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SURVEY

Brain–Computer Interface Controlled Drones: A Systematic Review

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ABSTRACT The goal of this systematic review is to examine the use of Brain-Computer Interfaces (BCIs) for controlling unmanned aerial vehicles (UAVs) in real-time. A comprehensive search across various online databases, including IEEE Explore, ScienceDirect, MDPI and PubMed, using the PRISMA research method, was conducted. The total of 42 experimental studies were identified, analyzed, and included in the final report. The review highlights several important research directions and areas that require further investigation in the field. Additionally, it identifies potential future possibilities and trends in BCI-controlled UAVs. Lastly, the review outlines the future challenges that researchers are likely to encounter, aiming to provide valuable insights and guidance for future studies in this area. To the authors' best knowledge, this systematic review represents the most extensive analysis in literature, both in terms of the number of studies included and the span of years considered.

INDEX TERMS Brain-computer interface (BCI), drones, unmanned aerial vehicles (UAVs), electroencephalography (EEG), BCI-controlled drones, systematic review.

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) have been a topic of increasing interest in recent years, as advancements in technology have made it possible to directly communicate with the human brain in new and exciting ways. BCIs refer to systems that enable direct communication between the brain and a computer, typically using non-invasive or invasive techniques. BCIs have the potential to revolutionize several fields, from medicine and rehabilitation to gaming and entertainment [1].

Non-invasive BCIs [2] rely on electroencephalography (EEG) technology to detect and interpret neural activity from the scalp. By analyzing patterns in EEG signals, researchers can develop algorithms that can be employed to control external devices, such as prosthetic limbs or wheelchairs, using only the user's thoughts. On the other hand, invasive BCIs [3] involves the placement of the electrodes directly into the brain. These electrodes can provide a more detailed and precise signal, without noise and artifacts, than non-invasive techniques, but they are also risky and are typically used for medical applications.

BCIs can improve the quality of life for people with disabilities, advance medical research, enhance productivity and performance, and improve safety and security in various settings [4], [5]. By enabling people with disabilities to control robotic arms, wheelchairs, or other assistive technologies, BCIs offer increased independence and new means of communication [6]. BCIs can increase efficiency and reduce the risk of repetitive stress injuries since they provide new ways of interacting with computers and other devices. Additionally, this technology can improve safety and security by controlling unmanned vehicles such as drones and identifying individuals based on brain patterns. The benefits of BCIs are only expected to increase as the technology continues to develop.

While BCIs have remarkable possibilities, there are also significant challenges that should be addressed for their wider adoption and impact. Firstly, the technology is still limited in terms of the precision and accuracy of brain signal

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detection and pattern recognition. This can result in a high error rate and reduced reliability of BCI systems, especially for real-world applications [7]. Secondly, there are issues with the adaptability of BCIs, due to the unique variations in individuals' brain signals which leads to personalized training and calibration. This can make it challenging to develop standardized and widely used BCI systems [6]. Thirdly, the use of invasive techniques (such as implantable electrodes) raises ethical concerns regarding patient safety. Additionally, there are concerns regarding the privacy and security of EEG data, as well as potential misuse by unauthorized parties. Overall, while BCIs offer exciting capabilities, significant technological and ethical challenges must be addressed to fully achieve their full potential.

Steady-state visually evoked potential (SSVEP) BCIs are a popular type of non-invasive BCI that rely on visual stimulation to evoke a stable, periodic response in the brain's electrical activity. This response, which occurs at the same frequency as the visual stimulus, can be detected and utilized to control a BCI system. SSVEP BCIs have several advantages over other BCI approaches, including high accuracy, fast response time, and low training requirements. They have been successfully used for a range of applications, including navigation, communication, and control of robotic devices [8], [9].

Despite their great potential, SSVEP-based BCIs also have some disadvantages. One disadvantage is the potential for interference from other visual stimuli that may be present in the user's environment, resulting in reduced accuracy and reliability of the system. Also, the limited number of distinct SSVEP frequencies that can be used without causing unwanted overlap or interference, can limit the number of commands that can be reliably detected [5]. Nevertheless, SSVEP-based BCIs are still a very promising technique for designing practical, reliable, and easy-to-use BCI systems.

P300-based BCIs are another popular type of non-invasive BCI that rely on the P300 event-related potential, which is a positive deflection in the brain's electrical activity that occurs approximately 300 milliseconds after a rare or unexpected stimulus is presented. They typically use an "oddball" paradigm, in which the user is presented with a series of stimuli, one of which is infrequent or unexpected, and the system detects the P300 response to the rare stimulus [10]. P300 BCIs have several advantages over the other approaches, including high information transfer rates, low training requirements, and relatively low susceptibility to interference from other stimuli.

Despite their advantages, P300 BCIs also face some challenges [11], [12]. One challenge is the relatively low signal-to-noise ratio of the P300 response, which can make it difficult to reliably detect and distinguish from other sources of noise. Another challenge is the limited number of stimuli that can be presented in the oddball paradigm, which can limit the number of commands that can be detected. Nevertheless, P300-based BCIs remain a promising approach for developing practical, accurate, and efficient BCI systems.

Motor Imagery (MI) BCIs are a widely used type of non-invasive BCI that rely on the user's ability to imagine performing a particular movement, such as moving a hand, or a leg, or making a specific gesture [13]. They can detect changes in the brain's electrical activity that correspond to the imagined movement, typically using EEG recordings. These changes can be translated into commands that control a device or an application.

One advantage of this BCI paradigm is that it can be employed to control a wide range of devices and applications, including prosthetic limbs, robotic devices, and virtual environments. MI BCIs are also relatively easy to use, as most people are able to imagine simple movements without requiring extensive training.

However, MI BCIs also have some disadvantages. One disadvantage is the variability in the brain patterns generated by different people, which can make it difficult to develop a universal BCI system that works accurately for everyone. Also, users must maintain focus and concentration while imagining movements, which can lead to frequent breaks due to mental fatigue [14]. Nevertheless, MI-based BCIs hold significant potential for improving the quality of life for individuals with disabilities and for enabling new forms of human-machine interaction.

The five primary components of a BCI system are: Signal Acquisition, Signal Processing, Feature Extraction, Feature Translation, and Device Output [15]. The first step is to record brain activity through Signal Acquisition, and then eliminate noise using Signal Processing. The signal is then filtered to extract features for the classification process in Feature Extraction. The classifier is responsible for converting the brain signals into commands for applications. Finally, most BCI systems provide feedback and allow the user to retrain themselves Fig. 1.

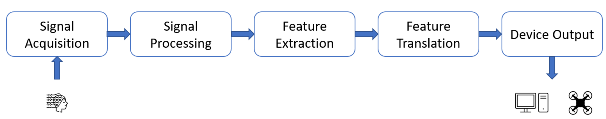

FIGURE 1. The five key components of a BCI system are presented in the figure: Signal acquisition, signal processing, feature extraction and translation, and device output.

BCI technology represents an exciting advancement in drone control, envisioning a future where human cognitive functions directly engage with aerial navigation. The application scope of BCI-controlled UAVs goes beyond conventional domains such as search and rescue missions and military operations, extending into environmental monitoring, smart agricultural management, and disaster response. Employing brain signals to command and manage drones can enhance operational efficiency and can potentially advance innovation across diverse sectors.

In recent years, there have been several successful demonstrations of brain-controlled UAVs, showcasing the potential of this technology. However, several challenges still need to be addressed before BCI-controlled drones and UAVs can be widely deployed. The main challenge is the need for a reliable and accurate BCI system capable of accurately interpreting user brain patterns with minimal training. Additionally, there are concerns about the safety and security of these systems, particularly in military applications. Despite these challenges, BCI-controlled drones drive continuous exploration of new solutions and the expansion of this rapidly evolving field. Also, it's worth noting that BCI control imposes no restrictions on drone size or weight, opening up possibilities for diverse applications across a wide range of drone configurations.

This systematic review focuses on exploring the advancements and trends in the field of BCI-controlled drones and unmanned aerial vehicles (UAVs). The primary objective of this review is to comprehensively analyze existing literature, highlighting key findings and emerging trends. By synthesizing the available knowledge, we aim to identify novel directions and potential future developments in this exciting domain.

II. RESEARCH METHODOLOGY

In this study the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) [16] guidelines to acquire relevant studies. The authors conducted a thorough screening process to determine the eligibility of the articles and evaluated the risk of bias in all the included studies. Disagreements between the researchers were resolved by engaging in discussions and reaching a consensus. The review protocol has been registered with the Open Science Framework [17].

A. DATA SOURCES

To acquire all relevant papers from the literature a comprehensive search was performed in May 2023 on the following databases:

1) ScienceDirect
2) IEEE Explore
3) PubMed
4) MDPI

The following query was applied to search the databases "((BCI) OR (Brain Computer Interface) OR (EEG)) AND ((drones) OR (UAV) OR (aerial vehicles))". All articles displayed by the search have been added to Rayyan [18]. Rayyan is a web tool designed explicitly for conducting systematic and other literature reviews. It offers a user-friendly interface that allows reviewers to import articles, collaborate with other team members, and efficiently screen and categorize studies based on predefined inclusion and exclusion criteria. In total, 1.362 papers were extracted from the search and introduced to Rayyan. After duplicate and based on the exclusion criteria removal, 653 articles remained, and after the title, and abstract screening, 128 articles remained for full-text review (Fig 2).

B. INCLUSION CRITERIA

This systematic review compiles articles that have focused on the development of BCI-controlled drones, UAVs, or other aerial vehicles. The primary criteria for inclusion in this review are that the studies should:

1) provide the ability to command the drones in real-time,
2) utilize EEG signals as a means of control and
3) employ non-invasive EEG technologies

Both real and virtual drones are considered, and the review encompasses various EEG analysis techniques, including P300, SSVEP, and MI. The objective of this review is to provide a comprehensive overview of the advancements, challenges, and potential applications of BCI-controlled drones and aerial vehicles while emphasizing the importance of real-time control and the utilization of EEG signals.

C. EXCLUSION CRITERIA

Several articles have been omitted from this review based on the following criteria:

1) Review articles (these studies have been used for comparison purposes, see Section V)
2) Book chapters and Encyclopedias
3) Conference info
4) Articles that were not written in English
5) Datasets
6) Research on animals
7) Meta-Analysis articles
8) Not BCI/EEG papers
9) Invasive EEG technologies
10) No Drone/UAV/aerial vehicle (real or virtual) papers
11) No Real-time BCI
12) BCI for Mental Workload/Fatigue
13) Research for Post-traumatic Stress Disorder (PTSD) Monitoring with EEG on drone operators
14) Artificial Intelligence research
15) Research on BCI Ethics
16) Not reporting results

D. DATA SYNTHESIS

A total of 42 studies that satisfied the inclusion criteria are identified, and the extracted data are subjected to analysis. The data encompassed several key aspects, including:

1) the total number of subjects involved
2) the type of EEG equipment used
3) the number of electrodes employed
4) the specific EEG analysis techniques employed and
5) the differentiation between conference papers and article papers

These parameters were carefully examined and evaluated to provide a comprehensive understanding of the literature in this field. The included papers in this review are classified into two main categories: Real and Virtual. These categories are further subdivided based on the specific EEG analysis techniques employed by each study. Within each category,

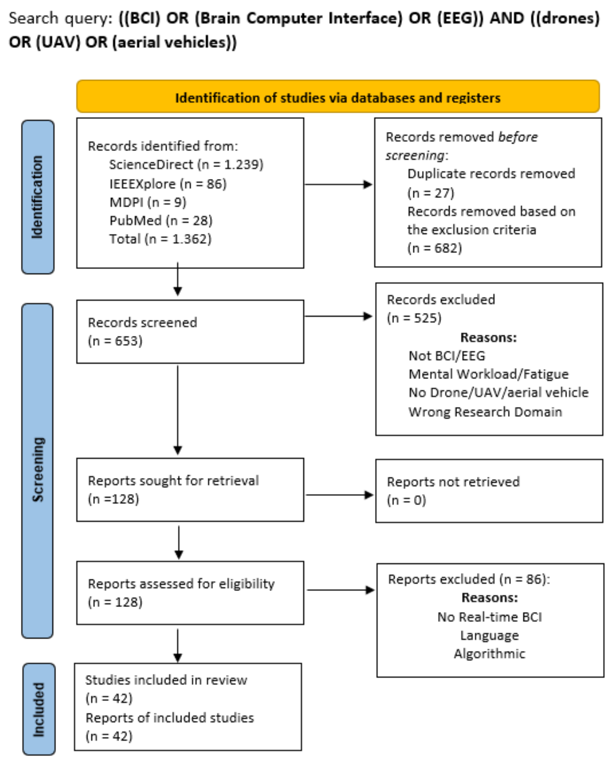

FIGURE 2. PRISMA Flowchart presenting search query, search strategy, database selection, screening process, and exclusion criteria for this review.

TABLE 1. This table presents the publication year of the 42 papers. The period of the selected papers is from 2010 to 2023.

Publication Year	Number of Articles
2023	3
2022	3
2021	14
2020	6
2019	3
2018	2
2017	2
2016	3
2015	1
2014	1
2013	3
2012	0
2011	0
2010	1
Total	**42**

the objectives, outcomes, frequency bands, preprocessing and artifact removal methods, classification methods, and statistical analysis methods are examined.

III. STUDY STATISTICS

The papers that are included in this article are published from 2010 to May 2023 (Table 1). The decision to include papers from this period is intentional since the goal of this review is to present a comprehensive overview of the advancements in BCI-controlled drones and examine the feasibility and usability of these systems. Excluding papers published before

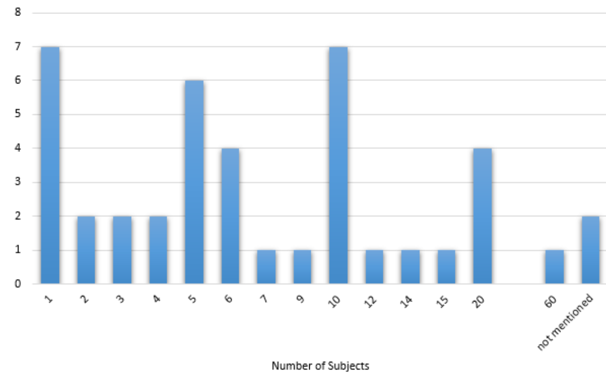

FIGURE 3. Distribution of the number of subjects employed in research papers presented in a diagram. The most frequently chosen subject group sizes include one, five, and ten.

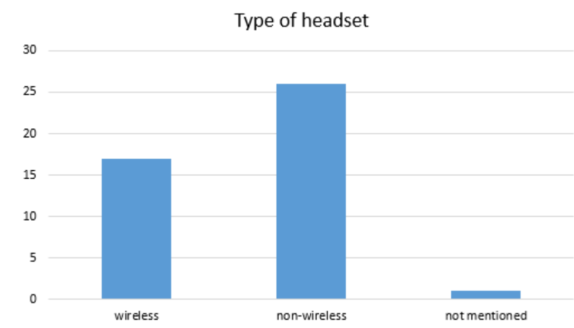

FIGURE 4. The figure presents the two types of EEG headsets, namely wireless and non-wireless, utilized in the reviewed studies. The majority of research utilized non-wireless headsets (26 papers), while newer studies tended to employ wireless headsets (16 papers).

2010 is driven by their potential obsolescence and limited relevance to the current state-of-the-art research that is rapidly evolving. Focusing on this specific timeframe is aimed to provide researchers with a coherent synthesis of relevant literature, resulting in a guideline for future efforts in developing and integrating BCI-controlled drones. The dataset comprises two types of studies: journal papers, which account for sixteen articles, and conference papers, which make up twenty-six studies.

A. SUBJECTS

In the reviewed manuscripts the number of subjects varies from one to sixty. The average number of subjects is 8.65. The most selected number of subjects are one, five, and ten, followed by six and twenty participants (Figure 3).

B. EEG DEVICES

The studies included in the analysis employed non-invasive EEG devices for data collection. These devices are categorized based on their wireless or non-wireless functionality. Out of the total studies, seventeen utilized wireless EEG devices, whereas twenty-six studies employed non-wireless EEG devices (see Fig 4). Notably, one study did not explicitly specify the type of EEG device used.

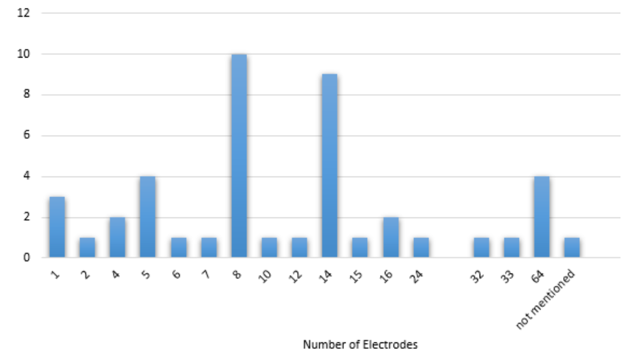

FIGURE 5. The figure displays the frequency of EEG channel usage across the reviewed studies. Eight and fourteen electrodes are the most commonly employed numbers.

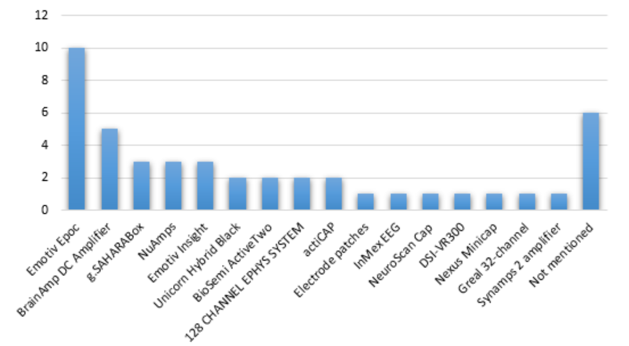

FIGURE 6. The figure presents the EEG devices utilized in the papers. The Emotiv Epoc with 8 channels emerges as the most frequently employed device.

TABLE 2. Distribution of techniques used in research articles and corresponding citations.

Technique	Number of Articles	Studies
Concentration and Eye Movement	1	[19]
Mental Arithmetic Task	2	[20] [21]
MI	19	[21]–[39]
P300	4	[40]–[43]
SSVEP	15	[21] [44]–[57]
Theta-Beta ratio	1	[58]
Visual Imagery	3	[38] [59] [60]

The studies examined in this analysis employed EEG devices with varying numbers of electrodes, ranging from one to sixty-four. The most frequently utilized numbers of electrodes were eight and fourteen, followed by sixty-four and five electrodes (Fig 5). Various EEG devices were used in the studies under review, with the Emotiv Epoc being the most frequently utilized (Fig 6).

C. EEG TECHNIQUE

The studies included in the systematic review use several EEG analysis techniques. The most common approach is MI followed by SSVEP. Additionally, some studies employ hybrid methodologies to enhance their outcomes by leveraging the advantages of each technique (see Tab 2).

TABLE 3. Distribution of articles based on drone implementation and the corresponding citations.

Type of Experiment	Number of Articles	Studies
Real	22	[19]–[26] [29]–[31] [33] [40] [42]–[47] [53] [57] [58]
Virtual	18	[27] [28] [34]–[38] [41] [48] [50]–[52] [54]–[56] [59]–[61]
Both	3	[32] [39] [49]

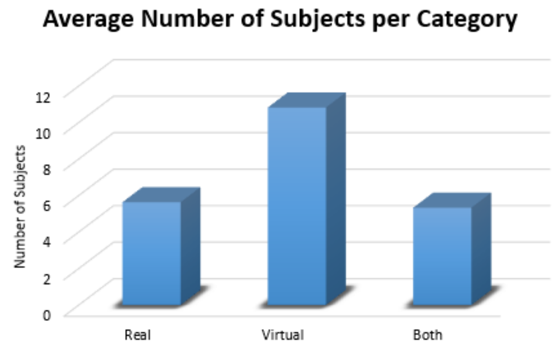

FIGURE 7. The figure displays the average number of subjects for each category. In the Real category, the average number is 5.63, for Virtual it is 10.82, and for the last category, it is 5.33.

D. REAL OR SIMULATED EXPERIMENT

The papers included in this review are categorized into two groups based on the type of experiments conducted: (a) Papers that utilized Real drones (twenty-two papers) in the experiments and (b) Papers that performed simulation in the experiments (seventeen papers). Additionally, three papers examined the performance of their BCIs by evaluating them in both simulated and real drone experiments (see Table 3).

Figure 7 illustrates the average number of subjects for each category. In the Real category, the average number of subjects is 5.63. In the Virtual category, the average number of subjects is 10.82. Lastly, in the third category, the average number of subjects is 5.33.

IV. RESULTS

This section provides an overview of the existing studies in the literature. It includes information about the number of participants involved, the processing of EEG signals, the classification algorithms used, the number of experiments conducted, and the effectiveness of each study. The studies are divided into two main categories: real or simulated UAVs. Within these categories, they are further classified into subclasses based on the type of analysis techniques employed, such as MI, SSVEP, P300, and Rest.

A. REAL DRONES OR UAVS EXPERIMENTS

This subsection focuses on studies involving real drones or UAVs. A total of twenty-two papers will be discussed and analyzed in this section. The results are grouped based on the EEG techniques employed by the primary studies.

1) MOTOR IMAGERY (MI)

The subclass mentioned, which specifically focuses on studies employing MI as their EEG technique, consists of eleven articles (Table 4) [21], [22], [23], [24], [25], [26], [29], [30], [31], [33], [39]. Additionally, one of the studies in this subclass involves the use of both a virtual and a real drone [39], while another study [21] utilizes a combination of MI, SSVEP, mental arithmetic, and eye movements.

Tothong et al. [31] developed a drone model and utilized a BCI to alter the drone's physical structure during flight. Emotiv Epoc, a fourteen-channel EEG device, was employed to collect the raw EEG data, which was then processed, trained, and classified using Emotiv's software. The study focused on three mental commands: a neutral state, push, and pull. Three participants took part in the experiments, aiming to manipulate the drone's morphology. The findings revealed that using cognitive commands proved to be faster compared to using physical actions to manipulate the drone's structure.

Marin et al. [22] developed a drone controlled by BCI utilizing the Emotiv Insight headset equipped with five sensors. The authors employed four mental commands, namely push, left MI, right MI, and neutral, to command the drone in real-time. The EEG signals were processed and classified using the Emotiv software. The system was trained and tested by a single participant, and the classified mental commands were transmitted from the Emotiv software to a Raspberry Pi Zero. Subsequently, Raspberry relayed the commands to the drone. The results indicated an 88% accuracy in successfully commanding the drone by a single user.

Shi et al. [30] designed a BCI to enable continuous control of a UAV's movement. Their approach combined MI commands with a semi-autonomous navigation system designed for obstacle detection. The study involved training three mental commands: left MI, right MI, and idle state. A ten-channel cap was used to record the raw EEG data, which were then processed using Independent Component Analysis (ICA) to remove artifacts. An improved Cross-Correlation method (CC) was employed for feature extraction. The mental commands were classified using a Logistic Regression model. The experiments included ten participants within an indoor environment. The system achieved high accuracy in both offline and real-time experiments.

Another research [25], developed a BCI-controlled drone. To record the brain signals two EEG devices were used: Emotiv Epoc with fourteen channels and Emotiv Insight with five channels. To process the signals a Bandpass filter was applied from 1 to 40Hz and the frequency bands were extracted. Then Discrete wavelet transform and an artificial neural network were employed. Twenty participants were instructed to perform four different mental tasks. Task one involved imagining the movement of the left hand, while Task two required imagining the movement of the right hand. Task three instructed participants to imagine the movement of the left hand along with finger and elbow movements, while Task four involved imagining the movement of the right hand along with finger and elbow movements. The proposed system was tested on two drones in real-time and the results showed great precision.

An et al. [26] introduced a BCI system to enable continuous control of a UAV within a 2D indoor space. Data from six subjects were recorded using a six-channel EEG cap in the study. The researchers captured two mental commands: left-hand motor imagery (MI) for flying upward or turning left, and right-hand MI for flying downward or turning right. To ensure data quality, the signals were bandpass filtered, and ICA was employed to eliminate artifacts. The classification algorithm utilized for this study was Linear Discriminant Analysis (LDA). Real-time experiments were conducted with the participation of all six subjects within an indoor environment.

Mamani et al. [23] used Emotiv Insight with five channels to command the movement of a BCI drone. To record, process, and classify the EEG data Emotiv software was employed. Five mental commands were trained: neutral state, push, pull, left MI, and right MI. A real-time experiment was conducted and the BCI drone was commanded by mental commands. The evaluation metric for this study was the effective response for every ten attempts per command. Another study [33] designed a BCI to manipulate a drone's movement using Emotiv Epoc as the EEG acquisition device. The raw data were filtered from 8-30Hz and Common Spatial Patterns (CSP) algorithm was employed for feature extraction. Two mental commands were recorded: left and right MI and classified with meta-cognitive interval type-2 neuro-fuzzy inference system (McIT2FIS). A single subject participated in the experiments in an indoor office. The classification accuracy was 80% and he managed to finish the predetermined route that the researchers had employed for real-time testing of the BCI system.

This study [24] investigated the feasibility of controlling both a single drone and a group of drones using a BCI. Emotiv Epoc was employed for recording the brain signals from a single subject. Five mental commands were recorded and trained by the participant: push, pull, left MI, Brow raise, and Clench. These commands corresponded to the actions of moving forward, moving backward, moving left, take-off, and moving right, respectively. To process the recorded signals, the researchers applied filtering techniques to remove artifacts and noise and Fast Fourier Transform (FFT) was employed to extract relevant features from the data. Two experiments were conducted, the first experiment aimed to evaluate the effectiveness of the commands in controlling a single drone, while the second experiment focused on testing the BCI system's performance in commanding a group of quadcopters.

Akce et al. [29] describes a BCI that allows remote control of unmanned aircraft using a minimal physical interface. The interface consists of an EEG for input and a graphical

TABLE 4. Real MI based BCI-controlled drones.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[31]	2021	14	3	Emotiv Software	3	Emotiv Software	Emotiv Software	Response Time
[22]	2020	5	1	Emotiv Software	4	Emotiv Software	Emotiv Software	Accuracy
[30]	2015	10	10	Logistic Regression	3	ICA	Improved Cross Correlation Method	Classification Accuracy Number of Commands Time Spent on Paths Success Rates Rotation Errors
[25]	2018	14 & 5	20	Artificial Neural Networks	4	Band Pass Filter 1-40 Hz Bands A, B, G, T, D	Discrete Wavelet Transform	Accuracy
[26]	2017	6	6	LDA	2	Band Pass Filter 0.5-30 Hz ICA	Inhomogeneous Spatial Filters	Distance Errors Rotation Errors Time Cost Classification Accuracy
[23]	2017	5	5	Emotiv Software	4	Emotiv Software	Emotiv Software	Effective Response Every 10 Attempts
[33]	2016	14	1	Meta-Cognitive Interval Type-2 Neuro-Fuzzy Inference System	2	Band Pass Filter 8-30 Hz	CSP	Classification Accuracy
[21]	2016	14, fNIRS (1)	3	LDA	5	A, B, D, T Bands	-	Commands Accuracy
[39]	2013	64	5	-	4	-	-	Average Rings per-Maximum Flight Average Ring-Acquisition Time ITR, PVC, PTC, PPC
[24]	2013	14	1	-	5	Fast Fourier Transformation (FFT)	-	-
[29]	2010	8	1	Hidden Markov Model (HMM)	2	-	Common Spatial Analytic Pattern	Time to Finish the Task

display showing video from the aircraft's onboard camera for feedback. The study involved one subject who participated in real-time experiments to test the BCI system. The evaluation metric used was the time taken to complete the assigned task. The EEG device employed was an 8-channel cap. To extract features from the EEG signals, Common Spatial Analytic Pattern (CSAP) was employed. The mental commands of left and right MI were classified using a hidden Markov model. The system also included an autopilot feature, where the operator provided commands to steer the aircraft along a predetermined route.

Lastly, one study [39] designed a virtual and a real BCI quadcopter. A sixty-four-channel EEG cap was used to record the raw EEG data from five subjects. The mental commands used to command the quadcopter were right-hand MI, left-hand MI, both-hand MI, and idle state. The participants received extensive training in virtual environments, which included tasks like controlling a cursor in one or two dimensions, operating a virtual helicopter, and simulating the control of an actual quadcopter. Once the participants became proficient in the virtual training, they were tested with the physical drone. The BCI system successfully translated their mental commands into drone control, with all subjects achieving high accuracy. The study also presented various evaluation metrics, including measures based on time and accuracy, to assess the performance of the BCI system.

2) STATISTICS

The average number of EEG channels is 14.41. The fewest number of EEG sensors reported in these papers is five [22], [23], [25] followed by six [26] and eight [29]. The most used number of sensors is fourteen [21], [24], [25], [31], [33] and the most sensors used is Sixty-four [39]. Reference [25] used two EEG headsets to evaluate the proposed BCI. Also, there is a single article using fNIRS technology and EEG sensors to record brain activity [21]. The average number of subjects is 5.09. The lowest number of participants is one [22], [24], [29], [33] followed by three [21], [31] by five [23], [39] and by six [26]. The largest number of participants is twenty [25] followed by ten [30]. The average number of Degree of Freedom (DoF) is 3.45. The most often DoF of these systems is four [22], [23], [25], [39] followed by two [26], [29], [33], five [21], [24], and three [30], [31].

For the classification process, six different classification algorithms were presented in these articles. The most used process is Emotiv's software built-in classification model that three studies have used [22], [23], [31] and the LDA algorithm that is employed in two papers [21] and [26]. Reference [30] used a Logistic Regression model to classify the three mental commands recorded by the participants. Reference [25] developed an ANN to group the four available commands of their system. For the categorization of two MI mental commands two different algorithms were presented in [29] and [33]. More specifically, a Meta-Cognitive Interval type-2 Neuro-Fuzzy Inference system was introduced in the first, and an HMM was employed in the second. Lastly, [24] and [39] didn't mention the classification process that was used in their works.

EEG processing is one of the most important steps in the development of BCIs. The articles in this category used various methods of artifact removal and processing of the raw EEG signals. Referenes [22], [23], [31] used Emotiv's built-in processing. Referenes [26] and [30] applied ICA to the raw signals to remove muscle movements and other artifacts. Moreover, [26] applied a bandpass filter between 0.5 to 30 Hz. Also, a bandpass filter between 8 to 30 Hz was used in [33] and between 1 to 40 Hz in [25]. References [21] and [25] split the EEG data into five bands: Delta, Theta, Alpha, Beta, and Gamma. Reference [24] used spectral analysis by employing the FFT algorithm. Lastly, [29] and [39] didn't mention the EEG processing that was used in their works.

After processing the raw signals, the next step of BCI development is feature extraction. Several algorithms can be used for extracting features from EEG signals to be fed into a classifier. References [22], [23], and [31] used Emotiv's built-in feature extraction process. Most of the studies employed spatial feature extraction algorithms. Reference [33] used CSP while [29] used CSAP. Reference [30] employed an improved cross-correlation method, [25] used the Discrete Wavelet Transform algorithm, and [26] applied inhomogenous spatial filtering. Lastly, [21], [24], and [39] didn't mention the feature extraction algorithm that was used in their works.

Various evaluation metrics were employed in these studies to assess the presented systems. The most common one is the Accuracy of the classification and or/and the real-time accuracy of the transmitted commands. Six studies [21], [22], [25], [26], [30], [33] included this metric in their analysis. A time-based metric was also employed in five studies. Moreover, the response time of the system was used to evaluate [26], [31], the time spent on a path or a task was employed in [29], [30], and [39]. The number of commands per path was presented in [30], while the effective response for every ten attempts was presented in [23]. Some error-based metrics were employed in [26] and some average task-related metrics were used in [39]. Lastly, [24] did not provide any metric to assess the proposed BCI system.

3) STEADY-STATE VISUALLY EVOKED POTENTIALS (SSVEP)

This section will showcase a set of nine articles that highlight the use of SSVEP-based BCI to control drones (Table 5).

Chiuzbaian et al. [53] proposed a four-class SSVEP BCI model to control the drone's movements in four directions: up, down, left, and right, as well as forward and backward. To record the brain signals an 8-channel EEG cap was employed and the signals were filtered from 2 to 15Hz. FFT was used to separate the four different frequencies employed for this system. Ten subjects participated in the real-time experiment and commanded the drone using only their thoughts. To finish the experiment successfully participants had to follow a predefined path. The average accuracy rate and the average Information Transfer Rate (ITR) were the evaluation metrics of this study.

A five-class SSVEP-controlled drone was developed in [44]. EG data was recorded using a single-channel EEG device, and a total of five subjects took part in the experiments. The classification algorithm employed was a Long-Short-Term Memory (LSTM) model. The study used a visual interface with different boxes representing specific commands. The box at the top, flickering at a frequency of 6.6 Hz, was associated with takeoff. The center box, flickering at 8.5 Hz, was associated with moving forward. The bottom box, flickering at 10 Hz, was associated with landing. The left box (12 Hz) and the right box (15 Hz) were associated with turning left and right, respectively. For real-time testing, three subjects participated and asked to perform three mental commands. The results demonstrated an impressive accuracy rate of 90% for the detection and classification of these mental commands.

Chang et al. [45] developed a BCI drone using SSVEP. The drone has six possible movements: forward, backward, left turn, right turn, ascent, and descent. Each movement has a specific frequency: 15Hz, 17Hz, 19Hz, 21Hz, 25Hz, and 27Hz. Only one electrode was used to capture the raw EEG data, and a single participant tested the BCI system. Three experiments were conducted to control the drone, resulting in an overall accuracy of 90%. In [57] the authors aimed to create BCI-controlled UAV specifically designed for firefighting purposes. The study utilized five different frequencies (6Hz, 7Hz, 9Hz, 11Hz, 13Hz) that corresponded to specific movements of the drone. The Mexican hat wavelet was employed to process the captured raw EEG data, and for feature extraction, the CSP algorithm was used. The experiments involved the participation of five subjects, and the evaluation metric used in this study was the correct recognition rate.

Chung et al. [47] designed an SSVEP BCI for controlling a UAV. A new approach to shorten the time analysis of the system was proposed with an overlapping time window that can give commands to the drone every second. To acquire the raw EEG data two channels were employed. The available movements for the BCI drone were three: turn left and right and fly forward. The frequencies used were 15 Hz, 23 Hz, and 31 Hz. The energy of the frequencies was calculated and FFT was employed for feature extraction. Ten subjects participated in the experiments that showed a 10% improvement in the accuracy of the system.

Chen et al. [46] developed a BCI-controlled drone with five available movements with frequencies at 6 Hz, 6.67 Hz, 7.50 Hz, 8.57 Hz, and 10 Hz for amyotrophic lateral sclerosis (ALS) patients. The EEG data were captured from a single electrode, the raw signals were filtered between 4 Hz to 60 Hz and FFT was employed for feature extraction. Then a new fuzzy tracking algorithm was developed to classify the five frequencies. The new algorithm was compared with Canonical Correlation Analysis (CCA) algorithm. Fifteen subjects participated in testing the proposed algorithm and the results showed that it outperformed the CCA in average recognition rate for the mental commands. In real-time experiments, five subjects with ALS tested the BCI system and flew the drone with success.

TABLE 5. Real SSVEP based BCI-controlled drones.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[53]	2019	14	10	Threshold Technique on Both Frequency & Magnitude Axis	4	8th Order Bandpass Filter 2-15Hz	FFT	ITR, PPV
[44]	2019	1	4	LSTM Network	3	Bandpass Filter 1-100Hz 50Hz Notch Filter	-	-
[57]	2019	-	5	-	5	Mexican Hat Wavelet Multi-Band Bandpass Filtering	CSP	Correct Recognition Rate
[45]	2021	1	1	-	6	-	-	Accuracy
[47]	2021	2	10	-	3	Energy of the Frequency	FFT	Accuracy of Commands
[21]	2016	14, fNIRS (1)	3	LDA	5	Alpha, Beta, Delta, Theta, Bands	-	Commands Accuracy
[46]	2016	1	15	Proposed Fuzzy Tracking Algorithm	5	Bandpass Filter 4-60Hz	FFT	Recognition Rate
[49]	2022	8	10	CCA	4	-	-	Accuracy ITR
[48]	2012	4	20	CCA	6	-	-	ITR Detection Acc Execution Time

Hsu et al. [48] designed an SSVEP-based BCI to control a drone. To record the brain signals a 4-channel cap was used and to visualize the target frequencies HoloLens AR device was employed. To classify six mental commands CCA algorithm was used. The target frequencies in this work were 19Hz, 21Hz, 23Hz, 25Hz, 27Hz, and 29Hz corresponding to backward, up, forward, left, down, and right movement. In order to assess the proposed BCI 20 subjects participated in real-time experiments and tried to fly the drone on a predefined path. The ITR, detection accuracy, and execution time were employed as the evaluation metrics of this system.

4) STATISTICS

The average number of EEG channels is 5.625 ranging from one to fourteen. References [44], [45], and [46] used a single sensor, [47] used two, [48] employed four sensors, [49] employed eight and [21], [53] used fourteen. Lastly, [57] did not mention the number of EEG channels that they employed in their proposed system. The average number of subjects for this category is 8.66 varying from one [45] to twenty [48] participants. Reference [21] conducted the experiments with three subjects, [44] with four while [57] with five. Ten participants were included in [47], [49], and [53] and lastly fifteen subjects were used in [46]. The average number of Dof is 4.55 which is higher than the average number of DoF in the MI category. This was expected because SSVEP-based systems usually employ more mental commands than MI-based systems. The lowest number of mental commands is three from [44] and [47] and the highest is six [45], [48] followed by five from [21], [46], and [57]. Lastly, two articles [49] and [53] employed four mental commands for their systems.

For the classification process, four algorithms were employed. The most used classification algorithm is CCA which three articles [46], [48], [49] have employed in their BCI systems. Additionally, [46] developed a fuzzy tracking algorithm to classify five mental commands. Reference [44] employed an LTSM network and [53] utilized a threshold technique on both frequency and magnitude axis for the classification process. Lastly, three studies [45], [47], [57] did not mention the algorithm used to classify the mental commands.

As mentioned before EEG processing is a key step to a successful BCI system. In this category four articles [44], [46], [53], [57] applied bandpass filters to the raw signals to remove noise and artifacts. Reference [53] applied an 8th-order Butterworth bandpass filter between 2 to 15 Hz, [44] implemented a bandpass filter of 1-100 Hz and a Notch filter at 50 Hz. Reference [57] after multi-band bandpass filtering utilized Mexican hat wavelet and [46] used a 2th-order Butterworth bandpass filter from 8 to 60 Hz. Reference [21] split the raw signals into five frequency bands: Delta, Theta, Alpha, Beta, and Gamma band. Reference [47] calculated the Energy of the frequencies to process the EEG data. Lastly, [45], [48], and [49] did not present the processing of the raw signals that were employed in the proposed systems.

For the feature extraction step, most of the papers in this category [21], [44], [45], [48], [49] did not present their implementations. The most employed algorithm is FFT used by three articles [46], [47], and [53]. Lastly, a single study [57] utilized a spatial feature extraction method, the CSP algorithm.

Several evaluation metrics were employed in the studies of this category. The most common is the accuracy of the system: real-time accuracy [45], [49], accuracy of commands [21], [47], and detection accuracy [48]. ITR is another common metric for BCIs and it was presented in [48], [49], and [53]. Also, [48] utilized a time-based metric: execution time. Other metrics employed in this category were the positive predictive value [53] and the correct recognition rate [57]. Lastly, [44] did not present any metrics to evaluate their system.

5) P300

The P300-based BCI-controlled drone subgroup will be presented. A total of three articles will be analyzed (Table 6).

TABLE 6. Real P300 based BCI-controlled drones.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[42]	2020	8	1	LDA	12	Bandpass Filter 2-30 Hz 60Hz Notch Filter	P300 Amplitude	-
[43]	2021	8	2	LDA	6	Bandpass Filter 0.5–30Hz	P300 Amplitude	Accuracy of Commands Transmitted Classification Accuracy
[40]	2020	4	10	Nearest Neighbour Approach	6	50Hz Notch Filter High Pass Filter 0.1Hz Low Pass Filter 30Hz	P300 Amplitude	Accuracy ITR

Al-Nuaimi et al. [42] developed a BCI-controlled drone employing P300. Unicorn hybrid black EEG headset with eight channels was used to record the raw EEG data and the signals were bandpass filtered between 2-30 Hz and then a noch filter was applied with a value of 60Hz. For feature extraction, the P300 Amplitude was used and the LDA algorithm was chosen to classify the mental commands. The DoF of the system was twelve: takeoff, right, left, up, down, move forward, move backward, take a picture, start the video stream, pause, land, and emergency stop. One user trained and then tested the BCI in real-time. The participant had to fly the drone while trying to chase another UAV that was in front of it. The user managed to successfully chase the other drone.

Another cooperative BCI system was presented in [43]. The BCI was designed to control a drone and a robot from two different users at the same time for military applications. Unicorn hybrid black was used to acquire the raw EEG signals and then a bandpass filter was applied between 0.5 to 30 Hz. LDA was employed for the classification of six mental commands for the drone movement and for twelve mental commands for the robot. Two users tested the proposed system in real-time, one controlling the robot and the other one commanding the drone. The robot was communicating with the drone to guide it to a safe path and the drone was following the instructions. The evaluation metrics for this article were the classification accuracy and the accuracy of the commands transmitted.

A graphical user interface (GUI) for a BCI-controlled drone was developed in [40]. To record the raw EEG signals, four channels were used. The data were filtered by three 4th-order Butterworth filters and Nearest Neighbour Approach (NNA) was employed to classify six mental commands. The six available movements of this system were forward, backward, up and down, and right and left turn. Ten healthy subjects participated in the experiment of flying the prototype drone. Classification accuracy and ITR were the evaluation metrics of this work.

6) STATISTICS

The average number of EEG channels is 6.66 varying from eight sensors [42], [43] to four [40]. The average number of subjects that participated in the experiments presented in these works is 4.33. The highest number of participants was ten in [40] and the lowest was one by [42] followed by two in [43]. The average number of mental commands (DoF) is eight, which is higher than the DoF of MI and SSVEP categories, ranging from twelve [42] to six [40], [43]. In the studies of P300 category two classification algorithms were presented. LDA algorithm was employed in [42] and [43] and Nearest Neighbour Approach was utilized in [40]. The studies in this category used filters to process the raw EEG data and remove artifacts. All of the articles cut off the signals at 30 Hz, [42] applied a bandpass filter at 2 to 30 Hz and a Notch filter at 60Hz, [43] utilized a bandpass filter between 0.5 to 30 Hz, and [40] employed a 50 Hz Notch filter, high pass filter at 0.1 Hz, and a lowpass filter at 30Hz. After the signals were processed, the P300 amplitude was calculated as the feature extraction method. The evaluation metrics employed by the studies of this category were the Accuracy of commands and classification accuracy [40], [43]. Also, [40] utilized ITR metric for the BCI assessment. Lastly, [42] did not present any metrics to evaluate the proposed system.

7) REST

The rest subgroup will be presented. A total of four articles will be analyzed (Table 7).

Cervantes et al. [58] designed the CogniDron-EEG BCI system for cognitive training purposes. The proposed system was controlling an indoor drone. Emotiv Epoc+ was used for recording brain signals, and the absolute power of theta and beta bands and the mean theta/beta ratio were used to fly the drone. This system offers nine movements for flying the UAV. Ten healthy children participated in the experiments and tested the CogniDron-EEG in real-time. The experiment flight routine consisted of fifteen movements that participants should perform. Pick a Mood (PAM), Self Assessment Manikin (SAM), and Game Experience Questionnaire (GEQ) were employed as the evaluation metrics of this work.

Kim et al. [19] designed a hybrid BCI system for controlling a UAV. EEG data and eye tracking were the means of control. Emotiv Epoc was used to record the brain signals and an eye-tracking camera was used to identify the eye movements. The mental commands that were recorded in this work were intentional concentration and non-concentration. To discriminate the two classes CSP algorithm was employed and SVM was used for classification. The DoF of the system was eight: up and down, left and right, forward and backward, and left and right turns. Five subjects were included in the

TABLE 7. Articles from the subclass Real Rest BCI-controlled drones.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[58]	2023	14	10	-	9	Mean Theta - Beta Ratio	Absolute Power of Theta and Beta Bands	Pick a Mood Self-Assessment Manikin Game Experience Questionnaire
[19]	2014	14	5	SVM	8	PSD	CSP	Traveled Distance Total Time Taken Normalized Path Length Area Under the Curve Speed of Control Success Rate
[20]	2018	fNIRS (16)	5	Vector Phase-Analysis SVM	1	Low Pass filter High-Pass Filter	-	Classification Accuracy
[21]	2016	14, fNIRS (1)	3	LDA	5	A, B, D, T Bands	-	Commands Accuracy

real-time testing in which they had to fly the drone. Six evaluation metrics were employed for this work: traveled distance, total time taken, normalized path length, Area Under the Curve, Speed of control, and Success rate.

Zafar et al. [20] developed a BCI-controlled drone using fNIRS technology. Sixteen channels were used to record the brain activity of five subjects performing mental arithmetic tasks. The functional movements of the drone were one, flying forward. A vector phase analysis algorithm was developed to classify the two classes: a mental arithmetic task and a non-mental arithmetic task. Real-time experiments showed that the vector phase analysis had better results from SVM in classifying the commands by 18% while also being faster. Lastly, all subjects managed to successfully navigate the drone in a forward direction.

Khan et al. [21] developed a hybrid BCI system acquiring data from EEG with Emotiv Epoc and functional near-infrared spectroscopy (fNIRS) from two electrodes for commanding a drone. The quadcopter's navigation system incorporates multiple input methods for control. Mental arithmetic tasks performed by the user are decoded using NIRS technology to move forward. Additionally, the user can manipulate the quadcopter's height by imagining left-hand clenches, with EEG technology decoding the corresponding brain activity. Eye movements, in the left or right direction, are utilized to control the system's rotation. As a fail-safe measure to prevent collisions, a frequency of 6 Hz in SSVEP is employed. LDA was employed to classify the mental commands. Online experiments were performed to evaluate the system and the metric employed was the commands accuracy.

8) STATISTICS

The average number of EEG channels is fourteen [19], [21], and [58]. Reference [21] used both an EEG headset and fNIRS technology to record the brain potentials while [20] used only fNIRS to capture the brain signals. The average number of participants is 5.75 ranging from ten [58] to three [21]. Also, two studies [19], [20] used five subjects for their experiments. The average DoF is 5.75 varying from nine [58] to one [20]. Eight mental commands were employed in [19] while five were employed in [21]. SVM algorithm was employed by two studies [19], [20] to classify the mental commands. Reference [20] also employed a Vector Phase Analysis algorithm for the classification process. A single article [21] utilized LDA and [58] did not present the classification algorithm used in their system. To process the EEG data the studies of this category employed several techniques. Reference [58] computed the mean theta and beta ratio, [21] filtered and split the signals into four (A, B, D, T) frequency bands, [19] employed PSD, and [20] applied lowpass and highpass filters with cutoff frequencies of 0.15 and 0.01 Hz. For the feature extraction process, [58] computed the absolute power of Theta and Beta bands, and [19] utilized the CSP algorithm. Lastly, two studies [20], [21] did not present their feature extraction process. To evaluate the proposed systems, several metrics were employed by the articles from this category. Reference [58] used three metrics: PAM (Pick a Mood), SAM (Self-Assessment Manikin), and GEQ (Game Experience Questionnaire). Furthermore, [21] used the accuracy of the commands, and [20] utilized the classification accuracies from the Vector Phase Analysis and the SVM. Lastly, [19] employed six different metrics to evaluate their work: traveled distance, total time taken, normalized path length, Area Under the Curve, speed of control, and success rate.

B. VIRTUAL DRONES OR UAVS EXPERIMENTS

This subsection focuses on studies involving simulated drone or UAV experiments. A total of twenty papers will be discussed and analyzed in this section.

1) MOTOR IMAGERY

MI paradigm is the first subcategory of virtual UAVs, and nine articles focused on this paradigm will be analyzed (Table 8).

Choi et al. [37] developed a BCI to control a virtual drone using MI mental commands. An EEG cap with thirty-three channels was used to record the brain signals from two participants. Two processing scenarios were employed for

TABLE 8. Virtual MI based BCI-controlled UAVs.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[37]	2021	33	2	LDA	4, 6	Band Pass Filter 8-28Hz Band Pass Filter 8-36Hz	CSP FBCSP	Accuracy Elapsed Time for- the Control Scenarios
[32]	2020	14	1	SVM	5	Outlier Removal Algorithm	Recursive Least Squares	Benefit Utility
[36]	2020	64	-	CNN	4	Bandpass Filter of 4–38 Hz	-	Accuracy Intra-Subject Accuracy Inter-Subject Accuracy
[27]	2021	8	60	RBF MLP-RNN	4	UWT Wavelet- Multiresolution Analysis ICA	Coefficient of Determination r2	Classification Accuracy Control Output Intensity
[38]	2021	64	5	LDA	11	60 Hz Notch Filter Zero Phase Band Pass Filter ICA	CSP	Accuracy
[34]	2023	15	12	CNN	4	Band Pass Filter 1–100Hz Band Pass Filter 8-30Hz	CSP	Classification Accuracy Number of Commands Time Cost Success Rate
[35]	2020	16	14	LDA	3	-	FBCSP	ERD Ratio Result Questionnaire Result
[39]	2013	64	5	-	4	-	-	Average Rings per- Maximum Flight Average Ring- Acquisition Time ITR, PVC, PTC, PPC
[28]	2012	8	20	Hidden Markov Model	2	Low Pass Filter	Common Spatial Analytic Pattern	Success Rate Safe Symbol-Length Input Error Input Rate Run Success Hit-Count

four and six MI commands. For the first scenario after the signals filtered between 8 to 28Hz, CSP was used for feature extraction and LDA was employed to classify the four mental commands. For the second scenario, a band pass filter between 8 to 36Hz was applied to the brain signals and then FBCSP and LDA were used. To examine the proposed system, two simulated tracks were developed in Unity Engine: a 2D track (four MI commands) and a 3D (six MI commands). The MI commands were a combination of imagining hand and/or foot movements. The subjects tested the BCI system in real-time by flying the drone in the virtual tracks and they managed to fly it successfully. The evaluation metrics of this work were the classification accuracy of the mental commands and the time to finish the track route with EEG compared to the keyboard.

Another BCI that controls a virtual quadcopter was designed in [32]. Emotiv Epoc+ was used to acquire the raw EEG data from a single participant. An outlier removal algorithm was employed for noise and artifact rejection and SVM was used for classification. The DoF of the system was five: backward, forward, neutral, right, and left. The real-time experiments conducted from a single subject showed good precision in flying the virtual drone and to evaluate their work two evaluation metrics were employed, Benefit and Utility.

Liu et al. [36] designed a BCI to control a virtual drone. A parallel spatial–temporal self-attention-based CCN was developed to classify four mental commands. The CCN was evaluated with two public datasets for intra-user and inter-user classification. A sixty-four-channel cap was used to capture brain activity from the subjects and then a band-pass filter of 4–38 Hz was applied to the signals. Then the features were fed to the CNN for a four-class classification. Participants commanded the virtual drone in real-time to further validate the proposed classification process. The evaluation metrics of this work were accuracy, intra-subject accuracy, and inter-subject accuracy.

Dumitrescu et al. [27] developed a BCI to control a virtual drone. An eight-channel cap was used to acquire the raw EEG data. UWT wavelet multiresolution analysis and ICA were applied to the signals to remove artifacts and noise. The coefficient of Determination r2 was employed for feature extraction and a hybrid neural network was used to classify the mental commands. The neural network was a combination of RBF and MLP-RNN. The Dof of the system was four: forward, stop, left, and right. Sixty subjects participated in the experiments and commanded the simulated quadcopter. The evaluation metrics employed in this work were the classification accuracy and the control output intensity.

Lee et al. [38] developed a BCI to control a virtual drone swarm. MI, Visual Imagery (VI), and Speech Imagery (SI) were used as endogenous paradigms to increase the DoF of the swarm. The EEG signals were recorded by a sixty-four-channel cap from five subjects. The signals were filtered and to remove artifacts ICA was performed. Then CSP algorithm was employed for feature extraction and LDA was used for classification. The DoF of the system was eleven: MI paradigm with four commands (left, right, up, and down), VI with three (fall-in, spread-out, and split), and SI with four (go, stop, follow me, and return). The subjects controlled the drone swarm in virtual scenarios and managed to perform all the available movements. The cross-validation results were the evaluation metrics of this system.

Shi et al. [34] developed a BCI that controls a virtual drone for indoor target search. The brain signals were recorded from fifteen channels. Two band-pass filters (1-100Hz, 8-30Hz) were applied, and then to extract features from the signals CSP algorithm was employed. A CNN was developed to classify the four mental commands. Left and right MI corresponded to left and right turning while feet MI and tongue MI corresponded to upward and downward movement. Twelve subjects participated in the experiments: six participated in the offline calibration of the system and all twelve participated in the real-time phase. To test the proposed BCI a virtual indoor target search was performed by the subjects. The evaluation metrics of this work were classification accuracy, the number of commands, the time cost, and the success rate.

Choi et al. [35] designed an MI-based BCI. A fifteen-channel EEG cap was used to record the raw data from twelve subjects. FBCSP algorithm was employed to spatial discriminate the mental commands and LDA was used to classify them. The Dof of this system is three: left, right MI, and neutral state. Two virtual scenarios were developed one with embodiable feedback and one without feedback. Fourteen subjects participated in the experiments and completed both of these scenarios. The results showed that the scenario with the embodiable feedback had better results. The evaluation metrics of this work were the ERD ratios and the questionnaire results.

Akce et al. [28] designed a BCI to navigate a virtual aircraft. An eight-channel EEG cap was used to capture the brain signals from twenty subjects. Common spatial analytic pattern (CSAP) was employed for feature extraction and Hidden Markov model (HMM) was used to classify two mental commands. The two mental commands in this article were left and right MI. Subjects trained and tested the proposed system in real-time. To evaluate this work eight metrics were employed: Success rate, Safe symbol-length, Input error, Input rate, ITR, Run success, Run success, and Hit-count.

2) STATISTICS

The average number of electrodes is 31.7 which is the highest average of all categories. Most sensors used in these articles are sixty-four [36], [38], [39] followed by thirty-three [37], sixteen [35], fifteen [34], and fourteen [32]. The fewest electrodes used in this category are eight [27], [28]. The average number of subjects is 13.22 ranging from sixty [27] to one [32]. Reference [28] used twenty subjects which is the second-highest number of participants followed by fourteen [35] and twelve [34]. Two studies [38], [39] employed five subjects and one article [37] employed two participants to take part in the experiments. Lastly, [36] did not present the number of subjects that were used in their work. The average number of mental commands is 4.11 varying from eleven [38] to two [28]. Five studies [27], [34], [36], [37], [39] employed four mental commands. Reference [37] has a DoF of six, [32] has five and [35] has three.

For the classification process, several algorithms were employed from the papers in this category. LDA algorithm was utilized by three articles [35], [37], [38] and it is the most common algorithm in this category followed by CNN that was employed from two studies [34], [36]. Reference [32] used SVM, [27] employed RBF and MLP-RNN, and [28] utilized a Hidden Markov Model. Lastly, one paper did not mention the classification algorithm that was used. To process the raw EEG signals several techniques were applied. Filtering was the most commonly used technique since five studies [28], [34], [36], [37], [38] applied filters to their signals. More specifically, [34] and [37] applied two bandpass filters, between 8-28 Hz and 8-36 Hz, and between 1-100 Hz and 8-30 Hz respectively, [36] applied a bandpass filter of 4-38 Hz, [38] employed a bandpass filter with a zero phase and a notch filter at 60 Hz and lastly [28] utilized a lowpass filter. Furthermore, ICA was employed in two articles [27], [38]. Reference [27] also utilized a UWT wavelet multiresolution analysis. Reference [32] used an outlier removal algorithm to process the raw EEG data. Lastly, two papers [35] and [39] did not present the processing technique that was utilized in their proposed systems.

For the feature extraction process, the CSP algorithm was the most used algorithm in this category since it was employed by three articles [34], [37], [38]. Moreover, two studies used FBCSP [35], [37] and one paper [28] utilized CSAP. Reference [32] employed a Recursive Least Squares algorithm and [27] utilized a Coefficient of Determination technique to extract features to feed the classifiers. Lastly, two studies [36], [39] did not mention their feature extraction methods.

Several evaluation metrics were employed in this category. The classification accuracy was used in five papers [27], [34], [36], [37], and [38]. Furthermore, ITR was employed in [28], and [39] while three studies utilized time-based metrics: [37] used an elapsed time for the control scenarios metric, [34] utilized a time cost metric, and [39] used an average ring acquisition time metric. Also, the success rate was used in two articles [28], [34]. Reference [32] employed two metrics: Benefit, and Utility, [36] utilized intra-subject and inter-subject accuracy and [27] used control output intensity as a metric. Reference [35] employed two different metrics to evaluate their work: ERD ratio results and Questionnaire results and [34] utilized the number of commands metric. Lastly, [39] employed the average rings per maximum flight (ARMF), PVC, PTC, PPC, and [28] utilized Safe

TABLE 9. Virtual SSVEP based BCI-controlled drones.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[49]	2022	8	10	CCA	4	-	-	Accuracy ITR
[50]	2021	8	-	-	6	-	-	Success Rate
[51]	2021	8	10	CNN	9	Band Pass Filter 6-80Hz	FFT	Accuracy
[56]	2022	8	10	CCA	7	-	-	Obstacle Avoidance Success Rate Accuracy
[55]	2021	12	6	CCA	20	50Hz Notch Filter Band Pass Filter 6-40Hz	-	Correct Rate of Area Selection Response Time ITR
[52]	2023	8	9	CCA	11	High Pass Filter Low Pass Filter	-	Accuracy Rate Average Amplitude Spectrum ITR
[54]	2022	14	5	LDA	4	Bandpass Filter for Fundamental-Second Harmonic Bands	CSP	Average Operating Accuracy

symbol-length, Input error, Input rate, Run success, and Hit-count as their evaluation metrics.

3) STEADY-STATE VISUALLY EVOKED POTENTIALS

Table 9 presents seven articles that employed the SSVEP paradigm to fly a simulated drone.

Niu et al. [49] developed a BCI system that commands both a virtual and a real drone at the same time. The available commands of the UAV were four: forward (5 Hz), backward (6 Hz), turn left (7 Hz), and turn right (8 Hz). The EEG signals were recorded from eight channels and the CCA algorithm was employed to classify the mental commands. Ten volunteers participated in the real-time experiment and they flew successfully a virtual and a real drone at the same time. The evaluation metrics of this work were the real-time accuracy of the commands and the ITR.

Wu et al. [50] designed a hybrid SSVEP and eye-tracking BCI to control a single or multiple UAVs. The EEG raw data were acquired from an eight-channel cap. The target frequencies in this work were 8Hz, 8.5hz, 9hz, 11hz, 12Hz, and 13Hz corresponding to fly commands for the UAVs. Real-time experiments were conducted to assess the feasibility of the proposed system. Subjects had to control four drones in a predefined path. The success rate was the evaluation metric of the system.

Another BCI that commands a virtual drone was presented in [51]. The raw signals were recorded from an eight-channel device from ten subjects. A 4th order band-pass filter between 6 to 80 Hz was applied to the signals and then FFT was computed. Then CCN was employed to classify nine mental commands. The functional movements of the drone were takeoff, land, move forward, move backward, turn right, turn left, go up, go down, and stop. The proposed system was evaluated in offline and online scenarios and the evaluation metric was the accuracy of the commands.

Huo et al. [56] developed a BCI to control a virtual robot swarm. A drone and a ground vehicle were commanded with EEG signals. An eight-channel cap was used to capture the brain data. The DoF of the system was seven: four movements for the drone (forward, backward, right, and left) and three for the vehicle. The corresponding target frequencies were 5Hz, 6Hz, 7Hz, 8Hz, 8.9Hz, 10Hz, 13.3Hz. To classify the mental commands CCA algorithm was employed. Participants assessed the proposed system in real-time experiments, one for the drone, one for the vehicle, and one for the robot swarm. The evaluation metrics for this work were accuracy and obstacle avoidance success rate.

Dai et al. [55] developed a BCI for controlling a robot-drone swarm. A twelve-channel cap was used to capture the EEG data from six participants. After the signals were filtered by a 50Hz notch filter and a 6-40Hz bandpass filter, the CCA algorithm was employed to classify twenty mental commands. The target frequencies for this system were varying from 8 Hz to 15.6 Hz in increments of 0.4 Hz. Both offline and online experiments were performed and all six subjects assessed the BCI after a long period of trials (500 trials per subject). ITR, response time, and correctness rate of subarea selection were employed as the evaluation metrics of this work.

Deng et al. [52] developed an SSVEP-based BCI to control a VR drone swarm. An eight-channel cap captured the brain signals from nine healthy subjects. The signals were filtered between 0.1 Hz to 30 Hz and then the CCA algorithm was employed to classify eleven mental commands. Both offline and online scenarios were evaluated. Experiments for a single drone movement and a UAV movement-formation swarm were conducted and successfully concluded. ITR, accuracy rate, and average amplitude spectrum were the evaluation metrics for this system.

Zhengdong et al. [54] designed a BCI to control a simulated aircraft. An Emotiv Epoc headset was used to acquire brain signals. CSP and LDA algorithms were employed for feature extraction and classification. The target frequencies for this work were 8.57 Hz, 10 Hz, 12 Hz, and 15 Hz corresponding to pitch up, roll left, roll right, and bend down, respectively. Five subjects participated in the experiments and evaluated the proposed BCI system by flying the aircraft. The average operating accuracies were presented as the metric for this work.

4) STATISTICS

The average number of channels is 9.42 ranging from fourteen [54] to eight [49], [50], [51], [52], [56]. A single study [55] employed twelve electrodes to record the raw EEG data. The average number of subjects is 7.14 varying from ten [49], [51], [56] to five [54]. Two studies [52], [55] used more subjects than the average number of this category, nine and six respectively while one study [50] did not present the number of participants that were used in their work. The average DoF of this category is 8.71. The highest number of mental commands was twenty [55] followed by eleven [52], nine [51], and seven [56]. The fewest DoF employed in this category was four [49], [54] followed by six [50]. For the classification process, three algorithms were utilized in this category. The most common one was CCA since it was employed in four studies [49], [52], [55], [56]. LDA and CNN were used once by [51] and [54] respectively while [50] did not mention the algorithm that was used to classify the mental commands in their system.

To process the raw EEG data four studies [51], [52], [54], [55] applied filters to the signals. [51] applied a 4th-order Butterworth bandpass filter between 6 and 80 Hz, [55] employed a notch 50 Hz and a bandpass filter from 6 to 40 Hz. Also, [52] utilized two filters, a highpass, and a lowpass one from 0.1 to 30 Hz while [54] applied a bandpass filter for fundamental and second harmonic bands. Lastly, three studies did not present the EEG processing methods that were employed in their works. For the feature extraction step only two studies [51], [54] present the methods they employed. [51] utilized FFT and [54] employed the CSP algorithm while five studies [49], [50], [52], [55], [56] did not mention the feature extraction process used in their systems.

Several evaluation metrics were employed from the studies in this category. The accuracy of the system is the most commonly used metric since it was utilized in four articles [49], [51], [52], [56]. Also, ITR was used in three papers [49], [52], and [55] and the success rate was employed as a metric in two, [50], [56]. Moreover, [55] utilized a response time metric and a correctness rate of subarea selection metric. [52] employed the average amplitude spectrum and [54] used the average operating accuracies to evaluate the proposed BCI system.

5) P300 AND REST

The decision to merge the P300 and Rest categories is due to the lack of extensive research focusing on P300 BCI implementations with simulated drone experiments. As a result, considering the limited number of studies available (one), it is deemed suitable to combine these categories into a unified subsection. The first entry of the table 10 is the article from the P300 category while the other three entries are the articles from the Rest category.

Kim et al. [41] designed a BCI to control a drone in both AR and VR environments. A seven-channel cap was used to capture brain activity from twenty subjects. A 5th-order Butterworth filter between 0.1 to 30 Hz was applied to the signals to remove artifacts. LDA algorithm was employed to classify seven mental commands (forward, up, down, right, right turn, left, and left turn). To conduct a comparison between AR and VR environments, the participants were divided into two equal groups. Half of the users started flying the drone using AR, while the other half began their drone flight with VR and when the first experiment was concluded they switched environments. Accuracy, Amplitude, Latency, User Satisfaction, and Questionnaires results were employed to evaluate the proposed systems.

Jeong et al. [59] developed a BCI to control a simulated drone swarm formation. A sixty-four-channel cap was used to acquire and record the raw EEG data from seven subjects. A 60 Hz Notch filter and a 2nd order bandpass Butterworth filter between 8-30 Hz were applied to the signals. Then CSP and LDA algorithms were employed for feature extraction and classification for four mental commands. A four-class VI paradigm is used in this work to control the formation of a virtual drone swarm in real-time. Subjects participated in the experiments and had to perform four VI commands that correspond to the four types of formation used in this system (Hovering, Splitting, Dispersing, and Aggregating). To evaluate this work, the accuracy of the classification was presented.

Another study implementing a VI paradigm BCI to control the formation of a simulated drone swarm was presented in [60]. A sixty-four-channel cap was used to capture brain patterns from six subjects. After the signals were filtered CSP and LDA algorithms were employed for feature extraction and classification. The DoF of the system was four: Hovering, Splitting, Dispersing, and Aggregating. The evaluation metric for this system was classification accuracy.

6) STATISTICS

The average number of EEG channels is 49.75 ranging from seven [41] to sixty-four [38], [59], [60]. The average number of subjects is 9.5. The largest number of participants recorded in this category is twenty [41], followed by seven [59]. On the other hand, the fewest number of subjects included is five [38], followed by six [60]. The average DoF is 6.5 varying from four [59], [60] to eleven [38]. Also, [41] employed seven mental commands to manipulate their proposed BCI system. All of the studies utilized the LDA algorithm for the classification process. For the EEG processing, all of the papers applied filters to the raw data. More specifically, [41] applied a 5th-order Butterworth filter from 0.1 to 30 Hz, [59] employed a 2nd-order Butterworth filter between 8 and 30 Hz and a 60 Hz notch filter. A 60 Hz notch filter was also applied in [38], [60]. Reference [60] employed four 2nd-order Butterworth filters from 8 to 13 Hz, 8 to 30 Hz, 0.4 to 13 Hz, and 4 to 40 Hz. Lastly, [38] utilized a bandpass filter with a zero phase and also used ICA. Most of the articles [38], [59], [60] employed the CSP algorithm in order to extract features and send them to the classifier while [41] did not mention the feature extraction method that was used in their work. Several evaluation metrics were

TABLE 10. Articles from the subcategories of virtual P300 (first row of the table) and Rest BCI-controlled drones.

Articles	Year	EEG Channels	Subs	Classification	DoF	EEG Processing	Feature Extraction	Evaluation Metrics
[41]	2021	7	20	LDA	7	Band Pass Filter 0.1–30 Hz	-	Questionnaires Result Accuracy Latency Amplitude User Satisfaction
[59]	2020	64	7	LDA	4	60Hz Notch Filter Band Pass Filter 8-30Hz	CSP	Classification Accuracy
[60]	2021	64	6	LDA	4	60Hz Notch Filter Band Pass Filter 0.4-13Hz Band Pass Filter 8-13Hz Band Pass Filter 8-30Hz Band Pass Filter 4-40Hz	CSP	Classification Accuracy
[38]	2021	64	5	LDA	11	60Hz Notch Filter Zero Phase Band Pass Filter ICA	CSP	Accuracy

employed in this category. The most used is classification accuracy which was utilized in [38], [41], [59], and [60]. Moreover, [41] used another four metrics: questionnaire results, latency, amplitude, and user satisfaction.

V. DISCUSSION
A. STUDY FINDINGS
This systematic review focuses on research articles that utilize EEG signals (BCI) to control drones and UAVs. The research is based on the findings from four well-established scientific databases: ScienceDirect, IEEE Explore, MDPI, and PubMed. The initial part of the review presents statistical findings from the articles, including the number of subjects, number of EEG channels, article types, and types of EEG headsets employed. In the second section, the articles are categorized into two main groups: Real drones and Virtual drones. These categories are further divided into four subgroups: MI, SSVEP, P300, and Rest. For each category, the review analyzes the EEG processing technique, classification algorithm, feature extraction process, DoF, and evaluation metrics.

Several classification algorithms were utilized in the studies presented (Figure 8). The predominant algorithm which is LDA, was employed in eleven papers and was most commonly used in the MI and P300 paradigms. Another popular choice was the CCA algorithm, which appeared in six studies specifically within the SSVEP category. Neural Networks were applied in five papers focusing on MI-based articles, while SVM and the built-in Emotiv classifier were each used three times. The Emotiv classifier was primarily employed in MI paradigms, whereas SVM was utilized in the Rest and MI categories. These five classification methods represent the 62% of the classifier algorithms that were employed in the studies.

Various feature extraction methods have been employed in the studies presented (Figure 9). The most commonly used method is CSP, along with its variations such as FBCSP and CSAP, which are utilized in twelve studies. The application of CSP and its variations extends to articles from the MI, SSVEP, and Rest categories. Another popular algorithm is FFT, which is utilized four times in SSVEP-based systems. P300 amplitude was employed in three articles from the P300 category. Lastly, Emotiv's built-in feature extraction process was used in three studies focusing on the MI paradigm. These five feature extraction methods encompass 52% of the methods employed in the literature.

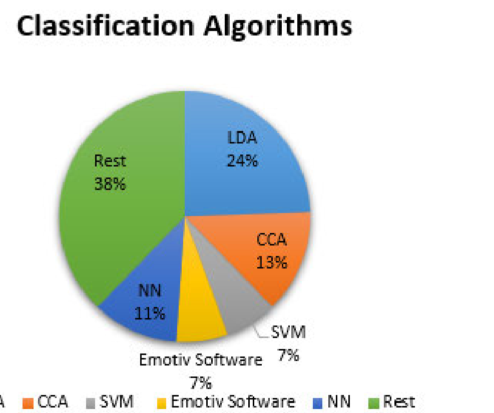

FIGURE 8. The figure presents a pie chart illustrating the distribution of classification algorithms utilized in the reviewed studies. Notably, the most employed algorithm is LDA, accounting for 24% of the papers.

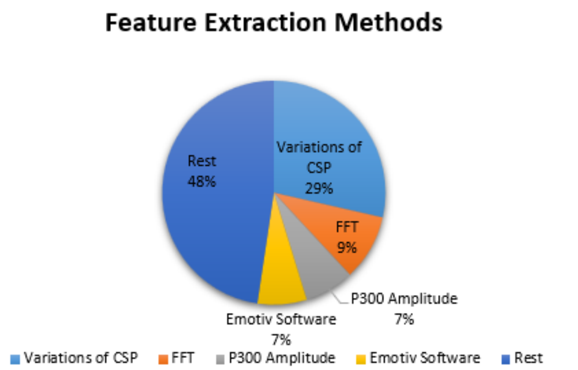

FIGURE 9. The pie chart showcases the distribution of Feature Extraction methods in the reviewed studies. The most frequently utilized method is CSP and its variations, comprising 29% of the total.

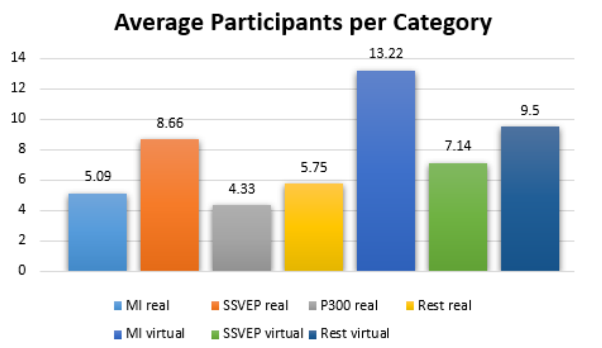

FIGURE 10. The figure displays the average number of participants involved in the evaluations of BCI-controlled UAVs across different categories. Notably, the highest average number of subjects employed is 13.22, in the MI virtual category.

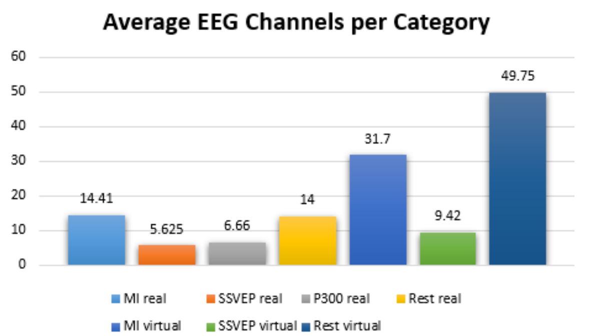

FIGURE 11. The figure presents the average number of EEG channels utilized across seven categories. The Rest virtual category recorded the highest average number of electrodes at 49.75, while the lowest is observed in the SSVEP real category at 5.625.

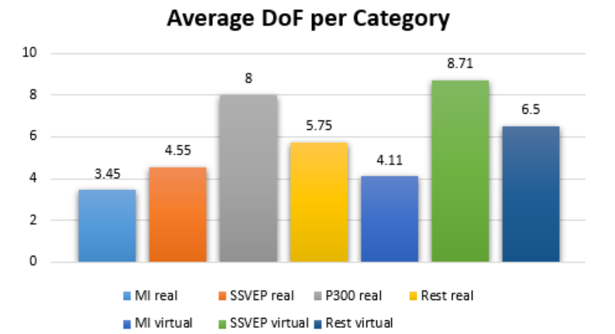

FIGURE 12. The figure displays the DoF across seven categories. The SSVEP virtual category recorded the highest DoF at 8.71, followed by P300 real at 8. As expected, the lowest average DoF is observed in the MI real and MI virtual categories at 3.45 and 4.11, respectively.

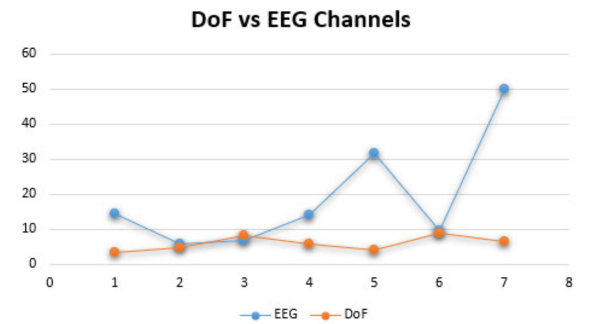

FIGURE 13. The figure presents a chart illustrating the DoF and the average number of EEG channels per category. Notably, there appears to be no clear correlation between these metrics across the categories.

The Result section of this review reveals several significant observations. To obtain more comprehensive insights, further analysis will be conducted on the EEG channels, subjects, and mental commands within each category. This analysis is crucial for identifying trends in BCI-controlled drones and gaining a deeper understanding of each category. In Figure 10, the average number of subjects per category is presented. The MI virtual category has the highest average number of participants, while the P300 real category has the lowest. The range of participants across studies varies, with the highest number being sixty and the lowest being one.

Surprisingly, it is noteworthy that the categories with the highest average number of participants also have the highest average number of EEG channels. Specifically, the MI virtual category and the Rest/P300 virtual category have the highest number of participants, with averages of 13.22 and 9.5, respectively. Additionally, these categories also utilize the most EEG channels, with averages of 31.7 and 49.75 sensors, as shown in Figure 11. On the other hand, the P300 real category has the fewest average subjects and the fewest average EEG channels. Another observation from Figure 11 is that the virtual categories employ a greater number of EEG electrodes compared to the real categories.

Figure 12 presents the average degrees of freedom (DoF) per category. The SSVEP virtual category has the highest number of mental commands employed, with an average of 8.75, followed by the P300 real category with an average of 8. On the other hand, the MI real category and MI virtual category utilize the lowest DoF, with averages of 3.45 and 4.11, respectively. Notably, the virtual categories tend to employ a greater number of mental commands. This can be attributed to the fact that real-world BCI applications are more challenging due to higher levels of noise and artifacts. Therefore, it is logical to use fewer mental commands in such scenarios. Additionally, it was expected that active paradigms like MI would have a lower average DoF compared to other categories.

Another noteworthy observation is that there is no clear correlation between the increase in EEG channels and the DoF, as depicted in (Figure 13). In fact, the average number of mental commands tends to decrease as the average number of EEG sensors increases. Specifically, the virtual SSVEP category and the real P300 category have the highest number of DoF but rank second to last and third to last, respectively, in terms of the average number of EEG channels. On the other hand, the active paradigms exhibit the fewest number of mental commands despite ranking second and third in terms of EEG sensors.

TABLE 11. Comparative Study of the review studies available in the literature.

Article	Year	Review Type	Year Range	# of Articles	Statistical Findings
Nourmohammadi *et al.* [62]	2018	Non-Systematic	2010-2015	14	Not Reported
Tezza and Andujar [63]	2019	Not Systematic	2014-2018	36, (11 with BCI)	Drone Models Publication Year
López *et al.* [64]	2020	Systematic	2010-2018	13	Not Reported
This work	2023	Systematic	2010-2023	42	Number of Subjects Article Types EEG Headsets Classification Algorithms Feature Extraction Methods Average Dof

B. LITERATURE COMPARISON

There have been a few attempts made to examine and summarize the techniques, challenges, and advancements in BCI technology to control drones. A comparative analysis (Table 11) will be conducted to review the type of review articles available, the number of articles included, the statistical discoveries made, and the methodologies employed for analyzing the papers in their investigation.

Nourmohammadi et al. [62] conducted a non-systematic review focused on BCI-controlled drones. The review specifically covered papers published between 2010 and 2015. The analysis included a total of 14 articles, which were examined using various criteria. These criteria encompassed the publication year, type of unmanned aerial vehicle (UAV), degrees of freedom (DoF), control commands, data acquisition methods, EEG paradigms, tasks, and classifiers utilized. The study initially provided a classification of available UAV types and subsequently presented the theoretical background of BCI technology. The authors then proceeded to analyze data acquisition methods, autonomy, training and feedback mechanisms, control strategies, preprocessing techniques, feature extraction methods, and classification processes. Finally, the review highlighted the trends observed within the field of BCI-controlled drones. The review mentioned does not include a statistical analysis of the articles it covers. It does not provide information regarding EEG channels/headsets, the number of participants, the average publication year of the articles, and the average DoF.

Tezza and Andujar [63] conducted a non-systematic review focused on human-drone interaction. Their search involved querying "human-drone interaction" in Google Scholar for the years 2014-2018, resulting in 182 articles. After a thorough review process, 36 articles were included for analysis. The review initially compared and analyzed commonly used drone models in terms of brand, model, flight time, speed, weight, range, SDK availability, picture resolution, video resolution, control interface, obstacle avoidance, and price. The review also explored various control human interfaces, including gesture, speech, BCI, and multimodal approaches. For the purpose of comparing their work with our study, we will focus on discussing the BCI interface, which was covered by 11 papers. The analysis of these articles included aspects such as publication year, drone brand, drone model, BCI equipment used, number of EEG channels, and number of participants. Additionally, the review discussed the challenges associated with human-drone interaction and presented future possibilities and trends. However, this study did not provide information regarding the specific classification algorithms, EEG processing methods, feature extraction techniques, or the DoF of the systems. These aspects were not included in the analysis.

López et al. [64] conducted a systematic review focused on BCI-controlled UAs as a serious game for dealing with attention deficit hyperactivity disorder. The review included papers published between 2010 and 2018. After screening titles, and abstracts, removing duplicates, and conducting full-text assessments, the review included a total of 13 articles. The search for relevant articles was performed across four major databases including PubMed, IEEE Xplore Digital Library, Scopus, and Google Scholar. Inclusion criteria involved English-written papers from 2010 to 2018, utilization of non-invasive BCIs for controlling real or virtual drones, non-invasive BCI systems based on single-modal or hybrid BCIs, studies with subjects, studies conducted in real or virtual environments, and BCI systems controlling UAVs for various purposes such as entertainment, healthcare, and research. The initial search resulted in 3,104 articles, which were subsequently narrowed down through abstract and title screening, removing 2,953 articles. Following duplicate removal, an additional 37 articles were excluded. Finally, after conducting a full-text analysis, 101 papers were excluded, leaving 13 articles for further analysis. The included articles were examined based on input signals, type of BCI, commands, UAV types, environment tests, human subjects, and results. The review also discussed the challenges and future trends associated with BCI-controlled UAVs. This review did not incorporate a statistical analysis of the covered articles. It did not provide information regarding the specific classification algorithms, EEG processing methods, feature extraction techniques, the number of electrodes used, or average participant and command numbers across all the included papers.

This work is a systematic review that focuses on drones controlled by BCIs. The search was conducted using the query "((BCI) OR (Brain Computer Interface) OR (EEG)) AND ((drones) OR (UAV) OR (aerial vehicles)" on four major online databases: Science Direct, IEEE Explore, PubMed, and MDPI. Various exclusion criteria were applied, such as excluding review articles, book chapters, conference proceedings, non-English articles, datasets, studies involving non-human subjects, articles not using real-time BCIs, articles related to mental workload or fatigue, and articles without results. Out of a total of 1.362 articles resulting from the search in the four databases, records were excluded after screening the title and abstract, removing duplicates, and applying the exclusion criteria. After reading the full texts, additional articles were excluded, leaving 42 papers that met the inclusion criteria.

The initial part of the review presents statistical findings from the included articles, including the number of subjects, number of EEG channels, article types, and types of EEG headsets used. The second section categorizes the papers into two main groups: real drones and virtual drones. These categories are further divided into four subgroups: MI, SSVEP, P300, and Rest. The articles are analyzed within each category based on EEG channels, number of subjects, classification algorithms employed, DoF of the systems, EEG processing techniques, feature extraction methods, and evaluation metrics. The review also highlights the most commonly employed classification algorithms and feature extraction techniques. The last section of the study discusses and presents future possibilities and trends in the field and future challenges.

Table 11 is employed to compare this study and other existing reviews in the field of BCI-controlled drones. Notably, there is a limited number of reviews addressing this specific topic. Among the available reviews, only one follows a systematic approach. This work is a systematic review and is the most up-to-date, covering the broadest time span by examining papers published from 2010 to 2023. Furthermore, 42 papers are included in this study, while the other reviews have considered between 13 to 36 studies. Lastly, we have conducted a comprehensive and in-depth analysis of these papers, presenting critical insights derived from them.

C. FUTURE TRENDS

The progress of augmented reality (AR) will have a significant impact on the future of BCI-controlled drones. AR technology can enhance the control experience by providing users with a more immersive interface. By employing an AR interface, users can receive visual feedback on the drone's flight path, assisting them in better BCI control. Currently, the penetration of AR technology in BCI-controlled drones is very limited however this is expected to be reversed with the development and commercialization of more reliable and affordable AR devices.

Multimodal Interfaces combine various input modalities, including BCI, with other sensors or devices and are a current trend in interface technology [65], [66]. Combining various input modalities such as speech recognition, gesture control, and eye-tracking with BCI has the potential to enhance interface systems, leading to improved ITR and better accuracy for users. Currently, very limited research attempts have been presented in the literature, most of them focusing on additional brain function recognition.

Many researchers are actively working on advancing the processing and classification of EEG signals, as well as exploring new methods for feature extraction [67], [68]. These improvements in the BCI pipeline have the potential to unlock new applications that can lead to a wider range of commands. Additionally, the integration of hybrid BCIs, where multiple BCI technologies work together, can enhance system accuracy and increase the DoF of the BCI. Specifically, by combining different EEG paradigms, researchers can achieve control over multiple drones (drone swarms) or achieve faster and more accurate classification for controlling all movements of a single drone.

Another possible trend in this research field is the transition towards utilizing BCI-controlled drone swarms for search and rescue operations. As BCIs continue to improve and offer higher DoF, researchers will concentrate on controlling multiple UAVs simultaneously to accomplish complex tasks. Moreover, it is predicted that in the future, there will be a fusion of ground vehicles and aerial vehicles for tasks such as area recognition.

BCI technology is a rapidly developing field that has made significant progress in recent years. The quality of commercial EEG headsets has been enhanced, and their size has been reduced, making them more compact and convenient. This reduction in size is particularly crucial for real-time BCI applications like controlling drones and UAVs. In the coming years, we can expect further advancements in this technology, resulting in a wider range of applications and more user-friendly hardware for researchers.

D. FUTURE CHALLENGES

The acquisition of a high-quality signal is the first step to having a robust and reliable BCI. EEG signals are noisy and contain several artifacts, so the growth of this research area needs to improve the data quality. Future research should focus on developing advanced signal processing techniques to extract meaningful information from brain signals while ensuring robustness and reliability.

Another challenge when developing a real-time BCI-controlled drone is the latency of the system. Reducing the latency in signal acquisition, processing, and drone feedback is crucial to ensure precise and timely control, which may involve advancements in hardware, algorithms, and communication protocols.

BCI systems usually require calibrating the system for each user to have a high performance and to be able to identify each user's brain patterns. Future research should focus on developing efficient calibration methods that minimize the time and effort required for initial setup. Additionally, researchers need to investigate ways to reduce the training time and improve the ease of use for participants.

VI. CONCLUSION

This review provides an overview of BCI-controlled UAVs, including research experimental articles from 2010 to 2023. The 42 articles were divided into two main categories: Real and Virtual, and further classified into four subgroups based on the EEG paradigm used. The review summarizes the experiments conducted, the outcomes obtained, and the signal processing methods employed. Additionally, areas requiring further investigation were identified. The objective of this systematic review is to serve as a valuable resource for new researchers venturing into this line of research. To the authors' best knowledge, this systematic review stands as the most comprehensive analysis in the field, encompassing the highest number of studies and covering the widest range of years.

In the field of BCI-controlled drones, upcoming trends involve integrating augmented reality (AR) interfaces for better control experiences and combining BCI with various input methods. Advances in EEG signal processing and feature extraction promise wider applications and improved system accuracy. Hybrid BCIs, which merge multiple BCI technologies, offer enhanced control capabilities, particularly for managing drone swarms or achieving rapid classification tasks. Challenges remain, such as refining signal processing for noisy EEG data and reducing system latency for real-time control. Efficient calibration techniques and streamlined training are crucial for user-friendly BCI systems. Ongoing research aims to address these challenges, resulting in more robust BCI-controlled drones with expanded features and improved user interactions

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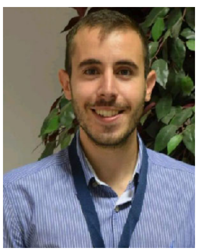

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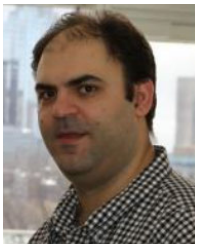

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