Research Article

Basic Information about BCI Systems

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Abstract: Brain Computer Interface (BCI) systems establish a one way communication link between man and computer. The main goal of this technology is to provide a link between the brain and the physical world without any physical contact. Indeed these systems interlink thought to action. As the result, the user would be able to control the environment via brain signals. Electro-Encephalogram Signals (EEG) is input signals for these systems that include two main stages for processing of those signals, feature extraction and classification. Almost researches in this field are done to find what feature extracting methods and classifier are suitable. As regard spread of the existing information in this field, in this study, we first introduce a BCI system and then try to collect and organize the most needed information for processing EEG signals in BCIs. This study with having sufficient references presents the basic information for researchers who want to start their studying in this field.

Keywords: Brain computer interface, EEG, feature extraction, physical contact

INTRODUCTION

Rain-Computer Interfacing (BCI) is a challenging problem that forms part of a wider area of research, namely Human-Computer Interfacing (HCI), which interlinks thought to action. BCI can potentially provide a link between the brain and the physical world without any physical contact. The main objectives of BCI are to manipulate the electrical signals generated by the neurons of the brain and generate the necessary signals to control some external systems. The most important application is to energize the paralyzed organs or bypass the disabled parts of the human body.

BCI addresses analyzing, conceptualization, monitoring, measuring and evaluating the complex neurophysiologic behaviours detected and extracted by a set of electrodes over the scalp or from the electrodes implanted inside the brain. The main and prominent activities in BCI (especially noninvasive BCI) are the Berlin BCI (BBCI) group (Blankertz *et al.*, 2006) Wadsworth BCI research (Wolpaw and McFarland, 2003), the Graz BCI activity lead by Pfurtscheller *et al.* (2005) and Muller-Putz *et al.* (2003) and the Martigny BCI (Millan *et al.*, 2004).

In this study, the fundamental concepts and the requirement for the BCI design using EEG signals are reviewed. We try to collect the most important information in BCI researches that are included the block diagram of BCI system, the concept of EEG signal, the important decomposition in EEG signal, important strategies in localization of the source's brain activity and finally assessment methods of the performance of these systems. This information is necessary for starting studying in BCI researches.

MATERIAL

State of the art BCI: The first step in developing an effective BCI paradigm is therefore to determine suitable control signals from the EEG. A suitable control signal has the following attributes: it can be precisely characterized for an individual, it can be readily modulated or translated to express the intention and it can be detected and tracked consistently and reliably.

There are some approaches towards BCI, that the first and second approaches are the more main of them:

- The first approach is based on the multiple sensor EEG activities recorded in the course of ordinary brain activity. This approach is more comprehensive than others and does not require any particular stimulus. Nowadays there are many attractions in using the normal EEGs (or Spontaneous Signals (SSs)) for BCI. A BCI system of this kind generates a control signal at given intervals of time based on the classification of EEG patterns resulting from particular Mental Activity (MA).

- Second approach based on Event Related Potentials (ERPs) that appears in response to some specific stimulus. The most widely used ERP

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evoked potential (EP) is the P300 signal, which can be auditory, visual, or somatosensory. It has a latency of approximately 300 ms and is elicited by rare or significant stimuli and its amplitude is strongly related to the unpredictability of the stimulus (Donchin *et al*., 2000). Another type of Visual EP (VEP) is those for which the ERPs have a short latency, representing the exogenous response of the brain to a rapid visual stimulus. The ERPs can provide control when the BCI produces the appropriate stimuli. The information achieved through ERP extraction and measurement is not accurate enough for extraction of movement related features and they have vast variability in different subjects with various brain abnormalities and disabilities. More importantly, the subject has to wait for the relevant stimulus presentation (Bayliss, 2001).

- The other approaches used for BCI is based on Steady-State Visual Evoked Responses (SSVERs), which are natural responses for visual stimulations at specific frequencies. The SSVERs are characterized by an increase in EEG activity around the stimulus frequency.
- The latest approach is Slow Cortical Potential Shifts (SCPSs), which are shifts of cortical voltage lasting from a few hundred milliseconds up to several seconds. This can be achieved if the subjects are provided with feedback on the evolution of their SCP and if they are positively reinforced for correct responses (Kubler *et al*., 1998).

In all types of BCI systems human factors such as boredom, fatigue, stress, or various illnesses are of great influence and therefore motivating the subject often becomes very important.

MAIN SECTIONS IN BCI

A simple BCI system setup is illustrated in Fig. 1. As mentioned previously, the major problem in BCI is separating the control signals from the background EEG. Meanwhile, cortical connectivity, as an interesting identification of various task related brain activities, has to be studied and exploited. Detection and evaluation of various features in different domains will then provide the control signals. To begin, however, the EEG signals have to be preprocessed since the signals are naturally contaminated by various internal and external interferences. Data conditioning such as pre-whitening may also be necessary before implementation of the source separation algorithms.

Preprocessing of the EEGs: In order to have an artifact-free EEG to extract the control signals, the EEGs have to be restored from the artifacts, such as eye-blinking (Ocular Artifact (OA)), Electrocardiograms (ECGs) and any other internal or external disturbing effects.

Most of the noises, external and even internal artifacts, such as ECGs, are filtered out by the hardware provided in new EEG machines. There have been some works by researchers to remove OAs such as trying to estimate the propagation factors for example PCA and SVMs that rely on the uncorrelatedness assumption of the EEGs and OAs (Lins *et al*., 1993), ICA (Jung *et al*., 1998) and Adaptive filtering (Celka *et al*., 2001).

In another recent attempt, an iterative SOBI-based BSS method followed by classification of the independent components using SVMs has been designed to effectively remove the EOG artifacts (Shoker *et al*., 2005). The method can also be easily extended to removal of the ECG artifacts. The proposed
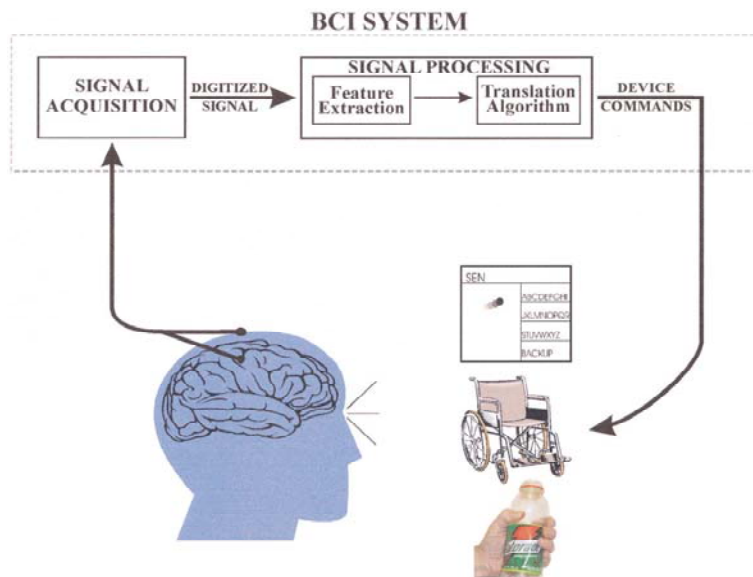

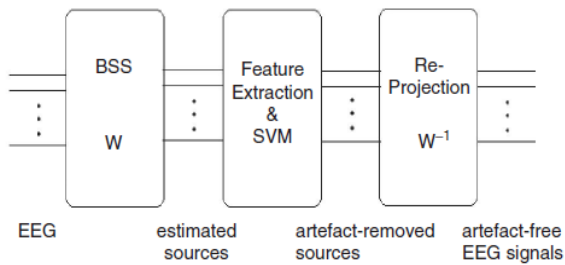Fig. 1: Basic design and operation of any BCI system

Fig. 2: A hybrid BSS-SVM artifact removal system (Shoker *et al*., 2005)

algorithm consists of BSS, automatic removal of the artifact ICs and finally re-projection of the ICs to the scalp, providing artifact-free EEGs. This is depicted in Fig. 2. Up to 99% accuracy in detection of the EOG ICs has been reported (Shoker *et al*., 2005).

Feature extraction: The digitized signals are then subjected to one or more of a variety of feature extraction procedures, such as spatial filtering, voltage amplitude measurements, spectral analyses, or single-neuron separation. This analysis extracts the signal features that (hopefully) encode the user's messages or Commands. These features are vectors of numbers that are assigned to each individual EEG window. BCIs can use signal features that are in the time domain (e.g., evoked potential amplitudes or neuronal firing rates) or the frequency domain (e.g., mu or beta-rhythm amplitudes). A BCI could conceivably use both time domain and frequency-domain signal features and might thereby improve performance (Noshadi *et al*., 2011). In general, the signal features used in present-day BCIs reflect identifiable brain events like the firing of a specific cortical neuron or the synchronized and rhythmic synaptic activation in sensor motor cortex that produces a mu rhythm. Knowledge of these events can help guide BCI development. The location, size and function of the cortical area generating a rhythm or an evoked potential can indicate how it should be recorded, how users might best learn to control its amplitude and how to recognize and eliminate the effects of non-CNS artifacts.

In summary Feature extraction is used to translate signal properties for comparing with other signals or determining their major properties. In the following, based on recent researches, different types of features were extracted from the signal for every trial mentioned (Lotte *et al*., 2007):

- **Statistical features:** These parameter calculated from a vector af numerical data are significant parameters for example variance, Root Mean Square (RMS), moments and etc.
- **Entropic based features:** First, Entropy idea is presented in dynamic but because of its ability is broached in other field engineering and specially in EEG signal processing. It introduced by Shannon and then researchers created different definitions for entropic parameter based on Shannon entropy, such as sample entropy,approximate entropy (Richman and Moorman, 2000). This feature could show effective influence in EEG signal processing, especially in BCI.
- **Parametric and nonparametric feature in time domain:** These features are good for real-time systems because they don't need prior information and have no more time for calculation. Although not have frequency resolution is a weakness of them. One of these features that correlate with the user's intent but do not necessarily reflect specific brain events are Autoregressive parameters which are used commonly in BCI research is.
- **Frequency based features:** Because of nature EEG signal, the most important information of EEG signal's intent is related to frequency domain. Almost all successful research in EEG signal processing has been done in frequency domain or in time-frequency domain. Therefore we attend to introduce some features that, almost, is used in EEG signal processing.
- **ERD and ERS:** ERD and ERS can be considered as event-related potentials (which can also include evoked potentials). The cortical mu rhythm is an example of ERD. ERD is due to blocking of alpha activity just before and during the real or imagery movement. ERD is measured in terms of the power of the peak in the alpha band to the bandwidth, that is:

$$\frac{\text{ERD}}{\text{ERS}} = \frac{P(f,n) - P_{ref}(f)}{P_{ref}(f)} \qquad (1)$$

where, $P(f, n)$ the value of a signal power is at a given time–frequency point of an average power map and $P_{ref}(f)$ is an average power during some reference time calculated for frequency f. This represents the level of rhythmic activity within the alpha band just before or during the movement. Any attention dramatically attenuates the alpha rhythms, while an increase of task complexity or attention results in an increased magnitude of ERD.

The cortical mu rhythm is of particular interest in BCI mainly because it can be modulated /translated through imaginary and can be monitored via a noninvasive technique. The overall alpha band may be divided into lower and higher alphas. Lower alpha ERD (6-10 Hz) is a response to any type of task and is topographically spread over almost all electrodes. Higher alpha ERD, restricted to parietooccipital areas, is found during visually presented stimulations. ERD starts over the contra lateral rolandic region and, during the movement, becomes bilaterally symmetrical with

execution of movement. It is of interest that the time course of the contra lateral mu de-synchronization is almost identical to brisk and slow finger movements, starting about two seconds prior to movement onset. In ERS, however, the amplitude enhancement is based on the cooperative or synchronized behavior of a large number of neurons. In this case, the field potentials can be easily measured even using scalp electrodes. It is also interesting to note that approximately 85% of cortical neurons are excitatory, with the other 15% being inhibitory (Lotte *et al.*, 2007).

- **Transient Beta activity after the movement:** This activity, also called Post Movement Beta Synchronization (PMBS), is another interesting robust event that starts during the movement and continues for about 600 ms (Pfurtscheller, 1999). It is found after finger or foot movement over both hemispheres without any significant bilateral coherence. The frequency band may vary from subject to subject; for finger movement the range is around 16-21 Hz whereas for foot movement it is around 19-26 Hz (Neuper and Pfurtscheller, 1996). The PMBS has similar amplitude for brisk and slow finger movements. Also the movement of more fingers results in a larger beta wave. Beta activity is also important in the generation of a grasp signal, since it has less overlap with other frequency components (Pfurtscheller *et al.*, 2005).

- **Gama band oscillation:** Oscillation of neural activity (ERS) within the gamma band (35-45 Hz) has also been of interest recently. Such activity is very obvious after visual stimuli or just before the movement task. This may act as the carrier for the alpha and lower beta oscillations and relate to binding of sensory information and sensor motor integration. Gamma, together with other activities in theabove bands, can be observed around the same time after performing a movement task. Gamma ERS manifests itself just before the movement, whereas beta ERS occurs immediately after the event.

- **Long delta activity:** Rather than other known ERS and ERD activities within alpha, beta and gamma bands a long delta oscillation starts immediately after the finger movement and lasts for a few seconds. Although this has not been reported often in the literature, it can be a prominent feature in distinguishing between movement and non movement states. The main task in BCI is how to exploit the behavior of the EEGs in the above frequency bands before, during and after the imaginary movement, or after certain brain stimulation, in generation of the control signals.

After extracting the features, they were normalized in order to prevent numerical computational errors. The normalization was done by subtracting the statistical mean of each feature from the original feature and dividing the result by the standard deviation of the same feature.

Classification or translation algorithms: The first part of signal processing simply extracts specific signal features. The next stage, the translation algorithm (classification), translates these signal features into device commands orders that carry out the user's intent. This algorithm might use linear methods (e.g., classical statistical analyses or nonlinear methods (e.g., neural networks). Whatever its nature, each algorithm changes independent variables (i.e., signal features) into dependent variables (i.e., device control commands). Effective algorithms adapt to each user on 3 levels. First, when a new user first accesses the BCI the algorithm adapts to that user's signal features. A BCI that possesses only this first level of adaptation, i.e. that adjusts to the user initially and never again, will continue to be effective only if the user's performance is very stable. However, EEG and other electrophysiological signals typically display short- and long-term variations linked to time of day, hormonal levels, immediate environment, recent events, fatigue, illness and other factors. Thus, effective BCIs need a second level ofadaptation: periodic online adjustments to reduce the impact of such spontaneous variations. The third level of adaptation accommodates and engages the adaptive capacities of the brain. When an electrophysiological signal feature that is normally merely a reflection of brain function becomes the end product of that function, that is, when it becomes an output that carries the user's intent to the outside world, it engages the adaptive capacities of the brain. Like activity in the brain's conventional neuromuscular communication and control channels, BCI signal features will be affected by the device commands they are translated into: the results of BCI operation will affect future BCI input. In the most desirable (and hopefully typical) case, the brain will modify signal features so as to improve BCI operation. If, for example, the feature is mu-rhythm amplitude, the correlation between that amplitude and the user's intent will hopefully increase over time. An algorithm that incorporates the third level of adaptation could respond to this increase by rewarding the user with faster communication. It would thereby recognize and encourage the user's envelopment of greater skill in this new form of communication. On the other hand, excessive or inappropriate adaptation could impair performance or discourage further skill development. Proper design of this third level of adaptation is likely to prove crucial for BCI development. Because this level involves the interaction of two adaptive controllers, the user's brain and the BCI system, its

design is among the most difficult problems confronting BCI research.

Some examples of used classifiers are KNN (K Nearest Neighbor), LDA (Linear Discriminant Analysis), Neural Network, SVM (Support Vector Machine) and etc (Tavakolian *et al*., 2006).

MULTIDIMENSIONAL EEG DECOMPOSITION

All movement-related potentials are limited in duration and in frequency. In addition, each channel contains the spatial information of the EEG data. Therefore multidimensional EEG decomposition methods are important procedure in some EEG processing. Two conventional algorithms, PCA and ICA, have been widely used in decomposition of the EEG multiple sensor recordings. However, an efficient decomposition of the data requiresincorporation of the space, time and frequency dimensions. There is some procedure for this goal that is described in following:

- **Time-Frequency (TF):** TF analysis exploits variations in both time and frequency. Most of the brain signals are decomposable in the TF domain. This has been better described as sparsity of the EEG sources in the TF domain. In addition, TF domain features are much more descriptive of the neural activities.
- **Space-Time-Frequency Transform (STFT):** STFT has been carried out for all the channels, representing the spatial information and the atoms are masked and clustered and used for both reconstruction of the desired sources and usually for classification of a finger movement signal based on the directionality of the motion of the sources. Using this method the location of the event-related sources can be tracked and effectively used in BCI.
- **Parallel Factor Analysis (PARAFAC):** PARAFAC also called canonical decomposition (CANDECOMP) is another similar approach for analysis of brain signals in multidimensional domain for BCI purposes. In this approach the events are considered sparse in the space-time-frequency domain and no assumption is made on either independency or uncorrelatedness of the sources. Therefore, the main advantage of PARAFAC over PCA or ICA is that uniqueness is ensured under mild conditions, making it unnecessary to impose orthogonality or statistical independence constraints. Harshman (1970) was the first researcher to suggest that PARAFAC be used for EEG decomposition

Empirical Mode Decomposition (EMD): EMD is a new method of time-frequency analysis. With this method, any signal can be decomposed into a finite and often small number of "Intrinsic Mode Functions" (IMF). The difference between the new method and the previous methods is that the new method is established on instantaneous frequency (Huang *et al*., 1998). EMD method is adaptive and, therefore, highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it is applicable to non-stationary processes. In last years, this method was very successful in EEG signal processing (Li *et al*., 2008; Cui *et al*., 2005).

OTHER TOOLS FOR STUDYING OF THE SOURCE'S LOCALIZATION DURING BRAIN ACTIVITIES

As mentioned, utilization of the ERP signals provides another approach in BCI design. The ERP-based BCI systems often consider a small number of electrodes to study the movement-related potentials of certain body organs and by using described procedure involved suitable feature and one classifier can be detected. However, in recent work multichannel EEGs have been used followed by an efficient means of the source separation algorithm in order to exploit the maximum amount of information within the recorded signals, such these algorithms played an important role in the number channel reduction. In the following, some strategies in this field listed and briefly explained:

Source localization and tracking of the moving sources: Source localization can be employed here to estimate the location of moving sources related to the finger movement. Application of the conventional dipole fitting localization algorithms, however, is subject to having a pre-assumption about the number of sources. A simple source localizer may be designed using a feedback BSS system followed by an LS-based geometrical localization system. In this simple method BSS separates the EEG signals into their independent sources for a number of consecutive overlapping segments of the EEGs. For each segment the corresponding independent component (estimated source) is reprojected to the scalp using an inverse of the separating matrix. The resulting topographies are compared and the moving sources with maximum spatial and frequency correlations are selected.

Determination of the propagation direction and frequency content of brain activity: Determination of the propagation of brain electrical activity, its direction and the frequency content is of great importance. Directed Transfer Functions (DTFs) using a Multivariate Autoregressive (MVAR) model has been employed for this purpose (Kaminski and Blinowska, 1991). In this approach the signals from all EEG channels are treated as realizations of a multivariate

stochastic process. A short-time DTF (SDTF) was also developed for estimation and evaluation of AR coefficients for short time epochs of the EEGs.

The direction of signal source movement is realized from the cross correlations between signals, which are computed for different time shifts in the procedure of correlation $R(n)$ matrix estimation. These time shifts are translated into phase shifts by transformation to the frequency domain. The phase dependencies between channels are reflected in the transfer matrix. The DTF values express the direction of a signal component in a certain frequency -not the amount of delay- (GinterJr *et al.*, 2001). Analysis of the DTF values, however, will be difficult when the number of channels increases, resulting in an increase in the number of MVAR coefficients.

Estimation of brain connectivity: The coherency of brain activities may be presented from a different perspective, namely brain connectivity. This concept plays a central role in neuroscience. Temporal coherence between the activities of different brain areas are often defined as functional connectivity, whereas the effective connectivity is defined as the simplest brain circuit that would produce the same temporal relationship as observed experimentally between cortical regions (Astolfi *et al.*, 2005). A number of approaches have been proposed toestimate how different brain areas are working together during motor and cognitive tasks from the EEG and FMRI data (Jancke *et al.*, 2000; Gerloff *et al.*, 1998).

Structural equation modeling (SEM), Bollen (1989) has also been used to model such activities from high-resolution (both spatial and temporal) EEG data. Anatomical and physiological constraints have been exploited to change an underdetermined set of equations to a determined one. The SEM consists of a set of linear structural equations containing observed variables and parameters defining causal relationships among the variables.

ASSESSMENT OF BOTH USER PERFORMANCE AND SYSTEM PERFORMANCE

Effective assessment of BCI performance requires two levels of evaluation: the user and the system. The user must control the signal features and the system must recognize that control and translate it into device control effectively and consistently. User performance can be defined as the level of correlation between user intent and the signal feature (s) the BCI employs to recognize that intent. One useful measure of this correlation is r^2 perfect correlation produces an r^2 value of 1.00. Evaluation of system performance has two parts: performance in a specific application, assessed as speed and/or accuracy and theoretical performance, measured as information transfer rate. Up to now, most studies have simply reported the accuracy and/or speed
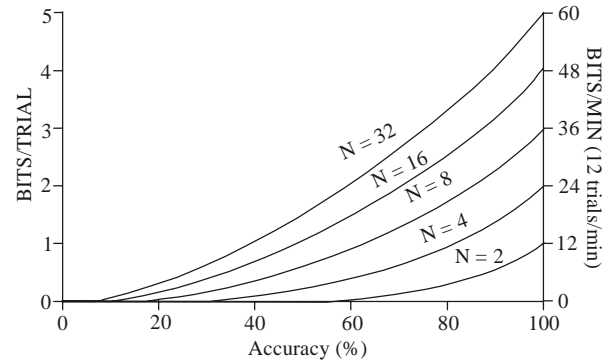

Fig. 3: Information transfer rate in bits/trial (Wolpaw *et al.*, 2002)

for specific applications. These data are certainly important. At the same time, they are affected by the characteristics of the application and the success with which the system interfaces the user's control of the signal features with that application. Thus, they make comparisons between different studies difficult and they do not reveal what might theoretically be done with the degree of control that the user has. The standard method for measuring communication and control systems is information transfer rate, or bit rate. It is the amount of information communicated per unit time. Derived from Shannon and Weaver (Shannon and Weaver, 1964), this measure incorporates both speed and accuracy in a single value. Figure 3 shows the relationship between accuracy and bit rate for different numbers of choices. Bit rate is shown both as bits/trial (i.e. bits/selection) and as bits/min when 12 selections are made per min (a rate comparable to that of several current BCIs (Birbaumer *et al.*, 2000; Donchin *et al.*, 2000; Wolpaw *et al.*, 2002). For example, the bit rate of a BCI that selects between two choices with 90% accuracy is equal to that of a BCI that selects among 4 choices with 65% accuracy. Bit rate is an objective measure for measuring improvement in a BCI and for comparing different BCIs.

EVALUATION IN RELEVANT SITUATIONS

BCI evaluation should also include testing in circumstances like those of real-life applications. As noted above, assessment of online performance is essential. In addition, BCIs should be tested under conditions in which the user chooses the message or command. This testing can reveal how well the BCI adapts to spontaneous variation in the signal features when it does not have the advantage of knowing what the output is supposed to be. It is also important to evaluate how well BCI operation combines with other brain functions. A BCI that requires total user attention might not support a conversation or other interaction in

which the user must continually choose the messages to send and evaluate the responses they elicit from the other person or from an external device.

CONCLUSION

A BCI allows a person to communicate with or control the external world without using the brain's normal output pathways of peripheral nerves and muscles. Messages and commands are expressed not by muscle contractions but rather by electrophysiological phenomena such as evoked or spontaneous EEG features or cortical neuronal activity. BCI operation depends on the interaction of two adaptive controllers, the user, who must maintain close correlation between his or her intent and these phenomena and the BCI, which must translate the phenomena into device commands that accomplish the user's intent.

These systems have been rapidly growing during the last three decades. A review of the ongoing research has been provided in this study. Static features measured in different EEG conventional frequency bands, dynamic features such as those characterizing the motion of movement related sources have been widely used in BCI systems. Finally, estimation of the cortical connectivity patterns provides a new tool in evaluation of the directivity of brain signals and localization of the movement-related sources. Although the advances in signal processing, especially in detection, separation and classification of brain signals, have lead to very exciting results in BCI, as yet not all physiological, anatomical and functional constraints have been taken into account. However, no robust solution to application of BCI for paralyzed subjects exists. The effectiveness of the solution depends on the type and the level of subject disabilities. Moreover, there has not been any attempt to provide BCIs for subjects suffering mental disorders.

Future progress hinges on attention to a number of crucial factors. These include: recognition that BCI development is an interdisciplinary problem, involving neurobiology, psychology, engineering, mathematics, computer science and clinical rehabilitation.

Generally, to achieve a clinically useful BCI (invasive or noninvasive) system stable, low noise and long recordings from multiple brain regions/electrodes are necessary. In addition, computationally efficient algorithms have to be developed in order to cope with the real-time applications. On the other hand, the subjects should learn how to use brain plasticity to incorporate prosthetic devices into the body representation. This will make the prosthetic feel like a natural part of the body of the subject and thereby enhance the lifestyle of the subject, our ultimate aim!

BCI systems could provide an important new communication and control option for those with disabilities that impair normal communication and control channels. They might also provide to those without disabilities a supplementary control channel or a control channel useful in special circumstances.

We hope the collected information in this study could be useful for researchers who want to start studying in this field.

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