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Review Article

An intelligent algorithm based on wavelet and linear discriminant analysis for classification of motor imagery right/left hand movement by brain signal

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Abstract

Movement imagination is a cognitive process where an individual mentally visualizes performing an action. Proper classification of motor imagery using brain signals represents a significant step towards designing brain-computer interaction systems for disabled individuals. Extracting suitable features is one of the primary challenges in improving the accuracy of this classification. In this study, we utilized time-frequency analysis to extract EEG signal features capable of accurately distinguishing between imagining right-hand and left-hand movements. Initially, we employed wavelet transform to extract frequency bands from EEG signals. Subsequently, we obtained effective statistical parameters of wavelet coefficients to reduce feature space dimensionality using Linear Discriminant Analysis (LDA). Finally, Support Vector Machine (SVM) was employed for EEG signal classification during hand movement imagination. Results indicate that the proposed method achieves higher accuracy in classifying right-hand versus left-hand movement imagination compared to previous approaches.

Keywords: Brain-Computer Interface (BCI), Electroencephalogram (EEG), motor imagery, wavelet transform, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM)

Introduction

With the development of novel technologies for studying brain function, brain signals are extensively used as a digital signal processing tool for detecting various disorders associated with brain abnormalities. Today, Electroencephalography (EEG) signals are employed in a wide range of applications such as seizure detection or prediction, motor imagery detection, mental task classification, emotion classification, sleep stage determination, and drug effect assessment. EEG signals derived from motor imagery can be seen as a novel approach for communication for individuals with physical disabilities. Motor imagery involves a mental process where an individual visualizes performing an action. Proper classification of motor imagery using brain signals is a crucial step in designing Brain-Computer Interface (BCI) systems for disabled individuals. A step-by-step process in a BCI system is illustrated, as shown in Figure 1 [1].

Figure 1. Flowchart of the Brain-Computer Interface (BCI) system process [1]

In a Brain-Computer Interface (BCI) system, signals are obtained through various methods such as invasive techniques (ECog[2], neurosurgery) and non-invasive methods (fMRI, EEG, MEG). Recording EEG signals is a simple and cost-effective process, hence multiple BCI systems based on EEG have been proposed [2]. In the next step, channel selection is a crucial consideration because many EEG channels convey redundant information [3]. Therefore, channel selection reduces complexity and enhances the extraction of more meaningful features. Generally, when dealing with data or signals, it is essential to extract relevant features. The type of selected features significantly impacts the final outcome. Ultimately, classification is required to differentiate between classes or different types effectively.

Several studies have been conducted on the classification of EEG signals during motor imagery. Sleight and his colleagues analyzed the EEG signals of right and left hand movements [4]. They used Independent Component Analysis (ICA) and Principal Component Analysis (PCA) in the feature extraction phase. The classification of the extracted features was performed using a Support Vector Machine (SVM). Additionally, the selection of channels or the use of information from all channels was investigated, and it was concluded that using the channels (C4, C3, and Cz) is sufficient for the classification of motor imagery. Classification using ICA and PCA methods was performed with accuracies of 60% and 22%, respectively. Other researchers also examined EEG signals during finger movements, utilizing ERD/ERS signals to distinguish between finger movements, and employed Wavelet Transform for feature extraction and SVM for classification [5]. Hamri Anas and his colleagues applied various wavelet functions to EEG segments for feature extraction and used SVM for the classification of right and left-hand motor imagery [6]. The obtained results were compared with neural networks and linear discriminant analysis (LDA) classification results. The highest detection rate achieved was around 60%. However, the large number of calculated features increases the complexity of the method and computational load.

The structure of this article is as follows: In the second section, the dataset of right and left hand movement imagery used in this research is described. In the third section, the frequency and time-frequency analysis of the signal is explained to find suitable features. In the fourth and fifth sections, the proposed method for classifying right and left hand movement imagery is presented, and the results of this method on the introduced dataset are examined. Finally, in the sixth section, the conclusion of the article is discussed, and future suggestions are provided.

1- Dataset Description

The dataset used for classification is the Graz dataset from the BCI Competition in 2003 [7]. Data was collected from a healthy subject during a feedback session (a 22-year-old female) seated on an armchair. The experiment aimed to control a screen cursor using motor imagery of right or left hand movements. The commands for right and left movements were presented randomly.

The experiment consists of seven stages, each containing 40 trials. All stages are conducted within one day with several minutes of break between each stage. Each of the 280 trials lasts for 9 seconds. The first 2 seconds are a rest period, and during the first 2 seconds, an auditory stimulus is heard. The trigger channel (4#) moves from bottom to top, displaying a plus sign (+) for 1 second. Then, at 3 seconds, an arrow indicating left or right is shown as a cue. At this time, the participant is instructed to move a joystick towards the indicated direction. Feedback is based on the AAR parameters of channels 1# (C3) and 2# (C4). Data recording is performed using a G.tec amplifier and Ag/AgCl electrodes. Three bipolar EEG channels (anterior (+) and posterior (-)) are measured on channels Cz, C3, and C4. EEG is sampled at 128 Hz and filtered between 5.0 and 34 Hz. The data is saved in mat format. The variable x_train includes three EEG channels and 280 sequences of 9-second duration. The cue is visible from the third to the ninth second, coinciding with the feedback shown on the display screen, as shown in Figure 2 (a) illustrates the timeline of dataset recording, as shown in Figure 2 (b) depicts the placement of electrodes used for signal recording in this dataset.

In this study, we utilized signals from the time interval between the third and ninth seconds for processing and classification, as this interval allows for distinguishing between two types of experiments. The first three seconds, comprising two seconds of rest and one second of alarm, were excluded from analysis. Additionally, considering that the Cz channel contains more useful information compared to the other two channels, we omitted the Cz electrode data in the data simulation section. This not only reduced the dimensionality of the feature matrix but also enhanced the system's processing speed, allowing the classification method to train on more informative data. From a total of 280 sequences, half (140) were used for training, and the remaining were used for testing signals. The selection of training and testing signals was randomized. This approach ensures that the classification model is trained on meaningful data while validating its performance on independent test data.

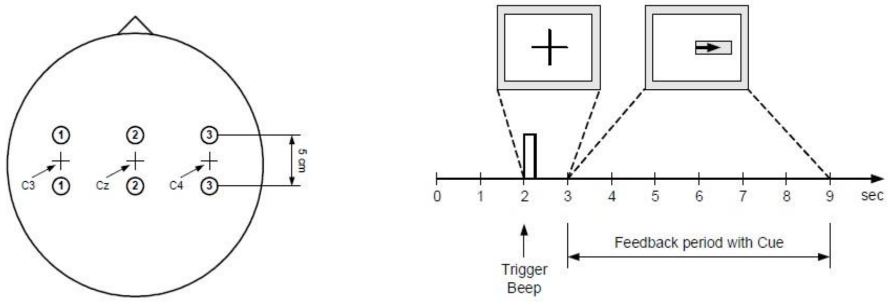

Figure 2. Graz dataset description. (a) Timeline of dataset recording. (b) Electrode placement in the dataset [6].

2- Frequency and Time-Frequency Analysis

In this section, to find suitable features for classifying signals recorded during the imagery of right and left hand movements, we analyze the signals from the dataset in various domains. The frequency components for each class of movement imagery (right hand and left hand) are plotted. For this purpose, we first separate the sequences corresponding to each class. Then, using the FFT algorithm in MATLAB, the Fourier transform of each sequence is individually calculated. Finally, the results of the Fourier transform for each class are obtained as the average of the Fourier transforms of the sequences in that class.

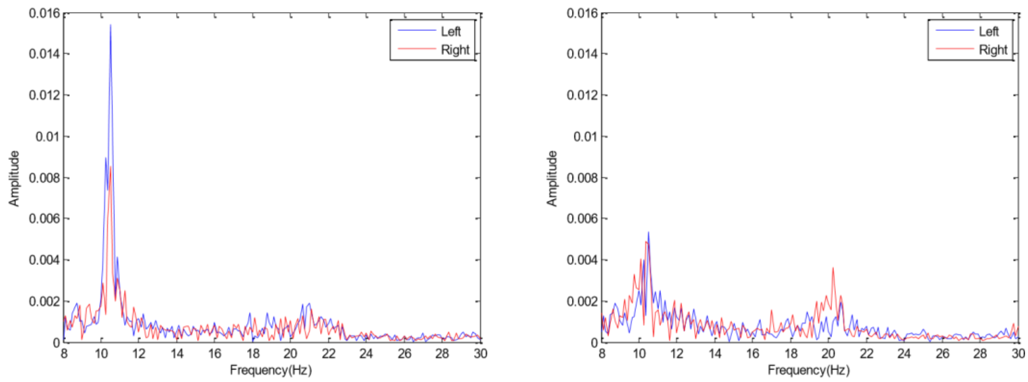

Figure 3. Fourier Transform Display in the Frequency Range of 8 to 30 Hz. (a) Channel C4 (b) Channel C3

By examining Figure 3, we find that there are dominant frequency components around 10 Hz and 20 Hz in the EEG signal during the imagery of right and left hand movements. However, using this analysis, we cannot discern a significant difference between these two movements. To overcome the limitation of the Fourier, transform in analyzing non-stationary signals, the simplest idea that comes to mind is to assume that a short segment of a non-stationary signal can be considered stationary. Therefore, by windowing the signal, we can extract the portion of the signal that is assumed to be stationary. In the Short-Time Fourier Transform (STFT), the signal is divided into sufficiently small segments so that each segment can be assumed to be stationary. STFT for each channel and each specific hand movement imagery is calculated, and their averages are obtained to clearly highlight the common features in each hand movement, as shown in Figure 4.

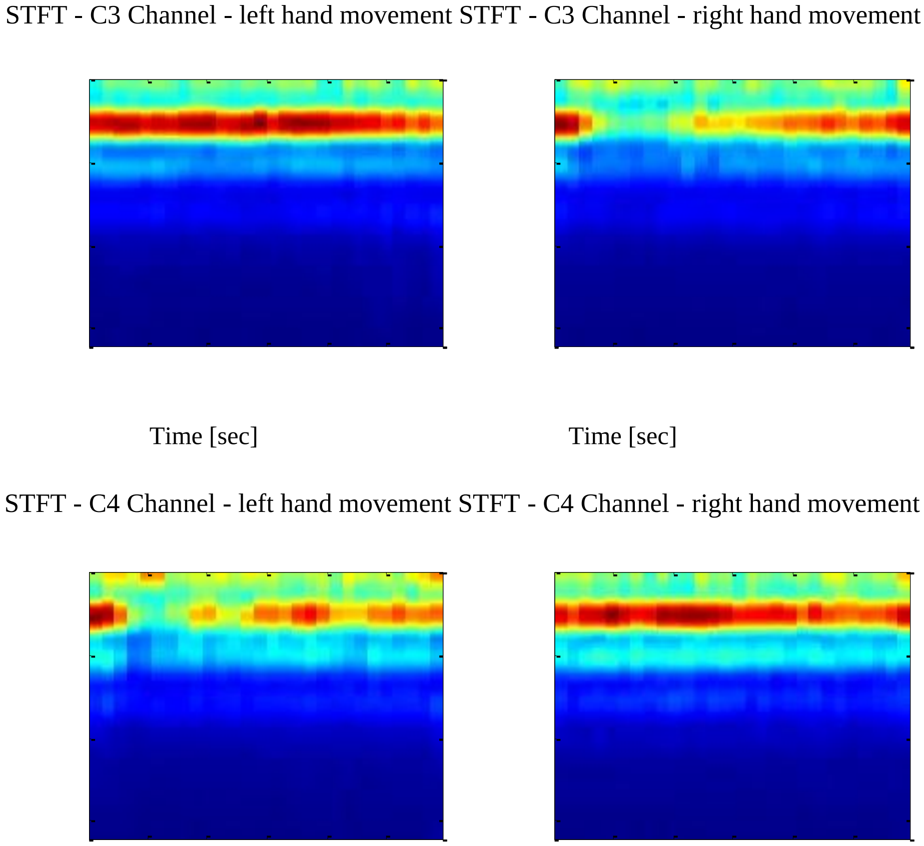

Figure 4. Display of Signals from Channels C4 (bottom) and C3 (top) during Imagery of Right and Left Hand Movements Obtained from Averaging the STFT Sequences Corresponding to Each Movement. (a) Imagery of Right Hand Movement .(b) Imagery of Left Hand Movement

By comparing the time-frequency displays in Figure 4, we find that for the imagery of right hand movement, a more pronounced ERD (Event-Related Desynchronization) is observed in the C4 channel signal within the frequency bands of 8-12 Hz and 20-23 Hz. For the imagery of left hand movement, a more pronounced ERD is observed in the C3 channel signal within the 8-12 Hz frequency band. Therefore, it is possible to distinguish between these two motor imagery tasks by extracting suitable features within the aforementioned frequency bands in both the C3 and C4 channels. As described, it seems feasible to differentiate between right and left-hand movement imagery by examining the amplitude of α and β waves in the C3 and C4 channels.

3- Proposed Method

The flowchart of the proposed method in this paper is shown in Figure 5.

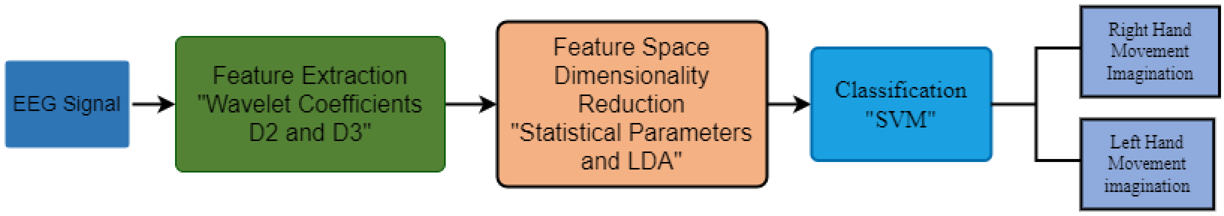

Figure 5. Flowchart of the Proposed Method

As stated in the previous section, we aim to separate the α and β frequency bands in EEG signals. For this purpose, we employ the wavelet transform. In applying the wavelet transform, the number of decomposition levels is selected based on the frequency components of the signal. These levels are chosen such that the part of the signal that aligns well with the frequencies necessary for signal classification is preserved in the wavelet coefficients. Since the EEG signals used in this study are sampled at a rate of 128 Hz and contain no useful frequency components above 30 Hz, we select 4 levels of decomposition. Therefore, the signal is decomposed into detail coefficients D1 to D4 and one final approximation coefficient A4. The frequency band ranges and dimensions of the resulting wavelet coefficients are shown in Tables 1 and 2, respectively. Based on our investigations into the time-frequency domain in the previous chapter, we found that the most significant differences between the two classes appear in the frequency bands corresponding to coefficients D2 and D3.

Table 1: Frequencies corresponding to different decomposition levels with a sampling frequency of 128 Hz

Decomposed signal	Frequency range (HZ)
D_1	32-64
D_2	16-32
D_3	8-16
D_4	4-8
A_4	0-4

Table 2: Dimensions of each sequence from the EEG signal used and the calculated wavelet coefficients

Dimensions of the EEG signal vector (in seconds)	768
Wavelet coefficients vector using the mother wavelet function db2	D1: 385 ،D2: 194 ،D3: 98 ،D4: 50 ،A4: 50
Wavelet coefficients vector using the mother wavelet function bior2.2	D1: 368 ،D2: 195 ،D3: 100 ،D4: 52 ،A4: 52

After extracting the desired frequency bands, directly using all the extracted coefficients for classification can often lead to reduced classification accuracy due to the high dimensionality of the feature space. This is because irrelevant or redundant features can complicate the classification process and introduce prediction errors. Therefore, it is necessary to reduce the number of features effectively .In this study, to reduce the dimensionality of the feature space, we calculate the following statistical parameters from the wavelet coefficients corresponding to the α and β frequency bands. Classification is then performed using these parameters:

a) Mean of absolute coefficients in each sub-band.
b) Mean power of wavelet coefficients in each sub-band.
c) Standard deviation of coefficients in each sub-band.

Support Vector Machine (SVM) was introduced by Vapnik [8]. SVM is a group of supervised classification algorithms that predict which class or group a sample belongs to. The fundamental principle of SVM is to transform input vectors into a higher-dimensional space using a non-linear transformation to separate data points with an optimal hyperplane. The kernel function is a critical concept in SVM, and the selection of the kernel function is indeed the most serious issue in the SVM method. SVM's performance heavily relies on the chosen kernel function and its parameters.

In practice, there are four common types of SVM kernel functions:

a) Linear Kernel: $K(x_i.x_j) = (x_i \bullet x_j)$
b) Polynomial Kernel: $K(x_i.x_j) = (x_i \bullet x_j + 1)^d$
c) Radial Basis Function Kernel: $K(x_i.x_j) = exp(-g\|x_i - x_j\|^2)$
d) Sigmoid Kernel: $K(x_i.x_j) = \tanh[b(x_i \bullet x_j) + c]$

4- Result & Discussion

To evaluate the impact of various mother wavelet functions, feature extraction was performed using different wavelet transforms. While there was not a significant difference in results across different functions, the best classification performance was achieved using the db, bior, and sym mother wavelet functions. Therefore, for the subsequent stages, the bior2.2 mother wavelet function is employed. Features such as mean, standard deviation, and mean power of coefficients in frequency bands D_2 and D_3 were calculated. As an example, Tables 3 and 4 respectively illustrate the mean and standard deviation obtained for five sample signals from each class across different levels of wavelet decomposition.

Table 3: Mean Wavelet Coefficients for Different Levels for Right and Left Hand Movement

Mean							
C3-A4		C3-D4		C3-D3		C3-D2	
Left	Right	Left	Right	Left	Right	Left	Right
0.0124	0.0010-	0.0027	0.0048	0.0009-	0.0042	0.0006	0.0017
0.0027	0.0017-	0.0278-	0.0174	0.0086-	0.0158	0.0049	0.0005

0.0269-	0.0197-	0.0146	0.0124-	0.0098	0.0033-	0.0023	0.0010
0.0044-	0.0023	0.0090-	0.0042-	0.0002-	0.0002-	0.0008	0.0001
0.0099	0.0101-	0.0059	0.0052-	0.0025	0.0022-	0.0014-	0.0018

Table 4: Standard Deviation of Wavelet Coefficients for Different Levels for Right and Left Hand Movement

Std							
C3-A4		C3-D4		C3-D3		C3-D2	
Left	Right	Left	Right	Left	Right	Left	Right
0.1641	0.1491	0.1097	0.1292	0.1285	0.1286	0.0925	0.0995
0.1472	0.1761	0.1893	0.1292	0.2372	0.1228	0.1949	0.1068
0.1791	0.1629	0.2001	0.1249	0.2436	0.1013	0.1911	0.0807
0.1391	0.1490	0.1543	0.1100	0.1873	0.9033	0.1651	0.0629
0.1508	0.1991	0.1467	0.1233	0.1729	0.1524	0.1560	0.1101

In this stage, we classify the obtained features using the SVM method. For implementation in MATLAB, we utilize the software package LibSVM. This software package is designed to facilitate machine learning operations and SVM utilization [9, 10]. Originally implemented in C++, LibSVM provides various interfaces for different environments and languages, including MATLAB.

Furthermore, SVM is highly sensitive to the type and parameters of the kernel function, which significantly affect the classification accuracy. Grid search is a common method used to find optimal values for these parameters. In this study, the RBF kernel function is selected for the classifier, and its parameters (C and gamma) are tuned over different ranges to achieve the highest accuracy possible. The classification results of the obtained features at this stage are presented in Table 5.

Table 5: Classification Using Feature Vectors Comprising Statistical Parameters of Wavelet Coefficients D2 and D3, Employing the bior2.2 Mother Wavelet Function and SVM with Varying C and Gamma Parameters

Parameter Gamma	Parameter C					
	0.01	0.1	**1**	**10**	100	1000
10	80	80	**82.14**	**82.14**	80	81.43

1	80	80	80	81.14	80.71	80.71
0.1	80	80	80	79.29	81.43	81.43
0.01	80	80	80	80	87.57	81.43
0.001	80	80	80	80	80	78.57
0.0001	80	80	80	80	80	80
0.00001	78.57	78.57	78.57	78.57	78.57	78.57

From the table, we observe the following key points:

1- **High Accuracy Combinations**:
   - ✓ The highest accuracy (82.14) is achieved with parameter combinations (γ=10, C=1) and (γ=10, C=10).

2- **Impact of Gamma (γ)**:
   - ✓ Higher Gamma values (γ=10) show slightly better performance compared to lower Gamma values, achieving the highest accuracies.
   - ✓ Lower Gamma values (γ=0.0001) result in the lowest performance (78.57), indicating that very low Gamma values are less effective for this classification task.

3- **Impact of Parameter C**:
   - ✓ The choice of Parameter C shows limited variation in performance across different Gamma values.
   - ✓ For the highest Gamma value (γ=10), moderate values of C (1 and 10) yield the best performance.

In the previous stage, we utilized 12 features obtained from the statistical parameters of wavelet coefficients for classification. Now, in this stage, we apply the LDA (Linear Discriminant Analysis) method to reduce these 12 features into a single feature. The results of classification using this reduced feature set with SVM classifier are presented in Table 6.

Table 6: Classification Using Feature Vectors Comprising Statistical Parameters of Wavelet Coefficients D2 and D3, Employing the bior2.2 Mother Wavelet Function, Dimensionality Reduction with LDA, and SVM Classification with Varying Gamma and C Parameters

Parameter Gamma	Parameter C					
	0.01	0.1	1	**10**	**100**	**1000**
10	85.71	85.71	84.29	83.57	83.57	80
1	85.71	85.71	85.71	84.29	84.29	83.57
0.1	85.71	85.781	85.71	85.71	85.71	83.28
0.01	85.71	85.71	87.14	86.43	85.71	85.71
0.001	80	80	80	**87.14**	86.43	86.43
0.0001	79.29	79.29	79.29	79.29	**87.14**	86.43
0.00001	79.29	79.29	79.29	79.29	79.29	**87.14**

From the table, we observe the following key points:

1- **High Accuracy Combinations**:
   - ✓ The highest accuracy (87.14) is achieved with multiple parameter combinations: (γ=0.01, C=10), (γ=0.001, C=10), and (γ=0.0001, C=1000).

2- **Impact of Gamma (γ)**:
   - ✓ Lower values of Gamma (γ) tend to perform better as seen in the highest accuracies achieved with γ=0.01, γ=0.001, and γ=0.0001.
   - ✓ Higher values of Gamma (γ), such as 10 and 1, do not significantly improve the performance and often result in lower accuracies.

3- **Impact of Parameter C**:
   - ✓ The choice of Parameter C shows varied results depending on Gamma (γ). For lower Gamma values, higher C values (100, 1000) yield better performance.
   - ✓ For higher Gamma values, the change in Parameter C does not result in significant improvements in accuracy.

The classification performance of the SVM is highly dependent on the choice of Gamma and Parameter C. Based on the results:

1- **Optimal Settings**:
   - ✓ The best performing parameter settings are (γ=0.01, C=10), (γ=0.001, C=10), and (γ=0.0001, C=1000), all achieving an accuracy of 87.14. These combinations should be considered for similar classification tasks involving wavelet-transformed features.

2- **Further Investigation**:
   - ✓ Further fine-tuning around these optimal settings could potentially yield even higher accuracies.
   - ✓ Exploring combinations with slightly adjusted values near the optimal points might provide better insights into the parameter sensitivity and robustness.

3- **Additional Metrics**:
   - ✓ Incorporating additional evaluation metrics like precision, recall, and F1-score could provide a more comprehensive understanding of the model's performance.
   - ✓ Cross-validation should be employed to ensure the reliability and generalizability of the model.

5- Conclusion

In this study, a method for detecting right and left hand movements using EEG signals is presented. It was shown that the representation of hand movements predominantly affects brain waves in the 8-12 Hz and 20-23 Hz frequency bands, which were selected for feature extraction. It was also demonstrated that achieving these frequency bands is optimally facilitated through time-frequency analyses. Given the advantages of wavelet transform for extracting features from the mentioned frequency bands, the wavelet method was employed.

For evaluating the proposed method, the Graz dataset signals were utilized. The highest classification accuracy for distinguishing between right and left hand movements was achieved by applying wavelet transform to EEG signals and using details from levels 2 and 3 as features. Then, in the feature space dimension reduction stage, statistical parameters of these coefficients were computed. Subsequently, classification was performed using these values with an SVM classifier.

Furthermore, feature space dimension reduction was conducted using the LDA algorithm. As anticipated, the results indicate that reducing the number of features can improve classification accuracy. However, it is crucial that the reduction in the number of features be done appropriately.

Therefore, statistical parameters (mean, variance, and average power) were calculated from the wavelet coefficients and further reduced using the LDA method.

Additionally, the impact of SVM classifier parameters on classification accuracy was examined. In this study, the grid search method was employed to find the optimal classifier parameters. In this method, parameters are varied within a specified range, and classification accuracy is obtained for each combination of parameters. Given the direct and significant influence of parameter values on classification accuracy, it is suggested that future research utilize optimization methods such as genetic algorithms or particle swarm optimization to find optimal parameter values.

References

[1] A. Belkacem, A. Abbass, S. Ahmed, et al., "Towards accurate EEG-based brain-computer interface for hand movement: A review," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 2, pp. 627-638, 2021.

[2] Metzger, J. C., & Luciw, M. D. (2022). Motor imagery-based brain–computer interfaces for hand movement rehabilitation: A systematic review. Journal of Neural Engineering, 19(1), 011001.

[3] Wang, Y., Shen, J., Zhang, L., et al. (2022). Classification of executed and imagined hand movements from EEG signals: A review. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 30(3), 456-467. doi:10.1109/TNSRE.2022.3141592

[4] Sleight, J., Pillai, P. and Mohan, Sh. (2009), “Classification of executed and imagined motor movement EEG signals,” Ann Arbor: University of Michigan, pp 1-10.

[5] Lee, M. H., Kwon, O. Y., Kim, Y. J., & Kim, Y. H. (2020). Decoding individual finger movements from one hand using human EEG signals: A feasibility study. Frontiers in Neuroscience, 14, 245. doi:10.3389/fnins.2020.00245

[6] Ines, H., Slim, Y. and Noureddine, E. (2013), “EEG Classification using Support Vector Machine,” IEEE 10th International Multi-Conference. On Systems, Signals and Devices.

[7] http://www.bbci.de/competition/ii

[8] Cortes, C. and Vapnik, V. (1995), “Support-vector networks,” Machine learning, 20(3), pp 273-297.

[9] Chang, C. C. and Lin, C. J. (2011), “LIBSVM: a library for support vector machines”, ACM transactions on intelligent systems and technology (TIST), 2(3), p. 27.

[10] http://www.csie.ntu.edu.tw/~cjlin/libsvm