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A Review of Past Discovery, Current Trends, and Future Directions in Brain-Computer Interface

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Abstract: Sundar Pichai once stated, "Artificial Intelligence will have a more profound impact on humanity than fire or electricity", proving it right, the technology of Brain-Computer Interface (BCI) is set to take over the world. In this review, precise information regarding the first brain wave, the first performed experiment, and the points related to prosthetic devices are covered. Further, an overview of BCI, as a technology, and literature surveys are provided. Finally, the interpretations and analysis regarding neuroscience, brain waves like EEG, ECoG, and MEG to be exact, and the method of signal processing and conditioning, including machine learning, accompanied by a summary, and future scope are furnished.

Keywords: Amyotrophic Lateral Sclerosis (ALS), Artificial Intelligence (AI), Artificial Neural Network (ANN), Brain-Computer Interface (BCI), Deep Learning (DL), Electrocorticography (ECoG).

INTRODUCTION

The journey of the Brain-Computer Interface goes back to the 1930s when young and passionate scientists were determined to unlock the mystery of the human brain. Lord Adrian and Hallowell Davis, English, and American scientists respectively, identified the alpha and beta frequencies as integral components of EEG signals, which were first discovered by Hans Burger, priorly. This discovery significantly impacted young encephalography innovators like Herbert Jasper, William Lennox, and Alfred Loomis. [1]

Discovery further extended to the 1970s, up to the labs of California's UCLA. Experimentation on animals began with the attempt to connect their minds to electronic devices. This seminal period they have culminated in 1973 with Jacques Vidal's pivotal paper, "Toward Direct Brain-Computer Communications," laying the groundwork for future advancements. In the 1990s more human trials were initiated to harness the utmost potential of BCI for humanity's use. [2]

In this journey two breakthroughs proved very crucial, they are, the description of direct current EEG in 1964 by Walter *et al.* and Kamiya's depiction of intentional control over EEG in 1968. The visualization of synchronized brain activity by artist Nina Sobell in the early 1970s and Jacques J. Vidal's seminal 1973paper, which coined the term "Brain-Computer Interface," further galvanized interest and research efforts. In 1988, *the* P300-speller was introduced by Farwell and Donchin which revolutionized the field of BCI. Jonathan Wolpaw's new perspective on BCI, around 2000, was indeed helpful for exploration. [3]

In the present timeline, Elon Musk's Neuralink is one of the most reputed companies attempting to achieve greater heights in BCI, founded in 2016, through invasive 0.004mm electrodes. Neuralink primarily strives to create a bridge between the human mind and devices through precise surgical procedures then building a neural network to acquire brain waves, and further, those brain waves are trained and tested for the application of machine learning and AI integration.

It aims to show a new world to disabled people and cure brain-related syndromes like schizophrenia, ALS, Parkinson's disease, epilepsy, and stroke. Besides the medical domain, BCI has proven to have wide applications in business, entertainment, virtual reality, and many more [21],[22].

OVERVIEW

The Brain-Computer Interface (BCI) also known as the Brain-Machine Interface (BMI) or Mind-Machine Interface (MMI) is pledged to build a direct connection between the human brain and high-level systems, without any external factors like peripheral nerves or muscles, for the betterment of humanity. The technology of BCI is a collection of prior knowledge regarding neuroscience, EEG**,** and ECoG signals, applying the techniques of signal processing to draw valuable information, integrating machine learning and AI into the method, and lastly allowing the processed data to perform its action of device control.

Neuroscience is a prerequisite for BCI. Although the whole neural anatomy need not be known, the basic idea regarding brain waves is essential. EEG waves are acquired through non-invasive electrodes, which give a clear picture of the brain's electrical activity, on amplifying [3]. MEG waves measure the magnetic field of the brain through neuron senses providing a temporal solution. MEG is used for epileptic surgeries and brain mapping [6]. ECoG is a method involving invasive electrodes that are placed in the cortex for brain monitoring. Compared to EEG and MEG, ECoG explores wider areas in the brain which tends to have more scope of exploration [5]. Apart from these, the knowledge of alpha and beta frequencies and functionalities of different brain lobes could be an added advantage.

After the acquisition of brain signals, the major part of BCI comes into the picture where the raw data is converted into useful information, that is, signal processing. Signal processing involves steps like digitalization, preprocessing, feature extraction, classification algorithms, and generating control commands for hardware devices. Signal processing is often considered essential as it improves the signal- to-noise ratio, identifies the rhythmic patterns, and classifies similar ones. In recent times, techniques like spike sorting, signal filtering, blind source separation, and classification algorithms have gone through significant advancement which has reduced the work time with an increase in work efficiency and durability. [8]

The techniques of AI and ML are used to build Artificial Neural Networks (ANN) or conduct Linear Dimensional Analysis (LDA)through Deep Learning (DL). For instance, consider a research article presented by Zee Wang, Boyu Wang, and other co-authors regarding ANNs. In this study, a method that integrates the knowledge of Steady-state visual evoked potential (SSVEP) recognition into neural networks by following the trends of AI and ML. Further, it transforms spatial filtering, reducing the network's complexity, which is similar to the process of building interpretable AI models. This method notably reduces the training parameters, nullifies overfitting, and reduces the expense [9]. Through this study, it is evident that the techniques of AI are used in the field of BCI for faster results by reducing the computational time over the period.

Hardware devices serve their applications in different domains of BCI. Firstly, while recording the EEG, MEG, and ECoG waves, electrodes, magnetometers, and microelectrodes are used respectively, Secondly, they are used for training huge datasets, for instance, Near Infrared Spectroscopy (NIRS) is one of them. Lastly, after signal processing, the worthwhile and significant data is transmitted through Bluetooth connectivity to the desired device, majorly, a microcontroller, which can take up the desired actions.

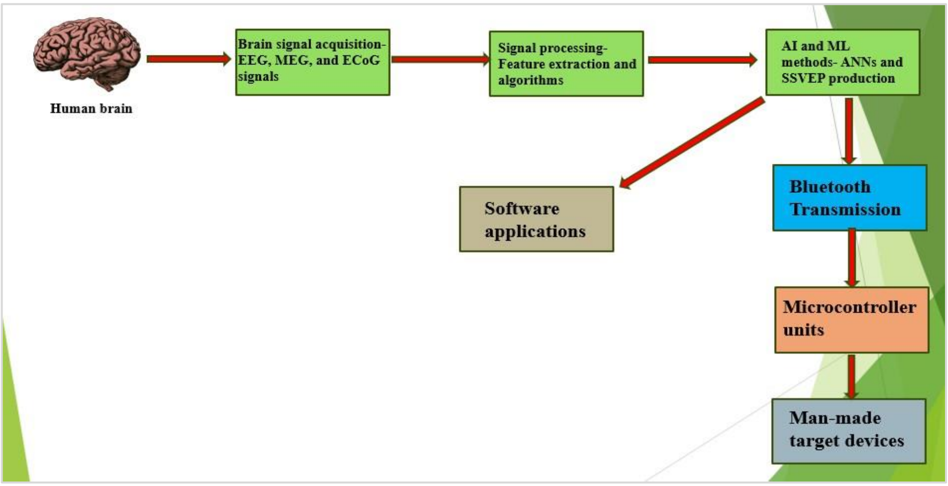

Figure 1. Workflow of BCI with block diagram.

LITERATURE SURVEY

As outlined by the scholarly work conducted by Vinay Jayram, Morteza Alamgir, Yasemin Altun, Bernhard Schölkopf, and Moritz Grosse-Wentrup titled "Transfer Learning in Brain-Computer Interfaces", an issue regarding the difference in datasets is been addressed [10]. The article began with anintroduction to BCI and moved forward by stating how datasets were classified to improve stability. Further study of the literature showed that three proven methods were used in data training. Domain adaptation, it's the process of finding common patterns, Rule adaptation, it's the

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process of transforming the data and Covariate shift, it's the process of data distribution. Later Multitask Learning and Pool-ridged Regression were introduced which are supposed to be the proposed methodologies. The multitask method involved two approaches, that is, training each subject individually or jointly. It included model parameters in the process. The pool-ridged method is more of a statistical approach, as it finds the relation between different factors affecting the outcome through mathematical calculations. Results showed that both these methods yielded 80-85% similar outcomes overpowering the previous methods. In the end, a new transfer method was found that minimized errors and increased efficiency when tested on motor imagery and cognitive paradigms [10].

In the academic study conducted by Minjun Zhang, Qingyi Hua, Wei Jia, Rui Chen, Hui Su, and Bo Wang, titled "Feature Extraction and Classification Algorithm of Brain-computer Interface Based on Human Brain Central Nervous System", an issue regarding the extra noise in BCI was addressed [11]. Firstly, the introduction to BCI was given which was followed by the technique of reducing the background noise, which was the main concern. Secondly, a methodology of combining EEG signals with fNIRS data was put up, where the process of applying digital filters to eliminate noise and retrieve frequencies. Alpha on beta bands of EEG signals were used to detect changes in action. fNIRS data showed the hemodynamic responses. EEG signals and fNIRS data are combined and features like band energy are extracted through machine learning techniques. Thirdly, results showed, that this process of combining two entities eliminated the majority of background noise through Principal Component Analysis(PCA) which was AI-driven. Finally, the article concluded by stating how the combination of EEG wavelet and fNIRS features can result in high accuracy and better task recognition in multimodal BCI [11].

The investigation led by Robert Leeb, Member, IEEE, Marcel Lancelle, Vera Kaiser, Dieter W. Fellner, and Gert Pfurtscheller titled "Thinking Penguin: Multimodal Brain-Computer Interface Control of a VR Game", mainly dives into an application of BCI, that is, Virtual reality and gaming [12].The article began with a question about whether people could control a virtual penguin through both, brainwaves and game controllers and whether can they successfully transmit their skills from training to the actual game. Fourteen healthy participants with non-invasive electrodes were made to sit in the environment and their brain waves along with muscle movements were recorded. In the methodology section, it was described how participants imagined leg movements and executed them while EEG and MEG waves were recorded. On the other hand, training sessions with manual controls were made familiar to the participants. at the end, respondents were asked to play a VR game, using both brain signals and manual controls, where a penguin collected fish. Further, results showed that this asynchronous VR gaming proved to be effective due to the previously conducted training sessions, as all skills were transferred with efficiency. though the levels increased the game was intact without any hindrance. It also opened the doors for BCI-supported multitasking. Lastly, the study concluded by stating how various modalities of BCI are usable and effective and the way a person can perform other different chores while using BCI after a minimal amount of training [12].

INTERPRETATION AND ANALYSIS

Neuroscience and Brain waves

Diving deep into the domain, the most important part of neuroscience required for BCI is the concept of brain waves. Majorly, EEG, and ECoG signals that capture the electrical impulse and magnetic field of thebrain are emphasized more. After discovering brain waves, it was first subjected to animal testing. In the past and even in the modern world, BCI testing on animals is not at a halt. The research studies conducted by Xilin Liu, Milin Zhang, Han Hao, Andrew G. Richardson, Travis J. Wiltshire, and Stephen M. Fiore titled "Wireless Sensor Brain- Machine Interfaces for Closed-loop Neuroscience Studies", and “Social Cognitive and Affective Neuroscience in Human-Machine Systems: A Roadmap for Improving Training, Human-Robot Interaction, and Team Performance”, respectively suggest that through SBMI sensors humans can establish communication with animals' brains and vice-versa. The motto behind this was to understand the functionality of the brain in a better way so that brain-related syndromes find their cure in no time. This process involves building small devices that can record and process brain signals simultaneously in the animal's brain [13], [14]. But creating those small devices is the clutch part. Researchers have not given up and they are still trying to find a way to make this communication system possible which might serve as a ray of hope for mental health-related issue victims.

Taking this to the next level, the signal acquisition was upscaled through Electrocorticography. The clinical review presented by Gerwin Schalk, and Eric C. Leuthardt titled "Brain-Computer Interfaces Using Electrocorticographic Signals" gives clear information about how ECoG is a process of recording brain signals through the skull and cortex, analyzing mu and beta bands of frequency, understanding stimuli-based activity and optimization, an upgradation from animal to human testing, challenges that are to be faced and concluding with the prospects of having an advancement in the medical field [15]. Taking a step back, similar to ECoG signals EEG signals have different bands of frequencies with different activities are represented in Figure 2.

SIGNALS	FREQUENCY RANGE	ACTIVITY
GAMMA	30-100 Hz	SYNCHORINIZATION, INSIGHTING
BETA	12-30 Hz	CONCENTRATIVE ALERTNESS
ALPHA	8-12 Hz	MEDITATION, CREATIVITY
THETA	4-8 Hz	DREAMING TRANCE, VISUALIZATION
DELTA	0.5-4 Hz	DEEP SLEEP AND RESTORATION

Figure 2. EEG bands with their activities

Signal Processing

Signal processing is the major part of this technology where the work should be efficient and precise results must be produced. Superficially, signal processing is a method of converting the raw brain waves into meaningful data by applying some simple and complicated techniques that are accompanied by certain calculations. The review work presented by Le Wu, Aiping Liu, Rabab K. Ward, Z. Jane Wang, and Xun Chen, titled "Signal Processing for Brain–Computer Interfaces" provides information on different processing techniques that are done in modern laboratories. Firstly, spike sorting, it's a method

involving the segregation of brain signals and identifying which brain lobe produces what type of signals. This method would help us to understand the brain and its functionality in a better way. Secondly, signal filtering, it's a process of filtering noise and unwanted information from the signals. This method improves efficiency and reduces the load on the system by disposing of all the junk that is not required. Thirdly, the blind source separation, method mainly focuses on the isolation of brain signals for better interpretation of physical activities. Lastly, this method helps us to analyze brain activity at different bands of frequency. Through this method, useful information can be extracted which can later be used in device control. [8]

Further, signal processing involves applying basic ML techniques like supervised and unsupervised learning to the processed brain signals. The scholarly work provided by Scott Makeig, Christian Kothe, Tim Mullen, Nima Bigdely-Shamlo, Zhilin Zhang, and Kenneth Kreutz-Delgado, titled "Evolving Signal Processing for Brain-Computer Interfaces" gives a clear idea regarding this part. Firstly, supervised learning involves the training of models based on brain signals, which are treated as datasets. Control commands are designed as per user. The model recognizes the signal patterns are predicts future actions. Lastly, unsupervised learning involves the training of models without any datasets or predefined labels. The model itself tries to find the patterns explicitly. They find out the hidden information that may not be noticed in the first check. [7]

Machine Learning and AI

Majorly, AI in BCI involves building Artificial Neural Networks for inter-communication. The esteemed study conducted by Ze Wang, Chi Man Wong, Boyu Wang, Zhao Feng, Fengyu Cong, and Feng Wan titled "Compact Artificial Neural Network Based on Task Attention for Individual SSVEP Recognition With Less Calibration" gives a clear picture of SSVEP targets and neural networks. Superficially, neural networks are of three layers, signal conducting layer, pattern recognition layer, and task combination layer. Correlation analysis was a major setback of this method hence SSVEP signalswere used to overcome it. SSVEP signals are steady and vary less concerning time, so they provide the required stability to neural mechanisms. This method ensured cross-validation, segregation of training sets and testing data, evaluation metrics, and the amount of data a user can transmit with classification accuracy and parametric comparisons. Hence, SSVEP signal usage was found useful in developing new neural networks for modern research. [9]

Overviewing another ML technique, it emphasizes the mathematical and statistical domain, which is a part of data science. The research journal presented by Heung-Il Suk and Seong-Whan Lee titled "A Novel Bayesian Framework for Discriminative Feature Extraction in Brain-Computer Interfaces" gives an application of the Bayesian algorithm in BCI. This method majorly focuses on better comprehension of brain signals by ignoring noise [16]. Two problems are addressed, finding appropriate frequency bands and measurement of signals respectively. Bayesian framework is used to calculate the probability of optimization of spatial bands. For understanding brain signals, particle-based estimation is used to figure that out. These methods were tested on three different datasets that were recorded in different sessions. The results that were yielded showed more accuracy than any previous methods. The reason for the accuracy is the usage of the Bayesian algorithm which is a prominent

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ML algorithm used in every domain of statistics. Additionally, this EEG operative, that is, EEG signal yields better results through this framework [16].

Feature extraction and classification algorithms are the major part of this domain. The scholarly research conducted by Tianwei Shi, Ling Ren, and Wenhua Cui titled "Feature Extraction of Brain- Computer Interface Electroencephalogram Based on Motor Imagery" gives a clear picture of how ML techniques are used in feature extraction [17]. This method has three main mottos, feature extraction, that is, information extraction from signals, differentiation, that is, recognizing significant patterns and correlation of datasets for task combination. Motor imagery activities are tasks where subjects just imaginetheir body movements with invasive electrodes implanted. Two methods were proposed for the extraction of this moto imagery task, Common Spatial Patterns (CSP) and Common Spacio-Spectral Patterns (CSSP) respectively. CSP involves the identification of spatial bands through EEG signals. CSSP is the process of combining spatial and spectral filters to find similar or distinct patterns. Filtering of EEG bands is basedon time and frequency analysis. Additionally, Adaptive-Auto Regressive mode was used for mathematical estimation of spectral filters which is further carried onto CSSP. Thus, combination of AAR, CSP, and CSSP serves as an application of feature extraction or machine learning in this domain [17].

Considering neuroscience as the prerequisite for BCI, then signal processing and ML techniques are the required skills one should master for complete command over interfaces. Although the techniques used here are complicated for a single individual to learn if mastered, they can serve for the betterment of society or the whole probable humanity.

APPLICATION AND SUMMARY

Diving into the applications of BCI technology in the modern era, an esteemed study done by Christopher G. Coogan AND Bin He titled "Brain-Computer Interface Control in a Virtual Reality Environment and Applications for the Internet of Things" describes BCI's role in the IoT field [18]. According to the trends, automation is the main fruit with BCI roots. Most of the things are controlled through the brain itself using prosthetic devices, daily chores can be performed easily without any hindrance and also support multi-tasking. BCI also paves the way for the betterment of communication throughout the globe. Medical applications of BCI serve as a great advantage in dealing with mental health and brain-related issues thereby reducing casualties. Another domain where BCI has spread its wings is the entertainment industry. Gaming, Virtual reality, and metaverse have seen a significant improvement under BCI[18].

Moving onto the next survey of applications, the scholarly work presented by Xiaotong Gu, Zehong Cao, Alireza Jolfaei, Peng Xu, and Dongrui Wu titled "Early Concept of BCIs: An early concept of BCI involved measuring and decoding brainwave signals to control a prosthetic arm and perform specific actions" gives clear information regarding the functions [19]. The use of BCI in neural computing to recognize patterns for research work is one of the uses. Through BCI emotions can be recognized easily through brain activities. Fatigue detection is another function of BCI which is made easier through spatial bands and some extra processing steps. Healthcare and clinical applications stand first as they provide greater value to humanity by dealing with brain-related issues and mental health thereby attempting to cure anxiety, panic attacks, and depression, which is a serious issue nowadays, hence decreasing the suicide rate, worldwide [19].

Apart from healthcare applications, BCI also has a stamp in the entertainment and security fields. The research work produced by Jan B.F. van Erp, Fabien Lotte, and Michael Tangermann titled "Brain- Computer Interfaces: Beyond Medical Applications" shows how BCI has distinct functions [20]. BCI is very much used in device control systems, monitoring and supervising, education and teaching, gaming and entertainment, and cyber security as well. Devices like prosthetic arms and wheelchairs are used by disabled people. Higher officials use BCI devices for supervising and maintaining the system. Professors use BCI as a teaching aid to guide the pupils and thoroughly explain complex concepts. Booming applications are seen in the field of entertainment and gaming. Motor imagery tasks are used in gaming for better experience and VR is used for visualizing the motion picture efficiently in the entertainment industry[20]. Lastly, in the field of security, BCI is used to protect confidential data through AI. Cloud security is being updated currently. In the coming years, surely the security of netizens' data will be in the hands of BCI-controlled AI robots or systems.

FUTURE SCOPE AND CONCLUSION

BCI would surely progress in the field of neurorehabilitation, where it will help disabled people to leadtheir lives with no disability using advanced prosthetic devices like brain sense. Clinical applicationswould see significant progress where most of the mental health issues would almost be eradicated improving the quality of physical therapy. The speed of the world, that is, communication and networkswould increase drastically making it easier to roam the globe through an electronic device much easier.The number of experiments is going to increase in the upcoming years which will be assisted by BCIrobots that would be trained in failure or disaster management. A secure and efficient digital security system will be seen soon through AI. The world of business will take a major turn when BCI steps into every small cottage. The

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education system will entirely find a new way of sharing knowledge in the bestpossible way[22].

Currently, Elon Musk's Neuralink has test subjects undergoing training for invasive electrode implantation. The sub-aim of neuralink is said to be the transmission of music directly into the human mind without any external connectivity, whereas the major aim is to find a permanent cure for brain- related issues like schizophrenia and Parkinson's disease [21] [22].

Concluding the review, BCI is an advanced technology with a lot of potential, that requires a lot of skills and knowledge to be mastered. It has use advantages in every possible field from business to cosmology. The current world is upscaling because of AI and will upgrade even more through BCI. Once the trend begins, the world will be fascinated to know that BCI will surely serve as a great servant to humanity if used wisely and within limits.

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