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BRAIN-COMPUTER-INTERFACE: A CONCEPTUAL WORKING APPROACHES FOR NEUROTECHNOLOGY

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ABSTRACT
This article addresses to the core part of a neurotechnology known as Brain-Computer-Interface and abbreviated as BCI. It is most growing research area in this era for neurotechnologists. Whole portion of this article broadly describe three working stages of BCI-System such as signal acquisition, signal processing and signal application, and signal processing further categorized as signal preprocessing, feature extraction, feature classification and feature translation. However working functionality varies according to its interfacing technique used as invasive-interface, semi-invasive-interface, and non-invasive-interface. These interfacing techniques used various kinds of hardware/machinery such as electrocorticograpgy, magnetic-resonance-imaging, electroencephalography and magnetoencephalography which are briefly described.

INTRODUCTION
Scientists digging knowledge from various fields of science and technology continuously, neurotechnology is also a modern field of research. Brain-Computer-Interface provides a communication pathway between brain and computerized devices, without using any peripheral neuromuscular pathways.[1][2] The term "BCI" coined by Professor Jacques Vidal and published the first review-article on this technology, after this research marks the first appearance of the expression Brain Computer Interface in scientific literature. Professor Vidal is recognized as the father of BCIs in the BCI community. However scientific research on BCIs initiated in the 1970s at the University of California; Los Angeles (UCLA) funded by National Science Foundation (NSF-Arlington Virginia US).[3][4]

Overall working system of BCI involves various stages i.e. Signal Acquisition, Signal Processing and Signal Application. Figure-1 shows the block diagram which is stepwise working functionality of BCI system. Signal acquisition is the first stage responsible for capturing the brain signals; Signal Processing is the second stage which is responsible for converting analog signals generated from brain into digital signals and prepares the signals in a suitable form for further processing. However signal processing stage involve three stages i.e. Signal Preprocessing which performs noise and artifact reduction, Feature Extraction which identifies information in the brain signals that have been recorded, Feature Classification which classifies the signals having various features, and Feature Translation which translates the signals into meaningful commands for any connected devices. Third and last stage is Signal Application responsible for using the commands from the feature translation algorithm operate the external device.[5][6]

BLOCK DIAGRAM OF BCI

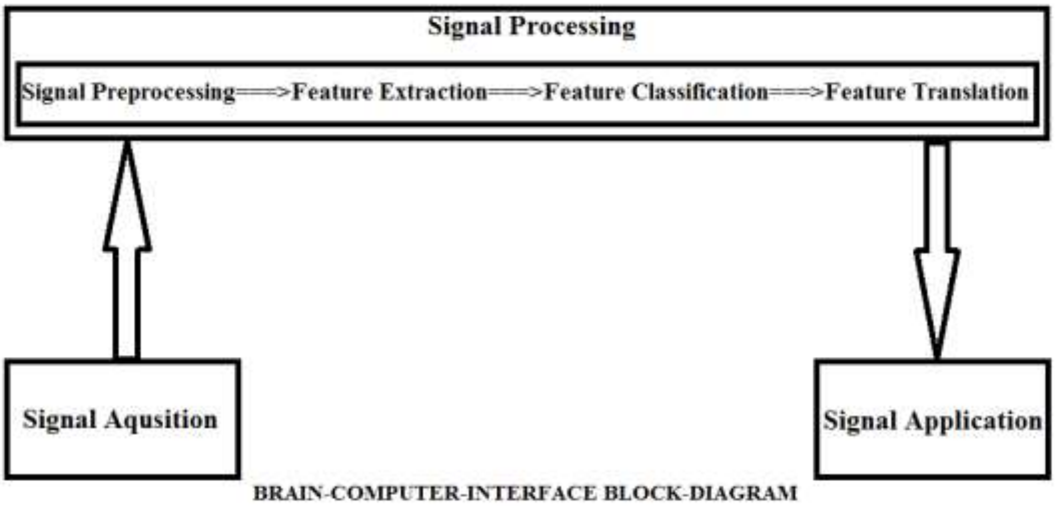

Fig.1 Block Diagram

WORKING STAGES OF BCI

Fig.2 Working Stages

Signal Acquisition: This stage captures the brain signals; signal acquisition is the process of acquiring brain signals using a particular sensor modality. The signals are amplified to makes suitable for electronic signal processing. The signals are then digitized and transmitted to a computer system for further analysis. First part of figure-2 identifies this process.[7] There are three general classes of brain acquisition techniques: invasive, semi-invasive and non-invasive interfacing technique, as shown in figure-3. In invasive technology, electrodes are surgically implanted inside the user's brain, in semi-invasive technology electrodes are implanted over the surface of the brain, and in non-invasive techniques; the brain activity is measured using external sensing device.[8]

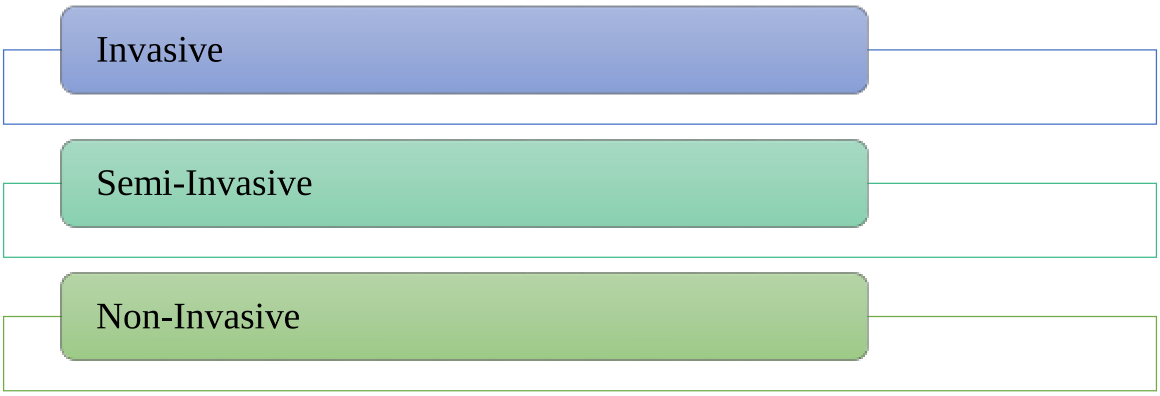

Fig.3 Brain Acquisition Techniques

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Invasive Technique: Invasive technique implanted electrodes under the scalp within grey matter and measure the neural activities of the brain in intra-cortically manner from the grey matter. These techniques produce spatial resolution and high temporal for enhancing the quality of the received signal and its signal/noise ratio. However, these techniques suffer from a lot of issues such as usability issues of surgical process, and problems related to the system's output quality have occurred. The small size of the brain regions handled by those implants is considered one of them. Once implanted, device cannot be shifted to measure brain activity in another region.[9][10]

Semi-Invasive Technique: Semi-Invasive technique implanted inside the skull but rest outside the brain rather than within the grey matter in invasive technique. These techniques produce better resolution than non-invasive technique where the bone and tissue of the cranium deflects signals. These have less risk of forming scar-tissue in the brain relative to invasive technique. These techniques measures the electrical signals of the brain taken from under the skull in a similar way to non-invasive technique, but the electrodes are covered in a thin plastic pad that is placed above the cortex, beneath the dura mater.[11] These are reliable intermediate signal acquisition techniques because it produces better signal/noise ratio, wider frequency range, higher spatial resolution, and less training than non-invasive technique. At the same time these have less clinical risk, less technical problems and probably superior long-term stability than intra-cortical recording technique. This feature in recent evidence of the high level of control with minimum training shows potential for real world application for people with motor disabilities.[12]

Non-Invasive Technique: Non-Invasive technique does not require implanting within the brain. Thus it avoids the surgical process or permanent device attachment as required in the invasive acquisition technique. Various acquisition technique for different types of measured signals such as positron emission topography, electro-encephalography, magneto-encephalogram, functional magnetic resonance imaging, and optical imaging near-infrared spectroscopy are more popular than the invasive techniques, though effective due to brain injuries in the latter as the electrodes are surgically implanted so there is possible experiments in humans using non-invasive neuroimaging technique. Non-Invasive techniques have been used for much broader variety of applications. However they are easy to wear and do not require surgical process, but non-invasive technique provides relatively poor spatial resolution and cannot use higher-frequency signals because the skull dampens signals, blurring and dispersing the electromagnetic waves generated from the neural system. Non-invasive techniques also require some time and effort prior to each usage session, whereas invasive technique may be ready to use any time after the initial surgery. However, the best technique for each user depends on numerous factors.[13]

Signal Processing:

Fig.4 Signal Processing Stages

Signal Preprocessing: This stage performs Artifact Reduction; First part of figure-4 identifies this process. Original data normally contain a lot of artifacts or noise. Some noise resources are power line interference, fluorescent lighting, baseline drift, electrocardiogram, electromyogram, and random noise. Simple frequency based filtering is normally sufficient to reduce the narrow band noises such as the power line interference, fluorescent lighting, and baseline drift. However, more significant methods such as principal component analysis and independent component analysis are popular to reduce electrocardiography and electromyography noises that have overlapping spectral information with electroencephalography.[14]

Feature Extraction: This stage performs Dimensionality Reduction. Second part of figure-4 identifies this process. This stage identifies information in the brain signals that have been recorded. Feature extraction is the task of analyzing the signals to distinguish significant signal features from general raw materials and representing them in a standard form suitable for translation into commands during feature translation.[15] When the input signals to an algorithm is too large and it is suspected to be redundant, then it can be transformed into a reduced set of features. The extracted features are expected to contain the valuable information, so that the desired task can be performed by using this reduced representation instead of the complete source data.[16]

Feature Classification: This stage performs Variability Reduction of feature values. Third part of figure-4 identifies this process. This stage classifies the extracted feature signals having different features in to account. The responsibility of the feature classifier algorithm is to use the feature-vector provided by the feature extractor assign the object to a category of feature. However complete classification is often impossible, so a more common task is to determine the probability for each of the possible categories of features. The problem of the classification depends on the variation in the feature values for certain objects in the same category relative to the variation between features values for certain objects in different categories. The variation of feature values for certain objects in the same category may be due to complexity of features, and may be due to noise in signals.[17]

Feature Translation: This stage performs Command Generation. Fourth part of figure-4 identifies this process. This stage translates the signals into meaningful commands for any connected device. The classified feature signals are translated by the feature translation algorithm, which converts the feature signals into the appropriate commands for the specific operations performed by the connected device.[18] In this context source feature signals are known as independent variable and targeted device control commands are known as dependent variable, as discussing translation process we can say that independent variable converted into dependent variable. Feature translation algorithms may be linear or nonlinear by using statistical analysis and neural network respectively.[19]

Signal Application:
This stage performs functions by using commands generated by feature translation algorithm, such as motor speed control, light intensity control, letter selection, mind gaming, robotic arm operation, wheel chair control, and cursor control. The device function provides feedback to the user, and generating the circular control over the device operation. Third part of figure-2 identifies this process.[20]

APPLICATION OF BCI
BCI applications broadly influence on medical field. Its contributions in medical fields range from prevention to neuronal rehabilitation for serious injuries such as preventing smoking, drug addiction, alcoholism, and motion sickness, detection and diagnosis of brain tumor, brain disorder, restoration of brain stroke, movement disabilities, easing chronic pain, treating emotional disorders as depression, anxiety, monitoring sleep states, sleep disorder, dream capturing, memory uploading and downloading. Apart from medical field various other applications of BCI are in virtual reality, machine control, neuroergonomics, smart environment, neuromarketing, advertisement, educational, self-regulation, gaming, entertainment, security and authentication.[21] Some popular projects are going on over the world for BCI research as Brain-Gate, BNCI-HORIZON-2020, BCI200, Open-BCI, Bionic-Vision, ASIMO, and Captain-Cyborg.

CONCLUSION
After discussing the contents of these article researchers able to explore various alternative applications of this technology, various interfacing techniques can be used as per suitability. However non-invasive techniques become increasingly popular in future among the researchers due to preventing surgical process and health issues. An optical technique known as optogenetics is also popular in modern neurological researcher used genetic behaviors. Various signal processing algorithms can also be explored for improving its quality and efficiency.

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