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Review Article

A Systematic Review of Brain-Computer Interface Based EEG

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Abstract
The futuristic age requires progress in handwork or even sub-machine dependency and Brain-Computer Interface (BCI) provides the necessary BCI procession. As the article suggests, it is a pathway between the signals created by a human brain thinking and the computer, which can translate the signal transmitted into action. BCI-processed brain activity is typically measured using EEG. Throughout this article, further intend to provide an available and up-to-date review of EEG-based BCI, concentrating on its technical aspects. In specific, we present several essential neuroscience backgrounds that describe well how to build an EEG-based BCI, including evaluating which signal processing, software, and hardware techniques to use. Individuals discuss Brain-Computer Interface programs, demonstrate some existing device shortcomings, and propose some eld's viewpoints.

KEYWORDS: Brain-computer Interface(BCI), EEG, EEG Application, Signal Acquisition.

I. INTRODUCTION

Brain-Computer Interface (BCI) is a pathway between the signals created by a human brain thinking and the computer that transforms patterns of human activity in the brain into patterns into commands or controls for outer environment communication [1]. Besides that, a few other definitions equivalent to BCI Mind Machine Interface [2], Human-Computer Interaction [3], Neural Control Interface, and Electronic neural interfaces [4]. They all define devices controlled entirely by human brain waves. BCI is a comprehensive hardware and software system to monitor machines and various communication devices.

Nevertheless, several other descriptions stated, like [5] in definition, the BCI as a device allows their users' interaction and controlling systems that do not rely on the brain's regular periphery nerve and muscle output channels. BCI research started in the 1970s at the California State University [6], for which researchers identified a set of experiments that were meant to demonstrate that direct human-machine communication is possible. Since scientists in research and business have invested significant effort to turn this theory into a viable modern technology and advancement in each of these advanced techniques and today's knowledge of the neuronal map has given rise to enhancements in BCI and a massive variety of BCI applications [7], [8]. In the last few decades, many BCI systems [9] are developed to provide a substitute communication platform for those who have severe muscular dystrophy that can be seen in amyotrophic lateral sclerosis, spinal cord injury, and stroke.

Through its earlier days, the researcher attempts to be using this technique to develop medicinal aids only. However, this technique has extended its use and has made its way to nonmedical implementations. It is discernible that a significant number of original papers and comments on BCI have been written over the last 30 years.

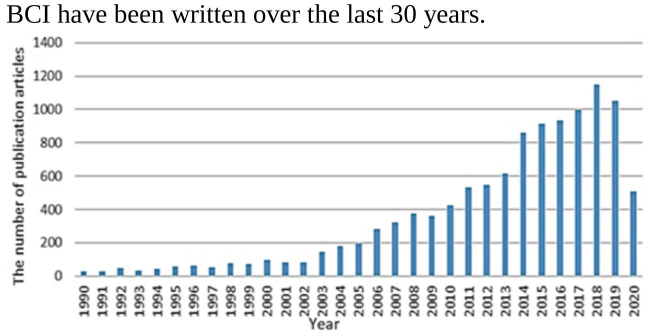

Fig 1: The Number of published articles from (1990-2020) indexed in PubMed [78]

The latest (2013-2020) EEG-based BCI survey papers focused mainly on summarizing statistical characteristics or patterns separately, gathering classification algorithms, or incorporating deep learning models. For example, a recent

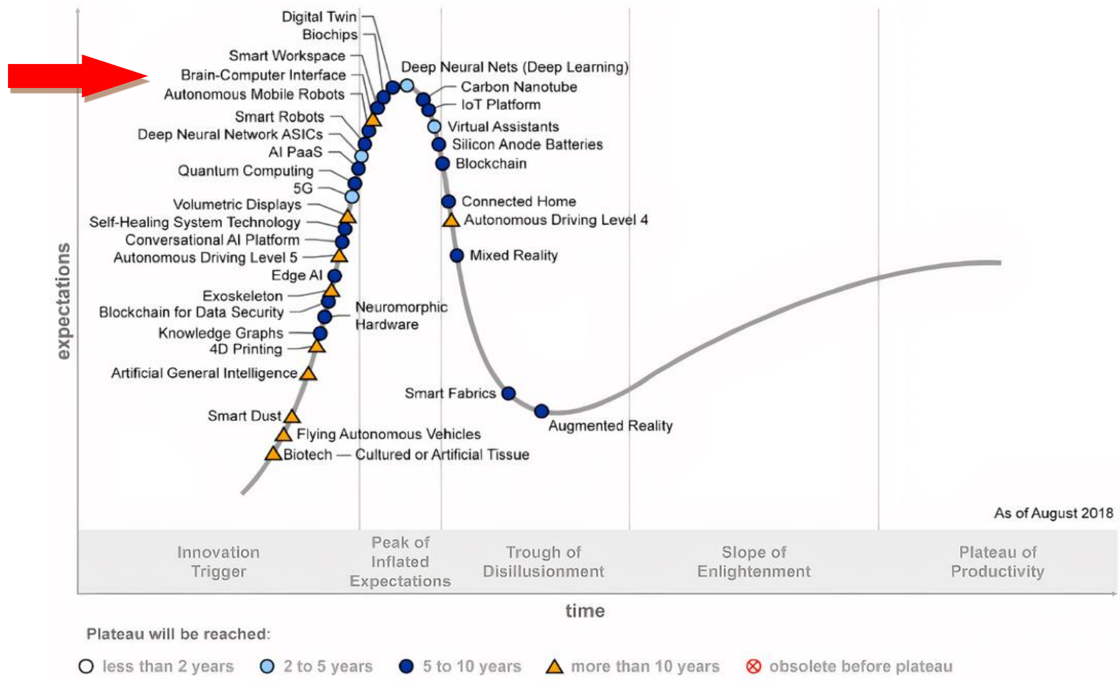

Fig. 2: 2018 Emerging Technologies Hype Cycle Garners Insights from More Than 2,000 Technologies shows the Brain-Computer Interface will be reached in more than 10 years [10]

survey in this article [75] includes a detailed overview of the state-of-the-art BCI framework. Firstly, it provides a brief description of BCI-based EEG. Second, several common BCI systems applications are reviewed. After this, it discusses some of the new BCI programs' challenges and proposes alternative ways to alleviate the problems.

Another review article [7] This paper illustrates the fields of application that could benefit from brain activity to enhance or reach the goals. It also describes maximum technical challenges facing the use of brain signals in different BCI system components. Various alternatives were also reviewed to limit and reduce their effects. An excellent analysis narrowly addressed electroencephalogram (EEG) control signals and their classifications [31]. In terms of both hardware and software, the researchers evaluated state-of-the-art BCI alternatives; nevertheless, it was notable that applications and signal processing methods were not considered.

Similarly, [76] Reviewed EEG-based BCI structures during 2007-2011. However, the review did not thoroughly represent the existing state-of-the-art and presented no areas for future research. Alternatively, the important components covering the full range of EEG-based BCI systems were reviewed in [77]; even so, the number of articles reviewed was restricted.

According to Gartner's 2018 Hype Cycle Study on trend technical subjects, the brain-computer interfaces are at the trigger phase of innovation. These scientists predict which BCI research in more than 10 years. This phenomenon is captured in (see Fig. 2).

II. COMPONENTS OF BCI

The various components of BCI which helps in recording the signals from brain to computer are discussed as follows:

1) **Brain Signal Acquisition**: The first layer in BCI architecture is used to acquire brain signals from the device by using either invasive or non-invasive methods. This step record brain signals coming from the electrodes placed over the or in the brain. The signals are send from the frm the brain neurons in the form of electrical spikes. Various companies are manufacturing either clinical or consumer graded devices to capture these electrical signals. Emotiv Epoc by Emotiv is the first consumer device with 14 electrodes which is used to read the brain signals, otherwise 1 electrode device is also there by NeuroSky. The information collected by these devices is send to computer wirelessly or through Bluetooth. These companies offer low-cost devices .
2) **EEG Signal Pre-Processing**: The pre-processing after signal acquisition is to remove any noise, artifacts which are recorded while capturing the signals of the devices. Some of the unwanted signals include: Whenever electronic device is mounted some inference is there. Some muscular activity leads to EMG signals, Eye movement or blinking cause ocular artifact. The unwanted noises present in the EEG recording will lead to wrong conclusions and may bias the analysis of the EEG readings. So various filter are used to remove out the noises from the signals [79].
3) **EEG Signal Extraction and Classification:** Basic functionality of classifier is to classify the results according to predefined choices. The feature extraction helps to identify the important features required for necessary classification. Suitable classifiers are chosen to classify the EEG signals. Some of the commonly used classifiers are Linear Discriminate Analysis (LDA), Support Vector Machine (SVM), Neural Network, Fuzzy Logic system [78].

TABLE I
SIGNAL ENHANCEMENT METHODS

S.No	Method	Advantages	Disadvantages
1	ICA	- Computationally efficient. - Shows High performance for large sized data.	- Requires more computations for decomposition.
2	CAR	- Outperforms all the reference methods - Yields improved SNR.	- Problems in calculating averages.
3	SL	- Robust against the artifacts generated at regions that are not covered by electrode cap.	- Sensitive to artifacts.
4	PCA	- Helps in reduction of feature dimensions.	- Not well as ICA.
5	CSP	- Doesn't require a priori selection of sub specific bands and knowledge of these bands.	- Requires use of many electrodes - Classification inaccuracies.
6	Adaptive Filtering	- aAbility to modify the signal features according to signals being analyzed - Works well for the signals and artefacts with overlapping spectra nature.	-

TABLE 2
FEATURE EXTRACTION METHODS

S.No	Method	Advantages	Disadvantages
1	ICA	- Decomposes signals into temporal independent and spatial fixed components.	- Can't be applicable for under determined cases. - Requires more computations for decomposition.
2	PCA	- A powerful tool for analyzing and for reducing the dimensionality of data without important loss of information	- Assumes data is linear and continuous. - For complicated manifold PCA fails to process data.
3	WT	- It can analyze signals both in time and frequency domains. - Can extract energy, distance or clusters etc.	- Lacking of specific methodology to apply WT to the pervasive noise. - Performance limited by Heisenberg Uncertainty.
4	AR	- Requires only shorter duration of data records. - Reduces spectral loss problems and gives better frequency resolution.	- Difficulties exist in establishing the model properties for EEG signals. -Not applicable to non-stationary signal.
5	WPD	- Can analyze the non-stationary signals.	- Increased computation time.
6	FFT	- Powerful method of frequency analysis.	- Applicable only to stationary signals. - Suffers from large noise sensitivity. - Poor time localization makes it not suitable to all applications.

TABLE 3
COMPARISON OF SIGNAL CLASSIFICATION

S.No	Method	Advantages	Disadvantages
1	LDA	- It has low computational requirements. - Simple to use. - It provides good results.	- It fails when the discriminatory function not in mean but in variance of the features.
2	SVM	- It provides good generalization. - Performance is more than other linear classifier.	- Has high computational complexity.
3	ANN	- Ease of use and implementation. - Robust in nature. - Simple computations are involved.	- Difficult to build. - Performance depends on the number of neurons in hidden layer.
4	NBC	- Requires only small amount of training data to estimate parameters. - Only variance of class variables is to be computed.	- Fails to produce a good estimate for the correct class probabilities.
5	K-NN	- Very simple to understand. - Easy to implement and debug.	- Poor runtime performance if training set is large. - Sensitive to irrelevant and redundant features.

III. BCI TECHNOLOGY BRANCHES

BCI systems can usually be classified into several categories [11]. Fig. 2 shows the three category schemes through dependability, brain signal recording, and operating methods. For instance, dependability, BCI may be categorized into either dependent or independent BCI. The dependent BCI provides specific motor control by the user [12], [13], Though independent BCI has no control. Dependent BCI can help make things simpler, including pushing a wheelchair and playing games.

However, on the other side, subjects with severe conditions will require autonomous BCI without brain activity. Conversely, autonomous BCIs do not demand any degree of consumer control; this BCI type is suitable for patients with stroke or severe disability. BCI may be categorized in the recording system as invasive and non-invasive. Through invasive BCIs [14] microelectrode arrays are commonly required inside the skull. Unless brain signals are earned from electrodes outer the scalp, it is regarded as BCI non-invasive, mostly used in non-invasive ways such as EEG, MEG, fMRI fNIRS, and PET. Within BCI, EEG is now the most frequent non-invasive mode, in which specific control channels that can be evoked, comprise P300, MI, SSVEP, ERP, and SCP [15]. Eventually, BCI will run, whether asynchronously neither synchronously. The BCI system is considered an asynchronous device when the user connects with the device for a specified time. In BCI asynchronous, often called "self-paced" [16], [17], The subject will perform its specific tasks at a particular time, or the machine will respond to its mental activity.

IV. Brain Signal Recording Methods

Many BCI researchers choose a non-invasive solution to reduce the danger of surgery. EEG, MEG, PET, fMRI, and fNIRS are some of the widely used non-invasive methods. The methodology is based on several criteria [18], including Risk, Spatial resolution, Temporal resolution, Signal-to-Noise Ratio, Portability, Cost, and Characteristic. According to its advantageous features, including higher time resolution, affordable prices, convenient portability, and non-invasiveness, EEG has been the most widely-used BCI research brain imaging method.

A. *Electroencephalography (EEG)*

EEG is by far the most widely used method for mensuration brain function. [19]–[23] EEG monitors voltage produced via electrical current in brain neurons. Electrodes on the scalp test EEG signals amplitude. EEG signals have poor resolution due to limited electrodes. EEG electrode locations typically follow regional 10-20 or intermediate electrode positions. The global 10-20 system splits the scalp across 10% and 20% parts and includes 21 electrode positions. The American Electroencephalographic Society standardizes the intermediate 10% electrodeposition and separates the scalp with 10% cycles comprising 75 Electronics electrodes. There are usually fewer than 75 channel electrode, 64 channel electrodes (BCI 2000 system) [24], [25], 32 channel electrodes (openBCI headset) [26], 14 channel electrodes (Emotiv EPOC+ headset) [27], and one channel electrode (Mindware headset) [28]. Temporal EEG-signal accuracy is much higher than spatial. The electrostatic support different rapidly, resulting in temporal resolution across 1000 Hz[29]. EEG signal-to-noise-ratio is quite low due to quantitative as well as emotional causes. Physical causes include ambient noise, cortex, and other tissue cortex-scalp obstruction, repeated neural stimulation. Subjective considerations include the mental stage of the subject, exhaustion state, and variation between various issues. EEG

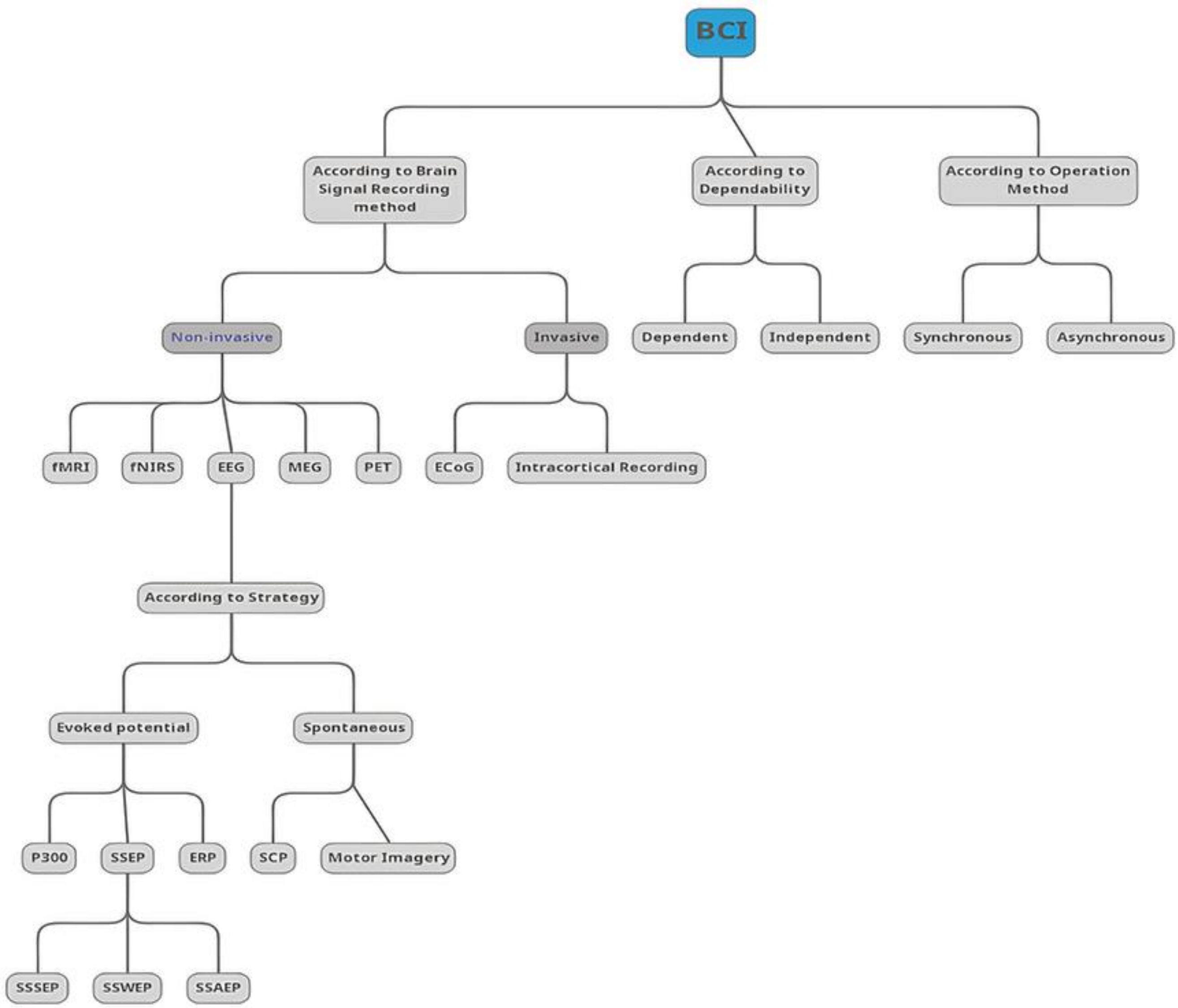

Fig.3: Categories of Brain-Computer Interface according to brain signal recording method, according to dependability and according to operation method

listening equipment may be mounted in a headset., The EEG device is mounted over the user's head. Compared to other brain impulses, EEG headsets are compact and much more available for most uses. EEG signals from any specific EEG device contain various non-overlapping frequency ranges (alpha, beta, theta, gamma, and theta) based on a robust intraband association with a distinct behavioral state. Every EEG pattern includes unique brain information-related signals [30], [31]. The degree of consciousness reflects the experience of individuals when faced with external stimuli. Could the Frequency band represent neural-state and objective perception review:

• Delta rhythm (0:5-4 Hz) leads during deep sleep while less conscious.
• Theta rhythm (4-8 Hz) represents low-aware at rest.
• Alpha signal (8-12 Hz) appears mostly in locked and fully calm eyes, leading to ordinary consciousness.
• Beta pulse (12-30 Hz) is the dominant frequency when eyes are open and highly receptive. The beta model represents almost all of our everyday tasks (eat, move, speak).

B. Magnetoencephalography (MEG)

MEG is a non-invasive brain neuronal function analysis technique. MEG plans brain function by measuring magnetic fields produced by electric current in the brain through information processing. The magnetic field produced is comparatively weak. Hence MEG utilizes a sensitive magnetometer named a SQUID [32]–[35]; SQUIDs are mounted on the scalp to monitor neuronal activation (majorly those closest to the magnetometer it is own).

Like the magnetic fields, MEG has several advantages, are less disturbed than electrical current and also great temporal resolution and proper spatial resolution even than EEG. Besides, MEG helps identify seizure patients with epilepsy and assists doctors in enabling surgery scheduling. MEG has such disadvantages. It only measures parallel-oriented magnetic fields (nerve cells in cerebral sulcus). It is noticeable that MEG technology is often very costly. Also, brain function on the surface or far below the brain surface can not be accessed. It showed external noise sensitivity.

C. Functional Magnetic Resonance Imaging (fMRI)

fMRI is a non-invasive technique used to mensuration blood oxygen level variability through brain function [36]–[39]. fMRI provides high spatial resolution, making it appropriate for locating active brain regions. Nevertheless, the fMRI time resolution varies around 1s to 2s. This also suffers from low head motions resolution and can create artifacts also Gives little information about their responses' temporal dynamics. Relatively inexpensive compared to EEG & PET. MRI is extremely noisy and moving-sensitive.

D. Optical Topography [Functional near-infrared spectroscopy (fNIRS)]

fNIRS one of the non-invasive techniques for measuring brain function using the flow of blood. Similar to fMRI, this approach is also BOLD (blood-oxygen-level-dependent) [40]–[42] based; however, it uses various methodologies for data gathering. fNIRS is focused on comparative tissue transparency to near-infrared light (NIR) [43]. Easy to quantify and does not require radioactivity. Nevertheless, the Poor Temporary Resolution and Time to Be Measurement (> 2–5s). The fNIRS system is a wearable head device with sensors and a source of light. The source of light generates NIR light straight upon the scalp, traveling through the skull. Several other lights are reflected. However, some resurface. Headset sensors record resurfaced light photons. Recordings are used to show a realistic brain image.

E. Electrocorticography (ECoG)

ECoG is an extracortical invasive (partial invasive) technique for measuring brain function. Electrodes gathering ECoG is tied to its brain, the dura mater above (epidural), or below (subdural) but not to the brain parenchyma itself. ECoG offers a trade-off for low SNRs Non-invasive recordings and lower intracortical recording risk.[44], [45]. This has better spatial accuracy and lowers surgical risk comparatively high SNR. Therefore, ECoG has better patient opportunities than intracortical data demonstrates the set strategy and signals. ECoG signals are more significant than non-invasive brain wave signals. E.g., ECoG is greater than 50 µV, and the EEG amplitude is typically less than 20 µV. Low amplitude reduces ECoG to artifacts such as eye blink behavior. ECoG's bandwidth 0-500 Hz is thus considerably higher than EEG (0-40Hz) due to the skull's low-pass filtering impacts. More frequency bands are greatly affected by functional brain areas (e.g., motor and language) and can thus shape a more effective BCI network. But even the disadvantages of invasive approaches like ECoG (such as dangerous surgery and the discomfort of permanently attached devices) inevitably limit its great real-world implementation Examples.

V. EEG PARADIGMS (MENTAL CONTROL SIGNALS CLASSIFICATIONS)

Relative to non-invasive technique (e.g., fNIRS, ECoG, fMRI, MEG), EEG has some significant benefits: 1) greater portability of the hardware at a far lower cost; 2) very high temporal resolution (millisecond level)8; 3) EEG is comparatively tolerant of subjecting agitation and errors, and current signal processing methods could reduce that; 4) the subject does not need to be revealed. EEG will thus support topics (such as metal-containing pacemakers) with metal implants in their body. As the most widely used signals, EEG signals have a vast number of subclasses. Here we discuss a formal overview of sub-class EEG signals. We separated EEG impulses into random EEG, evoked potentials, and desynchronization/sync related to events, as seen in Fig 2. Evoked potentials can be divided into event-related possibilities, and steady-state evoked potentials dependent on external stimulus size. Each potential contains potentials based on external stimuli, visual, auditory, and somatosensory. The dotted quadrilaterals, such as Intracortical, SEP, SSAEP, SSSEP, and RSAP, are not included in this study since deep learning algorithms operate on very few current studies. We list these signals for completeness.

1. Evoked signals

Evoked signals, also called Visual Evoked Signal (VEP), are the participant's impulses inadvertently produced upon receiving external stimuli. The most well-known is the Steady-State Evoked Potentials (SSEVP) and P300. Evoked signals rely on outer stimulation that the subject can feel awkward, shaky, and tiring.

1. Steady-State Evoked Potentials SSEP

Noticing a regular intervals stimulus as a flashing picture or amplitude-modulated sound, SSEP appears. SSEP's important feature is that EEG pulse frequencies are identical to relaxation frequency or harmonics. Stimulating a fixed rate evokes SSEP by generating the same frequency EEG response as the stimulus. SSEP can be further divided into Visually Evoked Potentials, Steady-State Auditory Evoked Potentials, and Steady-State Somatosensory Evoked Potentials, according to visual, auditory, and somatosensory stimulation.

The SSVEP-based BCI requires a certain amount of visual inputs, suggesting different commands for BCI output. These stimuli flicker in different frequency bands from 6 to 30Hz. If a subject focus on a similar flickering cue, it produces the same average of SSVEP as the intended flicker. For example, if the target stimulation frequency is 15Hz, the produced SSVEP is 15Hz. The user pays visual attention to a target, and the BCI determines the target by testing the SSVEP features [46]– [48].

2. P300 Components

This is an EEG signal that occurs when the user is subjected to unusual or unexpected activity after nearly 300 ms. This signal is typically generated by the "odd-ball" model, where the consumer is asked to follow a random series of stimuli with less frequency than the others [49]–[51]. This extraordinary stimulus triggers the P300 EEG signals when relevant to the subject. Again P300 needs no subject training; however, it involves repeated stimulation that may contribute to the subject's tiring and inconsistencies.

Author [50] described a different brain-computer-interface P300 framework. For robot steering, visual stimuli consisting of 8 randomly intensified arrows are used. The classification techniques were collected offline and tested offline and online.

1. Spontaneous Signals

Spontaneous signals are the signals produced by the subject without any external stimulations. Many well-known random signs are executive motor and sensorimotor patterns, Sluggish Cortical Potentials (SCP) [31], [52], and Non-motor functions.

2. Motor Imagery

Moving one arm or even maybe one muscle affects the brain function of the cortex. Preparation for motion or visual activity [also known as motor imagery (MI)] causes sensorimotor rhythms (SMR) oscillations in the brain motor regions. Within a limited frequency range, boosting and the oscillatory operation are indicated to event-related synchronization (ERS) and desynchronization (ERD). The commonly motor vision patterns are alpha and beta brain waves [53], [54]. Activity triggered by the left-hand and right-hand MI is produced by C3 and C4 regions of the brain, while the perception of foot movement comes by Cz [20]. At the EEG, the movements of the left and right foot are almost difficult to discern. Cortical regions must be broad enough to generate detectable standard EEG signals [55]. The right eye, left hand, foot cortical, and lips regions are vast and distinct. Therefore, BCI applications can monitor the movement of individual body limbs through imagination [80].

VI. BCI Technology

For every research area's progress, it needs two items that are powerful functionality and technological advances. This segment briefly discusses some existing hardware and software BCI developments. Hardware devices are used either by invasive or non-invasive methods to capture the signals. However, through smart algorithms, BCI software platforms are responsible for preprocessing and analyzing the hardware's signals and generating the external environment's control commands.

Hardware Technology for EEG Signal Acquisition

Generally, EEG signal acquisition can be divided into two key ways to transfer EEG data: portable wireless and wireless, EEG brain signal tests using conductive gel, or paste. However, this makes the electrode embedding process sluggish, repeated. Note, however, which dry electrodes required no conductive gels or pastes were suggested and validated. Despite this performance, it is notable that this system's total information processing efficiency is, on average, 30% lower than that obtained from an electrode-centered BCI using conductive gels or pastes. The wired frame, although well-established, has several major vulnerabilities. Connection with wires between electrodes and segment of retrieval is often tricky as it is a time-consuming process.

Furthermore, the restricted nature of cable regulations restricts market independence. Wireless BCI systems were then recognized due to their ability to solve the above limitations. A lightweight EEG headset advantage is non-invasive. It also doesn't hamper the user's movement. Table 4 lists EEG service types with their specifications. The EEG headset or product design depends on BCI tools.

VII. Application of The BCI Studies

BCI systems' promising future has enabled the researchers to explain brain activities to set up several BCI systems [7]. We discuss the widely known application fields that the BCI system has been extensively discussed and applied: the area in which BCI applications are commonly used as entertainment controllers [56]. Many BCI systems are affordable, handily portable, and simple to install, making their practical use widely for entertainment communities [57]. The built-in and portable BCI systems for the gaming industry are versatile and convenient, requiring reduced implementation effort. While they are not as effective as other BCI instruments used in medical fields, they are still useful for game designers and often advertised for entertainment [58]. Several particular systems are connected to sensors that detect additional signals, such as facial expressions, that can enhance entertainment. BCIs have played an essential role in neurocomputing in brain wave signals and computer and cognitive information studies. Recent studies [59]–[61] have shown that network biology approaches have been used to assess the neural network reorganization of human learning in various ways. These studies' results indicate that BCI models are refined, and neural bases and future BCI learning success are exposed. The brainwave headset, which can gather dynamic data with the manufacturer's application development kit, has already been used for the healthcare industries to make it easier for profoundly disabled people to monitor robots through simple motions such as turning their neck and blinking. BCI has enabled people who lacked the physical capacity to recover machine control and strength. A widespread therapeutic field is integrating BCI spelling methods, one of which is a well-known P300-based speller. Building on the P300-based speller [62] using a BCI2000 interface [63] to enhance BCI speller positively impacts the use of this brain-controlled spelling system non-experienced users. BCIs subsequently led to multiple study fields. As Fig. 3 briefed., they are involved in games [64], robot control [65], emotional interpretation [66], stress recognition [67], sleep quality assessment, and health fields [68] such as abnormal brain disorder detection and stroke prediction, Parkinson's disease, Alzheimer's disease, schizophrenia.

TABLE 4
OVERVIEW OF HARDWARE EEG TECHNOLOGY DEVICE

Device name	Channels No.	Sampling rate	Transmission	No. of publications
NeuroScan	64 /32/40/32	20kHz/4,096 Hz	Cable	12,300
Brain Products	8/16/32	250/500/1,000 Hz	Bluetooth	6,690
BioSemi	16, 32, or 64	2/4/8/16 KHz	Cable	5,750
Emotiv	14	128 Hz	Bluetooth	3,990
NeuroSky	1	512 Hz	Bluetooth	2,290
Advanced brain monitoring	24	256 Hz	Wireless	790
g.tec nautilus	64	500 Hz	WIFI	430
AntNeuro eego	64	2,048 Hz	Wireless	340

BCI applications BCI has applied in different fields of studies. For instance, in biomedical, neuroergonomics and communication, games and entertainment [69], environmental control [70], educational [71] and self-regulation [72], Security [73], and motor control [74]. The Fig. 3 shows different application the researchers have been studied the figure shows the increase in the number of published application articles such as mouse or explorer, Robot, Games, Navigation, and Speller.

1. Robot controller

The robot controller consists of a finite state automaton direct controller, a context-based filter autonomous controller, and a complex dynamic shared controller with additional static regularization based on external performance parameters. The direct controller and autonomous controller velocities are linearly combined in the shared controller to a final output velocity. The output velocity from the shared controller is interpolated from precious velocity to the new desired velocity for smooth driving, and generalized through standardized ROS messages for robot platform independence. Modularity is achieved by using the ROS-infrastructure during the system design. The discrete low throughput data of the BCI can easily be replaced with similar data to control the robot, such as eye-movement or speech. The controller subsystems can be replaced with other subsystems that follow the same interconnection, i.e., substituting the autonomous controller with an alternative navigational assisting system for different controller behavior

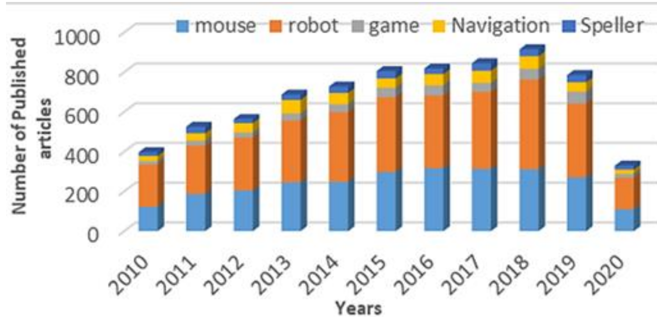

Fig 4: The Number of Published Articles In The Last 10 Years Of Top 5 Application of EEG Based Brain-Computer Interface Indexed By PubMed.

VIII. Conclusions

BCI is one of the essential fields concerned with brain functions. BCI technologies are expected to impact Everyone's modern lives significantly. This paper survey articles summarize the field and provide the readers with state-of-the-art research in this field. This article concentrates on the BCI concept. This also categorizes and describes the brain signals acquisition tool. This also reviews the existing BCI equipment. Nonetheless, it produces several roadmaps for BCI's future. Discuss current BCI proposals and their effects on society. Finally, discuss the recent Brain-Computer Interface Survey.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

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