Journal of Scientific and Innovative Research 2023; 12(3): 40-49
**Available online at: www.jsirjournal.com**


**Review Article**

ISSN 2320-4818
JSIR 2023; 12(3): 40-49

Received: 26-05-2023
Accepted: 23-07-2023
Published: 06-08-2023

***Srinath Akuthota***
*Department of ECE, SR University, Warangal, Telangana, India*

***K.Raj Kumar***
*Department of ECE, SR University, Warangal, Telangana, India*

***J.Ravi Chander***
*Department of ECE, SR University, Warangal, Telangana, India*

**Correspondence:**
***Srinath Akuthota***
Department of ECE, SR University, Warangal, Telangana, India
Email: srinath451@gmail.com

# A Complete Survey on Common Spatial Pattern Techniques in Motor Imagery BCI

*Srinath Akuthota, K.Raj Kumar, J.Ravi Chander*

## Abstract

Background: Brain-computer interfaces that use motor imagery hold promise for direct communication and control through brain signals. Common Spatial Pattern (CSP) techniques have emerged as powerful tools for extracting discriminative features from electroencephalogram (EEG) signals in tasks requiring motor imagery. Objective: This survey paper aims to provide a comprehensive analysis of different CSP techniques employed in motor imagery BCIs, highlighting their strengths and limitations. Methods: We reviewed the literature and identified various CSP techniques, including Riemannian CSP, deep learning-based CSP, multiway CSP, and temporally weighted CSP etc. For each technique, we examined their underlying principles, algorithmic implementation, advantages, disadvantages, filtering technique used, classification accuracy, dataset used and relevant comments. Conclusion: Understanding and comparing different CSP techniques are crucial for enhancing the performance of motor imagery-based BCIs. Each technique has its own advantages and considerations, such as computational complexity and adaptability to different BCI scenarios. This survey serves as a valuable resource for researchers and practitioners in selecting appropriate CSP techniques to advance the area towards successful brain-controlled systems by enhancing the reliability and accuracy of motor imagery-based BCIs.

**Keywords:** Brain Computer Interface (BCI), Electro Encephelo Gram, Common Spatial Pattern, Motor Imagery.

## INTRODUCTION

Brain computer interface systems that use motor imagery enable users to operate external devices or applications using their imagination of specific motor tasks, such as imagining moving their limbs[1]. These systems rely on capturing and interpreting the electroencephalogram (EEG) signals generated during motor imagery tasks. However, EEG signals are often contaminated by noise and contain a mixture of useful and irrelevant information. To address this challenge, Common Spatial Pattern techniques have been extensively utilised in motor imagery BCI for feature extraction and classification[2].

With various motor tasks, such as motor imagery using the left or right hand, CSP techniques seek to identify spatial filters that maximise differences in EEG signal patterns between two distinct mental states or classes of interest. The intention is to suppress irrelevant information and improve the discriminative information related to the motor imagery task. Finding a linear transformation, represented by a projection matrix, is the fundamental idea behind CSP. that converts the EEG signals into a fresh feature space with maximum separability for the classes of interest. The CSP algorithm achieves this by computing the spatial covariance matrices for each class and then deriving the projection matrix by performing an eigenvalue decomposition or singular value decomposition on the covariance matrices[3].

The eigenvectors with the largest eigenvalues are chosen to be the spatial filters. These spatial filters record the spatial patterns or channels that are most indicative of the distinctions between the various classes of motor imagery. Typically, the first few filters capture the most prominent discriminative patterns, while the last few filters capture less discriminative patterns or noise. By using these filters, a set of CSP features can be created from the original EEG signals, which can then be used for additional analysis and classification. The extracted CSP features can be fed into a classifier, such as Linear Discriminant Analysis[4] (LDA), support vector machines[5](SVM), or artificial neural networks[6] (ANN), to group the tasks involving motor imagery.

The classifier learns the decision boundaries based on the extracted features and can predict the intended motor imagery task from new EEG signals[7]. One of the advantages of CSP techniques is their ability to adapt to individual differences and subject-specific characteristics[8]. By individually tailoring the CSP filters to each user, the techniques can account for variations in EEG signal patterns, electrode placements, and brain activation patterns across different individuals[9].

CSP techniques have been widely applied in motor imagery BCI research and have demonstrated promising results in improving the classification accuracy and robustness of the systems. They have been applied in a variety of real-world contexts, including neurorehabilitation, prosthetic control, and assistive technologies[10]. Common Spatial Pattern (CSP) techniques offer a powerful technique for feature extraction and classification in motor imagery-based Brain-Computer Interface (BCI) systems.

By identifying spatial filters that maximize the differences between motor imagery tasks[11], CSP enables the enhancement of relevant information and the suppression of noise in EEG signals. This method has demonstrated great promise for enhancing the precision and usability of BCIs for motor imagery, opening the door for creative uses in the fields of neurorehabilitation and assistive technologies [12].

The goal of the research review article "A Complete Survey on Common Spatial Pattern Techniques in Motor Imagery BCI" is to present an in-depth analysis of the various common spatial pattern (CSP) techniques used in Motor Imagery based Brain Computer Interfaces (BCIs).

The introduction to the article discusses the significance of motor imagery BCIs in facilitating communication and control for people with motor disabilities. The benefits and potential applications of CSP methods for BCI systems' decoding and classification of motor imagery signals are highlighted.

The section on literature reviews thoroughly examines and summarizes studies that have used CSP methods in motor imagery BCIs. Highlights key concepts, strategies, and variations in the application of CSP techniques in various studies. Comparing advantages and disadvantages by referenced through Table 1.

The key findings of the review in discussion section, the performance and efficacy of various CSP techniques in motor imagery BCIs are analysed and compared. The discussion focus on emerging developments in CSP methodology, the different research papers analyzed in different parameters such as Proposed Methodology/Technique Adopted, CSPTechnique/Feature Extraction Technique, Filtering /Signal Preprocessing, Dataset, Classifier Average Accuracy referenced in Table 2. The review paper focus on key findings from the research papers make the comments on various issues in CSP techniques and signal preprocessing.

The key learnings from the review are outlined in the conclusion section. Highlights the value of CSP techniques in motor imagery BCIs and how they could enhance the precision and usability of these systems. The need for uniform evaluation metrics and procedures to allow for fair comparisons of various CSP techniques in future used in different real time applications.

The paper concluded with a list of references that properly cited each of the sources used in the review.

## LITERATURE REVIEW

In this literature review, we provide an in-depth analysis of various CSP techniques employed in motor imagery BCI methodology.

A comprehensive search of relevant literature conducted using different sources a comparison of different CSP techniques in Table 1 indicated below.

## DISCUSSION

The review paper discussing the different research papers and research findings.

According to "EEG Based Motor Imagery BCI Using MIF And CSP"[48], In this investigation, motor imagery BCI using EEG combines MIF and CSP algorithms. The research paper suggests a methodology for classifying motor imagery in brain-computer interfaces (bcis) using the multivariate iterative filtering (MIF) algorithm and the common spatial pattern (CSP), and the average accuracy obtained shows the efficacy of the proposed approach.

According to "Filter Bank Common spatial pattern algorithm on BCI Competition IV Dataset 2a and 2b"[49]. The application of the Filter Bank Common Spatial Pattern algorithm to the datasets 2a and 2b from the BCI Competition IV is covered in this article. A research paper suggests using the Filter Bank Common Spatial Pattern (FBCSP) algorithm for motor imagery classification in brain-computer interfaces (BCIS), but no specifics about average accuracy and classifier performance are given. The BCI Competition IV datasets 2a and 2b are used to evaluate the algorithm.

Using the multi-class filter bank common spatial pattern algorithm for a four-class motor imagery BCi is the main topic of the paper "Multi Class Filter Bank Common Spatial Pattern For Four Class Motor Imagery BCI"[50]. The multi class filter bank common spatial pattern (MC-FBCSP) algorithm is used in a research paper to introduce a novel approach for motor imagery classification in brain-computer interfaces (BCIS), but specific information about average accuracy and classifier performance is not given. The algorithm was created specifically to handle four different classes of motor imagery tasks.

The following is an excerpt from "Determination of the Type of the Imagined Movement of Organs in People with Mobility Disabilities Using CCSP"[51]. In this study, the type of imagined movement in people with mobility disabilities is investigated using the CCSP. This research study suggests using the common correlated spatial patterns (ccsp) algorithm to categorise the type of imagined movement in people with mobility disabilities. The high average accuracy attained shows the effectiveness of CCSP in this application. The algorithm's goal is to pinpoint the precise organs or body parts that participants in motor imagery tasks are visualising moving.

In "Learning Common Time Frequency Spatial Patterns For Motor Imagery Classification"[52]. The CTFSP Algorithm for motor imagery classification is introduced in this paper. According to a research paper, the proposed method for classifying motor imagery in brain-computer interfaces (BCIs) using common time-frequency spatial patterns (CTFSP) achieves a promising average accuracy by utilising multi-band filtering and sparse-CSP. To increase the precision of motor imagery classification, the CTFSP algorithm aims to capture both spatial and temporal information in the time-frequency domain.

The following describes "Temporally Constrained Sparse Group Spatial Patterns For Motor Imagery BCI"[53]. The Temporally Constrained Sparse Group Spatial Patterns (TSGSP) Approach For Motor Imagery BCI is presented in this paper. The Proposed Method Achieves A High Average Accuracy Of 88.5% By Including Temporal Constraints And Using A Time Window Within CSP. Using Temporally Constrained Sparse Group Spatial Patterns (TC-SGSP), a research paper suggests a novel method for classifying motor imagery in brain-computer interfaces (Bcis). The algorithm seeks to identify spatial patterns that are both temporally and discriminatively constrained, enhancing the classification accuracy of motor imagery.

The following is an excerpt from "A Novel Method For Classification Of Multiclass Motor Imagery Tasks Based On Feature Fusion[54]". The Becsp Method For Classifying Multiclass Motor Imagery Tasks is introduced in this study. The Proposed Method Achieves an Average Accuracy Of 85% By Combining Features Derived From The Bispectrum Entropy And Applying Common Spatial Pattern Techniques. The Use Of

Various Csp-Based Techniques And Algorithms For Motor Imagery Bci Is Demonstrated In These Papers Overall. They Experiment Different Scenarios To Showcase The Effectiveness Of Csp In Extracting Discriminative Features And Achieving Competitive Classification Accuracy.

A combined approach for motor imagery-based brain-computer interface (BCI) using four class iterative filtering (IF) and four class filterbank common spatial pattern (FBCSP) techniques is presented in the research paper "EEG Based Motor Imagery BCI using Four Class Iterative Filtering and Four Class Filterbank Common Spatial Pattern" [55].

During motor imagery tasks, the four class IF technique is a technique for enhancing the discriminative information in EEG signals. To extract features particular to each motor imagery class, iterative filtering is used. Using information specific to each class, this method seeks to increase classification accuracy.On the other hand, the four class FBCSP technique is a development of the initial FBCSP algorithm. The EEG signals are divided into various frequency bands using a filterbank approach. The spatial filters are then used to extract distinguishing features from each frequency band.

The filter bank common spatial pattern (FBCSP) algorithm is proposed in the research paper "Robust Filter Bank Common Spatial Pattern In Motor Imagery BCI"[56] for motor imagery-based Brain-Computer Interface (BCI) usage.

The FBCSP algorithm is a popular approach that combines spatial filtering and frequency decomposition to extract discriminative features from eeg signals during motor imagery tasks. However, the original fbcsp algorithm may suffer from limitations in terms of robustness to noise and variations in eeg signals.

The proposed "Robust Filter Bank Common Spatial Pattern" technique aims to address these limitations by incorporating additional robustness measures into the FBCSP algorithm. The specific details and enhancements of this technique are discussed in the research paper.

A method for classifying multiclass motor-imagery using sub-band common spatial patterns (CSP) is described in the research paper "Multiclass EEG Motor-Imagery Classification with Sub-band Common Spatial Patterns[57]".The method focuses on breaking down the EEG signals into various sub-bands in order to record frequency-specific data relevant to motor imagery tasks. It extracts discriminative spatial filters for each sub-band using the common spatial patterns (CSP) algorithm.

A Sliding Window Common Spatial Pattern (SW-CSP) technique is employed in EEG-based Brain-Computer Interfaces (BCIs) to improve motor imagery classification[58]. By incorporating temporal dynamics into the spatial filtering process, it enhances the performance of motor imagery classification.

The Frequency-Optimized Local Region Common Spatial Pattern (FO-LR-CSP) approach is a method created for EEG-based Brain-Computer Interfaces (BCIs) to classify motor imagery[59]. By taking into account the local frequency characteristics of the EEG signals, it seeks to optimise the spatial filtering procedure.

A modified version of the Common Spatial Pattern (CSP) algorithm for motor imagery classification in EEG-based Brain-Computer Interfaces (BCIs) is presented in the research paper "Feature Weighting and Regularisation of Common Spatial Patterns in EEG-Based Motor Imagery[60]". The suggested method combines feature weighting and regularisation to boost the CSP filters' ability to discriminate.

The research paper "Common Spatial Pattern and Linear Discriminant Analysis for Motor Imagery Classification [61]" investigates the use of the Common Spatial Pattern (CSP) algorithm and Linear Discriminant Analysis (LDA) for the classification of motor imagery in brain-computer interfaces (BCIs). The suggested methodology makes use of LDA for classification and CSP for feature extraction.

Classification of multiclass EEG motor imagery using sub-band common spatial patterns (SBCSP-SBFS): It classifies motor imagery using sequential feature selection and sub-band common spatial patterns. On the Emotiv Epoc dataset, it achieved an accuracy of 86.50% using SVM, NBPW, and KNN classifiers.

A Sliding Window Common Spatial Pattern to Improve the Classification of Motor Imagery in EEG-BCI: This technique measures the longest consecutive repetition (LCR) of predicted classes using a sliding window approach. Using the SW-LCR method, it was 80% accurate on the BCI Competition IV-2a dataset.

Motor Imagery Using a Frequency-Optimized Local Region Common Spatial Pattern Approach Classification: It applies the conventional common spatial pattern and uses the variance ratio dispersion score (VRDS) and inter-class feature distance (ICFD) for frequency optimisation. On the BCI competition III dataset IVa, BCI competition IV dataset I, and BCI competition IV dataset IIb, it obtained an accuracy of 91.68% using SVM.

EEG-Based Motor Imagery BCI: Feature Weighting and Regularisation of Common Spatial Patterns The common spatial pattern is subjected to feature weighting and regularisation (FWR) techniques in this method. On the BCI Competition III Dataset IIIa and IV Dataset IIa, it used notch filtering and obtained precise results using linear discriminant analysis (LDA).

"Transfer Kernel Common Spatial Patterns for Motor Imagery Brain-Computer Interface Classification[62]". The transfer kernel CSP (TKCSP) method, based on transfer kernel CSP and widely used spatial filters, is introduced.

The research paper discusses the various CSP techniques that are primarily used in Motor Imagery BCI that perform the various feature extraction methods that improve the classification accuracy and mean kappa value. However, compared to other paradigms present in BCI, average accuracy is most important for movement-based BCI technology in every part of BCI, most specifically signal preprocessing, Feature Extraction, and Classification.

Here, we discussed the findings of various standard research papers that mainly focused on improving classification accuracy by using the various data sets, filtering techniques, methodologies, and classifiers listed in Table 2 below. Web interface applications[63], neurodegenerative issues[64], hands-free and personal thought translation[65], BCI wheelchair, spellers[66], and neuroimaging[67] were a few of the varied applications for Motor Imagery BCI.

**CONCLUSION**

In conclusion, this survey paper thoroughly reviewed a variety of common spatial pattern (CSP) techniques in the context of motor imagery-based Brain-Computer Interfaces (BCIs). Traditional CSP, Riemannian CSP, deep learning-based CSP, multiway CSP, and temporally weighted CSP were among the techniques that were examined. Based on its methodology, CSP implementation, filtering or signal preprocessing, dataset used, classifier used, and average accuracy attained, each technique was assessed.

It is clear from the analysis of the research papers under discussion that CSP techniques are essential for motor imagery BCI applications. These techniques enable the extraction of discriminative features from electroencephalogram (EEG) signals, which enables the precise classification of motor imagery tasks. The papers that were reviewed demonstrated the use of various CSP techniques to produce high average accuracies that ranged from 70% to 95.29%.

The reviewed literature also demonstrated the variety of CSP techniques, with each technique offering unique benefits and considerations. Based on criteria like computational complexity, adaptability, and performance requirements for their particular applications, researchers and practitioners can choose the best CSP technique.

The study also demonstrated how crucial signal preprocessing and filtering methods are for improving the functionality of CSP-based motor imagery BCIs. Before applying CSP, preprocessing the EEG signals with band-pass filtering, multi-variate iterative filtering, and Chebyshev Type-II causal filters were some of the techniques that were frequently used.

This survey paper provides a thorough overview of the existing literature on CSP methods in motor imagery BCI, making it an invaluable tool for researchers and practitioners. It provides a clear understanding of the advantages, disadvantages, and potential uses of various CSP techniques, assisting in the decision-making process for choosing and putting into practise the most effective strategy for achieving high accuracy and effectiveness in motor imagery BCIs.

The literature review concludes by showing the value of CSP techniques as useful tools for feature extraction and classification in BCIs that employ motor imagery. More research and advancements in CSP methodologies are anticipated to support the ongoing development and improvement of motor imagery-based BCI systems, ultimately enhancing the communication and control abilities for people with motor disabilities.

**Acknowledgements**

The authors gratefully acknowledge the Science and Engineering Research Board (SERB) as a statutory body for monetary assistance from the Department of Science and Technology (DST), Government of India, under the Empowerment and Equity Opportunities for Excellence in Science scheme, Reference No: EEQ/2019/000624 to carry out this research.The researchers would like to acknowledge SR University in Warangal for contributing the necessary facilities.

**List of Abbreviations**

MIF: Multi variate Iterative Filtering.

FBCSP: Filter Bank Common Spatial Pattern.

SFS: Sequential Forward Selection Feature algorithm.

CCSP: Common Correlated Spatial Patterns.

CTFSP: Common Time-Frequency Spatial Patterns.

TSGSP: Temporally Constrained Sparse Group Spatial Patterns.

BECSP: Bispectrum Entropy Common Spatial Pattern.

FC-IF: Four Class Iterative Filtering.

FC-FBCSP: Four Class Filter Bank Common Spatial Pattern.

SBCSP-SBFS: Subband Common Spatial Pattern with Subset Band Frequency Selection

LCR: Longest Consecutive Repetition

SW-LCR: Sliding Window Longest Consecutive Repetition approach

VRDS: Variance Ratio Dispersion Score

ICFD: Inter-Class Feature Distance.

**Table 1:** Literature Review on different CSP techniques used in Motor Imagery BCI

| S. No | CSP Technique | Description | Advantages | Disadvantages |
|---|---|---|---|---|
| 1. | Conventional Common Spatial Pattern (CSP) [13] | Identifies spatial filters that maximize differences between motor imagery classes, enhancing relevant information and suppressing noise. | Effective in enhancing discriminative information. | Requires manual selection of spatial filters, limited to two-class classification. |
| 2. | Weighted CSP [14] | The weighted CSP algorithm is a development of the original CSP technique that gives each channel a different weight based on their ability to discriminate. | Improves classification accuracy compared to original CSP | Computationally more complex |
| 3. | Recursive CSP [15] | The recursive CSP algorithm is a variant of the original CSP technique, which updates the projection matrix recursively to allow for dynamic changes in the EEG data. | Can handle non-stationary and dynamic changes in EEG data | Can result in over fitting |
| 4. | Filter bank CSP [16] | The CSP algorithm is a modification of the original CSP technique that divides the EEG data into various frequency bands using a bank of bandpass filters. Then, using the CSP method on each frequency band separately, non-stationarity in the EEG data can be handled more effectively. | Can handle non-stationary and different frequency bands | Computationally more complex |
| 5. | Joint CSP [17] | A modification of the original CSP method that enables the combining of EEG data from various modalities, such as EEG and fMRI. | Can handle multiple modalities and improve classification accuracy | Computationally more complex |
| 6. | Riemannian CSP [18] | Considers the Riemannian geometry of covariance matrices to improve spatial filtering | Better modeling of EEG data, improves discriminative power of spatial filters | Increased computational complexit |
| 7. | Deep Learning-based CSP [19] | Utilizes deep neural networks to learn hierarchical representations of EEG data | Automatically learns discriminative features, potential for capturing complex spatial and temporal patterns | Requires a large amount of training data and computational resources |
| 8. | Multiway CSP [20] | Extends CSP to handle multi-class motor imagery tasks, enabling classification of multiple classes simultaneously | Enables classification of multiple motor | Increased complexity in handling multiple classes, requires a larger number of trials |

| | | | | |
|---|---|---|---|---|
| | | | | |
| 9. | Temporally Weighted CSP [21] | By taking into account the temporal dynamics of EEG signals, incorporates temporal information into CSP. | Considers temporal dynamics, captures time-varying patterns, improves classification performance | Increased computational complexity, may require additional parameters for temporal weighting function |
| 10. | Sparse CSP [22] | The sparse CSP algorithm is a variant of the original CSP method that imposes sparsity constraints on the spatial filters, resulting in a more compact and interpretable representation of the EEG data | Can result in more compact and interpretable spatial filters | More computationally complex than the original CSP method |
| 11. | Extended CSP [23] | The extended CSP algorithm is a modification of the original CSP method that allows for the incorporation of prior knowledge about the spatial distribution of the EEG sources, such as anatomical or functional constraints. | Can incorporate prior knowledge about the spatial distribution of the EEG sources. | Requires additional information about the spatial distribution of the EEG sources. |
| 12. | Regularized CSP [24] | Extends traditional CSP by incorporating regularization techniques to improve stability and generalization performance. | Improved stability and generalization performance of CSP filters | Increased computational complexity as a result of regularize inclusion. |
| 13. | Geodesic CSP [25] | Utilizes the Riemannian geometry of covariance matrices to perform CSP in the tangent space, considering the intrinsic structure of features. | Utilizes the geometric properties of covariance matrices for improved CSP performance. | Increased computational complexity due to the utilization of Riemannian geometry. |
| 14. | Task-Related CSP [26] | Incorporates task-related information, such as cue or task-related epochs, into the CSP algorithm to focus on relevant segments of the signal. | Improved focus on relevant segments of the motor imagery signal. | Requires additional information or annotations related to the task. |
| 15. | Hierarchical CSP [27] | Utilizes a hierarchical structure to classify motor imagery tasks at different levels of granularity, accommodating general and specific classes. | Accommodates classification of motor imagery tasks at different levels of granularity. | Increased complexity in designing and implementing a hierarchical classification framework. |
| 16. | Common Spatial-Temporal Pattern [28] | Extends CSP by incorporating both spatial and temporal information to enhance the discrimination between different motor imagery classes. | Enhanced discrimination by considering both spatial and temporal aspects of motor imagery signals. | Increased computational complexity due to the inclusion of temporal information. |
| 17. | Frequency Band Selection CSP (FBCSP) [29] | Selects specific frequency bands that are most informative for the discrimination of motor imagery classes, improving the performance of CSP. | Improved specificity and selectivity by focusing on frequency bands relevant to motor imagery task. | Requires prior knowledge or exploration to determine optimal frequency bands. |
| 18. | Channel Selection CSP [30] | Automatically selects a subset of channels that contribute the most discriminative information for motor imagery classification, reducing the computational burden. | Reduced computational complexity by focusing on a subset of channels. | May discard potentially useful information from non-selected channels. |
| 19. | Phase-Amplitude Coupling CSP [31] | Exploits the phase-amplitude coupling phenomenon in EEG signals to improve the separation of motor imagery classes by considering both phase and amplitude information. | Enhanced discrimination by utilizing both phase and amplitude characteristics of EEG signals. | Increased complexity in modeling phase-amplitude coupling. |
| 20. | Adapted Common Spatial Pattern [32] | Adapts the traditional CSP algorithm to handle non-stationary EEG signals by dynamically updating the spatial filters during online motor imagery classification. | Improved adaptability to non-stationary EEG signals. | Increased computational complexity due to online updating of spatial filters. |
| 21. | Deep Convolutional CSP (DC-CSP) [33] | Utilizes deep Convolutional neural networks (CNNs) to improve the differentiation of motor imagery classes by automatically learning spatial filters from raw EEG signals. | Automatic learning of discriminative spatial filters from raw EEG signals. | Requires Ample training data with labels for efficient learning. |
| 22. | Time-Frequency Common Spatial Pattern [34] | Extends CSP to capture the time-varying spectral properties of the motor imagery signal by performing spatial filtering in both the time and frequency domains. | Captures time-varying spectral patterns for improved discrimination. | Increased computational complexity due to joint time-frequency analysis. |
| 23. | Sparse Common Spatial Pattern [35] | Enhances the interpretability of the filters by incorporating sparsity constraints into the CSP algorithm to encourage the selection of discriminative spatial patterns. | Improves the interpretability of the spatial filters. | The addition of sparsity constraints has increased computational complexity |
| 24. | Dual Common Spatial Pattern [36] | Improves the ability to distinguish between different classes of motor imagery by separately applying CSP to two different sets of EEG channels and combining the resulting spatial filters. | Enhances the separation of motor imagery classes by utilizing different sets of EEG channels. | A rise in computational complexity brought on by the application of CSP separately to various channel sets. |
| 25. | Discriminative Common Spatial Pattern [37] | Incorporates a discriminative criterion, such as Fisher's ratio or mutual information, into the CSP algorithm to explicitly optimize the separation. | Explicitly optimizes the separability of motor imagery classes. | Added complexity to the computation as a result of the discriminative criterion. |

| | | | | |
|---|---|---|---|---|
| 26. | Kernel Common Spatial Pattern [38] | Applies CSP in a reproducing kernel Hilbert space using a kernel function, allowing for the use of non-linear transformations for improved discrimination. | Allows for non-linear transformations, capturing complex relationships in the data. | Increased computational complexity due to the use of kernel functions. |
| 27. | Enhanced Common Spatial Pattern [39] | Introduces additional preprocessing techniques, such as artifact removal or denoising, to enhance the quality of the input data before applying the CSP algorithm. | Improved data quality through preprocessing, reducing the impact of artifacts or noise. | Additional computational and processing steps required for preprocessing |
| 28. | Multi-Objective Common Spatial Pattern [40] | Incorporates multiple objectives, such as maximization of the spatial filter discrimination and minimization of the spatial filter complexity, to find a set of optimal spatial filters for motor imagery classification. | Enables simultaneous optimization of multiple objectives for the CSP algorithm. | Increased computational complexity due to the inclusion of multiple objectives and optimization. |
| 29. | Graph Regularized Common Spatial Pattern [41] | Utilizes graph-based regularization techniques to impose spatial structure or connectivity constraints on the CSP algorithm, enhancing the discriminative power and spatial. | Incorporates spatial structure and connectivity information into the CSP algorithm. | Additional computational complexity due to graph construction and regularization. |
| 30. | Permutation Invariant Common Spatial Patterns [42] | Addresses the permutation ambiguity problem in CSP by incorporating a permutation invariant criterion to find CSP filters that are invariant to the order of classes. | Resolves the permutation ambiguity problem in CSP. | Increased computational complexity. |
| 31. | Fractional Power CSP [43] | Provides better control over the sensitivity of spatial filters to different frequency bands. | Improves classification accuracy by focusing. | Requires selection and optimization of the fractional power parameter. |
| 32. | Wavelet-based CSP [44] | Captures spatial patterns specific to different frequency components. | Allows for better analysis of multi-frequency EEG signals. | Requires careful selection and design of wavelet functions. |
| 33. | Complex CSP [45] | Utilizes complex-valued spatial filters to capture both phase and magnitude information in the EEG signals. | Captures both phase and magnitude information, providing a more comprehensive representation of the EEG signals. | Increased computational complexity due to complex-valued operation. |
| 34. | Dynamic CSP [46] | Adjusts the CSP filters dynamically based on the temporal characteristics of the MI task for improved performance. | Adjusts CSP filters dynamically based on the temporal characteristics of the MI task, enhancing classification performance. | Increased complexity in modeling temporal dynamics and determining the optimal adjustment of CSP filters. |
| 35. | Temporally Weighted CSP [47] | Incorporates temporal information into CSP by considering the temporal dynamics of EEG signals. | Considers temporal dynamics of EEG signals, capturing time-varying patterns and improving classification performance. | Increased computational complexity due to the incorporation of temporal weighting. |

**Table 2:** The Complete Overview of Different Research Papers in Increasing Classification Accuracy

| S. No | Research Paper | Proposed Methodology/ Technique Adopted | Csp Technique/Feature Extraction Technique | Filtering /Signal Preprocessing | Dataset | Classifier | Average Accuracy |
|---|---|---|---|---|---|---|---|
| 1. | "EEG Based Motor Imagery BCI Using MIF and CSP"[68] | MIF & CSP algorithm | CSP | Multi variate iterative filtering | BCI competetion – IV dataset 2(a) | SVM & LDA | 83.18% |
| 2. | In the BCI competition IV Datasets 2a and 2b, the filter bank common spatial pattern algorithm was used.[69] | MIBIF & MZRSR algorithm | FBCSP | Chebyschev Type-II causal filter | BCI competition IV Dataset 2a and 2b | SVM | 90.3% |
| 3. | “Multi Class Filter Bank Common Spatial Pattern For Four Class Motor Imagery BCI”[70] | Multi Class FBCSP | FBCSP | Chebyschev Type-II causal filter | BCI competetion – IV dataset 2(a) | SVM | |
| 4. | “Determination Of the Type of the Imagined Movement Of Organs in People with Mobility Disabilities using CCSP”[71] | SFS Feature algorithm | CCSP | FIR filters | bbci.d | SVM | 93.6% |
| 5. | Understanding Common Time Frequency Spatial Patterns for the Classification of Motor Imagery" [72] | CTFSP | Sparse –CSP (SCSP) | Multi band filtering | BCI competition III dataset IVa, BCI competition III dataset | Radial Basis Function (RBF) SVM | 84.57% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 6. | The paper "Temporally Constrained Sparse Group Spatial Patterns for Motor Imagery BCI"[73] | TSGSP | Time Window within CSP | Band Pass Filtering | BCI competition III Dataset III a, BCI competition IV Dataset 2 a & 2b | Linear SVM | 88.5% |
| 7. | "A Novel Method for Multiclass Motor Imagery Tasks Classification Based on Feature Fusion" [74] | BECSP | Bispectrum Entropy Common Spatial Pattern | Band Pass Filtering | Data sets 2a and IVa from the BCI Competition IV and III, respectively. | SVM Based on RBF Kernel Function | 85% |
| 8. | The research paper "EEG Based Motor Imagery BCI using Four Class Iterative Filtering and Four class Filterbank Common spatial pattern"[75] | FC-IF & FC-FBCSP | FC-FBCSP | Iterative Filtering of bandpass filters | BCI competetion – IV dataset 2(a) | SVM & NB | 95.29% |
| 9. | “Robust filter bank common spatial pattern in motor imagery BCI”[76] | RFBCSP | Robust filter bank common spatial pattern | Spatial filtering and band-pass filtering | BCI Competition IV dataset IIa and IIb | Naïve Bayesian | 79.28% |
| 10 | "Multiclass EEG motor-imagery classification with common sub-band spatial patterns"[77] | (SBCSP-SBFS) | Common spatial patterns in the subband using sequential feature selection | Band pass filtering | Emotiv Epoc dataset | (SVM), (NBPW), (KNN). | 86.50% |
| 11 | The research paper "A Sliding Window Common Spatial Pattern for Enhancing Motor Imagery Classification in EEG-BCI"[78] | (LCR) SW-LCR. | common spatial pattern | (EMD)-based filtering approach | BCI Competition IV-2a | LDA | 80% |
| 12 | The "Frequency-Optimized Local Region Common Spatial Pattern Approach for Motor Imagery Classification" [79] | (VRDS) & (ICFD); | conventional common spatial pattern | frequency optimization using filter banks | The datasets for the BCI competitions III, IV, and IIb | SVM | 91.68% |
| 13 | A study entitled "Feature Weighting and Regularisation of Common Spatial Patterns in EEG-Based Motor Imagery BCI"[80] was conducted. | feature weighting and regularization (FWR) | conventional common spatial pattern | notch filter | BCI Competition III Dataset IIIa and IV Dataset IIa | linear discriminant analysis (LDA | 89.63% |
| 14 | "Common spatial patterns and linear discriminant analysis for motor imagery classification" [81] | amyotrophic lateral sclerosis (ALS) | common spatial pattern (CSP) | Independent Component Analysis | BCI competition IV dataset I | Linear discriminant analysis (LDA | 80% |
| 15 | “Transfer Kernel Common Spatial Patterns for Motor Imagery Brain-Computer Interface Classification.” [82] | transfer kernel CSP (TKCSP) | transfer kernel CSP | common spatial filters | dataset IVa for the third BCI Competition | SVM | 81.14% |
| 16 | "Using Source Reconstructed Dynamics of EEG Time-Series, Towards a More Theory-Driven BCI." [83]. | reconstructed EEG time-series | Conventional CSP | Low-resolution electromagnetic tomography analysis (LORETA), independent component analysis. | EEG-BCI dataset | SVM | 70% |

## REFERENCE


1. LaFleur K, Cassady K, Doud A, Shades K, Rogin E, He B. Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface. Journal of neural engineering. 2013 Jun 4;10(4):046003.
2. Wang H, Tang C, Xu T, Li T, Xu L, Yue H, Chen P, Li J, Bezerianos A. An approach of one-vs-rest filter bank common spatial pattern and spiking neural networks for multiple motor imagery decoding. Ieee Access. 2020 May 5;8:86850-61.
3. Barachant A, Bonnet S, Congedo M, Jutten C. Multiclass brain–computer interface classification by Riemannian geometry. IEEE Transactions on Biomedical Engineering. 2011 Oct 14;59(4):920-8.
4. Balakrishnama S, Ganapathiraju A. Linear discriminant analysis-a brief tutorial. Institute for Signal and information Processing. 1998 Mar 2;18(1998):1-8.
5. Suthaharan S, Suthaharan S. Support vector machine. Machine learning models and algorithms for big data classification: thinking with examples for effective learning. 2016:207-35.
6. Sharma K, Naik A, Patel P. Study of artificial neural networks. International Journal of Advanced Research Trends in Engineering and Technology (IJARTET). 2015;2(4):46-8.
7. Xu J, Zheng H, Wang J, Li D, Fang X. Recognition of EEG signal motor imagery intention based on deep multi-view feature learning. Sensors. 2020 Jun 20;20(12):3496.
8. Ince NF, Goksu F, Tewfik AH, Arica S. Adapting subject specific motor imagery EEG patterns in space–time–frequency for a brain computer interface. Biomedical signal processing and control. 2009 Jul 1;4(3):236-46.
9. Mehmood RM, Lee HJ. A novel feature extraction method based on late positive potential for emotion recognition in human brain signal patterns. Computers & Electrical Engineering. 2016 Jul 1;53:444-57.
10. Bamdad M, Zarshenas H, Auais MA. Application of BCI systems in neurorehabilitation: a scoping review. Disability and Rehabilitation: Assistive Technology. 2015 Sep 3;10(5):355-64.
11. Oikonomou VP, Georgiadis K, Liaros G, Nikolopoulos S, Kompatsiaris I. A comparison study on EEG signal processing techniques using motor imagery EEG data. In2017 IEEE 30th international symposium on computer-based medical systems (CBMS) 2017 Jun 22 (pp. 781-786). IEEE.
12. Rupp R, Kleih SC, Leeb R, del R. Millan J, Kübler A, Müller-Putz GR. Brain–computer interfaces and assistive technology. Brain-Computer-Interfaces in their ethical, social and cultural contexts. 2014:7-38.
13. Park Y, Chung W. Frequency-optimized local region common spatial pattern approach for motor imagery classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2019 Jun 13;27(7):1378-88.
14. Miladinović A, Ajčević M, Busan P, Jarmolowska J, Silveri G, Deodato M, Mezzarobba S, Battaglini PP, Accardo A. Evaluation of Motor Imagery-Based BCI methods in neurorehabilitation of Parkinson's Disease patients. In2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) 2020 Jul 20 (pp. 3058-3061). IEEE.
15. Qiu Z, Jin J, Lam HK, Zhang Y, Wang X, Cichocki A. Improved SFFS method for channel selection in motor imagery based BCI. Neurocomputing. 2016 Sep 26;207:519-27.
16. Kumar, S., Sharma, A., & Tsunoda, T. (2017). An improved discriminative filter bank selection approach for motor imagery EEG signal classification using mutual information. BMC bioinformatics, 18, 125-137.
17. Hong X, Zheng Q, Liu L, Chen P, Ma K, Gao Z, Zheng Y. Dynamic joint domain adaptation network for motor imagery classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2021 Feb 15;29:556-65.
18. Singh A, Lal S, Guesgen HW. Small sample motor imagery classification using regularized Riemannian features. IEEE Access. 2019 Apr 3;7:46858-69.
19. Majidov I, Whangbo T. Efficient classification of motor imagery electroencephalography signals using deep learning methods. Sensors. 2019 Apr 11;19(7):1736.
20. Liu Y, Zhao Q, Zhang L. Uncorrelated multiway discriminant analysis for motor imagery EEG classification. International journal of neural systems. 2015 Jun 18;25(04):1550013.
21. Kam TE, Suk HI, Lee SW. Non-homogeneous spatial filter optimization for ElectroEncephaloGram (EEG)-based motor imagery classification. Neurocomputing. 2013 May 2;108:58-68.
22. Zhang Y, Nam CS, Zhou G, Jin J, Wang X, Cichocki A. Temporally constrained sparse group spatial patterns for motor imagery BCI. IEEE transactions on cybernetics. 2018 Jun 14;49(9):3322-32.
23. Selim S, Tantawi MM, Shedeed HA, Badr A. A csp\am-ba-svm approach for motor imagery bci system. Ieee Access. 2018 Aug 31;6:49192-208.
24. Gubert PH, Costa MH, Silva CD, Trofino-Neto A. The performance impact of data augmentation in CSP-based motor-imagery systems for BCI applications. Biomedical Signal Processing and Control. 2020 Sep 1;62:102152.
25. Wang F, Xu Z, Zhang W, Wu S, Zhang Y, Ping J, Wu C. Motor imagery classification using geodesic filtering common spatial pattern and filter-bank feature weighted support vector machine. Review of Scientific Instruments. 2020 Mar 1;91(3).
26. Miladinović A, Ajčević M, Busan P, Jarmolowska J, Silveri G, Deodato M, Mezzarobba S, Battaglini PP, Accardo A. Evaluation of Motor Imagery-Based BCI methods in neurorehabilitation of Parkinson's Disease patients. In2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) 2020 Jul 20 (pp. 3058-3061). IEEE.
27. Lindig-León C, Gayraud N, Bougrain L, Clerc M. Comparison of hierarchical and non-hierarchical classification for motor imagery based BCI systems. InThe Sixth International Brain-Computer Interfaces Meeting 2016 May 30.
28. Talukdar U, Hazarika SM, Gan JQ. Adaptation of Common Spatial Patterns based on mental fatigue for motor-imagery BCI. Biomedical Signal Processing and Control. 2020 Apr 1;58:101829.
29. Feng JK, Jin J, Daly I, Zhou J, Niu Y, Wang X, Cichocki A. An optimized channel selection method based on multifrequency CSP-rank for motor imagery-based BCI system. Computational Intelligence and Neuroscience. 2019 May 13;2019:1-0.
30. Qiu Z, Jin J, Lam HK, Zhang Y, Wang X, Cichocki A. Improved SFFS method for channel selection in motor imagery based BCI. Neurocomputing. 2016 Sep 26;207:519-27.
31. Gwon D, Ahn M. Alpha and high gamma phase amplitude coupling during motor imagery and weighted cross-frequency coupling to extract discriminative cross-frequency patterns. NeuroImage. 2021 Oct 15;240:118403.
32. Talukdar U, Hazarika SM, Gan JQ. Adaptation of Common Spatial Patterns based on mental fatigue for motor-imagery BCI. Biomedical Signal Processing and Control. 2020 Apr 1;58:101829..
33. Zhang J, Yan C, Gong X. Deep convolutional neural network for decoding motor imagery based brain computer interface. In2017 IEEE international conference on signal processing, communications and computing (ICSPCC) 2017 Oct 22 (pp. 1-5). IEEE.
34. Yin X, Meng M, She Q, Gao Y, Luo Z. Optimal channel-based sparse time-frequency blocks common spatial pattern feature extraction method for motor imagery classification. Mathematical Biosciences and Engineering. 2021 May 1;18(4):4247-63.
35. Zhang Y, Nam CS, Zhou G, Jin J, Wang X, Cichocki A. Temporally constrained sparse group spatial patterns for motor imagery BCI. IEEE transactions on cybernetics. 2018 Jun 14;49(9):3322-32.
36. Miladinović A, Ajčević M, Accardo A. Performance of Dual-Augmented Lagrangian Method and Common Spatial Patterns

applied in classification of Motor-Imagery BCI. arXiv preprint arXiv:2010.10359. 2020 Oct 13.
37. Thomas KP, Guan C, Lau CT, Vinod AP, Ang KK. A new discriminative common spatial pattern method for motor imagery brain–computer interfaces. IEEE transactions on biomedical engineering. 2009 Jul 14;56(11):2730-3.
38. Hekmatmanesh A, Jamaloo F, Wu H, Handroos H, Kilpeläinen A. Common spatial pattern combined with kernel linear discriminate and generalized radial basis function for motor imagery-based brain computer interface applications. InAIP conference proceedings 2018 Apr 27 (Vol. 1956, No. 1). AIP Publishing.
39. Devlaminck D, Wyns B, Grosse-Wentrup M, Otte G, Santens P. Multisubject learning for common spatial patterns in motor-imagery BCI. Computational intelligence and neuroscience. 2011 Jan 1;2011:8-.
40. Kee CY, Ponnambalam SG, Loo CK. Multi-objective genetic algorithm as channel selection method for P300 and motor imagery data set. Neurocomputing. 2015 Aug 5;161:120-31.
41. Rithwik P, Benzy VK, Vinod AP. High accuracy decoding of motor imagery directions from EEG-based brain computer interface using filter bank spatially regularised common spatial pattern method. Biomedical Signal Processing and Control. 2022 Feb 1;72:103241.
42. Wu W, Chen Z, Gao X, Li Y, Brown EN, Gao S. Probabilistic common spatial patterns for multichannel EEG analysis. IEEE transactions on pattern analysis and machine intelligence. 2014 Jun 12;37(3):639-53.
43. Gürkök H, Poel M, Zwiers J. Classifying motor imagery in presence of speech. InThe 2010 International Joint Conference on Neural Networks (IJCNN) 2010 Jul 18 (pp. 1-8). IEEE.
44. Lee D, Park SH, Lee SG. Improving the accuracy and training speed of motor imagery brain–computer interfaces using wavelet-based combined feature vectors and Gaussian mixture model-supervectors. Sensors. 2017 Oct 7;17(10):2282.
45. Malan NS, Sharma S. Motor imagery EEG spectral-spatial feature optimization using dual-tree complex wavelet and neighbourhood component analysis. IRBM. 2022 Jun 1;43(3):198-209..
46. [46]. Belwafi K, Gannouni S, Aboalsamh H, Mathkour H, Belghith A. A dynamic and self-adaptive classification algorithm for motor imagery EEG signals. Journal of neuroscience methods. 2019 Nov 1;327:108346.
47. Kam TE, Suk HI, Lee SW. Non-homogeneous spatial filter optimization for ElectroEncephaloGram (EEG)-based motor imagery classification. Neurocomputing. 2013 May 2;108:58-68.
48. Das K, Pachori RB. Electroencephalogram based motor imagery brain computer interface using multivariate iterative filtering and spatial filtering. IEEE Transactions on Cognitive and Developmental Systems. 2022 Oct 14.
49. Ang KK, Chin ZY, Wang C, Guan C, Zhang H. Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b. Frontiers in neuroscience. 2012 Mar 29;6:39.
50. Chin ZY, Ang KK, Wang C, Guan C, Zhang H. Multi-class filter bank common spatial pattern for four-class motor imagery BCI. In2009 annual international conference of the IEEE engineering in medicine and biology society 2009 Sep 3 (pp. 571-574). IEEE.
51. Pirasteh A, Shamseini Ghiyasvand M, Pouladian M. Determination of the Type of The Imagined Movement of Organs in People with Mobility Disabilities Using Corrected Common Spatial Patterns. Signal Processing and Renewable Energy. 2022 Jun 1;6(2):17-9.
52. Miao Y, Jin J, Daly I, Zuo C, Wang X, Cichocki A, Jung TP. Learning common time-frequency-spatial patterns for motor imagery classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2021 Apr 5;29:699-707.
53. Zhang Y, Nam CS, Zhou G, Jin J, Wang X, Cichocki A. Temporally constrained sparse group spatial patterns for motor imagery BCI. IEEE transactions on cybernetics. 2018 Jun 14;49(9):3322-32.
54. Hou Y, Chen T, Lun X, Wang F. A novel method for classification of multi-class motor imagery tasks based on feature fusion. Neuroscience Research. 2022 Mar 1;176:40-8.
55. Chin ZY, Ang KK, Wang C, Guan C. Discriminative channel addition and reduction for filter bank common spatial pattern in motor imagery BCI. In2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2014 Aug 26 (pp. 1310-1313). IEEE.
56. Ang KK, Chin ZY, Zhang H, Guan C. Robust filter bank common spatial pattern (RFBCSP) in motor-imagery-based brain-computer interface. In2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2009 Sep 3 (pp. 578-581). IEEE.
57. Khan J, Bhatti MH, Khan UG, Iqbal R. Multiclass EEG motor-imagery classification with sub-band common spatial patterns. EURASIP Journal on Wireless Communications and Networking. 2019 Dec;2019:1-9.
58. Zhang S, Zheng Y, Wang D, Wang L, Ma J, Zhang J, Xu W, Li D, Zhang D. Application of a common spatial pattern-based algorithm for an fNIRS-based motor imagery brain-computer interface. Neuroscience letters. 2017 Aug 10;655:35-40.
59. Park Y, Chung W. Frequency-optimized local region common spatial pattern approach for motor imagery classification. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2019 Jun 13;27(7):1378-88.
60. Mishuhina V, Jiang X. Feature weighting and regularization of common spatial patterns in EEG-based motor imagery BCI. IEEE Signal Processing Letters. 2018 Apr 5;25(6):783-7.
61. Wu SL, Wu CW, Pal NR, Chen CY, Chen SA, Lin CT. Common spatial pattern and linear discriminant analysis for motor imagery classification. In2013 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB) 2013 Apr 16 (pp. 146-151). IEEE.
62. Dai M, Zheng D, Liu S, Zhang P. Transfer kernel common spatial patterns for motor imagery brain-computer interface classification. Computational and mathematical methods in medicine. 2018 Mar 18;2018.
63. Janapati R, Dalal V, Kumar GM, Anuradha P, Shekar PV. Web interface applications controllers used by autonomous EEG-BCI technologies. InAIP Conference Proceedings 2022 May 24 (Vol. 2418, No. 1). AIP Publishing.
64. Kumar RP, Vandana SS, Tejaswi D, Charan K, Janapati R, Desai U. Classification of SSVEP Signals using Neural Networks for BCI Applications. In2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP) 2022 Jul 21 (pp. 1-6). IEEE.
65. Janapati R, Dalal V, Anuradha P, Shekar PR. Various signals used for device navigation in BCI production. InIOP Conference Series: Materials Science and Engineering 2020 Dec 1 (Vol. 981, No. 3, p. 032003). IOP Publishing.
66. Janapati R, Dalal V, Sengupta R. Advances in modern EEG-BCI signal processing: A review. Materials Today: Proceedings. 2023 Jan 1;80:2563-6.
67. Janapati R, Dalal V, Govardhan N, Sengupta R. Signal processing algorithms based on evolutionary optimization techniques in the BCI: A review. Computational Vision and Bio-Inspired Computing: ICCVBIC 2020. 2021:165-74.
68. Im CH. Introduction to EEG-based brain-computer interface (BCI) technology. Journal of Biomedical Engineering Research. 2010;31(1):1-3..
69. Joy MM, Hasan M, Miah AS, Ahmed A, Tohfa SA, Bhuaiyan MF, Zannat A, Rashid MM. Multiclass mi-task classification using logistic regression and filter bank common spatial patterns. InInternational Conference on Computing Science, Communication and Security 2020 Mar 26 (pp. 160-170). Singapore: Springer Singapore.
70. Mahmood A, Zainab R, Ahmad RB, Saeed M, Kamboh AM. Classification of multi-class motor imagery EEG using four band common spatial pattern. In2017 39th Annual International

Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) 2017 Jul 11 (pp. 1034-1037). IEEE.
71. Bablani A, Edla DR, Tripathi D, Cheruku R. Survey on brain-computer interface: An emerging computational intelligence paradigm. ACM computing surveys (CSUR). 2019 Feb 13;52(1):1-32.
72. Wang T, Deng J, He B. Classifying EEG-based motor imagery tasks by means of time–frequency synthesized spatial patterns. Clinical Neurophysiology. 2004 Dec 1;115(12):2744-53.
73. Zuo C, Miao Y, Wang X, Wu L, Jin J. Temporal frequency joint sparse optimization and fuzzy fusion for motor imagery-based brain-computer interfaces. Journal of Neuroscience Methods. 2020 Jul 1;340:108725.
74. Razi S, Mollaei MR, Ghasemi J. A novel method for classification of BCI multi-class motor imagery task based on Dempster–Shafer theory. Information Sciences. 2019 May 1;484:14-26.
75. Akuthota S, Rajkumar K, Ravichander J. EEG based Motor Imagery BCI using Four Class Iterative Filtering & Four Class Filter Bank Common Spatial Pattern. In2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS) 2023 Apr 19 (pp. 429-434). IEEE.
76. Zahid SZ, Aqil M, Tufail M, Nazir MS. Online classification of multiple motor imagery tasks using filter bank based maximum-a-posteriori common spatial pattern filters. Irbm. 2020 Jun 1;41(3):141-50.
77. Sharbaf ME, Fallah A, Rashidi S. Shrinkage estimator based common spatial pattern for multi-class motor imagery classification by hybrid classifier. In2017 3rd International conference on pattern recognition and image analysis (IPRIA) 2017 Apr 19 (pp. 26-31). IEEE.
78. Saideepthi P, Gaur P, Chowdhury A, Nyati K, Dwivedi T, Sharma S, Pachori RB. Sliding Window along with EEGNet based Prediction of EEG Motor Imagery. IEEE Sensors Journal. 2023 May 3.
79. Park Y, Chung W. Filter-bank local region complex-valued common spatial pattern for motor imagery classification. In2020 8th International Winter Conference on Brain-Computer Interface (BCI) 2020 Feb 26 (pp. 1-5). IEEE.
80. Wang J, Feng Z, Lu N. Feature extraction by common spatial pattern in frequency domain for motor imagery tasks classification. In2017 29th Chinese control and decision conference (CCDC) 2017 May 28 (pp. 5883-5888). IEEE.
81. Wang Y, Gao S, Gao X. Common spatial pattern method for channel selelction in motor imagery based brain-computer interface. In2005 IEEE engineering in medicine and biology 27th annual conference 2006 Jan 17 (pp. 5392-5395). IEEE.
82. He H, Wu D. Transfer learning enhanced common spatial pattern filtering for brain computer interfaces (BCIs): Overview and a new approach. InNeural Information Processing: 24th International Conference, ICONIP 2017, Guangzhou, China, November 14-18, 2017, Proceedings, Part II 24 2017 (pp. 811-821). Springer International Publishing.
83. Janapati R, Dalal V, Sengupta R, Desai U, Raja Shekar PV, Kollem S. Towards a more theory-driven BCI using source reconstructed dynamics of EEG time-series. Nano Life. 2022 Jun 9;12(02):2250005.