ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

Exploring the Non-Invasive Methods of Brain-Computer Interface: A Comprehensive Review of their Advances and Applications

Harsha S. Krishna
Tbilisi State Medical University
Tbilisi, Georgia

Salama Pulikkal
Tbilisi State Medical University
Tbilisi, Georgia

Abstract:- The brain-computer interface technology allows the human brain to control external devices directly without using the brain's output channels or peripheral nerves. It helps individuals with motor impairments to use mechanical and external devices to communicate with the outside world. Non-invasive BCIs allow communication between the human brain and external devices without the need for surgeries or invasive procedures. Methods like EEG, MEG, fMRI, and fNIRS are used. EEG enables the acquisition of electrical activity along the scalp by measuring voltage fluctuations and neurotransmission activity in the brain. The electrodes are attached to a cap-like device and are placed on the scalp to record the electrical current generated by the brain. Unlike MEG, which necessitates specially constructed rooms, EEG is portable. Lab-grade EEG is expensive but cheaper than other forms of BCI. MEG uses magnetometers to measure magnetic fields produced by electric currents occurring naturally in the brain. MEG is better than EEG at measuring high-frequency activity. MEG signals are less distorted by the skull layer. FMRI records blood oxygen level-dependent (BOLD) signals with high spatial resolution across the entire brain. It does this by tracking the hemodynamic response, which is the increase in blood flow to active brain areas. It does this using the principle of nuclear magnetic resonance, where hydrogen atoms in water molecules in the blood emit signals when subjected to a strong magnetic field. It has an advantage over EEG due to its superior spatial specificity and resolution. FNIRS measures the blood flow and oxygenation in the blood associated with neural activity. It gains insight into the brain's hemodynamic response, which is essential for understanding neural functioning during BCI tasks.

Keywords:- *Brain-Computer Interface; Non-Inasive; EEG; MEG; Fmri; Fnirs;*

I. INTRODUCTION

Brain-computer interfaces present an innovative fusion of neuroscience, engineering, and computer science, aiming to create a direct communication pathway between the brain and external devices. These applications have the potential to reform various fields, from medicine and rehabilitation to gaming and beyond. While invasive BCIs involve surgical implantation of electrodes within the brain, non-invasive methods are more appealing due to their lower risk profiles and border accessibility.

Non-invasive BCI depends on external sensors to detect neural activity without the need for surgical intervention. These technologies capture brain signals through the scalp or other peripheral points and translate them into commands that can control computers, prosthetics, and other external devices. The main modalities in non-invasive BCIs include Electroencephalography (EEG), Functional magnetic resonance Imaging (FMRI), Functional Near Infrared Spectroscopy (FNIRS), and Magnetoencephalography (MEG). Each of these methods has unique advantages and challenges, influencing their application in different domains.
This comprehensive review explores the various non-invasive BCI technologies, inquiring about their underlying principles and potential applications.

II. BCI

Brain-computer interface or brain-machine interface is a technology that allows humans to interact with external devices by measuring and analyzing the signals produced by the central nervous system (CNS) and accomplishes the user's intention without using the brain's normal output channels like peripheral nerves or muscles. They analyze real-time electroencephalographic or other electrophysiological measures of brain activity, such as electrical signals recorded from the scalp, cortical surface, or within the brain, and translate them into commands. It helps individuals with motor impairment to use mechanical and external devices to communicate with the outside world. BCI creates a real-time interaction between the user and the world. [12]

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

Various neuroelectric signals have been utilized to trigger or cease the operation of external devices or computers encompassing EEG oscillations, electrocorticograms (ECoGs) recorded from implanted electrodes, event-related potentials (ERPs) like the P300 and slow cortical potential (SCP), as well as short latency subcortical potentials and visually evoked potentials. Among these BCIs can be of two types: dependent BCI and independent BCI. [9]

Dependent BCI (e.g. visually evoked potentials) relies on brain activity, such as EEG signals, to convey messages but does not utilize the brain's conventional output pathways for message transmission. Independent BCI (e.g. P300, mu and beta rhythms, etc.) in contrast, operates autonomously from the brain's conventional output pathways, eliminating reliance on peripheral nerves and muscles.

The notion that BCI is just a 'mind reading' system is wrong. It does not just passively observe brain activity through electrophysiological signals to discern an individual's desires. BCIs transform electrophysiological signals, initially reflective of central nervous system activity, into actionable outcomes: messages and commands that influence the external environment. Unlike traditional neuromuscular channels relying on feedback for successful operation, BCIs replace nerves and muscles with signals translated by hardware and software.

One of the most important aspects of BCI is its feedback mechanism. A system that just reads and analyzes the brain signals without giving the user feedback on his/her actions is not BCI. The user obtains feedback on this generated output, subsequently impacting the user's brain activity and influencing subsequent outputs.

A. Parts of a BCI

The first part of a BCI is signal acquisition. It consists of two phases: feature extraction and translation. For feature extraction, the goal is to measure the characteristics of signals that encode the desired output. These features encompass various measures, ranging from simple, such as amplitudes of specific evoked potentials (e.g., P300) or rhythms (e.g., sensorimotor rhythms) in EEG, to more intricate measures like firing rates of individual cortical neurons and spectral coherences. For optimal Brain-Computer Interface (BCI) performance, the feature-extraction process within the signal processing phase must concentrate on identifying features specifically linked to the relevant output (e.g., the intended letter for spelling) and ensure accurate extraction of these distinctive features. The second phase of BCI signal processing involves translating signal features into device commands through a dedicated translation algorithm. Brain signal characteristics, such as rhythm amplitudes or neuronal firing rates, are converted into commands specifying outputs like letter selection, cursor movement, or prosthesis operation. Translation algorithms vary in complexity, ranging from simple ones like linear equations to sophisticated models like neural networks or support vector machines. An effective translation algorithm ensures that the user can control the selected features within a range that covers the entire spectrum of device commands.

The second part of a BCI would be its output device. The output device in current Brain-Computer Interfaces (BCIs) typically involves a computer screen where users select targets, letters, or icons displayed on it. Various methods, such as flashing letters, indicate the selection process. Some BCIs offer additional interim output, like cursor movement towards the selected item before finalizing the choice. This output not only represents the intended outcome of BCI operation but also serves as feedback for the brain to enhance communication accuracy and speed.

B. Types of BCI

The three main types of BCI as described by Wolpaw are EEG-based BCI, ECoG-based BCIs, and Intracortical BCIs. In addition to the fundamental distinction between dependent and independent BCI, they can be also differentiated by whether they use invasive or non-invasive recording methods. They can also be classified by using the type of potential they use, that is if they use evoked or spontaneous potentials. Some BCIs can also use both non-invasive and invasive methods and both evoked and spontaneous potentials simultaneously. Here we focus more on their classification based on the type of recording.

There are three types of BCI based on how they record the signals. They are:

- Invasive - Invasive BCI necessitates a surgical procedure to implant electrodes beneath the scalp to transmit brain signals. Its primary benefit lies in delivering highly precise data acquisition.
- Partially invasive - Partially invasive BCI devices are surgically placed within the skull but remain external to the brain tissue, rather than being situated within the cerebral cortex.
- Non-invasive - Noninvasive BCIs gather data through sensors positioned on or in proximity to the head. These BCIs do not necessitate any surgical procedures for the implantation of recording equipment, and they steer clear of any discomfort or risky techniques.

III. NON-INVASIVE BCI

A. EEG

Electroencephalography (EEG) uses different types of electrodes to detect and record electrical activity generated by the brain. It is done by measuring the brain's electrical activity caused by the flow of electrical currents during the synaptic excitation of the dendrites by the electrodes that are placed on the scalp. This system provides a connection between the brain and the external device, enabling the researchers to analyze the biological signals. These signals provide information on the driving mechanism of the brain, recognizing various neurological disorders and the exploration of cognitive processes such as memory perception and attention.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

In EEG the signals are recorded without invading brain tissue by placing electrodes on the surface of the scalp. These electrodes extract the signals which vary with the position of the electrodes from the brain using them for further pre-processing. The signal amplitude recorded by the EEG will be much smaller than that measured by the invasive electrodes due to the interference caused by the cranium, skin tissue, and hair.

The choice of electrode type depends on factors such as the intended application, signal quality requirements, and comfort for the user. Some common types of electrodes used in EEG are wet electrodes, dry electrodes, non-contact electrodes, and common contact dry electrodes. [46]

Precise identification and analysis of EEG signals requires a thorough understanding of their complex and theoretical properties. The process of analyzing EEG data involves four important steps i.e.; preprocessing, feature extraction, feature collection, and classification. Each step plays an important role in converting raw EEG signals into meaningful information.

➢ *Pre-Processing of EEG data*

Signals in the non-invasive BCI have less clarity because the electrodes are not placed directly on the desired part of the brain. Therefore the removal of unwanted signals, noise, and artifacts is necessary. This step includes decomposing or noise reduction of the obtained signal to enhance the EEG signal. The widely used technique for removing noise from different types of signals is the use of filters. [21] Bandpass filtering can effectively reduce noise in EEG recordings, particularly from eye blinking, heart functioning, muscle artifacts, and non-physiological artifacts from power lines. EEG signals can be isolated into different frequency bands where each specific band is more prominent in certain states of mind. [21]

➢ *Feature Extraction*

This decision should be made on which features to extract from the signals in which the noise and artifacts have been removed and then to set data that will be used as input to a neural network [21]. The process involves cleaning EEG data, extracting key features, and estimating power distribution across different frequency bands. Time-frequency analysis, often using wavelet transforms, reveals changes in EEG power over time, revealing transient brain events and oscillatory responses. EEG signals are classified based on their frequencies into the delta, theta, alpha, beta, and gamma. Event-related potentials are extracted by averaging EEG epochs time-locked to specific stimuli or events, enabling cognitive and motor-process studies. The spectrogram is a feature that helps analyze the EEG signal in both frequency and power domains, which is essential since the EEG has different frequencies at different points in time.

➢ *Feature Collection*

Feature selection is important to acquire the signal characteristics that best depict EEG signals to be labeled within a wide range of extracted features. It reduces data features without altering properties but eliminates some based on certain conditions. Features selection helps reduce data size for classification modules by selecting features that contribute substantially to the outcome class after feature extraction. The importance of feature selection is shown in the following points [41]

- Reducing feature numbers allows monitoring relevant features to targeted preference states.
- Less reductant data reduces overfitting and noise-based prediction
- Reducing feature number reduces optimization parameters reducing overtraining
- Features selection improves classification performance with less misleading data and high-frequency

Feature selection methods can be classified based on the number of variables giving two classes: univariate and multivariate. Univariate methods consider the input features one by one. Multivariate methods consider whole groups of characteristics together.

➢ *Classification*

The last step of EEG involves classifying the EEG patterns into different brain states or conditions through machine learning algorithms. Support Vector Machines (SVM) is a powerful machine learning algorithm that has been widely used for the classification of EEG signals. SVMs are adaptable and show efficiency in managing high-dimensional data and nonlinear relationships. K-Nearest Neighbors (k-NN) is a versatile and another widely used machine learning algorithm. It is a simple and intuitive classification approach that does not require any assumptions about the underlying data distribution. Artificial Neural Networks (ANNs) are powerful tools for EEG classification, learning to recognize complex patterns by adjusting connection strengths between artificial neurons. [30]

These above-mentioned classifies can be either stable or unstable. Stable classifies exhibit low complexity and they do not affect their performance with small variations. For example, k Nearest Neighbors (kNN) is a common stable classifier whereas unstable classifiers have higher complexity and exhibit changes with minor variation in the performance. For example, linear support vector machine (SVM), multi-layer perceptron (MLP), and bilinear recurrent neural network (BLR-NN).

Overall, classification algorithms can be categorized based on different characteristics and properties, providing a wide range of options for various applications.

➢ *Applications*

EEG-based BCI applications are utilized in various fields, including medical, entertainment, art, and non-medical areas, such as developing devices to monitor employee alertness levels. Medical applications include communication aids, neurophysiology, rehabilitation, gaming, entertainment, neuroscience, education, and human-computer interaction. EEGs can help individuals with motor disabilities communicate, control prosthetic limbs, and train cognitive functions. They can also aid stroke rehabilitation by providing real-time feedback and encouraging brain activation. BCIs can also help individuals with attention, memory, and executive

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

functions and help individuals with attention-deficit/hyperactivity disorder (ADHD) learn self-regulation techniques for stress reduction and relaxation. They help individuals with anxiety and mood disorders modulate their brain activity patterns, potentially leading to symptom reduction. BCIs can also be used in gaming and interactive art installations, blurring the boundaries between art, technology, and neuroscience. They are valuable tools for studying brain function, cognitive processes, and neural correlates of behavior.

B. MEG

Magnetoencephalography (MEG) is a neuroimaging technique that measures noninvasively the magnetic field generated by the electrical activity of neurons in the brain. The MEG-based BCI utilizes these magnetic signals to allow communication and control between the brain and external devices. The first MEG signal was measured in 1986 by the physicist David Cohen using an induction coil made of copper as a detector. Later, superconducting quantum interference devices (SQUID) developed by James Edward Zinnerman were used as the state of art MEG sensors. The use of SQUID has increased the signal-to-noise ratio (SNR) of the MEG signals and acquired the MEG signals without signal averaging. The first whole-head SQUID array was developed in the 1990s and recent commercial MEG equipment, several sensors are placed on the head in a helmet model that enhanced the measurement and the special resolution of the MEG signals. Modern MEG systems now have 306 sensors, including magnetometers and gradiometers within one element, which improves signal-to-noise, ambient noise suppression, and suppression of nearby artifacts produced by stimulators like vagus nerve stimulators, cardiac pacemakers, and deep-brain stimulators. Optically pumped magnetometers (OPMs) have been developed to overcome certain SQUID limitations. MEG offers superior temporal and spatial resolution compared to other neuroimaging methods, allowing for brain dynamics capture even at sub-millisecond scales, and is not distorted by the high conductivity difference between skull and scalp.

- *Signal generation*

MEG is a neurophysiological signal primarily generated by cortical pyramidal neurons, which transmit signals via action potentials. When the membrane potential exceeds a threshold, neurotransmitters are released into the synaptic cleft, binding to the postsynaptic neuron's receptors. This results in ion channel opening and membrane potential changes. This leads to a graded postsynaptic potential along the dendrite and related intracellular currents. In a presynaptic axon, the generated magnetic fields cancel each other out, and the extracellular electric and magnetic fields attenuate rapidly as a function of distance. In the postsynaptic dendrite, the intracellular current flows in one direction, producing a magnetic field that can be measured outside the cell. Currents related to postsynaptic potentials are slower and easier to measure. The MEG signal reflects the net magnetic field of tens of thousands of postsynaptic currents, with MEG being most sensitive to currents oriented parallel to the scalp, corresponding to current sources in the walls of sulci where apical dendrites are tangential to the scalp.

- *Physics and instrumentation*

Magnetic fields measured by MEG are typically 100-500 fT (femtotesla) weaker than Earth's magnetic field, making them sensitive to external interference. To detect neural signals, measurements must be conducted with highly sensitive sensors in a magnetically shielded room. SQUIDs are kept below critical temperature by embedding them in a large dewar containing liquid helium for maintaining superconductivity. In SQUID-MEG, magnetic fields are picked up by flux transformers, which can be configured as magnetometers or gradiometers. Magnetometers measure the magnetic flux component perpendicular to their surface, while gradiometers measure the gradient between their two loops. Magnetometers are sensitive to both deep and superficial sources, while gradiometers are most sensitive to nearby superficial sources. The measured magnetic field induces a current in the flux transformer circuit, which is converted into magnetic flux through the SQUID loop. The SQUID converts the flux to a voltage, which is amplified and digitized.

- *Data analysis*

MEG analysis is crucial for reducing artifacts from both the subject and the environment. Signal space separation (SSS) is a powerful method for artifact removal, utilizing the physical properties of magnetic fields to separate signal and noise subspaces. However, it cannot suppress physiological processes like cardiac and muscle artifacts or eye blinks. To suppress artifacts, multi-channel signals can be decomposed into additive subcomponents using principal component analysis (PCA) or independent component analysis (ICA).

To increase the signal-to-noise ratio (SNR), raw MEG data can be filtered before further analyses. Band-pass filtering includes only the frequencies corresponding to the neural activity of interest in the passband. Spatial filtering creates linear combinations of sensor-level signals to maximize the SNR of the signal of interest. Supervised machine learning methods like common spatial patterns (CSP) and linear discriminant analysis can project data effectively between classes of interest.

Beamformers can be used to suppress activity originating outside the signal source if the location is known in advance. They are based on a spatial filter that selectively blocks contributions from all other sources except the predefined source. Averaging over epochs is often used to increase SNR in offline analyses, but it is not feasible in real-time signal analysis due to increased feedback latency. In SMR modulation analysis, averaging in frequency or time-frequency domains can reveal SMR modulation over epochs, sessions, and subjects.

- *Applications*

MEG is a valuable neuroimaging tool for identifying epileptic foci, preoperative evaluation for brain surgery candidates, and therapeutic planning for mental disorders like epilepsy, autism, schizophrenia, stroke, head trauma, and drug administration. Its first therapeutic setting was demonstrated for epilepsy patients. In epilepsy, certain areas of the brain produce abnormal electrical signals, which then generate magnetic signals that can be detected by MEG [18]. When

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

epileptiform spikes first appeared, MEG was utilized to locate their sources and track how quickly they traveled to the opposite hemisphere since it has better special accuracy and less distortion than EEG signals. Numerous origins of epileptic activity as well as different types of epilepsy have been found. With the use of a deep learning model, chronic brain cell-damaging conditions such as schizophrenia were detected. MEG can identify electrophysiological markers for schizophrenia by examining disturbances in oscillatory wave patterns. Resting state MEG has been used to study schizophrenia, suggesting neural abnormalities in synchronized oscillatory activity correlate with the pathophysiology of the disease. EEG studies have identified an increase in delta, theta, and beta waves and a decrease in alpha power patterns in Schizophrenic patients.[18] MEG is a non-invasive tool for diagnosing symptoms of Parkinson's disease (PD) due to its high temporal resolution. It can study neural activity and brain connectivity in patients with PD. MEG has been used to detect thalamocortical dysrhythmia, responsible for neurogenic pain, tinnitus, Parkinson's disease, or depression, under resting state conditions. Autism patients exhibit impaired activity in the gamma frequency band, while severe ASD patients show higher activity between the left and right temporo-parieto-occipital regions. Children with ASD are sensitive to illegal speech sequences during 504.63 Hz MEG recording. ASD patients have low social behavior and communication due to lower gamma band coherence in angular and middle temporal cortical regions. A connectivity-based laterality model was used to study the connectivity of the hemisphere containing the epileptic focus in white matter fibers of mTLE (mesial Temporal lobe epilepsy) patients. The importance of language mapping with MEG was also studied, highlighting the need for localization and lateralization with changes in language networks and identifying speech and social communication cortices in the brain.

C. FMRI

Functional magnetic resonance imaging (fMRI) is a non-invasive BCI with high spatial resolution and moderate temporal resolution. FMRI records brain signals by analyzing the vascular activity of the brain which corresponds to the electrical activity of the brain. It utilizes blood oxygen level-dependent (BOLD) signals and can access the whole brain with high spatial resolution. Electrical activity from the brain recorded by EEG and BOLD were found to be highly correlated.

Unlike EEG-BCI and its ambiguous localization of brain activity, fMRI-BCI can use brain activity in very specific areas of the cortical and subcortical parts of the brain. It offers the capability of real-time visualization and analysis of whole brain images. Subjects using fMRI-BCI can learn voluntary regulation of specific brain areas like the supplementary motor area (SMA), the posterior part of the superior temporal gyrus, the parahippocampal place area (PPA), the anterior cingulate cortex (ACC), insula, Broca’s area, and amygdala.

An fMRI-BCI system is a closed-loop system consisting of four major subsystems: signal acquisition, signal preprocessing, signal analysis, and signal feedback. These subsystems are typically installed and operated on separate computers connected via a local area network (LAN) to optimize system performance.

- *Signal Acquisition*

Whole brain images are acquired using an echo planar imaging (EPI) sequence, where the brain is divided into slices. The hemodynamic response due to the BOLD effect (blood oxygen level-dependent) is measured, reflecting neurovascular response to brain activity. Several factors affecting signal acquisition significantly impact real-time performance. These factors include static magnetic field (B0) strength, spatial resolution, temporal resolution, echo time, and magnetic field inhomogeneities. While high spatial resolution is preferred for detailed imaging, increasing spatial resolution can lead to reduced signal-to-noise ratio (SNR) and longer acquisition times. Therefore, a balance must be struck between spatial resolution, SNR, and acquisition time to optimize the performance of the fMRI-BCI system.

- *Signal Preprocessing*

In the fMRI-BCI system, the signal preprocessing component plays a crucial role in enhancing the quality of acquired images before further analysis. This component retrieves the reconstructed images from the signal acquisition part through a local area network (LAN) and conducts various preprocessing steps. Some common methods of signal preprocessing in fMRI-BCI include head motion correction and physiological noise correction. Head motion is a significant challenge in fMRI as it can lead to artifacts that interfere with the detection of neural signal changes. Two main types of head motion correction methods have been developed: retrospective and prospective. Retrospective correction involves realigning data to a reference image, while prospective correction adjusts scanning parameters before image acquisition based on tracking the moving anatomy. Breathing and cardiac activity can introduce physiological noise in fMRI data, potentially affecting the accuracy of the BOLD signal measurements. Changes in respiratory patterns and volume, as well as fluctuations in CO_2 levels due to breathing, and pulse, can lead to BOLD signal variations. While techniques exist to remove cardiorespiratory artifacts during offline analysis, these methods have not been adapted for real-time fMRI processing. A recent development by van Gelderen et al. involves a real-time shimming method to compensate for fluctuations in the main magnetic field induced by respiration. Implementing such techniques in fMRI-BCI systems could help correct physiological artifacts and noise, especially crucial at higher static magnetic field strengths where physiological noise becomes more prominent.

- *Signal Analysis*

The signal analysis subsystem performs statistical analysis and generates functional maps using methods such as subtraction of active and rest conditions, correlation analysis, multiple regression, general linear model (GLM), and pattern classification to analyze brain activity patterns. Two types of analyses can be done: univariate and multivariate analysis.

➢ *Signal Feedback*

Feedback is presented to the subject through various modalities like acoustic and visual cues. Different visualization methods are used, such as functional maps, continuously updated curves of mean activity in selected regions of interest (ROI), graphical thermometers showing activity levels in ROIs, and even virtual reality interfaces. The timing of feedback presentation is crucial for learning voluntary control of brain activity. Training individuals to self-regulate brain activity can be achieved through feedback of specific brain signals in functional magnetic resonance imaging-based brain-computer interfaces (fMRI-BCI). This feedback not only provides information on the blood-oxygen-level-dependent (BOLD) signal but also serves as a reward mechanism. Effective learning is facilitated by providing contingent feedback promptly after a response, with a high probability of occurrence. fMRI-BCI can operate in both feedback mode, focusing on self-regulation, and non-feedback mode, for applications like brain state detection such as lie detection. Various techniques are employed to identify, compute, and present feedback to the subject.

➢ *Applications*

The primary focus of fMRI-BCI and real-time fMRI systems in various studies has been on training individuals, both healthy subjects and patients, to intentionally regulate specific brain regions to explore their behavioral implications. [37] There have been studies [33] and subsequent investigations highlight the potential of fMRI-based brain-computer interfaces (BCIs) in clinical applications, particularly in the context of chronic pain management and emotional regulation. In the initial study by de Charms et al., the researchers aimed to determine whether training individuals to modulate activity in the rostral part of the anterior cingulate cortex (rACC), a region associated with pain processing, could influence pain perception. They trained healthy volunteers and chronic pain patients to intentionally control rACC BOLD activation using real-time fMRI feedback, which altered their perception of pain from thermal stimuli, a specificity confirmed by control experiments showing no similar effects with other feedback conditions. In a subsequent study, the application of fMRI-BCI in training psychopathic subjects to self-regulate the left anterior insula showed promising results, suggesting the potential for clinical rehabilitation in various conditions such as movement disabilities post-stroke, chronic pain management, and treatment of emotional disorders like depression and anxiety by addressing abnormal brain activity.

➢ *FMRI BCI can also be used for:*

- Language processing: In the study by Rota et al., the researchers investigated the human capacity for differential self-regulation of Blood Oxygen Level Dependent (BOLD) activity recorded locally in Broca's area (BA 45). The study's results demonstrated that up-regulation of the right BA 45 correlated with improved emotional prosody identification. This suggests that individuals trained to voluntarily modulate activity in Broca's area showed enhanced performance in recognizing emotional prosody, highlighting the potential for self-regulation in linguistic processing areas.

- Neuroplasticity of motor systems: In the context of neuroplasticity and functional reorganization for recovery after neurological diseases such as stroke, real-time fMRI feedback offers a potential avenue. In the study by Sitaram et al., four healthy volunteers were trained to control the Blood Oxygen Level Dependent (BOLD) response of the Supplementary Motor Area (SMA). The offline analysis revealed significant activation of the SMA with training. Interestingly, there was also a distinct reduction in activation in the surrounding areas, suggesting that volitional control training can specifically focus activity in the region of interest.

- Visual: fMRI-BCI to investigate the relationship between brain activity and conscious perception during binocular rivalry, specifically focusing on the perception of faces and houses. The experiment consists of three stages: pretest, volitional control training, and posttest. By combining fMRI-BCI with binocular rivalry, the proposed experiment seeks to explore the role of specific brain regions, such as the FFA, in modulating conscious perception of faces. The ability to volitionally control brain activity could provide insights into the neural mechanisms underlying visual perception.

There are also psycho-physiological treatments of fMRI- BCI. For Stroke rehabilitation, Treating chronic pain, treating emotional disorders, Psychopathy, and social phobia. In the psychiatric domain, fMRI has played a crucial role in advancing our understanding of psychopathology by revealing neural correlates of various mental health conditions. In neurology, fMRI has become a cornerstone technique for mapping neuroplasticity, aiding in the recovery process from conditions like stroke, and assisting in presurgical planning for tumor and epilepsy surgeries

D. FNIRS

Functional near-infrared spectroscopy (fNIRS) is a relatively new BCI modality that uses near-infrared-range light to measure the concentration changes of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR). The primary motor cortex and the prefrontal cortex are the predominant brain regions utilized in fNIRS-based BCIs. Motor imagery tasks are favored over motor execution tasks in the motor cortex to circumvent potential proprioceptive feedback. In contrast, the prefrontal cortex offers a notable advantage for fNIRS applications due to the absence of hair, enabling effective detection of cognitive tasks such as mental arithmetic, music imagery, and emotion induction.

FNIRS quantifies variations in blood flow within the local capillary network, reflecting neuronal activity. Employing near-infrared light emitter-detector pairs with multiple wavelengths, the method involves the transmission of light through the scalp and brain tissues, subjecting photons to multiple scattering. Subsequently, the photons exiting the cortical region carry data regarding the dynamic concentrations of oxygenated (HbO) and deoxygenated

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

(HbR) hemoglobin. The relationship between the intensities of exiting and incident photons is computed using the modified Beer-Lambert's law. [20] This calculation enables the assessment of changes in HbO and HbR concentrations along the path of the photons.

Brain-computer interfaces (BCIs) utilize brain signals to gather information about the user's intentions. When developing an fNIRS-based BCI system, the initial step involves acquiring appropriate brain signals. The primary motor cortex and the prefrontal cortex are the most commonly targeted brain regions for signal acquisition. Signals related to motor execution and motor imagery tasks are typically obtained from the motor cortex, while tasks like mental arithmetic, mental counting, music imagery, and landscape imagery are associated with the prefrontal cortex.

The primary motor cortex activities are considered advantageous for functional Near-Infrared Spectroscopy (fNIRS) Brain-Computer Interface (BCI) applications due to their natural ability to provide BCI control over external devices and their potential benefits for neurorehabilitation. The two most common activities acquired from the motor cortex are motor execution and motor imagery.

- Motor Execution: Involves physically moving a body part to activate the motor cortex, which triggers muscular tensions through muscular actions. Tasks like finger tapping, hand tapping, arm lifting, knee extension, and hand grasping have been utilized in previous studies.
- Motor Imagery: Refers to mentally imagining the movement of one's body part without actual muscular involvement. Motor imagery tasks include imagining actions like squeezing a ball, finger-tapping sequences, feet tapping, hand grasping, wrist flexion, and elbow movements. Unlike motor execution tasks, motor imagery signals are free of proprioceptive feedback.

On the other hand, prefrontal cortex activities are also favored for fNIRS-BCI due to their lower susceptibility to motion artifacts and signal attenuation caused by hair slippage. These activities are particularly effective for motor-function-related disabilities. Common prefrontal activities include mental arithmetic, music imagery, mental counting, and landscape imagery.

Various emitter-detector configurations have been utilized in these brain regions, with the emitter-detector distance playing a crucial role in fNIRS measurements. For instance, increasing the emitter-detector distance results in greater imaging depth.

The fNIRS signals obtained may exhibit different types of noise, including instrumental noise, experimental errors, and physiological noise. As instrumental noise and experimental errors are unrelated to brain activities, it is advisable to eliminate them before transforming the raw optical density signals into changes in HbO and HbR concentrations using the modified Beer-Lambert law. Physiological noise include heartbeats, respiration, blood pressure, etc. They can be removed by using bandpass filtering, advanced filtering methods, ICA, and PCA. Instrumental noise in fNIRS signals stems from hardware components or environmental factors, introducing high-frequency disruptions in the recorded data. To mitigate this noise, a low-pass filter with a defined cutoff frequency (e.g., 3-5 Hz) can be employed to filter out the high-frequency components linked to instrumental noise. Furthermore, reducing fluctuations in external light can also play a role in significantly decreasing instrumental noise levels.

Experimental errors in fNIRS data, such as motion artifacts resulting from head movements that displace optodes, can cause abrupt changes in light intensity, leading to spike-like noise in the recorded signals. Various correction methods have been proposed in scientific literature to address these motion artifacts and rectify experimental errors. [12]

➢ *Applications*

In recent years, remarkable strides have been achieved in the realm of fNIRS-BCI research; however, its applications have predominantly been tailored for training and demonstration purposes. The efficacy of fNIRS-BCI encounters challenges in real-world scenarios due to a slow information transfer rate and elevated error rates. Notably, testing often transpires in controlled laboratory environments, where user concentration on mental tasks is facilitated, contrasting with the more demanding nature of concentration-dependent tasks in real-life situations, such as motor imagery and mental arithmetic.

Within the domain of neuro-rehabilitation, fNIRS-BCI emerges as a potential tool for restoring lost motor and cognitive functions in individuals affected by stroke or spinal cord injury. Unlike EEG, which faces limitations in precise localization and subcortical accessibility, fNIRS, being low-cost, portable, and less sensitive to motion artifacts, offers an attractive alternative. Studies [25], [27] and [28] demonstrate the potential of fNIRS-based neurofeedback in regulating hemodynamic responses, especially in motor imagery and for stroke patients.

Communication applications of BCI, specifically for individuals with motor disorders like ALS and spinal cord injury, are highlighted. fNIRS-BCI system for binary communication based on prefrontal activations, achieving approximately 82% accuracy.[29] Furthermore, fNIRS-BCI finds significance in motor restoration/rehabilitation, where control commands generated can be employed for prosthetic limb or wheelchair control. Applications in environment control, entertainment, and potential use in brain-controlled video games are also explored.

Moreover, the application of functional Near-Infrared Spectroscopy (fNIRS) in BCI aligns with neuro ergonomics, enabling real-time assessment of mental workload and conditions. Studies employing fNIRS-BCI have identified three distinct levels of workload in tasks such as air traffic control [6], attention deficit tasks [15], and drowsiness detection in drivers [24]. Additionally, for cognitive and motor function restoration in stroke patients, neurofeedback processes utilizing fNIRS-BCI have been explored [28].

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

These processes involve subjects regulating hemodynamic responses to facilitate self-regulation of brain activity.

A notable advantage of fNIRS lies in its complementary integration with other modalities without introducing additional artifact noise in the readings, and vice versa. One commonly pursued combination is fMRI–fNIRS, capitalizing on the fact that fMRI setups struggle with experiments involving subjects in sitting or standing positions.

Additionally, fMRI lacks accessibility to working body parts for real-time control readings. Although fMRI provides highly accurate readings, to address these limitations without sacrificing benefits, an fNIRS setup can be coupled with the existing setup. Furthermore, fNIRS has been integrated with the EEG modality, creating a distinct neuromonitoring platform for investigating neurovascular coupling mechanisms. A modified version of fNIRS known as broadband-NIRS has been specifically applied in this context, utilizing Finite Impulse response functions within the General Linear model. This implementation has demonstrated the capability to measure hemodynamic and metabolic activity in the occipital cortex. [25]

FNIRS-BCI systems are extremely portable, providing flexibility in various settings, and have high experimental flexibility, allowing for versatile applications in research. However, one drawback of fNIRS-BCI is its slow information transfer rate, limiting its real-world applications. FNIRS-BCI systems may exhibit high error rates, impacting their reliability in certain contexts. FNIRS is a low-cost alternative to fMRI, making it more accessible for various applications. Its portable nature allows for usage in diverse settings, including ambulances, enhancing its practical applications. FNIRS holds great potential for neurofeedback studies. Understanding these pros and cons is crucial for optimizing fNIRS-BCI applications in different research and practical scenarios.

IV. CONCLUSION

In conclusion, the varied array of non-invasive methods of BCI have emerged as a promising application in the field of neuroscience that represents a significant advancement in bridging the gap between the human brain and external devices. These systems present a safe and accessible means of exploiting brain activity for various applications, ranging from controlling prosthetic devices to enhancing communication for individuals with disabilities. While each method has its strengths and limitations, together they contribute to the field of neuroscience with immense potential for improving human-computer interaction and advancements in healthcare practices. As research continues to evolve, the future of non-invasive BCIs holds great promise for unlocking new possibilities in technology and neuroscience.

REFERENCES

[1]. Abdulkader SN, Atia A, Mostafa MSM. Brain computer interfacing: Applications and challenges. Egyptian Informatics Journal. 2015 Jul;16(2):213–30.

[2]. A. Caria, R. Veit, T. Gaber, R. Sitaram, A. Kuebler, and N. Birbaumer, “Can we learn to increase our emotional involvement?real-timefMRIofanteriorcingulatecortexduringemotional processing,” in Human Brain Mapping, Florence, Italy, June 2006.

[3]. Alhudhaif, A. A novel multi-class imbalanced EEG signals classification based on the adaptive synthetic sampling (ADASYN) approach. PeerJ Comput. Sci. 2021, 7, e523.

[4]. Allison BZ, Krusienski D. Noninvasive Brain-Computer Interfaces. Encyclopedia of Computational Neuroscience [Internet]. 2014;1–13. Available from:

[5]. Al-Nafjan A. Feature selection of EEG signals in neuromarketing. PeerJ Comput Sci. 2022 Apr 26;8:e944. doi: 10.7717/peerj-cs.944. PMID: 35634118; PMCID: PMC9138093.

[6]. Ayaz, H.; Onaral, B.; Izzetoglu, K.; Shewokis, P.A.; McKendrick, R.; Parasuraman, R. Continuous monitoring of brain dynamics with functional near infrared spectroscopy as a tool for neuroergonomic research: empirical examples and a technological development. Front. Hum. Neurosci. 2013, 7, 871.

[7]. Belluscio, V.; Casti, G.; Ferrari, M.; Quaresima, V.; Sappia, M.S.; Horschig, J.M.; Vannozzi, G. Modifications in Prefrontal Cortex Oxygenation in Linear and Curvilinear Dual Task Walking: A CombinedfNIRSandIMUsStudy. Sensors2021, 21, 6159.

[8]. Besserve M, Jerbi K, Laurent F, Baillet S, Martinerie J, Garnero L. Classification methods for ongoing EEG and MEG signals. Biol Res. 2007;40(4):415-37. Epub 2008 May 28. PMID: 18575676.

[9]. Brain–computer interfaces for communication and control Jonathan R. Wolpawa,b,*, Niels Birbaumerc,d, Dennis J. McFarlanda , Gert Pfurtschellere , Theresa M. Vaughana a Laboratory of Nervous System Disorders, Wadsworth Center, New York State Department of Health, P.O. Box 509, Empire State Plaza, Albany, NY 12201-0509, USA b State University of New York, Albany, NY, USA

[10]. Brain–computer interfaces JONATHAN R. WOLPAW* Wadsworth Center, Laboratory of Neural Injury and Repair, New York State Department of Health and State University of New York, Albany, NY, USA, Handbook of Clinical Neurology, Vol. 110 (3rd series) Neurological Rehabilitation

[11]. Buccino, A.P.; Keles, H.; Omurtag, A. Hybrid EEG-fNIRS Asynchronous Brain-Computer Interface for Multiple Motor Tasks. PLoS ONE2016, 11, e0146610

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG1536

[12]. Cooper RJ, Selb J, Gagnon L, Phillip D, Schytz HW, Iversen HK, Ashina M, Boas DA. A systematic comparison of motion artifact correction techniques for functional near-infrared spectroscopy. Front Neurosci. 2012 Oct 11;6:147. doi: 10.3389/fnins.2012.00147. PMID: 23087603; PMCID: PMC3468891.

[13]. Chaddad A, Wu Y, Reem Kateb, Bouridane A. Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques. Sensors. 2023 Jul 16;23(14):6434–4

[14]. Daly JJ, Wolpaw JR. Brain–computer interfaces in neurological rehabilitation. The Lancet Neurology. 2008 Nov;7(11):1032–43.

[15]. Derosiere, G.; Dalhoumi, S.; Perrey, S.; Dray, G.; Ward, T. Towards a Near Infrared Spectroscopy-Based Estimation of Operator Attentional State. PLoS ONE 2014, 9, e92045.

[16]. Di Flumeri G, Aricò P, Borghini G, Sciaraffa N, Di Florio A, Babiloni F. The Dry Revolution: Evaluation of Three Different EEG Dry Electrode Types in Terms of Signal Spectral Features, Mental States Classification and Usability. Sensors (Basel). 2019 Mar 19;19(6):1365. doi: 10.3390/s19061365. PMID: 30893791; PMCID: PMC6470960.

[17]. fMRI Brain-Computer Interface: A Tool for Neuroscientific Research and Treatment Ranganatha Sitaram,1 Andrea Caria,1 Ralf Veit,1, 2 Tilman Gaber,1, 2 Giuseppina Rota,1, 3 Andrea Kuebler,1 and Niels Birbaumer1, 4 Hindawi Publishing Corporation Computational Intelligence and Neuroscience Volume 2007, Article ID 25487, 10 pages doi:10.1155/2007/25487

[18]. Fred AL, Kumar SN, Kumar Haridhas A, Ghosh S, Purushothaman Bhuvana H, Sim WKJ, Vimalan V, Givo FAS, Jousmäki V, Padmanabhan P, Gulyás B. A Brief Introduction to Magnetoencephalography (MEG) and Its Clinical Applications. Brain Sci. 2022 Jun 15;12(6):788. doi: 10.3390/brainsci12060788. PMID: 35741673; PMCID: PMC9221302.

[19]. F. Tong, K. Nakayama, J. T. Vaughan, and N. Kanwisher, “Binocular rivalry and visual awareness in human extrastriate cortex,” Neuron, vol. 21, no. 4, pp. 753–759, 1998.

[20]. G. Rota, R. Sitaram, R. Veit, N. Weiskopf, N. Birbaumer, and G. Dogil, “ fMRI-neurofeedback for operant conditioning and neural plasticity investigation: a study on the physiological self-induced regulation of the BA 45,” in Proceedings of the Cognitive Neuroscience Conference, San Francisco, Calif, USA, 2006.

[21]. Goyal I, Mehta A. Acquisition, Pre-Processing, and Feature Extraction of EEG Signals to Convert it into an Image Classification Problem [Internet]. International Research Journal of Engineering and Technology. [cited 2024 Aug 27]. Available from: https://www.irjet.net/archives/V8/i2/IRJET-V8I237.pdf

[22]. Halme HL. Development of an MEG-based brain-computer interface [Internet]. [cited 2024 Aug 27]. Available from: https://aaltodoc.aalto.fi/server/api/core/bitstreams/bd2c0df1-ec92-4e9e-b26a-38a4e732f653/content

[23]. Huppert, T. J., Hoge, R. D., Diamond, S. G., Franceschini, M. A., and Boas, D. A. (2006). A temporal comparison of BOLD, ASL, and NIRS hemodynamic responses to motor stimuli in adult humans. Neuroimage 29, 368–382. doi: 10.1016/j.neuroimage.2005.08.065

[24]. Khan, M.J.; Hong, K.-S. Passive BCI based on drowsiness detection: an fNIRS study. Biomed. Opt. Express 2015, 6, 4063–4078.

[25]. Kober SE, Wood G, Kurzmann J, Friedrich EV, Stangl M, Wippel T, Väljamäe A, Neuper C. Near-infrared spectroscopy based neurofeedback training increases specific motor imagery related cortical activation compared to sham feedback. Biol Psychol. 2014 Jan;95:21-30. doi: 10.1016/j.biopsycho.2013.05.005. Epub 2013 May 25. PMID: 23714227.

[26]. Li B, Cheng T, Guo Z. A review of EEG acquisition, processing and application. Journal of Physics: Conference Series. 2021 May 1;1907(1):012045.

[27]. Mihara, M., Hattori, N., Hatakenaka, M., Yagura, H., and Kawano, T. (2013). Near infrared spectroscopy-mediated neurofeedback enhances efficacy of motor imagery-basedtraining inpoststroke victims apilotstudy. Stroke 44, 1091–1098. doi: 10.1161/STROKEAHA.111.674507

[28]. Mihara,M.;Miyai, I.; Hattori, N.; Hatakenaka, M.; Yagura, H.; Kawano, T.; Okibayashi, M.; Danjo, N.; Ishikawa, A.; Inoue, Y.; et al. Neurofeedback Using Real-Time Near-Infrared Spectroscopy Enhances Motor Imagery Related Cortical Activation. PLoS ONE 2012, 7, e32234.

[29]. Naseer, N., and Hong, K.-S. (2013). Classification of functional near-infrared spectroscopy signals corresponding to the right- and left-wrist motor imagery for development of a brain-computer interface. Neurosci. Lett. 553, 84–49. doi: 10.1016/j.neulet.2013.08.021

[30]. Neuroelectrics. Guide to Electroencephalography: From EEG Data to Classification [Internet]. Neuroelectrics Blog - Latest news about EEG & Brain Stimulation. 2023. Available from: https://www.neuroelectrics.com/blog/2023/09/04/guide-to-electroencephalography-from-eeg-data-to-classification/

[31]. Noninvasive Brain–Computer Interfaces. Neuromodulation [Internet]. 2018 Jan 1 [cited 2021 May 1];357–77. Available from: https://www.sciencedirect.com/science/article/pii/B9780128053539000267

[32]. Paulmurugan K, Vijayaragavan V, Ghosh S, Padmanabhan P, Gulyás B. Brain–Computer Interfacing Using Functional Near-Infrared Spectroscopy (fNIRS). Biosensors. 2021 Oct 13;11(10):389.

[33]. Pinti, P.; Siddiqui, M.F.; Levy, A.D.; Jones, E.J.H.; Tachtsidis, I. An analysis framework for the integration of broadband NIRS and EEGto assess neurovascular and neurometabolic coupling. Sci. Rep. 2021, 11, 1–20
[34]. P. van Gelderen, J.A. de Zwart, P. Starewicz, R.S. Hinks, and J.H. Duyn, "Real time shimming to compensate for respiration-induced B0 fluctuations," Magn. Reson. Med., vol. 57, no. 2, pp. 362–368, 2007.
[35]. R. C. DeCharms, F. Maeda, G. H. Glover, et al., "Control over brain activation and pain learned by using real-time functional MRI," Proceedings of the National Academy of Sciences of the United States of America, vol. 102, no. 51, pp. 18626–18631, 2005.
[36]. Rieke, J.D.; Matarasso, A.K.; Yusufali, M.M.; Ravindran, A.; Alcantara, J.; White, K.D.; Daly, J.J. Development of a combined, sequential real-time fMRI and fNIRS neurofeedback system to enhance motor learning after stroke. J. Neurosci. Methods 2020, 341, 108719.
[37]. R. Sitaram, A. Caria, R. Veit, T. Gaber, A. Kuebler, and N. Bir baumer, "Real-time fMRI based brain-computer interface enhanced by interactive virtual worlds," in Proceedings of the 45th Annual Meeting Society for Psychophysiological Research, Lis bon, Portugal, 2005.
[38]. Shih JJ, Krusienski DJ, Wolpaw JR. Brain-Computer Interfaces in Medicine. Mayo Clinic Proceedings [Internet]. 2012 Mar;87(3):268–79.
[39]. Sitaram R, Weiskopf N, Caria A, Veit R, Erb M, Birbaumer N. [IEEE SIGNAL PROCESSING MAGAZINE [95]. 2008 [cited 2019 May 18]; Available from: https://www.bme.ufl.edu/labs/sitaram/files/2013/10/4.-IEEE-Signal-Processing-Sitaram-2008.pdf
[40]. Sorger B, Goebel R. Real-time fMRI for brain-computer interfacing. Handbook of Clinical Neurology [Internet]. 2020 [cited 2021 Aug 27];168:289–302. Available from: https://pubmed.ncbi.nlm.nih.gov/32164860/
[41]. Torres EP, Torres EA, Hernández-Álvarez M, Yoo SG. EEG-Based BCI Emotion Recognition: A Survey. Sensors. 2020 Sep 7;20(18):5083.
[42]. Värbu K, Muhammad N, Muhammad Y. Past, Present, and Future of EEG-Based BCI Applications. Sensors. 2022 Apr 26;22(9):3331.
[43]. Venkata Phanikrishna B, Pławiak P, Jaya Prakash A. A Brief Review on EEG Signal Pre-processing Techniques for Real-Time Brain-Computer Interface Applications [Internet]. www.techrxiv.org. 2021 [cited 2023 Jun 2]. Available from: https://www.techrxiv.org/articles/preprint/A_Brief_Review_on_EEG_Signal_Pre-processing_Techniques_for_Real-Time_Brain-Computer_Interface_Applications/16691605
[44]. Weiskopf N, Mathiak K, Bock SW, Scharnowski F, Veit R, Grodd W, et al. Principles of a Brain-Computer Interface (BCI) Based on Real-Time Functional Magnetic Resonance Imaging (fMRI). IEEE Transactions on Biomedical Engineering. 2004 Jun;51(6):966–70.
[45]. Weiskopf N, Sitaram R, Josephs O, Veit R, Scharnowski F, Goebel R, et al. Real-time functional magnetic resonance imaging: methods and applications. Magnetic Resonance Imaging. 2007 Jul;25(6):989–1003.
[46]. Wet, dry, active and passive electrodes. What are they, and what to choose? [Internet]. BuscaEU. 2023. Available from: https://brainlatam.com/blog/wet-dry-active-and-passive-electrodes.-what-are-they-and-what-to-choose-413
[47]. Wolpaw JR, Elizabeth Winter Wolpaw. Brain-computer interfaces : principles and practice. New York: Oxford University Press; 2012.
[48]. Yeom, H.G., Kim, J.S. & Chung, C.K. A magnetoencephalography dataset during three-dimensional reaching movements for brain-computer interfaces. Sci Data 10, 552 (2023). https://doi.org/10.1038/s41597-023-02454-y
[49]. Yoo SS, Fairneny T, Chen NK, Choo SE, Panych LP, Park H, et al. Brain–computer interface using fMRI: spatial navigation by thoughts. NeuroReport. 2004 Jul;15(10):1591–5.
[50]. Yuan H, Li Y, Yang J, Li H, Yang Q, Guo C, Zhu S, Shu X. State of the Art of Non-Invasive Electrode Materials for Brain-Computer Interface. Micromachines (Basel). 2021 Dec 8;12(12):1521. doi: 10.3390/mi12121521. PMID: 34945371; PMCID: PMC8705666.