How Visual Stimuli Evoked P300 is Transforming the Brain–Computer Interface Landscape: A PRISMA Compliant Systematic Review

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***Abstract*— Non-invasive Visual Stimuli evoked-EEG-based P300 BCIs have gained immense attention in recent years due to their ability to help patients with disability using BCI-controlled assistive devices and applications. In addition to the medical field, P300 BCI has applications in entertainment, robotics, and education. The current article systematically reviews 147 articles that were published between 2006-2021*. Articles that pass the pre-defined criteria are included in the study. Further, classification based on their primary focus, including article orientation, participants' age groups, tasks given, databases, the EEG devices used in the studies, classification models, and application domain, is performed. The application-based classification considers a vast horizon, including medical assessment, assistance, diagnosis, applications, robotics, entertainment, etc. The analysis highlights an increasing potential for P300 detection using visual stimuli as a prominent and legitimate research area and demonstrates a significant growth in the research interest in the field of BCI spellers utilizing P300. This expansion was largely driven by the spread of wireless EEG devices, advances in computational intelligence methods, machine learning, neural networks and deep learning.**

***Index Terms*— Brain–computer interface, electroencephalogram, P300, event related potential, machine learning, deep learning.**

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I. Introduction

A. Background

BRAIN-COMPUTER Interface (BCI) is an electrical brain activity measuring and interpretation technology (or mechanism) that generates control commands which further replace(s), restore(s), and/ or enhance(s) user capability bypassing the Human Central Nervous System. The BCI can be used as an assistive, adaptive, and rehabilitative technology to help monitor Electroencephalogram (EEG) activity and translate its features into commands to control various assistive applications.

To identify a person's intent for BCI, event-related potentials (ERPs), which correlate to stimulation in electroencephalography, are employed. The ERPs measure the variations in brain voltage that occur after the commencement of a distinct visual, auditory, or other sensory stimuli, as well as signals activating the motor preparation, motor execution, or covert mental functions. Time-locked ERPs aid in recording brain activity associated with both sensory and cognitive processes. Figure 1(e) illustrates the trend observed in ERP usage in BCI research over the last 20 years. The P300 [136] is a highly studied and referred ERP in BCI research. A P300 wave is an ERP component evoked roughly 300*ms* after the target stimulus is delivered, which is alternated with standard stimuli to generate a "oddball" paradigm in which two stimuli are presented randomly, one of which happens less frequently than the other (i.e., the oddball). The chance of an infrequent or task-related stimulus is inversely proportional to the magnitude of the P300 evoked potential. The BCI Speller [136] is an essential technology that may use P300 ERPs to work. A BCI speller is an application used to stimulate source-induced EEG signals to recognize the patients' anticipated characters. A P300 BCI may be described as a subject looking at a display with flashing characters, images, arrows, pictograms, etc and picking one character by paying attention to it. Figure 1(f) illustrates the trends observed in the usage of P300 in publications over the past 15 years.

B. Motivation

Reviewing past 20 years of research in BCI, it is evident that there has been a dramatic growth in the research field

TABLE I

COMPARISON BETWEEN THE PROPOSED ARTICLE AND THE EXISTING REVIEW ARTICLES BASED ON KEY FOCUS AREAS

Year	Study	Focus Areas					PRISMA Compliance	Description
		1	2	3	4	5		
2011	Mak et al. [145]	✓	×	×	×	×	×	These articles review studies that discuss P300 BCI over past years and presents a general description of one or more aspects like P300 spellers, signal recording, feature extraction methods and also discuss the recent trends, challenges faced, and the future scope of using P300 in different BCI applications.
2011	Hubert Cecotti [138]	✓	×	×	×	×	×	
2012	Fazel-Rezai et al. [137]	✓	×	×	×	×	×	
2020	Allison et al. [136]	✓	×	×	×	×	×	
2010	Syan and Harnarinesingh [142]	×	✓	×	×	×	×	These articles evaluate various classification techniques deployed over past years, types of spellers used, and which among those classification techniques provided best accuracy. Also discusses pre-processing techniques best suited for different classifiers.
2018	Lotte et al. [141]	×	✓	×	×	×	×	
2014	Marchetti and Priftis [126]	×	×	✓	×	×	✓	Amyotrophic Lateral Sclerosis (ALS)
2020	Wen et al. [125]	×	×	✓	×	×	✓	Rehabilitation in Neurological Disorders
2013	Feess et al. [147]	×	×	×	×	✓	×	Discusses optimal sensor selection approaches and their selection criteria based on reducing set of sensors.
2013	Kaplan et al. [139]	×	×	×	✓	×	×	Entertainment
2015	Zhao et al. [143]	×	×	×	✓	×	×	
2018	Cattan et al. [140]	×	×	×	✓	×	×	
2015	Al-qaysi et al. [146]	×	×	×	✓	×	✓	Motion (Mobility)
2020	Fang et al. [144]	×	×	×	✓	×	✓	
2023	**Proposed Study**	✓	✓	✓	✓	✓	✓	Discusses all listed focus areas in P300 BCI

Note- 1: General, 2: Classification & Pre-processing, 3: Application (Medical), 4: Application (Non-Medical), 5: Others. Notations ✓: Yes, and ×: No

(see Figure 1(e)). The influx of researchers from several areas such as clinical neurology, artificial intelligence, medical physics, and biomedical engineering has significantly grown BCI research. Many companies are now partnering with researchers worldwide to develop and test BCI technologies.

Various stimuli- visual, auditory, etc.- can elicit the P300 peak. Most studies have focused on BCIs designed for visual stimuli. Visual stimulation creates a spatial value for the target stimuli that projects onto the fovea in the retina. In contrast, non-target stimuli appear on the periphery of the visual field resulting in the differences in amplitudes of the corresponding Visually-evoked potentials (VEPs), resulting in high accuracy. However, during extended BCI operation, by both healthy individuals and patients with post-stroke and post-traumatic disorders (for whom the BCI technology is primarily designed), it becomes difficult to achieve high operating accuracy due to the requirement of continuously drawing attention to one or another character of a matrix.

C. Contributions

The current article is focused explicitly on BCIs using visual stimuli to elicit the P300 wave. We categorize the publications based on their: primary focus, orientation, participant age groups, assigned tasks, databases, the EEG devices used, classification models, and application domain (see Section III). We systematically include relevant publications that meet the defined criteria in the review. The application-based classification comprises of a vast horizon, including medical assessment, assistance, diagnosis, applications, robotics, entertainment, etc. Further, based on the classification, challenges in P300 BCI are discussed. While many of these challenges have previously been identified in different studies, these studies do not systematically put forth a comprehensive viewpoint. Given these complex issues of P300-based BCI design, current trends and future scope are discussed. Table I presents the systematic comparison of the present review with existing reviews, highlighting the need for the proposed review article.

The remaining article is organized as follows. Section II discusses the proposed article selection criteria followed in this study. Section III presents an in-depth discussion of the selected articles and their findings. The challenges and the current trends and future scope of the study are elaborated in Section IV and Section V respectively. Finally, the conclusions are presented in Section VI.

II. PRISMA-COMPLIANT RESEARCH METHODOLOGY

Articles on "ERP" are distributed across journals of various disciplines including social sciences, medical and non-medical. The current review uses a PRISMA-based systematic article selection approach (refer to Figure 1(a)). A literature classification scheme is developed to reveal how selected articles are classified. This system is based on classifying articles of various types depending on the research focus of the 147 articles that remained after filtering. A pictorial depiction of these categories, sub-categories and their relationships is shown in Figure 1(g). The research methodology is discussed in detail in the supplementary material.

III. RESULTS AND DISCUSSION

An exhaustive and comprehensive insight into EEG-based BCI systems is generated using 147 articles based on P300 ERP from 15 online databases and 53 different high quality journals. Figures 1(b) to (d) present an illustrative overview of publications, including temporal trends and information about the research domain, online databases, and the journal.

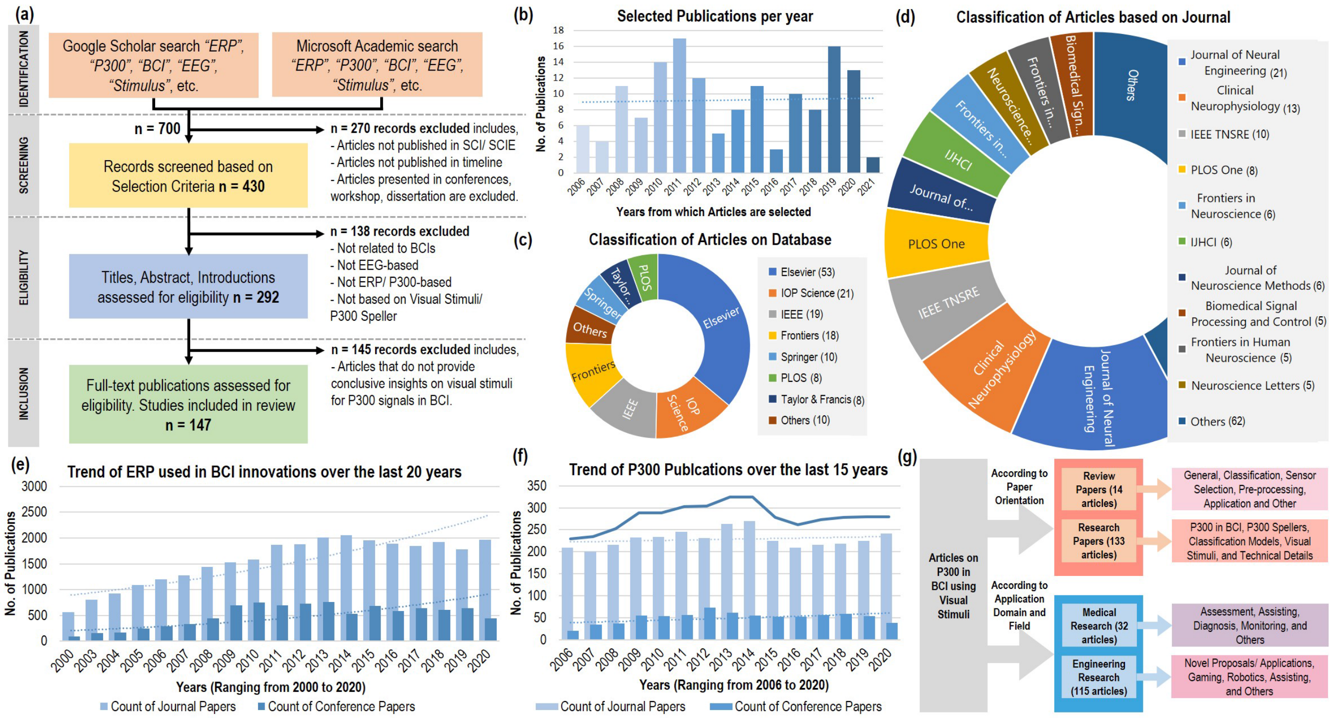

Fig. 1. (a) Procedure followed in selecting articles used in the study. (b) Bar graph between the number of publications over the years. Article classification based on (c) Database (d) Journal. (e) Trend of ERP used in BCI innovations over the last 20 years. (f) Trend of P300 publications over the last 15 years. (g) Classification of selected articles used in the study.

A. Classification by Article Orientation

1) Research Articles: There are 133 research articles published from 2006 to 2021*. Technical aspects of designing and implementing various P300 spellers are vital, and several techniques and design challenges are encountered during the selection process. Therefore, relevant information is extracted from the detailed study including participants and their age groups, EEG devices, datasets, and classification models.

2) Review Articles: 14 review articles are divided into 4 categories: general, classification, application, and others. These review articles are divided into categories such as general reviews (4), classification and pre-processing methods (2), application reviews (7), and one other review article based on sensor selection. Articles in the general category focus on past trends, current trends, current limitations, and the future scope of the design application of BCI using P300. Classification and pre-processing category manuscripts provided a comprehensive comparison between the techniques. Articles included in the application category are further divided into the medical and non-medical domains, which discuss different applications of P300; the article in the other category discussed approaches for sensor selection for recording EEG data.

B. Classification by Participant's Age and Tasks Given

Many articles deduce their results based on P300 detection experiments conducted on various participant age groups. We found most frequently appearing subjects were between 20-30 years old in 50.51% of articles. Most studies have preferred this age group since they are more active, respond better to a stimulus required for P300 detection, and achieve

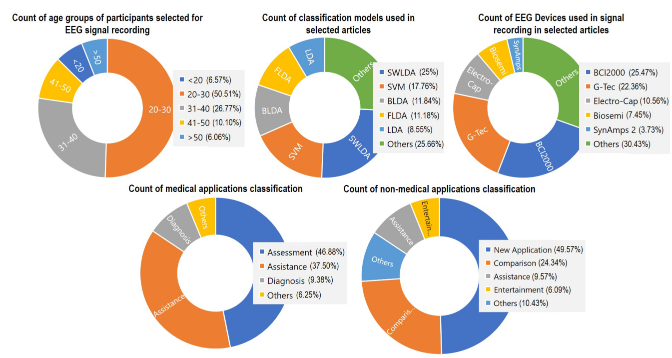

Fig. 2. (a) Count of participant age groups selected for EEG signal recording (b) Count of classification models used in selected articles (c) Count of EEG Devices used in signal recording (d) Count of medical applications classification (e) Count of non-medical applications classification.

better efficiency. Few studies (26.77%) have preferred an even higher age group of $31 - 40$ years old. The plot for the different age groups of the participants selected for EEG signal recording in the articles is shown in Figure 2(a).

For the collection of EEG data, most studies make participants perform several individual tasks. A popular experiment is using an 8×9 matrix of letters, numbers, and other keyboard commands. In a study, 29 participants completed the same 58 character sentence (i.e., correcting for errors) using the predictive speller (PS) and the non-predictive speller (NS), counterbalanced. The PS produced significantly higher output characters per minute (OCMs) than the NS. The time to complete the task in the PS condition was 12 min 43 secs

TABLE II
ELECTROENCEPHALOGRAPHY (EEG) DEVICES

Devices	Count	References
BCI2000	41	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41]
G-tec	29	[2], [42], [43], [7], [9], [10], [44], [45], [46], [23], [47], [48], [49], [50], [51], [52], [53], [29], [54], [55], [56], [57], [58], [59], [60], [40], [61], [62], [63]
Electro-Cap Intl.	17	[9], [19], [24], [30], [32], [45], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74]
BioSemi Active 2	12	[4], [20], [41], [75], [76], [77], [78], [79], [80], [81], [82], [83]
SynAmps 2	6	[72], [84], [85], [86], [87], [88]

TABLE III
CLASSIFICATION MODELS USED IN DIFFERENT ARTICLES

Models	Count	References
SWLDA	38	[1], [2], [7], [9], [10], [13], [14], [17], [18], [20], [22], [24], [26], [32], [42], [43], [46], [48], [57], [59], [64], [65], [66], [68], [69], [73], [75], [86], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99]
SVM	27	[4], [6], [13], [15], [16], [25], [27], [30], [39], [41], [64], [76], [78], [79], [84], [86], [92], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107]
BLDA	18	[22], [44], [48], [50], [51], [52], [53], [55], [58], [62], [77], [85], [86], [87], [88], [101], [108], [109]
FLDA	17	[17], [51], [52], [54], [56], [64], [77], [79], [83], [98], [107], [110], [111], [112], [113], [114], [115]
LDA	13	[16], [20], [38], [39], [41], [46], [47], [63], [92], [111], [116], [117], [118]

TABLE IV
DATASETS USED IN THE ARTICLES

Datasets	Count	References
BCI Competition III: Dataset II	12	[4], [8], [12], [13], [15], [22], [30], [34], [35], [36], [37], [39]
BCI Competition II: Dataset IIb	7	[8], [12], [21], [31], [35], [36], [37]
BNCI Horizon 2020	2	[36], [37]
P300 ALS	1	[23]
2018 WRC BCI Contest	1	[38]
P300-LINI	1	[37]

compared to 20 min 20 secs in the NS condition [13]. Another study proposed a novel 2×3 matrix consisting of home appliances visuals as a P300 paradigm task. Once the matrix visualization was completed, auditory feedback was provided, and the chosen command was executed. It enabled six menus to be navigated for handling six electronic systems with up to 30 control commands [115].

C. Classification by Datasets

Though BCI has gained immense attention in recent years, only limited BCI datasets are available. These are open-source and used by most researchers to test proposed spellers. Table IV lists some important datasets and corresponding references to the articles where these were used. However, most of the finalized articles discussed in the present review recorded and used the EEG signals during the experiments. These are described in Supplementary Material.

D. Classification by EEG Devices

A total of 36 different EEG devices have been utilized across research articles for collecting training and testing data. Out of the EEG devices used for data collection, BCI2000 was the most commonly used (41 articles). Other prominent devices include G-Tec, Electro-Cap International, BioSemi Active Two, and SynAmps 2. Table III provides the count of all EEG devices used in the selected articles. These EEG devices are described in detail in Supplementary Material.

E. Classification by Classification Models

The classification algorithm used in designing a BCI is primarily determined by the type of brain signals recorded and application controlled. Various ML (including SVM, SWLDA, FLDA, LDA) and deep learning approaches have been suggested in the literature. The count of all classification models employed in the selected studies is provided in Table III and Figure 2(b). These classification models are described in detail in the Supplementary Material.

F. Classification of Articles by Application Domain/ Field

The finalized 147 articles are further classified into real-world application domains, i.e., medical and non-medical applications. 32 of 147 articles are classified as medical applications, while the remaining 115 are classified as non-medical. The sub-classification of medical and non-medical articles are shown in Figure 2 (d-e) and Table V-VI.

1) Medical Applications: P300 BCI systems are useful for medical purposes and widely used to analyze neurological disorders, such as ADHD, Schizophrenia, etc.

a) Assessment: Typically, neurological studies strive to understand how defects in brain functioning can result in a variety of neuro-biological disorders that impact countless individuals worldwide. These studies are conducted to discover the changes other patients perceive when stimuli are generated.

b) Assistance: It discusses various test spellers that use visual stimuli. The experiments are carried out on healthy patients and people with specific neurological disabilities. These experiments focused on discovering how people with these disabilities could be helped and what new findings can ease their daily lives. The spellers used for collecting data provided helpful insights with respect to participants with specific disabilities. Example, using see-through head-mount display (HMD) to create control panels with flicker visual stimuli for motor disabled patients [7].

c) Diagnosis: It presents articles that discuss novel algorithms that could be used for helping patients with disabilities.

TABLE V
MEDICAL APPLICATIONS CLASSIFICATION

Focus	Count	Brief Description	References
Assessment	15	These articles assess performance as achieved from different speller types based on accuracy for ALS patients compared to those of healthy subjects. They also focus on patients with neurological disabilities and responding to various stimuli used during EEG signal recording.	[5], [10], [14], [23], [45], [47], [50], [54], [58], [60], [72], [73], [77], [96], [119]
Assistance	12	These provide insight into technologies for a patient with a disorder/learning problem through assistive tools like Home Appliances linked with P300 spellers, etc. Assistance occurs after P300 detection, which provides insight to identify skills and limitations of potential users.	[2], [6], [7], [9], [20], [33], [67], [68], [71], [120], [121], [122]
Diagnosis	3	These articles describe how P300 can be used for interpretation of a neurological disorder/ learning problem. They also talk about how P300 can be combined with psychological factors like motivation, introspective awareness, etc., to analyze user performance. The goal of these articles was to accurately detect disorders that are difficult to diagnose using subjective means.	[11], [123], [124]
Others	2	These report previous research efforts and serve to increase awareness of P300 and its applications in clinical practices to uncover potential neuro-physiological abnormalities.	[125], [126]

TABLE VI
NON-MEDICAL APPLICATIONS CLASSIFICATION

Focus	Count	Brief Description	References
New Method/ Application	57	These articles propose new spellers/ approaches for detecting P300 signals using different classification algorithms, signal processing methods, including feature extraction, selection, machine learning, and signal acquisition methods. These proposed systems aim to help in improving P300 detection accuracy by providing novel solutions.	[1], [3], [4], [8], [12], [13], [15], [17], [19], [21], [22], [25], [26], [27], [29], [31], [32], [34], [35], [36], [38], [39], [44], [46], [51], [57], [61], [63], [65], [66], [75], [78], [79], [81], [84], [85], [86], [87], [89], [90], [92], [93], [98], [102], [105], [107], [109], [110], [112], [115], [118], [127], [128], [129], [130], [131], [132]
Comparisons	28	These compare spellers, P300 detection methods, classifications and pre-processing techniques and determine their accuracy in different conditions. This help to determine most suitable parameters.	[16], [18], [24], [37], [41], [42], [43], [48], [52], [53], [56], [59], [62], [64], [69], [74], [76], [82], [83], [88], [91], [94], [95], [100], [101], [111], [116], [133]
Assistance	11	These articles show how different technologies can help assist patients with neurological disorders and in daily life procedures. These are used to improve behaviour, cognition, and mobility.	[28], [30], [40], [49], [55], [97], [99], [104], [109], [114], [134]
Entertainment/ Robotics	7	These articles observe relationship between P300 detection and different AR/ VR, board games, etc., used for designing spellers.	[70], [80], [103], [106], [113], [117], [135]
Others	12	These articles present a review based on classification techniques, speller designs, electrodes used for signal recording, etc.	[136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147]

They also compared how the proposed model was better than the present and how the P300 signal can help people interact with their surroundings more easily. These included helping them assess lights, doors, TV, etc. The results benefit people with diseases like spinal cord injury, spastic cerebral palsy, and locomotive disease. These articles provided much less talk about the application of EEG in diagnosing certain neurological disorders. The studies discussed how present results extended previous findings and provided even more convincing evidence of Heart Rate Variability's (HRV) capacity to index prefrontal inhibition in tasks requiring executive control.

d) Other: It discusses the subject's specific disease and provides a detailed study on the classification processes and spellers that will produce the best results. These articles also included detailed studies on previous research on various subjects as well as the future scope of research.

2) Non-Medical Applications: BCI has been used in various non-medical applications being employed for both healthy and disabled subjects, as discussed here.

a) New application: This category discusses various new spellers that provide better accuracy for specific classification algorithms, sensors, etc., by using visual stimuli like arrows of different colors or using faces as stimuli for greater attention, 3d speller, etc. These also discussed about different spellers that have not been used, such as using Devanagari characters instead of the usual English alphabets. The articles used various new pre-processing techniques and new approaches helping to reduce complexity and increase user interaction.

b) Comparison: These articles focus on building a comparison based upon paradigms, spellers, visual stimulus, analysis of best sensors, etc. A thorough comparison of classification techniques showed that SWLDA has potential advantages over other classification techniques because of its capability to eliminate insignificant features for large, unknown feature spaces. One of the articles proposed a novel approach of using dummy faces that are easy to edit for optimizing BCI stimuli.

c) Assistance: These articles provide valuable insights on making the current model optimal for better results and efficiency, giving spellers ease of gaze, in turn reducing fatigue. It also helps to understand how different hardware devices or locomotives like wheelchairs can be integrated with the speller systems. These research proposals are vital due to the expected progress of BCI-based technologies for controlling prosthetic devices, manipulators, and mobile robots.

d) Robotics: These articles provide a new direction to research for robotics and entertainment, which can be accessible to disabled people. One of the articles explores the concreteness of robot motion images on ERPs, which resulted in larger N200 and P300 potentials. It shows that brain signals can be used to command a humanoid robot for various tasks.

e) Entertainment: Various articles explored entertainment as a field to be made accessible for these people by providing them dynamic motion stimuli in addition to audio-visual ones and helping them to interact directly with virtual objects. One of the articles presents the possibility of composing complex music pieces encouraging self-expression for severely disabled people. Another article proposed a BCI game where P300 ERPs are translated into movements of a character on a 3D game board to provide richer interaction.

f) Others: The collection of these articles discuss BCI developments and their limitations. The articles include research outcomes based on reduced wheelchair drive-related risk factors and develop better control of wheelchair mobility and applications in various other fields like gaming, painting, etc.

IV. Challenges

There are many challenges in P300 BCI. First, a significant challenge in P300 BCI is that of "replication". There exists extreme variability in elicitation of P300 signals across different sessions as they provide varying results. This variability is true even for healthy patients. This necessitates additional training sessions [12], [15], [27], [84].

Second, the classification processes or the computation of results which takes more than 1 or 2 sessions of data recording, making it a time-consuming procedure that exploits several computational resources and results in higher costs in terms of system integration and human capitalization [12].

Third, the results obtained from P300 detection-based devices often tend to be inaccurate because P300 detection is a "gaze-dependent process", which makes it challenging especially for people with disabilities to concentrate for an extended period [5], [79], [88], [97], [101], [107], [108], [120], [127]. Moreover, the conducted experiments are relatively unfamiliar for all subjects and have real-time constraints, so much so that once results are obtained, they cannot be changed after the recording is completed.

Fourth, the sophisticated and delicate nature of P300 controlled devices make them challenging to handle and prone to many safety issues [137], [145]. Even a small paradox can result in high variance from the actual recordings. Non-invasive BCI devices, which allow for sending messages or commands to devices or people to direct non-invasive measures of brain activity, unfortunately, detect only a few brain signals making it difficult to get accurate results.

Many end-users want a device to accomplish a goal, such as moving a wheelchair to a particular room or directing a mobile robot to retrieve an item [80]. Therefore, BCI systems must manage tasks such as finding a path to the target location and avoiding obstacles or directing the movements of a robotic arm [80]. BCIs for spelling and other goals do not require this intermediate computation layer. This "shared control" can require extensive additional programming and testing.

V. Current Trends and Future Scope

Recently, a P300-based system has been developed to select different actions [97], including switching on TV to control an innovative home environment. The BCI system was combined with a P300 system to switch on/off the flashing matrix. The speller consists of images of devices like TV, Refrigerator, AC, etc. This helps people with disabilities to control their environment with the help of BCI system [97]. Using various algorithms like ANN, CNN, and other deep learning algorithms for classification has increased the accuracy of generated results [6], [8], [12], [16], [35], [37], [72], [76], [81], [101].

The CNN's can directly take multi-dimensional data as input, avoiding the complicated artificial feature extraction processes, which can extract specific feature information. Novel GUIs that use familiar faces as the target instead of letters or characters are widely used [19], [42], [50], [53], [85], [88]. It produces better results than a simple character or letter-based speller and is currently being researched extensively. Moreover, articles are coming up with processes and techniques to improve the process's speed and reduce the latency of the procedure so that the results are more accurate [12], [78], [81], [130]. Nowadays, P300 is being used increasingly in communication in the fields of entertainment as well [139], [140]. It has made many advancements in household appliances, virtual reality, etc [6], [103], [125], [140]. P300 BCIs are also used to control wheelchairs which can help people control them without anyone else's assistance [49], [97], [105], [110], [146]. Its increasing use in robotics has given an edge to the research being carried out for the same [80], [105], [143].

The crucial problem to be addressed when designing a practical BCI is to reduce the considerable space of features extracted from raw EEG signals. One of the strategies used for feature selection is based on genetic algorithms [99]. The BCIs that facilitate the completion of more natural or intuitive tasks seem to have been shown to yield numerous benefits. The development of the P300 BCI application known as "Brain Painting (BP)" was created with a "user-centered design" in mind. By analyzing the wishes of end-users, e.g., patients diagnosed with Amyotrophic Lateral Sclerosis, the BP application fulfills basic human requirements of assisting expression, albeit through an "alternative communication channel" [68]. In this case, the alternative channel as a creative means of picture drawing has resulted in a novel BCI design. It improves mood, motivation, and quality of life in patient users [123]. The positive emotions exhibited during creative and playful expression have been well documented ins helping with patient rehabilitation [123]. One of the areas where there is much scope for research is using ECoG for recording the P300 signals. Present models use scalp-based EEG recordings, which are limited to the communication performance of a few speller characters per minute. ECoG improves the performance by 3 to 4 times and has higher temporal and spatial resolution than scalp EEG. It also does not suffer from the attenuation of signals by the skull and scalp. Therefore, ECoG has a significantly better SNR than scalp EEG. Many researchers are working on creating BCI robots and wheelchairs [49], [80], [97], [105], [110], [143], [146]. Different optimizations, spellers, and classification techniques have been introduced to improve how these robots can be controlled better. It will be beneficial for patients with disabilities, who can handle things with the help of BCI and require minimum human assistance.

VI. Conclusion and Future Work

Recent developments in BCI technologies have facilitated the detection of P300 signals. They have helped to elicit valuable insights on brain activity and leveraging to ease the lives of specially-abled people. In addition, many research articles suggest novel ideas in terms of classification, feature extraction technique, use of some particular sensor, or use of other language or shapes for the spellers. The proposed methods improved accuracy and decreased latency and proved to be the stepping stones for research in these fields. The study aimed to review published articles on BCI, P300, visual stimuli, and current and future trends in these fields. We mined 15 online databases, selected 50 journals, and extracted 147 articles on P300 detection systems. Each article is differentiated, sorted, and analyzed according to the publication year, classification process, EEG device used, the dataset used, and domain.

There are few systematic reviews on P300 detection using visual stimuli; even if present, they have used auditory stimuli or a hybrid of auditory and visual stimuli. P300 has not been used as the principal ERP for collecting EEG data in many research articles, so reviewing articles that have used P300 potential has also opened up new avenues for research in the same. This review also details various advancements that have taken place in the field over the past 15 years and will help pave the way for future research in this field. There has been an increase in the number of published articles over the years. Scientists are using this technology for medical diagnosis, assistance, telecommunication, entertainment, robotics, etc. As anticipated by any new research field, EEG-based P300 detection and recognition is fraught with challenges. Nevertheless, the challenges provide zeal for researchers to work through them and give new innovative and life-changing breakthroughs to the field. It is highly recommended to consider various algorithms for validating proposed processes, including pre-processing and classification techniques. It is advised to compare the accuracy achieved by deploying various classification techniques before selecting the most appropriate technique per various parameters considered.

The present study was confined to "Visual Stimuli evoked P300-based BCI". Future work can focus on reviewing other categories of the EEG Signals like SSVEP(s) [148], EEG-EOG [149], miniature-event-related potentials [151], and stimuli like tactical stimuli [150], very small lateral stimuli [151], decoding N2pc components [152], tensor based frequency features combinations [153], etc.

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