

An Experimental Investigations on Classifiers for Brain Computer Interface (BCI) based Authentication

Dr. E. Grace Mary Kanaga^[1], Muthu Kumaran.R^[2], M.Hema^[3], R.Gowri Manohari^[4], Tina Anu Thomas^[5]

Abstract—Brain signal based authentication system is relatively new when compared to other types of biometric data. This paper is based on Brain-Computer Interface (BCI) technique using Electroencephalography (EEG) signals to authenticate a system for paralyzed persons. Brain-computer interface (BCI) is a direct communication between computer(s) and the human brain. It is a system that facilitates the external device control by using the signals measured from the brain. BCI measures brain activity and by the way, those different brain signals are translated into control signals. An electroencephalograph (EEG) would read those brain waves using non-invasive electrodes that record the signals. The unique patterns can be used as a password or biometric identification. When we perform mental tasks like picturing a shape or performing an event, our brain generates unique neuronal electrical signals. Individuals are asked to perform some events for specified duration and their signals are acquired. These acquired signals are pre-processed, and the necessary time domain and frequency domain features are extracted and given to the classifiers for training. These classified signals are used for authentication purpose.

Keywords- Brain-Computer Interface; Electroencephalography; Authentication; Classification techniques

I. INTRODUCTION

The goal of user authentication is to establish a user's identity using one or more mechanisms. While textual passwords are the most commonly used method for user authentication in computer systems, the use of textual passwords for user identification has several well-known limitations: passwords have low entropy in practice are often difficult to remember, and are vulnerable to "shoulder surfing", or observation by nearby third parties. While proposed replacements for passwords typically do not have these same limitations, most schemes have other limitations or requirements. For example, biometric systems rely upon¹ unchanging features that have a lifetime as long as the

individual; this characteristic, combined with the threat of theft leaves biometrics unsuitable for remote authentication.

If we could authenticate by using a brain signals, we can avoid the shoulder surfing problem. This type of authentication might also provide a "who we are" by the uniqueness of our individual brains. A recent advance in Brain-Computer Interface (BCI) technology gives evidence that authenticating with our minds is within our technological reach.

BCI research has been focused on enabling a user to control something external using their brain waves. For a user to provide control commands using their brain signals must undergo translation. Recorded brain signals should undergo feature extraction to filter out the non-repeatable parts. A variety of EEG signal features can be extracted; they can be characterized as time-domain or frequency-domain.

A. Brain Computer Interface

Brain-computer interface (BCI) is collaboration between the brain and a device that enables signals from the brain to direct some external activity, such as control of a cursor. The interface enables a direct communications pathway between the brain and the object to be controlled. Monitoring brain activity in order to design future man-machine interfaces is the aim of Brain-Computer Interfaces [9].

There are basically two types of BCI systems: invasive and non-invasive. Invasive systems require surgery to implant electrodes on or near the surface of the brain. Most non-invasive systems use electrodes placed on the scalp and it requires the use of conductive gel which must be wiped or washed out of the hair after use. The electrodes, whether invasive or non-invasive, are connected to a computer. The

¹ Dr. E.Grace Mary Kanaga, Associate Professor, Department of CST, Karunya University, Coimbatore, India. (e-mail: grace@karunya.edu)

² Muthu kumaran is currently pursuing his UG final year programme in Karunya University, Coimbatore, India (e-mail : muthukumaranr95@gmail.com)

³ M.Hema is currently pursuing her UG final year programme in Karunya University, Coimbatore, India (e-mail : hemapmm@gmail.com)

⁴ R.Gowri Manohari is currently pursuing her UG final year programme in Karunya University, Coimbatore, India (email: gowrimanohari3121@gmail.com)

⁵ Tina Anu Thomas is currently pursuing her UG final year programme in Karunya University, Coimbatore, India (e-mail: tinaanu111@gmail.com)

brain signals that are picked up by the electrodes are sent to the computer, which uses sophisticated software to translate the brain signals into computer commands.

B. EEG Waves

The electroencephalogram (EEG) is the depiction of the electrical activity occurring at the surface of the brain. This activity appears on the screen of the EEG machine as waveforms of varying frequency and amplitude measured in voltage. EEG recording also provides high temporal resolution [1]. EEG waveforms are generally classified according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. The most familiar classification uses EEG waveform frequency. Based on their frequencies, EEG signals are classified into Beta, Alpha, Theta, and Delta waves [3].

- *Beta waves*

The rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μ V. Beta is the brain wave usually associated with active thinking, active attention and focus on the outside world or solving concrete problems. It can reach frequencies near 50 Hz during intense mental activity.

- *Alpha waves*

The rate of change lies between 8 and 13 Hz, with 30-50 μ V amplitude. Alpha waves have been thought to indicate both a relaxed awareness and also inattention. It is frequent to see a peak in the beta range as high as 20 Hz. Alpha seems to indicate an empty mind rather than a relaxed one, a mindless state rather than a passive one, and can be reduced by opening the eyes, by hearing unfamiliar sounds, or by anxiety or mental concentration.

- *Theta waves*

Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V. Theta arises from emotional stress, especially frustration or disappointment. Theta has been also associated with access to unconscious material, creative inspiration and deep meditation. The large dominant peak of the theta waves is around 7 Hz.

- *Delta waves*

Delta waves lie within the range of 0.5 to 4 Hz, with variable amplitude. Delta waves are primarily associated with deep sleep, and in the waking state, were thought to indicate physical defects in the brain. It is normally seen in adults with a slow wave sleep and as well as in babies. It tends to be the highest in amplitude and the slowest waves.

C. BCI Applications

Brain computer interfaces have contributed in various fields of research. As briefed in Fig. 1, they are involved in medical, educational and self-regulation, games and entertainment, and Security and authentication fields.

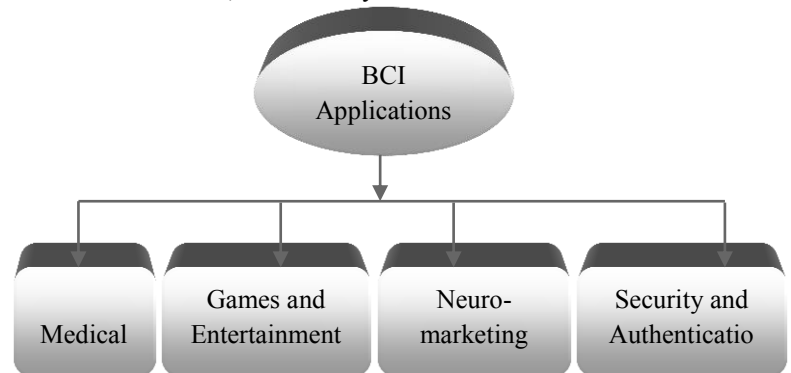


Fig. 1. BCI Applications

- *Medical Applications*

Healthcare field has a variety of applications that could take advantage of brain signals in all associated phases including prevention, detection, diagnosis, rehabilitation and restoration.

- *Games and Entertainment*

Various games are presented like in where the helicopters are made to fly to any point in either a 2D or 3D virtual world. In other case, two players can also join a collaborative or competitive football game by means of two BCIs. They can score goals by imagining left or right hand movements.

- *Neuro-marketing*

Marketing field has also been an interest for BCI researches. The research in has explained the benefits of using EEG evaluation for TV advertisements related to both commercial and political fields. BCI based assessment measures the generated attention accompanying watching activity. On the other hand, the researchers of have considered the impact of another cognitive function in neuro-marketing field. They have been interested in estimating the memorization of TV advertisements thus providing another method for advertising evaluation.

- *Security and Authentication*

Cognitive biometrics or Electro-physiology, where only modalities using bio-signals (such as brain signals) are used as sources of identity information. The motivation behind exploring the feasibility of electrophysiology is that bio-signals cannot be casually acquired by external observers. They also can be of great value for disabled patients or users missing the associated physical trait. This makes such signals

difficult to synthesize and therefore improves the resistance of biometric systems to spoofing attacks.

Besides electroencephalogram (EEG), as a biometric modality, could be used to send covert warning when the authorized user is under external forcing conditions.

II. STATE OF ART WORK

A. Available Authentication Techniques

Textual passwords enjoy popularity due to low cost, user familiarity and the lack of better alternatives. One of the most important problems with textual passwords is their vulnerability to dictionary attacks. It is a brute-force guessing attack where an attacker draws candidate guesses from a dictionary of “likely passwords”. If a password is correctly guessed or obtained, the attacker can easily masquerade as a legitimate user with minimal threat of being caught. To reduce the effectiveness of the dictionary attacks, many techniques for improving password quality have been developed, including proactive password checking, automatically generated passwords, password construction rules and passphrases. However, for various reasons these measures do not guarantee uniformly passwords in practice.

One of the problems for passwords is shoulder-surfing. The ubiquity of cell phone cameras and wireless video cameras brings a new ever-present threat upon us: recorded shoulder-surfing [12]. As users, we can no longer simply look over our shoulder to be aware of an adversary observing our password. To combat such a threat, we require an authentication method that is unobservable under any circumstance.

Another problem for passwords is acoustic attacks, whereby an audio recording of user’s typing session is analyzed and allowing recovery of 80% of passwords within 75 guesses. This is the problem with keyboards leaking acoustic information; unfortunately, producing a keyboard that does not leak acoustic information would be expensive.

In order to overcome these problems, we are moving to the system which uses pass-thoughts for authentication.

B. BCI based Authentication Techniques

Although the first research relating to BCIs appeared in the 1960s, it is still in its infancy for a variety of historic reasons. First, the chance of extracting a user’s intended message from the brain signals appeared to be extremely remote. Second, it is only in the recent years the cost of the computers with sufficient processing power to analyze electroencephalography (EEG) signals in real time has become affordable. Third, there was not much resulting interest in the limited applications that a first generation BCI was likely to offer. The first intra-cortical BCI was built in the early 90’s. The electrodes were inserted inside a monkey’s cranium after taking the risky step, research developed much more rapidly. Experiences started to

be carried out on humans [4]. EEG was first recorded by Berger in 1929 by externally attaching several electrodes on the human skull [8]. Recent changes in technology and advances in research have changed the environment for BCI research. Advancements include enabling monkeys to control a robotic arm and a computer cursor through their thoughts in the year 2000, and enabling a paralyzed 25-year old man to do the same in the year 2004.

Biometrics attempt to solve the problem of “what you know” and “what you have” authentication methods by the use of an appealing concept: authentication by using the unique physical or behavioural characteristics of users, e.g. fingerprints, the iris, voice recognition, and keystroke dynamics. Biometric suffer from a major drawback: they cannot be (easily) changed [11]. Because biometric information is valid for the lifetime of the user and risks being stolen, such information cannot be used as keying material for remote authentication purposes. Furthermore, even when performing local identification, certain types of biometric readers cannot detect fraudulent inputs, e.g. for fingerprints, it has been shown that a gelatine finger that models a legitimate user’s fingerprint (e.g. lifted from a glass) can fool many commercial fingerprint readers.

III. PROPOSED FRAMEWORK OF THE SYSTEM

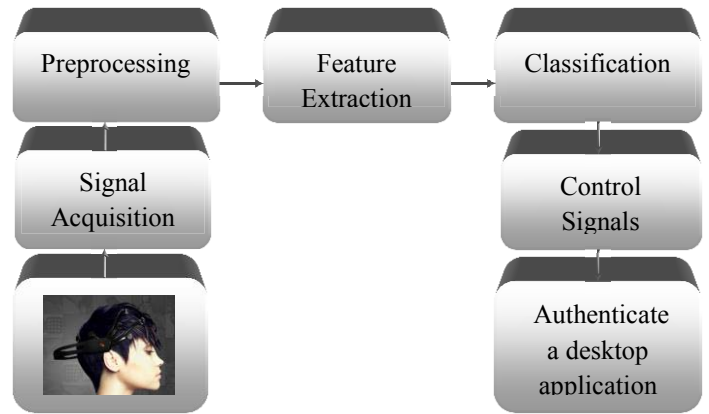


Fig. 2. Proposed Framework for BCI based Authentication System

As mentioned in Fig. 2, the proposed framework for BCI consists of the following functionalities: Signal Acquisition, Pre-processing, Feature Extraction, Classification and Application Interface. The brain signals are given as an input to BCI and control signals are given to the application to authenticate it.

A. Types of BCI Signals

- *Steady State Visually Evoked Potential (SSVEP)*

Steady State Visually Evoked Potentials are the signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus

ranging from 3.5 Hz to 75 Hz, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus.

SSVEP are brain signals which occur in response to visual stimulation. These signals may be triggered by any repeatedly flashing light, such as your computer screen refreshing every 60Hz.

- *Motor Imagery*

Motor imagery can be defined as a dynamic state during which an individual mentally simulates a given action. This type of phenomenal experience implies that the subject feels himself performing the action. Motor imagery is a mental process by which an individual rehearses or simulates a given action. It is widely used in sport training as mental practice of action, neurological rehabilitation, and has also been employed as a research paradigm in cognitive neuroscience and cognitive psychology to investigate the content and the structure of covert processes (i.e., unconscious) that precede the execution of action.

- *P300*

The P300 wave is an event related potential (ERP) component elicited in the process of decision making. It is considered to be an endogenous potential, as its occurrence links not to the physical attributes of a stimulus, but to a person's reaction to it. More specifically, the P300 is thought to reflect processes involved in stimulus evaluation or categorization. When recorded by electroencephalography (EEG), it surfaces as a positive deflection in voltage with latency (delay between stimulus and response) of roughly 250 to 500 milliseconds[5]. The signal is typically measured most strongly by the electrodes covering the parietal lobe. We are using p300 wave for recording the brain signals.

B. Signal Acquisition

As an interface between brain and machine, BCI needs to obtain information about what is going on in the brain. In this project, EEG is used for signal acquisition purpose. EEG signals are acquired using scalp electrodes, placed according to the 10-20 International System depicted in Fig. 3. The “10” and “20” refer to the percentage of the distance between the landmark points, namely the inion, the nasion and the preauricular points as shown in Fig. 3.



Fig. 3. Signal Acquisition using 10-20 International System

Electrodes positioned on the scalp register differences of potentials between the various regions of the brain and generate a graph called Electroencephalogram that expresses data from neuronal activity over time. The number of channels used in this project is 8 (FP2-F4, F4-C4, C4-P4, P4-O2, FP1-F3, F3-C3, C3-P3 and P3-O1). EEG waves obtained from 3 healthy persons for the events such as eyes-closed, eyes-blinked, teeth-bite, simple addition, and complex addition. For each subject, number of trials was taken and each trial constitutes 10 seconds.

- Subject 1 (15.03.2017, Female)
- Subject 2 (16.03.2017, Female)
- Subject 3 (17.03.2017, Female)

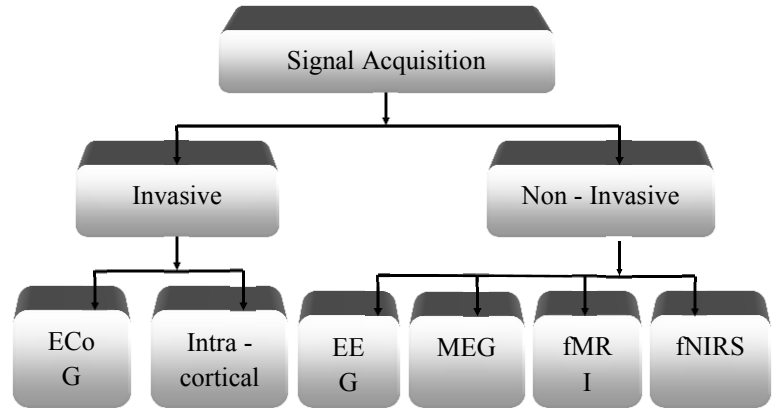


Fig. 4. Signal Acquisition Methods

As mentioned in the Fig.4. Signal Acquisition includes invasive and non-invasive methods. Invasive method comprises of Electro-corticography (ECoG) [10] and Intra-cortical. Non-invasive method comprises of EEG (Electroencephalography), MEG (Magneto-encephalography), fMRI (Functional Magnetic Resonance Imaging), fNIRS (Functional Near-Infrared Spectroscopy).

C. Pre-Processing

After acquiring the data, it is necessary to process the raw signal before it can be classified by the computer. Preprocessing is necessary to remove the unwanted noise.

D. Feature Extraction

Next, this signal is subjected to a feature extraction procedure, which aims at describing the EEG signals by a few relevant values called “features”. According to [7], feature extraction in EEG processing is a component “that translates the input brain signal into a value correlated to the neurological phenomenon”. These features capture the information embedded in EEG signals that is relevant to describe the mental states to identify, while rejecting the noise and other non-relevant information[6]. Through the feature extraction, we expect to be capable of recognizing a specific activity from the user’s brain. The procedure used must be

able to discriminate which information is relevant and which is not. Features like mean, min, max for time domain and frequency domain has been measured.

E. Classification Techniques

The next step of a BCI system is the classification of the signal, in which it is necessary to create an algorithm which translates the signal features into orders recognizable by the computer. There are two different methods: linear and non-linear method. An effective translation algorithm is the one that can adapt itself to its user, thus increasing the performance of the BCI, because it has a better performance in classifying features extracted from the user's signal[9]. Many of the characteristics of a BCI system depend critically on the employed machine learning algorithm. Important characteristics that are influenced by the machine learning algorithm are classification accuracy and communication speed, as well as the amount of time and user intervention necessary for setting up a classifier from training data [2]. Different Classification methods have been used for BCI systems.

- *Support Vector Machine*

Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in n-dimensional space (where n - number of features) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the classes very well. SVM has several advantages. It is known to have good generalization properties, to be insensitive to overtraining and to the curse-of-dimensionality. Finally, SVM shows good performance results in both evoked potential and ERD/ERS BCI.

- *K-Nearest Neighbor*

The k-Nearest Neighbors algorithm is an easy algorithm to understand and to implement. The model for kNN is the entire training dataset. When a prediction is required for an unseen data instance, the kNN algorithm will search through the training dataset for the k-most similar instances. The prediction attribute of the most similar instances is summarized and returned as the prediction for the unseen instance. In the case of regression problems, the average of the predicted attribute may be returned. In the case of classification, the most prevalent class may be returned. The kNN algorithm belongs to the family of instance-based, competitive learning and lazy learning algorithms. Finally, kNN is powerful because it does not assume anything about the data, other than a distance measure can be calculated consistently between any two instances. As such, it is called non-parametric or non-linear as it does not assume a functional form.

- *Linear Regression*

Linear Regression technique is usually which people pick when learning predictive modelling. Here, the dependent variable is continuous, the independent variable can be continuous or discrete, and the nature of the regression line is linear. This method establishes a relationship between dependent variable and one or more independent variables using a best fit straight line. This task of finding the best regression line can be easily accomplished by Least Square Method. It is the most common method used for fitting a regression line. It calculates the best-fit line for the observed data by minimizing the sum of the squares of the vertical deviations from each data point to the line. This output is used to predict the value of target variable based on given predictor variables. This technique is very sensitive to outliers and it can terribly affect the regression line and eventually the output values.

IV. RESULTS AND DISCUSSION

The accuracy results obtained for the events like eyes-closed, eyes-blinked, teeth-bite, performing simple addition and complex addition during classification using the classifiers such as Support Vector Machine, KNN and Linear Regression are listed in Fig.5.

A. Performance Metrics

A clean way to present the prediction results of a classifier is to use a confusion matrix (also called as contingency table).

TABLE I
TRUTH TABLE – CONFUSION MATRIX

	Positive	Negative
Positive	True Positive	False Positive
Negative	False Negative	True Negative

In this table, “true positive”, “false negative”, “false positive” and “true negative” are events which can be described as:

- TP - True Positive (Samples the classifier has correctly classified as positives)
- TN - True Negative (Samples the classifier has correctly classified as negatives)
- FP - False Positive (Samples the classifier has incorrectly classified as positives)
- FN - False Negative (Samples the classifier has incorrectly classified as negatives)

From the terms listed above, accuracy of a classifier (i.e. the number of correct predictions from all predictions made) is calculated. Accuracy is the most popular performance measure used. It is extremely helpful, simple to compute and easy to understand. It is defined as “the proportion of the correctly classified samples and all the samples”.

It is determined by the equation(1) and the parameters are mentioned above.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

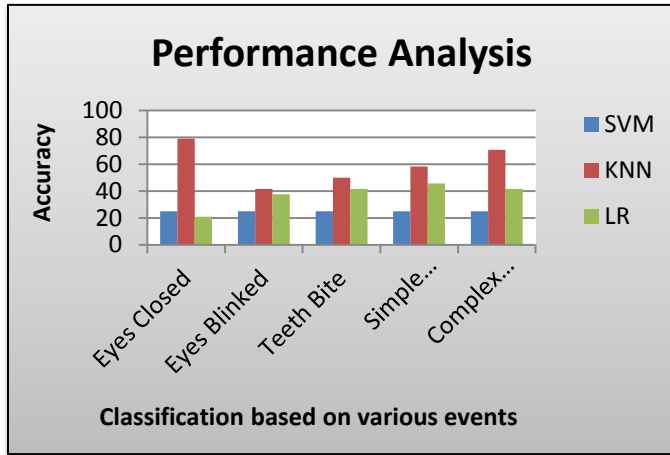


Fig. 5. Performance analysis for various classifiers

Different trials for three subjects were taken for these events.

V. FUTURE SCOPE

New ways of controlling consumer electronics goods with both basic voice and gestures are suddenly common, but we could soon be operating computers not by barking out instructions or waving, but purely by thinking. Research into the long researched brain-computer interface (BCI) - also known as the 'mind-machine' interface - is becoming so advanced that it's set to create a whole new symbiotic relationship between man and machine. It could even lead to a situation where speech is rendered useless, and people wirelessly communicate through universal translator chips. A brain-computer interface encompasses any form of controlling a computer via a direct electrical connection to the human body. That connection can be any form of nerve signal or impulse accessed from the surface of the human body, including head and limbs, or muscle impulses picked up by electrodes on the arm, hand, face or forehead generated by physical movement.

BCIs that are the primary interface for the task the user is explicitly performing, such as using brain signals to control the movement of a prosthetic.

BCIs that directly support the task the user is performing but are not the primary interface, such as a system that monitors the user's brain signals in order to predict performance while driving and to mitigate periods of predicted poor performance.

VI. CONCLUSION

In this paper, we are trying to do an offline analysis on BCI based Authentication system using EEG signals in the place that requires high security and also used for paralyzed persons to authenticate a desktop application. The advantages of this system over many of the existing authentication technologies include changeability, shoulder-surfing resistance, and protection against theft and user non-compliance. If the recording and processing of brain signals can be accurate and repeatable, this technique might become a viable and useful form of authentication.

VII. REFERENCE

- [1] Sarah N. Abdulkader, Ayman Atia, Mostafa-Sami M., Mostafa, "Brain Computer Interfacing: Applications and Challenges" Egyptian Informatics Journal, pp. 213-230, vol.16, 2015.
- [2] Ulrich Hoffmann, Jean-Marc Vesin, Touradj Ebrahimi, Karin Diserens, "An efficient P300-based brain-computer interface for disabled subjects", pp.1 - 14, 2007
- [3] S. Sanei and J. Chambers, "EEG Signal Processing", John Wiley & Sons Ltd, 2007.
- [4] André Zamith, António Caetano, João Carreiras), Pedro Osório Brain Computer Interface (BCI) based on Electroencephalography (EEG), , Lisboa, pp. 1 - 9, 2006.
- [5] Reza Fazel-Rezai and Waqas Ahmad, "P300- based Brain Computer Interface Paradigm Design, Recent Advances in Brain-Computer Interface Systems", 2011, ISBN: 978-953-307-175-6.
- [6] Fabien Lotte, "A Tutorial on EEG Signal Processing Techniques for Mental State Recognition in Brain-Computer Interfaces", pp.1 - 32, 2014.
- [7] S. Mason, A. Bashashati, M. Fatourehchi, K. Navarro, and G. Birch, "A comprehensive survey of brain interface technology designs", Annals of biomedical engineering, vol. 35, no.2, pp. 137-169, 2007.
- [8] E. Tamil, et al. "Electroencephalogram(EEG) Brain wave Feature Extraction using short time Fourier Transform", University of Malaya, 2007.
- [9] J.R. Wolpaw, N.Birbaumer, D.J.. McFarland, G.Pfurtscheller and T.M.Vaughan, "Brain-computer interfaces for communication and control", Clinical Neurophysiology, .pp.767-791, vol. 113,2002.
- [10]. Pinki Kumari, Dr. Abhishek Vaish, "Brainwave based Authentication System: Research Issues and Challenges", International Journal of Computer Engineering and Applications, Volume IV, pp. 89 - 108, 2014.
- [11]. P. Geethanjali et. al, A Low-cost EMG-EOG Signal Conditioning System for Brain Computer Interface Applications, International Journal of Engineering and Technology, PP. 2268 - 2271, Vol 5, 2013
- [12].<http://www.extremetech.com/computing/152827-berkeley-researchers-authenticate-your-identity-with-just-your-brainwaves-replace-passwords-with-passthoughts>, Dated: 21st December 2013