ORIGINAL ARTICLE

Investigating Optimal EEG Channels and Features for Brain-Computer Interfaces: An Exploration Using Evolutionary Algorithms and Machine Learning

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Received: 27 June 2024 / Accepted: 25 December2024

Abstract

Purpose: Brain-Computer Interfaces (BCI) are advanced systems that enable a direct neural pathway between the human brain and external devices. The importance of BCI is underscored by its profound implications for medical therapeutics, particularly in neurorehabilitation.

Materials and Methods: This study developed an algorithm to detect 8 motion commands for a robot using individuals' EEG signals (Electroencephalogram). These signals were recorded during imagined and expressed commands. The research aimed to identify optimal features for extracting and classifying EEG signals for robot commands and to pinpoint the best EEG channels for a cost-effective, efficient signal acquisition system. Four categories of features, including temporal, frequency, wavelet, and combined features were extracted from the EEG signals. The Imperialist Competitive Algorithm (ICA) and Cuckoo Optimization Algorithm (COA) were utilized for feature selection.

Results: Findings revealed that wavelet features are most effective for analyzing and classifying EEGs. For imagined commands, optimal features from all channels achieved a 96.3% classification accuracy, while expressed commands reached 96.5%. The frontal and parietal lobes were identified as the prime EEG channels for command detection, achieving accuracies of 91.5% and 86.9% for imagined commands, and 92.7% and 86.1% for expressed commands, respectively. The result also indicated that the brain's midline and left hemisphere (containing the Broca area) outperformed the right hemisphere in classification.

Conclusion: By focusing on the optimal EEG channels, a more cost-effective hardware system can be designed, surpassing the traditional 21-channel system and requiring only 14 electrodes in the frontal and parietal regions.

Keywords: Brain-Computer Interface; Robot Controlling; Brain Regions; Electroencephalogram; Evolutionary Optimization Algorithms.

DOI: https://doi.org/10.18502/fbt.v12i2.18275

1. Introduction

Brain-Computer Interface (BCI) research aims to develop tools for individuals with disabilities resulting from stroke, neurological disorders, muscular impairments, or spinal cord injuries, enabling them to interact with their environment. Among the various applications of BCI systems, one of the most significant is the control of robots or computers by individuals with disabilities [1]. The term "Brain-Computer Interface" was coined by Vidal et al. in the late 1960s and early 1970s, with their pioneering work demonstrating that humans could control a computer cursor using Electroencephalogram (EEG) signals [2].

BCI systems enable the transmission of commands from the brain to robots or receivers. In addition to this approach, voice command receiver systems have also seen extensive development for controlling robots or computers. These systems act as a crucial interface that bridges the gap between humans and machines in the field of robotics and automation. Extensive research has focused on utilizing voice commands to facilitate robot movement. A computer or a receiver on the robot captures voice commands, and command recognition algorithms, were trained. These algorithms discern voice commands and issue corresponding instructions to the robot [3-6]. However, voice command systems face challenges such as susceptibility to ambient noise interference, linguistic variability, and potential misinterpretations, which can result in latency issues. In contrast, BCI offers a direct and noise-immune method of control by interpreting neural signals, enabling immediate and accurate command execution [7, 8].

BCI offers a direct neural interface that allows users to interact with external systems, such as robots, by recording and analyzing the brain's electrical activities. The use of EEG signals is a promising technique for establishing this connection. EEG signals are advantageous due to their non-invasiveness and relatively low cost, allowing the recording of a large volume of signals. The most common approaches for measuring EEG signals in BCI interfaces include Motor Imagery (MI), P300, and Steady-State Visually Evoked Potential (SSVEP). The SSVEP and P300 approaches interpret brain activity using external visual stimuli, while MI-based BCIs rely on imagined movements without external stimuli [9]. Previous studies have explored the utilization of EEG signals to control robots in many different applications, where imagined movements correspond to specific robot actions [10].

The classification of commands and brain messages from EEG signals is a crucial aspect in the field of BCI research. Classification studies focusing on imagined hand movements have reported varying results. They have employed different types of feature vectors and classifiers [11-13]. Recent research has proposed novel methods, such as employing Recurrence Plot (RP) and Bayesian Convolutional Neural Network (BCNN) to improve classification accuracy beyond 90% in EEG-based MI-BCIs [14]. Furthermore, BCI systems have been developed for controlling wheelchairs, achieving a classification accuracy of 75% by analyzing eye movements in the parietal and frequency domains [15]. Other studies have explored the correlation between brainwave power and robot control, demonstrating the association of alpha frequency band power with robot speed control and delta or theta frequency band power with classifier output probability [16]. BCI systems for robot movement in different directions have achieved accuracies of up to 92.1% using alpha band EEG features and artificial neural networks for classification [17]. Additionally, EEG-based BCIs have been developed for controlling robot arms with an accuracy of over 85% in four movement directions [18]. A recent study [19] employed a fuzzy-logic processing technique to increase the performance of a BCI system. Recent studies suggest using task-relevant autoencoding [20] and reinforcement learning through machine learning [21].

It is of utmost importance to carefully choose the most suitable channels and perform effective feature extraction from EEG signals within the realm of BCI research. Selecting the appropriate channels helps capture relevant brain activity while reducing noise, improving signal quality, and enhancing BCI system performance. Feature extraction converts raw EEG signals into meaningful patterns or characteristics that correspond to the user's mental states or intentions. By optimizing channel selection and feature extraction procedures, BCI systems can achieve high classification accuracy, reduce computational complexity, and enhance overall efficiency. This leads to improved reliability, accuracy, and robustness, empowering users to effectively control robots or computers using their brain signals. There are various feature selection techniques available for BCI, including step-wise regression [22], fast correlation-based filters [23], neural networks [24], and deep learning [25]. Meta-heuristics have proven to be highly effective in solving intricate optimization problems [26]. Heuristics are problem-specific strategies that iteratively enhance a potential solution, whereas meta-heuristics generalize these strategies into problem-independent frameworks [27]. In a study by Bin Shih et al., some search algorithms were used to optimize channel selection for motor imagery-based BCI. The results demonstrated that the binary harmony search algorithm requires less time compared to other methods for optimal channel selection [25]. Additionally, He et al. proposed a genetic algorithm based on Rayleigh coefficients for channel selection in BCI systems, which improved computational load and classification accuracy [26].

This study combines the classification of expressed and imagined commands in a dual-task framework, employs advanced feature selection techniques, and proposes a cost-effective EEG setup with reduced electrode count, enhancing both methodological and practical contributions to BCI research. In this study, we propose a novel algorithm to identify and classify commands for controlling a robot or wheelchair, based on two categories of EEG data. The first category includes EEG signals captured during the imagination of commands, while the second involves signals recorded during the verbal expression of movement commands. To achieve accurate command classification, the EEG signals were processed, and an evolutionary algorithm was applied to select optimal features. By analyzing these features, we identified the brain regions that contribute most effectively to precise command classification.

The remainder of this paper is organized as follows: Section 2 provides comprehensive details about the database, as well as the steps involved in feature extraction and selection. In Section 3, the results obtained from the research are presented. The subsequent section, titled "Discussion," elaborates on the findings and their implications. Finally, in Section 5, the study is concluded, summarizing the key takeaways and potential avenues for future research.

2. Materials and Methods

2.1. Database and Preprocessing

The EEG signals were recorded by a digital device (SEGAL SENSE-EEG PU 212) in the Biomedical faculty of Islamic Azad University, Science and Research Branch (Tehran, Iran). EEG recording was performed based on 10-20 international electrode placement systems by 21-channels (Fp1, Fp2, F7, F3, AFz, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, POz, O1, O2) with A1 and A2 electrodes as references located on earlobes. The dataset utilized in this study comprised. Participants were 3 males and 3 females, aged between 18 and 28 years old. It should be noted that the data acquisition protocol was approved by the Institutional Review Board (IRB) and the Ethical Committee of Islamic Azad University. All subjects signed the consent form to participate in this experiment. Two states of EEG recordings were included: vocal command expression and command imagination. In the first scenario (expressing the commands) participants were instructed to vocally articulate each of the eight predefined commands (e.g., "Up," "Down") while EEG signals were recorded. Participants were asked to mentally imagine the commands (speech imagination) without any vocal or physical expression in the imagination scenario. This approach focused on capturing brain activity related to motor imagery and cognitive processing. Each recording lasted 2 seconds, and the sampling frequency was set to 2000 Hz. The participants were instructed to express or imagine each command listed in Table 1. It is important to note that each command was repeated 10 times to ensure an adequate amount of data for analysis. Subsequently, the recorded signals were down-sampled to 512 Hz.

Table 1. Commands for the classification of EEG signals

Number	Command	Number	Command
1	Up	5	Front
2	Down	6	Back
3	Right	7	Start
4	Left	8	Finish

The preprocessing step holds significant importance in all biomedical signal-processing research, including the analysis of brain signals. This is primarily due to the presence of various types of noise that can contaminate the recorded brain signals. A filtering procedure was implemented to mitigate these noise sources. In this study, a band-pass Finite Impulse Response (FIR) filter within the range of 0.5 to 35 Hz was applied. The filter had an order of 8, a ripple of 0.1 peak-to-peak in the passband, and an attenuation of 70 dB in the stopband. It is worthwhile mentioning that by inspiration of Makoto's EEG preprocessing pipeline bad channel rejection and re-referenced to the average channel were implemented [28].

2.2. Feature Extraction

The feature extraction step enables the discrimination of commands from one another in the feature space. In this study, four categories of signal features were considered: Temporal features, Wavelet features, Frequency features, and Combined features. Altogether, a total of 83 features were extracted.

2.2.1. Temporal Features

Temporal features, derived from the analysis of EEG signals in the time domain, are widely recognized as a powerful tool. In this study, a total of 18 temporal features were computed [29, 30]. Table 2 presents these features along with their corresponding computational formulas.

2.2.2. Frequency Features

The frequency domain features consisted of three main features in Table 3 [31, 32].

Table 3. Frequency features and formulas.

Feature	Formula
Mode Frequency	$S(f_{mod}) = Max(S(f))$
Median Frequency	$\int_0^{f_{median}} S(w)d(w) = \int_{f_{median}} S(w)d(w)$
Mean Frequency	$f_{mean} = \dfrac{\int_0 f.S(f)df}{\int_0 S(f)df}$

Table 2. Temporal features and formulas

Feature	Formula
Latency ($t_{s_{max}}$)	$t_{s_{max}} = \{\{t \mid s(t) = s_{max}\}\}$
Maximum of Amplitude (s_{max})	$s_{max} = max\{s(t)\}$
Latency/Amplitude	$t_{s_{max}}/s_{max}$
Absolute value of amplitude	$\lvert A_{pn}\rvert$
Absolute value of the latency /amplitude ratio	$\lvert t_{s_{max}}/s_{max}\rvert$
Positive level (A_p)	$A_p = \sum_{t=400ms}^{800ms} 0.5\,(s(t) + \lvert s(t)\rvert)$
Negative level (A_n)	$A_n = \sum_{t=400ms}^{800ms} 0.5\,(s(t) - \lvert s(t)\rvert)$
Absolute value of negative level (ANAR)	$\lvert A_n\rvert$
Level summation (A_{pn})	$A_{pn} = A_p + A_n$
Absolute value of Level summation	$\lvert A_{pn}\rvert$
Absolute value of level summation ($A_{p\lvert n\rvert}$)	$A_{p\lvert n\rvert} = A_p + \lvert A_n\rvert$
Average absolute value of the slope	$\lvert s\rvert = \frac{1}{q}\sum_{t=400ms}^{800ms-\tau} \frac{1}{\tau}\lvert s(t+\tau) - s(t)\rvert$
Peak to Peak (pp)	$pp = s_{max} - s_{min}$
Time window of Peak to Peak (t_{pp})	$t_{pp} = t_{s_{max}} - t_{s_{min}}$
Slope of Peak to Peak (m_{pp})	$m_{pp} = \frac{pp}{t_{pp}}$
Zero Crossing (n_{zc})	$n_{zc} = \sum_{t=t_{s_{min}}}^{t_{s_{max}}} \delta(s)$
Zero Crossing Density (d_{zc})	$d_{zc} = \frac{n_{zc}}{t_{pp}}$ $\delta(s) = \begin{cases} 1 & if\ s(t) = 0 \\ 0 & Otherwise \end{cases}$
Slope Sign Change (n_{ssc})	$n_{ssc} = \sum_{t=400ms+\tau}^{800ms-\tau} 0.5 \left\lvert \frac{s(t-\tau) - s(t)}{\lvert s(t-\tau) - s(t)\rvert} + \frac{s(t+\tau) - s(t)}{\lvert s(t+\tau) - s(t)\rvert} \right\rvert$

Definitions of symbols: s = signal, t = time, A = amplitude, p = positive, n = negative, pn = positive to negative, pp = peak to peak, q = number of samples, m = slope, τ = delay

2.2.3. Wavelet Features

Each recording underwent a decomposition process into frequency levels: 128-64 Hz, 64-32 Hz, 32-16 Hz, 16-8 Hz, 8-4 Hz, and 4-0.5 Hz. It is important to note that frequencies above 35 Hz were not considered to contain useful information and were therefore excluded due to the application of a filter. The B-Spline Quadratic wavelet was chosen as the decomposition technique to separate the signal into its constituent frequency components. Specifically, a total of 8 coefficients from the 4-0.5 Hz band (delta), 8 coefficients from the 8-4 Hz band (theta), and 16 coefficients from the 16-8 Hz band (alpha) were selected for subsequent analysis [33]. The B-Spline Quadratic wavelet was chosen for EEG signal decomposition due to its ability to balance time and frequency resolution, making it well-suited for analyzing the non-stationary and transient nature of EEG signals. Its smooth basis functions and compact support effectively minimize artifacts while preserving key signal features.

2.2.4. Combined Features

The last category of features extracted from EEG signals is called combined features. This feature category includes 30 features, which are specified in Table 4 [34, 35].

2.3. Feature Selection Using Evolutionary Algorithms

After performing data cleaning and feature extraction, the next step is feature selection to identify the most informative features for further analysis. Two evolutionary algorithms, namely the Cuckoo Optimization Algorithm (COA) and the Imperialist Competition Algorithm (ICA), were employed for this purpose [36].

2.3.1. Imperialist Competitive Algorithm (ICA)

The ICA is based on the concept of imperialist nations and colonies. It is a population-based optimization algorithm that includes a competition mechanism between imperialists and colonies [37]. The ICA operation involved the following steps:

1. Initialization: A population of imperialist countries and their colonies (solution vectors) was initialized.
2. Fitness Evaluation: The fitness of each solution was evaluated using an objective function specific to our feature selection problem.
3. Power Calculation: The fitness-based power of each imperialist country was determined.
4. Competition: A competition was performed between imperialists and their colonies, where weaker colonies could revolt and join other imperialists.
5. Position Update: The positions of imperialists and colonies were updated based on the competition results.
6. Optional Refinement: Local search or other optimization techniques were optionally applied to further refine the solutions.
7. Termination: The steps above were repeated until the termination condition was met.

The ICA algorithm aimed to enhance the exploration and exploitation capabilities of the search

Table 4. Combined features

Features		
Skewness	Tsallis Entropy	Minimum Value
Hjorth Complexity	Log Root Sum of Sequential Variation	Maximum Value
Hjorth Mobility	Mean Teager Energy	Auto-Regressive Model
Hjorth Activity	Mean Energy	Median Value
Band Power Delta	Mean Curve Length	Variance
Band Power Theta	Normalized Second Difference	Standard Deviation
Band Power Alpha	Second Difference	Arithmetic Mean
Band Power Beta	Normalized First Difference	Renyi Entropy
Band Power Gamma	First Difference	Log Energy Entropy
Ratio of Band Power Alpha to Beta	Kurtosis	Shannon Entropy

process by simulating the competition between imperialist nations and the assimilation of weaker colonies. This iterative process aimed to converge toward an optimal or near-optimal feature subset for our feature selection problem [38].

2.3.2. Cuckoo Optimization Algorithm (COA)

The COA is inspired by the behavior of cuckoo birds laying their eggs in the nests of other bird species. In the feature selection process, the COA aimed to improve the quality of the solution population iteratively [39]. The COA operation involved the following steps:

1. Initialization: A population of solution vectors (feature subsets) was initialized.
2. Fitness Evaluation: The fitness of each solution was evaluated using an objective function tailored to our specific feature selection problem.
3. Random Walk: A subset of solutions (cuckoos) was selected to undergo a random walk.
4. Levy Flight: New solutions were generated by performing a Levy flight (random walk) with step size adjustment.
5. Replacement: Some existing solutions were replaced with newly generated solutions based on a selection criterion.
6. Optional Refinement: Local search or other optimization techniques were optionally applied to further refine the solutions.
7. Termination: The steps above were repeated until the termination condition was met.

The COA algorithm aimed to mimic the nest selection behavior of cuckoo birds by exploring the search space through random walks and replacing poor solutions with better ones. This iterative process sought to find an optimal or near-optimal feature subset for the feature selection problem. The Cuckoo Optimization Algorithm (COA) demonstrated superior performance by reducing the feature set from 83 to 28, retaining only the most discriminative features, and enhancing classification accuracy.

2.4. Classification and Cross-Validation

The Hold-Out method was employed to validate the classification procedures. This method involved randomly splitting the data into training and testing sets, with 80% of the data allocated for training and 20% for testing. This process was repeated 10 times to ensure the robustness of the classification results [40]. Among the various classifiers commonly used in EEG signal processing, the K-Nearest Neighbors (KNN) classifier was employed. The KNN classifier assigns a test sample to the class that obtains the majority votes from its K nearest neighbors [41]. The proximity of a sample to its neighbors is typically measured using the Euclidean distance. In this research, the K parameter of the KNN classifier was set to 5. This value was selected based on preliminary experimentation with the dataset, where k=5 provided the best balance between minimizing noise and maintaining classification accuracy. Smaller values of K were more sensitive to noise, while larger values led to overly generalized predictions.

In this study, we used pooled data from all six participants to evaluate the overall performance of the proposed methodology. This group-level analysis helps assess the robustness and generalizability of the classification pipeline across inter-subject variations. Such an approach is particularly valuable in the initial stages of BCI research to validate the effectiveness of feature extraction and selection methods before moving to subject-specific adaptations.

3. Results

To identify the optimal brain regions for command detection, it was essential to segment the brain based on the placement of electrodes. The specific brain regions considered in this study are presented in Table 5, and a visual representation is demonstrated in Figure 1.

Table 5. Brain Region Segmentation

Regions	Associated Brain Channels in Each State
All channels	21 brain channels
Frontal	Fp1, Fp2, AFz, F3, F4, Fz, F7, F8
Occipital	POz, O1, O2
Parietal	C3, Cz, C4, P3, Pz, P4
Temporal	T3, T4, T5, T6
Right hemisphere	Fp2, F8, F4, C4, P4, T4, T6, O2
Left hemisphere	Fp1, F7, F3, C3, P3, T3, T5, O1
Brain midline	AFz, Cz, Pz, POz

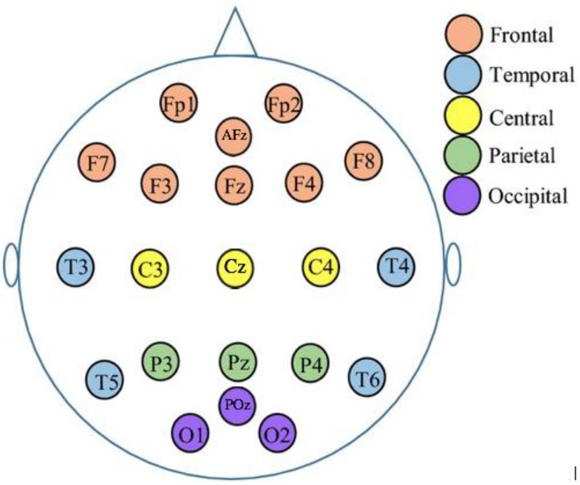


Figure 1. Brain Channels and Lobes

The parameters of the two optimization algorithms were adjusted as Table 6.

Table 7 presents the average and standard deviation of classification results for imagery and verbal command signals across eight specified classes (commands) in three different states. These states correspond to the utilization of two feature selection algorithms, COA and ICA, as well as a state where no feature selection algorithms were employed. The values in the table represent the performance of the feature selection algorithms (classification accuracy in percent) within each brain region.

According to Table 7, without the utilization of feature selection algorithms, the classification accuracy was lower. Furthermore, the results indicate that the COA outperforms the ICA. These findings emphasize the importance of feature selection in improving classification accuracy and highlight the effectiveness of the COA in extracting the most relevant features for accurate classification. Therefore, the Cuckoo Algorithm was selected as the preferred feature selection algorithm, and all subsequent processing steps were performed using this algorithm.

Figure 2 showcases the classification accuracy with selected features in the command imagination scenario, utilizing all brain channels and the COA. As depicted in the figure, after approximately 1000 iterations of the COA, the classification error rate stabilizes, implying that the optimal feature set has been extracted.

Table 6. Table of determined parameters for the two feature selection algorithms

	$N_{country}$	$N_{Imperialist}$	Iteration	β	γ	ζ
ICA	400	1000	1000	2	π/4	0.05
	$N_{country}$: The total number of countries $N_{Imperialist}$: The number of imperialist countries Iteration: The number of iterations or generations β (revolution rate); determines the probability of a colony country rebelling against its imperialist and becoming an imperialist itself. γ (assimilation coefficient): which controls the rate at which imperialist countries assimilate colonies. A higher value of γ implies faster assimilation. ζ (assimilation factor): determines the degree of assimilation when colonies are merged with imperialists.					
	N_{max}	Var_{low}	Var_{hi}	Iteration	w	α
COA	500	5	10	1000	π/6	1
	N_{max}: The maximum number of nests or solutions Var_{low}: The lower bound or minimum value for the search space Var_{hi}: The upper bound or maximum value for the search Iteration: It represents the maximum number of iterations or generations w (worse nests probability): It determines the probability of replacing a nest with a new random nest. α (step size scaling factor): It controls the step size or magnitude of the random walk performed by cuckoo birds during the search process.					

Table 7. Classification results (%)

Regions	Imagination						Verbal expression					
	AVG WO-FS	STD	AVG COA	STD	AVG ICA	STD	AVG WO-FS	STD	AVG COA	STD	AVG ICA	STD
All channels	61.3	7.6	96.3	2.1	67	3.9	59.4	6.0	96.5	2.0	68.7	5.2
Frontal	56.5	6.5	93.6	2.3	61.3	4.1	54.2	7.2	92.2	2.2	62.9	3.8
Occipital	51.3	5.2	81.6	4.3	56.3	5.6	51.3	3.5	60.1	3.2	60	4.4
Temporal	51.2	4.9	58.4	4.1	53.8	4.5	51.6	3.6	88.7	3.7	62.6	5.1
Parietal	53.7	3.8	60	4.2	60	5.2	53.7	4.7	56.1	4.0	60	3.9
Right hemisphere	52.3	5.0	56.5	3.6	53.7	4.3	54.2	6.0	55.8	3.4	55.7	3.9
Left hemisphere	53.9	5.2	58.6	3.8	58.4	4.1	50.4	6.1	60.3	4.4	60.5	3.5
Midline	52.1	4.3	68	4.5	68.4	5.0	54.8	6.0	70.7	4.9	68.4	3.8

(AVG= Average, WO-FS= Without Feature Selection, STD= Standard Deviation)

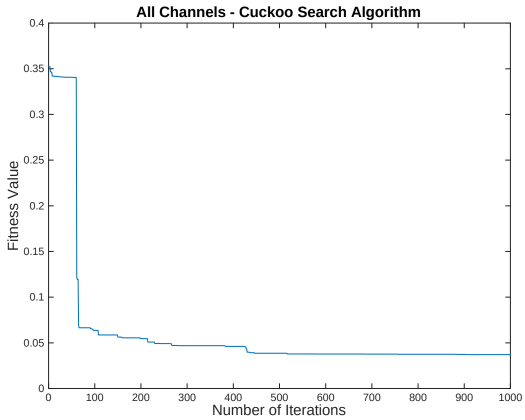
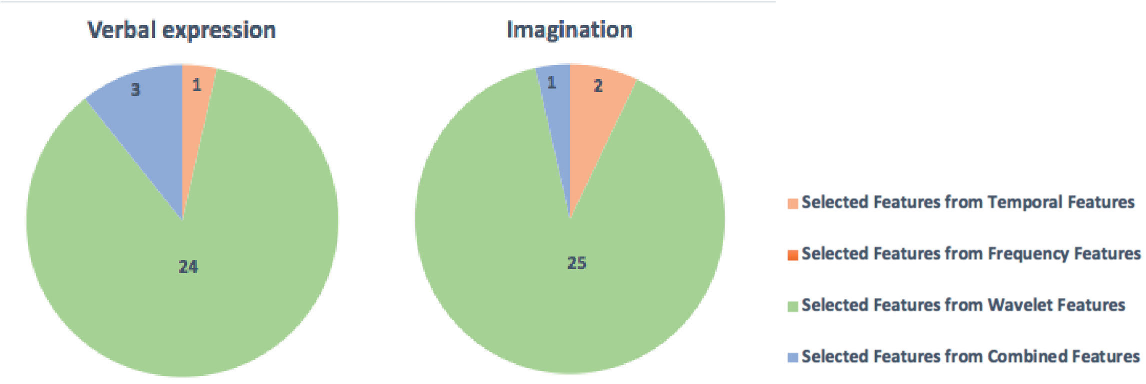


Figure 2. Classification error with COA

Figures 3a and 3b illustrate the distribution of optimal feature sets in the command expression scenarios command imagination with COA, respectively. It can be observed that among the four feature sets extracted from the EEG signals, the Wavelet features exhibit the highest frequency of occurrence in the selected features.

As depicted in Figure 3, a total of 28 out of 83 features were identified as the selected features in both the command imagination and command expression scenarios. Subsequently, these selected features were utilized in the subsequent stages of classification, while the remaining features were set aside. The classification outcome using the selected feature set in the command imagination scenario is presented in Figure 4.

According to Figure 4b, the highest classification accuracy rate for commands was achieved when utilizing all brain channels, reaching 96.3%. According to Figure 4a, when categorizing the brain channels into the four main lobes (frontal, occipital, temporal, and parietal), the highest classification accuracy was obtained using the 8 electrodes located in the frontal lobe, with an accuracy of 91.5%. The parietal lobe, consisting of 6 electrodes, ranked as the



a b

Figure 3. Distribution of the number of selected features using COA in the imagination scenario (a) and verbal expression scenario (b).

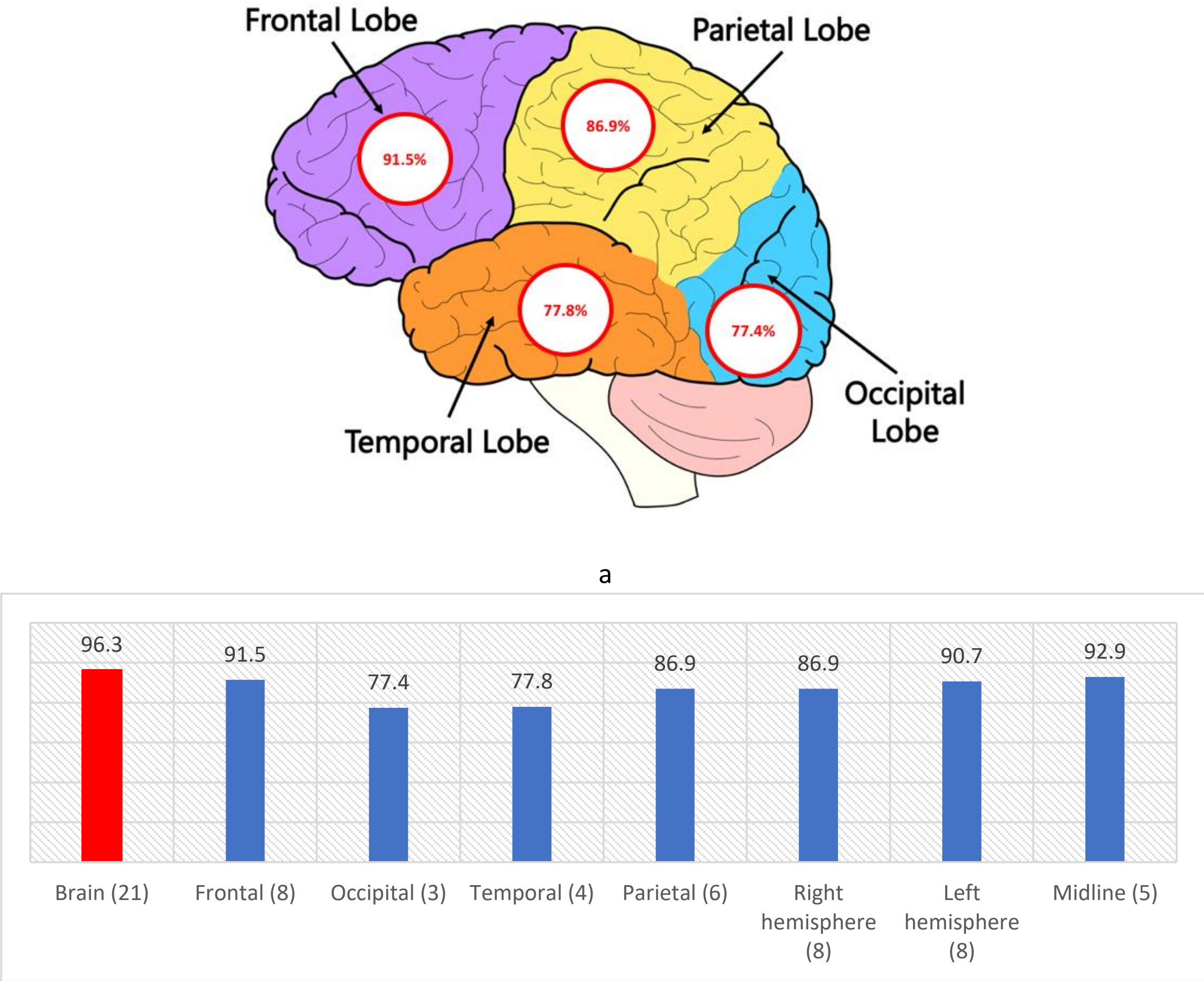
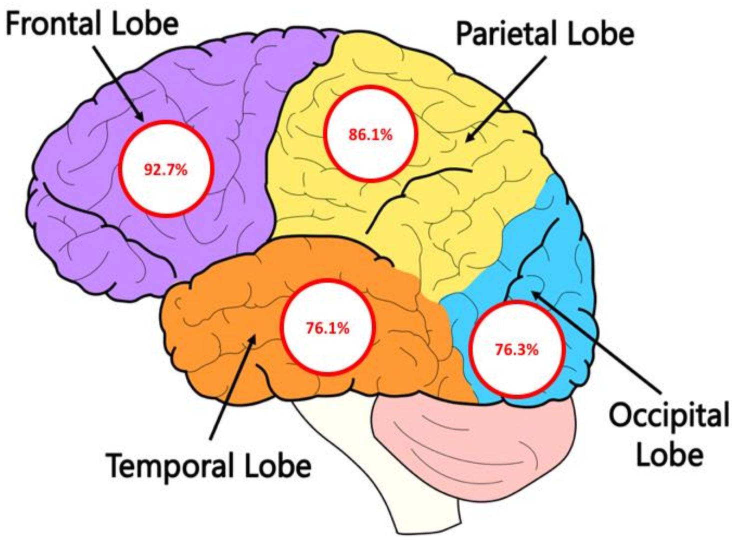


Figure 4. The results of a classification in the command imagination scenario in (a) each brain lobe and (b) each brain region

second-best region for command classification, achieving an accuracy of 86.9%. Additionally, when dividing the surface electrodes into three groups - left hemisphere, right hemisphere, and midline - the best classification performance was observed using the 5 electrodes located on the midline, with an accuracy of 92.9%. Following that, the electrodes in the left hemisphere, comprising 8 electrodes, achieved the second-highest accuracy of 90.7%. These findings suggest that the frontal and parietal regions yielded the most favorable results compared to other brain regions. Moreover, despite the smaller number of electrodes on the midline compared to the left and right hemispheres, the midline electrodes demonstrated superior performance in command classification. The left hemisphere also exhibited higher accuracy compared to the right hemisphere.

In the command expression scenario, the results presented in Figure 5 were similar to those obtained in the command imagination dataset. The highest classification accuracy of 96.5% was achieved when utilizing all brain electrodes as shown in Figure 5b. According to Figure 5a, when comparing different brain regions, the electrodes associated with the frontal and parietal regions showed the highest classification accuracies, reaching 92.7% and 86.1%, respectively. However, when classifying using electrodes related to the brain hemispheres and the midline, the highest accuracy was observed with the electrodes in the left hemisphere, achieving an accuracy of 92.3%. The midline electrodes ranked second in classification with an accuracy of 88.9%.

It is worthwhile mentioning that the high classification accuracy (96.3% for imagined commands, 96.5% for expressed commands) is



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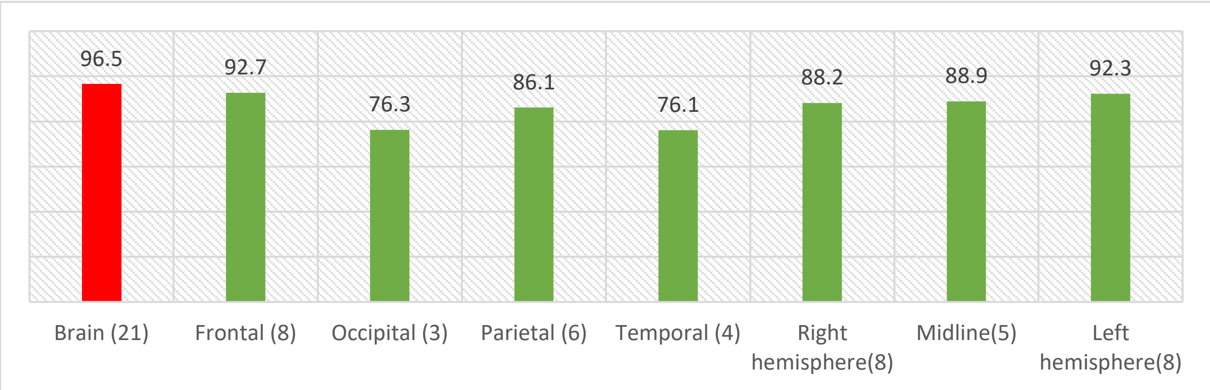

b

Figure 5. The classification results in the verbal expression scenario in (a) each brain lobe and (b) each brain region

attributed to task simplicity, controlled data collection, rigorous preprocessing, and the dominance of wavelet features. COA's ability to select task-relevant features further enhanced accuracy. These results are consistent with findings that tasks with distinct commands produce better classification performance.

4. Discussion

In this study, an algorithm was developed to detect commands using EEG signals obtained from both imagined and expressed commands. To ensure accurate classification, a total of 83 features from the EEG signals were extracted, and categorized into temporal, wavelet, frequency, and combined features. To optimize the command detection process and identify the most relevant features, evolutionary optimization algorithms, specifically ICA and COA, were employed for feature selection.

Findings indicate that, in the majority of input conditions, the COA algorithm outperformed the ICA algorithm in terms of command detection accuracy. Furthermore, the study revealed that the COA algorithm predominantly selected wavelet coefficient features from the four considered feature categories. This suggests the significance of wavelet coefficients in distinguishing and classifying command-related EEG signals. The classification results using the optimal features indicate that in both the command imagination and expression scenarios, the highest accuracy was achieved when utilizing electrodes from the entire brain surface as input. The accuracy rate for command imagination was 96.3%, while for command expression it was 96.5%.

Motor imagery studies using deep learning techniques report accuracies around 80–85% for 4-class tasks, with accuracy dropping for higher class counts due to overlapping cortical activations and complex motor planning processes [42, 43]. Imagined speech classification studies often achieve accuracies below 80% for 5–6 classes, reflecting challenges in distinguishing subtle and distributed neural patterns associated with linguistic processing [44, 45]. Studies integrating advanced machine learning techniques (e.g., CNNs, RNNs) for multi-class classification still report significant variability, particularly when subject-specific models are used [46]. In contrast, our study achieved classification accuracies of 96.3% for imagined commands and 96.5% for expressed commands. These results suggest that the combination of wavelet features and the Cuckoo Optimization Algorithm (COA) for feature selection is highly effective for this task, potentially outperforming many existing methods.

In terms of classification accuracy, the electrodes located in the frontal region consistently performed the best in both scenarios, achieving an accuracy of 91.5% for command imagination and 92.7% for command expression. Following the frontal region, the parietal lobe exhibited the next highest classification accuracy for commands, with 86.9% for command imagination and 86.1% for command expression. These findings highlight the significance of the frontal and parietal regions in accurately classifying commands from EEG signals. These results are consistent with previous research findings [47, 48] and align with neuroscience knowledge, further emphasizing the importance of these brain regions in command classification. The frontal lobe of the brain is responsible for controlling voluntary motor functions, cognitive skills, and decision-making processes. On the other hand, the parietal lobe plays a role in sensory processing, attention mechanisms, and speech comprehension and production. Considering that motor commands originate from cognitive processes and planning at the brain's surface, particularly in the frontal region.

Moreover, the results indicate that a specific area known as Broca's area, located at the border between the parietal and frontal regions in the left hemisphere, is involved in speech production. Broca's area exhibits the highest activity just before speech initiation and plays a role in transmitting information to the motor cortex, which controls movements of the mouth. Therefore, when commands are conceived in the brain, they involve not only the motor aspect but also activate Broca's area, since imagining words activates this region as well [49]. In the case of command expression, Broca's area is fully engaged as neural messages from this area need to be transmitted to the motor region responsible for lip and mouth movements. Consequently, it can be inferred that the presence of Broca's area, involved in speech production and imagination, along with the decision-making processes in the frontal region, makes these two areas optimal for command detection.

The study's results also indicate that the electrodes located in the midline and left hemispheres of the brain yield better classification accuracy for command detection. The activity of Broca's area, found in the left hemisphere and responsible for command production, provides a rationale for the superior performance of the electrodes in the left hemisphere compared to the right hemisphere. In fact, the electrodes in the left hemisphere reported the highest classification accuracy, achieving 92.3% for command expression and 90.7% for command imagination. Furthermore, it is noteworthy that despite having fewer electrodes, the midline of the brain demonstrated reasonably good classification accuracy in both scenarios, underscoring the significant role of these brain regions in command production and imagination.

This finding provides valuable insights for the design of a hardware signal acquisition system that enables brain command classification with a smaller dataset and lower manufacturing cost. By utilizing a system with 14 electrodes strategically placed in the frontal and parietal regions, rather than the conventional 21 electrodes, the command classification process can still be effectively performed. This reduction in the number of signals acquired does not result in a significant decrease in classification performance. Thus, this approach allows for a more cost-effective and streamlined signal acquisition system without compromising the accuracy and efficiency of command classification.

The forthcoming study has several limitations that can be addressed in future research. These include the limited number of subjects and recorded data, which could be improved to enhance result reliability. Additionally, developing online command classification algorithms would allow for real-time extraction and classification of commands from EEG signals. By addressing these limitations, future research can advance the field of EEG-based command classification and improve the overall quality and applicability of the results.

Task simplicity, a controlled environment, a comprehensive feature vector, and an effective feature selection method are factors that may have contributed to the high accuracy observed in this study. While promising, the study's small participant pool and controlled experimental setup may limit the generalizability of the findings to more diverse or real-world settings.

5. Conclusion

This study introduces a novel approach to command detection in BCI systems by leveraging EEG signals and employing advanced feature extraction techniques. The COA algorithm outperforms the ICA algorithm, underscoring the importance of appropriate feature extraction methods. By identifying task-relevant channels and leveraging wavelet features, this study proposes a streamlined 14-electrode setup that retains high classification accuracy, offering practical insights for cost-effective BCI system design. The study highlights the significance of electrode placement, particularly covering the frontal and parietal regions, for optimal performance. Additionally, electrodes in the left hemisphere, especially along the midline, enhance command classification accuracy. Furthermore, the study reveals that features extracted from the wavelet domain make the largest contribution to optimal feature selection. These findings have implications for the design of cost-effective hardware signal acquisition systems, enabling efficient command classification with reduced manufacturing costs while maintaining accuracy. Although this study focused on pooled data, the proposed methodology is inherently adaptable for personalized BCI systems. The feature selection and classification framework can be applied to individual datasets to account for inter-subject variability, a critical aspect for tailoring BCIs to specific users. Future work will focus on exploring these personalized adaptations and evaluating their performance. Overall, this study represents a significant advancement in BCI systems, offering promising possibilities for improved connectivity and interaction with the environment for individuals with disabilities.

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