Image Retrieval and Interested Image Detection for Thought Processing Using EEG Signals

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Abstract-- **Paralysis is the loss of the power to move a part of the body due to injury or disease of the nerves that supply the muscles involved in moving the part of the body. In this paper we will deal with the conversion of human thoughts into signals. The cortex which was a part of cerebral cortex is associated with thinking. The thoughts can be converted into (EEG) electroenceplogram signals by fitting electrodes inside the brain. The thoughts converted to EEG signals further used to retrieve the interested images from the database. Section I discusses introduction to the different Disorders that may/may not affect nervous system, BCI systems that helps to overcome these disabilities using Computer Interface , Section II discusses existing systems, while Section III discusses our proposed system.**

Keywords: **Image retrieval, EEG, Thought processing, TTD (Thought Translation Device) and Spelling Device.**

I. Introduction

Brain-computer interface (BCI) is an emerging technology which aims to convey people's intentions to the outside world directly from their thoughts. It is especially appealing to severely paralyzed patients, since motor ability is no longer a prerequisite for this communication. It also offers a promising tool for normal people to enhance their communications with computers. It has not only introduced new dimensions in machine control but the researchers round the globe are still exploring the possible uses of such applications. BCIs have given a hope where alternative communication channels can be created for the persons having severe motor disabilities.

"Mind Control is generally regarded as scary. But recent refinements of brain- machine interfacing (BMI) may redefine the expression to mean totally different". [2] The need of new communication channels was strongly felt for the disabled people, who can't move their muscles, can't communicate with the outside world, so that they can also be able to lead an independent life. Thus, the idea is why not to use one's brain to control one's own environment. It is now a proven fact in medical sciences that the blockage of neural pathway between the cognitive part of brain (the signal generator) and the part which has to respond causes paralyses [3].Though the signals are being generated in most of the cases but somehow or the other are not communicated properly because of disorder. So, if such an artificial system could be devised which can use electrophysiological signals of brain to perform the task which brain is trying to instruct, will truly be BCI system. Extracting reach information from brain signals is of great interest to the fields of brain computer interfaces (BCIs) and human motor control.

To date, most work in this area has focused on invasive intracranial recordings; however, successful decoding of reach targets from noninvasive electroencephalogram (EEG) signals (Figure 1 shows typical structure of EEG) would be of great interest. BCIs are being developed for a variety of applications ranging from assistive technologies for patients with motor disabilities to entertainment devices. Across the wide range of applications [4], all BCI systems share the same set of underlying components, which can be broken down into three main segments: brain signal acquisition, brain state decoding, and computer-mediated performance of a task. Some BCIs decode the brain state into a set of discrete classes such as yes/no commands, while other BCIs decode continuous data such as a reaching trajectory. One goal of BCI research is to develop systems capable of decoding neural representations of natural movement planning and execution.

A. *Disorders/Diseases*

Paralysis is often caused due to damage of central nervous system or brain especially the spinal cord, through some fatal accidents and due to some disease like stroke, trauma, and multiple sclerosis. Many diseases that paralyze people leave their brains unaffected. These people can think

Proc. of the Intl. Conf. on Advances in Computer, Electronics and Electrical Engineering
Editor In Chief Dr. R. K. Singh. ISBN: 978-981-07-1847-3
doi:10.3850/978-981-07-1847-3_P0650

about moving or talking but can't because they have problems in their spinal cord, nerves, muscles, or maybe they don't have a limb. Table 1 shows what the deaf and paralyzed persons can/can't do.

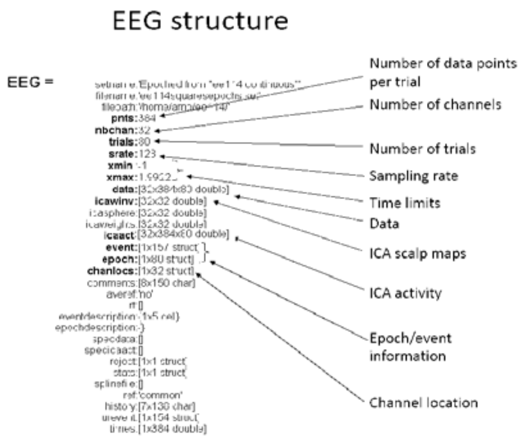

Figure 1. The structure of EEG

TABLE I: DEAF AND PARALYZED ACTIVITIES

Deaf people's viewpoint	DEAF	BLIND	PARALYZED
Driving a vehicle	yes	no	maybe
Riding a motorcycle/bicycle	yes	no	maybe
Playing a musical instrument	yes	yes	maybe
Everyday visual skills	yes	no	yes
Walking independently	yes	no	not yet
Ability to use computer keyboard	yes	yes	maybe
Ability to read text (flat copy)	yes	no	yes
Ability to carry on signed conversation	yes	yes	possibly
Ability to carry on written conversation	yes	no	possibly
Ability to play team sports	yes	no	yes
Ability to play Olympic-style sports	yes	no	yes
Ability to use text pager	yes	no	maybe
Ability to send and receive E-mails	yes	yes	yes
Ability to send and receive faxes	yes	no	maybe
Ability to write and read letters (flat copy)	yes	no	yes

[2]Brain-computer interfaces (BCIs) provide a connection. They record electrical activity in the brain and translate it into real commands such as moving a computer cursor or controlling an electric wheelchair. BCIs, already implanted in humans and animals, have potential to change lives. The human thoughts are converted into signals and these signals are converted into actions that the paralyzed people want to do. The process is being tested by Simulation in some project work. The human thoughts normally arise in the Motor Cortex (part of cerebral cortex) of the brain. The thoughts are converted into four types of EEG (Electroencephalogram) signals namely Alpha, Beta, Theta, and Delta by fitting tiny electrodes in the human brain. Among these EEG signals, Beta signal is associated with thinking so we choose beta wave as an input to our project. Then these Beta waves are converted into binary data. These binary data is then fed as input to the Back propagation network which produce the final output.

The thoughts can be converted into (EEG) electroenceplogram signals by fitting electrodes inside the brain. There are four types of [5] EEG signals generated which are alpha, beta, theta and delta.

Alpha – The alpha waves are associated with meditation state.

Beta – Beta waves emitted by human brain are often associated with active concentration and busy thinking.

Theta – Theta waves occur during emotional stress adults particularly during disappointment and frustration.

Delta – Delta waves occur during the state of deep sleep.

Figure 2 shows the states in EEG signals. The beta signal was associated with thinking so most of the work has been done using beta signals and so we have chosen beta signal as an input.

Schematic (Figure 3) showing the essential components of the BCI system BCI replaces nerves, muscles, and the movements they produce with electrophysiological signals (i.e., EEG, electrocorticography, single unit action potentials) and hardware and software that translate those signals into actions. The essential elements to practical functioning of a BCI platform are as follows: 1) signal acquisition, the BCI system's recorded brain signal or information input. This signal is then digitized for analysis; 2) signal processing, conversion of raw information into a useful device command. This involves both feature extraction, determination of a meaningful change in signal, and feature translation. The conversion of that signal alteration to a device command; 3) device output, overt command or control functions that are administered by the BCI system. These outputs can range from simple forms of basic word processing and communication to higher levels of control such as driving a wheel chair or controlling a prosthetic limb. As a new output channel, the user must have feedback on their overt device output to improve performance of how they alter their electrophysiological signal. All these elements play in concert to make manifest user's intention to his or her environment.

II. Existing Systems

Locked-in patients have now a way to communicate with the outside world, but even with the last modern techniques, such systems still suffer communication rates on the order of 2-3 tasks/minute. In this module the Beta signal is generated in between the frequency range of 13-30HZ and with a voltage range of 3-13µv. Various form of beta signal is generated by giving the frequency and voltage in the above specified range. Figure 5 shows the typical diagram for spelling device.

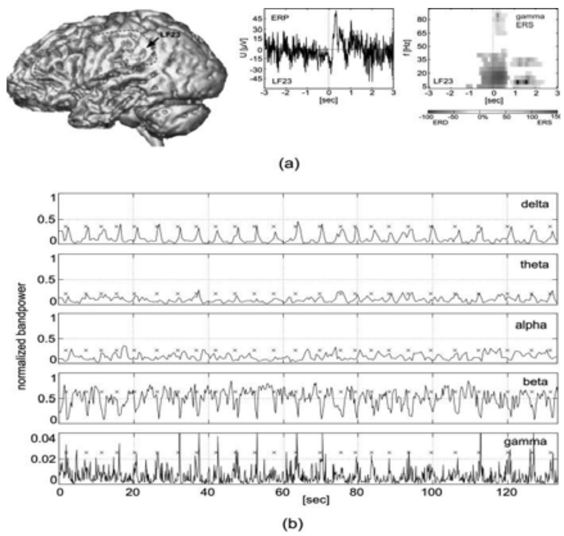

Figure 2. States of EEG Signals

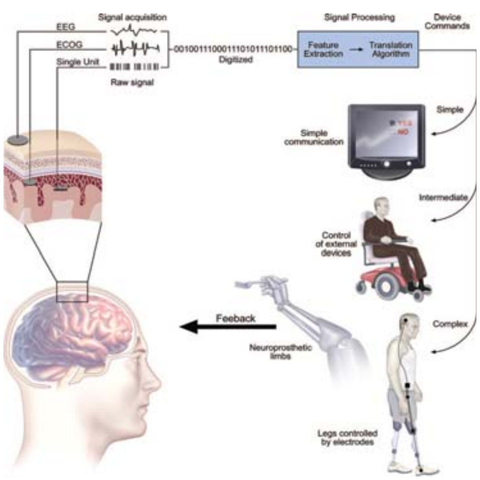

Figure 3. Schematic of Essential Component of BCI Systems


Figure 4. Example of an EEG-based BCI platform Notable elements include the electrode cap worn (asterisk) by the subject and the viewer screen (double asterisks) for which the subject controls the cursor on the screen (BCI computer not shown) by various EEG signals and signal processing methods (i.e., sensorimotor rhythms, SCP, or P300 paradigm)

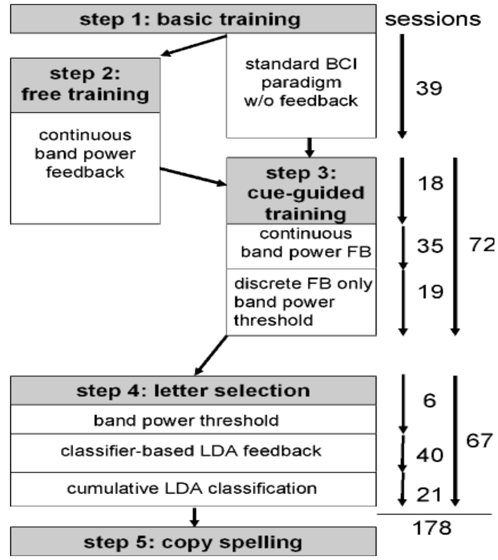

Figure 5. Diagram of training steps as described in the text, and corresponding number of performed sessions (right side)

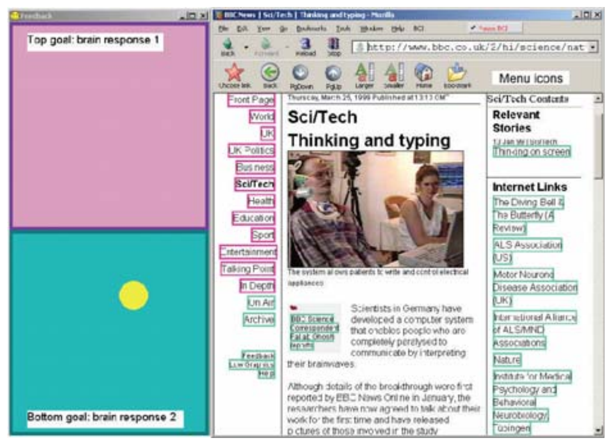

Figure 6. Web surfing with Nessi. Colored in-place link markers correspond to brain responses of the user, which are shown as goals in the BCI feedback window (left). After a page has loaded, the link markers are applied to a set of menu icons (top), allowing the user to choose a link, go back, scroll down the page, and use other configurable options. The number of goals and accordingly link marker colors can be increased for multiclass BCIs.

Figure 7. Virtual keyboards for entering text into web forms, displaying the LSP transducer (center) and the Huffman-coded transducer (bottom), which are used in the simulations

Steady-state visual evoked potentials (SSVEPs) recorded from the occipital scalp are used as the input of several BCI systems. SSVEP-based BCI is essentially EEG-based vision-tracking system. This system relies on the user's ability to control eye movements. The disadvantage with these systems is even after several months of practice, no voluntary control of SCPs could be attained. Therefore, the question arose whether it was possible for such a patient to learn to control specific frequency components of the sensorimotor EEG by using an imagery strategy.

III. Proposed Model

A. *Event Related Potentials (ERP)*

Event Related Potentials (ERP) are 'time locked' responses of electrical activity in the brain which occur at approximately the same time after a given event or stimulus (Luck, 2005). Whilst individually observed events will have variance with the exact time and strength of brain activity, by taking a large sample of these we are able to construct averages which demonstrate the existence of an ERP in response to stimulus. The act of averaging multiple time locked readings should make a signal observable over the background activity measured by the EEG. Therefore, if we have multiple readings of brain activity, taken at specific times after certain events, we have a set of data which can be utilized, either to average so as to demonstrate a particular ERP occurring, or alternatively to use the multiple individual samples to create models which can be used to classify a given time locked ERP response. The taking of multiple samples to construct an average sample is known as producing a 'grand average'. The proposed system involves following steps:

1. Training subjects with the sequence of images of the brushing (Figure 8), drinking water (Figure 9), and eating an apple (Figure 10).
2. The recording of a subject's EEG data was taken from multiple sites on the subjects scalp, namely sites Pz, Cz, P3, P4, where these site locations are defined according to the international 10-20 system. The selection of these sites is centred on the area of the brain which is most likely to present a P300 ERP. The selection of these sites was based upon domain-expert advice, where our objective was to capture as much data from a P300 event, given that there would be some variability in the placement of nodes on the subjects scalp [14].
3. These mapping has been analyzed with the classification algorithms [15].
4. Target image has been retrieved from the database according to the classified patterns.

Figure 8. Scene 1: Brushing teeth

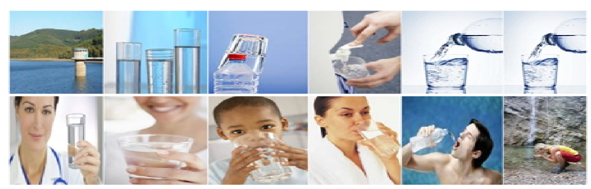

Figure 9. Scene 2: Drinking water

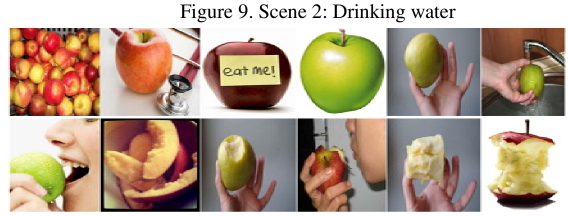

Figure 10. Scene 3: Eating an apple

B. *Results of the study*

It is well known from neurophysiological studies that when subjects look at images which arouse mental response such as surprise, anticipation, and etc., their parietal cortex is excited in a very characteristic way: a synchronized peak in the global electrical activity of large groups of neurons in the parietal area arises after approximately 300 ms after the stimulus (image) presentation. This electrical activity can be recorded with an Electro-Encephalography (EEG) instrument as an electric positive potential wave and is commonly referred to as P300 [16].

An efficient P300-based BCI system for classification of brainwaves associated to scientific interest in image stimuli was presented in [13]. It was shown that relatively high classification accuracies can be obtained for most of the users of the system. It has been observed that increasing the speed of image presentation will decrease the classification accuracy. However with an image presentation frequency of 3.33 Hz, it is still possible to have relatively good classification results for most of the subjects.

The key idea of this work is to use temporal modulation of EEG by imagining temporal patterns, such as images (static/scene) imagining a task at a frequency of 1 Hz, to enhance the correct decoding rate. Traces of neural activity caused by mental imagery will be picked up by sensors (EEG) and will be classified in discrete categories. These categories will correspond to retrieval of the relevant images from database to describe the need of the paralyzed person.

C. *Outcomes of the Model:*

The model generates the EEG database of healthy/unhealthy subjects. This data can also be used for the human identification and intention detection system proposed by the researchers of the relevant field [17] [18] [19] [20] [21] [22].

IV. Conclusion

This research work deals mainly with the recording and data analysis of EEG signals. Using the results for clinical studies (e.g. functional electro-stimulation of muscles or nerves) would become feasible when the success rate of correct interpretation of EEG signals has been improved. This paper also shows that the use of training the paralyzed subjects with the sequence of images/scenes is easy and less time consuming than training them using motion of eyes, fingers and training with the letters.

Acknowledgments

This work has been carried out under the Multi-modal Biometric Research lab. We would like to acknowledge and extend our heartfelt gratitude to the UGC who have funded for development of UGC SAP (II) DRS Phase-I F.No-3-42/2009 major research project entitled "Biometrics: Multimodal System Development". We again acknowledge here to Dr. B. W. Gawali, for their help in the acquisition process of the EEG signals.

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