Chapter

Brain-Computer Interface: Use of Electroencephalogram in Neuro-Rehabilitation

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Abstract

Brain-computer interface is a technology that has been under enormous research in the last few decades. It uses brain signals by converting them into action to control the external environment. The focus of the future is the application of such technology in rehabilitating patients with physical disabilities. This chapter will mainly explore the use of EEG (electroencephalogram), a popular non-invasive method, on which the brain-computer interface is based. The process of signal extraction, selection and classification will be discussed. The challenges and techniques in communication and rehabilitation of people with motor impairment, along with the recent research study in this field, will be mentioned.

Keywords: brain-computer interface, electroencephalogram, neuro-rehabilitation, sensorimotor rhythm, evoked potential, motor imagery, hybrid, applications

1. Introduction

People with neuromuscular disorder suffer from various degrees of physical disabilities that limit them from interacting with the external world. Patients, who have developed stroke for instance resulting in paralysis and speech difficulties, would undergo training in traditional ways offered by physiotherapists, occupational and speech therapists. However, these trainings do require users' active participation to make rehabilitation effective. By performing such trainings, neuroplasticity can be induced through re-establishment of connections between the infarcted regions and other functional areas. As people do find traditional training to be tedious and slow, they are less motivated in engaging such therapy that results in suboptimal outcome. Besides, severely disabled patients who are tetraplegic or in lock-in state may not even benefit from the traditional rehabilitation at all. The invent of brain-computer interface (BCI) has opened up a new dimension of neurorehabilitation in this much needed population. BCI can as well improve neuroplasticity by using the signals from the brain and translating them into actions to control the external environment including robotic arms. Even just by thinking of a movement can exert similar control, a huge milestone for the severely disabled individuals to finally regain some control over their lives.

2. Overview of EEG-based BCI

Brain signals can be retrieved via invasive or non-invasive method. Invasive methods such as electrocorticography (ECoG) or intracortical point signal acquisition have the advantages of high temporal and spatial resolution with low artifact vulnerability. But with time, the signal quality and sensitivity would diminish. Non-invasive methods include electroencephalogram (EEG), magnetoencephalography (MEG), functional MRI (fMRI) and near-infrared spectroscopy (NIS) in general have high temporal resolution but with variable signal quality and spatial resolution [1].

2.1 Brain signals

EEG is our main focus in this chapter, and its use is widely popular due to low cost, low risk, portability and easy to set up. The downside would be poor signal quality and low spatial resolution. The signal can also be affected by external noise and artifact, along with mood and posture of the subjects. Upright posture can improve EEG quality due to stronger high-frequency content [2–4]. These brain signals can be classified as endogenous (spontaneous) and exogenous (evoked). The commonly used endogenous patterns are slow cortical potential (SCP) and sensorimotor rhythm (SMR); whereas, exogenous patterns are visual evoked potential (P300) and steady state visual evoked potentials (SSVEP) [1].

2.1.1 Slow cortical potential

Slow cortical potential arising from intracortical or thalamocortical region is projected to different cortical layers that harbor apical dendrites of pyramidal neurons. Firing from these neurons can generate motor or cognitive tasks. A negative voltage shift causes depolarization of the cortical network, while a positive voltage shift an inhibition (**Figure 1**). Intense training is required to control the shifting in the SCPs in order to perform basic tasks. As a result, these long training hours might hinder the popularity of the use of such brain signals [1].

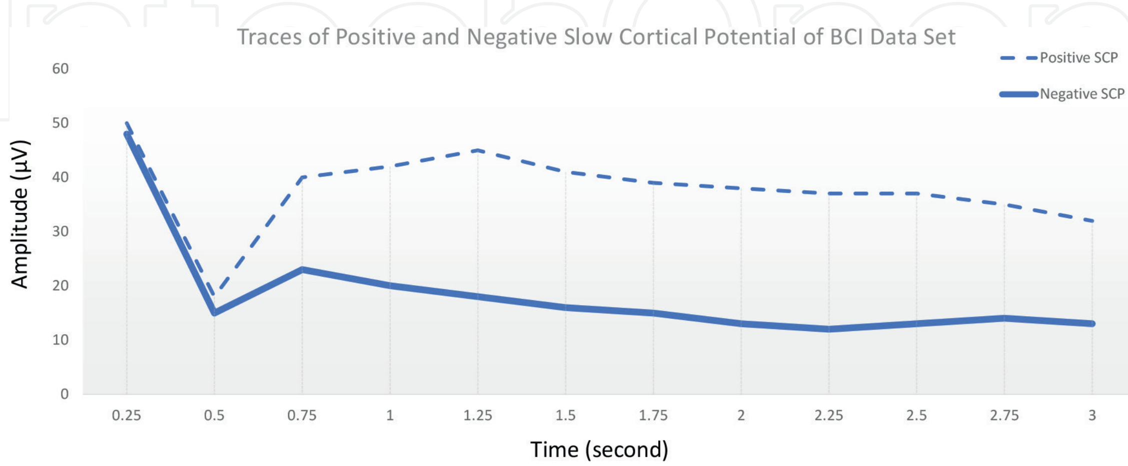

Figure 1.
Mean traces of positive SCP and negative SCP of a BCI data set.

2.1.2 Sensorimotor rhythm

The sensorimotor rhythm arising from sensorimotor areas generates β (beta) and μ (mu) rhythm mainly used for specific voluntary regulations such as preparation, control and execution of motion. Merely the thought of a movement (**Figure 2**), without any external stimuli, can regulate the rhythm amplitudes in these central motor areas, which makes it appealing for users with severe motor disabilities. The change in the power of band frequency helps differentiate the type of mental tasks being carried out. A decrease in band frequency termed event-related desynchronization (ERD) occurs up to 2 seconds before the actual movement. Event-related synchronization (ERS) signifies an increase in the band frequency that occurs before the end of a movement. The classes of movement that can be identified through SMR are left hand movement, right hand movement, movement of the feet and movement of the tongue. But the movement between left and right foot and between particular fingers of one hand are indistinguishable due to their small representation in the cortical homunculus. Again, it requires intensive training and sufficient mental capacity and attention to generate this motor imagery-based EEG signals [1, 4].

2.1.3 Visual evoked potential

Visual evoked potential (P300) occurs at 300 milliseconds after a triggering stimulus (**Figure 3**). Because the potential occurs with high consistency, this positive voltage peak has been used to mark an event. Although it requires less extensive

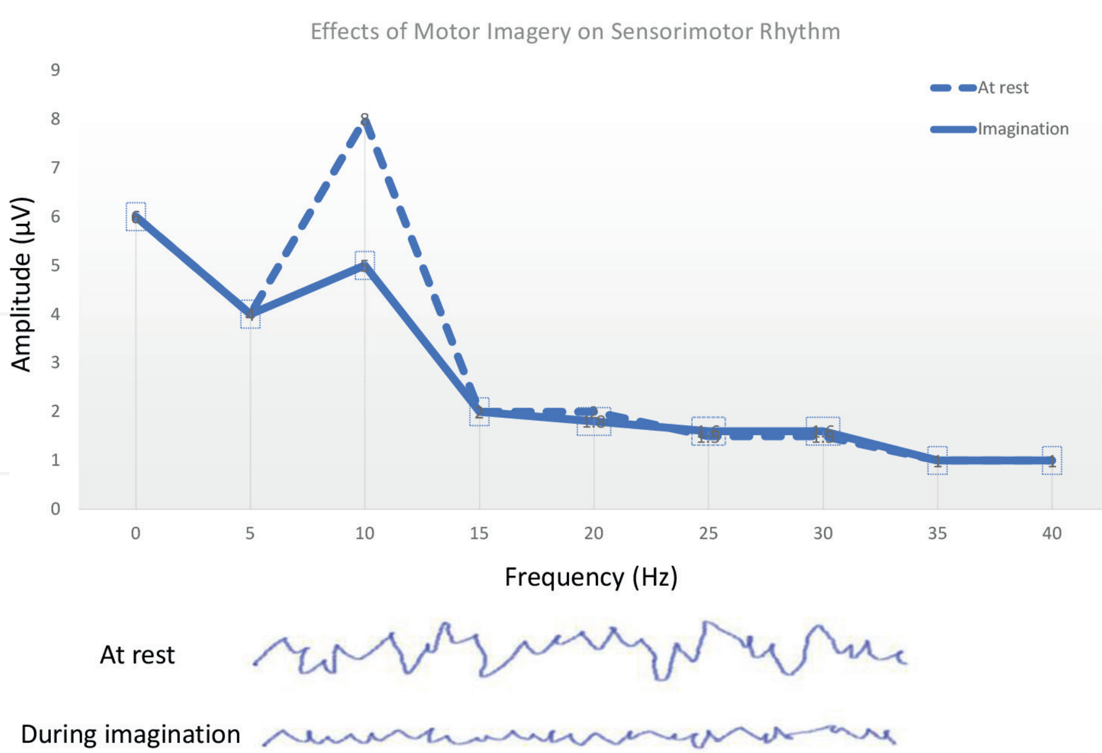

Figure 2.
Effects of motor imagery on sensorimotor rhythm. On the top shows the frequency spectra during movement at rest (dashed line) and during imagination (solid line). During imagination, the amplitude of EEG tracing is attenuated as shown on the bottom.

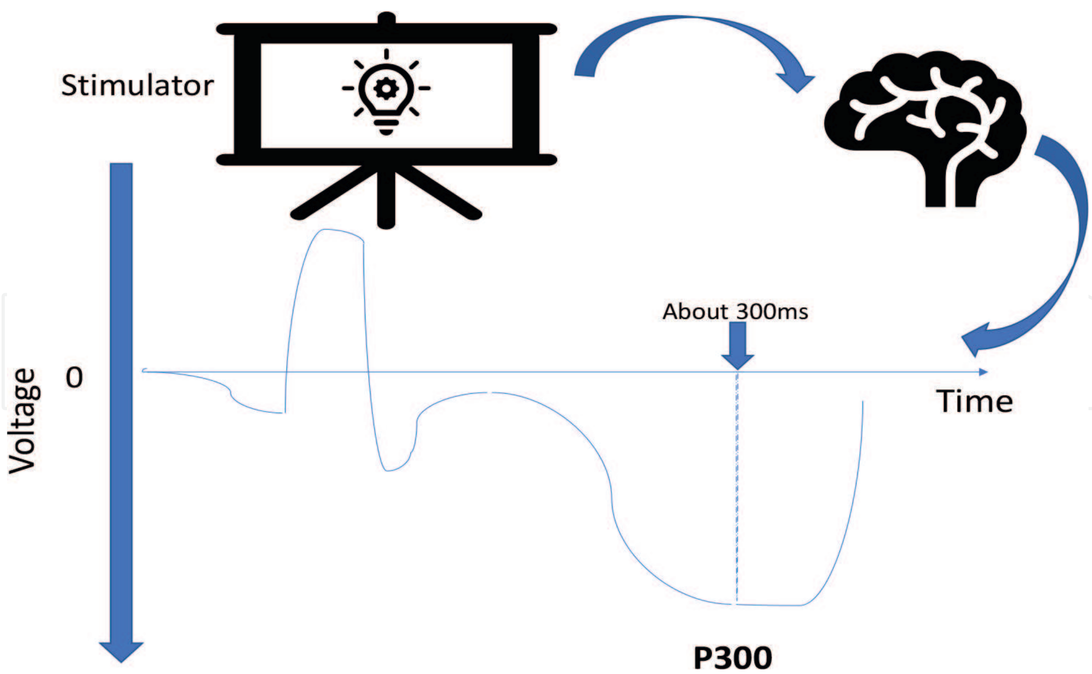

Figure 3.
Visual evoked potential. This is initially stimulated by flashes on the screen, then captured by the brain producing a positive voltage potential occurs at 300 ms after the stimulus.

training compared to SCP and SMR, the usefulness of P300 may be hampered by the severity of motor disabilities and degree of fatigue. Another visual evoked potential, called steady state visual evoked potentials (SSVEP), requires users' attention and the ability of visual fixation. The potentials are triggered by an oscillating stimulus at a fixed frequency, like a flashing letters or digits on a screen. That results in an increase in EEG activity, or SSVEP response, at the occipital area with the same frequency as the stimulus. However, the requirement of an intact oculomotor function and gaze fixation for a period of time has been challenging for some groups of patients. A study performed on amyotrophic lateral sclerosis (ALS) patients did not have much success due to their inability to control eye movement [1].

2.1.4 Other brain signals

Other techniques that are used to obtain EEG data include auditory evoked potential (a corresponding EEG pattern generated after an auditory stimulation), vibrotactile evoked potential (a corresponding EEG activity generated after physical vibrations at a particular frequency), imagined speech (imagination of words or sentences for evoking EEG signals), and error-related potential (an activity when a mismatch between the subject's intention and the output response from the BCI application is detected). One of the increasingly popular way to obtain EEG data is by analyzing EEG spectral changes to monitor users' drowsiness, attention, mental workload, emotions and other states of the mind [2]. This can become handy in detecting drivers' concentration at work, or in criminal cases when lie detector machine is employed.

2.2 Architecture of BCI system

Figure 4.

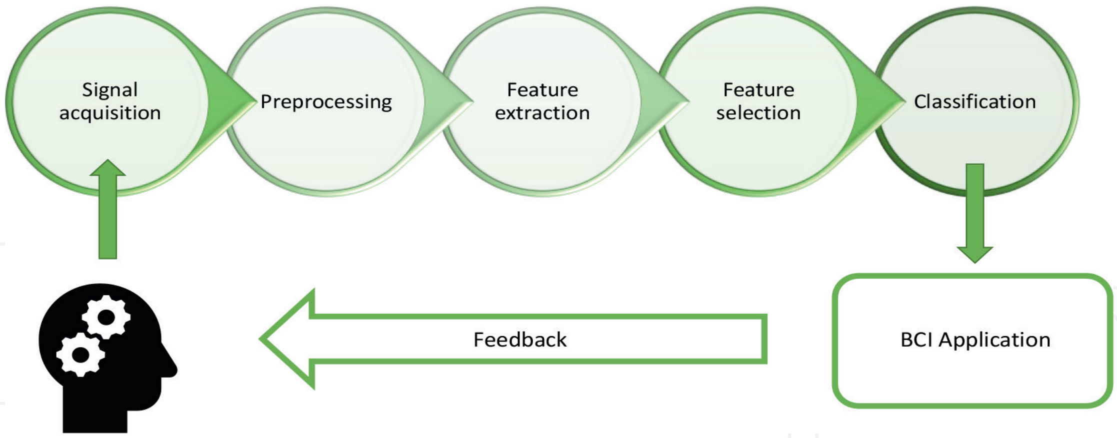

Figure 4.
The architecture of a brain computer system consists of signal acquisition from the brain, pre-processing, feature extraction, feature selection, classification and eventually application to external devices that provides feedback to users.

2.2.1 Data acquisition and pre-processing

After the raw EEG data has been detected via the scalp electrodes, the data needs to remove any signals originated in areas other than the brain such as using the 60 Hz notch to clean the intervening frequency and the EMG activity before further analysis [1, 3]. After this pre-processing step, signal processing is performed using many different feature extraction techniques to identify specific brain signals that would later be translated to system commands [5].

2.2.2 Feature extraction

There are numerous techniques that enable proper signals to be retrieved during feature extraction. We will not go into detail into each of the techniques, but some common ones are briefly discussed in this section. Time-domain and frequency-domain are two basic techniques often applied in studies. Using quaternions to represent objects within a three-dimensional space offers a better method to aid in extracting signals in time-domain analysis especially from motor imagery EEG. Fast Fourier transform theory and local characteristic-scale decomposition are approaches that are often utilized in frequency-domain analysis. In order to relate the frequency content to the temporal domain and vice versa, time-frequency domain analysis helps compensate each other's deficit in decomposing signals in a more dynamic fashion. Common spatial pattern (CSP) is advantageous in motor imagery EEG processing as it can extract particular information from a particular frequency band. Different modifications of CSP are available, and sub-band common spatial pattern offers a much better classification accuracy by initially filtering EEG at different sub-bands and then tabulating CSP features for each of the bands [4, 5].

2.2.3 Feature selection and classification

The most common feature selection techniques include principal component analysis (PCA), filter bank selection and evolutionary algorithms. PCA helps to reduce dimensionality, while filter bank selection is specific for CSP extraction technique. Due to the high computational demands and large size feature set, evolutionary algorithm can further select a more appropriate feature by hybrid approach so to improve accuracy at the cost of time [4, 5]. For classification and modeling of the control system, linear discriminant analysis (LDA), support vector machines (SVM) and artificial neural networks (ANN) are the frequently used classifiers [6]. LDA is a linear classifier that is simple to use but it may not be good enough to process non-linear EEG data. SVM is a non-linear classifier that handles well with high dimensionality data; however, it takes more time for processing. ANN is another non-linear classifier that requires long handling time to process large computational data. It is known to be highly adaptive but also over-fitting; therefore, it may fail to predict future observations reliably [6]. Eventually, neurofeedback system relays back to the users so they can make modification in their brain patterns and improve the system.

3. Use of brain signals in reality

3.1 Slow cortical potential

Slow cortical potential as mentioned previously requires subjects to control the upward and downward shifting of polarity to select letters, words or pictograms. A system is developed to allow subjects to communicate through writing: first phase requires basic training for regulating own SCP amplitude by mental strategies either above or below a certain threshold to move the cursor at a specific space or time; and, the second phase requires selecting and rejecting letters by self-managing own SCP amplitudes to form words and phrases. One study also helps subjects to browse the Internet by training them to self-regulate SCP amplitudes to move up or down the cursor in order to select or discard a command [1].

3.2 P300 evoked potential

P300 is late positive evoked potential occurs after an external task-stimulus. The users are given different options of commands or stimuli, and the system needs to detect which stimuli can elicit P300 to exert its role on various systems like painting, spelling, web browsing and controlling of external devices [1]. Various BCI-controlled humanoid applications have been discussed in [6] like grasping a glass of water by robotics in ALS patients, controlling the navigation of a robot via telepresence. Using hybrid BCI by combining the brain signals (P300) and the biological feedback signals generated by some other parts of the body are also seen in executing the command [6]. The advantage of using P300 is its high accuracy. However, the performance is not consistently at a high level, mainly affected by the severity of the disease and the lack of motivation by repeatedly doing the same training routine [1].

3.3 Sensorimotor rhythm

Sensorimotor rhythm requires subjects to use mental strategies or motor imagery to enable motor execution (ME). For subjects who have motor disabilities, the thought of movement can suppress EEG rhythm leading to desynchronization, resulting in movement initiation. Motor imagery can enhance motor learning process by neuroplasticity [7, 8]. With both MI and ME derived from sensorimotor areas such as primary motor area, supplementary motor area and premotor cortex, SMR can be manipulated to help the disabled towards rehabilitation. The differences in the

BCI performance may be related to the number of folds and thickness of individuals' cortices which may have an impact on the functional networks. The emotional and mental processes such as fatigue, memory load, attention and reaction time, along with gender, age and lifestyle all contribute to the inter- and intra-variability in SMR-based BCI motor performance. Overall, subjects with high motor variability including force field adaptation, speed/trajectory, motivational factors and strong resting EEG amplitudes have a higher probability of achieving better BCI performance, hence better neuroplasticity and rehabilitation outcome [8].

Many BCI systems have been using SMR by means of spelling, cursor movement, and control of external devices for communication to the external world. Creating a virtual environment to work under, subjects are more motivated in controlling movement in this framework resulting in better performance with fewer runs of training [1].

4. BCI applications in rehabilitation

The applications for BCI systems in rehabilitation include motor neuroprosthetics, computer/machine interfaces, video games, speech and communication, meditation, and even art. The famous Hebbian theory, developed by Canadian psychologist Donald Hebb, described that with repeated stimulation of the postsynaptic neurons by presynaptic neurons, the efficacy of synaptic transmission would increase resulting in neuroplasticity. Besides, using the traditional rehabilitation therapy, BCI system can help "replace" and "restore" neurological functions by training patients to produce more reliable brain signals and to activate devices to assist movement [1, 3]. Patients with different cortical lesions may produce different oscillatory rhythm of neural activation [3].

4.1 Motor imagery

Evidence shows by using motor imagery, SMR can be trained to translate into commands to control and regulate voluntary activity. Just by imagining left or right hand movement, the right or left hemisphere respectively is activated, and the signals can be further processed and classified. To master MI-based BCI, subjects can undergo two approaches. The discrete trial, considered as tedious and lengthy, instructs them to perform cues within a timeframe while providing on-screen feedback on their results. On the other hand, continuous pursuit looks more promising as subjects are told to control a cursor in a moving icon on-screen. This provides a game-like approach so the subjects are more engaged with stronger brain signals being detected along with fewer training sessions required [9]. The challenges of using motor imagery are the requirement of a near-intact neurophysiological and psychological state of the users. This becomes a challenge to post-stroke patients with reduced in such mental and physical capacities [4].

4.2 Other paradigms

Other paradigms including spelling, induced emotions and facial-movement have also been tested to control wheelchair, prosthetic hand and robotic arm. Spelling the desired command has a higher accuracy but subjects may get fatigue with continuously spelling words to elicit the command. Inducing emotions is mentally demanding, while facial movement is more intuitive and easier to generate. Besides, this movement has lower illiteracy rates and higher accuracy rates. Merging different paradigms, for example combining traditional MI and facial movement, can increase the number of classes or control functions to overcome poor classification accuracy of MI system. Some studies require subjects to perform sequential movement to bring out a command. This increases the latency as each command takes up around 3 seconds. Therefore, more time is required for execution. No comparisons have been made so far between traditional and sequential command paradigm. Whether it is feasible to increase accuracy at the expense of increasing latency remains a question to be explored [9]. Combining another biosignal to increase the number of commands is called hybrid BCIs. To enhance the control of prosthetics or orthotics, merging EEG with EMG has become increasingly popular [9].

4.3 EEG: EMG application

Combined use of EEG and surface EMG in rehabilitative applications can control the effector's devices with a pathway starting from the cortical level down to the muscular level. EEG first explores the whole brain neuronal network, while EMG measures the train of motor unit action potentials that can help in motor planning with quantitative measurement in motor control abnormalities and muscular activation patterns. They combine with BCI or biofeedback methods to control external devices and guide rehabilitation. Using cortico-muscular coherence as signal analysis, it can "detect voluntary movements in spastic subjects, assess the effectiveness of rehabilitation strategies and serve as biomarker for motor recovery" [10]. As most of the experiments are done as pilot studies, more clinical trials are needed to evaluate the EEG–EMG applications [10].

4.4 Other studies

Voznenko [11] studies the design of wheelchair control that uses thoughts, voice or gestures to mobilize a wheelchair. The use of combined BCI-FES (functional electrical stimulation) as designed by Muller-Putz study [4] helps send impulses to the patients' paralyzed arm/leg by artificially contracting the muscles. Therefore, the patients can have a more authentic experience. In [4], a number of studies have also been mentioned. Muller-Putz and Pfurtschscheller's study [12] uses 4 flickering stimuli with each one representing a different function of the arm based on SSVEP system. Subjects can select a movement by looking at a particular stimulus. Elstob and Secco [13] uses motor imagery-BCI to control a prosthetic arm that consists of 5 different types of movement. Using virtual reality, BCI controlled robotic arms can potentially guide subjects' arm movement in post-stroke rehabilitation, like the system proposed by Luu [14]. It is suggested that brain activities be measured while users are moving on a treadmill, and then "provide visual feedback to the user on their movements through a virtual avatar" [4].

4.5 Modalities in rehabilitation

While research has mainly focused on motor rehabilitation, targets on improving tactile stimulus alone has been lacking. Sensory and motor cortices share the same somatic organization and are inseparable in improving and restoring function. Without sensory input, the rehabilitation of limbs would not be complete. Development of sensory-motor closed loop systems, or the bidirectional BCI, should improve the efficiency of rehabilitation in the future. In communication rehabilitation, patients with aphasia can regulate their evoked potentials (SCP, SMR, P300) to communicate by producing letters via a speller system. Limited by the severity of cognitive impairment in poststroke or neurodegenerative patients, they may not be benefited from BCI as some basic cognitive levels are required to understand and manipulate the application. Providing neurofeedback via motor imagery and P300 system may enhance the rehabilitative process in this group of populations. In sum, there is still a lot of research required in poststroke cognitive training [3].

5. Challenges and future direction

Finding the most effective technique for features extraction and selection has been a challenge as each technique has its own advantages and disadvantages. Besides, EEG itself is also highly non-linear and artifact-prone. Together, a low classification accuracy may result. Combining different classifiers or biosignals can improve this accuracy, but the training time to master the control is much prolonged which in turn affects the overall efficiency. Future studies using subjects with pathological disorders instead of healthy ones are encouraged so to increase the generalizability in the biomedical field. In terms of non-biomedical applications such as art, gaming and entertainment, this is a potential market that contributes to economic growth. However, developing a “dependable system with stable performance with different mental states” that can adapt to different environments is the main goal to gain its public acceptance in the next decade (**Table 1**) [4].

Method	Description	Characteristics	Application in reality
Slow cortical potential (SCP)	• Endogenous signal to cause voltage shifting • Negative voltage shift causing depolarization • Positive voltage shift causing inhibition	• Requires intense training	Formation of words and phrases, browse internet by moving cursor to select or discard a command
Sensorimotor rhythm (SMR)	• Endogenous signal to generate β (beta) and μ (mu) rhythm • Regulate rhythm amplitudes in central motor areas by motor imagery • Change in power of band frequency to differentiate the type of mental tasks	• Requires intense training • Requires mental capacity	Spelling, cursor movement, controlling external devices [11, 13]
Visual evoked potential	• Exogenous signal to generate a potential: • at 300 ms after a triggering stimulus (P300) • triggered by an oscillating stimulus at a fixed frequency (SSVEP)	• High consistency and accuracy • Requires intact oculomotor function and gaze fixation • Requires shorter training time	Painting, spelling, controlling external devices [12]

Table 1.
Comparative analysis of various methods used for recording features.

6. Conclusion

We have discussed the basic architecture of BCI system using EEG as brain signals to control external devices in rehabilitation and communication. Exogenous and endogenous signals elicited by external stimuli and motor imagery respectively can enhance neuroplasticity and improve motor function. However, research on other modalities such as sensory and cognition are still at its primitive stage. Applications in the biomedical field are blooming but challenges in creating the best system that fits in all conditions still remain.

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