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Brain Computer Interface applications and classification techniques

T. Shashibala, Bharti W. Gawali

Department of CS and IT, Dr. B.A.M.University,

Aurangabad, Maharashtra, India.

shashibala.rao@gmail.com

bharti_rokade@yahoo.com

Abstract: Brain Computer Interface(BCI) has provided a direct medium of communication between human beings and external devices. It is a boon for people with severe motor disorders as it provides means of control and communication for them. Recently more efforts on out of the lab BCI based research with the help of Electroencephalogram (EEG) signals from brain has provided many applications. In this technology, specific features of brain activity are considered and transformed into device control actions. This kind of interface would help disabled individuals to become independent thus improving their quality of life.

Keywords: Brain Computer, Electroencephalogram, brain activity, device control**.**

1. Introduction

Brain computer interface (BCI), a hardware and software system, provides interaction to a computer directly from the user's brain has received considerable attention in the past years. BCI has the ability to transfer and use information from distinct brain states for communicating with a machine. It can offer people with severe disabilities an additional means of communication, and restore the damaged motor control function. The communication systems based on brain activity play an important role and provide a new form of communication and control, either to increase the integration into the society or to provide to these people tools for interaction with their environment without constant support.

Now it is possible to distribute tasks of a complex system over different computers communicating with each other and to process acquired data in a parallel manner and in real-time. New developments in computer hardware and software has boosted the growth of BCI based research in the past decade. There have been speculations that it could be used to translate thoughts or intents, such that a person will be able to control devices directly from the brain, with the help of electrical devices, bypassing the normal channels of peripheral nerves and muscles [1]. BCI technology has also found its use for non-medical purposes. Here, not only communication is central, but BCI technology has gained popularity in the form of measurement devices for brain states such as attention, performance capability, emotion etc., in real-time. The signals extracted by BCI techniques are then employed to optimize and to enhance human performance and to achieve potentially novel types of skills. A wider use of BCI technology has become possible only through the use of modern machine learning and signal processing methods, that allowed to relocate the burden of training from a learning subject toward statistical learning machines and thereby achieve BCI communication for a naive user [2]. The focus of evaluation for communication and functional applications should be on usability and functionality, while the focus of entertainment applications should be on pleasure and entertainment [3].

2. Types of BCI

Signal recordings of brain activity used by BCI can be either:
1 Invasive - Invasive BCI require surgery to implant electrodes directly on or inside the cortex, the advantage are the electrodes lie in the gray matter of the brain and invasive BCI produces the highest-quality signals. The disadvantage being the surgery is dangerous and risky and it is very expensive.
2 Partially invasive - Partially invasive BCI devices are implanted inside the skull, but rest outside the brain rather than within the gray matter. The advantage are better quality signals than non invasive BCI and less risky than invasive BCI. The disadvantage being this approach typically results in a permanent hole in the skull.
3 Noninvasive - Whereas in noninvasive BCI, there are no implants. The advantages are it is applicable even in low quality signal and It is safest, as no surgery is required. The disadvantage being Muscle movement in noninvasive BCI can create artifacts and noninvasive implants produce poor signal resolution[4]. Noninvasive BCI can use various brain signals as inputs, such as electroencephalograms (EEG), magnetoencephalograms (MEG), blood-oxygen-level-dependent (BOLD) signals, and (de) oxyhemoglobin concentrations [5].

2.1 Electroencephalogram (EEG)

Since the first mention of alpha rhythm by Hans Berger [1929], EEG signals have been mostly used for diagnosis of neurological problems and the functioning of the brain. However, due to the large amount of data to be analyzed, it could attract serious scientific attention only in the last decade. Working with EEG is the most convenient method and therefore the BCI is based on detecting the EEG signals associated with certain mental states [6].

EEG signals are created by the firing of neurons in the brain. They are measured using electrodes attached to the scalp, which are sensitive to changes in postsynaptic potentials of neurons in the cerebral cortex. It is usually initiated in the cell body and normally travels in one direction. The membrane potential depolarizes (becomes more positive), producing a spike. After the peak of the spike the membrane depolarizes (becomes more negative). The potential becomes more negative than the resting potential and then returns to normal. The action potentials of most nerves last between 5 and 10 milliseconds. Postsynaptic potentials are created by the combination of inhibitory and excitatory potentials located in the dendrites.The average of the potentials are amplified and combined to show rhythmic activity that is classified by frequency. Electrodes are usually placed along the scalp based on 10-20 system as shown in figure 1 [7] to measure brainwaves of different frequencies. There are five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called delta (δ) having range of 0.5 - 4 Hz, theta (θ) with range of 4 - 7Hz , alpha (α) in the range of 8 - 13Hz, beta (β) having range of 13 - 30Hz and gamma (γ) the range is higher than 30 Hz [8].

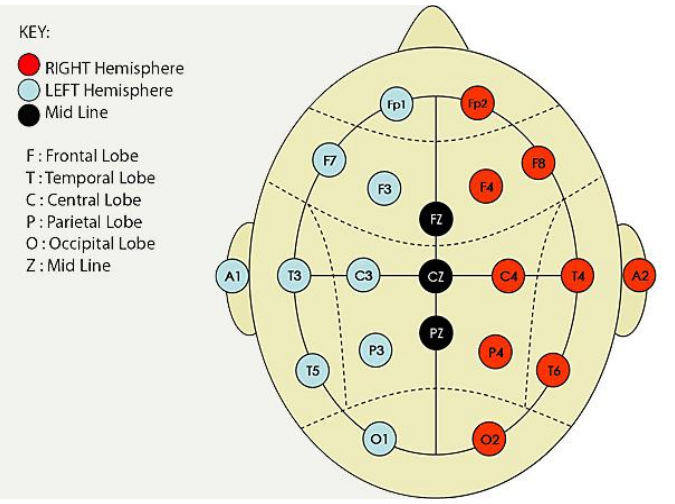

Figure 1: International 10-20 system of electrodes placement

2.2 EEG Devices for BCI

Depending on the type of connection between the electrodes, analog circuit, digital system and computing devices, we can divide BCI systems into two kinds, wired and wireless BCI systems [9].

Wired EEG devices mostly used in research,the advantage is low noise, more accuracy, disadvantage being more preparation time, inconvenient for user and immobility. Some of commercially available devices are Advanced brain mapping, Nihon kohden, neurosoft, RMS India as seen in figure 2.

Figure 2: Wired EEG devices

Wireless mostly used for gaming, entertainment and research. Advantages are easy to use, convenient for user and very less preparation time. Disadvantage is noisy signals may be captured. Some of the companies manufacturing wireless eeg are emotiv, neurosky, mattel as in figure 3.

Figure 3: Wireless EEG devices

2.3 BCI based tasks

2.3.1. Visual-evoked potentials

Visual-evoked potentials (VEPs) define a dependent BCI, i.e., they depend on oculomotor control of gaze direction, such that activity in the normal information pathways, e.g., peripheral nerves and muscles is needed to generate the brain activity. A dependent BCI is essentially an alternative method for detecting messages carried out in the brain’s normal output pathways, but does not give the user a new communication channel that is independent of conventional channels.

2.3.2. P300-based BCI

BCI systems are defined to be independent, if they do not rely on any muscular activity, if the message is not carried by peripheral nerves and muscles, and, furthermore, if activity in these pathways is not needed to generate the brain activity (e.g., EEG) that does carry the message. For example, a subject waiting for the occurrence of a rare stimulus on the background of a series of standard stimuli evokes a Positive peak over parietal cortex about 300 ms (P300) after appearance. However, those techniques remain limited to letter selection paradigms, similar to that one described in the previous subsection. Approaches for independent BCIs are of greater theoretical interest than for dependent BCIs, because they offer the brain a completely new output pathway and are likely to be more **useful** for people with most severe neuromuscular disabilities.

2.3.3. BCI based on motor imagery

In Albany, New York, Jonathan Wolpaw directs the development of a BCI system that lets the user steer a cursor by oscillatory brain activity into one of two or four possible

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targets [10]. In the first training sessions most of the subjects use some kind of motor imagery, which is then, during further feedback sessions, replaced by adapted strategies. Well-trained users achieve hit rates of over 90% in the two-target set-up; however, each selection typically takes 4–5 s. The lab in Graz of Gert Pfurtscheller develops a BCI system that is based on event-related modulations of the mu and/or the central beta-rhythm of sensorimotor cortices. For control paradigm the focus is on motor preparation and imagination. Feature vectors calculated from spontaneous EEG signals by adaptive auto-regressive modelling are used to train a classifier.

2.3.4. ERD and ERS

The ERD and ERS are event-related components that occur in relation to a response rather than a stimulus. The ERD and ERS are desynchronization and synchronization events, respectively (Schomer and Lopes da Silva 2011), around a motor response. The ERD occurs in the 1 s that precedes a response in both the mu (8–14 Hz) and beta bands (14–25 Hz). In contrast, the ERS is only shown in the beta band and is strongest in the 1–2 s period after a response [11].

2.3.5. Slow cortical potentials

Slow cortical potentials (SCP) are voltage shifts generated in cortex lasting over 0.5–10 s. Slow negative shifts are usually associated with cortical activation, e.g., evoked by the implementation of a movement or by the accomplishment of a mental task, whereas positive shifts indicate cortical relaxation. After repeated training sessions over months, through which patients achieve accuracy over 75%, they are switched to a letter support program, which allows selection of up to 3 letters/min. A new letter selection protocol, involving a predictive algorithm that uses a set of first letters of a word to select the whole word from a lexicon which adapts to the user's vocabulary simultaneously, increases the communication rate and provides Internet access to a disabled user [12].

3 General Structure of BCI

Figure 4: General BCI structure

Figure 4 shows the functional model of a BCI system. The figure depicts a generic BCI system in which a person controls a device in an operating environment (e.g., a powered wheelchair in a house) through a series of functional components. In this context, the user's brain activity is used to generate the control signals that operate the BCI system. The user monitors the state of the device to determine the result of his/her control efforts. In some systems, the user may also be presented with a control display, which displays the control signals generated by the BCI system from his/her brain activity. The electrodes placed on the head of the user record the brain signal from the scalp, or the surface of the brain, or from the neural activity within the brain, and convert this brain activity to electrical signals. The feature extraction block shown in figure 4 removes the artifacts from the electrical signal after it has been amplified. Note that many transducer designs do not include artifact processing. The classification block transforms the resultant signals into feature values that correspond to the underlying neurological mechanism employed by the user for control. For example, if the user is to control the power of his/her mu (8–12 Hz) and beta (13–30 Hz) rhythms, the feature generator would continually generate features relating to the power spectral estimates of the user's mu and beta rhythms. The control interface translates the logical control signals into semantic control signals that are appropriate for the particular type of device used.

4 Classification Techniques

Widely used classification techniques in BCI research are support vector machines (SVM), linear discriminant analysis (LDA), Artificial Neural Network (ANN), Hidden Markov Model(HMM) and statistical classifiers.

4.1 Support Vector Machine(SVM)

SVM is a useful technique for data classification. Even though it's considered that Neural Networks are easier to use than this, however, sometimes unsatisfactory results are obtained. A classification task usually involves with training and testing data which consist of some data instances. Each instance in the training set contains one target values and several attributes. The goal of SVM is to produce a model which predicts target value of data instances in the testing set which are given only the attributes.

Classification in SVM is an example of Supervised Learning. Known labels help indicate whether the system is performing in a right way or not. This information points to a desired response, validating the accuracy of the system, or be used to help the system learn to act correctly. A step in SVM classification involves identification as which are intimately connected to the known classes. This is called feature selection or feature extraction. Feature selection and SVM classification together have a use even when prediction of unknown samples is not necessary. They can be used to identify key sets which are involved in whatever processes distinguish the classes. There are many linear classifiers (hyper planes) that separate the data. However only one of these achieves maximum separation. The reason we need it is because if we use a hyper plane to classify, it might end up closer to one set of data sets compared to others and we do not want this to happen and thus we see that the concept of maximum margin classifier or hyper plane as an apparent solution. The next illustration gives the maximum margin classifier example which provides a solution to the above mentioned problem Expression for Maximum margin is given as

$$\text{margin} \equiv \arg\min_{\mathbf{x}\in D} d(\mathbf{x}) = \arg\min_{\mathbf{x}\in D} \frac{|\mathbf{x}\cdot\mathbf{w} + b|}{\sqrt{\sum_{i=1}^{d} w_i^2}}$$

For calculating the SVM we see that the goal is to correctly classify all the data. For mathematical calculations we have,

$$wx_i + b \geq 1$$

In this equation x is a vector point and w is weight and is also a vector. So to separate the data should always be greater than zero. Among all possible hyper planes, SVM selects the one where the distance of hyper plane, as in figure 5 is as large as possible. If the training data is good and every test vector is located in radius r from training vector. Now if the chosen hyper plane is located at the farthest possible from the data. This desired hyper plane which maximizes the margin also bisects the lines between closest points on convex hull of the two datasets [13][14].

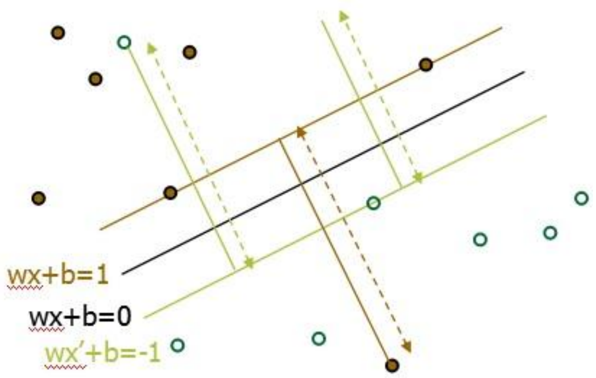

Figure 5: Representation of Hyper planes.

4.2 Linear Discriminant Analysis (LDA)

LDA is a transform-based method which attempts to minimize the ratio of within-class scatter to the between class scatter. The mathematical formulation involved in the theory of LDA is explained in the following sections. A within-class scatter matrix defines the scatter of samples around their respective class centers (means).

Given a matrix A ε RNxn , LDA aims to find a transformation G ε RN1that maps each column ai of Ai for 1≤ i ≤ n , in the N-dimensional space to a vector bi in the 1-dimensional space. That is G : ai ε RN > bi = GT ai ε Rl (l < N). LDA aims to find a vector space G spanned by gi where G = {g1, g2,…gl} such that each ai is projected onto G by (g1T.ai ,……..,g1T.ai) ε Rl.

Assume that the original data in A partitioned into k classes as A = { п1, п2, …., пk} where п, contains ni points from the ith class, and ∑ki=1 ni =n. LDA aims to find the optimal transformation G such that the class structure of the original high dimensional space is preserved in the low dimensional space.

In general if each class is tightly grouped, but well separated from the other classes, the quality of considered to be high. In discriminant analysis, two scatter matrices, called as within class (Sw) and between class (Sb) matrices are defined to quantify the quality of cluster as follows:

Sw = ∑ i = 1k ∑ x ε пi (x – mi) (x – mi)T

Sb = ∑ i = 1k ni (mi - m) (mi - m)T

Where mi = ¹/ni ∑ x ε пi , x is the global mean. It is easy to verify that trace (Sw) measures the closeness of the vectors within the classes, while trace (Sb) measures the separation between classes[15].

Where mi = ¹/ni ∑ x ε пi , x is the global mean. It is easy to verify that trace (Sw) measures the closeness of the vectors within the classes, while trace (Sb) measures the separation between classes[15].

4.3 Artificial Neural Network (ANN)

Computational models of neurons McCulloch and Pitts proposed a binary threshold unit as a computational model for an artificial neuron (see Figure 2). This mathematical neuron computes a weighted sum of its n input signals,x, j = 1,2, . . . , n, and generates an output of 1 if this sum is above a certain threshold µ. Otherwise, an output of 0 results. Mathematically,

$$y = \theta \left[\sum_{j=1}^{n} w_j x_j - u \right]$$

where θ(.) is a unit step function at 0, and w, is the synapse weight associated with the jth input. For simplicity of notation, we often consider the threshold µ as another weight w0 = - µ attached to the neuron with a constant input x0= 1. Positive weights correspond to excitatory synapses, while negative weights model inhibitory ones. McCulloch and Pitts proved that, in principle, suitably chosen weights let a synchronous arrangement of such neurons perform universal computations. There is a crude analogy here to a biological neuron: wires and interconnections model axons and dendrites, connection weights represent synapses, and the threshold function approximates the activity in a soma. The McCulloch and Pitts model, however, contains a number of simplifylng assumptions that do not reflect the true behavior of biological neurons. The McCulloch-Pitts neuron has been generalized in many ways. An obvious one is to use activation functions other than the threshold function, such as piecewise linear, sigmoid, or Gaussian, as shown in Figure 3. The sigmoid function i s by far the most frequently used in A"s. It is a strictly increasing function that exhibits smoothness and has the desired asymptotic properties. The standard sigmoid function is the logistic function, defined by

$g(x) = 1/(1 + \exp\{-\beta x\})$

where β is the slope parameter.

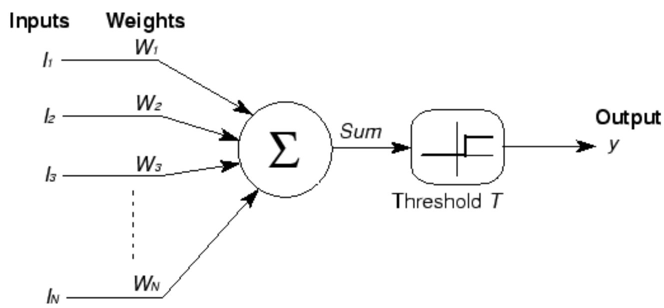

Figure 6: McCulloch and Pitts model

Network architectures

ANNs can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges (with weights) are connections between neuron outputs and neuron inputs. Based on the connection pattern (architecture), ANNs can be grouped into two categories (see Figure 7) :

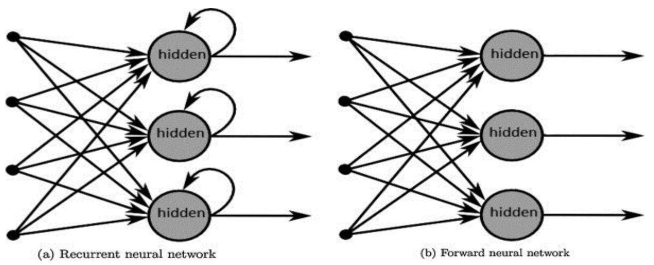

Figure 7: Recurrent and FeedForward model

* feed-forward networks, in which graphs have no loops
* recurrent (or feedback) networks, in which loops loops, and occur because of feedback connections [16].

4.4 Hidden Markov Model(HMM)

The Hidden Markov Model(HMM) is a powerful statistical tool for modeling generative sequences that can be characterized by an underlying process generating an observable sequence. HMMs have found application in many areas interested in signal processing, and in particular speech processing, but have also been applied with success to low level NLP tasks such as part-of-speech tagging, phrase chunking, and extracting target information from documents.

The formal definition of a HMM is as follows:

$\lambda=(A,B,\pi)$ (1)

S is our state alphabet set, and V is the observation alphabet set:

$S = (s1, s2, \cdots, sN)$ (2)
$V = (v1, v2, \cdots, vM)$ (3)

We define Q to be a fixed state sequence of length T, and corresponding observations O:
$Q = q1, q2, \cdots, qT$ (4)
$O = o1, o2, \cdots, oT$ (5)
A is a transition array, storing the probability of state j following state i . Note the state transition probabilities are independent of time:

$A = [aij] , aij = P(qt = sj |qt-1 = si)$. (6)

B is the observation array, storing the probability of observation k being produced from the state j, independent of t:

$B = [bi(k)] , bi(k) = P(xt = vk|qt = si)$. (7)

π is the initial probability array:

$\pi = [\pi i] , \pi i = P(q1 = si)$. (8)

Two assumptions are made by the model. The first, called the Markov assumption, states that the current state is dependent only on the previous state, this represents the memory of the model:

$P(qt|q1t-1) = P(qt|qt-1)$ (9)

The independence assumption states that the output observation at time t is dependent
only on the current state, it is independent of previous observations and states:

$P(ot|o1t-1 , q1t) = P(ot|qt)$ (10) [17].

A variety of classifiers have been used to translate these extracted features from EEG signals into an output command, from simple classifiers such as nearest neighbor, linear discriminant analysis (LDA), to nonlinear neural networks (NN), support vector machines (SVM), Hidden Markov Model (HMM) and statistical classifiers.
LDA is a widely used linear classifier. Compared with the other methods, the main advantages of LDA include the following: 1) It is simple to use and 2) it has low computational complexity. Thus, numerous brain-controlled mobile robots used LDA to develop the classifiers of BCI systems. Artificial neural network (ANN) is a widely used nonlinear modeling method for regression analysis and classification, which is based on biological neural networks. The main advantage of ANN as a classification method is its ability to approximate arbitrary nonlinear decision functions by minimizing the error in classifying training data. Unlike ANN, SVM does not need to set up many configurations and parameters. Another advantage of SVM is that it has good generalization characteristics and is especially suitable for the cases, where a small amount of training data is gained. In addition, the two kinds of classifiers were widely applied into brain-controlled mobile robots. Statistical classifiers classify one new instance into a particular class by selecting the highest one from the estimated posterior probabilities of all classes based on observed features of the new instance and prior knowledge. The main advantage of statistical classifiers is that it can represent the uncertainty of EEG signals and has been applied into brain-controlled mobile robots. However, the robustness of all existing BCI systems is not satisfactory due to the nonstationary nature of noninvasive EEG signals. Considering that the natural change of brain signals over time and the change of brain activity patterns since the users develop new capabilities as subjects gain experience, Mill´an et al. proposed that a possible research direction to improve the robustness is the online adaptation of the classifier during its use to drifts in the brain signals, and preliminary results have shown the feasibility and advantage of this method . In addition, there are a few software tools that are widely used to process the EEG data such as EEGLAB and BCI 2000, which can help researchers develop brain-controlled mobile robots[18].

For BCIs that use the mu and beta rhythms, the common average referencing (CAR) and Laplacian methods are superior to the ear reference method. This may be because these methods use high-pass spatial filters and enhance the focal activity from the local sources (e.g. the mu and the beta rhythms) and reduce the widely distributed activity, including that resulting from distant sources (e.g. EMG, eye movements and blinks, visual alpha rhythm). Comparing the two variations of the Laplacian filtering methods (the large Laplacian and the small Laplacian), it is shown that the large Laplacian method is superior to the small Laplacian method in BCI systems that use the mu rhythm [19]

5. BCI Applications

BCI applications have been seen in several ways; driving a robot or wheelchair, operating prosthetic devices, selecting letters from a virtual keyboard, internet browsing, navigating in virtual realities, and controlling computer games. Users of BCI train to modulate their brainwaves so as to generate distinct brain patterns. In some cases, user training is complemented with machine learning techniques to discover the individual brain patterns characterizing the mental tasks executed by the user.

Computer applications for BCI might be divided into 3 broad categories programs for communication, tools for functional control, and entertainment applications. Entertainment programs can further be subdivided into games, tools for creativity and interactive media. Description of BCI based applications is given below and Figure 8.

5.1 Prosthetic Control

It is a well-known fact that the brain controls our actions and is the origin of all decisions, normally performed by modulating specific brain waves in the areas specialized for those tasks. In recent years BCI using EEG is emerging as a means to give communication and control. EEG provides a medium for recording and accessing neural activity, thus facilitating computer retrieval and analysis of information from the brain signals produced by a thought. BCI research often focuses on finding a substitute for the broken mind body chain that can help paralyzed patients move and communicate. The main purpose of BCI is converting a person's intent into action. Thought-controlled arms, as shown in Figure are far from new, but an international team of researchers has apparently created an apparatus that aims to make the lives of paralyzed individuals easier. Though BCI application-oriented research has had beneficial results, including controlling wheelchairs, it uses expensive and bulky EEG equipment and highly skilled manpower. Technology is continuously getting smaller and cheaper, however, and recently several inexpensive consumer-grade devices have become available.

5.2 Detecting Fatigue and Driver Alertness

Driver drowsiness is one of the major causes of serious traffic accidents. According to the National Highway Traffic Safety Administration (NHTSA), there are about 56,000 crashes caused by drowsy drivers every year in India, The National Sleep Foundation also reported that 60% of adult drivers have driven while feeling drowsy in the past year, and 37% have actually fallen asleep at the wheel. For this reason, a technique that can detect real-time driver drowsiness is of utmost importance to prevent drowsiness-caused accidents. If drowsiness status can be accurately detected, incidents can be prevented by countermeasures, such as arousing of the driver and deactivation of cruise control. The sleep cycle is divided into no-rapid-eye-movement (NREM) sleep and rapid-eyemovement sleep. Sleepiness in drivers has been identified as a causal component in numerous accidents, because of the marked decrease in drivers' view of danger and acknowledgment of threat, and their lessened capacities to take care of their vehicles [4].

5.3 The P300 Speller18

A positive deflection in an EEG over the parietal cortex of about 300 ms is generated after infrequent stimuli. This response is termed the "P300" or "oddball" potential. Cz is the electrode around which the spatial amplitude distribution of P300 is centered. It is largest as the parietal electrode gets attenuated as the recording sites move to central and frontal locations. Temporally, a typical P300 response has a width of 150e200 ms and a triangular shape. The peak potential of a P300 is typically 2e5 mV. Thus a single P300's signal-to-noise ratio is low, and is typically enhanced by averaging over multiple responses. The P300 potential has been used as the basis for a BCI system in many studies. The user selects a character by focusing attention on it and counting how many times it flashes. The row or column that contains this character evokes a P300 response, whereas all others do not. After averaging several responses, the computer can determine the desired row and column (ie, the row/column with the highest P300 amplitude), and thus the desired character.

5.4 Entertainment

The area of entertainment has typically had a lower priority in BCI work, compared to more "functional" activities such as basic communication or control tasks. For the purposes of this survey, entertainment encompasses everything from video games, to interaction with collections of media to control of ambient features, such as wall displays, lighting, and music. In tasks such as music or images, the feedback from even a "wrong" selection is usually pleasant (assuming the user likes the music or images in their collection), and interaction techniques can be focused on more exploratory approaches to browsing collections. Such systems might also provide opportunities for users to express their emotional state, or desires to a caregiver more rapidly and expressively than using written language. As an example of this BCI approach to entertainment, very recent work has begun to gather experience with synchronous and asynchronous BCI "painting" applications which allow the user creative expression. Preliminary results indicate that the application provides pleasure to patients, healthy volunteers, and artists.

Figure 8: Applications of BCI.

6 Discussion

The research and development of brain-controlled mobile robots have received a great deal of attention because they can help bring mobility back to people with neuromuscular disorders and thus improve their quality of life. The paper discusses a review of the applications, complete systems, key techniques, and evaluation issues of brain-controlled interfaces. Researchers have developed various brain interfaces using different BCI techniques as well as other techniques such as intelligence techniques (in sensing situations, localization, and path planning) and shared control techniques. Still more work has to be done before to make more robust brain-controlled interfaces. The overall driving performance of the BCI system and standard evaluation method to facilitate the research and development of brain-controlled devices. First, improving the BCI system performance (especially robustness) is critical to make the interfaces usable in real-world situations. One possible research direction is the online adaptation of the BCI classifier to drifts in the brain signals, considering the natural change of brain signals over time and the change of brain activity patterns as the users develop new capabilities with experience; preliminary results have shown the feasibility and advantage of this method. The BCI systems that are used in all existing brain-controlled systems rely on only one type of suitable brain signals (such as P300, ERD, or SSVEP) to translate user intentions into commands. However the BCI systems that are based on a single signal do not work for all users. Some users cannot produce the necessary brain activity patterns for a particular kind of BCI systems. Recent studies have shown that some subjects could not yield corresponding brain activity patterns for an ERD BCI, but they could produce the needed activity patterns for an SSVEP BCI and vice versa. Moreover, all the subjects who could not generate the ERD or SSVEP patterns could likely use a mixed BCI that combines the two approaches to improve accuracy. Furthermore, discovering some new modes of brain signals that are more stationary and distinguishable, and developing corresponding BCI systems represents another open and challenging research direction to improve the BCI system performance [18].

7 Conclusion

Research on brain-controlled systems has gained wide momentum with notable significant milestones. Future research would lead to the development of robotic systems that can be used by disabled users, and thus improve their mobility, independence, and quality of life. If online database are made available by major BCI research groups, many upcoming research groups will be able to benefit, providing new expansions to ongoing work.

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Author Profile

T. Shashibala is currently pursuing Ph.D in the domain of BCI.

Bharti W. Gawali is Professor and Research guide, she specializes in the domain of BCI, speech recognition, Remote sensing and many more. She has successfully guided many Ph.D. And M.Phil students.