Baghdad Science Journal

Volume 22 | Issue 10 Article 28

10-28-2025

An Analytical Review of Brainwave Analysis for Mind-Controlled Drones: Utilizing Hybrid Neural Networks and Motor Imagery

Ather Salah Hadi Al-isawi
Department of Software Engineering and Information System, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400-Selangor, Malaysia, gs69090@student.upm.edu.my

Sufri Muhammad
Department of Software Engineering and Information System, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400-Selangor, Malaysia, sufry@upm.edu.my

Novia Indriaty Admodisastro
Department of Software Engineering and Information System, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400-Selangor, Malaysia, novia@upm.edu.my

Siti Anom Ahmad
Department of Electrical and Electronic Engineering, Faculty of Engineering, University Putra Malaysia, Serdang 43400-Selangor, Malaysia, sanom@upm.edu.my

Raihani Mohamed
Department of Computer Science, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400-Selangor, Malaysia, raihanimohamed@upm.edu.my

How to Cite this Article

Al-isawi, Ather Salah Hadi; Muhammad, Sufri; Admodisastro, Novia Indriaty; Ahmad, Siti Anom; and Mohamed, Raihani (2025) "An Analytical Review of Brainwave Analysis for Mind-Controlled Drones: Utilizing Hybrid Neural Networks and Motor Imagery," *Baghdad Science Journal*: Vol. 22: Iss. 10, Article 28.
DOI: https://doi.org/10.21123/2411-7986.5100

BAGHDAD SCIENCE JOURNAL 2025;22(10):3530–3545

RESEARCH ARTICLE

An Analytical Review of Brainwave Analysis for Mind-Controlled Drones: Utilizing Hybrid Neural Networks and Motor Imagery

Ather Salah Hadi Al-isawi [1,*], Sufri Muhammad [1], Novia Indriaty Admodisastro [1], Siti Anom Ahmad [2], Raihani Mohamed [3]

[1] Department of Software Engineering and Information System, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400 Selangor, Malaysia
[2] Department of Electrical and Electronic Engineering, Faculty of Engineering, University Putra Malaysia, Serdang 43400 Selangor, Malaysia
[3] Department of Computer Science, Faculty of Computer Science and Information Technology, University Putra Malaysia, Serdang 43400 Selangor, Malaysia

ABSTRACT

Brain-computer interfaces (BCIs) provide direct drone control by interpreting motor imagery brain impulses. This review paper critically assesses the progress made in using hybrid neural networks and motor imagery to operate mind-controlled drones and addresses the challenges of encoding and decoding complex brain signals for precise and reliable drone control. In this review paper, the primary objective is to analyze and synthesize the latest brainwave analysis technologies, focusing on hybrid neural networks and motor imagery tasks for drone control via brain-computer interfaces. This study aims to provide insights into the effectiveness of these technologies in enhancing the accuracy and reliability of mind-controlled drone systems. The method of conducting the review process is PRSM. This review paper shows that signal analysis reliability dictates a model that accurately decodes motor imagery-related brain signals and converts them into drone control commands. The integration of machine learning algorithms with neurophysiological principles has demonstrated significant improvements in the performance of mind-controlled drone systems. In conclusion, the synergistic utilization of hybrid neural networks and motor imagery techniques holds great potential for advancing the field of mind-controlled drones. Further research and optimization of signal processing algorithms are essential for enhancing the speed, precision, and robustness of mind-controlled drone systems, ultimately leading to transformative advancements in human-machine interactions across various domains. This review paper lays the groundwork for future research endeavours aimed at unlocking the full potential of brainwave analysis for mind-controlled drones.

Keywords: Brain-computer interfaces (BCI), Hybrid neural networks, Mind-controlled drones, Motor imagery, Signal processing algorithms

Introduction

Human-Computer Interaction (HCI) is increasingly important in computer science as Technological advances to connect people and machines. Brain-Computer Interfaces (BCIs) enable mind-controlled manipulation of electronic devices, such as drones, through brainwave communication. This article reviews recent BCI developments and challenges in brainwave analysis for controlling drones with the mind.[1] By analyzing existing literature, strengths, weaknesses, and conflicting views are identified

Received 13 April 2024; revised 27 December 2024; accepted 29 December 2024.
Available online 28 October 2025

* Corresponding author.
E-mail addresses: gs69090@student.upm.edu.my (A. S. H. Al-isawi), sufry@upm.edu.my (S. Muhammad), novia@upm.edu.my (N. I. Admodisastro), sanom@upm.edu.my (S. A. Ahmad), raihanimohamed@upm.edu.my (R. Mohamed).

https://doi.org/10.21123/2411-7986.5100

based on empirical data. The researcher explores past research methods and hardware to ensure reliable results and proposes using a hybrid neural network for improved motor imagery identification.[2] The review highlights significant achievements, identifies research gaps, and outlines future research directions.[3] The implications of BCI technology on healthcare, military, entertainment, and ethical considerations are also discussed.[4] The integration of BCI with drones opens up new possibilities for HCI, shaping its future while raising ethical concerns that need to be addressed. The researcher aims for this evaluation to advance the field of study further.

Human-Computer Interaction (HCI) has progressed from conventional command-line interfaces to sophisticated brain-computer interfaces (BCIs) that establish direct neural connections between the brain and external devices via brainwave signals. BCIs have been employed in the realm of drone control by decoding brainwave patterns associated with motor imagery. Early endeavours in this domain utilized electroencephalography (EEG) to capture brain wave activity for drone manipulation, albeit encountering obstacles arising from the intricate and unpredictable nature of human brain signals.[5] To overcome these challenges, a recent development involves the integration of hybrid Radial Basis Function-Multi-Layer Perceptron (RBF-MLP) neural networks to enhance the precision and reliability of motor imagery detection.[6,7] By amalgamating the distinct advantages of RBF and MLP networks, the control of drones through brainwave interpretation has attained greater accuracy.[6,8] Nonetheless, the optimization of system design and implementation in this rapidly evolving field necessitates further exploration.[9] A comprehensive understanding of motor imagery and intention is imperative for elucidating the neural processes underpinning movement planning and execution in the domain of neuroscience, furnishing invaluable insights into cerebral function.

Current challenges

Research in the field of brainwave analysis for detecting and interpreting intended motor imagery of human organs faces significant challenges and limitations, such as low accuracy, limited reliability, and difficulties in detecting and interpreting brainwave signals.[10] The primary challenge highlighted in this review paper pertains to the paucity of research dedicated to optimize the encoding and decoding processes of Motor Imagery Electroencephalography (MI-EEG) signals through the integration of hybrid neural network architectures. These obstacles impede the progress of brain-computer interfaces and mind-controlled technology. To address these issues, there is a focus on enhancing brainwave analysis techniques and overcoming these limitations within a different environment. The study is dedicated for finding solutions that improve the accuracy, reliability, and practicality of brainwave analysis, with the ultimate goal of advancing the field of brain-computer interfaces and unlocking the potential for mind-controlled technology to revolutionize various aspects of human-machine interaction. research gaps exist in terms of the long-term usability and robustness of these BCI systems in real-world drone control scenarios, as well as in understanding the psychological and physiological variations across subjects that may impact BCI performance consistency. Further studies focusing on individual differences in cognitive processes, attentional mechanisms, and physiological responses to BCI stimuli could help elucidate these cross-subject variations and inform personalized BCI design strategies for improved performance reliability.

Research objectives

The scientific objective of this review is to explore signal processing techniques to enhance the detection and interpretation of brainwave signals related to intended motor imagery, with a focus on reducing noise and improving signal clarity. The study aims to investigate methods for extracting meaningful features from brainwave data to enhance the classification accuracy of different motor imagery tasks. Additionally, the research will evaluate the effectiveness of hybrid neural network architectures in optimizing the encoding and decoding processes of Motor Imagery Electroencephalography (MI-EEG) signals to improve accuracy and reliability.

Main contributions

The review paper explores key challenges in brainwave analysis for detecting and interpreting intended motor imagery, with a focus on enhancing accuracy, reliability, and practicality. By investigating signal processing techniques and evaluating hybrid neural network architectures, the paper aims to provide valuable insights and solutions to advance the field of brain-computer interfaces and mind-controlled technology.

1. Addressing Challenges: The review paper tackles significant obstacles in brainwave analysis, such as low accuracy, limited reliability, and difficulties in detecting and interpreting brainwave

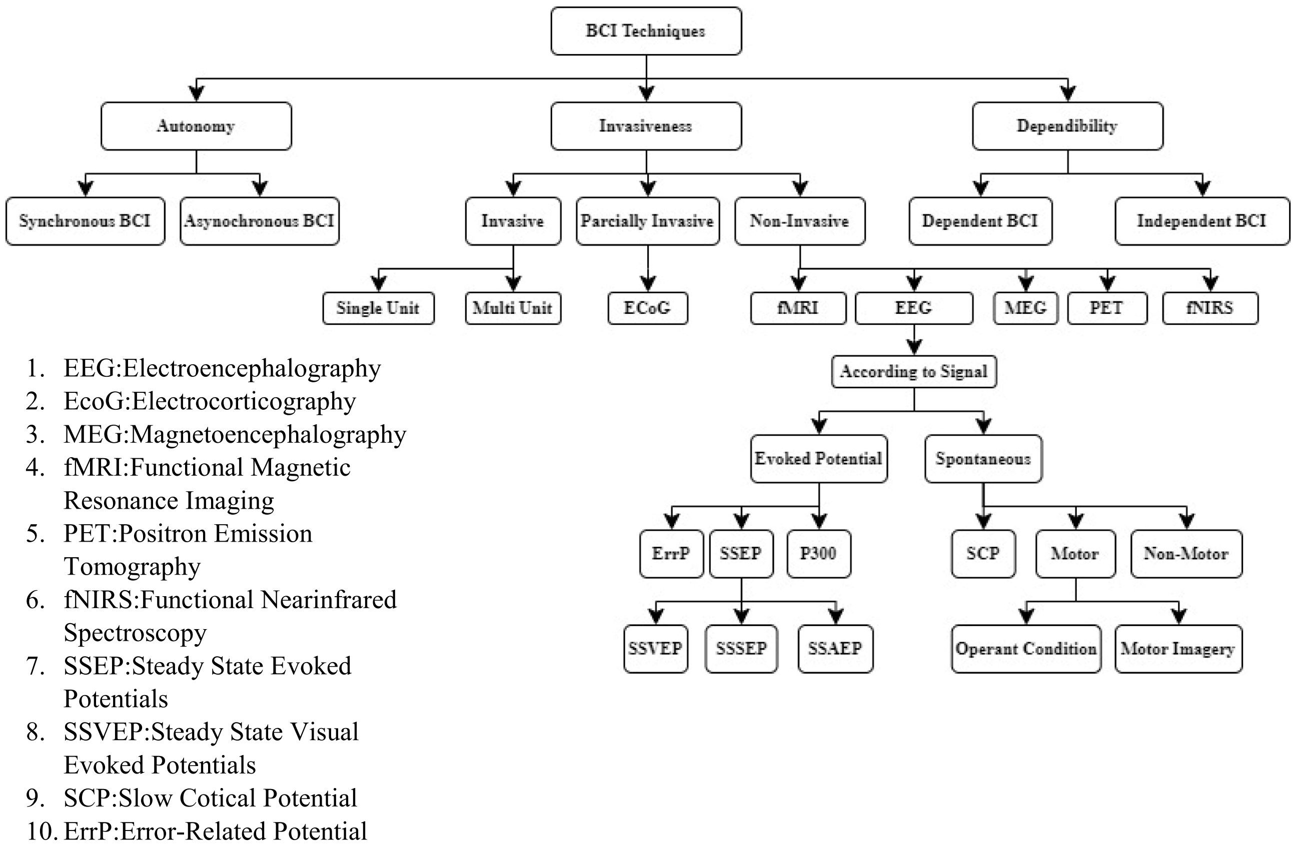

Fig. 1. Taxonomy of BCI system. “Mridha 2021, Rashid 2020”

signals, emphasizing the need for improvement in these areas.

2. Signal Processing Techniques: By exploring signal processing techniques, the paper offers novel approaches to enhance the detection and interpretation of brainwave signals, with a specific focus on reducing noise and improving signal clarity.
3. Feature Extraction Methods: The investigation into methods for extracting meaningful features from brainwave data contributes to enhancing the classification accuracy of various motor imagery tasks, offering valuable insights for improving performance in brainwave analysis.
4. Evaluation of Hybrid Neural Networks: The review paper evaluates the effectiveness of hybrid neural network architectures in optimizing the encoding and decoding processes of MI-EEG signals, presenting a promising avenue for improving accuracy and reliability in brainwave analysis.

In conclusion, the review paper makes significant contributions to the field by proposing solutions to overcome existing challenges in brainwave analysis and unlock the potential for advancing brain-computer interfaces and mind-controlled technology. The insights provided on signal processing techniques, feature extraction methods, and hybrid neural networks offer valuable contributions towards enhancing the accuracy, reliability, and practicality of brainwave analysis for improved human-machine interaction.

Background study

Process and mechanisms

The proposed work examination of motor imagery and Intention involves studying the cognitive processes and neural mechanisms underlying the mental simulation of movement and the intention to move. Motor imagery is the mental rehearsal of a specific movement without actually physically performing it, while intention refers to the conscious desire or readiness to execute a specific action.

Taxonomy of motor imagery and intention

The taxonomy of the BCI system can be classified depending on dependability, invasiveness, and autonomy, as illustrated in Fig. 1.[11,12] A range of studies have explored the use of motor imagery and intention in drone control. Tawiah and Gubán both emphasize the importance of machine vision-based techniques for navigation and control in autonomous vehicles, including drones.[13,14] Israr focuses on the use of optimization algorithms and fuzzy adaptive controllers for UAV attitude control and motion planning, respectively.[15,16] Mansur and Dekkata present specific applications of control approaches, such as incremental nonlinear dynamic inversion for altitude trajectory control and model predictive control for unmanned ground vehicles.[17,18] Hussien and Megyesi further enhance the control of UAVs through the use of L1 adaptive controllers and adaptive control algorithms, respectively.[19,20] These studies collectively highlight the potential of motor imagery and intention in enhancing the control and performance of drones. The taxonomy of motor imagery and intention can be categorized based on various dimensions, as Fig. 1 shows, including the neurophysiological processes involved, the cognitive mechanisms at play, and the behavioral outcomes observed. One common framework used to classify motor imagery and intention is based on the distinction between explicit and implicit processes. Explicit motor imagery and intention involve conscious, deliberate mental simulation and intention formation. Individuals engaging in explicit motor imagery are aware of the movement they are imagining and actively control the mental representation of the action.[21] This process often recruits regions of the brain associated with motor planning and execution, such as the premotor cortex and the supplementary motor area. On the other hand, implicit motor imagery and intention refer to the unconscious or automatic processes involved in movement preparation and execution. These processes may occur without explicit awareness or conscious effort on the part of the individual.

Implicit motor imagery is thought to rely on more automatic and procedural memory systems, involving regions like the basal ganglia and the cerebellum. Another dimension along which motor imagery and intention can be classified is the perspective taken during mental simulation. First-person perspective involves imagining oneself performing the action, as if looking through one's own eyes, while third-person perspective entails observing the movement from an external viewpoint. Studies have shown that different perspectives can engage distinct neural networks and may have implications for motor learning and performance.

Applications and implications

The taxonomy of motor imagery and intention affects rehabilitation, sports psychology, and cognitive neuroscience. Motor imagery-based motor rehabilitation programs use the brain's plasticity to improve motor recovery for those with movement impairments or injuries. In sports psychology, players practice complicated actions using motor imagery to improve performance. Visualizing successful acts may increase motor skills, confidence, and competitive anxiety in athletes. Research on the neurophysiological basis of motor imagery and intention illuminates motor control and cognition. The brain's representation and processing of motor intentions help us understand human behavior and build brain-computer interfaces and neuroprosthetic devices.

Technologies in BCI

Scientific research that interprets human brain impulses and converts them into instructions that operate physical equipment on the ground needs algorithms to identify and filter possible brain signals. Next, the algorithm model training process is a major challenge. Some devices for reading brain signals can be expensive, so most researchers use a ready-made database that has been documented by others in the same field to train potential algorithms. However, various physiological, physical, and psychological variables influence the formation of these brain signals, which affect their perception and translation into instructions that operate actual objects.[6,22] The suggested work environment lets users and researchers/programmers interact realistically and dynamically with recorded data. The researcher or programmer can solve issues more efficiently and dynamically, improving the user experience.[23] The proposed working environment is implemented based on an EEG brain signal classification algorithm selected depending on the literature with the highest accuracy obtained, which is the RBF-MLP algorithm, regardless of the domain in which this algorithm is applied.[6,22]

Analysis techniques

All researchers attempt to create an approach that produces accurate results, since the accuracy of assessing and interpreting raw data is valued. By tracing events from the origin to the downstream, researchers learn about prospective future research in the same field that is related to their current work and connected with their goals. In this work, the researcher hopes the latest findings will soon influence UAV control. This is vital since UAVs are used for surveillance, rescue, finding and monitoring missing people across wide regions, military activities, and saving lives. Some literature in the same sector has disappointing outcomes due to restriction and existentialism, which may help find new ideas and develop

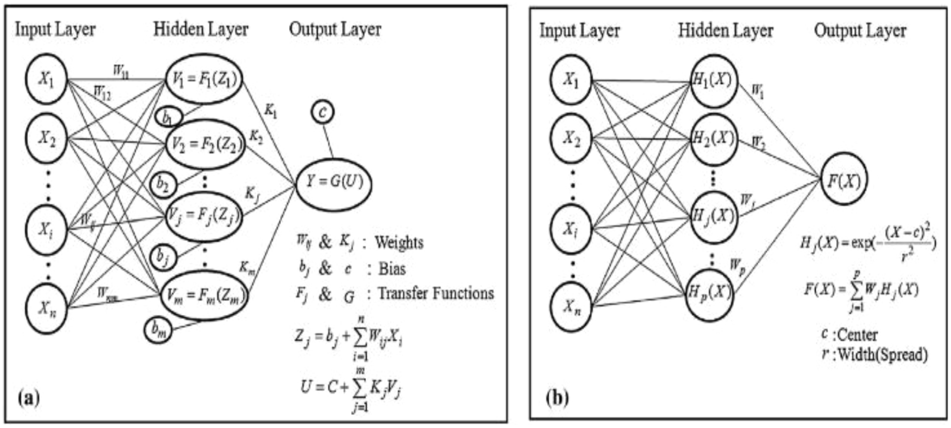

Fig. 2. Simple configuration of a-MLP and b-RBF neural networks. "Ghorbani 2016"

current approaches to achieve the intended aims with proven results.[24–26] A mix of the Radial Basis Function (RBF) and Multilayer Perceptron (MLP) neural network models makes up the RBF-MLP algorithm. It combines the powerful feature learning capabilities of MLP with the ability of RBF networks to approximate complex functions. Here is a basic formulation of the RBF-MLP algorithm:

1. MLP Layer:[27]
   – Initialize the weights and biases of the MLP network.
   – Train the MLP network using the RBF layer outputs as inputs.
   – Reduce the discrepancy between expected and actual results as much as possible by updating the biases and weights using back propagation and gradient descent.
2. Prediction:[27]
   – For a given input, pass it through the RBF layer to obtain the RBF neuron activations.
   – Use the MLP layer to generate the final output based on the RBF layer outputs.
3. Model Evaluation.[27]
   – Evaluate the performance of the RBF-MLP model using appropriate evaluation metrics (e.g., accuracy, mean squared error) on the testing dataset.
   – Adjust the hyper parameters (e.g., number of RBF neurons, learning rate) and repeat the training process to optimize the model's performance.

It is worth noting that the RBF-MLP algorithm can be implemented in various ways, and the specific details may vary depending on the implementation and requirements of your application. For instance, Ghorbani in[22] argues for a comparative study of artificial neural networks (MLP-RBF) and support vector machine models for river flow prediction. On the other hand, Dumitrescu in emphasizes,[6] according to the results they have gotten, the use of the MLP-RBF algorithm through a brain-computer interface to control a virtual drone using non-invasive motor imagery and machine learning. The above formulation provides a general outline of the algorithm's key steps.[27–30] An approach, known as back propagation learning, is used to train the MLP. A three-layer structure (MLP) with an input layer, hidden layer, and output layer is depicted in part a of Fig. 2. The data are received by the input layer, processed by the hidden layer, and then shown by the output layer as the model's outputs. Compared to the MLP neural network, the RBF neural network architecture is more popular and easier to implement. An input, hidden, and output layer make up the RBF, as shown in part b of Fig. 2. The RBF activation function, or h(x), is a network neuron that makes up the hidden layer. Although there are several varieties of radial basis functions, the Gaussian function is the one that is most frequently employed.[22] The researcher relies on some of the best literature that can support his work, trying to pose his ideas in the HCI field.

An RBF-MLP neural network uses the Radial Basis Function (RBF) for non-linear approximation and the Multilayer Perceptron (MLP) for processing and learning. Equations for an RBF-MLP network: From Fig. 2 part b, the RBF component: The output of a Radial Basis Function neuron in the RBF layer can be calculated using the Eq. (1) formula shows:[22,27]

$$H_j(X) = exp\left(-\frac{(X-c)^2}{r^2}\right) \tag{1}$$

Where:

– H_j is the output of neuron j in the RBF layer.
– X is the input to the RBF-MLP network.
– c is the center of the RBF neuron.
– r is the width of the RBF neuron (spread).

The output of the RBF layer is a vector of activations from all RBF neurons. From Fig. 2 part a, the MLP component: The output of a neuron in a hidden layer of the MLP network can be calculated using the Eq. (2) formula illustrate:[22,27]

$$Z_j = b_j + \sum_{i=1}^{n} W_{ij} X_i \tag{2}$$

Where:

- -Z_j is the output of neuron j in the hidden layer.
- -W_{ij} is the weight connecting RBF neuron i to hidden neuron j.
- b_j is the bias term for neuron j.
- n is the number of RBF neurons.

The output of the MLP network can be calculated by propagating the RBF activations through the hidden layers to the output layer. The final output of the RBF-MLP network is computed by combining the outputs of the RBF and MLP components, typically through a linear combination or another suitable method.

Qualification assessment

The integration of drones with BCIs

Real drones in Brain-Computer Interface (BCI) research and applications provide several benefits and new human-machine interface possibilities. The drone-BCI connection offers several advantages. An engaging and interactive platform is a possible drone utility in BCIs. Drones make BCI experiments and presentations physical and participatory. Brain signals may make controlling a real drone fun and engaging, making the technology more accessible and desirable. Additionally, there are real-world applications. Researchers can test BCI technology in real life using drones. Airborne surveillance, search and rescue, product delivery, environmental monitoring, and more are included. Brain signal-controlled autonomous systems may be tested in real-world conditions utilizing actual drones, integrating of many technologies. EEG (electroencephalography) for brain signal capture, signal processing techniques, machine learning models, and drone control systems are widely used in BCI drone control systems.[31–33] Researchers may create and test sophisticated multidisciplinary systems that advance human-machine interaction by merging various technologies. Also, feedback and adaptation: real drones provide users with real-time visual and aural feedback on their brain instructions as shown in Fig. 3, like the process shown in Fig. 3. Users need this feedback loop to learn and change their brain activity for drone control. Actual drones can adapt to changing environmental circumstances, requiring operators to change their mental orders.[11,34]

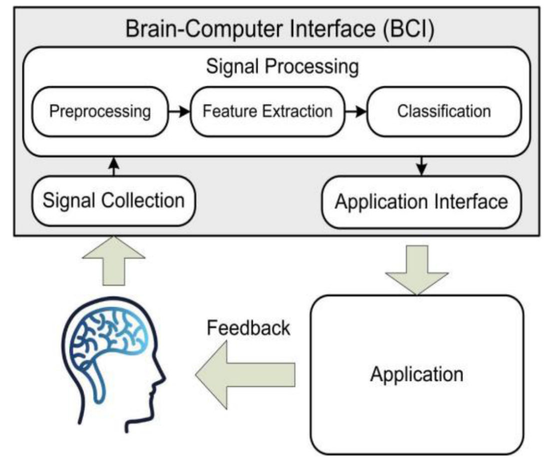

Fig. 3. Brain-computer interaction process. "Peksa 2023, Mridha 2021"

Additionally, UX and Motivation: Real Drone BCI Studies boost user experience and motivation. Mental manipulation of a physical thing might encourage users. This might increase BCI training and rehabilitation. Innovation and exploration last. Real drones assist BCI in research advancement. Researchers may explore novel control methods, adaptive algorithms, and user interfaces to improve BCI system performance and usability. Various drones enable brain-controlled technology. Finally, BCI research with drones lets researchers explore neurology, technology, and robotics. As a real and interactive platform, drones can help researchers understand brain-machine interfaces and develop novel social applications.

Motor and sensorimotor rhythms

Motor and sensorimotor rhythms are related. Sensorimotor rhythms, as shown in Fig. 4, are electrophysiological brain oscillations in the mu (Rolandic band, 7–13 Hz) and beta (13–30 Hz) frequencies. Using motor imagery conditions, participants translate their motor intentions into control signals.[35] A left-hand motion may cause EEG signals in the and rhythms and a reduction in motor cortex regions (8–12 Hz) and (18–26 Hz).[36] Depending on motor imagery rhythms, mouse control and gaming are possible.[11]

Task efficiency and reliability

Efficiency and reliability in task completion are essential for both the Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP) algorithms in machine learning. The RBF algorithm's efficiency and reliability are influenced by factors such as its data

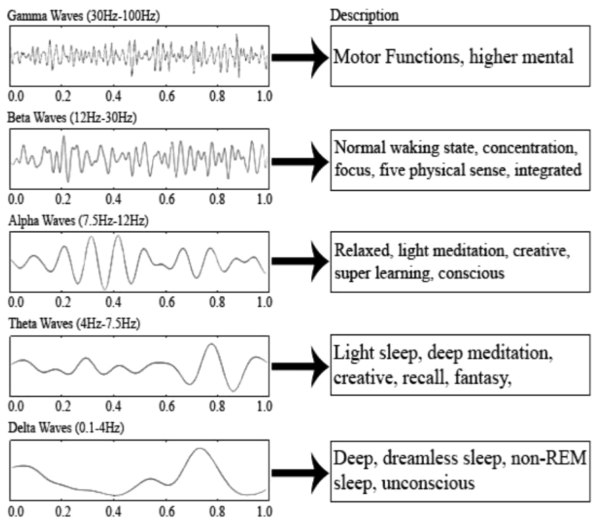

Fig. 4. Brain waves description. "Srimaharaj 2018"

representation, which impacts how well it can model complex relationships within the data. Additionally, the computational complexity of the RBF algorithm plays a key role in determining its efficiency and reliability, as more complex computations can lead to longer processing times and higher resource usage.[6,37,38] On the other hand, the efficiency and reliability of the MLP algorithm are closely tied to its network architecture and the learning algorithms used during training. The design of the MLP network, including the number of layers and neurons, can significantly affect its efficiency and reliability in learning complex patterns within the data. Moreover, the choice of learning algorithms, such as backpropagation, optimization techniques, and regularization methods, can impact the speed and accuracy of the MLP algorithm in training and prediction tasks.[6,39] Both the RBF and MLP algorithms require careful consideration of various factors to ensure their efficiency and reliability in different applications. Optimizing data representation, computational complexity, network architecture, and learning algorithms are crucial steps in improving the efficiency and reliability of these algorithms and achieving optimal performance in machine learning tasks.[6]

Usability and accessibility

The use of the error back-propagation approach in supervised training of multilayer perceptron has successfully resolved several complex and diverse problems. This approach employs error-correction learning. The network's synapses demonstrate substantial interconnectedness. Modifications in network connectivity need corresponding adjustments in the populations or weights of synaptic connections. Hidden neurons assimilate salient features from input patterns (vectors) to facilitate the network's acquisition of complex tasks. It is important to emphasize that nonlinearity has a continuous and seamless behavior. A separate nonlinear activation function is modeled for each.[27] By seeing neural network building as approximating high-dimensional curves, learning is defined as finding a surface in a multidimensional space that best matches the training data using statistical techniques measuring accuracy. Generalization uses a multidimensional surface to extrapolate test findings. The radial-basis function approach, which uses exact interpolation in multidimensional space, was inspired by this perspective. The hidden units of a neural network create radial-basis functions that may be used to represent input vectors in the hidden space. Real multivariate interpolation originally employed radial-basis functions.[27]

The importance of the BCI process

The brain waves graphic shows brain electrical activity as Fig. 4 illustrates. It reveals brain activity and conditions. Delta, theta, alpha, beta, and gamma brain waves are usually shown on the chart. Delta waves are the slowest and largest. Deep slumber and unconsciousness are related.

Light sleep, intense relaxation, and meditation produce quicker theta waves. When the brain is relaxed, such as during daydreaming or mild meditation, alpha waves are quicker. Beta waves are quicker and more connected with concentrated thought, problem-solving, and active thinking. Gamma waves, the fastest brain waves, improve cognition, memory, and perception. By analyzing the brain waves shown in Fig. 4, researchers and healthcare professionals can gain insights into an individual's mental state, level of arousal, and overall brain health. This information can be used to diagnose and treat various neurological conditions, monitor sleep patterns, enhance meditation practices, and optimize cognitive performance.[40,41]

EEG control signals used in BCI application

The BCI interprets neurophysiological EEG control signals to understand the subject's intent. BCI recognizes neurophysiological impulses and directs them. Certain control signals are easy to detect and control. SCP, P300, MI, MRCP, ErrP, SSVEP, SSAEP, and SSSEP are prominent EEG controls, as illustrated in Fig. 1.[11,12]

The diagnostic technique known as electroencephalography (EEG) allows for the measurement and recording of brain electrical activity. Depending on the need for surgical intervention, the EEG measurement can be categorized as invasive or

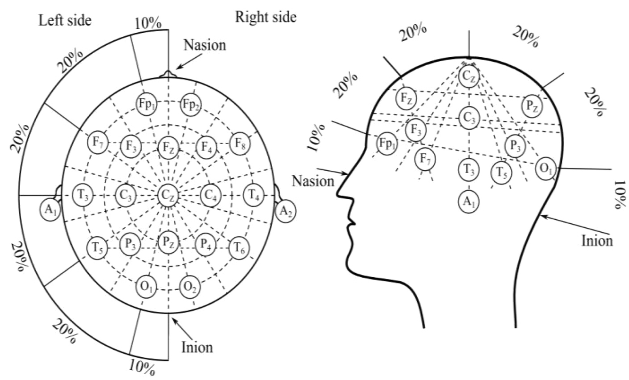

Fig. 5. Classify human head as sensor positions. The letters used are: F-frontal lobe, T-temporal lobe, C-central lobe, P-parietal lobe, O-occipital lobe. "Martinek 2021"

non-invasive.[42] Electrodes applied to the scalp in line with the "10–20" system (or its variants, such as "10–10" or "10–5"), are the basis of the non-invasive measuring approach,[43] as Fig. 5 illustrates.

Part A of Fig. 6 shows that the MW2 device and the application technique, fp1 electrodes, are placed based on 10–20 electrode positioning standards. The MW2 headset is non-invasive, portable, small, and user-friendly with low power consumption, while part B of Fig. 6 shows the experimental procedure block diagram.[40]

The detected instruction is often sent via a pre-programmed algorithm to an external device for additional processing, but highly specialized systems may handle this function on their own. In the end, the received instruction is decoded on the controlled device according to its particular properties,[11,34] as illustrated in Fig. 3. HCI endeavors to enhance the usability of computer systems, guaranteeing that they are straightforward to acquire, effective to use, and provide a satisfying user experience. For mind-controlled drones, the aim is to provide an interface that enables users to efficiently operate the drone by using their intended motor images.

The Fig. 7 depicts the four-step process for EEG signal analysis. The EEG signal analysis involves four stages: acquisition, denoising, feature engineering, and classification.[44] HCI strives to ensure that computer systems are accessible to people with a wide range of skills and requirements. This purpose entails the consideration of several elements, including visual, auditory, and motor limitations. Regarding mind-controlled drones, the objective is to provide an interface that caters to users with different degrees of motor skills, enabling them to efficiently operate the drone by using their intended motor images.

The PRSM (Performance Review and Self-Management) method, it has been implemented to conduct the review, focuses on integrating performance reviews with self-management practices. This approach encourages the researcher to take an active role in his performance assessment and development, emphasizing personal accountability and continuous improvement. First of all, the researcher set clear goals, measurable, achievable, relevant, and time-bound (SMART) goals aligned with organizational objectives. Second, there is a need to meet Self-Assessment when he regularly assesses his performance against these goals, reflecting on achievements and challenges. Next, Collect Feedback which is encouraging ongoing feedback from peers, supervisors, and stakeholders to supplement self-assessments. Followed by doing action planning based on self-assessments and

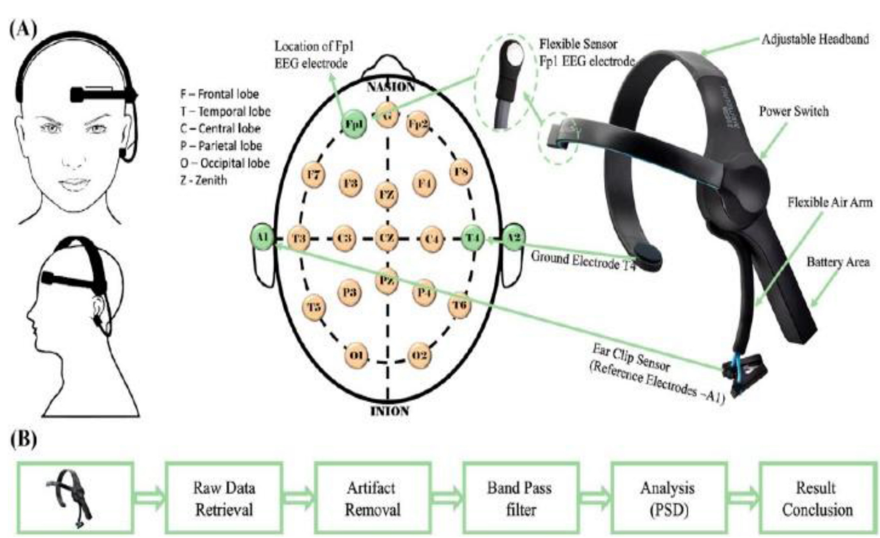

Fig. 6. Sensor kind headset in this work. "Ali 2022"

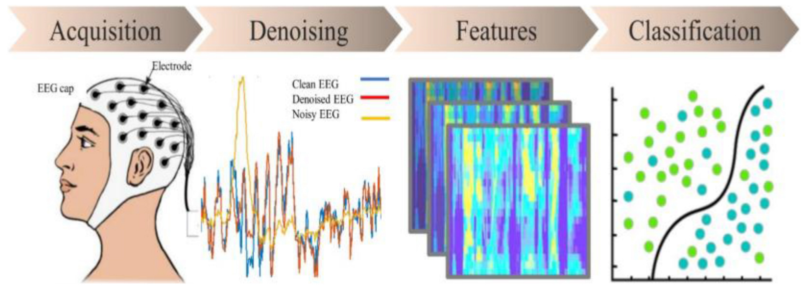

Fig. 7. Service analysis and composition of the EEG brainwave. "Chaddad 2023"

feedback, he creates action plans outlining steps for improvement and professional development. Finally, reviewing and adjusting to conduct formal performance reviews periodically to evaluate progress, adjust goals, and refine action plans. The emphasis on setting SMART goals ensures that his performance is closely aligned with the review objectives. The PRSM Method empowers the researcher to take an active role in his performance management process. This research can benefit from integrating this method into the researcher's performance review practices, fostering a culture of continuous feedback, personal accountability, and collective improvement.

Results and discussion

Recent research has advanced Brain-Computer Interface (BCI) systems for drone control through various innovative approaches. Key developments include a visual imagery paradigm, a P300-based BCI for virtual and augmented reality, and a hybrid BCI for multidirectional control of quadcopters. Additionally, systems have been proposed for UAV target searching and low-complexity control of robot swarms. Challenges in automated control and fault tolerance in drone networks have also been addressed, highlighting the diverse methods enhancing BCI-based drone control.

The methodologies, which are shown in Table 1 employed by researchers reflect a diverse range of approaches in the development of Brain-Computer Interface (BCI) systems for drone control. One group utilized EEG signals and classification methods such as Linear Discriminant Analysis (LDA) and P300-based BCIs. Another focused on developing versatile architectures and hybrid BCIs for precise control of robotic devices using eye-blinking commands. Some explored the application of BCI systems for UAV target searching and robot swarm control, while others addressed automated control in drone networks and investigated fault-tolerant control in drone interceptors. These methodologies collectively demonstrate the innovation and variety in techniques used to advance the integration of BCI systems for drone control applications. In their respective studies, researchers measured various outcomes to evaluate the effectiveness of BCI systems for drone control. One study confirmed the feasibility of EEG-based drone swarm control and achieved robust classification performance. Another found no significant difference in online performance and user experience between virtual and augmented reality environments in P300-based BCI drone control. Others presented versatile architectures for BCI development and testing, while precision in controlling robotic devices using eye-blinking commands was demonstrated in both real and virtual environments.

Performance assessments of BCI systems for UAV target searching focused on factors such as distance error, rotation error, time cost, and classification accuracy. Additionally, the development of low-complexity BCIs for controlling high-complexity robot swarms emphasized efficient, robust, and scalable interaction algorithms. Overall, these diverse outcomes highlight the advancements and capabilities of BCI systems in drone control applications.

The comparative analysis of the methods and methodologies used by researchers referred in Table 1, that sheds light on the multifaceted approaches to BCI-based drone control. By synthesizing key findings and contributions from these studies, this article underscores the importance of interdisciplinary collaboration and innovation in advancing BCI technology for real-world applications such as drone control. Future research in this area can benefit from building upon the diverse methods and methodologies discussed here to further enhance the capabilities and usability of BCI systems for drone control.

One of the studies in Table 1 focused on a visual imagery paradigm for BCI-based drone control, aiming to assess the feasibility of using EEG signals from visual imagery tasks to control drones. In another approach, a P300-based BCI was utilized

Table 1. Comparative analysis of studies.

Reference	Domain scenario	Method/ Model	Methodology	Modality comb.	Experimental techniques	Ac.Class.	Outcome measured
Drone Control/EEG Signals [45]	Drone control using EEG signals.	Linear discriminant analysis (LDA) with a one-versus-rest strategy.	Recruited seven healthy subjects, acquired EEG signals with 64 electrodes, designed a drone swarm control simulator, and employed EEG data analysis techniques.	Visual imagery paradigm.	EEG signal acquisition, preprocessing, common spatial pattern (CSP) algorithm application, and LDA for classification.	75.7%	Validated EEG-based drone swarm control, robust categorization, and sophisticated BCI-based drone control systems.
Drone Control in VR and AR Environments [26]	Drone control in VR and AR environments.	Linear Discriminant Analysis (LDA).	Used a P300 BCI drone control application in AR and VR environments, conducted experiments with 20 healthy subjects, and analyzed classification accuracy and ERP signals.	P300-based BCI.	Questionnaires, statistical tests.	Not mentioned	No significant difference ($p > 0.05$) in online performance and user experience between VR and AR environments.
Hexapod Robot/Drone Control/Eye Blinking [39]	Controlling a hexapod robot and a drone using eye blinking signals.	Various classification methods for EEG signals.	Developed a modular hardware-software architecture for BCIs, trained classifiers with EEG signals, and tested precision of controlling robotic devices using eye blinking commands.	Versatile architecture for BCI development.	EEG signal processing with various filters, classification methods, adaptability, and reconfigurability focus.	91.7%	Precision in controlling the hexapod robot, average accuracy, and control in real and virtual environments.
Quadcopter Flight Control in 3D Space [46]	Multidirectional control of a quadcopter.	CCA and CSP using Linear Distinction Analysis.	Used a hybrid BCI approach, conducted online experiments with five subjects, recorded scalp EEG, and processed data through preprocessing and classification steps.	Hybrid BCI for multidirectional control.	CCA, CSP, linear distinction analysis, evaluation of BCI control capacity.	87.09%	Average classification accuracy of EEG-based commands and information transfer rate.

(Continued)

for drone control in virtual and augmented reality settings to compare online performance and user experience between the two environments. One study emphasized the effectiveness and accuracy of visual imagery tasks, while another delved into the impact of different immersive environments on BCI performance and user engagement. Additionally, a hybrid BCI was designed in another study shown in Table 1 for multidirectional control of a quadcopter, showcasing the integration of MI-EEG signals with advanced algorithms for improved control accuracy. While one study focused on architecture flexibility

Table 1. Continued

Reference	Domain scenario	Method/ Model	Methodology	Modality comb.	Experimental techniques	Ac.Class.	Outcome measured
BCI System for UAV Target Searching [47]	UAV indoor space target searching.	"One versus one" (OVO) and "one versus rest" (OVR) strategies with Common Spatial Pattern (CSP) for feature extraction.	Utilized a BCI system for UAV target searching, incorporating monocular vision navigation, OVO and OVR strategies, and a 2-layer HSVM for classification.	Neuroscan with 40 channels Ag/AgCl electrodes.	EEG signal processing, OVO and OVR strategies, reduction of error by about 21%.	Not mentioned	Distance error, rotation error, time cost, classification accuracy.
Low-Complexity BCI for Robot Swarm Control [48]	High-complexity robot swarm control.	Posterior matching algorithm.	Used feedback information theory, a robust interaction algorithm, an EEG MI classifier, posterior matching to manage a simulated robot swarm, and SCINET in a cyber-physical system.	Low-complexity BCI.	Large-scale user study, EEG MI classifier training, posterior matching for simulated robot swarm control, demonstration of SCINET on a physical robot swarm.	75.7%	SCINET interaction algorithm's efficiency, robustness, and scalability in controlling complex effectors.
Automated Control in Drone Networks [49]	Automated control in drone networks.	SwarmControl as a software-defined control framework.	SwarmControl for UAV wireless networks presented a centralized abstraction, dissected network control issues, developed distributed numerical solution methods, and was tested in flight.	Automated control in drone networks.	Extensive flight experiments, evaluation of SwarmControl distributed optimization.	159% to 231%	Average throughput improvement (159%–231%) above state-of-the-art systems.
Fault Tolerance in Drone [50] Networks [50]	Fault tolerance in drone networks.	Fault Weighting Dynamic Control Allocation (FWDCA) algorithm.	Numerical simulations evaluated a drone interceptor fault-tolerant control system using a virtual control law and FWDCA algorithm.	Fault tolerance in drone networks.	Numerical simulations, zero-order holders modeling, actuator fault scenarios.	60.4%	Performance of the fault-tolerant control system under various conditions.
Drone Control/EEG [6]	Drone control using EEG signals.	ICA, r 2, hybrid neural network (RBF and MLP-RNN), CSGD, LabVIEW software environment	Experimental studies to improve stimuli and tasks in a motor imagery-based BCI architecture, ICA and r2 feature extraction from EEG signals, LabVIEW implementation, and fully connected multilayer perceptron (MLP) classification are used.	Visual imagery paradigm.	LabVIEW, MATLAB-LabVIEW, UWT wavelet multiresolution analysis, ICA method, RBF/MLP-RNN hybrid neural network, SGD/CSGD optimization, and LabVIEW 3D animation. RBF-MLP-RNN classificatory.	95.67%	The maximum classification rate with hybrid RBF MLP-RNN neural network was 95.67% for three channels (C3, CP3, P3) and motor imagery left-hand tasks.

and efficiency, the other demonstrated the benefits of hybrid algorithms in enhancing control precision. Through detailed experimental analyses, each study contributed valuable insights into the design and optimization of BCI systems for drone control, highlighting the importance of adaptable architectures and algorithmic advancements in advancing the field. Recent studies on Brain-Computer Interface (BCI) systems for drone control have shown significant advancements and diverse methodologies that enhance their potential. Key findings include successful EEG-based control of drone swarms, enabling applications like search and rescue, and equivalent user performance in virtual and augmented reality, which enhances accessibility. Improvements in flexible BCI architectures and the integration of Motor Imagery EEG signals with advanced algorithms have increased control accuracy and adaptability. Low-complexity BCIs are also capable of managing complex operations effectively. However, addressing challenges in automated control and fault tolerance is crucial for reliability in dynamic environments. Additionally, a new framework for hybrid algorithms is suggested to further advance the field. Overall, these innovations position BCI systems to greatly impact various industries, improving drone operations in real-world scenarios.

The studies in Table 1 highlight significant advancements and methodologies that enhance their potential across various applications. The successful use of EEG-based control for drone swarms demonstrates the ability to manage multiple drones simultaneously, revolutionizing fields like search and rescue, surveillance, and agriculture. Findings also show no significant difference in user performance between P300-based BCIs in virtual and augmented reality environments, increasing accessibility for training and operations. Flexible BCI architectures and the integration of Motor Imagery EEG signals with advanced algorithms further improve control accuracy for quadcopters. Moreover, insights from BCI systems for UAV target searching indicate effectiveness in military and security applications. Addressing challenges in automated control and fault tolerance is essential for reliability in dynamic environments. Importantly, proposing a framework to tackle issues related to the psychology and physics of the human brain can lead to new models that overcome limitations from previous literature. Overall, these innovations position BCI systems to significantly impact various industries, fostering more efficient drone operations and paving the way for advanced, user-friendly applications.

In conclusion, the studies by Jeong et al, Kim et al, Martinez-Ledezma et al, and Yan et al. collectively offer significant contributions to the field of brain-computer interface (BCI) technology for drone control.[26,39,45,46] Jeong and Kim's investigations into different BCI *paradigms and immersive environments* shed light on the varying factors influencing BCI performance and user experience in drone control applications. The emphasis on visual imagery tasks and P300-based BCIs, as well as the exploration of virtual and augmented reality settings, provides valuable insights into the potential applications and challenges within this domain. However, research gaps exist in terms of the long-term usability and robustness of these BCI systems in real-world drone control scenarios, as well as in understanding the *psychological* and *physiological* variations across subjects that may impact BCI performance consistency. Further studies focusing on individual differences in cognitive processes, attentional mechanisms, and physiological responses to BCI stimuli could help elucidate these cross-subject variations and inform personalized BCI design strategies for improved performance reliability. Furthermore, the research of Martinez-Ledezma et al. and Yan et al. on architecture adaptability,[39,46] scalability, and hybrid algorithms for precise control of robotic devices underscores the importance of innovative design strategies and algorithmic advancements in optimizing BCI systems for enhanced control accuracy. Future studies could delve deeper into the interoperability of these different BCI architectures with varying drone models and environmental conditions to assess their generalizability and scalability. By synthesizing these diverse perspectives and experimental findings, a more comprehensive understanding of the complexities and opportunities in BCI-based drone control emerges, paving the way for future advancements and applications in this evolving field. It is clear from the previous table, that although the classification accuracy is high, the reliability of the analysis remains based on the model used in the field of drone control. The aim of this review paper is to stand on the benefit of MI-EEG signals only in generating brain signals that in turn will be classified for their corresponding control instructions within the movement displacement. Thus, the result finding would be the suggested model.

The limitations of the proposed study

The limitations identified in the research underscore the necessity for future investigations to broaden the scope of application contexts, encompass various cognitive processes, fortify data reliability, and incorporate user-centric perspectives to guarantee the effective and ethical deployment of brainwave analysis methodologies in practical environments.

Subsequent studies could concentrate on the development and implementation of dynamic learning algorithms in real-time for brainwave analysis during tasks involving motor imagery. These algorithms would continuously calibrate and optimize parameters based on user input and performance, thereby enhancing the precision and dependability of brain-computer interfaces. Through the integration of adaptable machine learning techniques tailored to individual brainwave patterns, researchers can elevate the utility and efficiency of neuro technology controlled by the mind.

Conclusion

The conclusion highlights both theoretical and practical implications of the research on Brain-Computer Interfaces (BCIs) for drone control. Theoretically, it aims to enhance understanding of various BCI paradigms' effectiveness and usability in different environments, contributing to frameworks that account for psychological and physiological variations among users. Practically, the research seeks to inform the design and optimization of BCI systems by examining adaptability, scalability, and algorithmic advancements, leading to more robust systems tailored to individual users and conditions. These insights could guide personalized design strategies to improve control precision and user experience in real-world drone applications.

This research identifies significant gaps in the research on Brain-Computer Interfaces (BCIs) for drone control, despite progress in the field. Key issues include the insufficient focus on the long-term reliability and robustness of BCI systems, which is crucial for their practical effectiveness in real-world scenarios. There is also a need for more research on the real-world implementation of BCI-controlled drones, user experience, and ergonomics of BCI interfaces. Additionally, the lack of interoperability and standardization could impede collaboration and innovation, while cybersecurity and privacy concerns related to BCI data remain underexplored. However, recent advancements in mind-controlled drones using Motor Imagery Electroencephalography (MI-EEG) combined with hybrid algorithms. Finally, understanding how to scale and adapt BCI systems for various drone types and applications is essential. Addressing these gaps is vital for advancing mind-controlled drones and their successful integration into various industries.

The conclusion of the research paper highlights significant advancements in brainwave analysis for detecting motor imagery intentions, focusing on improving accuracy, reliability, and practicality. It discusses the exploration of signal processing techniques, feature extraction methods, and hybrid neural networks to enhance brain-computer interfaces and mind-controlled technology. The study also emphasizes the optimization of pre- and post-processing techniques, algorithm adjustments, and consideration of individual differences to improve signal quality and personalize analysis. Overall, these methodological advancements aim to foster more effective human-machine interactions across various applications.

Acknowledgment

The authors would like to be thankful for the support of the Universiti Putra Malaysia under GP-IPM - Geran Putra Inisiatif Putra Muda (UPM).

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Putra Malaysia.

Authors' contribution statement

A. A. and S. M. have designed the study. A. A. has examined many literature experiments in the domain of brain-computer interaction. Both S. M. and N. I. have guided the research from the origin to the downstream. Both S. A. A. and R. M. have observed and evaluated the demonstration of this work. A. A. has analyzed the data and written the paper with the inputs that have been collected. As a matter of fact, A. A. has proposed a new technique for controlling a mind-controlled drone utilizing the RBF-MLP model.

References

1. Ahmed I, Nowrin H, Dhar H. Stopping power and range calculations of protons in human tissues. Baghdad Sci J. 2020;17(4):1234–1240. https://doi.org/10.21123/bsj.2020.17.4.1223.

2. Bayram M, Palluel-Germain R, Lebon F, Durand E, Harquel S, Perrone-Bertolotti M. Motor imagery training to improve language processing: What are the arguments? Front Hum Neurosci. 2023;17:1–13. https://doi.org/10.3389/fnhum.2023.982849.
3. Park J, Park J, Shin D, Choi Y. A BCI Based Alerting System for Attention Recovery of UAV Operators. Sensors. 2021;21(7):2447. https://doi.org/10.3390/s21072447.
4. Azar AT, Koubaa A, Ali Mohamed N, Ibrahim HA, Ibrahim ZF, Kazim M, Ammar A, Benjdira B, Khamis AM, Hameed IA, *et al.* Drone Deep Reinforcement Learning: A Review. *Electronics*. 2021;10(9):999. https://doi.org/10.3390/electronics10090999.
5. Jembre YZ, Nugroho YW, Khan MTR, Attique M, Paul R, Shah SHA, Kim B. Evaluation of Reinforcement and Deep Learning Algorithms in Controlling Unmanned Aerial Vehicles. Applied Sciences. 2021;11(16):7240. https://doi.org/10.3390/app11167240.
6. Dumitrescu C, Costea IM, Semenescu A. Using Brain-Computer Interface to Control a Virtual Drone Using Non-Invasive Motor Imagery and Machine Learning. Appl Sci. 2021;11(24):11876–11888. https://doi.org/10.3390/app112411876.
7. Tibrewal N, Leeuwis N, Alimardani M. Classification of motor imagery EEG using deep learning increases performance in inefficient BCI users. PLoS One. 2022;17(7):1–18. https://doi.org/10.1371/journal.pone.0268880.
8. Liu W, Bao F. Signal recognition methods in motor imagery BCI. In: Hu N, Zhang G, editors. Third Int Semin Artif Intell Networking, Inf Technol (AINIT 2022). SPIE;2023:84–92. https://doi.org/10.1117/12.2667874.
9. Barhoun P, Fuelscher I, Do M, He JL, Cerins A, Bekkali S, *et al.* The role of the primary motor cortex in motor imagery: A theta burst stimulation study. Psychophysiology. 2022;59(10):1–19. https://doi.org/10.1111/psyp.14077.
10. Al-Saegh A, Dawwd SA, A-J JM. Deep learning for motor imagery EEG-based classification: A review. Biomed Signal Process Control. 2021;63:102172. https://doi.org/10.1016/j.bspc.2020.102172.
11. Mridha MF, Das SC, Kabir MM, Lima AA, Islam MR, Watanobe Y. Brain-Computer Interface: Advancement and Challenges. Sensors. 2021;21(17):1–13. https://doi.org/10.3390/s21175746.
12. Rashid M, Sulaiman N, P. P. Abdul Majeed A, Musa RM, Ab. Nasir AF, Bari BS, *et al.* Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review. Front Neurorobot. 2020;14(6):35–46. https://doi.org/10.3389/fnbot.2020.00025.
13. Tawiah TAQ A review of algorithms and techniques for image-based recognition and inference in mobile robotic systems. Int J Adv Robot Syst. 2020;17(6):1–25. https://doi.org/10.1177/1729881420972278.
14. Gubán M, Udvaros J. A Path Planning Model with a Genetic Algorithm for Stock Inventory Using a Swarm of Drones. Drones. 2022;6(11):364–377. https://doi.org/10.3390/drones6110364.
15. Liu B, Wang Y, Wen J, Zhao C. Fuzzy PD controller of UAV attitude under wind interference. Joo J, editor. MATEC Web Conf. 2020;309:1–11. https://doi.org/10.1051/matecconf/202030904010.
16. Israr A, Ali ZA, Alkhammash EH, Jussila JJ. Optimization Methods Applied to Motion Planning of Unmanned Aerial Vehicles: A Review. Drones. 2022;6(5):126–138. https://doi.org/10.3390/drones6050126.
17. Mansur A, Lanteigne E. Altitude Trajectory Control of an Unmanned Airship Using Incremental Nonlinear Dynamic Inversion. Prog Can Mech Eng. Charlottetown, P.E.I.: University of Prince Edward Island. Robertson Library;2020;3:1–9. https://doi.org/10.32393/csme.2020.33.
18. Dekkata SC, Yi S, Muktadir M, Garfo S, Li X, Tereda AA. Improved Model Predictive Control System Design and Implementation for Unmanned Ground Vehicles. J Mechatronics Robot. 2022;6(1):90–105. https://doi.org/10.3844/jmrsp.2022.90.105.
19. Hussien M, Elnaggar M, Kamel AM, Fattah HAA. Unmanned Aerial Vehicle Attitude Control Using L 1 Adaptive Controller. IEEE Access. 2021;9:131916–131925. https://doi.org/10.1109/ACCESS.2021.3114508.
20. Megyesi D, Bréda R, Schrötter M. Adaptive Control and Estimation of the Condition of a Small Unmanned Aircraft Using a Kalman Filter. Energies. 2021;14(8):2292–2301. https://doi.org/10.3390/en14082292.
21. Almajidy RK, Mottaghi S, Ajwad AA, *et al.* A case for hybrid BCIs: combining optical and electrical modalities improves accuracy. Front Hum Neurosci. 2023;17:1162712. Published 2023 Jun 7. https://doi.org/10.3389/fnhum.2023.1162712.
22. Ghorbani MA, Zadeh HA, Isazadeh M, Terzi O. A comparative study of artificial neural network (MLP, RBF) and support vector machine models for river flow prediction. Environ Earth Sci. 2016;75(6):476–487. https://doi.org/10.1007/s12665-015-5096-x.
23. Duan X, Xie S, Xie X, Meng Y, Xu Z. Quadcopter Flight Control Using a Non-invasive Multi-Modal Brain Computer Interface. Front Neurorobot. 2019;13:1–11. https://doi.org/10.3389/fnbot.2019.00023.
24. Echtioui A, Mlaouah A, Zouch W, Ghorbel M, Mhiri C, Hamam H. A Novel Convolutional Neural Network Classification Approach of Motor-Imagery EEG Recording Based on Deep Learning. Appl Sci. 2021;11(21):1–18. https://doi.org/10.3390/app11219948.
25. Abdulwahhab AH, Myderrizi I, Mahmood MK. Drone Movement Control by Electroencephalography Signals Based on BCI System. Adv Electr Electron Eng. 2022;20(2):216–224. https://doi.org/10.15598/aeee.v20i2.4413.
26. Kim S, Lee S, Kang H, Kim S, Ahn M. P300 Brain–Computer Interface-Based Drone Control in Virtual and Augmented Reality. Sensors. 2021;21(17):1–16. https://doi.org/10.3390/s21175765.
27. Haykin SS. Neural networks: a comprehensive foundation. Upper Saddle River, N.J.: Prentice Hall;1999.
28. WZ ou, Z T. An efficient learning algorithm for improving generalization performance of radial basis function neural networks. J Neural Netw. 2000;13(4–5):545–553. https://doi.org/10.1016/S0893-6080(00)00029-0.
29. Bodyanskiy Y, Chala O, Filatov V, Pliss I. Neo-Fuzzy Radial-Basis Function Neural Network and Its Combined Learning. Comput Eng. 2023;1107:323–340. https://doi.org/10.1007/978-3-031-37450-0_19.
30. Oyang YJ, Hwang SC. An efficient learning algorithm for function approximation with radial basis function networks. In: Proc 9th Int Conf Neural Inf Process ICONIP. Nanyang Technol. Univ;2002:1037–1042. https://doi.org/10.1109/ICONIP.2002.1198218.
31. Choi JW, Kim BH, Jo S. Asynchronous Motor Imagery Brain-Computer Interface for Simulated Drone Control. In:9th Int Winter Conf Brain-Computer Interface. IEEE. 2021;5:1–7. https://doi.org/10.1109/BCI51272.2021.9385309.
32. Hong J, Qin X. Signal processing algorithms for SSVEP-based brain computer interface: State-of-the-art and recent developments. J Intell Fuzzy Syst. 2021;40(6):10559–10573. https://doi.org/10.3233/JIFS-201280.

33. Huang X, Xu Y, Hua J, Yi W, Yin H, Hu R, *et al.* A Review on Signal Processing Approaches to Reduce Calibration Time in EEG-Based Brain–Computer Interface. Front Neurosci. 2021;15:1–17. https://doi.org/10.3389/fnins.2021.733546.
34. Peksa J, Mamchur D State-of-the-Art on Brain-Computer Interface Technology. Sensors. 2023;23(13):6001–6012. https://doi.org/10.3390/s23136001.
35. Golub MD, Chase SM, Batista AP, Yu BM. Brain–computer interfaces for dissecting cognitive processes underlying sensorimotor control. Curr Opin Neurobiol. 2016;37:53–58. https://doi.org/10.1016/j.conb.2015.12.005.
36. Gu X, Cao Z, Jolfaei A, Xu P, Wu D, Jung TP, *et al.* EEG-Based Brain-Computer Interfaces (BCIs):A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and Their Applications. IEEE/ACM Trans Comput Biol Bioinform. 2021;18(5):1645–1666. https://doi.org/10.1109/TCBB.2021.3052811.
37. Yang Q, Ye Z, Li X, Wei D, Chen S, Li Z. Prediction of Flight Status of Logistics UAVs Based on an Information Entropy Radial Basis Function Neural Network. Sensors. 2021;21(11):3651–3663. https://doi.org/10.3390/s21113651.
38. Wang L, Liu Y, Gu K, Wu T. A radial basis function artificial neural network (RBF ANN) based method for uncertain distributed force reconstruction considering signal noises and material dispersion. Comput Methods Appl Mech Eng. 2020;364:112954. https://doi.org/10.1016/j.cma.2020.112954.
39. Martinez-Ledezma JA, Barron-Zambrano JH, Diaz-Manriquez A, Elizondo-Leal JC, Saldivar-Alonso VP, Rostro-Gonzalez H. Versatile implementation of a hardware–software architecture for development and testing of brain–computer interfaces. Int J Adv Robot Syst. 2020;17(6):837–858. https://doi.org/10.1177/1729881420980256.
40. Ali A, Afridi R, Soomro TA, Khan SA, Khan MYA, Chowdhry BS. A Single-Channel Wireless EEG Headset Enabled Neural Activities Analysis for Mental Healthcare Applications. Wirel Pers Commun. 2022;125(4):3699–3713. https://doi.org/10.1007/s11277-022-09731-w.
41. Srimaharaj W, Chaisricharoen R, Chaising S, Sittiprapaporn P. Classification of human brain attention focused on meditation, effected by L-theanine acid in Oolong tea. In: 2018 Int Conf Digit Arts, Media Technol. IEEE;2018:262–266. https://doi.org/10.1109/ICDAMT.2018.8376536.
42. Huang Z, Wang M. A review of electroencephalogram signal processing methods for brain-controlled robots. Cogn Robot. 2021;1:111–124. https://doi.org/10.1016/j.cogr.2021.07.001.
43. Martinek R, Ladrova M, Sidikova M, Jaros R, Behbehani K, Kahankova R, *et al.* Advanced Bioelectrical Signal Processing Methods: Past, Present and Future Approach—Part II: Brain Signals. Sensors. 2021;21(19):6343–6355. https://doi.org/10.3390/s21196343.
44. Chaddad A, Wu Y, Kateb R, Bouridane A. Electroencephalography Signal Processing: A Comprehensive Review and Analysis of Methods and Techniques. Sensors. 2023;23(14):1–27. https://doi.org/10.3390/s23146434.
45. Jeong JH, Lee DH, Ahn HJ, Lee SW Towards Brain-Computer Interfaces for Drone Swarm Control. In: 8th Int Winter Conf Brain-Computer Interface. IEEE. 2020:1–4. https://doi.org/10.1109/BCI48061.2020.9061646.
46. Yan N, Wang C, Tao Y, Li J, Zhang K, Chen T, *et al.* Quadcopter Control System Using a Hybrid BCI Based on Off-Line Optimization and Enhanced Human-Machine Interaction. IEEE Access. 2020;8:1160–1172. https://doi.org/10.1109/ACCESS.2019.2961246.
47. Shi T, Qiang J, Chang G, Ren L. Brain Computer Interface System for UAV Target Searching. Proc Bulg Acad Sci. 2023;76(5):760–768. https://doi.org/10.7546/CRABS.2023.05.12.
48. Canal G, Diaz-Mercado Y, Egerstedt M, Rozell C. A Low-Complexity Brain–Computer Interface for High-Complexity Robot Swarm Control. IEEE Trans Neural Syst Rehabil Eng. 2023;31(Xx):1816–1825. https://doi.org/10.1109/TNSRE.2023.3257261.
49. Bertizzolo L, D'Oro S, Ferranti L, Bonati L, Demirors E, Guan Z, *et al.* SwarmControl: An Automated Distributed Control Framework for Self-Optimizing Drone Networks. In: IEEE INFOCOM- IEEE Conf Comput Commun. IEEE. 2020:1768–1777. https://doi.org/10.1109/INFOCOM41043.2020.9155231.
50. Xu B, Ma Q, Feng J, Zhang J. Fault Tolerant Control of Drone Interceptors Using Command Filtered Backstepping and Fault Weighting Dynamic Control Allocation. Drones. 2023;7(2):106–119. https://doi.org/10.3390/drones7020106.

مراجعة تحليلية لتحليل موجات الدماغ لغرض تحكم الطائرات المسيرة ذهنياً: إستخدام الشبكات العصبية الهجينة والتخيل الحركي.

العيساوي اثير صلاح هادي[1]، سفري محمد[1]، نوفيا اندرياتي آدموديساسترو[1]، سيتي انوم احمد[2]، ريحاني محمد[3]

[1]قسم هندسة البرامجيات ونظم المعلومات، كلية علوم الحاسبات وتكنولوجيا المعلومات، جامعة بوترا الماليزية، سردانك 43400-سيلانكور، ماليزيا.
[2]قسم الهندسة الكهربائية والالكترونية، كلية الهندسة، جامعة بوترا الماليزية، سردانك 43400-سيلانكور، ماليزيا.
[3]قسم علوم الحاسوب، كلية علوم الحاسوب وتكنولوجيات المعلومات، جامعة بوترا الماليزية، سردانك 43400-سيلانكور، ماليزيا.

الخلاصة

لقد احدثت واجهات الدماغ والحاسوب تحولاً كبيراً في مجال المركبات الجوية المسيرة من خلال تسهيل التحكم المباشر بالطائرات المسيرة من خلال تفسير اشارات الدماغ المرتبطة بمهام التصوير الحركي. تقوم هذه الورقة البحثية بتقييم التقدم المحرز في استخدام الشبكات العصبية الهجينة والتصور الحركي ذهنياً لتشغيل الطائرات المسيرة ذهنياً مع معالجة التحديات التي تفرضها الادبيات الحالية فيما يتعلق بتشفير وفك تشفير اشارات الدماغ المعقدة لتحقيق التحكم الدقيق والموثوق به للطائرات المسيرة. الهدف الاساسي من هذه الدراسة هو تحليل وتوليف احدث تقنيات تحليل الموجات الدماغية, مع التركيز بشكل خاص على تطبيق الشبكات العصبية الهجينة ومهام التصوير الحركي للتحكم بالطائرات المسيرة عبر واجهات الدماغ والحاسوب. تهدف هذه الدراسة الى تقديم رؤى حول فعالية هذه التقنيات في تعزيز دقة وموثوقية انظمة الطائرات المسيرة المتحكم بها بواسطة الدماغ. طريقة ادارة عمليات المراجعة هذه هي PRSM. تشير نتائج هذه المراجعة الى ان موثوقية تحليل الاشارة تظل تصر على اقتراح نموذج يجب ان يفك رموز انماط الدماغ المرتبطة بالصور الحركية بدقة ويترجمها الى اوامر قابلة للتنفيذ للتحكم بالطائرات المسيرة. لقد اظهر دمج خوارزميات التعلم الآلي مع المبادىء العصبية الفسيولوجية تحسنات كبيرة في اداء انظمة الطائرات المسيرة المقادة ذهنياً. وفي الختام, فإن الاستخدام التآزري للشبكات العصبية الهجينة وتقنيات التصوير الحركي يحمل امكانيات كبيرة لتطوير مجال الطائرات المسيرة المقادة ذهنياً. ان اجراء المزيد من البحوث وتحسين خوارزميات معالجة الاشارات امر ضروري لتعزيز سرعة ودقة ومتانة انظمة الطائرات المسيرة المقادة ذهنياً, مما يؤدي في النهاية الى تقدم تحويلي في التفاعل بين الانسان والآلة عبر مختلف المجالات. تضع ورقة المراجعة هذه الاساس لجهود بحثية مستقبلية تهدف الى اطلاق العنان للامكانيات الكاملة لتحليل الاشارات الدماغية تجاه الطائرات المسيرة المقادة ذهنياً.

الكلمات المفتاحية: واجهات الدماغ والحاسوب (BCI)، الشبكات العصبية الهجينة، الطائرات المسيرة المقادة ذهنياً، التصور الحركي ذهنياً، خوارزميات معالجة إشارات الدماغ.