A Comprehensive Approach for Enhancing Motor Imagery EEG Classification in BCI's

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Abstract. Electroencephalography (EEG) based on motor imagery has become a potential modality for brain-computer interface (BCI) systems, allowing users to control external devices by imagining doing particular motor activities. The existence of noise and the complexity of the brain signals, however, make it difficult to classify motor imagery EEG signals. This work suggests a systematic method for classifying motor imagery in the EEG. A technique known as Multiscale Principal Component Analysis (MSPCA) is used for efficient noise removal to improve the signal quality. A unique signal decomposition technique is proposed for modes extraction, allowing the separation of various oscillatory components related to motor imagery tasks. This breakdown makes it easier to isolate important temporal and spectral properties that distinguish various classes of motor imagery. These characteristics capture the dynamism and discriminative patterns present in motor imagery tasks. The motor imagery EEG signals are then classified using various machine learning and deep learning-based models based on the retrieved features. The findings of the classification show how well the suggested strategy works in generating precise and trustworthy classification success for various motor imaging tasks. The proposed method has enormous potential for BCI applications, allowing people with motor limitations to operate extrasensory equipment via brain signals.

Keywords: Motor Imagery EEG · Brain-Computer Interface · MSPCA · Signal Decomposition · Classification

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1 Introduction

Brain-computer interface (BCI) systems have numerous applications [1] and can enable disabled individuals to interact with the real world using their thoughts alone [2,3]. These systems collect electrical signals generated by brain activity and translate them into control outputs through nonmuscular channels [6]. Motor imagery (MI) imagery is a commonly used mental rehearsal technique in BCI applications [4,5,7], where participants imagine themselves performing specific motor actions without physical muscle activation [8]. BCIs based on MI have attracted extensive interest in recent years [9,28], and various clinical methods such as electroencephalography (EEG) [29], magnetoencephalography (MEG) [30], functional magnetic resonance imaging (fMRI) [31], positron emission tomography (PET) [32], and single-photon emission computed tomography (SPECT) [33] have been employed to monitor brain activities during motor rehearsal. Among these methods, EEG signal analysis is the most widely used due to its affordability, ease of use, excellent temporal information, and noninvasive nature [9–15].

Currently, most motor imagery BCIs operate as pattern recognition systems. They initially identify EEG signals using feature extraction and detection schemes and subsequently translate these signals into corresponding task commands. Capturing and classifying EEG signals with high accuracy is crucial for BCI development, and various signal processing techniques have been proposed in the literature [34–40]. These techniques can be categorized into Fourier transform (FT)-based methods, autoregressive (AR) model-based methods, common spatial pattern (CSP)-based methods, sparse representation (SR) methods, and signal decomposition (SD)-based methods. FT-based methods are typically used for EEG signal power spectral analysis but lack time domain information [34,35]. AR model-based methods are computationally efficient and suitable for online systems, but they suffer from artifacts that reduce BCI system reliability [36–40]. Spatial pattern-based methods, which employ appropriate spatial filtering techniques for analyzing oscillatory EEG components, have also been proposed [42–50]. These methods have improved the overall classification accuracy of EEG signals but are often limited by small sample sizes and may suffer from overfitting issues.

To further improve classification accuracy, clustering-based least square support vector machine (LS-SVM) classifiers [51], iterative spatio-spectral pattern learning (ISSPL) methods [52], and feature extraction techniques such as covariance-based second-order dynamic features [53] and constraint-based independent component analysis [54] have been proposed. These methods have achieved higher accuracy but often neglect the selection of optimal regularization parameters. Higher order statistics (HOS) features, including signal skewness (Sk) and kurtosis (Kt), have also gained popularity for analyzing biomedical signals [41,55].

Recently, deep learning approaches based on convolutional neural networks (CNNs), recurrent neural networks (RNNs), and sparse Bayesian extreme learning schemes have been applied to EEG signal feature extraction and classification

[56–59]. While these methods show promise, their classification accuracies are often limited by the lack of extensive training data, and their practical application is hindered by high computational requirements and system complexity [24–27].

Signal decomposition (SD)-based methods are relatively new for MI task classification. These methods decompose EEG signals into different sub-bands and extract desired coefficients separately. Empirical mode decomposition (EMD), discrete wavelet transform (DWT), and wavelet packet decomposition (WPD) are three SD-based methods that have been proposed [41]. While they have achieved classification accuracies of 62.8%, 81.1%, and 92.8%, respectively, they suffer from relatively low success rates and challenges in selecting the appropriate number of decomposition levels, especially for WPD [41]. Empirical wavelet transform (EWT) is a relatively new SD-based method for signal analysis [61] and has applied to MI-based EEG signal classification. However, it required large number of modes, restricting its practical applicability [16–23].

This paper focuses on the feasibility of Sliding Singular Spectrum Analysis (SSA) for classifying motor imagery (MI) electroencephalography (EEG) signals. We introduce a new data adaptive decomposition method to analyze the non-stationary and nonlinear characteristics of MI EEG signals. By applying SSA, we decomposed the signals into adaptive frequency modes. From these modes, we extract statistical features that capture meaningful information of the SSA decomposition. Additionally, we employed a wide range of classifiers to assess the effectiveness of our approach. To evaluate the proposed SSA-based framework, we conducted experiments using the benchmark dataset IVa from BCI competition III. The results of our experiments validate the efficacy of the proposed SSA-based framework for MI EEG signal classification.

2 Materials

The study utilized the publicly available benchmark dataset IVa, which is obtained from BCI competition III [62]. This dataset was generously provided by the Institute of Medical Psychology and Behavioral Neurobiology at the University of Tübingen, headed by N. Birbaumer, the Max-Planck-Institute for Biological Cybernetics in Tübingen, headed by B. Schökopf, and the Department of Epileptology at Universität Bonn. The IVa dataset comprises two motor imagery (MI) tasks: right hand (RH, class 1) and right foot (RF, class 2). The recordings were conducted with five healthy participants who were seated in a relaxed state in a chair throughout the experiment. EEG signals were acquired using BrainAmp amplifiers and a 128-channel Ag/AgCl electrode cap manufactured by ECI. The EEG channels were positioned according to the extended international 10/20 system [63].

3 Methods

In this study, a Sliding Singular Spectrum Analysis (SSA)-aided automated framework is proposed for the identification of right hand and right foot motor

imagery (MI) EEG signals. The framework consists of dataset preparation, noise removal, SSA for generating dominant components, extraction of statistical features, and classification models. The proposed framework is illustrated in Fig. 1 as,

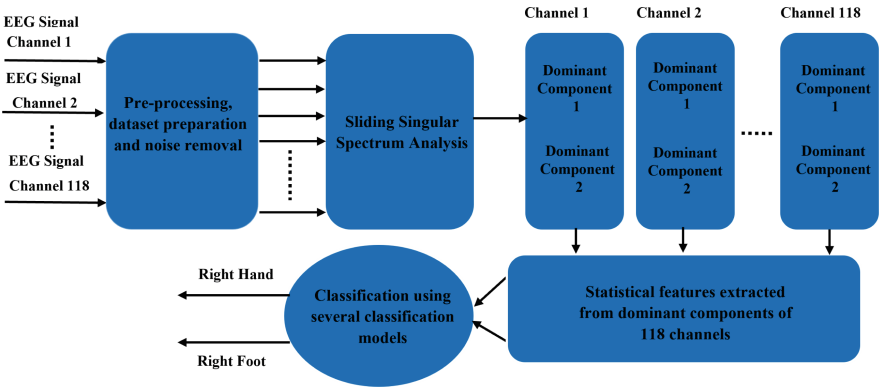


Fig. 1. Block diagram of the proposed automated SSA framework for Motor Imagery EEG Classification

3.1 Module 1: Pre-processing

The IVa dataset that we used comes with position indicators determining the data points from 280 sessions with 118 EEG electrodes for every single subject. The participants "aa", "al", "av", "aw", and "ay" in both groups had initial data lengths that were the following: 298458×118, 283574×118, 283042×118, 282838×118, and 283562×118. The EEG segments that matched particular MI (motor imagery) activities were the focus of our attention. To identify these segments, we relied on the position markers that indicated the start of each trial. The original dataset was recorded with a sampling frequency of 1000 Hz Hz. However, for consistency with previous studies, we used a down-sampled version of the dataset that was available at a rate of Fs=100 Hz. For our analysis, we selected a duration of 4 s from each EEG segment in both classes, resulting in 400 samples (4xFs). Consequently, we obtained a data matrix of size 400×118 for each EEG segment of a specific class, which was used for each participant in our study. We used a multiscale principal component analysis method to remove noise due to the fragile and vulnerable traits of EEG data acquired from the subject's scalp.

3.2 Module 2: Sliding Singular Spectrum Analysis for Meaningful Components Extraction

Sliding Singular Spectrum Analysis (SSA) is a technique used for extracting meaningful components from time series data, such as EEG (Electroencephalogram) signals, particularly those related to motor imagery tasks. It applies Singular Value Decomposition (SVD) to decompose the time series into a set of basis functions called singular vectors, which capture the dominant patterns present in the data.

The motivation behind using SSA for EEG analysis, specifically for motor imagery tasks, is to identify and extract relevant brain activity patterns associated with the imagination of movement. Motor imagery EEG signals capture the brain's electrical activity when an individual mentally simulates or imagines performing a specific motor action, without actually executing the movement. Analyzing these signals can provide insights into the brain's motor processes and assist in developing brain-computer interfaces and rehabilitation techniques.

Let's delve into the mathematical equations involved in the Sliding SSA algorithm in the context of motor imagery EEG signals:

1. Given a time series of EEG data for 5 subjects, represented by matrices X_1, X_2, X_3, X_4, X_5 of size $(n \times m)$, where n is the number of time steps and m is the number of electrodes or channels. In this case, $m = 118$ according to the 10–20 framework.
2. Sliding SSA applies a sliding window of length L to the time series. The window moves step-by-step, extracting segments of length L from the EEG data for further analysis.
3. For each window, the Singular Value Decomposition (SVD) is performed on the windowed matrix. SVD decomposes the windowed data matrix W into three matrices: U, Σ, and V.
   $W = U\Sigma V^T$ Here, U represents the left singular vectors, which capture the spatial patterns or topographies of the EEG components related to motor imagery. Σ is a diagonal matrix containing the singular values, which represent the magnitudes or strengths of the corresponding singular vectors. V consists of the right singular vectors, which describe the temporal dynamics or time courses of the EEG components associated with motor imagery.
4. To extract the dominant components, we retain only the first k singular values and their corresponding singular vectors. The value of k is determined based on the desired level of decomposition or the explained variance.
   U_k, Σ_k, and V_k represent the truncated matrices that retain the first k singular vectors and singular values from U, Σ, and V, respectively.
5. The reconstructed window is obtained by multiplying the retained left and right singular vectors with their corresponding singular values: Reconstructed Window $RW = U_k \Sigma_k V_k^T$ Here, U_k represents the truncated matrix of left singular vectors, Σ_k represents the truncated diagonal matrix of singular values, and V_k^T represents the transpose of the truncated matrix of right singular vectors.

6. The reconstructed windows from each sliding window are collected and concatenated to obtain the final SSA reconstructed time series.

The Sliding SSA algorithm enables the identification and isolation of meaningful EEG components related to motor imagery tasks by exploiting the temporal and spatial characteristics of the data. By decomposing the time series into singular vectors through SVD and retaining the most important components, Sliding SSA facilitates the identification of prominent brain activity patterns associated with motor imagery from the noisy EEG signals.

This approach can be valuable for various applications, such as decoding motor intentions from EEG signals, developing neurorehabilitation strategies, and controlling prosthetic devices through brain-computer interfaces, all of which rely on understanding and analyzing the specific brain activity patterns elicited.

3.3 Module 3: Feature Extraction

In this study, a set of statistical features was extracted from the motor imagery EEG signals for the classification of right hand (RH) and right foot (RF) tasks. The following statistical features were computed for each EEG signal segment:

- **Mean:** The average value of the EEG signal.
- **Median:** The middle value of the sorted EEG signal.
- **Std:** The standard deviation of the EEG signal, which measures the dispersion of data points around the mean.
- **Min:** The minimum value of the EEG signal.
- **Max:** The maximum value of the EEG signal.
- **MAD:** The Median Absolute Deviation of the EEG signal, which quantifies the dispersion of data points around the median.
- **Q1:** The first quartile of the EEG signal, representing the value below which 25% of the data points fall.
- **Q3:** The third quartile of the EEG signal, representing the value below which 75% of the data points fall.
- **IQR:** The Interquartile Range, calculated as the difference between the third and first quartiles, indicating the spread of the middle 50% of the data.
- **Skewness:** The measure of the asymmetry of the EEG signal distribution.
- **Kurtosis:** The measure of the "tailedness" of the EEG signal distribution, indicating the presence of outliers or extreme values.

These statistical features provide valuable information about the amplitude, variability, and shape characteristics of the EEG signals. They are commonly used in motor imagery EEG classification tasks to capture relevant patterns and discriminate between different tasks or classes. The extracted statistical features were then used as inputs for the classification models to differentiate between the right hand and right foot motor imagery tasks.

3.4 Module 4: Classification

In this study, several classification models were employed to classify the statistical features extracted from the right hand (RH) and right foot (RF) motor imagery EEG signals. The following classifiers were utilized [13,64–74]:

- **BayesNet:** BayesNet is a probabilistic classifier based on Bayesian networks. It models the dependencies between features using a directed acyclic graph and calculates the posterior probabilities of class labels using Bayes' theorem.
- **Naïve Bayes:** Naïve Bayes is a simple probabilistic classifier based on the assumption of independence between features. It calculates the posterior probabilities of class labels using Bayes' theorem and the assumption of feature independence.
- **Logistic Regression:** Logistic Regression is a linear classifier that models the relationship between the input features and the class labels using logistic functions. It estimates the probability of each class label and makes predictions based on a decision boundary.
- **Multilayer Perceptron (MLP):** MLP is a feedforward neural network model with multiple layers of nodes. It learns the complex non-linear relationships between the input features and the class labels using backpropagation algorithm.
- **Simple Logistic:** Simple Logistic is a logistic regression classifier that handles multi-class problems by combining multiple binary logistic regression models. It makes predictions based on the maximum posterior probability.
- **SMO:** SMO (Sequential Minimal Optimization) is an efficient algorithm for training support vector machines (SVMs). SVMs construct a hyperplane that maximally separates the data points of different classes in a high-dimensional feature space.
- **K-Nearest Neighbors (KNN):** KNN is a non-parametric classifier that assigns a class label to an input sample based on the majority class labels of its k nearest neighbors in the feature space.
- **Adaboost:** Adaboost is an ensemble learning algorithm that combines multiple weak classifiers to create a strong classifier. It iteratively trains classifiers on different weighted versions of the training data to focus on misclassified samples.
- **Bagging:** Bagging is an ensemble learning technique that trains multiple classifiers on different bootstrap samples of the training data and combines their predictions through voting or averaging.
- **LogitBoost:** LogitBoost is an ensemble learning algorithm that combines multiple weak classifiers using a forward stagewise additive modeling approach. It iteratively fits classifiers to the residuals of the previous iterations.
- **JRIP:** JRIP (Jumping Rule Inference Prism) is a rule-based classifier that generates a set of IF-THEN rules to classify the data. It uses a jumping rule search algorithm to find a compact set of rules that accurately represent the data.

- **J48:** J48 is an implementation of the C4.5 decision tree algorithm, which constructs a decision tree by recursively splitting the data based on the attribute that maximizes the information gain or the gain ratio.
- **LMT:** LMT (Logistic Model Trees) is a decision tree algorithm that combines the advantages of decision trees and logistic regression. It constructs a decision tree and fits logistic regression models at the leaf nodes.
- **Random Forest (RF):** Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. It trains each tree on a random subset of the training data and a random subset of the input features.

These classifiers were chosen for their diverse modeling techniques and ability to handle different types of data. They were trained and evaluated on the extracted statistical features to classify the motor imagery EEG signals into the right hand and right foot tasks.

4 Results and Discussions

In this study we employed several performance evaluation parameters for EEG classification. The details of these parameters is detailed as,

- **Percent Correct:** This metric indicates the overall accuracy of the classifier in correctly classifying the instances. It represents the percentage of correctly classified instances.
- **True Positive Rate:** Also known as sensitivity or recall, this metric measures the proportion of true positive instances (correctly classified as positive) out of all actual positive instances.
- **True Negative Rate:** Also known as specificity, this metric measures the proportion of true negative instances (correctly classified as negative) out of all actual negative instances.
- **IR Precision:** This metric represents the precision or positive predictive value for the class of interest (IR class). It measures the proportion of true positive instances out of all instances classified as positive.
- **IR Recall:** This metric represents the recall or true positive rate for the class of interest (IR class). It measures the proportion of true positive instances out of all actual positive instances.
- **F-Measure:** This metric combines precision and recall into a single score. It provides a balanced measure of the classifier's performance by considering both false positives and false negatives.
- **Matthews Correlation:** This metric evaluates the quality of binary classifications. It takes into account true positives, true negatives, false positives, and false negatives, providing a correlation coefficient that ranges from -1 to 1. Higher values indicate better performance.
- **Area Under ROC:** This metric is a common measure used in evaluating binary classifiers. It represents the area under the receiver operating characteristic (ROC) curve, which illustrates the trade-off between true positive rate and false positive rate at various classification thresholds. A higher value indicates better performance.

By examining these metrics, we can assess the classification performance of each classifier for five subjects and compare their effectiveness in accurately classifying the right hand and right foot signals based on the given statistical features. The results are shown in Fig. 2(a–e).

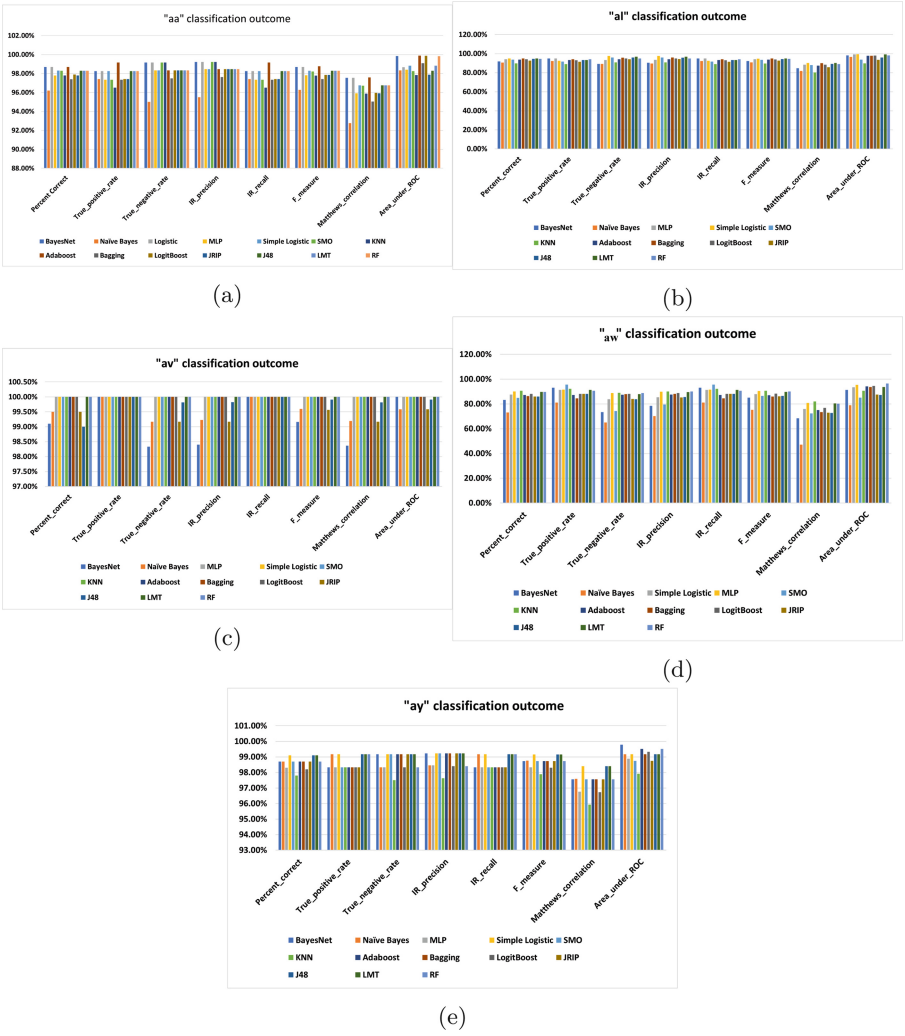


Fig. 2. MI EEG Classification using Sliding Singular Spectrum Analysis

5 Conclusion

In conclusion, this article presents a systematic approach for classifying motor imagery electroencephalography (EEG) signals in the context of brain-computer

interface (BCI) systems. The study addresses the challenges posed by the complexity and noise in EEG signals, which make accurate classification of motor imagery tasks difficult. The proposed method utilizes Multiscale Principal Component Analysis (MSPCA) for efficient noise removal and a unique signal decomposition technique for extracting oscillatory components associated with motor imagery. This decomposition allows for the identification of important temporal and spectral properties that distinguish different classes of motor imagery. By applying machine learning and deep learning-based models to the extracted features, the researchers achieved precise and reliable classification of motor imagery EEG signals. The findings demonstrate the effectiveness of the suggested approach in generating trustworthy classification results for various motor imaging tasks. The implications of this research are significant for the development of BCI systems, particularly in enabling individuals with motor limitations to control external devices through their brain signals. The proposed method offers a potential solution to enhance the usability and effectiveness of BCI technology, opening up new possibilities for individuals with motor impairments. Further exploration and validation of the proposed method in real-world BCI applications are warranted to establish its robustness and generalizability. Overall, this study contributes to the advancement of EEG-based motor imagery classification and underscores its potential for improving the quality of life for individuals with motor disabilities.

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