35],[77],(high frequency)[78],[79],[80],[81],[82], [83],[84],[85],[86],[87],[88],		
Other works using P300				[5],[7],[8],[9],[15],[22],[26],[34],[51],[89],[90],[91],[92],[54]		

3.2 Navigation of Brain-Actuated Robot

Assistive robots can help patients with impaired motor skills complete the behaviors in their daily lives, thereby providing convenience for the disabled community. However, for patients with more severe damage of motor function like those with ALS disease, the interactive methods designed for the disabled such as sip-and-puff systems or simple switches cannot meet their interactive needs, let alone ordinary keyboard and mouse input. On the other hand, despite the assistance of automatic navigation systems, the user interface of such systems still requires the user to provide high-level control instructions which the user is unable to give due to loss of muscle functionality. The BCI controlled robot can help the people with severely impaired muscle function to operate auxiliary equipment so as to facilitate their daily use of electronic equipment and improve their quality of life.

Brain controlled mobile robot can be divided into two categories: one is similar to that of the low-level command paradigm aforementioned, which directly controls every movement command of the robot through brain electrical signals. Another one is shared control that combines user intention output and intelligent navigation system functions. The main advantages of the former are low price and low technical complexity, but it also has all the shortcomings of low-level command control as mentioned above. Although the shared control method is costly and the equipment is complicated, it can effectively prevent user from fatigue and ensure the user's safety by using highly intelligent planning algorithms. One of the examples of shared control is the double-layer control method, the actual control layer outputs a control intent to the virtual control layer using the subject's brain signal[92], and the virtual control layer determines whether the subject's command conforms to the security requirements defined dynamically according to the current environment.

There is a tradeoff between enhancing the relative adaptability to the environment and reducing the user's mental load. On the one hand, a navigation system with low-level control can provide users with more freedom of movement than a navigation system with high-level control. The high-degree-of-freedom navigation system enables users to make reasonable choice of movement commands according to the environment, avoiding the dilemma of too rigid control paradigm unable to travel through complex terrain. On the other hand, it is not easy for the user to maintain a certain mental state which is strong enough to provide signals that can be effectively identified by the classifier for a considerably amount of time, and to quickly adjust the mental state according to the interaction between the wheelchair and the environment is beyond some user's capabilities. This can easily cause the user's mental load to be too high, resulting in fatigue and affecting task performance. Ref. [5] combined the two control modes. Users can switch between high-level commands and low-level commands through the P300 interface (figure 7), which provides a valuable solution for this balance problem.

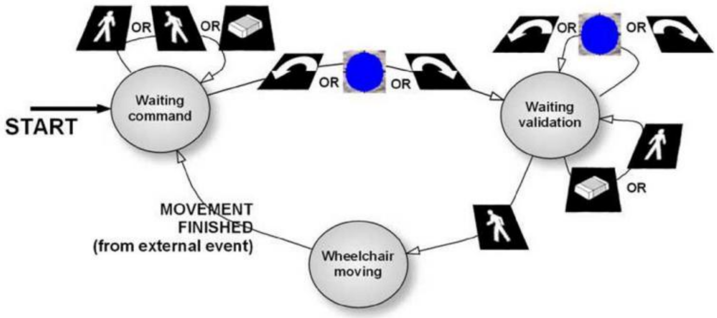

Figure 7 The control strategy used in Ref. [5], left turn and right turn sign represents low-level command while blue point represents places to go chosen by the user from the constructed map

Table 3 Different BCI-controlled wheelchair applications

	paradigm	preprocess	feature extraction	classifier	navigation mode	mode	feedback	characteristics
[3]	SMR	0.1Hz high-pass filtered, common average reference	power spectrum density + canonical variates analysis	Gaussian classifier	low-level command with collision detection	asynchronous	visual observation	virtual environment training in advance
[5]	P300	0.5-30Hz band-pass filtered	raw signal with channel selection	stepwise linear discriminant analysis	high-level command and low-level command	synchronous	3d reconstruction virtual environment	hierarchy of command, 3d reconstruction of environment
[15]	P300	1-35Hz band-pass filtered	raw signal	SVM	low-level command	synchronous	visual observation	
[16]	SMR	8-40Hz band-pass filtered	band power	dynamic Elman neural network	low-level command	asynchronous	visual observation	
[6]	SMR	8-32Hz band-pass filtered and common average reference	CSP	LDA	low-level command	asynchronous	visual observation	
[7]	P300				switching between low-level command and high-level, only requires user input if necessary	synchronous	visual observation	
[17]	Mental Non-motor Imagery	0.1-40Hz band-pass filtered	power spectral density	Artificial Neural Network	low-level command	asynchronous	visual observation	
[18]	SSVEP	6-30Hz band-pass filtered	CCA	max value	switching between low-level command and high-level, only requires user input if	synchronous	visual observation	

					necessary			
[34]	P300	0.1-20Hz	raw signal with segment selection	SVM	high-level command	synchronous	2d interface	
[20]	SMR	5-17Hz band-pass filtered	band power	LDA	low-level command	asynchronous	visual observation	trainned in virtual environment in advance
[77]	SSVEP	Common Average Reference，0.1-100Hz band-pass filtered	Spectral F-test	rule based classifier	low-level command	synchronous	visual observation	
[35]	SSVEP	8-30Hz band-pass filtered	power spectrum density	SVM	low-level command with collision detection	synchronous	visual observation	
[22]	P300	0.5-25Hz band-pass filtered	raw signal	template matching	switching between low-level command and high-level，switching by eye blinking	asynchronous	visual observation	
[31]	sequential SMR	8-12Hz band-pass filtered	CSP	SVM	low-level with motion switch	asynchronous	visual observation	motion switch
[8]	P300	0.1-30Hz band-pass filtered	raw signal	LDA-LASSO	switching between low-level command and high-level，only requires user input if necessary	synchronous		
[89]	P300							
[21]	sequential SMR	9-15Hz band-pass filtered	band power	LDA	low-level command	asynchronous	visual observation	trainned in virtual environment in advance
[32]	sequential SMR	4-30Hz band-pass filtered	CSP	LDA	low-level command	asynchronous	visual observation	virtual environment training in advance

Table 4 Different Brain-controlled mobile robot navigation applications

	paradigm	preprocess	feature extraction	classifier	navigation mode	UI	actuator	characteristics
[72]	alpha-activity	Raw signal	Raw signal	LinearClassifier	semi-autonomous	predefined target images	images	
[93]	rhythmic activity				semi-autonomous	predefined target images	Sony AIBO，ambient control	adaptaion to different level of disabilities，robust to the setting
[33]	SMR	laplacian filter	bandpower，Fisher score	intentional activity classifier（LDA）+Motor direction classifier（QDA）	manual control		humanoid robot	

[52]	P300	0.5-30Hz band-pass filter	r2 metric	StepWise Linear Discriminant Analysis (SWLDA)	semi-autounomous	dynamic video-based GUI	Wheeled robot	robot navigation and camera exploration
[19]	SMR	8-16Hz band-pass filtered	CSP	LDA	manual control		humanoid robot	only one motor imagery
[94]	high frequency SSVEP	1-100Hz band-pass filtered	bandpower	max feature	manual control with collision detection	SSVEP flickers	Robot Pioneer 3-DX with Canon VC-C4 camera	
[23]	SSVEP	8-19Hz band-passed	canonical correlation analysis (CCA)	LDA	manual control	SSVEP flickers	Wheeled robot	
[95]	SSVEP	5-30Hz band-pass filtered	multivariate synchronization index (MSI)	max feature	semi-autonomous	SSVEP flickers	Wheeled robot	use of vSLAM to produce low-level commands
[96]	SSVEP	0.5-30Hz band-pass filter	CCA	max feature	semi-autonomous	SSVEP flickers	Wheeled robot	cooperation with a manipulator，switching between low-level control and high-level control
[79]	SSVEP	5-12Hz band-pass filtered	bandpower	fuzzy feature threshold	manual control	SSVEP flickers	Wheeled robot	one-channel
[9]	P300	0.5-30Hz band-pass filtered	raw signal with channel selection	stepwise linear discriminant analysis	high-level command	dynamic video-based GUI	Wheeled robot	3modes

3.3 Navigation of Unmanned Aerial Vehicles

Unmanned Aerial Vehicles(UAV) can perform task that cannot be completed by land robots, including rapid movement in large scenes ignoring ground obstacles, etc. These functions can provide extended possibilities for patients with impaired motor functions and can be used for entertainment purposes for healthy people. However, the instability of UAVs brings great difficulties to the design of robust UAV control algorithms.

UAV can be divided into three types according to their kinematics-dynamics : rotary crafts, airship and fixed-wing crafts[97]. Rotary crafts are widely used in indoor applications due to their easy handling and economic characteristics, making them the first choice for developing brain-controlled UAV prototypes.

The control system of the UAV is also composed of a mixture of manual control and automatic control. Due to the low information transmission rate of BCI and the instability of UAV, the current mainstream brain-controlled UAVs mostly adopt semi-autonomous control, i.e. shared control of autonomous system and manual instructions.

The autonomous attitude control of drones guarantees stable motion output. Therefore, the research of brain-controlled drones mainly focuses on optimizing the timing of converting high-level brain-controlled commands into low-level motion commands to balance the tradeoff between robustness of the command and the pace of operation caused by low BCI ITR and the high-speed requirements of UAV control. One solution is to improve the accuracy of the BCI classification system through training, thereby increasing the ITR of the command input. The paradigm used by most brain-controlled drones is SMR[98-100], which requires a lot of calibration effort for a subject-independent classifier to be built. At the same time, the improvement of the control dimension also helps to improve ITR. In Ref. [101], the subjects used kinesiology to control the up and down as well as left and right movements of the virtual helicopter, and in Ref. [102] the two-dimensional movement of the virtual helicopter was extended to 3D. Another method is to increase the degree of autonomous control of UAVs by improving the control mode to reduce the demand for BCI ITR. Different from the control strategy that directly controls the moving direction of the UAV(figure8) , Ref. [98] allows the subjects to select the flight trajectory of the UAV for the next period, thus making full use of the UAV’s on-chip computing resources.

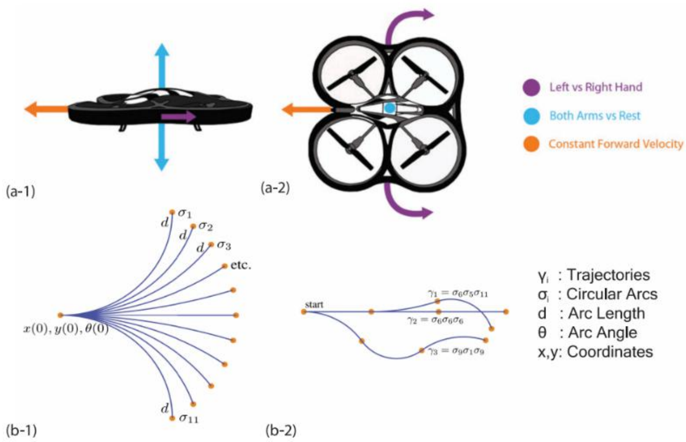

Figure 8　Different control mode of UAV in virtual environment[97]

It is necessary to find more innovative application fields for drones controlled by brain-computer interfaces that are more in line with market needs. Compared to the unstable BCI control limited by poor signal quality and sub-optimal algorithm, there are more easy-to-learn, robust and mature UAV control methods using other modalities. Advances in intelligent planning and controlling algorithms have made some UAV systems no longer rely on operators to manually give motion instructions.

In contrast, the main advantage of using brain signals to control drones lies in its considerable potential. In the future, signal processing algorithms based on error-related potentials can help the UAV control system adjust the UAV's pose and actions in real time according to the user's movement intention. The hierarchical user cognition model can decode the user's high-level semantic instructions into the individual low-level motion instructions of the drone swarm, so that the operator can obtain the macroscopic semantic control ability of the autonomous navigation drone swarm. Related applications can help people who temporarily or permanently lose conventional input methods gain control of their surrounding devices, and further improve the ability of healthy users to interact with electronic devices.

4 Trends and Challenges

From the initial type of application where the avatar's one-dimensional motion is controlled by one-task motor imagery task, to systems using more control instructions where the user's IC / NC states are detected in real-time by intelligent algorithms, navigation applications based on brain computer interface are increasingly refined with the development of more robust signal classification methods and user-friendly training protocol.

4.1 Human Factors in BCI Navigation

Human factors must be considered when designing BCI-based navigation applications. It will affect the participant’s learning efficiency of the BCI system, which indirectly affects the information transmission rate of the system. Taking the brain-controlled electric wheelchair as an example, the design for human factors is dedicated to enabling users to use the minimum energy to achieve the purpose of movement that meets the user's expectations. Factors that can be considered include design of seat, pedals, arm rests[103], etc. However, the most important factor is the design of the control mode of the wheelchair movement.

In the design of the BCI-based electric wheelchair, the target user has suffered a certain degree of trauma and is prone to mental fatigue. Concentrating on generating control commands that meet the characteristics of the EEG recognition system for too long may increase the mental burden of the user, thereby reducing the usability and promotion of the brain-controlled auxiliary device.

In order to enhance the ergonomics of the system, it is necessary to optimize the design of the brain-controlled navigation system from both hardware and software sides. In terms of hardware, wireless devices that can provide high-speed data transmission which will effectively expand the user's activity space and reduce user fatigue caused by the mental feeling of being restrained. The future trends at the software level is more diverse. High-level commands need to cooperate with advanced autonomous navigation systems to provide users with efficient interaction paradigms and comparable obstacle avoidance performance to low-level command controls. The development of adaptive user model will give the navigation system capacity to switch between multiple tasks in a complex environment using the minimal interfere of human instructions, thereby reducing the user's cognitive load. Accurate detection of the user’s intent to stop the interaction can also reduce the user's mental workload by transferring control authority to autonomous navigation system whenever user feels exhausted.

There are several requirements for the design of BCI with regard to navigation application. In Ref[104] the author divides the design space of virtual navigation application into two dimensions: speed control and direction control. The two dimensions of control put forward different requirements for the design of BCI. BCI for controlling speed does not need continuous input in most applications of this review, but maintains a specific speed value unless the user wants to switch the state. The BCI for the control direction needs to output continuous values and stop the steering intention in time. The former is more suitable for goal oriented BCI, while the latter is suitable for BCI implementation of process control type.

In the real environment, the navigation application designed for wheelchair should consider the safety of users. Considering the unstable characteristics of BCI[37], The recognition results of subjects' motor imagery should be confirmed multiple times to achieve stable control.At the same time, objective detection and dodge should be incorporated into the shared control framework to further reduce security risks.

4.2 Hybrid BCI Paradigm and “Brain-switch” Design for Asynchronous Control

According to the types of different combined signals that the system output depends on, the hybrid BCI can be roughly divided into two categories: those produce final system output by mixing the classification results of multiple BCI paradigms and those compile BCI with other biological signals such as EMG or EOG. The former requires subjects to adjust their mental state and simultaneously generate multiple control signals.

The introduction of the second control paradigm provides the possibility for applications other than navigation, or adds new dimensions to motion control. Representatives of the former include controlling additional robotic arms to complete task instructions, or controlling electrical facilities in the environment. The newly added motion control dimension in the latter type of application includes changing the acceleration of the motion[105] or switching the states of the system[106].

One of the motivations for introducing the hybrid control paradigm is to increase the movement speed of a brain-controlled wheelchair or a brain-controlled robot. A typical system[107] uses the SSVEP paradigm to control the forward and backward movement of the wheelchair while using SMR to control the steering. Compared with the non-hybrid system, it greatly reduces the completion time of the movement task.

At the same time, the hybrid BCI also provides the possibility for the design of “brain switch”. Patients who use low-level commands to continuously control a brain-controlled wheelchair usually report that they cannot maintain the mental state required to output forward and backward commands which account for most of the time in the free control process[108]. This is where “brain switch” comes into play. In Ref. [109] “brain switch” is defined as the control paradigm whose output can decide which of its subsequent paradigms can be activated. In the context of a brain-controlled wheelchair, “brain switch” can be used to activate/deactivate the wheelchair’s forward command[110], thus reducing the burden on users to maintain their mental states. Ref[111]used the post-imagery beta ERS is detected in the EEG during motor imagery to realize a practical brain switch. A brain switch can also rely on SSVEPs with a high amplitude threshold[112].

In the future, intelligent “brain switch” combined with novel user mental states recognition algorithm can be developed to let automatic navigation system take control of the electric wheelchair whenever the user feels needed, so that the user can not only control the wheelchair to safely drive through the complex environment using low-level commands, but also enjoy the convenience brought by intelligent high-level control instructions.

5 Conclusion

Brain computer interface is used in navigation application in both virtual and real environment as an alternative option for users with impaired motor functions to convey locomotion intensions. This paper gives a brief overview of BCI navigation applications that have been used in both real and virtual environments in the past 20 years. The shift of control mode from synchronous to asynchronous is shared by navigation applications both in the virtual and real environment, as the latter is more intuitive and poses much higher information transfer rate. The contradiction between high-level commands and low-level commands is introduced as the main line to review the two major applications of BCI navigation designed for electric wheelchairs and mobile robot. Research challenges including suboptimal classification methods, insufficient consideration of human factors should be solved to provide a better user experience. Finally, new trends including hybrid BCI for BCI navigation may provide possibilities toward the popularization of BCI navigation applications to scenarios outside the laboratory.

References

[1] NICOLAS-ALONSO L F, GOMEZ-GIL J. Brain Computer Interfaces, a Review[J]. Sensors, 2012, 12(2): 1211-1279.
DOI: 10.3390/s120201211

[2] BEVERINA F, PALMAS G, SILVONI S, et al. User adaptive BCIs: SSVEP and P300 based interfaces[J]. Psychology Journal, 2003, 1(4): 331-354.

[3] WANG Y, WANG R, GAO X, et al. A practical VEP-based brain-computer interface[J]. IEEE Transactions on Neural Systems & Rehabilitation Engineering, 2006, 14(2): 234-240.
DOI: 10.1109/TNSRE.2006.875576

[4] GALáN F, NUTTIN M, LEW E, et al. A brain-actuated wheelchair: asynchronous and non-invasive Brain-computer interfaces for continuous control of robots[J]. CLINICAL NEUROPHYSIOLOGY -SHANNON-, 2008, 119(9): 2159-2169.
DOI: 10.1016/j.clinph.2008.06.001

[5] ITURRATE I, ANTELIS J M, KUBLER A, et al. A Noninvasive Brain-Actuated Wheelchair Based on a P300 Neurophysiological Protocol and Automated Navigation[J]. IEEE Transactions on Robotics, 2009, 25(3): 614-627.
DOI: 10.1109/TRO.2009.2020347

[6] TSUI C, GAN J Q, HU H. A Self-Paced Motor Imagery Based Brain-Computer Interface for Robotic Wheelchair Control[J]. Clinical Eeg & Neuroscience, 2011, 42(4): 225-229.
DOI: 10.1177/155005941104200407

[7] LOPES A C, PIRES G, NUNES U. RobChair: Experiments evaluating Brain-Computer Interface to steer a semi-autonomous wheelchair[C]. 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2012 : 5135-5136.

[8] OMAR P R, RAQUEL V C, OSCAR Y S. Scenario Screen: A Dynamic and Context Dependent P300 Stimulator Screen Aimed at Wheelchair Navigation Control[J]. Computational and Mathematical Methods in Medicine,2018,(2018-2-14), 2018, 2018: 1-16.
DOI: 10.1155/2018/7108906

[9] ESCOLANO C, MURGUIALDAY A R, MATUZ T, et al. A Telepresence Robotic System operated with a P300-based Brain-Computer Interface: Initial Tests with ALS patients[J]. Conf Proc IEEE Eng Med Biol Soc, 2009, 2010(10): 4476-4480.
DOI: 10.1109/IEMBS.2010.5626045
[10] VOURVOPOULOS A, FERREIRA A, BADIA S. NeuRow: An Immersive VR Environment for Motor-Imagery Training with the Use of Brain-Computer Interfaces and Vibrotactile Feedback[C]. International Conference on Physiological Computing Systems, 2016 : .
[11] LEEB R, SETTGAST V, FELLNER D, et al. Self-paced exploration of the Austrian National Library through thought[J]. International Journal of Bioelectromagnetism, 2007, : .
[12] LEEB R, KEINRATH C, FRIEDMAN D, et al. Walking by Thinking: The Brainwaves Are Crucial, Not the Muscles![J]. Presence Teleoperators & Virtual Environments, 2006, 15(5): 500-514.
DOI: 10.1162/pres.15.5.500
[13] PFURTSCHELLER G, LEEB R, KEINRATH C, et al. Walking from thought[J]. Brain Research, 2006, 1071(1): 145-152.
DOI: 10.1016/j.brainres.2005.11.083
[14] LEEB R, SCHERER R, KEINRATH C, et al. Exploring virtual environments with an EEG-based BCI through motor imagery[J]. Biomedizinische Technik Biomedical Engineering, 2005, 50(4): 86-91.
DOI: 10.1515/BMT.2005.012
[15] SHIN B G, KIM T, JO S. Non-invasive brain signal interface for a wheelchair navigation[C]. 2010 International Conference on Control, Automation and Systems (ICCAS 2010), 2010 : .
[16] HEMA C R, PAULRAJ M P. Control Brain Machine Interface for a Power Wheelchair[M]. 5th Kuala Lumpur International Conference on Biomedical Engineering 2011, 2011.
[17] CHAI R, LING S H, HUNTER G P, et al. Mental non-motor imagery tasks classifications of brain computer interface for wheelchair commands using genetic algorithm-based neural network[C]. The 2012 International Joint Conference on Neural Networks (IJCNN), 2012 : .
DOI: 10.1109/IJCNN.2012.6252499
[18] DUAN J, LI Z, YANG C, et al. Shared control of a brain-actuated intelligent wheelchair[J]. IEEE, 2015, : .
DOI: 10.1109/WCICA.2014.7052737
[19] JIANG J, AN W, YU G, et al. Brain-actuated humanoid robot control using one class motor imagery task[C]. 2013 Chinese Automation Congress (CAC), 2013 : .
[20] VARONAMOYA S, VELASCOALVAREZ F, SANCHAROS S, et al. Wheelchair navigation with an audio-cued, two-class motor imagery-based brain-computer interface system[J]. IEEE, 2015, : .
DOI: 10.1109/NER.2015.7146588
[21] RONANGEVIN R, FERNáNDEZRODRíGUEZ Á, VELASCOáLVAREZ F. Brain-Controlled Wheelchair Through Discrimination of Two Mental Tasks[J]. Springer, Cham, 2016, : .
DOI: 10.1007/978-3-319-56994-9_38
[22] PUANHVUAN D, KHEMMACHOTIKUN S, WECHAKARN P, et al. Navigation-synchronized multimodal control wheelchair from brain to alternative assistive technologies for persons with severe disabilities[J]. Cognitive Neurodynamics, 2017, 11(2): 117.
DOI: 10.1007/s11571-017-9424-6
[23] FARMAKI C, CHRISTODOULAKIS G, SAKKALIS V. Applicability of SSVEP-based brain-computer interfaces for robot navigation in real environments[C]. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016 : .
[24] KUCUKYILDIZ G, OCAK H, KARAKAYA S, et al. Design and Implementation of a Multi Sensor Based Brain Computer Interface for a Robotic Wheelchair[J]. Journal of Intelligent & Robotic Systems, 2017, 87(2): 1-17.

[25] MALETE T N, MORUTI K, THAPELO T S, et al. EEG-based Control of a 3D Game Using 14-channel Emotiv Epoc+[C]. 2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM), 2019 : .
[26] HACHEM, A., LAMTI, et al. When mental fatigue maybe characterized by Event Related Potential (P300) during virtual wheelchair navigation: Computer Methods in Biomechanics and Biomedical Engineering: Vol 19, No 16[J]. Computer Methods in Biomechanics & Biomedical Engineering, 2016, : .
DOI: 10.1080/10255842.2016.1183198
[27] HAZRATI M K, HOFMANN U G. Avatar navigation in Second Life using brain signals[C]. IEEE International Symposium on Intelligent Signal Processing, 2013 : 1-7.
[28] CONGEDO M, LOTTE F, LéCUYER A. Classification of movement intention by spatially filtered electromagnetic inverse solutions[J]. Physics in Medicine and Biology, 2006, 51(8): 1971-1989.
DOI:10.1088/0031-9155/51/8/002
[29] LOTTE F, LECUYER A, ARNALDI B. FuRIA: An Inverse Solution Based Feature Extraction Algorithm Using Fuzzy Set Theory for Brain–Computer Interfaces[J]. IEEE Transactions on Signal Processing, 2009, 57(8): 3253-3263.
DOI: 10.1109/TSP.2009.2020752
[30] RIVET B, SOULOUMIAC A, ATTINA V, et al. xDAWN algorithm to enhance evoked potentials: application to brain-computer interface[J]. IEEE transactions on bio-medical engineering, 2009, 56(8): 2035.
DOI: 10.1109/TBME.2009.2012869
[31] WANG H, BEZERIANOS A. Brain-controlled wheelchair controlled by sustained and brief motor imagery BCIs[J]. Electronics Letters, 2017, 53(17): 1178-1180.
DOI: 10.1049/el.2017.1637
[32] YANG Y, LIU Y, JIANG J, et al. An Asynchronous Control Paradigm Based on Sequential Motor Imagery and Its Application in Wheelchair Navigation[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2018, PP(12): 1-1.
DOI: 10.1109/TNSRE.2018.2881215
[33] CHAE Y, JO S, JEONG J. Brain-actuated humanoid robot navigation control using asynchronous Brain-Computer Interface[J]. International IEEE/EMBS Conference on Neural Engineering, 2011, : .
DOI: 10.1109/NER.2011.5910600
[34] RUI Z, LI Y, YAN Y, et al. An intelligent wheelchair based on automated navigation and BCI techniques[J]. Conf Proc IEEE Eng Med Biol Soc, 2014, 2014: 1302-1305.
DOI: 10.1109/EMBC.2014.6943837
[35] LIN Y T, KUO C H. Development of SSVEP-based intelligent wheelchair brain computer interface assisted by reactive obstacle avoidance[C]. IEEE International Conference on Industrial Technology, 2016 : 1572-1577.
[36] WOEHRLE H, KRELL M M, STRAUBE S, et al. An Adaptive Spatial Filter for User-Independent Single Trial Detection of Event-Related Potentials[J]. IEEE transactions on bio-medical engineering, 2015, 62(7): 1696-1705.
DOI: 10.1109/TBME.2015.2402252
[37] LOTTE, F., BOUGRAIN, et al. A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update[J]. Journal of neural engineering, 2018, : .
DOI: 10.1088/1741-2552/aab2f2
[38] KALUNGA E K, CHEVALLIER S, BARTHéLEMY Q, et al. Online SSVEP-based BCI using Riemannian geometry[J]. Neurocomputing, 2016, : 55-68.
DOI: 10.1016/j.neucom.2016.01.007
[39] LAWHERN V J, SOLON A J, WAYTOWICH N R, et al. EEGNet: A Compact Convolutional Network for EEG-based Brain-Computer Interfaces[J]. Journal of Neural Engineering, 2016, 15(5): 056013.056011-056013.056017.
DOI: 10.1088/1741-2552/aace8c

[40] KWAK N S, MüLLER K, LEE S W. A convolutional neural network for steady state visual evoked potential classification under ambulatory environment[J]. PLOS ONE, 2017, 12.
DOI:10.1371/journal.pone.0172578
[41] SCHIRRMEISTE R T, SPRINGENBERG J T, FIEDERE L, et al. Deep learning with convolutional neural networks for EEG decoding and visualization[J]. Human Brain Mapping, 2017, : .
DOI: 10.1002/hbm.23730
[42] SANNELLI C, VIDAURRE C, MüLLER K-R, et al. A large scale screening study with a SMR-based BCI: Categorization of BCI users and differences in their SMR activity[J]. PLoS ONE, 2019, 14(1).
DOI: 10.1371/journal.pone.0207351
[43] CHAN S, MINKYU. Performance variation in motor imagery brain-computer interface: A brief review[J], : .
[44] GAYRAUD N, RAKOTOMAMONJY A, CLERC M. Optimal Transport Applied to Transfer Learning For P300 Detection[J], 2017, : .
[45] HSU W Y. EEG-based motor imagery classification using enhanced active segment selection and adaptive classifier[J]. Computers in Biology & Medicine, 2011, 41(8): 633-639.
DOI: 10.1016/j.compbiomed.2011.05.014
[46] WU Z, LAI Y, WU D, et al. Stimulator selection in SSVEP-based BCI[J]. Medical Engineering & Physics, 2008, 30: 1079--1088.
DOI: 10.1016/j.medengphy.2008.01.004
[47] STAMPS K, HAMAM Y. Towards Inexpensive BCI Control for Wheelchair Navigation in the Enabled Environment – A Hardware Survey[J]. Springer-Verlag, 2010, : .
[48] XU M, XIAO X, WANG Y, et al. A Brain—Computer Interface Based on Miniature-Event-Related Potentials Induced by Very Small Lateral Visual Stimuli[J]. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING BME, 2018, : .
[49] DIEZ P F, MUTT V A, LACIAR E, et al. Mobile robot navigation with a self-paced brain–computer interface based on high-frequency SSVEP[J]. Robotica, 2014, 32(pt.5): 695-709.
DOI: 10.1017/S0263574713001021
[50] FA RWELL L A, DONCHIN E. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials[J]. Electroencephalography & Clinical Neurophysiology, 1988, 70(6): 510-523.
DOI: 10.1016/0013-4694(88)90149-6
[51] NAWROJ A I, WANG S, YU Y C, et al. A brain-computer interface for robot navigation[C]. Bioengineering Conference (NEBEC), 2012 38th Annual Northeast, 2012 : .
[52] ESCOLANO C. A telepresence mobile robot controlled with a noninvasive brain-computer interface[J]. IEEE Transactions on Systems Man & Cybernetics Part B, 2012, 42(3): 793-804.
[53] RON-ANGEVIN R, DíAZ-ESTRELLA A, VELASCO-ÁLVAREZ F. A two-class brain computer interface to freely navigate through virtual worlds / Ein Zwei-Klassen-Brain-Computer-Interface zur freien Navigation durch virtuelle Welten[J]. Biomedizinische Technik Biomedical Engineering, 2009, 54(3): 126-133.
DOI: 10.1109/TSMCB.2011.2177968
[54] ED LINGER G, HOLZNER C, GUGER C, et al. Brain-computer interfaces for goal orientated control of a virtual smart home environment[C]. International IEEE/EMBS Conference on Neural Engineering, 2009 : .
[55] GENTILETTI G G, GEBHART J G, ACEVEDO R C, et al. Command of a simulated wheelchair on a virtual environment using a brain-computer interface[J]. Irbm, 2009, 30(5-6): 218-225.
DOI: 10.1016/j.irbm.2009.10.006
[56] JAYARAM V, ALAMGIR M, ALTUN Y, et al. Transfer Learning in Brain-Computer Interfaces[J]. IEEE Computational Intelligence Magazine, 2015, 11(1): 20-31.
DOI:10.1109/MCI.2015.2501545

[57] KINDERMANS P J, SCHREUDER M, SCHRAUWEN B, et al. True Zero-Training Brain-Computer Interfacing – An Online Study[J]. PLoS ONE, 2014, 9(7): e102504.
DOI: 10.1371/journal.pone.0102504
[58] GENG T, DYSON M, TSUI C, et al. A 3-class asynchronous BCI controlling a simulated mobile robot[J]. Conf Proc IEEE Eng Med Biol Soc, 2007, 2007: 2524-2527.
DOI: 10.1109/IEMBS.2007.4352842
[59] VELASCO-LVAREZ F, RON-ANGEVIN R. Asynchronous Brain-Computer Interface to Navigate in Virtual Environments Using One Motor Imagery[C]. International Work-Conference on Artificial Neural Networks, 2009 : .
DOI: 10.1007/978-3-642-02478-8_87
[60] Brain-computer communication: motivation, aim, and impact of exploring a virtual apartment[J]. IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society, 2007, : .
DOI:10.1109/TNSRE.2007.906956
[61] FRIEDMAN D, LEEB R, GUGER C, et al. Navigating virtual reality by thought: What is it like?[J]. Presence, 2007, 16(1): 100-110.
DOI: 10.1162/pres.16.1.100
[62] ZICH C, DEBENER S, KRANCZIOCH C, et al. Real-time EEG feedback during simultaneous EEG-fMRI identifies the cortical signature of motor imagery[J]. Neuroimage, 2015, 114: 438-447.
DOI: 10.1016/j.neuroimage.2015.04.020
[63] JEANNEROD M. Mental imagery in the motor context[J]. Neuropsychologia, 2011, 33(11): 1419.
DOI: 10.1016/0028-3932(95)00073-C
[64] PINEDA J A, SILVERMAN D S, VANKOV A, et al. Learning to control brain rhythms: Making a brain-computer interface possible[J]. IEEE Trans Neural Syst Rehabil Eng, 2003, 11(2): 181-184.
DOI: 10.1109/TNSRE.2003.814445
[65] BAYLISS J D. Use of the evoked potential P3 component for control in a virtual apartment[J]. IEEE Trans Neural Systems & Rehabilitation Engineering, 2003, 11(2): 113-116.
DOI: 10.1109/TNSRE.2003.814438
[66] SUH D, CHO H S, GOO J, et al. Virtual Navigation System for the Disabled by Motor Imagery[M]. Advances in Computer, Information, and Systems Sciences, and Engineering, 2006.
[67] LEEB R, FRIEDMAN D, MüLLER-PUTZ G, et al. Self-Paced (Asynchronous) BCI Control of a Wheelchair in Virtual Environments: A Case Study with a Tetraplegic[J]. Computational Intelligence & Neuroence, 2007, 2007: 7.
DOI: 10.1155/2007/79642
[68] TSUI C S L, GAN J Q. Asynchronous BCI Control of a Robot Simulator with Supervised Online Training[C]. Intelligent Data Engineering and Automated Learing(IDEAL 2007), 2007 : .
[69] FUJISAWA J, TOUYAMA H, HIROSE M. EEG-based navigation of immersing virtual environment using common spatial patterns[C]. IEEE Virtual Reality Conference, 2008 : .
[70] SCHERER R, LEE F, SCHLGL A, et al. Toward Self-Paced Brain;Computer Communication: Navigation Through Virtual Worlds[J]. IEEE Transactions on Biomedical Engineering, 2008, 55(2): p.675-682.
DOI: 10.1109/TBME.2007.903709
[71] LU W, WEI Y, YUAN J, et al. Tractor Assistant Driving Control Method Based on EEG Combined With RNN-TL Deep Learning Algorithm[J]. IEEE Access, : .
DOI: 10.1109/ACCESS.2020.3021051
[72] ELENI A. Control of medical robotics and neurorobotic prosthetics by noninvasive Brain-Robot Interfaces via EEG and RFID technology[C]. IEEE International Conference on Bioinformatics & Bioengineering, 2008 : .

[73] FEI W, ZHOU C, XIANG H, et al. BCI control system for humanoid robot based on motor imaginary[C]. Chinese Control and Decision Conference, 2013 : .
[74] ZHENG Y C, KAI K A, WANG C, et al. Navigation in a virtual environment using multiclass motor imagery Brain-Computer Interface[C]. Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB), 2013 IEEE Symposium on, 2013 : .
[75] SCHERER R, FRIEDRICH E, ALLISON B Z, et al. Non-invasive Brain-Computer Interfaces: Enhanced Gaming and Robotic Control[C]. Advances in Computational Intelligence - 11th International Work-Conference on Artificial Neural Networks, IWANN 2011, Torremolinos-Málaga, Spain, June 8-10, 2011, Proceedings, Part I, 2011 : .
[76] VELASCO-LVAREZ F, RON-ANGEVIN R, SILVA-SAUER L D, et al. Audio-Cued SMR Brain-Computer Interface to Drive a Virtual Wheelchair[C]. Advances in Computational Intelligence - 11th International Work-Conference on Artificial Neural Networks, IWANN 2011, Torremolinos-Málaga, Spain, June 8-10, 2011, Proceedings, Part I, 2011 : .
[77] MüLLER S, DIEZ P F, BASTOS-FILHO T F, et al. Robotic Wheelchair Commanded by People with Disabilities Using Low/High-Frequency SSVEP-based BCI[M]. World Congress on Medical Physics and Biomedical Engineering, June 7-12, 2015, Toronto, Canada, 2015.
[78] ERIC, LACIAR, ENRIQUE, et al. Mobile robot navigation with a self-paced brain-computer interface based on high-frequency SSVEP[J]. Robotica: International journal of information, education and research in robotics and artificial intelligence, 2014, 32(Aug. Pt.5): 695-709.
[79] CHEN S C, CHEN Y J, ZAENI I, et al. A Single-Channel SSVEP-Based BCI with a Fuzzy Feature Threshold Algorithm in a Maze Game[J]. International Journal of Fuzzy Systems, 2017, : .
DOI: 10.1007/s40815-016-0289-3
[80] LIU Y, LI J, LI Z. An Indoor Navigation Control Strategy for a Brain-Actuated Mobile Robot[C]. 2018 3rd International Conference on Advanced Robotics and Mechatronics (ICARM), 2018 : .
[81] YUAN Y, LI Z, LIU Y. Brain Teleoperation of a Mobile Robot Using Deep Learning Technique[C]. 2018 3rd International Conference on Advanced Robotics and Mechatronics (ICARM), 2018 : .
[82] LIU Y, LI Z, ZHANG T, et al. Brain-Robot Interface-Based Navigation Control of a Mobile Robot in Corridor Environments[J]. IEEE Transactions on Systems Man & Cybernetics Systems, 2018, PP: 1-12.
DOI: 10.1109/TSMC.2018.2833857
[83] FARMAKI C, KRANA M, PEDIADITIS M, et al. Single-Channel SSVEP-Based BCI for Robotic Car Navigation in Real World Conditions[C]. 2019 IEEE 19th International Conference on Bioinformatics and Bioengineering (BIBE), 2019 : .
[84] KOO B, LEE H, NAM Y, et al. Immersive BCI with SSVEP in VR head-mounted display[C]. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015 : 1103-1106.
DOI: 10.1109/EMBC.2015.7318558
[85] TATTOLI G, BUONGIORNO D, LOCONSOLE C, et al. A novel BCI-SSVEP based approach for control of walking in Virtual Environment using a Convolutional Neural Network[C]. International Joint Conference on Neural Networks, 2014 : .
[86] DIEZ P F, MUT V A, PERONA E, et al. Asynchronous BCI control using high-frequency SSVEP[J]. Journal of NeuroEngineering and Rehabilitation, 2011, 8(1): 39.
DOI: 10.1186/1743-0003-8-39
[87] CHUNG M, CHEUNG W, SCHERER R, et al. Towards hierarchical BCIs for robotic control[C]. Neural Engineering (NER), 2011 5th International IEEE/EMBS Conference on, 2011 : .
[88] LEGéNY J, ABAD R V, LéCUYER A, et al. Navigating in virtual worlds using a self-paced SSVEP-based Brain-Computer Interface with integrated stimulation and real-time feedback[J]. Presence, 2014, 20(6): 529-544.
DOI: 10.1162/PRES_a_00075
[89] ANNESE V F, MEZZINA G, VENUTO D D. Wireless Brain-Computer Interface for Wheelchair Control by Using Fast Machine Learning and Real-Time Hyper-Dimensional Classification[J]. Springer, Cham, 2017, : .

[90] YU Y C, NAWROJ A, WANG S, et al. Mobile robot navigation through a brain computer interface[C]. 2012 IEEE Signal Processing in Medicine and Biology Symposium (SPMB), 2012 : .
DOI: 10.1109/SPMB.2012.6469469
[91] CURTIN, AYAZ, LIU, et al. A P300-based EEG-BCI for spatial navigation control[J]. Conf Proc IEEE Eng Med Biol Soc, 2012, : .
DOI: 10.1109/EMBC.2012.6346805
[92] LOPES A C, PIRES G, VAZ L, et al. Wheelchair navigation assisted by Human-Machine shared-control and a P300-based Brain Computer Interface[C]. IEEE/RSJ International Conference on Intelligent Robots & Systems, 2011 : .
[93] CHERUBINI A, ORIOLO G, MACRI F, et al. Development of a multimode navigation system for an assistive robotics project[C]. Robotics and Automation, 2007 IEEE International Conference on, 2007 : .
DOI: 10.1109/ROBOT.2007.363668
[94] DIEZ, P. F, MUT, et al. Mobile robot navigation with a self-paced brain-computer interface based on high-frequency SSVEP[J]. Robotica Cambridge, 2014, : .
[95] SU W, LI Z. Brain-computer interface based stochastic navigation and control of a semiautonomous mobile robot in an indoor environment[J], 2017, : 718-723.
DOI: 10.1109/ICARM.2017.8273250
[96] ZHANG Z, WANG W, SONG P, et al. Design of an SSVEP-based BCI System with Vision Assisted Navigation Module for the Cooperative Control of Multiple Robots[C]. 2017 IEEE 7th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER), 2018 : .
DOI: 10.1109/ICARM.2017.8273250
[97] NOURMOHAMMADI A, JAFARI M, ZANDER T O. A Survey on Unmanned Aerial Vehicle Remote Control Using Brain–Computer Interface[J]. IEEE Transactions on Human-Machine Systems, 2018, PP(99): 1-12.
DOI: 10.1109/THMS.2018.2830647
[98] AK CE A, JOHNSON M, BRETL T. Remote teleoperation of an unmanned aircraft with a brain-machine interface: Theory and preliminary results[C]. IEEE International Conference on Robotics & Automation, 2010 : .
[99] LAFLEUR K, CASSADY K, DOU D A, et al. Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain-computer interface[J]. Journal of Neural Engineering, 2013, 10(4): 046003.
DOI: 10.1088/1741-2560/10/4/046003
[100] KIM B H, KIM M, JO S. Quadcopter flight control using a low-cost hybrid interface with EEG-based classification and eye tracking[J]. Computers in Biology & Medicine, 2014, 51: 82-92.
DOI: 10.1016/j.compbiomed.2014.04.020
[101] ROYER A S, DOUD A J, ROSE M L, et al. EEG Control of a Virtual Helicopter in 3-Dimensional Space Using Intelligent Control Strategies[J]. IEEE Transactions on Neural Systems & Rehabilitation Engineering, 2010, 18(6): 581-589.
DOI: 10.1109/TNSRE.2010.2077654
[102] DOUD A J, LUCAS J P, PISANSKY M T, et al. Continuous Three-Dimensional Control of a Virtual Helicopter Using a Motor Imagery Based Brain-Computer Interface[J]. Plos One, 2011, 6.
DOI: 10.1371/journal.pone.0026322
[103] ALRAJHI W, HOSNY M, ALWABIL A, et al. Human Factors in the Design of BCI-Controlled Wheelchairs[C]. Springer International Publishing, 2014 : .
DOI: 10.1007/978-3-319-07230-2_49
[104] MAJED, AL, ZAYER, et al. Virtual Locomotion: a Survey[J]. IEEE Transactions on Visualization & Computer Graphics, 2018, : .
DOI: 10.1109/TVCG.2018.2887379
[105] LONG J, LI Y, WANG H, et al. A Hybrid Brain Computer Interface to Control the Direction and Speed of a Simulated or Real Wheelchair[J]. IEEE Transactions on Neural Systems & Rehabilitation Engineering, 2012, 20(5): 720-729.

DOI: 10.1109/TNSRE.2012.2197221
[106] CAO L, LI J, JI H, et al. A hybrid brain computer interface system based on the neurophysiological protocol and brain-actuated switch for wheelchair control[J]. Journal of Neuroence Methods, 2014, 229: 33-43.
DOI: 10.1016/j.jneumeth.2014.03.011
[107] Evaluation and application of a hybrid brain computer interface for real wheelchair parallel control with multi-degree of freedom[J]. International Journal of Neural Systems, 2014, 24(04): 1450014-.
DOI: 10.1142/S0129065714500142
[108] ÁLVARO F, FRANCISCO V, MANON B S, et al. Evaluation of Switch and Continuous Navigation Paradigms to Command a Brain-Controlled Wheelchair[J]. Frontiers in Neuroence, 2018, 12: 438-.
DOI：10.3389/fnins.2018.00438
[109] PFURTSCHELLER G, ALLISON B Z, BRUNNER C, et al. The Hybrid BCI[J]. Frontiers in Neuroscience, 2010, 4(30): 30-30.
DOI: 10.3389/fnpro.2010.00003
[110] LI Y, PAN J, WANG F, et al. A Hybrid BCI System Combining P300 and SSVEP and Its Application to Wheelchair Control[J]. IEEE Transactions on Biomedical Engineering, 2013, 60(11): 3156-3166.
DOI: 10.1109/TBME.2013.2270283
[111] PFURTSCHELLER G, NEUPER C, BRUNNER C, et al. Beta rebound after different types of motor imagery in man[J]. Neuroscience Letters, 2005, 378(3): 156-159.
DOI: 10.1016/j.neulet.2004.12.034
[112] NAITO E, KOCHIYAMA T, KITADA R, et al. Internally simulated movement sensations during motor imagery activate cortical motor areas and the cerebellum[J]. J Neurosci, 2002, 22(9): 3683-3691.