International Journal of Theoretical & Applied Computational Intelligence
https://ijtaci.com

Research Article

Enhancing Hand Gesture Recognition Accuracy from Brain Signals Using Sparse Transforms

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Received: 8/12/2025; Accepted: 21/02/2026; Published: 10/03/2026
https://doi.org/10.65278/IJTACI.2026.47

Abstract: Brain Computer Interfaces (BCIs) offer a framework for classifying motor tasks such as hand movements and extracting features from electroencephalogram (EEG) signals. However, excessive noise levels and the processing requirements of existing approaches sometimes limit the accuracy of these classifications. For individuals with spinal cord injuries, whose limb movements are restricted, this challenge is particularly significant. Highly accurate classification algorithms are necessary for precise EEG-based control of neural prostheses. In this study, we propose a novel approach to EEG signal-based hand movement detection. Empirical Mode Decomposition (EMD) is used to preprocess EEG data before wavelet scattering and the Discrete Wavelet Transform (DWT) are applied to recover sparse features. Then, the Whale Optimization Algorithm (WOA) is employed to efficiently select features and reduce dimensionality. Three widely utilized algorithms—Random Forest, K-Nearest Neighbor KNN and Support Vector Machine (SVM)—are used to classify the refined features. According to experimental data, the proposed method classifies hand gestures with a precision of 99.14% and an accuracy of 98.58% using SVM. Comparative studies demonstrate that this approach outperforms current methods for identifying and categorizing hand movements in terms of accuracy and efficiency. These results show great potential for developing brain prosthetic devices and enhancing BCI systems.

Keywords: Brain-Computer Interface (BCI), Electroencephalogram (EEG) signals, Sparse transforms, Whale Optimization Algorithm

1. Introduction

In the late 20th century, the concept of using brain impulses to operate external devices, including prosthetic limbs, was first proposed. This idea has evolved over time into the field of BCIs, which has experienced rapid growth in both applications and research [1]. BCIs translate brain activity into control commands for external devices by integrating concepts from signal processing, neuroscience, electronics, psychology, and pattern recognition. In addition to assisting individuals with motor impairments, these technologies also enable healthy people to perform a variety of daily tasks [2]. Electrodes for recording brain signals, acquisition hardware, data processing algorithms, and a control interface that converts neural activity into executable commands are all common components of a BCI system [3].

The EEG is a widely used BCI modality. By detecting electrical activity in the brain, EEG-based BCIs enable users to operate devices directly through thought. In addition to supporting individuals with disabilities, EEG-based systems are rapidly being applied in fields such as gaming, art, medicine, and sports [4]. BCI systems establish a connection between the brain and external devices. They serve two primary purposes: closed-loop feedback for neurorehabilitation and brain activity regulation, and direct device control without rehabilitation objectives [5]. Brain activity can be recorded using either electrocorticography (ECoG) or EEG. Although non-invasive alternatives such as fMRI provide higher spatial resolution, EEG remains the preferred approach due to its affordability, portability, and ease of use. EEG is frequently employed for both rehabilitation and device control in individuals with neurological disorders [6]. One of the major challenges in BCI research is understanding the complex relationship between brain activity and bodily movement. This challenge is most pronounced in tasks involving the upper limbs and mental processes such as motor imagery. EEG can also be used to study neurological and motor disorders and to diagnose clinical conditions such as epilepsy, schizophrenia, and Alzheimer's disease [7]. Portability, safety, affordability, and superior temporal resolution are among the primary advantages of EEG-based methods. Specific methods for training and simulating brain activity are required for EEG-based BCIs. EEG signals are typically recorded from the scalp during visual or motor imagery exercises, enabling users to control external devices and modulate neural activity [8]. One of the most active areas of BCI research is hand gesture recognition using EEG signals [9]. Research in this field aims to identify patterns of brain activity associated with hand movements by having participants perform or imagine specific gestures while EEG data are recorded. Alpha, beta, and gamma frequency band oscillations, which correspond to particular motor or cognitive activities, are commonly observed in these signals [10]. After discriminative features are extracted from EEG data using signal processing methods, these features are classified and modeled as hand gestures. Such approaches are particularly valuable in developing prosthetic devices for individuals with motor disabilities [11,12].

Classification and regression are required after EEG signals have been collected and preprocessed. By automatically identifying valuable patterns, information, and decision-making rules within EEG data, machine learning—a key aspect of artificial intelligence plays a crucial role in this stage. The choice of algorithm significantly influences overall performance and classification accuracy, as these learned patterns allow BCIs to accurately interpret operations and discern user intentions. Machine learning in BCIs typically involves four key steps: preprocessing EEG signals, feature extraction, classification, and recognition. Proper preprocessing is essential, as it enhances system performance by reducing noise while preserving relevant information. Common preprocessing steps include channel selection, downsampling, time-windowing, filtering, and artifact removal [13,14]. To maximize the distinctions between EEG signal types, feature extraction is the next crucial step. Discrete Fourier Transform (DFT) [15], Discrete Wavelet Transform (DWT) [16] and Discrete Cosine Transform (DCT) [17] are examples of transform-domain techniques that are frequently used. Additionally, time-domain approaches have been applied, including statistical analysis, information theory methods, and Local Binary Patterns (LBP). Despite their reliability, spectral-domain features can be unstable due to the inherently dynamic nature of EEG signals [18].

Therefore, more effective feature extraction methods are needed to improve classification accuracy and robustness. EEG features have been extracted using conventional handcrafted techniques such as LBP, Histogram of Oriented Gradients (HOG), and Gabor filters. However, these methods often suffer from low accuracy and high computational complexity, necessitating the use of more advanced approaches. Sparse-transform algorithms, such as DWT, have become popular for decomposing EEG data while leaving only a small number of non-zero coefficients. This technique, which has proven highly effective for hand gesture recognition, reduces data size while preserving distinctive and discriminative features [19, 20]. By decomposing EEG signals into multiple frequency bands, DWT achieves an optimal balance between frequency and temporal resolution. DWT enhances the representation of motor-related brain activity by separating signals into detail coefficients (fine features) and approximation coefficients (coarse features), thereby increasing both the efficiency and accuracy of classification for hand and finger movements. More advanced variants, such as the Stationary Wavelet Transform (SWT), are shift-invariant, which improves artifact removal and signal fidelity, thereby enhancing robustness in EEG-based BCIs. Dimensionality reduction is essential in BCI applications, alongside feature extraction. Feature selection reduces computational costs while preserving critical information by transforming high-dimensional EEG data into a low-dimensional set of significant features [21-23]. Sparse-transform-based techniques, including DWT and random projection matrices, are frequently used to compress EEG data, lower complexity, and improve classification performance.

The main findings of this study are summarized as follows:

- Sparsity-based dimensionality reduction: DWT and random matrices are used to reduce EEG signals while preserving key features.
- Reduced computational complexity: The use of random binary matrices as sparse projection tools decreases computational overhead without compromising accuracy.
- Hand movement classification with sparse features: Multiple classifiers are employed to enhance brain-device interaction and accurately identify hand movements.

The remainder of this paper is organized as follows: Section 2 reviews the research background. Section 3 explains the proposed method. Section 4 presents experimental evaluations. Finally, Section 5 concludes the paper and suggests potential directions for future research.

2. Related works

MEG-RPSnet, a BCI neural network developed in [24], decodes rock-paper-scissors hand gestures using MEG sensors. Through advanced preprocessing techniques and a convolutional deep learning architecture, the system successfully classified 12 participants with an accuracy of 85.56%. Notably, MEG-RPSnet outperformed traditional EEG-based and machine learning techniques, suggesting that regional MEG sensors can compete with whole-brain approaches. This demonstrates that non-invasive hand movement decoding in BCIs is feasible. In [25] explored how deep learning could be applied to enhance hand movement recognition. Their study examined the use of deep learning models for classifying motor imagery, detecting epileptic seizures, and monitoring driver attention using EEG data, while also discussing current challenges and future objectives in EEG-based BCI research. To identify hand movements, in [26] analyzed EMG data from 20 healthy individuals performing seven upper-limb movements using a Myo-band. Classifiers including logistic regression, linear discriminant analysis (LDA), KNN, and decision trees were applied to evaluate the data. The findings showed that hand flexion and extension achieved the highest detection accuracy, indicating that EMG-based methods are suitable for gesture recognition.

In [27] a 2D convolutional neural network (CNN) to classify hand gestures from video recordings of 10 distinct movements, combined with sEMG data from a Myo armband. Performance metrics such as precision, recall, and F1-score demonstrated the potential of combining visual and sEMG modalities for reliable gesture recognition. An EEG-based system was developed in [28] to detect hand opening and closing movements. Features were extracted using the Fast Fourier Transform (FFT), while classification was performed using SVM, AdaBoost, Decision Tree, and Random Forest algorithms. The Random Forest classifier achieved the highest accuracy (78.62%), confirming its effectiveness for binary hand gesture detection. In [29] proposed an automatic hand movement recognition approach based on discrete wavelet decomposition of sEMG data. The Decision Tree classifier achieved 93% accuracy, outperforming KNN, thus confirming the effectiveness of wavelet-based EMG feature extraction combined with tree-based learning techniques. In [30] enhanced EEG-based gesture recognition by first applying Independent Component Analysis (ICA) to remove artifacts, followed by feature extraction and selection using the Filter Bank Common Spatial Pattern (FBCSP) method. Compared to benchmarks, classification using an SVM with optimized kernel parameters yielded reduced error rates and higher accuracy.

For EEG classification, in [31] developed a zero-shot learning model that outperformed conventional techniques based on predefined classes, recognizing both known and unseen categories with an accuracy of 91.81%. Similarly, in [32] evaluated AlexNet, ResNet50, and InceptionV3 for motor imagery EEG classification. InceptionV3 achieved the highest accuracy (82.78% on BCI competition data and 83.79% on experimental data), highlighting the potential of deep transfer learning in BCIs. After removing EOG artifacts from EEG recordings, in [33] used deep architectures, including Long Short-Term Memory (LSTM) and Deep Belief Networks (DBN), for classification. Without further optimization, accuracies of 50.35% and 49.65% indicated challenges in applying deep models to EEG tasks. In [34] developed a three-stage BCI for hand movement control, consisting of feature extraction, classifier training, and online prediction. EEG features were extracted using Autoregressive (AR) and Common Spatial Pattern (CSP) techniques, and Principal Component Analysis (PCA) was applied for dimensionality reduction. An SVM classifier achieved 97.5% online accuracy, demonstrating the potential for reliable real-time control.

In [35] employed spatial mode filters to enhance signal quality and mitigate noise and artifacts in EEG recordings. Their findings confirmed that this type of filtering significantly improves both EEG clarity and response time, which are critical for real-time BCI applications. While each method offers advantages in feature extraction and signal classification, a review of these studies reveals shared challenges such as reliance on large training datasets, sensitivity to parameter changes, and the inherent complexity of EEG signal processing. Sparse feature extraction techniques present a promising strategy by reducing data dimensionality while retaining the most informative coefficients. This approach is particularly effective for handling noisy, high-dimensional EEG and EMG data, as it enhances computational performance, reduces processing overhead, and strengthens the robustness and scalability of classification models. Integrating sparsity-based techniques into feature extraction could greatly improve the accuracy, efficiency, and practicality of existing BCI systems.

3. Proposed method

The proposed method recognizes hand gestures using EEG signals within a BCI framework. To enhance performance, the technique employs the WOA and feature selection-based classification. Essential features, such as frequency-domain characteristics and those derived from sparse transforms, are extracted after the EEG data have been preprocessed. WOA is used to identify the most discriminative features to improve classifier accuracy. This process retains the most valuable components of the EEG signal while reducing the dimensionality of the data. The selected features are then fed into several classifiers, including RF, KNN, and SVM, to accurately detect hand gestures. The proposed approach consists of four main steps: signal preprocessing, feature extraction, dimensionality reduction, and classification. This process is schematically illustrated in Figure 1.

3.1 Preprocessing

EEG signal preprocessing is employed in this study to eliminate distortions and noise from the recorded brain signals. First, the EMD algorithm is applied to decompose the EEG signal into 10 Intrinsic Mode Functions (IMFs). The DWT is then used to remove high-frequency noise components (IMF1 and IMF2), while median filtering is applied to eliminate low-frequency noise components (IMF9 and IMF10) [36]. After noise removal, the remaining IMFs are combined to reconstruct the clean EEG signal. Since EMD represents the input signal as a combination of IMFs and a residual component, it is highly effective for processing non-stationary and nonlinear signals. By efficiently identifying key signal characteristics and removing noise, this technique prepares the EEG data for feature extraction and further analysis [36].

3.2 Feature Extraction

Feature extraction is employed in this study to reduce the dimensionality of large EEG datasets and eliminate redundant or unnecessary data. The method focuses on sparse and frequency-domain features, which are particularly useful for detecting hand movements. Due to the non-stationary nature of EEG signals, traditional Fourier transform-based methods are inadequate for their analysis. Instead, the wavelet transform provides a powerful tool for handling non-stationary signals. In particular, orthogonal Daubechies wavelet filters are used because of their high accuracy in both signal decomposition and reconstruction. After applying the wavelet transform to EEG signals at various levels, both high- and low-frequency components from the second decomposition level are employed for feature extraction. This technique ensures that only the most discriminative information is retained for classification by reducing data dimensionality and eliminating redundant or irrelevant features. Figure 2 illustrates the application of the DWT to the EEG signal, while Table 1 summarizes the extracted features.

Table 1: Frequency and Temporal Domain Features Extracted from EEG Recordings

Subset	Feature Type
1- DWT 2- SWT	Features Based on Sparse Transforms

As shown in Figure 3, both the high-frequency (detail) and low-frequency (approximation) components of the signal lose information when the number of wavelets transform levels increases. In this study, features are extracted using both high- and low-frequency data from the second decomposition level.

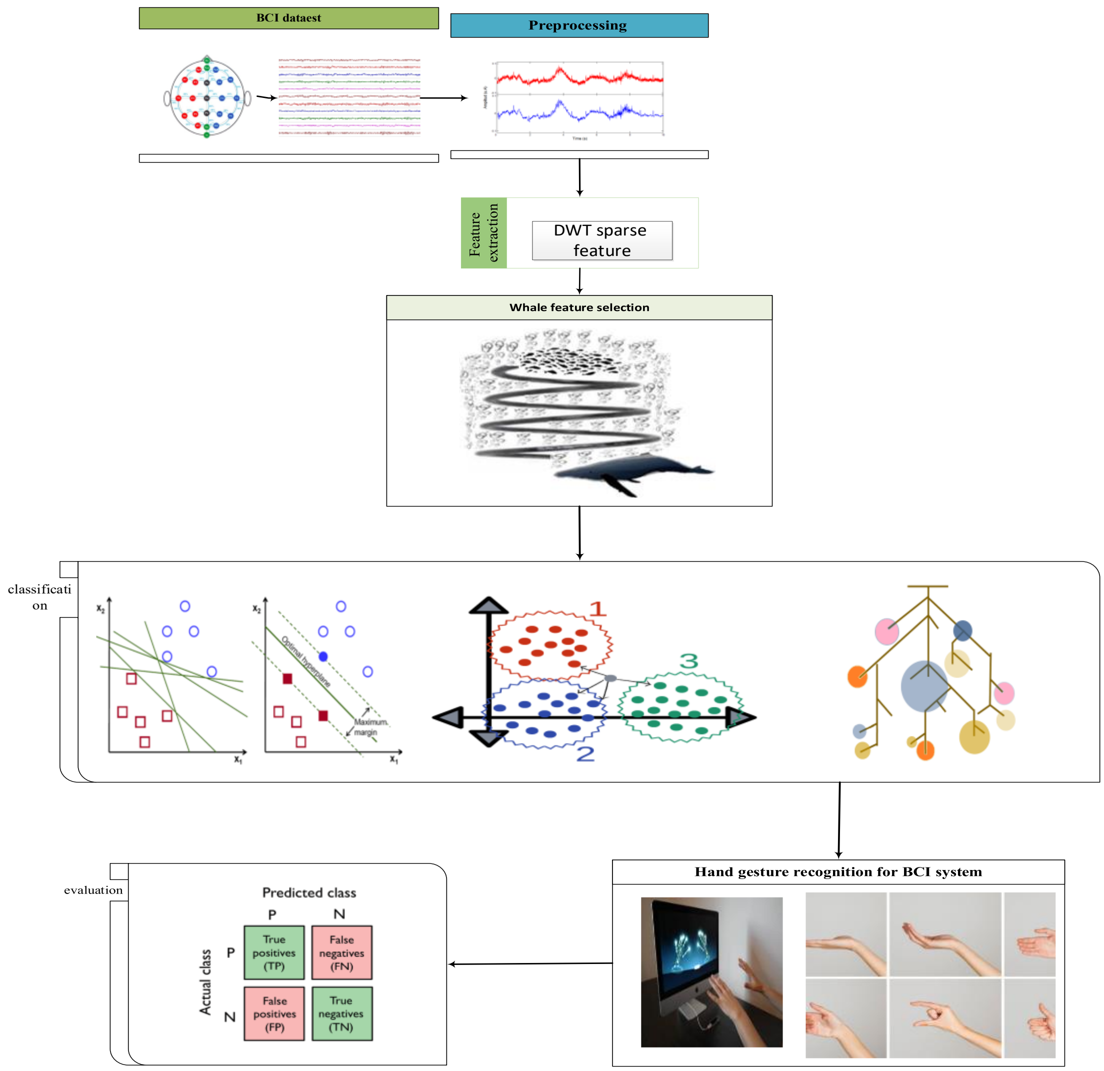

Figure 1: Block diagram of the proposed EEG-based hand gesture recognition method

3.3 Dispersion Wavelet Transform

Due to variations in a person's mental and physical state, EEG signals are highly variable; even minor adjustments can significantly affect the recorded signals. The Scatter Wavelet Transform (SWT) provides greater stability over temporal variations by cascading absolute value operators, whereas the traditional DWT may fail to detect these subtle changes. By iteratively computing wavelet coefficients through multiple layers, this method enhances signal identification while conserving energy at larger scales. In this process, the scaling factor plays a crucial role—particularly for low-frequency EEG components that are prone to distortion after noise reduction. Using filter banks, the process is performed across multiple layers, and the first-order dispersion coefficients are obtained by averaging the absolute values of the wavelet coefficients, as described below:

$$S_1x(t,\lambda_1) = \left|x * \psi_{\lambda_1} * \phi(t)\right| \tag{1}$$

This approach uses the first filter bank to process the original signal (x). The transformation in the subsequent layer is then computed using the absolute value coefficients generated from the previous layer.

$$U_2x(t,\lambda_2) = \left\| x * \psi_{\lambda 1} \right| * \psi_{\lambda_2} \right|,$$
$$S_2x(t,\lambda_2) = \left\| x * \psi_{\lambda 1} \right| * \psi_{\lambda_2} \right| * \phi(t). \quad (2)$$

The calculation of coefficients in the successive layers of the transform is illustrated in Figure 4. The dispersion coefficients suppress the high-frequency components of the signal while remaining consistent in response to signal variations. In the following layers, wavelet transform filter banks are applied to reconstruct these high-frequency components. The Morlet wavelet is used for processing the high-frequency elements [38].

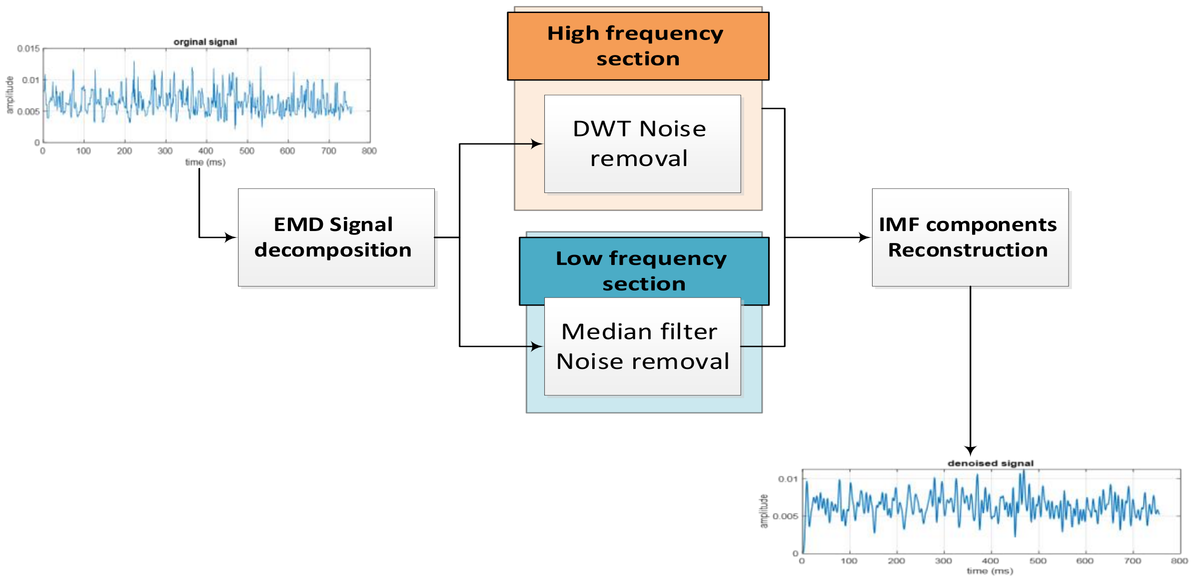

Figure 2: Preprocessing process in the proposed method 3.3 Feature Selection with WOA

3.3 Feature Selection with WOA

The WOA is a nature-inspired optimization method based on the social and hunting behaviors of humpback whales. This approach is frequently used for feature selection in data analysis and classification tasks. WOA simulates how whales hunt cooperatively, particularly how they search for and encircle their prey.

In this algorithm, whales update their positions in two ways: by randomly exploring the search space for new possible solutions and by moving toward the most promising known solution (exploitation). This dual strategy enhances classifier performance and accuracy in high-dimensional data environments by allowing the algorithm to efficiently identify the optimal feature subsets while avoiding local minima.

During the feature selection stage, the WOA considers each feature as a point within the search space. The objective is to identify the best subset of features that optimize classifier performance, with each whale (or candidate solution) representing a specific feature subset. After redundant and irrelevant features are eliminated using optimization criteria modeled on whale hunting behavior, the classifier is provided with the selected set of important features.

In addition to reducing data dimensionality, this method decreases computational complexity and improves the accuracy of machine learning models. The main steps of the WOA feature selection algorithm are as follows:

- Initialization of Positions (Features): A population of whales, each representing a subset of features, is initialized. Each whale's position in the feature space corresponds to a distinct set of selected features.
- Fitness Evaluation: An objective function, such as classification accuracy, is used to evaluate each whale (feature subset). This function assesses how much each subset contributes to improving classifier performance.

$$itness(X) = \frac{Accuracy(X)}{Error\ (X)+1} \quad (3)$$

Let (X) represent a selected feature set, (X) the classifier's accuracy based on those features, and (X) the classifier's error rate. According to the fitness function, higher fitness values correspond to higher accuracy and lower error rates.

- Preserve the Best Solution: At the end of each iteration, the feature subset with the highest fitness value is stored. Other whales then use this solution as a reference for updating their positions.
- Whale Movement: Each whale modifies its position either randomly within the search space or toward the best solution, depending on its current location and that of other whales. These movements occur in two main ways:
  - ✓ Exploitation: Whales move closer to the best feature subset to obtain better solutions.
  - ✓ Exploration (Random Movement): Whales move randomly through the feature space to discovr new optimal subsets.
- Position Update: After movement, whale positions are updated. These flexible updates allow the algorithm to explore and refine the selected features dynamically.
- Iteration: The above steps are repeated multiple times. With each iteration, the whales converge toward an optimal feature subset.
- Final Output: After a predetermined number of iterations, the best-performing feature subset is selected as the final output. This subset is then provided as input to the classifier model.

As a result, the WOA enhances hand gesture recognition performance by rapidly eliminating redundant and irrelevant features while selecting the most valuable ones for machine learning models.

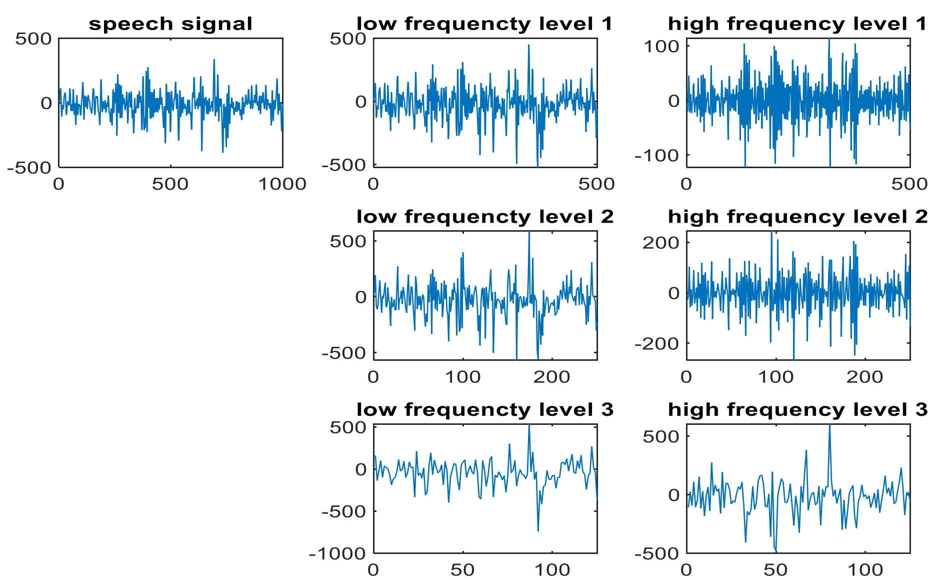

Figure 3: EEG signal used in the study and its decomposition using the DWT with Daubechies filter bank.

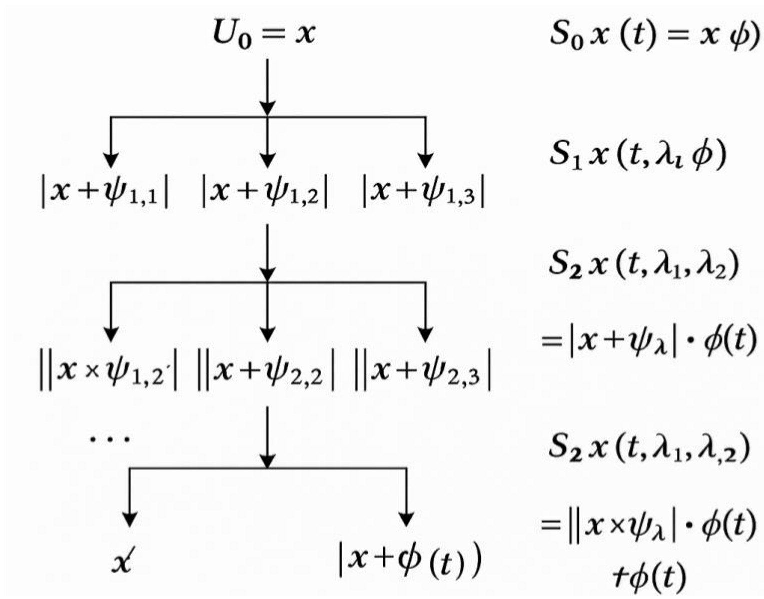

Figure 4. Coefficient calculation in the subsequent layers of the transform.

3.4 Classification and Motion Detection

Once the feature vectors have been optimized using the proposed WOA, they are organized into a feature matrix. These selected features are then input into hand motion detection classifiers, which employ 5-fold cross-validation to ensure reliable evaluation. The Support Vector Machine (SVM) classifies data by mapping them into a high-dimensional space and identifying a hyperplane that separates the classes. This method ensures that different classes are well distinguished by maximizing the margin between the hyperplane and the nearest data points. The K-Nearest Neighbor (K-NN) algorithm is a supervised learning method that calculates the distance between a test sample and its k nearest neighbors in the training set. The class of the test sample is then determined based on the majority vote of these neighbors.

The Random Forest (RF) algorithm is an ensemble learning approach that constructs multiple decision trees based on training data and randomly selected attributes. Each tree is built independently, and the final classification is determined through a majority vote across all trees. This technique effectively reduces noise sensitivity and minimizes overfitting. Using EEG-derived data, the system employs these classifiers to accurately identify and categorize various hand gestures.

4. Results

The hand gesture detection system proposed in this study was implemented on a PC running Windows 10, equipped with a 7-core Intel® Core™ i7 CPU operating at 2.60 GHz and 16 GB of RAM. All simulations were executed using MATLAB 2020b. Several metrics—including accuracy, precision, recall, sensitivity, specificity, and the F1-score—were used to evaluate the performance of the proposed approach. These indicators provide a comprehensive understanding of classification performance. The metrics are calculated using the following formulas:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{Precision}=\frac{TP}{TP+FP} \tag{5}$$

$$\text{ACC}=\frac{TN+TP}{TN+FN+FP+TN} \tag{6}$$

$$\text{Sensitivity}=\frac{TP}{TP+FN} \tag{7}$$

$$\text{Specificity}=\frac{TN}{TN+FP} \tag{8}$$

$$\text{F\_Measure}=\frac{2*TN}{2*TP+FP+FN} \tag{9}$$

In the equations above, recall represents the recall rate, precision corresponds to precision, and accuracy denotes the accuracy correction coefficient (ACC). The true positive rate is represented by sensitivity, the true negative rate by specificity, and the harmonic mean of precision and recall is denoted by F-Measure (F1-score). True positives are denoted by TP, true negatives by TN, false positives by FP, and false negatives by FN. These definitions provide a solid foundation for understanding the performance metrics of the classifier.

4.1 Dataset

The EEG dataset used in this study is publicly available and described in references [33, 34]. The collection includes over 1,500 EEG recordings from 109 volunteer participants, each lasting one to two minutes. EEG signals were recorded using a 64-channel EEG system integrated into the BCI2000 platform (http://www.bci2000.org).

- Real Movement (Left/Right Hand): A cue appears on either side of the computer screen. The participant repeatedly opens and closes the corresponding fist until the stimulus disappears, at which point they relax.
- Imagined Movement (Left/Right Hand): A cue appears on one side of the screen. The participant imagines opening and closing the corresponding fist until the cue disappears, then relaxes.
- Real Movement (Hands/Feet): A cue appears at the top or bottom of the screen. When the cue is at the top, the participant opens and closes both fists; when it is at the bottom, they open and close both feet. The participant relaxes once the cue disappears.
- Imagined Movement (Hands/Feet): A cue appears at the top or bottom of the screen. The participant imagines opening and closing both feet (for a bottom cue) or both fists (for a top cue) until the cue disappears, then relaxes.

4.2Evaluation

Two scenarios were used to evaluate the proposed EEG-based method for hand gesture recognition: with dimensionality reduction, and without dimensionality reduction.

In both cases, features derived from the frequency domain and sparse transform-based representations were analyzed separately and then input into the selected classifiers. The extracted features were organized in matrix form. Three supervised learning algorithms were applied for classification using KNN, RF and SVM.

Before classification, noise and artifacts were removed using a filter-based method. Then, the proposed WOA was employed for optimal feature selection, focusing on sparse transform-based features. Finally, the previously mentioned classifiers were used to perform the classification process.

The evaluation results for frequency-domain features are shown in Figure 5. As expected, across most performance metrics, the SVM classifier outperformed both KNN and RF classifiers. Before feature selection, Figure 6 presents the results for sparse transform-based features. The results clearly demonstrate that recognition performance improved significantly after feature selection, confirming the effectiveness of the proposed WOA-based feature selection approach. All recognition metrics including accuracy, precision, and sensitivity showed improvement following the feature selection process, as illustrated by the comparison between Figures 5 and 6.

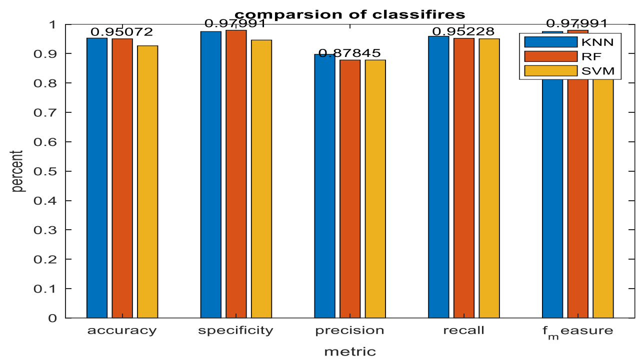

Figure 5: Results of the evaluation criteria for sparse features before feature selection.

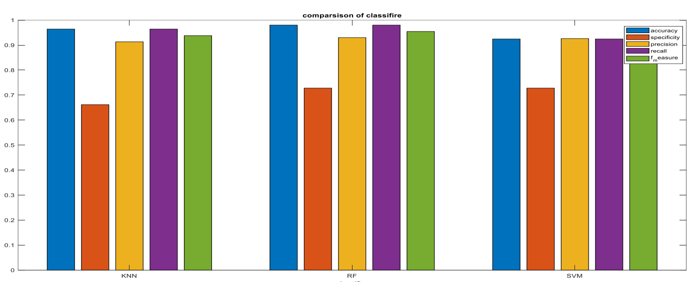

Figure 6: Results of the evaluation criteria for sparse features after feature selection.

The Receiver Operating Characteristic (ROC) measure was applied to the three classifiers used in this study, as well as to the extracted features, to further evaluate the proposed method for hand gesture detection using EEG data. The ROC curve represents a classification model's performance across all thresholds by plotting two parameters: the True Positive Rate (TPR) and the False Positive Rate (FPR). The ROC curves for the SVM, KNN, and RF classifiers, illustrating hand gesture recognition with sparse features from the test, training, validation, and total datasets, are shown in Figure 7. Similarly, Figure 8 presents the ROC curves obtained after feature selection and dimensionality reduction using the proposed method. The validation results for each of the three classifiers confirm the effectiveness of the proposed approach in distinguishing hand gestures and its robustness to variations in EEG signal characteristics.

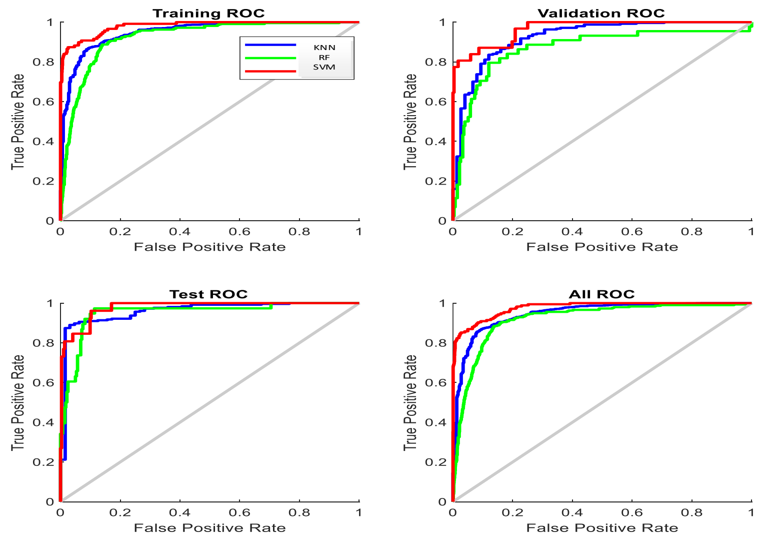

Figure 7: Comparison of ROC curves for the SVM, KNN, and RF classifiers in hand gesture recognition using sparse features before feature selection.

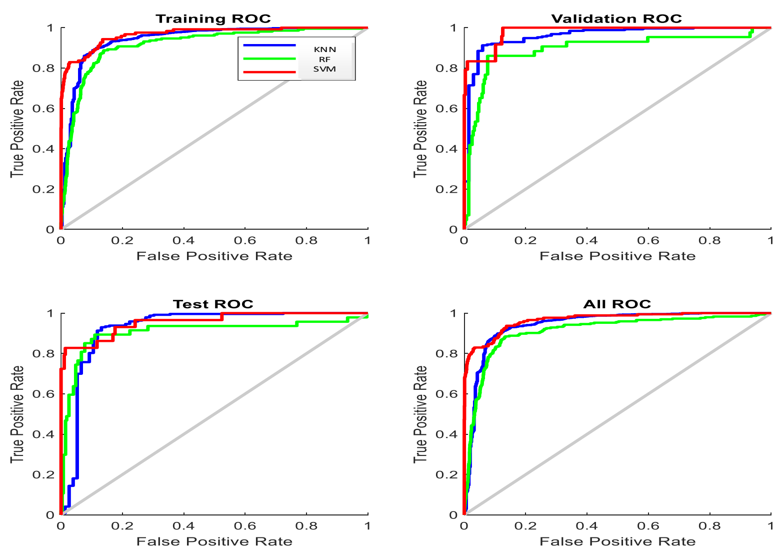

Figure 8: Comparison of ROC curves for the SVM, KNN, and RF classifiers in hand gesture recognition using sparse transform features after feature selection.

The ROC value of the SVM classifier is significantly closer to one for the training, testing, validation, and total datasets, as shown in Figures 7 and 8. This demonstrates that the proposed approach maintains consistent performance even when the extracted features vary, achieving exceptional stability and robustness in hand gesture recognition.

4.3 Comparison with Other Studies

To provide a more comprehensive evaluation of the proposed method, the approach based on features extracted from sparse transforms combined with the proposed feature selection was compared with several alternative methods. A summary of this comparison is presented in Table 2. In [37], an artificial neural network was combined with geometric dispersion features. In [38] a convolutional neural network (CNN) was integrated with two-dimensional features and features derived from sparse transforms. In [39], a Support Vector Machine (SVM) classifier was paired with low-rank tensor evolution for feature extraction. In [40], features derived from sparse transforms were combined with two-dimensional orthogonal Tucker decomposition.

Table 2: The proposed method outperforms the other approaches under consideration

% Accuracy	%Precision		Method
78.3	77.6	MST + NN+3D point cloud	[37]
-	89.11	2D+3D +CNN	[38]
-	82.89	2D+3D + low-rank tensor completion +SVM	[39]
-	95.49	2D+3D +Orthogonal tucker decomposition +SVM	[40]
96.5	97.5	Sparse based feature + Proposed feature selection	Proposed

As shown in Table 2, the proposed method outperforms the other approaches under consideration. This improvement can be attributed to the construction of a feature matrix derived from sparse transformations and the subsequent feature extraction process performed using this matrix. Furthermore, these results were significantly enhanced by the proposed feature selection method. While the approach in [38] utilizes deep learning, and the methods in [39] and [40] employ tensor decomposition to extract features from sparse transformations, the proposed approach in this study achieved superior performance compared to both traditional machine learning and deep learning-based techniques.

4.4 Discussion

The results of this study showed that the use of DWT and SWT along with WOA plays a very effective role in increasing the accuracy and stability of hand movement classification from EEG signals. The outstanding feature of this method is its ability to extract stable wavelet coefficients that are resistant to time changes and instantaneous signal fluctuations. While in classical methods, the phenomenon of minor changes in the mental and physiological states of individuals can lead to a decrease in model performance, the use of sparse and multilayer transforms in this study resulted in the preservation of important signal information and at the same time the suppression of high-frequency noise in an effective way. This feature significantly improved the accuracy and precision in classifying movement patterns, so that the proposed model performed better than other machine learning-based methods. On the other hand, the results obtained showed that reducing the data dimension using optimal feature selection not only reduced the computational load and training time, but also helped to prevent overfitting in learning models. In fact, the intelligent combination of wavelet bank filters and bio-optimization algorithms provides a flexible solution for identifying distinctive features of the EEG signal that is highly robust to noise, individual variations, and environmental conditions. This stability is especially important in real-world applications of BCI and neural prosthesis control, because in these systems, even minor fluctuations in the input signal can significantly affect the final performance. Compared to previous studies, the method presented in this study has been able to achieve higher accuracy and precision in hand movement recognition by combining the wavelet transform and the Wall algorithm. This indicates the superiority of the model in extracting hidden patterns from EEG signals and can be used as a basis for developing adaptive and intelligent user interfaces in the design of new-generation BCI systems. The results also indicate that the proposed model has good generalizability and can maintain its performance in real-world conditions, even with new and noisy data. However, it should be noted that the high accuracy of the model depends to some extent on the quality of the input data and the selected parameters in the wavelet transform. In future studies, by examining the effect of selecting different wavelets, the size of the time windows, and using deep neural networks (such as CNN and LSTM) in addition to extracting sparse features, hybrid models can be achieved that have a higher ability to understand the temporal dynamics of the brain signal. In addition, evaluating the model in online and real-time environments (Real-time BCI) and on people with movement disorders can further reveal the validity and practical efficiency of this method. Overall, the findings of this research offer a new path for improving mental movement recognition and developing rehabilitation tools based on EEG signals, which could play a significant role in medical, robotics, and human-machine interaction applications.

5. Conclusion

This study presented a novel method for classifying hand movements from EEG signals in BCI systems. First, EMD preprocessing was applied to reduce noise in the EEG signals. Then, the DWT was used to extract sparse features, improving both data quality and classification accuracy. The WOA was employed to efficiently select the most relevant features while reducing the feature space. Several classification techniques were used, including RF, K-NN, and SVM. The results demonstrated that the proposed method achieved excellent performance, recognizing hand movements with 98.58% accuracy and 99.14% precision. A comparison with previous studies confirmed the superior effectiveness of the proposed approach in recognizing and categorizing hand movements from EEG data. These findings have a significant impact on the performance of BCI systems and the control of brain prostheses, contributing to the advancement of more precise and reliable brain-controlled technologies

Funding Statement: The author(s) received no specific funding for this study.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest regarding this study.

Authors contributions. Conceptualization: PS, MS; methodology: PS, MS; validation: PS; writing—original draft preparation: PS, MS; writing—review and editing: PS; visualization, supervision and project administration: MS All authors had approved the final version.

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