# Technology Development for Unblessed People using BCI: A Survey

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## ABSTRACT
The Brain Computer Interface (BCI) systems enable unblessed people to operate devices and applications through their mental activities. It is believed that the BCI technology should be a blessing for the unblessed persons who may be suffering from severe neuromuscular disorders. So in this paper, we present a review on the progress of research efforts and then we analyze the challenges in BCI research and development for unblessed people. Here, a general Electro-Encephalogram (EEG) based BCI system is discussed which can assist the paralyzed or physically or mentally challenged people in performing their various routine tasks or applications.

**Keywords: –** Interface, Brain-Computer Interface, Electro-encephalogram, Unblessed.

## 1. INTRODUCTION
The Human Computer Interface (HCI) is an interdisciplinary field of knowledge and Brain Computer Interface (BCI) is its' subfield. The BCI techniques acquire signals from a subject's brain, extract knowledge from the acquired signals and using this knowledge determine the intention of the subject that might have generated those signals. In order to develop the computer systems with good and maximum usability and interactivity, extensive research work has been done using human bio-signals [32]. These human bio-signals can be acquired from an organ or a nervous system. In practice, signals acquired from heart are referred to as Electrocardiogram (ECG), from muscles Electro-myogram (EMG), Electro-oculogram (EOG), and from brain Electro-Encephalogram (EEG). The Brain Computer Interface (BCI) system involves recording and analyzing the Electro-Encephalogram signals. The BCI systems are well described in [34].

A Brain-Computer Interface (BCI) system is diagrammatically depicted in Figure1. As depicted, the input to a BCI system is the brain signals which are being referred to as EEG signals. The EEG signal is a fundamental element in BCI systems. It is not new; it was first introduced by Hans Berger [2]. Now it has gained importance as it is widely used as integral diagnostic tools for analyzing the brain signals and patterns. Basically, EEG contains information related to the functional, physiological, and pathological status of the brain which is essential for the identification of mental disorders and brain rhythms which are extremely useful for the diagnosis and monitoring of brain activities.

The BCI systems can be categorized: invasive and non-invasive categories. In invasive systems, electrodes are implanted into brain tissues. This technique is used on animals. In non-invasive systems, the brain activities are recorded *via* electroencephalography (EEG) from the scalp of a subject. In this case, the EEG electrodes are placed on the scalp and conductive gel is applied between each electrode and the scalp. The EEG can measure the activities of millions of brain cells. The recording by this method is convenient, safe, and inexpensive. The most important advantage of (EEG) signal is that being a noninvasive technique it does not harm the subject [23].

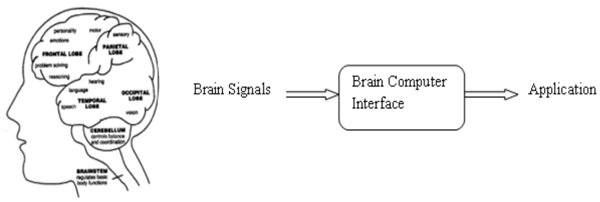



**Figure1. A BCI System**

There are various systems that have been developed for implementing the BCI applications. These systems can be roughly categorized as systems for interpreting thoughts [12], processing data, and controlling devices [23]. Among all the applications, the most important application of BCI systems is that it can make life easier for disabled people—especially for those who may need to operate some assistive devices, through intentions and/or emotions, to perform the routine tasks. In practice, despite tremendous technological advancements, embedding device controlling abilities through intentions is not impossible but an extremely difficult task—it poses almost insurmountable challenges. It requires solution(s) of several complex problems such as: (a) signal acquisition that requires maintenance of good signal quality (b) efficient signal processing, (c) intelligent knowledge discovery processes (d) reliable signal classification/recognition methods [34] and conversion of recognized signals into device control commands and invocation of the desired actions.

As mentioned before, this paper presents the state-of-the art of the BCI research and technology development, and its importance in unblessed people's life. The organization of the paper is as under.

In Section II we explain the literature review on BCI system which assist the physically and mentally challenged people. Section III discusses applications of BCI systems for unblessed people. In Section IV we outline different phases of a BCI system. Section V and VI explain conclusion and an idea about Future Scope.

## 2. LITERATURE SURVEY
The Brain Computer Interface (BCI) systems assist unblessed people. A detail discussion on their usefulness is presented in Section III. In this Section we discuss various Brain Computer Interface (BCI) systems that have been developed during different time span and brief description of the work. These are summarized below in Table 1.

**Table 1. Work in BCI for Unblessed People**

| S.N | Work | Description | Year |
|---|---|---|---|
| 1 | Brain–Computer Interfaces Based on the Steady-State Visual-Evoked Response [27]. | A brain–computer interface system hat interprets the steady state visually evoked response into a control signal for operating a physical device or computer program [27]. | 2000 |
| 2 | Human / Brain Computer Interfaces: Challenging puzzles to solve [36]. | A BCI system that uses EEG signals, and provides a new mechanism for communication with the external world and controlling remote devices and computers. | 2003 |
| 3 | Identification and Classification for finger movement based on EEG [10]. | An experiment with Common Spatial Subspace Decomposition (CSSD) algorithm was reported for classifying single-trial EEG during the preparation of left-right finger movements. | 2005 |
| 4 | A Comparison of Time, Frequency and ICA Based Features and Five Classifiers for Wrist Movement Classification in EEG Signals [11] | The study reports a comparison of two methods to extract features for the classification of wrist movements (flexion, extension, pronation, supination). | 2005 |
| 5 | Two Channel EEG Thought Pattern Classifier [12]. | A real-time EEG identification system for hands free control, and its flexibility was tested in controlling a powered wheelchair. | 2006 |
| 6 | On the Time Series K-Nearest Neighbor Classification of Abnormal Brain Activity [28]. | A quantitative analysis EEG recordings, in classifying the normal and abnormal (subject suffering from epileptic) brain activities. | 2007 |
| 7 | Multilayer Perceptron for EEG Signal Classification during Listening to Emotional Music [13]. | An EEG signal-based emotion classification system. The system was trained to learn four targeted emotion categories, including joy, angry, sadness, and pleasure. | 2007 |
| 8 | Human-Machine Interface Based on Muscular and Brain Signals Applied to a Robotic Wheelchair [29]. | A Human-Machine Interface (HMI) system. The system is use signals generated by eye blinks or brain activity. It operability was tested on in operating a robotic. | 2007 |
| 9 | Prosthetic Controlled System Based on Signal Pattern Recognition of Electroencephalogram [30]. | A prosthetic controlled system. It uses EEG signals. | 2008 |
| 10 | Automatic Sleep Stage Classification Using Two Facial Electrodes [14]. | A system for determining the sleep disorders (light sleep and deep sleep) from brain signals. | 2008 |
| 11 | Multiclass Voluntary Facial Expression Classification based on Filter Bank Common Spatial Pattern [15]. | An EEG and EMG signal based system for classifying multiple facial expressions. | 2008 |
| 12 | Emotion Classification Based on Gamma-band EEG [16]. | An EEG signal based system for classifying the happiness and sadness of a person. | 2009 |
| 13 | Study on EEG-Based Mouse System by Using Brain-Computer Interface [17]. | An EEG-based mouse designed for Brain–computer Interface (BCI) system to move a cursor on a computer display. | 2009 |
| 14 | Classification of Single Trial EEG during Imagined Hand Movement by Rhythmic Component Extraction [18]. | An EEG signal based Rhythmic Component Extraction (RCE) system to extract a feature corresponding to (left/right) hand movement. | 2009 |
| 15 | Feature Extraction and Classification of EEG Signals for Rapid P300 Mind Spelling [19]. | A Brain-Computer Interface (BCI) system that enables subjects to spell text on a computer screen by detecting P300 Event-Related Potentials in their electroencephalograms. | 2009 |
| 16 | An On-Line BCI System for Hand Movement Control Using Real-Time Recurrent Probabilistic Neural Network [20] | An EEG-based Brain-Computer Interface (BCI) system for on-line controlling the hand movement in a virtual reality environment. | 2009 |

# 3. THE BCI FOR UNBLESSED PEOPLE

As mentioned before the BCI systems convey commands, *via* brain signals. Due to their enormous application potentials, a large number of varied applications of BCI systems are being developed to assist disabled people to communicate with Thought Translation Devices [12]. The P300-based BCI systems are developed for motor-impaired patients. Such system handles real-time applications like the cursor motion control in graphical interface [33], and their reliability and performance are well tested [8]. Very useful systems are being developed for locked-in patients suffering from epileptic seizures and paralysis. Such systems are proving beneficial in providing communication and control with patient's environment. In an interesting application described in [22], in this application a telepresence robot—a small round mobile platform—was designed for disable users to control it. Two patients mentally controlled the robot's drive through shared control mechanism.

Advancement in signal acquisition technology is making possible to create many more such applications. Some of them are listed below:

a) Detecting wrist movement direction intention[11],
b) Emotional stress recognition,
c) Emotional states classification, [24]
d) Emotion recognition in speech,
e) Emotion classification,
f) Rapid P300 mind spelling [19]
g) Detecting epilepsy or detection of epileptic seizures.
h) Classification of abnormal brain activity
i) Finger movement task [10]
j) Facial expression classification or Face and facial expression recognition from images and videos [14]
k) Imagined hand movement [18][20],
l) Diagnosis of depressive disorder and risk for depression in adolescents using acoustic speech analysis [6],
m) Detection of distressed and depressed affect in speech [9],
n) Speaker verification using information theoretic learning,
o) Development and reliability study of the new back strain monitor, and
p) Bio-signals for lip reading.

In addition, the EEG based BCI systems are proving useful in medical applications like in diagnosing the health conditions in brain injuries, tumors, strokes, epileptic seizure, liver, cerebral palsy, and alzheimer disease. The BCI systems also facilitate in assessing medical issues like dizziness, blackout, headaches, weakness etc. [2]. All these applications, and many more waiting to be discovered, are revealing the fact that the EEG signal is one of the most important and useful bio-signals to poke inside the user's head to observe their mental state.

# 4. THE BCI SYSTEMS

As mentioned in Section I the BCI systems are being developed using noninvasive EEG signals. The general EEG based BCI systems mainly consist signal acquisition, signal processing and classification subsystems.

An architecture of a BCI system is shown in Figure2 that has following components:

- Signal Acquisition,
- Signal Processing,
- Feature Extraction,
- Classification, and
- Application.

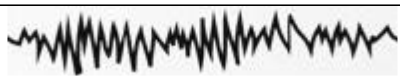
The first step in developing a BCI system is brain signal acquisition through invasive or non-invasive methods. Once the signals are acquired, it is necessary to clean or remove the noise from the signal to improve the signal accuracy. In this process, the signals are amplified and sampled. In the next step features are extracted from the processed signals. Afterwards, based on extracted features, signals are classified and the classification results are used the specified application. The functions of these components are described in detail below.

## 4.1 EEG Signal Acquisitions

As mentioned before, the EEG signals or raw EEG data can be collected *via* invasive or noninvasive method. Generally speaking in most of the applications, the noninvasive method is used. In this methods the EEG signals are obtained either by placing electrodes on the scalp or by using a wearable cap. The signal acquisition process initiates from postsynaptic potentials which gets combined at the cortex and transmitted to scalp through the surface of the skull where the electrodes are attached. These acquired signals are then preprocessed which includes amplification; filtering and then the signals are digitized for further feature extraction and classification purpose.

There are four types of brain waves or EEG signals or spectral components: *alpha, beta, delta, and theta* as shown in Table 2. In general, for normal human beings the EEG can be recorded through ≤ 128 channels with the frequencies vary in the range of 1-30Hz or 0-40 (250) and amplitude vary in the range of 10-500 μV [31]. The BCI systems use three types of signals. These ares low cortical potentials (SCPs), sensorimotor rhythms (SMRs) and event-related potentials (ERPs) [26]. Out of these the ERPs are more beneficial to use because of higher rate of information transfer [26].

**Table 2. Types of spectral components**

| Wave Type | Pattern | Frequency |
|---|---|---|
| Alpha |  | 8-13 Hz |
| Beta |  | 13-30 Hz or >13 Hz |
| Delta |  | 0.5-4 Hz |
| Theta |  | **3.1** Hz |

## 4.2 Signal Processing

After acquiring raw EEG signals the signal enhancement methods are applied to get the noise free, clear signals. The signal enhancement is basically is a part of signal processing operation which includes filtering. There are various signal processing methods like Independent Component Analysis (ICA), Principle Component Analysis (PCA), Common Spatial Pattern (CSP) and their combinations. The ICA and PCA are two different methods. ICA divide the source channel into many independent components that are quasi-synchronous activity within a cortical patch, or sometimes within two cortical patches connected by corpus callosum—or else, artifact sources —eyes, muscle, ECG, line noise, electrode noise, etc. whereas PCA gathers the best possible channel activity into each component. The PCA maximizes the variance in the data into any number of dimensions [37]. The Common Spatial Pattern (CSP) is used to design spatial filters that lead to new time series of EEG whose variances are optimal for the discrimination of two classes of EEG [15].

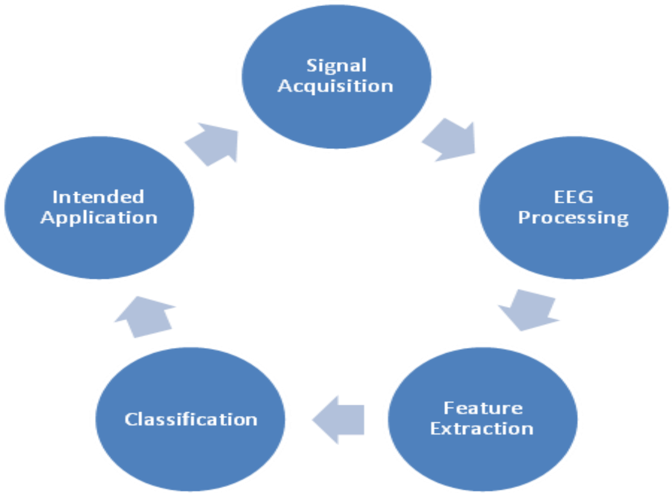



**Figure2. General BCI System**

## 4.3 Feature Extraction

The enhanced EEG signals are then processed further for feature extraction and classification. To select and apply appropriate classifier, it is very essential to know what and how features are used. Also it is very important to understand the properties of the signals. A variety of feature extraction methods were developed according to respective neuro-mechanism as shown in Table 3. Features are basically properties needed for analyzing the signal for determining the subject's messages or commands [26].

**Table 3. Feature extraction methods**

| Neuromechanism | Feature extraction method |
|---|---|
| **Sensorimotor activity** | Spectral parameters |
| | Time–frequency representation method |
| | Cross-correlation-based template matching |
| | Signal complexity Combination of different feature extraction methods |
| **Slow cortical potentials (SCP)** | Calculation of Slow cortical potentials amplitude |
| | Time–frequency representation method |
| | Mixed filter |
| **P300** | Cross-correlation |
| | Stepwise discriminant analysis |
| | Matched filtering |
| | Piecewise Prony method |
| | Time–frequency representation method |
| | Peak picking |
| | Area calculation |
| | Area and peak picking |
| **Visual evoked potential (VEP)** | Spectral parameters |
| | Lock-in amplifier |
| | Asymmetry ratio of different band powers |
| | Cross-correlation |
| **Response to mental tasks** | Spectral parameters |
| | Parametric modeling (AR & AAR parameters) |
| | Eigen values of correlation matrix |
| | LPC using Burg's method |
| **Activity of neural cells (ANC)** | Cross-covariance−PCA |
| | LBG vector quantization (VQ) |
| | Filtering – rectification – thresholding |
| | Averaging |
| | TFR methods |

After feature extraction various feature selection or dimensionality reduction methods are applied like Genetic Algorithm (GA), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) (discussed in 3.4), Support Vector Machine (SVM), etc [26].

## 4.5 Classification

The extracted features are classified according to intended application. The purpose of classification is to translate the EEG signals into commands. A variety of techniques exists for classification purpose artificial neural network, Back-propagation Neural Network, Hidden Markov Model (HMM), Bayes Network etc [5]. In artificial neural network, the Widrow-Hoff LMS algorithm is used to train Single Layer Perception (SLP) and a back-propagation algorithm is used to train Multi-Layer Perception (MLP). As compared to MLP, the HMM can deal with spurious misclassification that saves computational time. But HMM was only applicable to pointing movements. So for structured type movements, Bayes network was introduced. Support Vector Machines (SVMs) are closely related to Neural Networks and when a sigmoid function is used it is equivalent to Perceptron. Basically SVM classify the data into classes by an N-dimensional hyperplane [16].

**Table 4. Feature and Classifier Performance**

| S.No. | Feature Type | Classifier | Application | Performance |
|---|---|---|---|---|
| 1 | Event Related Synchronisation (ERS) | Brute Force | A Virtual Reality BCI Application [1]. | 93% of the subjects (21) were able to reach an accuracy equal or greater than 60% |
| 2 | Autoregressive coefficients | SVM | A spelling application for paralyzed patients (suffering from focal epilepsy) [21]. | the training with locked-in patients, an accuracy of 70% reported |
| 3 | P300 evoked potential | LDA | A P300-based BMI system developed for remote writing using human brain-actuated robot arm. [22]. | high accuracy (>90%) even with only 6 flashes per trial |
| 4 | Event-related potential (ERP) P300 | Step-wise Linear Discriminant Analysis (SWLDA), | A BCI commanded wheelchair systems [23]. | The system performs a real-time wheelchair navigation task using BCI. |
| 5 | amplitudes of evoked potentials or sensorimotor cortex rhythms, firing rates of cortical neurons | Minimum Euclidean Distance, k-nearest-neighbor, Fisher linear discriminant | An application to extract features that the user can control and translate into device commands [2] | Minimum Euclidean Distance 84.7% k-nearest-neighbor 87.5% Fisher linear discriminant 90.3% |
| 6 | Imagined motor movement | SVM | A system for classifying EEG signals corresponding to imagined motor movements [3]. | Better classification error rate for Fourier and CTFR based features than LDA. |
| 7 | Movement-Related Potentials (MRP's) | SVM | A EEG based system to classify contralateral finger movements [4]. | 10 subject-specific features and attain an average of 77% accuracy in classification |
| 8 | Event-related synchronisation/desyn chronisation | SVM | A EEG based system to extract the task-related features using wavelet decomposition [24]. | 91 |
| 9 | motor imagery | Back-propagation NN | A new EEG recognition algorithm for integrating discrete wavelet transform (DWT) with BP neural network [5]. | 92.4 |
| 10 | Steady-State Visual Evoked Potential (SSVEP) activity | Convolutional Neural Network | A new technique developed for the classification of EEG Steady-State Visual Evoked Potential (SSVEP) activity for non-invasive BCI system [6]. | 95 |
| 11 | P300 evoked potential | SVM | A P300 word speller system [25]. | 95 |
| 12 | Features are extracted from theta, mu and beta rhythms | a Fisher Linear Discriminant and a Minimum-Squared-Error Linear Discriminant Function | Single trial classification of EEG sequences for left/right self-paced tapping discrimination [7]. | 96 |

These are being used to recognize and classify different brain wave or signal patterns associated with intended application summarized in Table 4.

## 4.6 Applications

The application can involve a spelling device, Neuroprosthetics, Wheelchair control, recognition of human or subject's operations, feelings or emotions, etc. The application also generates feedback to inform the subject about the outcome of classification [23] [16] [14].

## 5. CONCLUSION AND FUTURE WORK

An EEG based BCI system involves various phases: signal acquisition, signal processing, feature extraction, Classification, application. The signal acquisition can be done in two ways: invasive and non-invasive method. Also there are various methods for signal processing, feature extraction, Classification. This survey paper presents work done in BCI for Unblessed people. The feature and classifier performance have been summarized for various applications. The future work is to study the spontaneous behavior of EEG signals. And to identify the feature extraction and classification method for handling such signals.

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