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Developments in Hybrid Brain-Computer Interfaces: Foundations, Architecture, and Uses

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Abstract: Two major issues have plagued traditional brain-computer interface (BCI) systems: the control command issue and the low detection performance. In order to overcome these obstacles, the researchers have suggested a hybrid brain-computer interface (hBCI). This study analyzes three forms of hBCI: multisensory hBCI, hBCI based on multimodal signals, and hBCI based on multiple brain models. It also primarily discusses the research progress of hBCI. By examining the general concepts, paradigm designs, experimental findings, benefits, and uses of the most recent hBCI system, we discovered that utilizing hBCI technology can enhance BCI detection performance and accomplish multidegree/multifunctional control, which is noticeably better than single-mode BCIs.

1. Introduction

All The technique known as brain-computer interface (BCI) converts impulses produced by brain activity into control signals without the use of muscles or peripheral nerves. These signals are then used to operate external devices [1]. Because of its potential for clinical use, BCI has garnered more and more attention in recent years from both the public and academia. Patients with severe motor impairment, for instance, may benefit greatly from BCI's ability to enhance or repair motor function. Nonimplanting techniques such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), electroencephalography (EEG), and functional near-infrared spectroscopy (fNIRS) are the most widely utilized techniques for obtaining brain signals [2]. Because EEG is noninvasive, portable, inexpensive, performs well, responds in real time, and has fewer technological requirements than other brain signals, it has been utilized extensively in BCI despite having a low signal-to-noise ratio and spatial resolution. The EEG-based BCI is mostly described in this publication. The P300 visual-evoked potential, which was proposed by Farwell and Donchin in 1988 [3], the steady-state-evoked potential (like the steady-state visual-evoked potential (SSVEP)) [4], and event-related desynchronization/synchronization (ERD/ERS) produced by motor imagination (MI) [5] are common brain models utilized in EEG-based hybrid BCIs.

A single-signal input (such as EEG, electromyography (EMG), and electro-oculogram (EOG)), a single sensory stimuli (such as visual, auditory, and tactile only), or a single brain pattern (such as the above P300 potential and SSVEP) are often the only components of conventional EEG-based BCI. The paradigm design, brain signal processing algorithms, and applications of the single-mode BCI system have advanced significantly. Low information transfer rates (ITRs), low man-machine adaptation, and high dynamics/nonstationarity of brain signals are only a few of the difficulties modern BCI systems have been dealing with [6, 7]. Here, we primarily examine two basic issues and present a hybrid BCI method designed to resolve them:

(1) Multidegree/multifunctional control: Many devices, including wheelchairs, robots, and artificial limbs, require multidegree/multifunctional control. For example, the wheelchair control has features for direction, speed, and start/stop. However, producing efficient multiple control signals is challenging for a traditional simple BCI [8].
(2) Enhancement of detection performance: Despite numerous attempts over the years to enhance BCI's detection performance, many applications, particularly those involving patients, still lag behind in terms of classification accuracy, information transfer rate (ITR), and false-positive rate (FPR). The condition for managing a BCI application is not met by about 13% of healthy users who are BCI illiterate [9]. Furthermore, the BCI systems' complexity and user acceptability ought to be mentioned as significant performance factors.

Some researchers have suggested a hybrid BCI (hBCI) as a solution to the two basic problems mentioned above. According to Allison [8], a hBCI system is made up of a BCI system and an add-on system, which may be a second BCI system but is made to accomplish particular tasks more effectively than a traditional BCI. Overcoming the current drawbacks and restrictions of traditional BCI systems is the primary objective of hBCI. To show how hBCI techniques could be used to overcome these issues, this research evaluated recent advancements in hBCIs. Three primary categories of hybrid BCIs have been developed, and the definition of hBCIs has been revised and expanded. By examining the paradigm designs, control strategies, and experimental outcomes of each form of hybrid BCI, the concept was summed up and a number of representative hybrid BCI systems were identified. Lastly, the research path and future prospects of hBCI were discussed.

2. Overview of Hybrid BCI

Despite having existed prior to 2010, the development of hBCI has accelerated in recent years. Only three journal articles were located prior to 2010 using the "Web of Science" search engine and title-abstract-keyword (such as "brain-computer interface" or "BCI") and "hybrid" or "multimodal"). However, throughout the two periods of 2010–2014 and 2015–2019, this number increased to 148 and 293, respectively. It is clear that there has been a sharp increase in hBCI publications in recent years. It should be noted that research on a single BCI that combines just features and methods that can enhance performance is not included. The terms "multimodal BCI" and "hybrid BCI" are actually very similar. According to Li et al. [9], "multimodal BCI" and "hybrid BCI" are equivalent terminology that share the same concept of BCI.

According to Pfurtscheller et al. [10], the type of hBCI should fulfill the following four requirements in addition to the straightforward integration of various BCIs: (1) The activity originates directly from the brain; (2) it should be recorded using at least one brain signal acquisition technique, which may involve electrical, magnetic, or hemodynamic changes; (3) the signal needs to be processed online or in real time to create communication between the brain and the computer in order to produce control commands; and (4) feedback needs to be given based on the brain activity results for communication and control.

Figure 1 illustrates the two steps of brain signal processing that make up the signal flow of a hBCI system. (1) Several signals (like EEG and NIRS) or brain patterns (like P300 and SSVEP) that are triggered by multisensory stimuli (like audiovisual stimuli) may be used as the signal input in the signal acquisition process. (2) An hBCI system can only offer either a single-output/control signal or multiple-output/control signals during signal processing. In the former scenario, data fusion is typically needed at the feature or decision level when there are many brain patterns or signals involved. In the latter scenario, distinct brain patterns identified by the system may independently regulate numerous control signals, and it is typically not required for these patterns to fuse. The three primary types of hBCI are as follows, as seen in Figure 1:

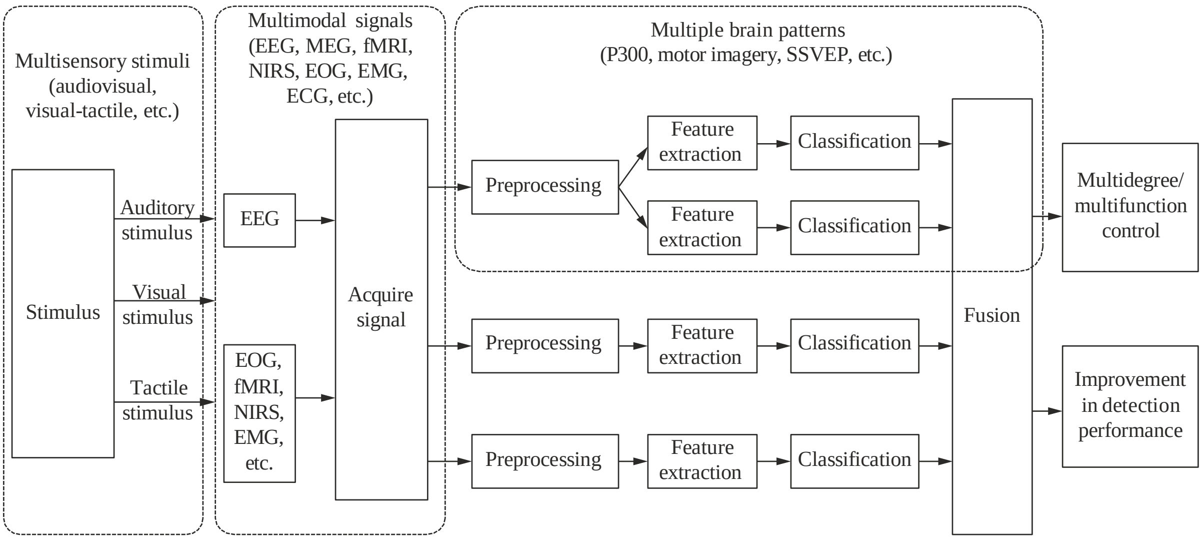

Figure 1: The signal flow of hybrid brain-computer interface discussed in this paper.

(1) hBCI is based on several brain patterns; it employs a minimum of two brain modes, such as MI and P300 or P300 and SSVEP. In this kind of hBCI, a single sensory event can trigger several different brain patterns. According to a number of studies, hybrid integration combined with multimodal stimuli may improve brain patterns, which could improve BCI performance [11].
(2) hBCI with multisensory stimuli: several sensory stimuli, including audiovisual stimuli, can simultaneously generate its brain pattern. Multisensory stimuli are used in this hBCI to induce one or more brain patterns. Multisensory BCIs, according to some researchers, might provide more flexible and approachable paradigms for feedback and control [12].
(3) Multiple signal-based hBCI: this type of hBCI usually combines two or more input signals, such as EEG, MEG, fMRI, fNIRS, EOG, or EMG, with a hybrid BCI system. Different brain signals can be employed for

different purposes and have unique signal properties.

The next sections provide an overview of the state-of-the-art for the three aforementioned types of hBCI, covering their general principles, stimulus paradigm, control techniques, corresponding experimental results, and benefits.

3. Multiple Brain Patterns-Based hBCI

P300, SSVEP, MI, and other brain signals are combined in the first class of hBCIs. Numerous applications have been developed for it, including spell check [13], idle state detection [14], orthotics [15], wheelchair navigation, and control of computer components such the mouse [17], mail client [18], and two-dimensional (2D) cursor [16]. The representative hBCI applications of various brain patterns in recent years are listed in Table 1. This section primarily discusses three types of hBCI: based on MI and SSVEP, based on P300 and SSVEP, and based on MI and P300.

3.1. hBCIs based on SSVEP and P300

Because visual stimuli can elicit both P300 potential and SSVEP, participants can complete a visual attention test without experiencing additional mental strain. The time domain and frequency domain are where the P300 and SSVEP features are found, and there is a notable independency between the two brain patterns. The use of both P300 and SSVEP features may lead to the performance enhancement. Classifying a target from a nontarget may be made easier with the use of extra information provided by the EEG function. In order to build speed-direction-based cursor control, Bi et al. [22] suggested a hybrid paradigm based on SSVEP and P300. In this work, the P300's stimulation was dispersed across the top and bottom of the screen, while the left and right sides of the screen showed the stimulus for detecting SSVEP, which rotates the control device either clockwise or counterclockwise. The accuracy of the hBCI was greater than 90%, according to the results of the support vector machine classification approach. Pan et al. [29] used a hybrid paradigm of SSVEP and P300 to detect awareness in eight patients with disorders of consciousness (DOC). As directed, the patient's SSVEP was evoked by the left and right photographs flickering on a black background at predetermined frequencies of 6.0 and 7.5 Hz, respectively. The BCI system employed the features of P300 and SSVEP to determine which photo the patient had observed. In the meantime, each of the two picture frames was displayed five times at random to induce P300, with each appearance lasting 200 ms and the delay between two consecutive appearances being 800 ms. The experiment involved eight patients: three were in the minimally conscious state (MCS), one was in the locked-in syndrome (LIS), and four were in the vegetative state (VS). One VS patient, one MCS patient, and one LIS patient were able to choose pictures of themselves or other people using the SVM-based classifier (classification accuracy, 66%–100%). This suggests that the patient can be controlled with a hybrid BCI and further demonstrates their cognitive awareness and abilities.

3.2. hBCIs based on SSVEP and MI

Combining SSVEP and MI is justified for four reasons: (1) SSVEP-related brain patterns were generated concurrently; (2) SSVEP is an evoked potential that can be reliably detected in unfamiliar subjects with minimal training, although most new users find it challenging to adjust to the MI task; (3) SSVEP can be detected by a single trial based on EEG data, and the detection does not require an averaging process; and (4) nonvisual training will frustrate subjects, whereas SSVEP offers a potential way to entice them to complete the MI task. In order to offer 24 subjects with effective continuous feedback for MI training, Yu et al. [26] coupled SSVEP and MI based on the aforementioned concepts. To receive accurate feedback at the start of the training process, the classifier first gives the SSVEP a higher weight. Participants' visual attention to SSVEP stimuli decreased throughout the course of the training, but they continued to pay consistent attention to MI conceptual activities. The classifier moves the weight to MI when individuals become accustomed to rhythmic activities. The outcome shown that, after just five sessions, a hBCI can enhance MI training and generate distinct brain patterns (about one and a half hours).

3.3. hBCIs based on MI and P300.

Multidimensional control, which incorporates several independent control signals, is a crucial component of the EEG-based BCI system. Several brain patterns, including MI and P300, can provide these regulatory signals. MI is more efficient at producing sequential control commands, while P300 is a dependable brain pattern for producing discrete control output directives.

For 2D cursor control and target selection, Li and colleagues [16] suggested hBCI that combines P300 potentials with MI brain patterns. The GUI is displayed in Figure 2, where the target and cursor are represented by a square and a circle, respectively. The target's color (blue or green) and cursor's initial position are both randomly supplied. To elicit P300 potentials, the three "UP," three "DOWN," and two "STOP" buttons flash in a random order. Moving the cursor to the target and choosing or rejecting the green or blue target is the user's task. Below is a description of the user's control strategy. To induce P300 potentials, the user can move the cursor to the left or right by visualizing their own left- or right-hand movement, respectively, and to the up- or down-direction by concentrating on one of the three flashing "UP" or "DOWN" buttons. The user can concentrate on one of the two "STOP" buttons if they do not want to advance the pointer vertically.

Target selection and rejection features are necessary to advance the implementation of a BCI mouse. In particular, the user can choose the target by concentrating on a flashing "STOP" button while simultaneously keeping motor imagery in an inactive state once the cursor lands on the target of interest (green square). The user can reject the goal (blue square) if it is not of interest by continuing to visualize movement to the left or right while avoiding any flashing buttons.

The two components of the 2D cursor control method are motor-imagery detection for horizontal movement control and P300 detection for vertical movement control; the specifics are described in [19]. Three steps make up the signal processing process for P300 detection: SVM classification, P300 feature extraction, and low-pass filtering. Common average reference (CAR) spatial filtering, band-pass filtering of the particular mu rhythm band (8–13 Hz), feature extraction using a CSP method, and SVM classification are the signal processing steps for motor imagery recognition. The hybrid characteristics of P300 potentials and MI served as the foundation for the target selection or rejection algorithm. The same algorithms mentioned above are used to extract the features of the P300 potentials and MI. Then, for each trial, a hybrid feature vector is created by concatenating the MI's feature vector with the P300 potentials' feature vector. This feature vector is then fed into the SVM for classification.

The online experiment, which involved one session of 80 trials per individual, was completed by eleven healthy participants. There were two consecutive tasks in each trial. In the first exercise, participants were told to move the cursor to a target that appeared on the screen at a randomly chosen location. The subject was given instructions to complete the second task, which involved choosing or rejecting the target based on its color (green for selection and blue for rejection), after the cursor had touched the target. The second task's time interval was set at two seconds. All subjects had an average trial duration of 18.96 seconds, an accuracy of 92.84% for successful trials, and an accuracy of 93.99% for target selection when the cursor was successfully moved to the target. To further illustrate the benefits of P300 potential and MI hybrid features for target selection/rejection in comparison to the usage of P300 potential or MI features alone, a number of datasets were additionally gathered for offiine analysis. The accuracy of using the hybrid features was much greater than using only the MI or P300 potential features, according to the experimental data (hybrid features: 83.10 ± 2.12%; MI features: 71.68 ± 2.41%; P300 features: 80.44 ± 1.82%). Long et al. [28] developed a hybrid BCI paradigm based on MI and P300 that uses the BCI cursor to operate real wheelchairs by giving five subjects orders for direction (left or right) and speed control (acceleration and deceleration).

There are three benefits to each of these hybrid systems. First, using the MI and P300 potential, two separate control signals are produced. Second, the user has the ability to move the pointer to a randomly chosen target from any place. Third, compared to control strategies utilizing MI-only or P300-only, the hybrid control technique utilizing MI and P300 potential offers superior identification performance.

4.hBCIs with multiple senses

Humans have several senses that offer channels for taking in information about the outside world. Top-down attention is improved when various sensory stimuli are integrated, and these improved effects could help BCI systems function better. Taking this into account, a visual-tactile and audiovisual hBCI was proposed, utilizing bimodal stimulation to enhance system function. The representative uses of multimodal hBCIs in recent years are listed in Table 2.

4.1.audiovisual hBCIs.

An official audiovisual-based P300 speller and related data analysis findings were proposed by Belitski et al. [30]. Their investigation of seven healthy participants revealed that the P300 reaction was more intense under audiovisual circumstances as opposed to only visual or auditory ones. Parallel spellers for BCI unrelated to gaze for healthy patients, in which the visual and auditory domains are independent of one another, were also investigated by An et al. [32]. According to their findings, 15 users have an average accuracy rate of 87.7% when it comes to spelling online. According to these current findings, audiovisual integration might be a viable strategy to modify brain patterns and boost BCI functionality. A unique audiovisual BCI system based on time-synchronous visual and auditory inputs was proposed by Wang et al. [33]. Two speakers are positioned laterally to the display, and two number buttons—two randomly selected from 0 to 9—are situated on the left and right sides of the GUI of this audiovisual BCI. Each of the two buttons flashes differently. The ipsilateral speaker presents the cor-responding spoken number when a number button is visually enhanced. Ten healthy volunteers took part in the experiment, which involves presenting the user with an audio-visual stimulus that is temporally, spatially, and semantically coherent and lasts for 300 ms. The time between stimuli is randomized from 700 to 1500 ms. Three sessions, representing the visual-only, audio-only, and audiovisual conditions, were conducted in a random order throughout the experiment. The subject completed a training run of ten trials and a test run of thirty trials in each session. For all healthy subjects, the online average accuracy of the visual-only, auditory-only, and audiovisual sessions was 62.33%, 86.33%, and 95.67%, respectively. The visual-only and auditory-only BCIs were greatly outperformed by the audiovisual BCI. Seven DOC patients had their conscientiousness detected using this audiovisual hBCI technique. According to the experimental findings, the audiovisual BCI can yield more accurate findings than the behavioral observation scale.

4.2. tactile-audio hBCIs.

The aforementioned bimodal BCI can only be used by users who have full gaze control and adequate vision because it requires visual interaction to focus on stimuli and feedback. A bi-modal audio/tactile-based approach may enable visual scanning of unrelated BCI since the user does not need visual contact when using tactile or auditory BCI. A dual-mode P300 BCI with the same direction was proposed by Yin et al. [34]. It was presented concurrently with touch and auditory inputs from the same spatial direction. Eleven users with visual and auditory impairments had their tactile and auditory BCIs examined by Rutkowski and Mori [35].

The numerous benefits of BCI auditory-tactile are demonstrated by these current findings. In visual computer applications, auditory-tactile hBCI offers an appealing possibility of target sensory fields that can induce potential without relying on visual stimuli, although the performance achieved by using this system is lower than that of BCI dependent on gaze transfer. Firstly, the auditory-tactile dual-mode BCI has better overall system performance than the auditory or tactile single-mode P300 BCI. Third, for users who have vision impairments, there is visual-tactile hBCI.

5. Multimodal Signal-Based hBCI

Multimodal signals, including as EEG, MEG, fMRI, EOG, fNIRS, and EMG, can be used to build hBCI systems. Different brain signals can serve a variety of purposes and have unique signal properties. A number of hybrid BCIs that rely on several signals have been published recently. The representative hBCI applications based on multimodal signals over the past few years are included in Table 3.

5.1. hBCIs based on EEG and EMG

An hBCI that combines EEG and EMG was proposed by Leeb et al. [50]. Using visual cues (arrows to the left or right), 12 healthy participants were given instructions to repeat the exercise with their left or right hand (holding the hand with the fist) for five seconds in each session. EEG and EMG signals were analyzed and categorized independently by the researchers before being combined. Stable features were identified by cross-validating a Gaussian classifier using training data, and subject-specific features that maximized separability across tasks were chosen using canonical variable analysis. Subject-specific thresholding, normalization, and maximum distance classification were applied to the resultant features. Lastly, a control signal was produced by fusing the probabilities of two classifiers using the Bayesian approach. A single EEG activity had an accuracy of 73%, whereas a single EMG activity had an accuracy of 87%. Nonetheless, the hBCI's accuracy increased to 91%. Additionally, the EMG channel's amplitude was reduced throughout operation (from 10% to 100%) to mimic fatigued muscles. As EMG muscles grow more fatigued, EEG activity becomes more significant in fused data. The outcomes demonstrated a notable benefit for BCI systems based on EEG and EMG.

5.2. hBCIs based on EEG and EOG

EEG and EOG have recently been integrated in several research to provide a hBCI. For many users of the BCI system, EOG signals are a suitable option because many individuals with disabilities can control their eye movements. A speller system with a high typing speed was implemented by Lee et al. [41] using hBCIs based on EEG-EOG. The hBCI system included a visual feedback module, an EOG-based command detector, and a traditional ERP-based speller. The categorization probabilities for each candidate character from the EEG epoch were calculated using the online ERP speller. Based on the ordering of probabilities, the character with the highest likelihood was chosen as visual feedback. Across 20 individuals, the innovative speller system's accuracy was 97.6%, and its ITR was 39.6 ± 13.2 bits/min. The outcome demonstrated that this speller, which is based on EEG and EOG, performs better than the traditional ERP-based speller.

5.3. Other multimodal signal-based hBCIs

There have also been reports of other hybrid BCIs that use numerous signals. Combining fMRI and EEG in BCIs allows for the full utilization of the spatial and temporal formation of brain activity. The ability of EEG to give subjects online slow cortical potential (SCP) feedback is a significant benefit of EEG-fMRI combined BCI. It also reveals the fundamental psycho-physiological mechanisms, like the relationship between SCP alterations and local BOLD responses, which aids in the creation of new training protocols and paradigms. fNIRS is portable and captures the hemodynamic response of brain activity, despite having a lower spatial resolution than fMRI.

The authors in [45] demonstrated that combining EEG and NIRS greatly enhanced the performance of a MI-based BCI. It enables meaningful classification rates for people who cannot use BCI based solely on EEG. While MEG is unaffected as long as the electric inhomogeneities are concentric, EEG is readily altered by the extracerebral tissues' inhomogeneities. As a result, MEG signals can offer more spatial information and are more local than their comparable EEG signals. Three tetraplegics' finger motions were indexed in [47] using the MEG and EEG data produced in the sensorimotor brain.

6. Conclusion and Discussion

The performance analysis of various hBCI types and stimulus designs is the main emphasis of this paper. First, we outlined three categories of hBCIs: multimodal signals, multisensory hBCIs, and hBCIs based on numerous brain patterns. We examined a number of representative hybrid BCI systems for each type of hBCI, including their design philosophies, paradigms for stimuli, control strategies, experimental findings, and associated benefits. We will go into further detail about the advantages of hybrid BCI systems and upcoming research in the sections to follow.

The benefits of hybrid BCI can be summed up in two ways after taking into account the three different varieties and their corresponding uses. First, the classification performance can only be enhanced by a single control signal or output from the hBCI system. These improvements can be achieved in two main ways: (1) combining multiple brain patterns (like MI, P300, and SSVEP) or fusing multiple signals (like EEG, EMG, EOG, and NIRS) at the feature level; and (2) improving brain patterns by applying multiple sensory stimuli, like audiovisual stimuli. Second, hBCI systems try to perform multi-degree object control when there are many control signals or outputs available. The multi-dimensional or functional control approach based on hybrid BCIs and a few application systems is introduced in this paper. There are two primary approaches that can be used: (1) integrating different brain patterns to generate multiple independent control signals, like orthopaedic control based on MI and SSVEP and 2D cursor control based on MI and P300; (2) employing distinct signal properties to carry out distinct tasks, like robot control based on EEG and EOG.

6.1. hBCI design and implementation

From the perspective of the user, the hBCI system is typically more sophisticated than the traditional simple BCI. When designing and implementing hBCI, user acceptability is a crucial performance factor that must be properly taken into account. Finding the optimal mix of brain patterns to accomplish the intended goals is a challenge in the design of a brain pattern-based HCI, as the combination may differ from user to user. For instance, it should be taken into account that prolonged usage of P300 and SSVEP would exacerbate visual fatigue. Making ensuring that numerous sensory stimuli boost the intended brain patterns is a difficulty when designing a couple sensory hBCI. According to earlier research [33], a visual P300-based BCI that combines auditory stimuli with naturally uttered words can lessen the mental strain. As a result, future studies can take into account additional combinations of various sensory stimuli that involve tactile and aural patterns. One of the challenges for the hBCI that uses several signals is how to fully utilize each signal's unique properties to maximize system performance. Furthermore, the low temporal resolution of fMRI data and the high noise, delayed response, and high dimensionality of EEG data (produced by the fMRI scanner) are not insignificant when building the real-time hBCI based on EEG and fMRI.

6.2. hBCI brain mechanisms

Multiple brain modes, multiple sensory modes, or multimode signal inputs may be used by the hBCI system. Studying the pertinent brain mechanisms is required to make sure that these elements are successfully coordinated in the hBCI system. For instance, a neural mechanism for multisensory BCI may be provided by cross-modal integration and interaction in the brain. Nevertheless, research on the brain mechanism of hBCI has been limited thus far.

6.3. Clinical Use

The majority of hBCI systems, including BCI wheelchairs and browsers, were created for healthy subjects up until this point. Patients must be included, and their value must be expanded to include clinical applications. A growing number of hBCIs have been employed in therapeutic settings in recent years, including DOC [53] and the rehabilitation and treatment of hemiplegic patients [51, 52]. The distinctions between patients and healthy participants must be taken into account when developing these hBCI systems for patients. Sometimes only one patient design is required. Although the use of hBCI for DOC patients is still in its infancy, hBCI-based communication and rehabilitation is a crucial area for our future studies. Furthermore, BCI has been integrated with a range of intelligent technologies, including intelligent robotics and automatic navigation systems. By enabling the subject to concentrate on the end result and disregard the minute details involved in carrying out the activity, this combination not only significantly lessens the user's workload but also increases the BCI system's dependability, flexibility, and power. For patients with limited recognition and control abilities, this holds promise. Future studies should thus concentrate on these patient-developed systems.

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