# BRAIN COMPUTER INTERFACES

## FEASIBILITY REPORT
## BME – 620 Fall'14

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# BRAIN COMPUTER INTERFACE

**Abstract:**
This aim of this report is to bring out an analysis of the scope and effectiveness of a brain computer interface (BCI). In order to realize this it is important to know the related physiology and pathology that engenders the creation of this technology. Many physiological conditions disrupt the body's neuromuscular network hampering the person's ability to have voluntary control over ones body. A list of such diseases include multiple sclerosis, amyotrophic lateral sclerosis, brain-stem stroke, etc that destroy the neural pathway for controlling muscles. The approach to help these patients was to work out a way enhance the activity of available minimal muscle control to substitute the non-functioning ones. Another option was to redirect the neural signals so as to externally stimulate muscles and the last option was of creating a neuromuscular connectivity independent system also called the BCI. A BCI aids patients with neuromuscular disorders that lead to complete loss of voluntary control in the body and serves as a communicative link with the surrounding. Many methodologies have been applied including EEG, MEG, fMRI, etc. to acquire neural signals from the brain so as to effectively understand their relationship with any given voluntary task.

Of these systems the BCI involving use of EEG has been the most efficient in terms maintaining a balance of cost, mobility, effective output and higher speeds. The device typically consists of an EEG unit to obtain neural signals followed by a signal-processing unit that enhances the desired component of the EEG signal. This is followed my a feature extraction-translation system that uses machine learning principles to classify the signals into different categories that correspond to brining about a certain output on the display screen. This screen is not only a mode for the user to communicate with people around him, but also to provide a feedback to the user's brain. A few signal processing method include averaging, filtering, Fourier transform and sampling and some of the machine learning methods usually used are linear discriminant analysis and support vector machine. In recent researches, the output these systems produce are basic cursor movements and spelling prediction, which in them are of great relief to the users and the people around them as well.

There are many neuronal signals of interest that could be successfully detected through EEG and controlled by a user. These include slow cortical potentials (SCP); Mu-Beta rhythms (SMR) and P300 evoked potentials that are described further in the paper. These signals are translated into spelling devices so that a patient can communicate using words. There also exists cursor control and selection mechanism where the patient moves the cursor on the screen toward a target location using his brain signals. The peculiar aspect of this device is that it needs to first be trained using EEG signals called as the offline component. Once a system is created, a user needs to be trained in generating the appropriate EEG signal to use it called the online component. The effectiveness of the device is how well it can be trained and also how well can it decide what the user is trying to communicate. This can be determined by conducting clinical trials with the patient population. In these trials, there must be an offline section wherein the patient is made to do a task and EEG obtained is used to train the device. This is followed by an online system where the trained device is used by a patient to complete designated tasks where the patient trains his neural activity to be produced similar to what was used to train the device. On successfully doing so, the device can match the patient's EEG with its trained EEG on real-time basis to produce a corresponding output action. Many such trials have been conducted; the results of some of them have been discussed in this report.

The overall conclusion derived by analyzing the above-mentioned factors suggests that successful operation requires that the user and the BCI device have to primarily adjust to each and continue to do so for a steady presentation. The most easy to control signal appears to be the P300 type however the best signal for training even though time consuming would be credited to SMR. This signal shows promise for complicated applications, which may not be associated with specific events. Designing the most acceptable BCI system is a research involving interdisciplinary knowledge and application. There exists a lot of scope in developing better algorithms of the existing BCI systems as well as developing new methodologies in the existing framework for new ways of communication to introduce more colors in the life of Locked-in patients.

## Physiology and Pathology

The need for invention of BCI comes as result of existing neurological diseases, which do not have a cure, and the urge to aid such patients by creating a mode of communication. It is important to know the physiology of motor control to understand the need for a BCI. The function of sensorimotor control system is control of all voluntary functions of the body along with certain involuntary movements. The system follows a certain hierarchy wherein the intent to move is produced in the cognitive areas of the brain involved with emotion, memory, motivation, etc. Such signals provide activation to the sensorimotor areas of the cerebral cortex, basal ganglia, cerebellum and brain stem. These areas are responsible for determining the postures and movements required to perform the necessary movement. The information is then relayed via descending pathways to motor neurons and interneurons that innervate the area involved in producing voluntary/involuntary function[1]. The diagram shows a representation of the sensorimotor control system:

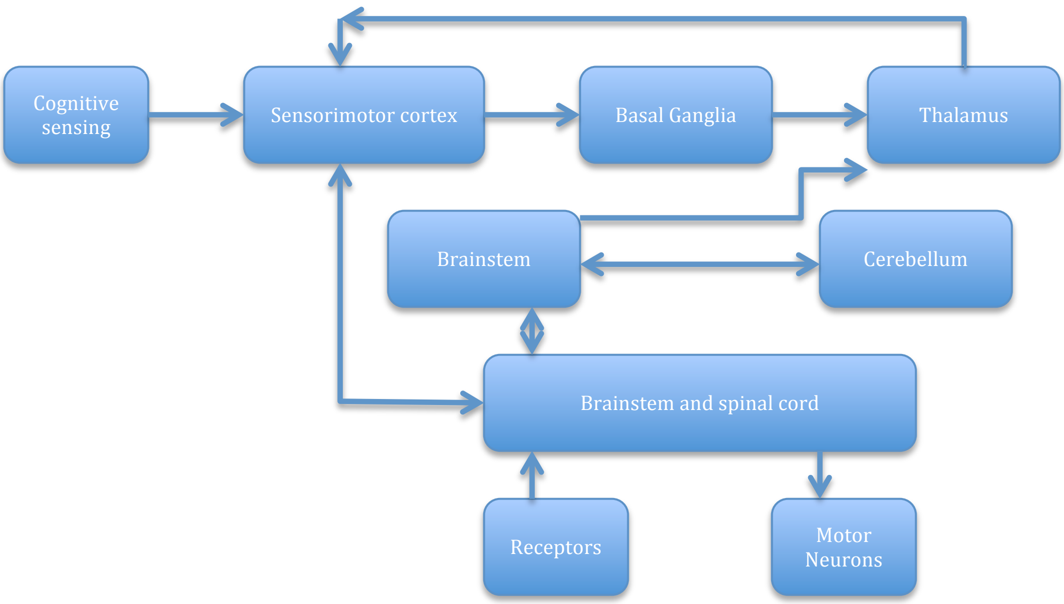


Figure 1: Sensorimotor control system

A very important factor that determines the proper functioning of the motor control system is the existence of good nerve impulse conduction. Long peripheral nerves run throughout the body to perform motor control. Nerve action potential thus needs to be transmitted over long axons, and they travel unidirectionally along the axon. Such function is not possible in an unmyelinated axon unless it is very large in diameter, which is unsuitable for the complex functioning of the human body. Motor nerves are hence, myelinated in order to ensure faster and faithful conduction of impulses to perform voluntary movements. Schwann cells (Myelin) insulate the nerves exposing them at certain intervals where the nerve action potential is regenerated allowing it to travel longer distances without increasing the diameter of the neuron[2]. This function in the nervous system is extremely important as it improves the speed of conduction, distance, and also reduces the expense of energy during impulse conduction. Neurological disorders affecting motor function are characterized by improper structuration or complete absence of myelin, and the degeneration of the neurons. This affects the nerve conduction velocity and also the energy of the impulse that is necessary to bring about movement at the target location[2].

There are a number of neurological diseases that affect voluntary function of the body. Diseases bringing about a severe outcome condition like the "Locked-In Syndrome" (LIS) requires the aid of a system like the BCI. A few causes for LIS are[3]:

1. *Amyotrophic Lateral Sclerosis:*
   This is a progressive neurodegenerative disease that affects both upper and lower motor neurons. Anterior and lateral spinal cord is replaced by fibro-astrocytes and the motor axons progressively die leading to locked-in syndrome.

2. *Brainstem stroke:*
   It may occur due to transfer of blood clot from different parts of the body into the arteries of the brainstem leading to nerve death and paralysis. It may also occur due to hemorrhage of blood vessels.

3. *Multiple Sclerosis:*
   This is an immune-mediated inflammatory disease that affects the myelinated axons of the central nervous system. It progressively destroys the myelin of brain and spinal cord nerves leading to loss of conduction of impulses leading to disability.

4. *Central Pontine Myelinolysis:*
   Loss of myelin in the brain stem leads to disconnection between the brain and peripheral nerves. It affects speech, balance, and motor function and causes permanent nerve damage.

5. *Traumatic Injury:*
   Any trauma to the brain like head injuries or hemorrhage may lead to multiple effects on the motor function including slurred speech, loss of coordination and nerve cell death.

LIS is a condition where the patient retains his/her cognitive functions but is unable to perform any muscular movement leaving no mode of communication of needs feasible. In certain cases a patient may have eye movements and bladder control intact. Patients are able to perceive through most senses but are unable to communicate their emotions leaving them locked in their body. No standard treatment or cure is available for such diseases and there has thus been a lot of scope in devising aid for such patients in any form possible, mainly being the creation of a mode for communication. Brain Computer interface serves as an aid to this condition amongst its other applications.

An EEG is the device that is used to obtain neural signals. Actions potentials in the neurons last for a very short duration of the order of 3ms, difficult to obtain a pattern to study brain function. The attention thus drives to studying Excitatory and Inhibitory Post Synaptic Potentials (EPSP and IPSP), which has timing of the order of 50-100ms on an average. These signals occur from millions of non-coherent sources and add up to form an EEG signal. The EEG signal has been studied over a long period of time and different frequency components of the signal have been classified in terms of different conscious states.

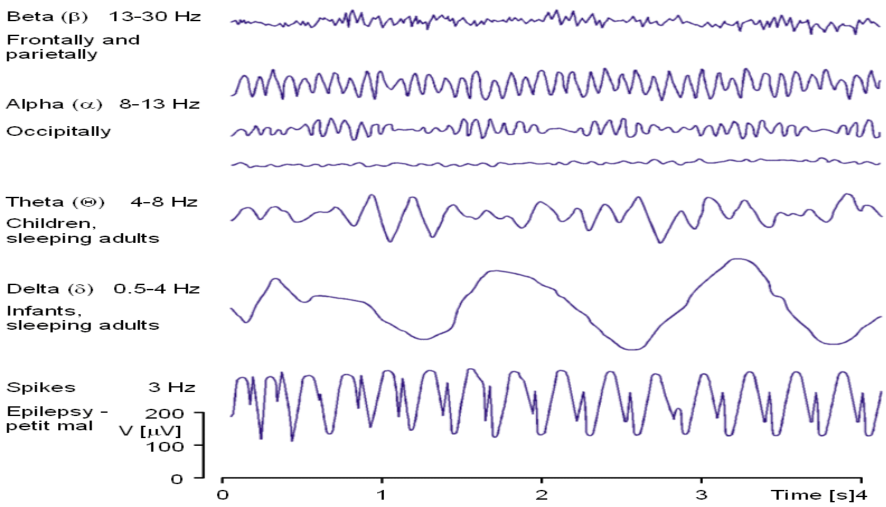


Figure 2: EEG components demonstrating the various conscious states of the brain.
(Image ref: http://www.bem.fi/book/13/13x/1305x.htm)

The Frequency components of these signals are:

| | |
|---|---|
| δ | 0.5 – 4Hz. (Deep Sleep) |
| θ | 4 – 7Hz. (Deep Sleep) Thalamic Rhythm |
| α | 8 -13Hz. (Relaxed state) |
| β | 13 -30Hz. (Thinking State) |
| **Spikes** | 100 Hz. (Epileptic State) |

Table 1: Types of neural activity states.

A person in a locked in state is capable of training himself to generating these brain signals to a desired extent as he retains his cognitive function. Such brain signals are translated into devices to aid these patients in communication and performing tasks.

## The Brain Computer Interface

The brain computer interface (BCI) is essentially an interaction scheme between the brain and the surrounding environment of a patient that enables them to communicate with the situation. The system consists of an input in the form of a neural signal from the brain, which is processed to produce a desired communicative output. It has a feedback loop, visual or auditory, which evokes the required neural activity in the brain. The block diagram for a BCI can be shown as follows:

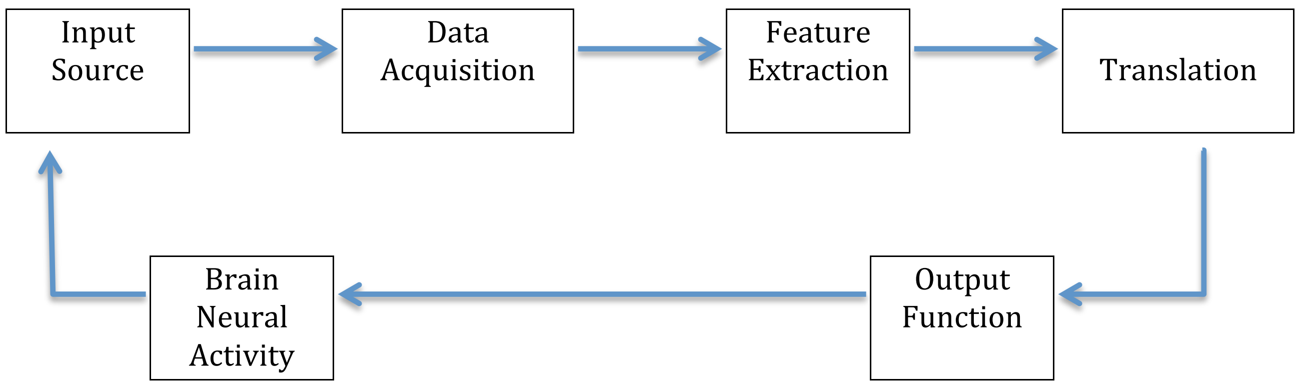


Figure 3: Brain Computer Interface block representation

A brain computer interface receives input from the motor cortex through EEG consisting of 10-20 electrode system and use of about 8 channels for acquiring signal data. The signals are detected by averaging method, i.e. several trials are averaged based on the focused stimulus. The signal is then preprocessed to improve signal to noise ratio and removal of high frequency artifacts by use of band pass filters. To devise a good understanding of the EEG and obtain outputs from its characteristics it is very important to classify the signal components. To prepare the signal data for effective classification, it is subjected to decimation to remove unwanted data.
There are different types preprocessed EEG signal outputs that are used as input in various applications like Slow-cortical potentials, Mu-Beta rhythms and P300 wave (Event related potential).

- *Slow-cortical potentials* feature the low frequency components of the EEG measured at the cortex lasting up to 0.5-10 seconds[4]. Negative potential value on this signal component represents movement action and positive change in potential represents reduced cortical activation. This positive change represents the learning of the definite motor activity.
- *Sensorimotor rhythms* also called, as Mu-Beta rhythms are those EEG components that like in the range of 8-12Hz and 18-26Hz for Mu and Beta signals respectively[4]. These signal occurrences in the cortex have a peculiar de-synchronization during start of movement and synchronization during end of movement.
- *P300* is the most well studied event related potential peak, which is characterized by a sudden deflection in the EEG occurring at 200ms – 600ms after the onset of a sudden attention-attracting stimulus[5].

These signals are obtained by processing the EEG signals generated by the patient or subject by use of various signal-processing techniques like filtering, averaging, feature extraction algorithms. The resultant data trains an output device by using machine-learning techniques. These algorithms help classify the acquired data to correspond to a specific output function. Some of the machine learning techniques and their applications are listed as follows[6]:

- *Linear Discriminant Analysis (LDA):* This method determines the maximum distance between two classes of data. It is favorable in eliminating noise and for binary output applications in BCI.
- *Support Vector Machine (SVM):* This is also used in binary classification; lags behind LDA in noise removal but it has high translation rates and works faster. The Gaussian SVM is a non-linear method that supports Speller applications of BCI and is difficult to compute.

Most BCIs are trained to perform operations like communicating in yes/no; speller systems; cursor movement; prosthetic device movements, etc. that aid locked-in patients to convey their needs. For the purpose of comparison let us understand the functioning of 3 types of Brain Computer interface systems.

*P300 Speller*:

This system uses the event related P300 signal produced in a subject's brain as an input to build a speller system to provide for a communication mode for a locked-in patient. This signal is usually elicited by an oddball paradigm, i.e. infrequent interruption of repetitive visual stimuli with an expected deviant stimulus. When a user registers this infrequent stimulus, a P300 wave is generated in the brain about 300ms after the occurrence[7]. The device presents the user a 6 X 6 matrix of alphanumeric characters and the subject is given a phrase or sentence that he need to develop one letter at a time. The visual stimulus is provided such that each row and column (12 highlights) of the matrix is emphasized for 100ms each with a relaxation period of 75ms per iteration corresponding to one character at a time. This system observes the production of a P300 wave at 2 out of 12 highlights corresponding to the row and column of where the desired character is present. This EEG data is exploited in a machine learning system to provide for a speller output.

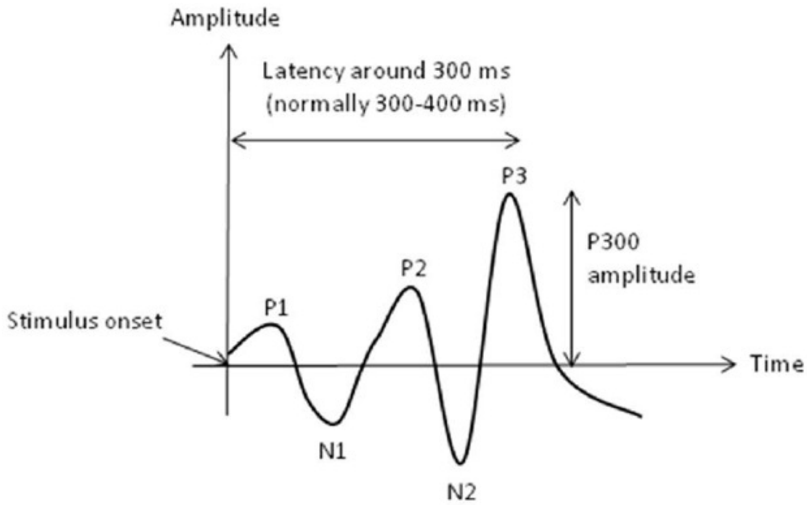


Figure 4: EEG graph showing a P-300 response and latency period.

*Sensorimotor cursor-control*:

Sensorimotor components of EEG are obtained on measuring along the right and left sensory and motor cortex of the brain. These signals have mu rhythms between 8-13Hz and beta rhythms between 13-30Hz, which show a decrease during the start of a movement and increase after completion of a movement. The key element is this that this phenomenon occurs during motor imagery, i.e. when movement is imagined and hence, actual movement need not be performed[8]. BCI systems link this motor imagery to a visual feedback system involving cursor movement on the screen. The exemplary device acquires EEG using 10-20 electrode system with a sampling rate of about 1000/sec[9] and data is acquired from paraplegics and normal subjects for actual movement of limbs and motor imagery of movement of limbs. The signal processing involves removing noise and obtaining the power spectrum by Fast Fourier Transform (FFT) of the recorded EEG to analyze the energies of Mu and Beta rhythms during action/motor imagery and relaxation. This Power Spectrum data is classified using SVM technique to translate the signal levels specific trained cursor movements.

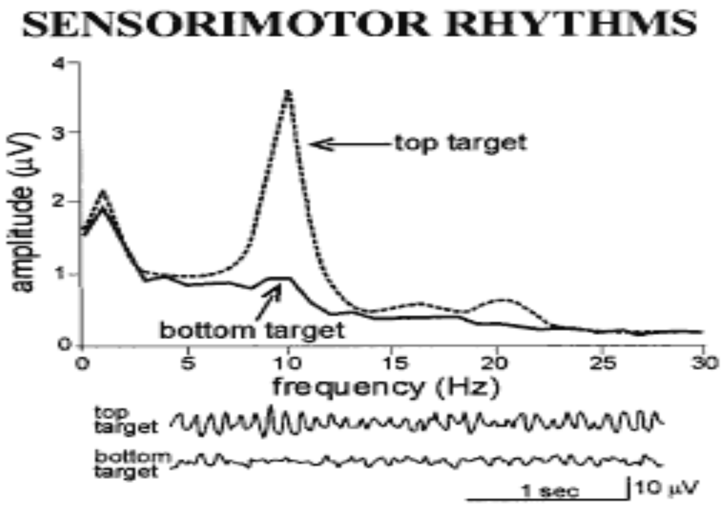


Figure 5: Image representing the power spectrum during presence and absence of SMR activity. (Image ref: http://www.aksioma.org/brainloop/bci_wadsworth.html)

*Slow cortical cursor-control*:

In this system slow cortical potentials are produced during sustained cortical activity involving simultaneous depolarization of large number of neurons are controlled by the user. Here the frequency range of interest is between 0.1Hz to 1Hz acquired using low pass filtering and averaging window of about 500ms with rate of 16/second. The subjects are trained to control the negativity or positivity of cortical potentials by providing a visual feedback of the potential[10]. The negativity of SCP is engendered with intent to move or utilization of resources for cognitive jobs, and the positivity of SCP is produced while executing the tasks or simply in inactive conditions. This system is capable of providing binary outputs, which can be translated into a cursor control system. In this system threshold values can be set to differentiate between negativity and positivity usually done using Linear Discriminant analysis classification technique[11]. The level of signal in each category corresponds to upward (-ve) or downward (+ve) movement of cursor. A threshold level is also set for performing a selection response so the region on the screen can be selected for further action. To produce an effective computation signals were recorded with a feedback followed by performing the same action without feedback where the subject has to purely apply mental strategy.

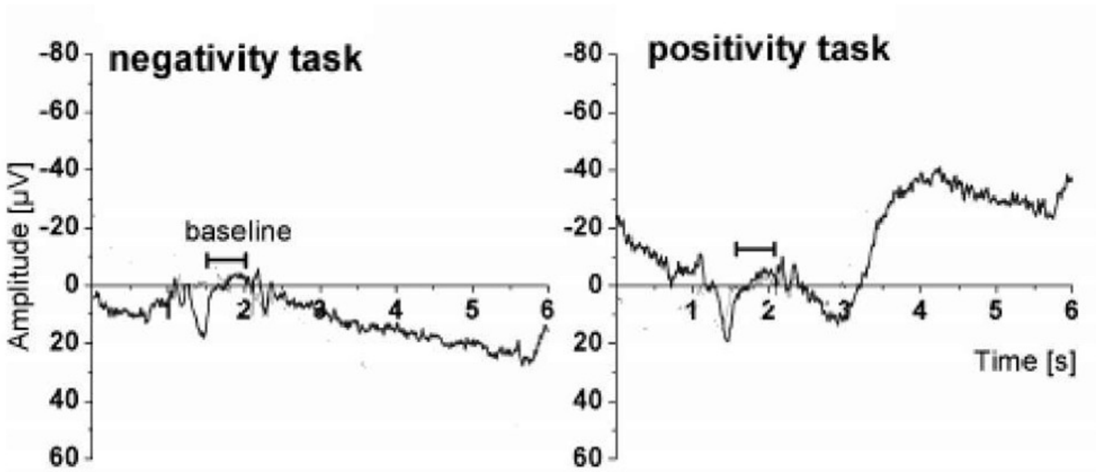


Figure 6: SCP activity for Negative and Positive potential generation. (Image ref: Here)

## Scientific Analysis of Brain Computer Interface Systems

Many studies have been conducted by the use of the above-mentioned BCI systems on different patient populations. The aim of these studies has been to device a good training system for these patients and also to gauge the ease of learning to control these signals with an aim to produce an enhanced communication interface. The working of a brain computing system can be affected by the quality of functioning of all its components and it is important to know what are the good characteristics of signal processing, machine learning and the signals themselves. The success of a system also depends on the success of training subjects to use it and the accuracy of the system to provide for the desired output on doing so.

Most BCI systems are trained using the following steps: (1) Subjects both healthy and Locked-in are made to perform a certain desired task. (2) During this activity, EEG signal data is collected and processed to enhance a desired feature i.e. p300/SMR/SCP is extracted. (3) This data is classified using machine learning techniques mainly LDA and SVM and a system is trained where every class of data is translated into a desired output cum feedback property i.e. cursor movement and speller system. This portion of training is the "device training" or "offline training". The next step is where the accuracy of this system and the ease of training a user come into picture. (4) In this step, the subject is trained to use his brain signals to bring out a desired output from the system mentioned in step 3. (5) The user is provided with a certain action (motor imagery) or sentence (Speller) which one needs to accomplish by trying to control his brain signals on real-time. This also tests the classification ability of the system and this immediate feedback training is also called "subject training" or "online training"[5]. Many such training protocols have been conducted on the previously described BCIs and their key features and results are the way to predict the success, feasibility and improvements this class of communicating devices.

Prior to studying clinical experiments, it is important to know that the quality of signal processing and machine learning used in a device plays a major role in its accuracy. The major signal processing techniques used include:
(1) *Averaging:* In EEG the signal is acquired using multiple electrodes placed based on the 10-20 system. A key point is that it is difficult to localize the source of the signal along with the adding up of noise and artifact from each source. Averaging the signal detected over all electrodes helps in smoothening the signal and the noise. Higher the numbers of electrodes better the averaging and quality of the signal.
(2) *Filtering:* The EEG signals of interest are confined in the frequency range 0.1-40Hz, the detected signal contains noise and artifact and it is important to use filters to remove unwanted components. The main feature of a filter is its order, if too high can maintain a very crisp cut-off but introduce a delay. On the other hand, lower orders can provide for a smoothened signal but may not completely eliminate unwanted signals. It is important to choose the best for the application based on requirement.
(3) *Sampling:* The main role of sampling is to quantize the acquired EEG in to specific values over time that is capable of faithfully representing the signal. It is necessary to satisfy nyquist criterion. Very low sampling rates introduce quantization noise but very high sampling rate requires more memory.
(4) *FFT:* A Fast Fourier Transform on a signal gives the energy of each of its frequency components. This feature has been of supreme importance in designing the SMR BCI. This technique is used in knowing the change in amplitude at a given frequency over time and also in identifying noise.
It is important that one selects these signal processing parameters in best accordance with the required signal enhancement.

The next important component is classifying the acquired EEG data in terms of its features. The most commonly used methods and their key features are as follows:
(1) *Linear Discriminant Analysis (LDA):* LDA reduces noise by only picking the data that contributes the most to the classification task. It projects data from a higher dimensional space to a lower dimensional space upon which the classification task can be done. It makes computation easier and

much faster since the number of features is greatly reduced. Any general classifier can be used using this lower dimensional data. Hence, it is highly suitable for binary type translations as seen in SCP BCIs. However, some important classification criteria may be lost while projecting to a lower data samples. This will result in a lower accuracy as compared to using all data.
(2) *Support Vector Machine (SVM):* SVM classifies data based on minimizing margin loss. It is highly useful in training huge amount of data, with respect to both number of data instances and number of dimensions. SVM is one of the most common classifier used in SMR and P300 type BCI and there are many efficient classifiers implemented in most commonly used programming languages. However, SVM is slow since it does convex optimization for a very high dimensional space.

It is also important to determine the success rate of clinical trials to understand the feasibility of these devices. Clinical trials represent the success of a device in terms of the users ability to use the BCI with training and also the ability of the BCI to translate user intent correctly. Here are some studies of the P300, SMR and SCP systems and their results:

*Slow Cortical potentials:*

| **Training Protocol** | **Results** |
|---|---|
| In this study, 11 subjects were first asked to generate SCPs w/o feedback by using indicators flashing on screen A-generate –ve SCP and B-generate +ve SCP. Training with feedback followed this, where a ball moved towards a target on the screen. 35 sessions were conducted with each having 70 +ve and –ve SCP generation tasks.[11] | The learning rate was slow with achieving about 1 target per minute. Over the time 7 trainings were terminated due to multiple reasons and 4 subjects continued with achieving about 75% accuracy in generating SCPs over a long period of months. |
| Another SCP BCI study had 8 subjects working in screen with a horizontal target line and an cursor displayed on the screen and the subjects had to generate SCP to move the cursor adjacent to the target, +ve for downward and –ve for upward to hit the target line.[12] | This study showed successful differentiation in 20 sessions scheduled in gaps of a week with 1 subject achieving improvement in response response. |
| The second SCP study was translated into a Language support program, where the subjects could choose between letters displayed on the screen by two choice selections by using SCP to select between 2 halves and then 2 quarters of the screen. The system also had a predictive algorithm.[11] | The system achieved 65-90% accuracy in predicting the user's selection but with a rate of 0.15-3 letters/min and about 2-36 words/hour. |

Table 2: Comparative table for training of SCP BCI systems.

*Sensorimotor Rhythms:*

| **Training Protocol** | **Results** |
|---|---|
| 5 subjects attempted to generate cortical activity with direct EEG recording feedback. The subjects were informed of expected activity through a video based on which they made attempts.[13] | Subjects were initially unsuccessful but eventually gained control of up to 71.4 % exhibiting the possibility of using these signals for communication purpose. |
| Another study was performed in 7 subjects using motor imagery and power spectrum analysis of the signal. Performing baseline tasks, mathematical tasks as well as stationary cursor task where the user will observe no response on the cursor were the feedbacks.[14] | This system successfully depicted that it was possible to distinguish movement related SMR in 6/7 subjects with about 70% accuracy. More over the subject's cortical activity was interpreted by the device with about 80% accuracy. |

| | |
|---|---|
| 7 subjects were provided with a target vertical bar at random locations on the right side of screen with cursor on left. The cursor has rapid horizontal movement while the vertical movement is controlled by SMR activity.[12] | 4 subjects completed training in 20 sessions with a success rate of about 75%, which is sufficient in building a speller program. 3 subjects were halfway with minimal improvement in the ability to control SMR |

Table 3: Comparative table for training of SMR BCI systems.

*P300 Event Related Potential:*

| **Training Protocol** | **Results** |
|---|---|
| 100 normal subjects were tested to spell 5 character word 'water' and 'lucas' after a 5-minute training. The EEG signal translated outputs were calculated using two methods "row-column"(RC) and "single-character"(SC) to judge the accuracy and ease of use.[15] | 72.8% of 81 were able to achieve 100% accuracy in RC and 55.3% of 38 in SC. More over 89% of 81 demonstrated 80-100% accuracy with the device use. This provided for the urge to test such a system in locked-in patients. |
| An RC type speller on 9 subjects during training sessions has 10 round in each session with increment in the total number of characters to be identified. The subjects were required to identify 3 characters in round 1; 8 in next; so on with 13,16,21,25,29,32,37,41.[7] | The accuracy in identifying characters incremented gradually and stabilized into a plateau after 25 characters. Most subjects achieved 90% accuracy by the $7^{th}$ round with some going up to 95%. |
| 7 patients were presented with a matrix of alphabets with rows and columns flashing in random. The task was to count the number of time a specific character "P" flashed. The target character flash was expected to initiate a p300 response.[12] | 4 out of 7 patients were successfully in 10 sessions with accuracies ranging from 13.5% and 86.6%. Of these subjects, 2 patients achieved 100% percent accuracy. The remaining 3 patients did not show any significant improvement in training. |

Table 4: Comparative table for training of P300 ERP BCI systems.

Many such studies have been proceeding over the last 2-3 decades with an aim to improve the life of locked-in patients. Analysts have observed that all these methodologies come with their perks and abscond.

**<u>Conclusions</u>**

Brain Computer interfaces converts the electrical activity of a large number of neurons into useful communicative outputs. Irrespective of the quality of these outputs, the patient population that is aided by them acquires more than expectation from every development in this area. These devices depend on feedback as much as a normal neuromuscular system for bringing out an output. It is expected that these devices function in an adaptive manner with both the user's brain signals as well as the translation algorithms within it to provide for a helpful output. Moreover, in order to use a BCI, the user needs to develop a new skill in controlling his electrophysiological signals, which is not exactly similar to performing movement. The key factor for the success of a BCI is its ability to translate the user intent maximally.

We have in the previous section described the various parameters and factors that are involved in resulting an acceptable BCI. It is important conduct a thorough analysis while selecting these parameters and also clearly defines the range of acceptability of the device performance. The results of offline training and online performance of a BCI helps demonstrate its scope and areas of improvement. The studied clinical trials demonstrate that:

- It is very difficult for subjects to control their slow cortical potentials however they are faster at picking up control over SMR and P300 potentials.

- On the other hand, it is also seen that SCP signals exist in the brain even if there is complete disconnect with motor periphery and its electrophysiology is well understood and it is easier to train a device with these signals.
- A very important advantage of the SMR BCI is that it represents motor imagery, which is suitable for larger scope of application like training a robotic arm to perform movements along with basic spelling program. Its control can be learnt much faster than SCP along with achieving good accuracies.
- P300 has been the fastest system with least amount of training required in using the device with high device accuracy. However, some populations of patients fail to successfully train themselves in using the device.

Some drawbacks for the use of these systems are that, using it requires constant attention, which is very difficult considering the health of the user. Its constant use will cause fatigue due to which a subject may demonstrate inconsistent performance while using the device leading to improper judgment of the device's ability. The performance and suitability of the device also varies with the user's state of health i.e. disease progression. The device in itself also faces certain drawbacks as EEG signals lie in a very small spectrum of frequency with low amplitude making its detection, processing and feature extraction difficult. A major problem is the fact that the brain signals produced by patients is subject to change making it necessary for a BCI to adapt to such change. Sometimes this may also mean completely retraining the device. A very small population of patients currently uses these devices and as this number expands, we are prone to expect more problems in the use of this device.

Although, all of the above methodologies have their own specialties, they are all assisted by some undesirable characteristics. In general it can be understood that in presence of good cognitive function, the overall performance of SMR BCI can have a lot of scope for extrapolation into varied applications for long-term effectiveness that can aid Locked-in patients. The future scope lies in reducing or eliminating the undesirable fallouts as well as in maximizing the ability by improvising upon aspects like algorithms, artifact removal, well-defined objectives for judging performance, optimized identification of signals, projecting the long-term performance of device. The scope also lies in designing new applications in the areas of communication, movement control, environmental control and locomotion.

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