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A Survey in Implementation and Applications of Electroencephalograph (EEG)-Based Brain-Computer Interface

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K E Y W O R D S

BCI, EEG signals, application, signal enhancement, signal processing, feature extraction

A B S T R A C T

A Brain-Computer Interface (BCI) is an external system that controls activities and processes in the physical world based on brain signals. In Passive BCI, artificial signals are automatically generated by a computer program without any input from nerves in the body. This is useful for individuals with mobility issues. Traditional BCI has been dependent only on recording brain signals with Electroencephalograph (EEG) and has used a rule-based translation algorithm to generate control commands. These systems have developed very accurate translation systems. This paper is about the different methods for adapting the signals from the brain. It has been mentioned that various kinds of surveys in the past to serve the purpose of the present research. This paper shows a simple and easy analysis of each technique and its respective benefits and drawbacks, including signal acquisition, signal pre-processing, feature classification and classification. Finally, discussed is the application of EEG-based BCI.

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1. Introduction

The ability to control a vehicle using only your brain without moving any muscle contributes a promising technique for our society [1], not least for people with a movement hindering disability. An electroencephalogram (EEG) is a non-invasive, portable, and relatively inexpensive recording technique that measures the ongoing brain activity with high temporal resolution[2]. Thanks to these advantages, it is often used as a tool in Brain-Computer Interface (BCI) based robot controllers for different vehicles[1], [3]. For example, a BCI-maneuvered wheelchair is only one out of many promising applications [4].EEG has a relatively low signal-to-noise ratio and low spatial resolution, which means that the signals need to undergo several signal processing steps before being utilized in a BCI robot controller. This can be accomplished with bandpass filters and artifact removal algorithms together with continually evolving classification and feature extraction methods. Even with well pre-possessed EEG data, the BCI has limitations when the brain is used by itself to control the robot [5], [6].

Mental commands generated from the EEG by today's standards can be unreliable due to a variety of different sources such as mental fatigue or muscle signal noise. Tariq et al. 2018 [7] attempted to overcome these issues by developing a reliable BCI-based robot controller that only partly uses the EEG data's command. The mental command extracted from the brain activity was especially merged with environmental information from a laser scan plot generated by the vehicle that is supposed to be controlled. The vehicle's direction and velocity were determined by each input's relative weight in the objective of reliably and intuitively maneuvering a vehicle in a simulated environment. The mental command was extracted from a recorded EEG activity simultaneously as the subject was imagining a pre-denied body movement. The intelligent system, consisting of intelligent interpretation of the laser scan data, would help with the navigation if the EEG signals were too noisy or unreadable and make decisions when the mental commands in question are limited. With learning algorithms, the EEG signals' mental commands can be classified and then recognized for later use. This is done by selecting specific features for these mental commands and then using a classification algorithm to recognize these features[8].

The classification in [9] generated an over-representation of wrongly classified classes, which supposedly obscured the robot's navigation. For a robot controller, it is paramount that the classified signals are of the correct task. Otherwise, the robot might turn the completely wrong way, which can have dire consequences. This specific reason makes it more valuable to toss uncertain trials to increase the quality at the expense of generating fewer mental commands. Various classification methods utilize threshold altering, which could increase classification accuracy by generating true and false positives. The algorithm can then be targeting the false positives to try and minimize their presence. Proposed an interesting cluster analysis method that could be expanded into a threshold altering classification algorithm to filter out false positives [10]. In recent years, a growth in demand can be seen for medical and interactive technologies in the BCI framework. BCI is a system that connects human brain and machine directly[25] in **Error! Reference source not found.** shows the number of growth articles over three decades the number of the published articles over the three decades gathering through PubMed [26]. To push the machine, users just have to worry about movement. The use of BCI is also one of the most critical methods for the operation of a robot by a seriously disabled person

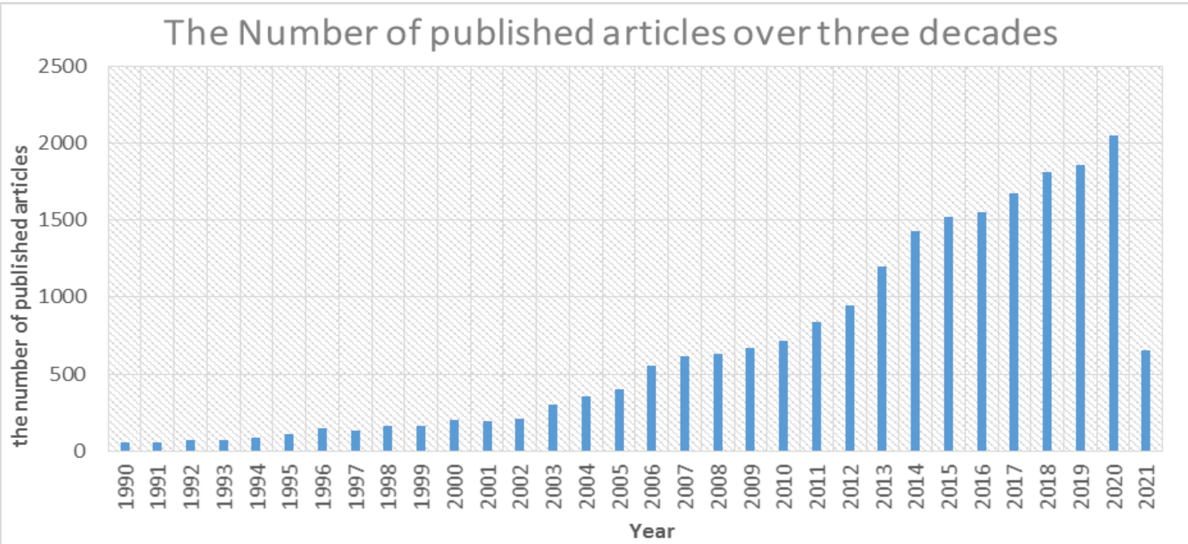

Figure 1: The number of published articles of Brain-Computer Interface from(1990-2021) indexed by PubMed [11][12]

2. The Brain Parts

Brain lobes are classified according to the functionality described in [13]. Furthermore, the brain signals recorded within each lobe pair will be associated with their work, creating new forms of brain-computer interaction.

1. Frontal lobe: It covers the frontal and upper areas of the cortex. The functionality includes thinking, decision making, planning, speaking, memory, judgment, consciousness, personality, intelligence, self-awareness.

2. Parietal lobe: Upper, back part of the cortex is the parietal lobe. Functionality includes sensation, touch, pressure, reading, knowing left-right, spatial, and visual attention, interpret language, words.

3. Temporal lobe: Bottom middle part of the cortex, right behind the temples. smell, hearing, i.e., processing auditory information from the ears, categorizing the objects.

4. Occipital lobe: It resides in the bottom, back part of the cortex, whose functionality is the vision, identification of color, and object movement.

3. Brain-Computer Interface

A BCI is an interface between a brain and a computer that translates brainwaves to actual actions that can be performed by other software or hardware[14][15]. It can also present feedback to the subject in the forms of visual and physical stimulus.MI as mental commands with the ERD/ERS signals acquired from the EEG. These MI commands represented the different directions of a moving vehicle [16]. The subject was imagining the right arm's movement, left arm, feet, and tongue to distinguish between these commands. A simplified flowchart of a BCI can be seen in Figure 2.

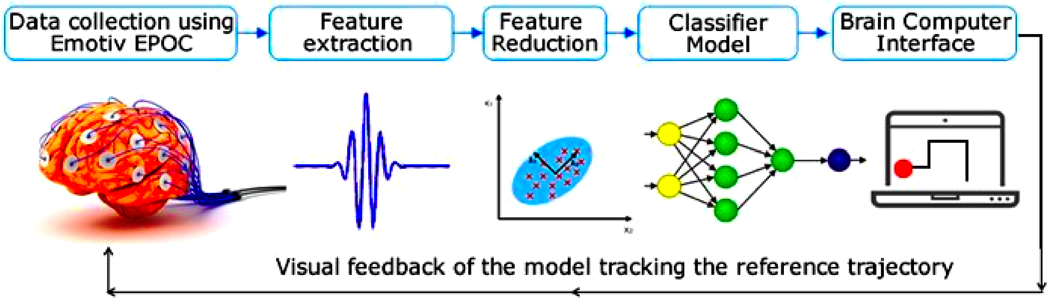

Figure 2: A simplified block diagram showing the different steps performed in a BCI. In an online recording, the subject is getting feedback in real-time. In an offline recording, the feedback can be given after the commands are performed [17]

I. Types of BCI

Interaction of the brain with the computer or any controlling device is done by sending electrical neuro signals from the brain. This is done either by implanting a chip-like device called an 'electrode' directly into the brain or by some external device. A variety of brain-reading sensors are available, which are used to record signals and divided into invasive and non-invasive techniques[18]there are many types of signal acquisition as shown in Table I.

Invasive: In this, electrodes are implanted directly into the user gray matter to produce high-quality signals. The advantage of higher reading activity is that it is the first choice for rehabilitation projects and is preferred over non-invasive technology. Imaging tools like Functional magnetic resonance imaging (FMRI)and others are used to select the appropriate implantation region as this is the brain region that provides information to paralyzed persons for communication and interaction[19]. While using the invasive technology, a condition must be met for how much time the electrodes should be kept in the human brain for stable recording. The Brain Gate [20] implant proved to be the most suitable and viable implant on the gray matter as it works efficiently even after nearly 2.7 years. This type of implantation makes patient completely map their activities onto the interface.

A. Non-Invasive: The electrodes are placed on the top of the skull, making it a commonly used brain mapping technique. This method does not require any surgery as the signal can be recorded by placing the device overhead. Here the information transfer rate is slower. Nevertheless, the fact is such technology requires a simple wearing of a specialized cap or headband. Every consumer based BCI company develops non-invasive devices like Emotiv Epoc, Neurosky usually offering relatively simple features, such as detecting the user's focus or mental stress levels. However, recent advances in this field have improved its bit rate sufficiently for non-invasive BCI's being considered neural rehabilitation tools as shown in Figure 3

A) EEG B) FMRI C) NIRS D) MEG

Figure 3: Signal acquisition Methodologies

In the non-invasive type of BCI systems, electrodes are placed on the scalp for recording the signals coming from the brain. Also, it is a low-cost consumer-grade system. These BCI's are more manageable and provide the right signals due to advancement in technologies, also does not present any risk to the user's health [2][21].

TABLE I: Comparison of Signal Acquisition Methods Used in Non-Invasive BCI System [22][23][2][13][11]

S. No	`	Signals captured	Advantages	Disadvantages
1	EEG	Electrical Signals on brain Scalp	High Temporal resolution Safe and easy technique	Susceptible to EOG signals, ECG signals, muscular activities and power line interference Low spatial resolution Nonstationary signal
2	fMRI	Metabolic signals using BOLD response	High temporal and spatial resolution	Set up cost is more. Delay in data acquisition process
3	NIRS	Metabolic signals using BOLD response	High spatial resolution Inexpensive Portable	Low temporal resolution Hinder transformation rates Less performance
4	MEG	Magnetic Signals generated by electrical activities	Wider frequency range Excellent spatial-temporal resolution	Needs bulky setup. Expensive experimental setup

4. ELECTROENCEPHALOGRAPH (EEG)

The most preferred functionality of reading signals from the brain is through EEG. It is a type of non-invasive BCI. It measures the potential variation in the neurons whenever any outside activity occurs—the change in the signal affects the location of synapses. The working of cerebral activity is better seen over the region where the activity is more[24]. The barrier which is created between the neurons and the sensors makes frequencies over 40Hz almost invisible, sometimes restricting the measurement of EEG signals[11][25].

I. Various Brain Rhythms

Various rhythmic signals of different frequencies are coming from the brain, as described below.

1) **Delta (0-4 Hz):** High amplitude brain waves, recorded with deepest stages of sleep. Changes in the depth occur due to various physiological and neurological disorders Figure. 4. Disrupted sleep due to depression, anxiety, ADHD usually occurs in adults and posteriorly in children[26].

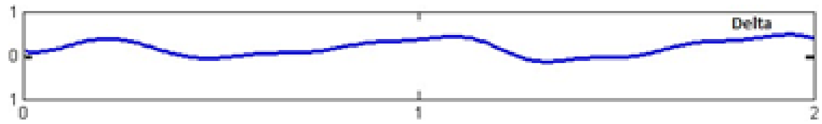

Figure 4: The Delta Rhythm

2) **Theta (4-8 Hz):** Related to the alertness, activeness, meditation, short-term memory task, sleep stages not related to deep sleep. Very much seen in young or older children and adults [27] is shown in Figure 5.

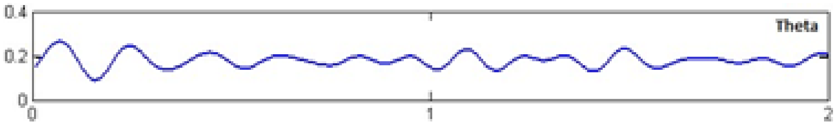

Figure 5: The Theta Rhythm

3) **Alpha (8-14 Hz):** This band is mostly seen when some metal arithmetic tasks is done, visualizing images, doing short-term memory tasks Figure 6 below depicts it. Nevertheless, are suppressed when eyes are open, the person is feeling drowsiness and sleepy. It consists of various small and large alpha waves, which represent active engagement and disengagement in the given task [28].

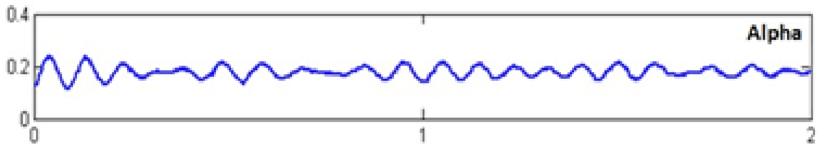

Figure 6: The Alpha Rhythm

4) **Beta (14-30 Hz):** This rhythm is related to the active thinking, alertness of the individuals' brain activity. It also represents perception, cognitive tasks. Beta wave presents a resynchronization which occurs when an external stimulus takes place. This wave is an indicator of movement preparation. It is found on both sides with symmetrical distribution, most evident frontally can be seen in Figure. 7 below.

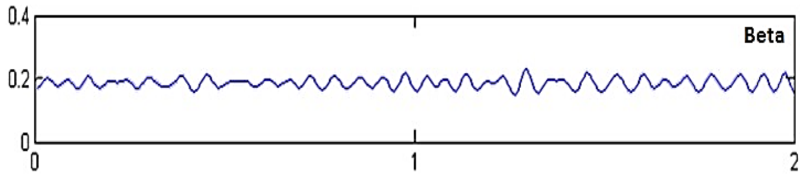

Figure 7: The Beta Rhythm

5) **Gamma (30Hz -above):** Gamma waves are the fastest of the brainwave frequencies and signify the highest state of focus possible. They are associated with peak concentration and the brain's optimal frequency for cognitive functioning[27]. Figure 8 shows the gamma wave.

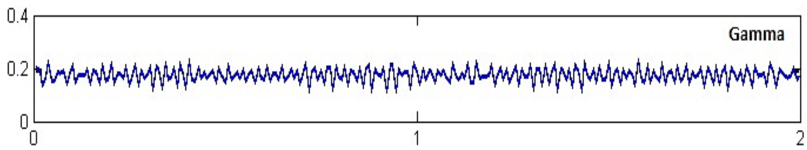

Figure 8: The Gamma Rhythm

II. EEG Setup

To measure EEG signals, non-invasive electrodes are typically placed along the scalp of the subject's head. However, invasive electrodes do exist and are used in methods such as Electrocorticography (ECoG)[19]. For non-invasive electrodes, a variety of gels and sanitation methods need to be applied to get a good signal acquisition[29]. If the applying speed is more important than the signal clearness, specific caps can be used that have the electrodes already correctly placed. The number of electrodes applied varies depending on the area of use and the spatial resolution needed for the procedure. With a higher amount of electrodes, the spatial resolution increases[30]. For example, beamforming analysis (a brain source reconstruction spatial filter) requires high spatial resolution, thus performs better with a higher amount of electrodes, up to 256 [31]. 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 comprising75 Electronics electrodes. There are usually fewer than 75 channel electrode, 64 channel electrodes (BCI 2000 system)[32], 32 channel electrodes (open BCI headset)[33], 14 channel electrodes (Emotiv EPOC+ headset)[34], and one channel electrode (Mindware headset) [35].

III. EEG Signals

The data collected by the EEG needs to be correctly interpreted by the BCI. Suitable EEG signals for a BCI are event-related desynchronization/synchronization (ERD/ERS), steady-state visual evoked potentials (SSVEP), and the P300 component of event-related potentials [25]. SSVEP and P300 both need a specific monitor for the subject to look at. Depending on the setup, the monitors have different command sections on the screen that the subject needs to focus on to generate a specific stimulus for the brain to create the signal. ERD/ERS, on the other hand, is event-related, which means that the signal correlates with an event in the brain, for example, motor imagery (MI) [15]. ERD/ERS measures rhythmic electrical activity to find and classify its changes. The synchronization and desynchronization originate from the idea that thousands of neurons in the brain synchronize or desynchronize their activation, thus creating electrical rhythmic activities that can be measured by the EEG sensors. MI commands are handy when controlling a robot via BCI since no specific stimuli are required to create the signal [36]. This gives freedom in how the commands are generated to control the robot, and the subject can even see the robot in action when performing the MI commands since there is no monitor required, which gives visual feedback [24]. Several ways are used to incite the emotion in the individual so that the intent of the person can be recorded [9]. The types are1) Visual Evoked Potentials -VEP 2) Slow Cortical Potentials - SCP 3) P300 based evoked potentials 4) Event-Related Desynchronization/Synchronization ERD/ERS

5. PRE-PROCESSING

The signal acquired from the EEG is very noisy due to the low signal-to-noise ratio and low spatial resolution, as well as various outer sources such as artifacts and interfering frequencies. The low signal-to-noise ratio comes from the fact that the EEG electrodes are applied on the surface of the scalp. Comparing EEG with ECoG, where the electrodes are placed directly on the brain, the signal-to-noise ratio is much higher. This noise needs to be processed to extract meaningful information from the signal. The frequency range usually sought after when performing EEG-generated MI is between 8-30 Hz when ERD/ERS is used [37]–[40]. Unwanted signals Higher frequency is typically generated by electromyography (EMG) from the muscles in the subject's body [41]. Standard power lines can create interference as well in the frequency range of 50-60 Hz. Interference in frequencies below 8 Hz is typically created by electrooculography (EOG) activity but also working memory activation generated from the brain itself [41]. A bandpass filter can be utilized to focus the attention on the desired frequencies.

Before signal capture, we remove any unwanted noise and artifacts. Signals that are undesirable include: Even when electronics are attached, there will be an inference to be made. While certain muscle activity will result in EMG readings, Eye movement, or blinking can result in OAAs. An undesirable noise will interfere with the interpretation of the EEG measurements, and this will lead to erroneous results. Noises in the signals are thus removed using a variety of filters.[42].

Controlling a BCI can be tired, often as the subject must sit still and be totally comfortable in the body to eliminate objects while simultaneously concentrating on a very mundane task, including flickering blocks of stimuli. Fatigue or lack of concentration means lower quality data, and high-quality data is vital for any BCI to function. Short sessions and refreshments during breaks should be available for the subject to stay concentrated during data acquisition. Also, the subject should be told about objects and the importance of obtaining high-quality data[43].

The protocol dictating any aspect of the data acquisition session should be determined in advance and remain unchanged throughout all sessions. Removing objects have both benefits and disadvantages, and it is currently debated whether to delete a present item. Objects can add evidence to non-task-related brain function. Removing EOG objects from data manually can boost performance, but doing so would add data bias, making reproducing performance harder[44].

In comparison, manually deleting artifact-containing trials decreases the number of trials in the results, ensuring the classifier has less detail. Automatically eliminating EOG objects prevents bias, encourages results replication, and may not decrease the volume of data, but the results can be unsatisfactory. The last choice is not to destroy objects. Classifiers can manage arbitrarily scattered objects in the data, and the removal of objects is by far the most computationally efficient process[8].

I. Filtering

One high pass FIR filter of order 3000 and cutoff frequency of 2 Hz and a low pass FIR filter of order 100 and a cutoff frequency of 40 Hz were applied to the data. The band of interest is 4 Hz to 30 Hz, but to avoid edge artifacts in the wavelet transform, margins were added[38].

To begin, it is important to improve the quality of digitizing of raw EEG signals by amplifying the signals between 500-2000-fold. When interpreting the raw EEG data, the various preprocessing procedures are used. A common approach to starting a band-pass filter (BPF) with an approximate cutoff frequency between 5-500 Hz, and a low-pass filter (LPF) above 500Hz, and a high-pass filter (HPF) higher than 5Hz has been in use in EMG sensors. The notch filter is also used to cancel power line interference (PLI) at frequencies of 50/60 Hz. An analog to digital converter turns the filtered signals into a digital form.[45][46]

II. Artifact removal

Artifacts can occur from various sources and need to be reduced for a cleaner signal. EMG and EOG artifacts get mostly eliminated by the bandpass filter, but other sources like eye-blinking or similar facial movements are more prominent even with the bandpass filter active[47], [48]. There must be taken care of by other means. A widely used method is Independent Component Analysis (ICA), which divides the signal into its statistically independent components [49], [50]. The artifacts are then visually selected and removed.

The ICA algorithm for artifact removal used by [51] will not work in real-time and must be performed in a different fashion. One promising approach is used by Matsusaki et al., which expands the ICA-based algorithm for online usage[52].

Artifacts and sources of error must be addressed during pre-processing. To remove artifacts from EMG and EOG, manual or automated methods are available. During the EEG recording session, the EMG and EOG behavior can be calculated using extra sensors, and any test containing artifacts can be manually extracted from the session. Any algorithms can also automatically remove EOG objects[36].

ICA was used to detect and remove blink artifacts from the EEG data. The blink component was found by visual inspection of all ICA components. The effect of artifact removal was examined by comparing the EEG data before and after the removal of the blink component[53]. As shown in Table II some of different type of signal enhancement methods and their advantages and dis advantages.

TABLE II: Signal Enhancement Methods [47], [48], [54][11]

S. No	Method	Advantages	Disadvantages
1	ICA	Computationally efficient. Shows High performance for large sized data. Decomposes signals into temporal independent and spatial fixed components	Cannot be applicable for under determined cases. Requires more computations for decomposition.
2	CAR	Outperforms all the reference methods. Yields improved SNR	Finite sample density and incomplete head coverage cause problems in calculating averages
3	SL	Robust against the artefacts generated at regions that are not covered by electrode cap. It solves electrode reference problem	Sensitive to artefacts Sensitive to spline patterns
4	PCA	Helps in reduction of feature dimensions. Ranking will be done and helps in classification of data	Not well as ICA.
5	CSP	Does not require *a priori* selection of sub specific bands and knowledge of these bands	Requires use of many electrodes. Change in position of electrode may affect classification accuracies.
6	Adaptive Filtering	Ability to modify the signal features according to signals being analyzed. Works well for the signals and artefacts with overlapping spectra nature	

III. FEATURE EXTRACTION

After obtaining the noise-free signals from the signal enhancement phase, essential features from the brain signals were extracted. For feature extraction from EEG signals use methods like Adaptive Auto Regressive parameters (AAR), bilinear AAR, multivariate AAR, Fast Fourier Transformations (FFT), PCA, ICA, Genetic Algorithms (GA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD) [10] [33-39]. Among these ICA, PCA, WT, AR, WPD, FFT are mostly used.

In Table III various feature extraction methods are compared and their advantages, disadvantages are presented.

TABLE III: Feature Extraction Methods [14], [36], [51][11]

S. No	Method	Advantages	Disadvantages
1	ICA	Computationally efficient. Shows High performance for large sized data. Decomposes signals into temporal independent and spatial fixed components	Cannot 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	Capable to analyze signal with discontinuities through variable window size. It can analyze signals both in time and frequency domains. Can extract energy, distance, or clusters etc.	Lacking 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 and linear random processes. Suffers from large noise sensitivity. Poor time localization makes it not suitable to all kinds of applications.

6. CLASSIFICATION

After feature extraction the signals are classified into various classes using various classifiers. Different types of classifiers include linear classifiers, Artificial Neural Networks (ANN) based classifiers, nonlinear Bayesian classifiers and, nearest neighbor classifiers [42]. Of these classifiers linear classifiers and nonlinear Bayesian classifiers are mostly used in BCI design[21].

In Table IV, comparison of various signal classification methods was given.

TABLE IV: Comparison of Signal Classification [65][15], [66]–[68][11]

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. For non-Gaussian distributions it may not preserve the complex structures.
2	SVM	It provides good generalization. Performance is more than another linear classifier.	Has high computational complexity.
3	ANN	Ease of use and implementation. Robust in nature. Simple computations are involved. Small training set requirements are required.	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 and no need to compute the entire covariance matrix.	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. On difficult classification tasks outperformed by other classification methods.

According to **Lotte et al.**[59], SVM should be a reasonable classification algorithm for EEG-based BCI. Many of the papers referred to in their analysis performed well with SVM, which implies that it should be possible to increase the classification accuracy.

According to many sources, a Gaussian classifier could be more suitable for a high-dimensional EEG-based robot controller[7], [77]. [78] uses Gaussian classifiers for their EEG-based robot controller for classifying EEG-data and is a promising technique to get reliable classification accuracy for a BCI. This was explicitly suggested. Additional to the Gaussian classification algorithm, Mill' an et al. utilizes a threshold method that functions as a filter for unrecognizable MI tasks/trials. This was done to minimize false positives in the classification.

Batres-Mendoza [79] used k-Nearest Neighbor (k-NN) and Linear Discriminant Analysis (LDA) as classification algorithms for their EEG-based BCI and presented promising results with up to 82% classification accuracy[80]. Mean Derivative (MD) and Hilbert Transformation (HT) were used to extract the features to represent the signals. These are other classification algorithms that might be interesting to utilize the data.

Vishwakarma et al. [49] compared the LDA and SVM classification methods with a Gaussian (GNB) classifier for their MI-based BCI. They proposed that the GNB method would improve the classification accuracy over the other two. This further implies that a Gaussian method would be a suitable classifier for EEG data. They also stated that the method could be further implemented for a real-time MI-based BCI system.

A new cluster separability analysis method proposed by Tiwari et al. [14]suggests that a cluster-based classification method could work on EEG data if the clusters are separable enough. The cluster analysis uses the intra and inter-cluster distances to calculate a discrimination value that represents the separability of two clusters. The method has not yet been extended as a classification algorithm and therefore has been applied on the EEG data for this thesis, and with good results, a new cluster based supervised SVM learning algorithm has been implemented.

7. Robot control

The classification algorithm plays a big part in how reliable the BCI-based robot control is. If the classification error is too high, the robot will be unreliable and might cause devastating damage. The signals generated from the brain are individual to the subject performing the MI tasks. Therefore, several signals from different subjects cannot be collectively assembled to get quality out of quantity. When performing the mental commands in the training stage of the classification, the signals must be subject-specific, and it can take several attempts for the subject before the results are satisfactory. Dai et al. had two subjects participating in their Gaussian classification algorithm[78]. In the beginning, before the subjects were familiarized with the mental commands in question, the classification accuracy was low, i.e., false-positive rates were high. Nevertheless, after several days of familiarizing themselves with the commands, the accuracy went up, although at a different pace and fashion. The first subject, who had more experience with MI commands, had a linear descent of false positives. The second subject had the false positive rate vary from day to day but with an overall descending trace. This shows that the performance of the robot controller is dependent on the subject and can vary from day today.

When there exists a rest state or a discarding state where uncertain trials are disposed, the false-positive rate determines the performance of the BCI, as stated by Le et al. [81]. False positives are trials that should have been in the rest state but are instead classified as active classes, which is undesirable. Liu et al. developed an SVM-based binary classifier that uses false favorable rate control schemes to force the false positive rate into a desirable amount. The effect is subject independent, which can increase the robot controller performance for a subject with minimal MI command experience.

8. Visual feedback

Classification of EEG data can be done both offline and online. Offline means that the training data and prediction data are prerecorded. For a MI (motor imagery) drove BCI, the subject performing the tasks gets no feedback on how the classification of the MI commands worked until after the whole session. In an online scenario, the training data is typically performed beforehand, which allows the classification to learn how to recognize the MI commands. However, the prediction data is recorded and predicted simultaneously, which creates opportunities for the subject to adapt depending on the feedback of the BCI [82]. While operating a BCI, visual feedback has been shown to promote higher performance resulting from neural learning and adaptation[83], [84]. When doing MI commands, a visual representation of the commands is often visualized by a moving cursor or a simplified robot simulation. [85] used Gazebo, which is a Linux-based simulation tool specializing in simulating different models of robots and environments. The Gazebo is a toolbox that comes with ROS (Robot Operating System), an operating system dedicated to controlling and simulating robots. [5] used this tool for visual validation in an offline scenario. To fully justify a BCI-based robot controller, it must be implemented in an online scenario that provides the moving vehicle's visual input while performing the mental tasks.

9. Applications of BCI

Researchers have started using BCI technology in various applications[1], [86] and show below in Figure 9. Some of the applications where it is used now a day are as follows:

1) Device control: For people with severely amputee hands, legs, or persons with full limb disability, BCI has opened doors for them by helping them to control the device through their brain signals. BCI assists users with full muscular control. However, a device does not offer reasonable accuracy, speed but has already benefited its users. For example, if a user with no left arm wants to pick up the glass of water with his left hand, to complete the command, this BCI user has to imagine the movement, the signals are sent through the electrodes, and the system will be able to process the required movement.

2) User-state Monitoring: Monitoring the user's intention of doing and understanding things has enabled the BCI researchers to develop a device that can interpret the information. These types of systems gather information and interpret it. It enables the user to be strict with diet, alerts the sleepy drivers, helps manage the stress, mental workload, anxiety, and depression.

3) Evaluation: BCI for evaluating applications that are either online or offline have been used these days. These applications help to continuously provide information in real-time or stored information for later evaluation. Two sub-areas where BCI is used are neuroergonomics and neuromarketing [87]. Neuroergonomics evaluates the user's state and provides how well it matches capabilities and limitations. Recently researchers studied brain images that were talking while driving with hands-free or voice-activated phone is as dangerous as driving while intoxicated. Another is the study on neuromarketing, where the impact of brain responses to various advertisements is seen. The motive is to record which advertisement has the highest impact.

4) Gaming and entertainment: The recent growth in the entertainment industry has led the companies like Emotiv, Neurosky, Mind Games to develop mind-based applications. They capture various gestures, emotions which the users experience while playing and provide an interactive application that can relate to the mind. Some of the games offered by Emotiv are Son of Nor, Brain Battle which offers a 3D experience while interacting through the brain[88], [89].

5) Cognitive improvement: Some argue that people are already taking steps to enhance their cognitive output by, for instance, becoming more mentally alert by drinking caffeinated drinks. The argument about the merits of cognitive enhancement is stimulated by more severe behavior, such as taking prescription medication without a medical explanation. The widespread use of BCI called neurofeedback is used to train to modify brain activity to enhance memory, attention, and other cognitive functions.

6) Safety and security: By using EEG for security will open new doors in the safety of the individuals. Nevertheless, EEG alone or combining it with other physiological behavior will open doors for a robust security system and will prove helpful while identifying the hidden targets that might otherwise get unnoticed. Although this a new application but it will have a high societal impact[30].

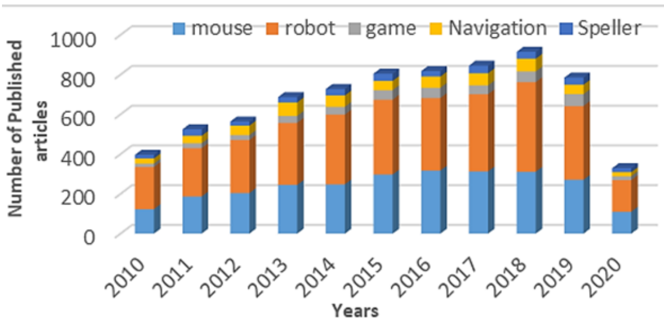

Figure 9: the number of published articles in the last ten years of top 5 application of EEG based brain-computer interface indexed by PubMed [11]

10. CONCLUSIONS

A brain-computer (BCI) interface is a system that uses brainwave information gathered by a specified brain monitoring device to connect with a computer machine. Many BCI applications have been developed in various fields over the past four decades, from entertainment to fields of medicine or rather data security frameworks. BCI systems have so far focused on enhancing their precision, reliability, and user-friendliness, and not enough time and interest have been expended in protecting these devices and the confidential data they collect.

BCI technology is a growing research area with many applications. It includes medical sciences from prevention to neuronal recovery for severe injury situations. Mind reading and distance communication have excellent fingerprints in many fields such as manufacturing, marketing, education, self-regulation, security, games, and entertainment. It gives users and surrounding systems a shared understanding that could benefit from brain waves in achieving the goals. There are, however, significant technological difficulties facing the use of brain signals in various BCI device components. Entertainment and gaming applications have opened the market for non-medical device interfaces in recent years. It is interesting to note that helicopters are made to fly anywhere in either a 2D or 3D virtual world55 today. Combining existing games with brain control capabilities, it has now successfully grown to include a multi-brain gaming experience56. In addition, several extreme EEG games were used for emotional management and neuroprosthetic therapy involving either a new or updated game idea. Brain ball game aims to lower the stress level today, whereby users can only move the ball by relaxing57 and so the calmer player is more likely to be the winner and therefore learn to manage their stress while having fun.

As a well-known and noteworthy example of the use of Bain Machine Interfaced technology, we can mention the name of Stephen William Hawking, who was unique in being a theoretical physicist working on some of the fundamental problems in physics had a rare slow-progressive early-onset. Even after losing his voice, he was able to communicate using a voice-generating system, first using a handheld switch and fbraininally using a single cheek muscle. Researchers engaged in BCI technology believe that a holistic approach would allow a wide range of task-oriented and opportunistic applications to sense and integrate essential brain, behavioral tasks, and environmental information.

Brain signals reflect the handled activities and controlling behavior of the brain or the influence of the received information from other body parts either sensing or internal organs. Brain Computer Interfacing provides a channeling facility between brain and external equipment. BCI applications have attracted the research community. Several studies have been presented in this paper regarding the growing interest in BCI application fields such as medical, organizational, transportation, games and entertainment, and security and authentication fields. It also demonstrates the various devices used for capturing brain signals.

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