"EEG-based brain-computer interface paradigms: A review."

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Abstract: The advancements of BCI in different fields can be seen very rapidly in the last decade. Some typical medical and non-medical applications that use BCI are paralysed patients, stroke rehabilitation and cognitive training, neuro-computing, wheelchair control, brain-to-brain interfaces, gaming, robotics and virtual reality etc. The developments in every aspect of BCI can be seen in past BCI research, i.e. in the sensor development, neurological, technological or socioeconomic perspective. Different EEG-based BCI paradigms/protocols are available in the present BCI system. The brain's connection to any external device depends on these functional paradigms. Thus, it is essential to understand the different EEG-based BCI paradigms and to select the most appropriate BCI paradigm for the specific BCI application to properly manipulate a neural signal that can be further used for neuro-rehabilitation. The paper describes different BCI-based EEG paradigms, their basic explanation, and advanced research in this field. Visual BCI advancements are also included in this paper. Ultimately the article discussed the potential problems in EEG-based BCI systems and proposed possible solutions.

Keywords: brain-computer interface, electroencephalogram, BCI paradigms, hyper scanning.

1. Introduction

The concept of BCI was introduced in the early 70s when the brain signal was utilised to control prosthetic arms [1]. Since then, researchers have been trying to develop more accurate, convenient, easy-to-use and cheap systems that control the devices using human brain signals. Further, this research field was named Brain-computer interface (BCI). Currently, the BCI systems have huge applications in the medical and non-medical fields, such as neurorehabilitation [2], drowsiness detection [3], virtual reality [4], fatigue detection [5], robotic control [6], stroke rehabilitation [7], emotion recognition [8], stress detection [9], video games [10], wheelchair control [11], biometrics [12], neurocomputing [13] and many more. In recent years BCI approaches have been utilised to detect the covid-19 [14] and the vital changes that occur in humans due to this pandemic [15]. Typically, in a BCI system, a sensor records the brain activity, and this activity may be utilised as a command to control any external device. In between the execution of any command to control the device, there are some important BCI components, such as data acquisition, pre-processing, feature extraction and classification or decoding mechanism. The brain activity recording is the first and essential step of this whole BCI system. Brain activity can be recorded by various available techniques [16]. These techniques can broadly be categorised into two categories: invasive and non-invasive. The non-invasive techniques are more frequently used for research purposes due to their easy availability, uncontaminated nature, high temporal resolutions and many more [17]. Whereas in invasive approaches such as ECoG, any neurosurgeon or medical practitioner places the electrodes inside the scalp [18]. Invasive technologies record signals from within the brain using action potentials. The advantages of such techniques are that these signals' good-quality spatial and temporal attributes can be extracted easily. The risk of performing surgery is always involved in invasive techniques [19]. Therefore, non-invasive approaches such as fMRI, EEG, MEG, and NIRS are always preferred instead of invasive ones in human participants. From these techniques, the fMRI has a higher spectral resolution. But the EEG has become the most popular method among them because of its direct measurement of neural activity, affordability and user-friendliness for biomedical uses [20, 21]. EEG records the brain's neural activity induced by the passage of electric currents during the oscillations of neuronal dendrites, particularly inside the cortex, but also in the mysterious brain networks [22]. The EEG electrodes capture the brain activity by placing them in different scalp positions. These positions can be 10-20,10-10, or 10-5, according to the requirement [23]. From these placement methods, the 10-20 EEG placement system is used more frequently worldwide [24]. Currently, EEG signals are utilised frequently to operate wheelchairs and other BCI-driven systems. In the past years, EEG has become an important and successful method to establish a connection between neurorehabilitative devices and the brain [25]. EEG provides a suitable mechanism to connect the brain with different external assistive devices (brain-controlled) for disabled users due to stroke and other neurological defects [26, 27]. One of the most important and challenging topics in BCI is to find and analyse the correlation between recorded brain signals and substantive changes in the human body biomechanics and cognitive approaches. Investigation of relationships between EEG signals and real/imagined upper limb rehabilitation has evolved into a mesmerising area of research in previous years [28, 29]. A unique set of rules or protocols have opted for the specific application to demonstrate an EEG-based BCI system. A standard BCI system needs signal acquisition, appropriate paradigm selection, various classification algorithms and a feedback system. Paradigms are specially designed mental tasks for modulating brain signals [30-32]. Generally, brain signals can be extracted by external stimuli or internal stimuli. As shown in fig. 1, the external stimuli may be visual or auditory, whereas the endogenous stimuli may be any mental task or cognitive activity or may be due to sensation, perception etc. BCI paradigm is an important protocol implemented in an EEG-based BCI system for any specific application [33]. A particular paradigm has been required for different experiments. According to the desired requirement, the subject has to perform a particular task. This task may be a visual task or an imagery one. These particular tasks modulate brain activity during the EEG signal recording [34]. The acquired EEG as a training signal originates a neuronal decoder for the protocol. Various important EEG-based BCI literature has been reported in the last decade [35-39]; however, very few can review or guide about different EEG-based BCI paradigms. In this paper, the authors aim to review the most commonly used EEG-based BCI paradigms. Depending on the patient's physical condition and usability, each of these paradigms has pros and cons of its own. It is studied how these paradigms might be used in the present and future for manipulating external objects and for entertainment, rehabilitation, restoration, and augmentation. Despite all this, this article addresses current problems and limitations of EEG paradigms, and the future prospects for developing new paradigms are addressed.

2. Types of EEG-based BCI paradigms

Brain signals can be stimulated by exogenous stimuli or endogenous mental tasks. Fig.1 The exogenous stimuli may be audio and video-based stimuli, while the endogenous components depend on the brain's cognitive ability and other mental attention/task-based approaches. Some of them are motor imagery that induces motor and sensory-related brain activities. The visual cortex-related paradigms are also designed frequently, i.e. the steady-state visually evoked potentials [40]. Some others are related to cognitive brain activities, such as the P300 paradigm [41].

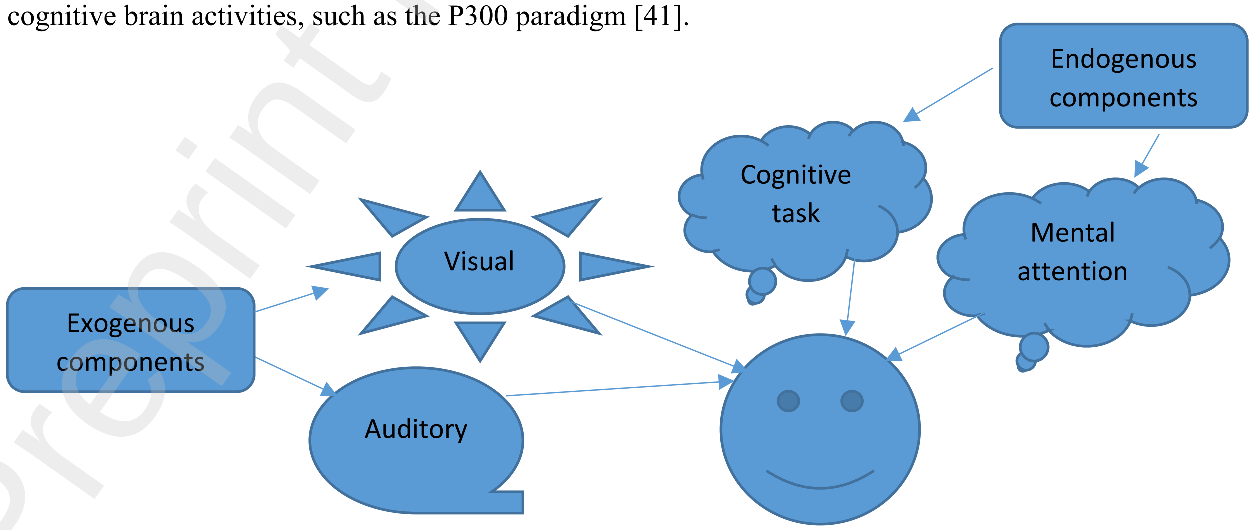

Fig1: BCI system: Exogenous and endogenous components

Paradigm design is essential in determining the primary type of EEG-based BCI. Brain activities often occur simultaneously, i.e. it is difficult to distinguish any particular type of activity directly. A well-designed paradigm is mainly used during signal-acquisition phases to extract the desired brain activities. The paradigm is like an encoder that excites the brain to induce the targeted brain activities [42]. The last decade was perfect for BCI paradigms, and various BCI paradigms have been developed in this era. Each paradigm has its benefits and drawbacks depending on the subject's physical condition and user-friendliness. The paradigms' current and critical future applications are rehabilitation, restoration, enhancement, entertainment, etc. This section explains different BCI paradigms with their recent developments, limitations and future possibilities.

2.1. Sensory and motor-related paradigms

Sensory and motor-related paradigms can modify neuronal activities originating in the primary sensory and motor cortex. A sensory-related paradigm is steady-state somatosensory evoked potential (SSSEP). Movement-related cortical potential (MRCP) and motor imagery (MI) are common paradigms concentrating on motor-related activities. Without actually completing the movement or tensing their muscles when subjects engage in a paradigm, it is known as Motor imagery (MI) [43]. The MI paradigm can vary in sensorimotor rhythms (SMRs) [44]. Event-related desynchronisation (ERD) and Event-related synchronisation (ERS) are the two most frequent occurrences in SMRs due to MI-based BCIs. The former reduces the power in specific frequency bands, i.e. 8-13 Hz and 14-26 Hz. At the same time, the latter boosts power in other specific frequency ranges. ERD and ERS are important parameters; with their help, variations in the neural area are possible for a large group of populations [45]. The MI-based BCI generates impulses by distinguishing various ERD/ERS from the acquired EEG waves. The early MI paradigms concentrated on picturing motions with various joints, expanding from 2-class MI tasks [46, 47] to 4-class MI tasks [48, 49]. Yi et al. [50, 51] created compound and sequential joint MI challenges rather than envisioning single-limb movements. Ofner et al. [52] suggested a paradigm that required individual subjects to categorise six MI tasks of the same limb. A MI paradigm was created by Edelman et al. [53] for the intricate activities using only one limb, specifically for the right hand's four-hand movements. Wang et al. [54] presented a MI paradigm that calls for seeing various right-hand clench force loading. The movement-related cortical potential (MRCP) is another motor-related paradigm that is characterised by a steady decline in EEG amplitude and occurs during the planning and execution of actions [55]. The readiness, motor, and movement-monitoring potential components of MRCP are to reflect the movement planning, movement implementation, and perform it, respectively [56, 57]. EEG Signals below 2 Hz can be extracted by MRCP, which contains kinematic data regarding imagined regular movement [58, 59]. Kim et al. [60] examined the eye-movement contamination issue in MRCP scenarios for the right arm movements. Schwarz et al. [61] presented a paradigm that distinguishes between three reach-and-grasp motions from EEG signals and provides BCI systems with greater organic control. Wang et al. [62] recent investigation into the potential for detecting movement intentions before actual movements produced encouraging findings for creating a novel MRCP-based paradigm. An SSSEP-based BCI paradigm that required vibration stimuli from index fingers was proposed by Muller-Putz et al. [63]. Subjects are told to pay close attention to the target finger and count any twitches that emerge, which increases the target frequency's spectral amplitude [64]. Breitwieser et al. [65] demonstrated that SSSEP could categorise different fingers by applying it to five fingers of the hand. Su et al. [66] examined how stimulation levels and SSSEP are related. The findings showed how the stimulus intensity varies with SSVEP.

2.2. Vision-related paradigms

In EEG-based BCIs, vision-related paradigms are significant. These paradigms can vary the neural activities in the primary visual cortex. Regan [67] discovered a form of visual evoked potential (VEP) known as the steady-state VEP. SSVEP is a type of exogenous event-related potential (ERP) dependent on sensory input's physical characteristics. A visual stimulus that flickers sinusoid ally in SSVEP causes a steady VEP with a tiny amplitude and the appropriate flickering frequency. Light-emitting diode (LED) sources were the foundation for early SSVEP-BCI development [68, 69]. SSVEP was implemented by Cheng et. [70] When comparing SSVEP elicited by LCD, LED and CRT and recommended to use of LED for a BCI that was extremely complex. However, due to their high refresh rate, convenience in constructing complicated stimulation patterns, and dependability in reproducing stable stimulus, LCD monitors are now used for most SSVEP experiments [71]. Nakanishi et al. [72] constructed various targeted SSVEP paradigms. Further, Cao et al. demonstrated an SSVEP-based real-time multiphase BCI [73]. Tang et al. [74] created a 32-target multifocal SSVEPs paradigm with five indications on each target, each flashing at a different frequency. Large-size stimuli in the fovea are preferred by conventional SSVEP paradigms, which can quickly lead to visual fatigue. Recently Zhao et al. [75] created a comfortable SSVEP-based BCI paradigm. The micro VEP BCI illustrates a promising approach to achieving a more at ease and natural BCI system by placing the visual stimuli beyond the fovea vision on the lateral side, which only occupies 0:5 of visual angle and induces miniature potentials about 0:5lV in amplitude. In addition, the authors suggested a Steady-State Asymmetric Visual Evoked Potential (SSaVEP) paradigm, which used four high-frequency stimuli outside the fovea to transfer information at an average rate of 87.2 bits per minute for ten encoded commands [76].

2.3. Cognition-related paradigms

In contrast to paradigms relating to vision, many paradigms connected to cognition have been developed within the previous few decades. Here, we focus on introducing the P300, ErrPs, and CVSA (covert visuospatial attention) paradigm. Event-related potentials (ERPs) have been used initially by researchers to get some insights [77]. P300 is an endogenous ERP connected to cognitive processes without relying on the physical characteristics of sensory stimuli. In an unconventional paradigm with two types of stimuli, i.e. target and non-target. Compared to the frequent non-target stimulus, the infrequent target stimulus causes a greater positive peak, known as the P300 peak, roughly 300 milliseconds after the stimulus onset [78]. Visual and auditory stimuli have the same effect on the generation of P300, even though visual stimuli are more frequently utilised in P300-based BCIs. For BCI speller systems, the vision-based P300 paradigm is typically employed. The row-column (RC) paradigm refers to the original P300 speller, which uses six × six matrices of characters with random flashes in each row and column [79]. The target character is the one that the subject is supposed to focus on, and flashes of that character's row and column can elicit the P300 component. A single-character (SC) paradigm that randomly flashes one character at a time was proposed by Guan et al. [80]. Despite being slower than the RC paradigm, the SC paradigm produces greater P300 amplitudes [81]. Acqulagna [82] created the rapid serial visual presentation (RSVP) paradigm, which can also elicit the P300 component, in which all characters are presented sequentially at one central position without regard to gaze movements. Lin et al. [83] expanded RSVP's single-character presentation to include triple characters. Xu et al. [84] created a novel time-estimating paradigm wherein participants estimated that the visual stimulus would appear 400 or 600 milliseconds following the cue. They discovered that time and frequency domain features were connected to time estimation. After the anticipated instant, there were positive P300-like deflections in the time domain. The observation is in line with the theory that the positive deflections represent a P300 response to processing non-occurrence information. This study discovered a relationship between high-frequency energy features and the time estimation process, which may offer new neural evidence in support of the idea that the P300 is a multifaceted electroencephalographic response with distinctive features in both the frequency domain and the time domain [85, 86]. In addition to showing that the cognitive EEG feature elicited by time estimation can function as a novel signal for active BCIs, the results reported by [87] may have also identified a new pattern that may improve the performance of P300-based BCIs by introducing detection and analysis of frequency-domain features. The ERP components known as the error-related potentials, such as the feedback-related negativity (FRN) and the error-related negativity (ERN), are elicited when subjects become aware that they have made mistakes [88, 89]. Iturrate et a. [90] have discovered that ErrPs are quite complex and that their latencies vary based on the tasks. Chavarriage et al. [91] successfully detected ErrPs in a single trial and confirmed that ErrPs exist after feedback of wrong replies in a human-robot interaction experiment. Salazar et al. [92] developed a closed-loop robotic control system incorporating ErrPs detection to repair errors. BCI applications have also used covert visuospatial attention (CVSA), concentrating attention on various areas of the visual field without overt eye movements [93]. Zhang et al. [94] developed an SSVEP-based BCI system in which individuals were told to do so without making overt eye movements. With a 400 ms data length and the N2pc and SSVEP characteristics, Xu et al. [95] developed a quick CVSA detection paradigm and achieved an average accuracy of 72.9%. Wai et al. [96] investigated the differences in SSVEP with CVSA in more detail. They concluded that covert attention could produce consistent SSVEP responses regardless of visual angles and spatial stimulus resolution. However, Tonin et al. [97] developed a BCI based on pure CVSA, illustrating the viability of constructing BCIs based on CVSA by asking individuals to maintain covert attention on two different orientations.

2.4. Hybrid paradigms

Hybrid paradigms combine at least one EEG channel with two or more physiologic inputs. Hybrid paradigms utilize several different subsystems to increase system performance. A hybrid paradigm combines different BCI paradigms or one built using EEG and other physiological inputs, such as EMG. Typically, hybrid BCIs integrate paradigms meant to elicit several brain activities. A hybrid paradigm combining MI and SSVEP was developed by Allison et al. [98] and required people to look at SSVEP stimuli while simultaneously visualising movements. Pfurtscheller et al. [99] presented an MI-SSVEP hybrid paradigm with sequential switching between paradigms in place of a simultaneous hybrid paradigm. Li et al. [100] asked participants to visualise movements or focus on the flickering stimulus to control a 2D cursor. Additionally, there are hybrid paradigms that combine SSSEP and MI. Yao et al. [101] instructed participants to visualise left- and right-handed actions or pay close attention to wrist vibrations. They discovered that combining both paradigms could enhance the left and right categorisation performance. Elsayed et al. [102] improved performance noticeably by doing MI while using a hybrid paradigm. A hybrid paradigm that combines MI and ErrPs was recently proposed by Mousavi et al. [103], showing noticeably increased performance in online BCI systems. Additionally, hybrid paradigms for the same brain function combine paradigms. P300 and SSVEP were linked by Panicker et al. [104] to create an asynchronous P300- speller that utilised SSVEP to identify participants' control states. By temporarily moving a portion of the stimulus from the SSVEP paradigm to the P300 paradigm, Li et al. [105] presented a hybrid paradigm. Yin et al. [106] constructed two hybrid forms of the stimulus configuration and proposed a 32-character speller with a flickering stimulus delivered in the P300 paradigm. A new hybrid paradigm invoking SSVEP and P300 was created by Yin et al. [107].

2.5. Advantages of visual BCI

Researchers are now interested in vision-based BCI since it has a greater data rate than other BCI paradigms, requires easy system configuration, and requires much less training [108]. Some common visual paradigms are the steady-state visual evoked potential (SSVEP)-based BCI, the P300-based speller, and their hybrid BCIs. Some important papers are included in Table 1 and discussed in this section. The brain's reactions to visual stimuli are reflected in VEPs. The brain's VEPs process visual information. SSVEP is dependent on frequencies lower than 6Hz. The SSVEPs have occurred mostly in the occipital region since vision is connected to this area. But a common issue that arises in SSVEP-based BCI is that high user variation. Different information transfer rate (ITR) for different subjects is common. To minimise this issue, user variation can be significantly decreased by the appropriate selection of the channels/ locations, the stimulus frequency and the selection speed. All these parameters affected the BCI performance. Wang et al. [109] proposed a practical SSVEP-based BCI used in a real-world environment. The system was established to detect of subject's gaze position. This experiment correctly considered system design, optimisation, channel placement, stimulus frequency, and selection speed. The ITR has been checked in two different conditions, i.e. in a laboratory and in a rehabilitation facility. Additionally, it has been shown that the approach works for more than 90% of the people living in normal living conditions.

Table 1: Some Important articles on the visual BCI

S.No.	Reference	Feature/Method used	Application
1	Wang et al.	Frequency-coded steady-state VEP	Determine the Gaze direction of the person
2	Chen et al.	FBCCA and CCA-based methods	Classification accuracy and ITR enhancement

3	Nakanishi et al.	Task-related component analysis(TRCA)	Online applications in communication/control
4	Xu et al.	Discriminative canonical pattern machine learning	Visual fatigue detection via developing small stimuli
5	Xu et al.	Using P300 and SSVEP features	The number of command codes increased
6	Bin et al.	Code modulated VEP	ITR enhancement
7	Xu et al.	Using P300 and SSVEP blocking (SSVEP-B)	Improved BCI performance
8	Xiao et al.	ERPs, Discriminative canonical pattern matching(DCPM)	Classification algorithm development to adapt the ERP diversities.
9	Zhou et al.	A multiclass discriminative canonical pattern	Visual fatigue minimization
10	Jiang et al.	SSVEP, dynamic stopping strategy	SSVEP-based high-speed BCI

Nowadays SSVEP based BCI are widely utilising canonical correlation analysis (CCA) because of its great efficiency, resilience, and ease of implementation. Chen et al. [110] propose a filter bank canonical correlation analysis (FBCCA) technique to enhance the identification of SSVEP by including the fundamental and harmonic frequency components. Three distinct strategies were utilised to compare and improve the blank filter design. The standard CCA technique and the three FBCC approaches have been applied to an online dataset of 12 subjects, and the classification accuracy and information transfer rates were calculated. The results showed that the FBCCA Approach considerably outperformed the conventional CCA method. Also, ten subjects were examined using an online BCI speller with the best FBCCA method. The online BCI speller acquired an average ITR of 151.18+ 20.34 bits/min at a pace of 33.3 characters per minute. The suggested FBCCA approach considerably enhances the SSVEP-based BCI's performance and facilitates its practical use, such as high speed.

Nakanishi et al. [111] proposed an improved SSVEP for a high-speed BCI system using a unique data-driven spatial filtering technique. A task-related component analysis (TRCA) was suggested to increase SNR by eliminating background EEG interferences and improving the reliability of SSVEP over numerous trials. By recording a 40-class SSVEP dataset, a BCI performance comparison between a TRCA-based approach and a canonical correlation analysis (CCA)-based approach has been conducted for 12 individuals. And the finding suggested that the TRCA-based method increases the classification accuracy significantly. The SSVEP-based high-speed BCIs can be used in different applications in communication. Except for the speed of the BCI and the ITR, one issue that is always present in the visual BCIs is the large size of the stimuli. The traditional BCI system has made use of large-size stimuli. These stimuli caught the participants' attention and caused various EEG characteristics to appear. These visual cues only operate as the characters' secret codes. Several problems, like visual fatigue, might arise when using such large stimuli. Xu et al. [112] suggested using tiny stimuli to alleviate these problems. Using discriminative canonical pattern machine learning, 32 encoded characters were used to create small asymmetric visual elicited potentials (aVEPs). The SSVEP-BCI instructions take little time to encode, but the small EEG spectrum restricts the available SSVEP frequencies. Therefore, combining the P300 and SSVEP paradigms effectively addresses this drawback and broadens the instruction set. The performance of the BCI system can suffer if we increase the number of commands. For example, a higher number of instructions would frequently lengthen the time required to output a command, decrease the accuracy required, and decrease the ITR. Adding more instructions might reduce the overall BCI performance. To our knowledge, no research has yet used more than 100 instructions for BCIs. Further, Xu et al. [113] developed a hybrid high-speed P300 and

SSVEP-based BCI system having 108 instructions. The online and offline experiments have been carried out. The offline experiment demonstrated that the simultaneous P300 and SSVEP characteristics could better classify the 108 characters in 1.7 seconds. The online results also showed that this new BCI mechanism could reach an average ITR of 172.46 and 164.69 bits/min. Due to their non-invasive nature EEG-based, BCIs have recently gained a lot of interest in the domains of neuro-engineering and neuro-rehabilitation. However, the present BCI systems' slow connection speeds severely restrict their usefulness. Bin et al. [114] demonstrated a fast BCI that uses code modulation of VEPs (c-VEP). The unknown binary pseudorandom sequence that was time-shifted modulated 32 target stimuli. Target identification was accomplished using a multichannel technique based on canonical correlation analysis (CCA). The average information transmission rate (ITR) for the online system across five individuals was 108 bits per minute, with a high ITR of 123 bits per minute for a single person. Hybrid brain-computer interfaces (BCIs) be more successful in mental control. The combination of a steady-state visual evoked potential (SSVEP) and a P300 potential provides the quickest and most accurate EEG-based BCIs. Xu et al. [115] created a unique hybrid BCI system to concurrently use P300 potential and SSVEP blocking (SSVEP-B) with a similar target stimulus.Twelve participants participated, and each completed two rounds of offline spelling using the hybrid and control P300 spellers. Character accuracy and ITR has been used to gauge the performances after adopting a feature analysis approach with the perspectives of the time, frequency, and spatial distribution SSVEPs are a clear EEG component during the non-target phase of the hybrid paradigm, but they are ignored and replaced by P300 potentials following the target stimuli. Target and non-target responses may be easily distinguished from one another due to the lack of an SSVEP termed SSVEP-B. The hybrid speller improves accuracy and ITR over the control P300-speller by combining characteristics. The findings show that the P300 and SSVEP-B combination significantly enhances target discrimination and that the suggested hybrid paradigm outperforms spelling performance. The results, therefore, give the latest method for enhancing BCI capabilities. Commonly used control signals for brain-computer interfaces are event-related potentials (ERPs) based BCI. ERP patterns have been used in various BCI studies because they are very weak and sensitive to the experiment. Xiao et al. [116] Developing a generic decoding method that can accommodate the ERP variations of various BCI datasets with minimal training sets is still difficult. According to study findings, the DCPM beat other classifiers for each dataset evaluated, indicating that it is a reliable classification technique for assessing various ERP components. Visual brain-computer interfaces (v-BCIs) have significantly increased speed in past years. The conventional v-BCI paradigms demand that users look at the intensely flashing objects that may lead to serious issues, including visual fatigue. Therefore, creating a user-friendly v-BCI is an essential Approach. Zhou et al. [117] proposed a unique BCI paradigm to identify the fixation point of eyes using a little visual stimulus that subtended just 0.6° in visual angle and was outside of the central visual field, following the retina-cortical connection. In this research, twelve volunteers were used, and for each trial, they were instructed to look at one of the 16 spots. The authors discovered that the visual stimulus landmark produced various spatial event-related potential patterns at various fixation positions. The experimental findings of this research show the possibility of utilising a minor visual stimulus as a landmark to monitor the relative location of the fixation point. The suggested novel paradigm offers a possible solution to the issue of grating stimuli in v-BCIs, which may increase the scope of BCI applications. Brain-computer interfaces confront several difficulties due to the non-linear and non-stationary nature of EEG data. Dynamic stopping (DS) techniques may be used to acquire enough EEG data to solve this issue adaptively. The steady-state visual evoked potential (SSVEP)-based high-speed BCI has made great strides recently. By using the DS approach, Jiang et al. [118] seek to enhance the high-speed SSVEP-based BCI even further. This work developed two distinct DS procedures for a high-speed SSVEP-based BCI. The ensemble task-related component analysis and the extended canonical correlation analysis (CCA), two of the most successful SSVEP identification techniques, were compared (TRCA). For all datasets, the DS techniques considerably outperformed the FS approach regarding information transfer rates (ITRs), with improvements of 9.78% for the Bayes-based DS and 6.7% for the discriminant-based DS. For our data, the discriminant-based DS method with ensemble TRCA had the greatest performance, averaging 353.3 67.1 bits per minute with a peak of 460 bits per minute. For the public dataset, the Bayes-based DS method utilising ensemble TRCA had the greatest ITR, averaging 230.2 65.8 bits per second with a peak of 304.1 bits per second. Significance. This research shows that the suggested dynamic stopping tactics may improve an SSVEP-based BCI's performance and potential for real-world use.

2.6 A new revolutionary paradigm; Hyper scanning:

As discussed in numerous papers [119-121], analysing the human brain in social contexts has shown task-specific stimulation of various brain areas involved in cognition. The perspective of inter-brain dynamics during data acquisition from different persons has permitted researchers to explore further the evidence of these neural systems [122]. Hyper scanning (HS) is a method that allows anyone to record the brain signals of two or more persons at the same time [123, 124]. Duane and Behrendt [125] made the initial electroencephalography (EEG) attempt to record the signals of two brains simultaneously. To comprehend the changes in the brain caused by HS, several studies were conducted on healthy volunteers [126-128], musical performance [129], and motor activities [130]. Group dynamics have also been studied in motor rehabilitation with a similar interest in studying interpersonal interactions [131, 132]. Patients with various neurologic diagnoses benefit from this treatment method because it offers more peer support. Cognition is evaluated using stimuli in a controlled laboratory setting [133]. In order to gain a fuller understanding of social cognition, it is especially important to analyse simultaneous activity from several brains because day-to-day happenings are most often practised in groups of individuals. Neuroimaging methods are typically employed in single-subject recordings [134, 135]. fMRI, fNIRS, EEG, and MEG are the four main functional neuroimaging methods that have been used to validate HS. The localisation of hemodynamic movement from the cortex to inner brain areas using fMRI, is possible [136]. However, fMRI-HS paradigms are restricted to examining tiny, isolated behaviours and judgement-making responsibilities because of the size restrictions of the scanner and its relatively low temporal resolution. High spatial and temporal resolution is provided by MEG, which measures magnetic fields generated by electrical potentials inside the brain. Studies in the field of neuroscience have investigated how numerous individuals have interacted over the previous two decades. As a result, many review papers describing the various social contexts that have been investigated using HS setups have just recently been published [137, 138]. Studies have shown greater synchrony when children cooperate with their mothers during a cooperative activity than when they interact with a stranger [139], as well as higher connectivity and concert in passionate spouses versus outsiders during button-pressing tasks [140]. Additionally, during a cooperative computer exercise, distinct areas of inter-brain consistency between identical-sex and diverse-sex dyads have been discovered [141]. These results highlight the significance of interpersonal interactions in addition to the task's design and assigned roles for inter-brain synchronisation. Through the use of hand motion imitation in pairs, one EEG-HS study [142] investigated the connection between behavioural and brain synchronisation. A second EEG-HS investigation of finger movements that are rhythmic [143]. The same study team went into greater detail about these results [144], concentrating on mu band power modulation. They discovered that variations in mu band power throughout regular finger motions were detected in a variety of circumstances. Together, the results of these investigations highlight the significance of the mu (alpha) band and its importance in the interpretation of HS measurements taken during coordination and imitation. In an EEG-HS investigation, unobserved fingertip movements across dyads were compared before and after cooperative training activities to determine the basis of implicit social coordination [145]. Musical performance with HS setups has been used to study more sophisticated motor behaviours in addition to simple combined actions. One set employed an EEG-HS system to link the musical roles of leader and supporter with irregular epochs of phasing locking at the front and central electrodes in a guitar duet setting [146]. In a later study, the same team expanded on this paradigm by assessing the information flow between the leader and follower in a guitar duet using a directional measure of connectedness [147]. Another study examined synchronous brain activity in guitar quartets with EEG-HS, demonstrating activity networks with intra- and inter-brain connections [148]. Up until now, the main emphasis of HS has been on inter-brain interactions in healthy participants. Although the field is still young, adding patient populations would be highly beneficial.

3. Current challenges and future directions

BCI research has significantly advanced assistive device technology and neurorehabilitation during the past few years. A brain-controlled prosthetic device helps people with fatal mental and physical injuries and other essential communication problems, including ALS, LIS, and multiple disorders; all of the approaches have a bright future for further research. Without any question, there is a good chance that customised BCI setups will soon be made available for purchase for a typical user. In reality, a few commercially produced devices are already on the market. Some initiatives, such as the BCI Horizon project 2020, have created a blueprint for the development of BCI architectures [149]. Few publications discuss problems like platform dependability. Additionally, a BCI experiment's behavioural, mental, audio-visual, and motor imagery results are frequently not apparent. However, the BCI community must focus on and resolve some significant restrictions and difficulties with different BCI paradigms and platforms. As a typical practice, in most BCI literature, study findings have been reported regarding classification accuracy. The authors think future studies should focus on these significant difficulties to develop BCI research for real-world applications.

3.1 Training time reduction: Human minds need some training and knowledge about the benefits and drawbacks of anything new if he/she wish to adapt to it. In the case of BCI, user training presents a substantial issue. The amount of training is necessary for any BCI user to become compatible with the device, and it is one of the major obstacles facing BCI developers. It takes a lot of practice and a lot of time. The applicant must comprehend how to use a response signal to operate the system and be compatible with it. The user is taught to assimilate and react to the feedback signal during the initial phase of training. The training sets might be modest or substantial, depending on how usable the system is. Instead of laboratory-based BCIs, the design of BCIs for daily usage is also a crucial task. There are fewer plug-and-play and simple-to-use BCIs available nowadays. Most paradigms require lengthy training periods, which may tire individuals. However, some instances of stimulus-based BCI have been used for extended periods [150, 151]. Some EEG paradigms, like P300-based BCIs, may lead to weariness after repeated use. Additionally, it may be necessary for BCI developers to gather standardised data at the start of each experiment due to subject dependence and even inter-session variability. Several recent works have developed a generic BCI model with zero training using techniques like transfer learning to address this issue [152-156].

3.2. Present signal processing and classification tools: Recent research has examined various data processing techniques [157] as well as classification patterns [158]. However, the signal-to-noise ratio of the signal derived from EEG waves is insufficient to control a device with several degrees of freedom, such as a neuroprosthetic arm. In order to be capable of guiding a system having various degrees of freedom, more reliable, accurate, and quick online algorithms are needed. Recent years have seen several academics propose that active data selection and source localisation of EEG can enhance classification ability [159]. Advanced machine learning and deep learning techniques may be used, according to suggestions made by other researchers [160-163]. These techniques can extract more features that can enhance categorisation. To account for the non-stable character of any EEG dataset, some developers have suggested adaptive approaches and decoders [164]. Meanwhile, a specialised, standardised framework is required to assess decoding approaches' performance in specific BCI applications and systems [165].

3.3. Control of closed-loop BCIs: A closed-loop BCI is viewed as a collaborative and interdependent training system where humans and computers gain knowledge from one another while also undergoing modification in neural circuits and coding algorithms. The BCI mechanism was referred to as the "two-learner system" by Millan [166]. The contributions of both humans and machines in carrying out the control work were also referred to as "shared control" and "hybrid control" [167-172]. High and low-level controlling mechanisms are both included in the same BCI system. Traditional control mechanisms charge low-level control purposes, whereas the brain generates high-level control commands. It's interesting to note that in high-level control, the natural mode of control and subject tiredness are always in competition. The ideal BCI system with mutual interaction can be characterised as a supervisory control system in which the subject is the leader with minimal participation (in high-level control), and the BCI system functions as an intelligent system (in low-level control) [173, 174]. Instead of constantly dealing with control commands, the user can supervise the external autonomous system through cognitive monitoring. Currently, there is debate regarding what constitutes a closed-loop control system [175, 176]. In fact, some artificial sensory feedback kinds, except for visual feedback [177], should be considered in an EEG-based BCI to give the person the most reliable sense of control for a closed-loop arrangement. Contrarily, touch is a feeling that invasively controlled prosthetic arms incorporate, which increases the cognisance of closed-loop BCIs.

3.4 Latest EEG sensor developments: Scalp EEG has the potential to be marketed for the general population because it is seen as a cheap and low-cost brain monitoring technique [178]. There is research to assess behavioural changes with applicability to drowsy driving to evaluate alertness/ drowsiness from brain dynamics. Using a portable EEG headset makes it easier to comprehend the brain dynamics that underlie how the brain integrates perceptual functions in various situations. According to particular research, there are connections between brain oscillations and various sensory inputs, like haptic feedback, and behavioural moves reacting to somatosensory signals in a moving situation. Many developers have considered creating wireless and easy-to-wear EEG headsets as part of technological evolutions [179,180]. Additionally, dry EEG electrodes have advanced in various aspects, such as the skin preparation and gel application steps needed for traditional wet sensors are not necessary for these electrodes [181-184]. The advancement of these recent EEG devices may make BCI applications more widespread than they are now. For instance, a sleep management system that can rate sleep quality can be built on a forehead EEG-based BCI. The tool might also be utilised as a screening system for depression treatments that would assess and forecast the effectiveness of quick-acting antidepressants. However, the dry electrode technology is still constrained. For instance, the sensors hurt the scalp and are extremely sensitive to movement and muscle distortions. Additionally, the recording quality of modern dry headsets often deteriorates after about an hour.

3.5 Neurofeedback and future paradigms: Neurofeedback is one potential application for BCI in the future [185]. The act of self-generating brain oscillations to enhance different elements of cognitive function is known as neurofeedback, which is a kind of biofeedback. In some circumstances, neurofeedback-based BCIs may be able to replace drugs and lessen their adverse side effects. For instance, this technology might aid in treating neurological and cognitive disorders like migraines. An automated system for managing migraines can alert migraine sufferers to impending headaches days in advance and provide neurofeedback as a kind of treatment. BCIs based on neurofeedback may be created to aid in treating addiction, obesity, autism, and asthma [186]. Additionally, new EEG paradigms can be created to support environmental interaction [187,188] and cognitive control [189]. Since ErrP enables a user to observe and spontaneously create the desired change in a BCI system without the need to do a control task, it can be utilised, for example, as a beneficial tool to augment neurofeedback. Several cognitive deficiencies, such as ADHD, epilepsy, brain injury, Alzheimer, and stress disorders, can be treated using new cognitive approaches based on neurofeedback models [190-196]

3.6 Electrophysiological Issues: The human brain is far more complex than a communications system, being the most complex biological system. When designing a reliable BCI system, its inherent features, such as nonlinearity and non-stationary, provide significant hurdles. These electrophysiological problems significantly impact the performance of BCI. These concerns should be considered and resolved while proposing and executing a system to create a workable one.

3.6.1. EEG nonlinearity: Population dynamics of neuronal ensembles can be seen in the brain, which is a non-linear system [197]. Non-linear dynamic approaches are preferable to linear methods for characterising their activities, such as EEG signals [198, 199]. The visual-BCI and audio-BCI systems must adequately handle the nonlinearity in recorded EEG signals. In general, it might have two opposing effects on BCI performance. First, it can result in more information for better classification. For instance, SSVEP signal production in the human visual cortex exhibits nonlinearity. Brain responses that are uniform, symmetrical, and subharmonic with stimulus frequency can be used to distinguish the non-linear resonance phenomena of SSVEPs [200]. As a result, the harmonic components can offer useful information for identifying the stimulus frequency in addition to the fundamental frequency component. The SSVEP-based BCIs have successfully illustrated the effectiveness of merging several harmonic features [201, 202], and [203]. Second, the performance of the BCI could suffer if certain non-linear brain characteristics cause a degradation in the task-related EEG signals. ERP signals, which are very sensitive to neurophysiological factors, frequently experience this condition [204]. The rate at which the brain can process incoming stimuli, for instance, has a limit. The response to the second stimulus is noticeably slowed when two stimuli must be evaluated quickly (psychological refractory period). Similarly, to this, when two visual targets are presented rapidly one after the other, people frequently miss the second target (attentional blink). The P3 component exhibits non-linear modulation as a result of these processes [205,206]. Avoiding these situations when they happen must be considered during system design to create a reliable BCI.

3.6.2. Nonstationary in EEG: Over time, there is a consistent nonstationarity in brain activity associated with various mental and behavioural states [207]. It can be brought on by both internal and external influences in the brain, including variations in neurophysiological conditions and psychological aspects, changes in electrode contact and location, movement artefacts, and background noise. Similar to other BCIs, the intersession nonstationarity in the EEG data is a significant difficulty in the visual-BCI and audio-BCI systems and frequently results in decreased BCI performance. The distinctions between a training and testing session and the variations between numerous online sessions are specifically responsible for intersession nonstationarity in EEG categorisation [208]. Adaptable classification techniques that may dynamically update the decoders during live BCI performances have been created [209,210] to solve this issue. Additionally, zero training techniques are receiving more and more attention in current BCI investigations [211, 212] and [213]. The zero-training approaches integrate data from various sessions or subjects to address the nonstationarity issue in feature extraction and classification. The intertrial nonstationarity in EEG signals is another difficulty on a shorter time scale. The SNR in single-trial EEG data may change as a result of trial-to-trial fluctuation [214]. Therefore, one of the key components of EEG classification is adjusting parameters for single-trial EEG signals. For instance, a common issue in the ERP-based BCI is the quantity of target identification trial repetitions needed, which is essential for cutting down on target detection time. Advanced data analysis techniques may also help to solve the non-stationary issue.

3.7. ITR improvement:

The performance benchmark, which is mainly related to the inadequate SNR of EEG signals, is one of the primary obstacles to the advancement of visual and auditory-BCI technology [215]. Numerous measures have been developed to assess the effectiveness of BCI systems [216]. ITR is currently the most important aspect of using any BCI system. One can read more about ITR evaluation in online BCI research. Several studies independently considered the three variables (i.e. target detection accuracy, class size and target detection time) to make it easier to summarise the previous investigations on ITR.

(1) Increasing Target Detection Accuracy: Generally, there are two strategies to increase target detection accuracy: (a) by increasing the SNR of EEG signals and (b) by optimising the invariance of several classes. The task-related EEG signals' feature amplitude and dimension have been increased to meet these objectives. Additionally, modern BCI systems frequently include complex data processing methods and machine learning techniques [217-221].

(a) Signal-to-Noise Ratio: By raising the signal intensity and lowering the noise level, EEG signal SNR can be improved. First, by using cutting-edge signal processing techniques, SNR can be increased. Current visual-BCI and auditory-BCI systems frequently use averaging methods, which are commonly used to enhance the SNR in ERP research [222]. In a collaborative BCI, trial averaging across participants has recently been used to boost an individual BCI's performance [223, 224]. Multichannel EEG data can be projected into a less-dimensional space using spatial filtering to remove unnecessary task elements and boost the SNR of the recorded EEG signals. For instance, the frequency detection of SSVEP was much enhanced by the canonical correlation analysis (CCA) method [225-227]. Independent component analysis (ICA) is another technique for spatial filtering that is frequently employed [228-229]. Enhancing task-related EEG signals can also result in higher SNR. ERP signal amplitude always correlates with the user's attentional and emotional cognitive states. Therefore, cognitive tasks might be incorporated into the stimulus design to produce more reliable ERP signals. Recent research has demonstrated the remarkable effectiveness of this strategy. As counting was used to identify targets in a motion VEP-based BCI, the amplitude of the motion VEP signals dramatically improved when compared to staring [230]. In recent work, Lakey et al. [231] used a brief mindfulness meditation induction (MMI) to influence attention in a P300-based BCI and discovered that MMI subjects produced considerably bigger P300 amplitudes than control subjects. To improve the P300, Belitski et al. [232] used simultaneous visual and auditory stimuli, which increased the performance of the traditional visual P300 speller. Compared to checkerboard stimuli, visual stimuli involving expressive human faces considerably increased the amplitude of the SSVEP signals in an affective SSVEP-based BCI [233].

(b) Multiple Class Separability: Accurate target detection depends on the capacity to separate numerous classes. The accuracy of target detection in BCI systems has been significantly increased by applying machine learning techniques [234]. Various strategies for feature selection, feature combination, and classification are used in modern BCIs [235, 236]. The use of multiple EEG signals conveying specific information to create a hybrid EEG signal has recently been suggested. Another study used facial image stimuli to activate the face-sensitive ERP component N170 in the oddball paradigm, which was then coupled with P300 to improve target detection [237]. Another effective strategy is to utilise intricate coding techniques, like CDMA technology, in system architecture. Orthogonal m-sequences were employed in the code-modulated VEP-based BCI to elicit VEP signals that could be easily distinguished using crosscorrelation analysis [238, 239].

(2) Increasing Class Size: A BCI system depends on the size of its class structure. A large number of classes to create complicated applications when compared to other BCIs. A significant number of classes can be realised by the P300 BCI and the SSVEP BCI, respectively [240, 241]. MA methods make it easier to implement many classes in these two types of BCIs. Target stimuli are commonly encoded using the TDMA approach by P300 BCI devices. To enhance the row/column system, new stimulus display techniques have recently been created. For instance, a 7 x 12 matrix speller was constructed using the strategy of flashing quasi-random groupings of characters [242]. The VEP-based BCI systems have utilised FDMA and CDMA, among other stimulus coding techniques. The BCI system, for instance, can implement paradigms with 32 or 64 classes utilising code-modulated VEP

[243,244]. The SSVEP BCI currently uses frequency coding the most frequently. The number of classes has also been increased using multiple-frequency coding techniques [245,246].

(3) Shortening the Target Detection Time: The following factors can generally shorten the target detection time. First off, single-trial categorisation has the potential to be far more effective than trial averaging. Single-trial analysis based on machine learning is currently popular [247]. Third, quicker target detection is possible with improved stimulus presentation. The P300 BCIs have extensively examined this technique. Reducing the ISI between two flashes during stimulus presentation is a simple method [248]. In order to improve system performance, a trade-off between accuracy and ISI must be made. The stimulus coding approach can also be optimised. For instance, coding quasi-random sets of characters can improve the conventional row/column coding method [249]. This will drastically decrease the flashes needed to recognise a target character during each trial.

3.8. Using in Real-World Applications: The BCI community is currently faced with formidable obstacles when attempting to transition a BCI system from laboratory to real-world applications [250-252]. The user experience and usability of the BCI technology will be crucial in expanding its scope of use. A practical BCI system must overcome the following concerns: simple operation, affordable hardware and software, and reliable system performance are priorities [253]. Design of Mobile Systems: Numerous BCI applications can be made possible and made easier in real-world settings by a mobile BCI platform technology. The following three significant difficulties should be considered while implementing a mobile BCI system. A mobile BCI first needs mobile hardware for the EEG, data platform, and stimulation devices. Using big, pricey, wired hardware components would hinder users' ability to accomplish standard tasks in addition to causing discomfort and irritation. The development of mobile EEG technology, which uses a dry electrode and a small wireless EEG amplifier, has advanced quickly recently [254-256]. Mobile BCIs have since grown fast [257]. For instance, phone-dialling software using SSVEPs was used to show a mobile BCI system based on a cell phone [258]. While subjects were outside walking, a mobile P300-based a-BCI was demonstrated [259]. Second, fewer electrodes must be used in order to simplify system operation and lower system costs. In BCI investigations, many electrode selection techniques have been put forth [260], [261], and [262]. For instance, the choice of a bipolar electrode in the SSVEP BCI effectively elicited SSVEP-based paradigms with a higher SNR [263]. Third, since movement artefacts and background noise are significantly more prevalent in real-world settings, the system must be able to address the issue of artefacts in EEG signals. The new mobile brain imaging (MOBI) technology [264] could be able to aid with this issue. 2) Reducing fatigue as a result of extended durations of cognitive work, mental tiredness is the temporary inability to maintain peak cognitive performance. The amplitude of EEG signals can deteriorate due to mental tiredness since it can lead to pain and decreased concentration [265]. In order to keep the v-BCI and a-BCI systems useful for daily usage, mental tiredness should be minimised to the greatest extent feasible. These systems require visual or aural stimulation. Generally speaking, this can be accomplished by enhancing the stimuli' physical characteristics. Visual fatigue is now one of the most significant drawbacks of v-BCI systems, severely limiting their applicability in practical applications. Researchers have worked hard to optimise the physical characteristics of the visual stimuli in an effort to address this issue and lessen the pain.

4. Conclusions: Presently, researchers are highly interested in non-invasive BCIs. The advancements in computational capabilities, signal processing methodologies, ergonomically designed and low-cost sensors, and excellent temporal resolutions of EEG devices are all such positive factors that make the BCI system more accessible to the scientific community and the typical user. The article describes the EEG-based BCI paradigms in depth. Their applications, usability, and how to choose the accurate, reliable and most convenient paradigm for the specific BCIs all are explained in the article. The advantages of visual BCIs over the sensory and cognition-related paradigms are also described. The revolutionary hyper-scanning-based paradigm, its usability, benefits are also included in the article. Finally, challenges in present EEG-based BCI paradigms and their solutions are also discussed in this article.

Funding statement: The authors received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflicts of interest: The authors have no conflicts of interest to declare.

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