

An Optimized SWCSP Technique for Feature Extraction in EEG-based BCI System

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Abstract—Multichannel electroencephalography (EEG) is an often used non-invasive method of providing input signals to motor imagery (MI)-based brain-computer interface (BCI) systems. At present, its use is severely limited due to lack of the required level of classification accuracy. Machine learning is used in BCIs to identify hidden patterns in EEG data and then classify them into appropriate MI tasks. In this study, an approach called optimized spectrally weighted common spatial pattern is proposed to improve feature extraction in an EEG-based BCI system. It enhances information gain by optimizing weights of spectral and spatial coefficients, to extract discriminating features from event-related desynchronization (ERD) brain activity. The proposed approach is evaluated by executing it on benchmark dataset 2a of BCI Competition IV. The independent component analysis method is used for the removal of noise whereas the linear discriminant analysis method is used for classification. The experimental results using the proposed approach yield higher classification accuracy as compared to other approaches reported in the literature.

Index Terms—Brain-computer interface; Common spatial pattern; Electroencephalogram; Feature extraction, Motor imagery.

I. INTRODUCTION

Brain-computer interface (BCI) is a technique for establishing a direct communication interface between the brain of a user and an external device, without using normal nerve pathways (Dai, et al., 2019). It is an advanced technology that can be used for the rehabilitation of patients suffering from nervous system disorders, by directly translating their intention into corresponding commands (Mason and Birch, 2003). The human brain controls and coordinates different body parts by the transmission of neural signals. Electroencephalography (EEG) can be used for recording functional brain activity

as it is non-invasive, safe, and easy to use, as compared to invasive techniques in which sensors are implanted directly into the brain during neurosurgery (Bernardi, Pimenta, and Moreno, 2019). These signals reflect a particular motor imagery (MI) activity of hands, foot, or tongue movements (Lotte, et al., 2018). The past decades have seen the advent of powerful computer hardware and software, which have encouraged researchers to provide more efficient, robust, and efficient BCIs for rehabilitation (Wolpaw, et al., 2002). Although the field of BCI research has seen many advances, the desired level of accuracy in the estimation of MI tasks is not yet achieved. The EEG signals are adversely affected by noise from external environmental and physiological resources. These signals are then preprocessed to improve their signal-to-noise ratio. It is then followed by spatial and/or spectral domain-based feature extraction techniques to extract discriminating features from the denoised signals. Finally, a classification algorithm is used for estimating the class of the brain activity pattern. Various state-of-the-art algorithms can be used for the implementation of the various BCI stages. The improvement in classification accuracy achieved can enhance the reliability of BCI systems, which are then safe to use for health-related purposes. The users of an MI-based BCI system produce various brain activity patterns corresponding to MI tasks, by following experimental protocols as per visual clues flashed on the screen. The subject is signaled to envisage moving a particular limb but withholding its physical movement. Spontaneously, EEG signals are fetched whereas the subject executes specific MI tasks of the left hand, right hand, both feet, tongue movement, etc. (Gaur, et al., 2018). It generates a reduction in mu and beta rhythms, called event-related desynchronization (ERD). These rhythms called event-related synchronization (ERS) subsequently increase after the completion of such a task. The pattern in changes of ERD and ERS can be used for input to a BCI system. The ongoing research in BCI primarily emphasizes improving classification accuracy to attain sufficient robustness in MI-based BCI systems. Its overall performance is dependent on efficiency attained at its different sequential stages of acquiring signals, their preprocessing, extraction of features, and classification, as shown in Fig. 1. The EEG signals are acquired from different positions of the scalp of a

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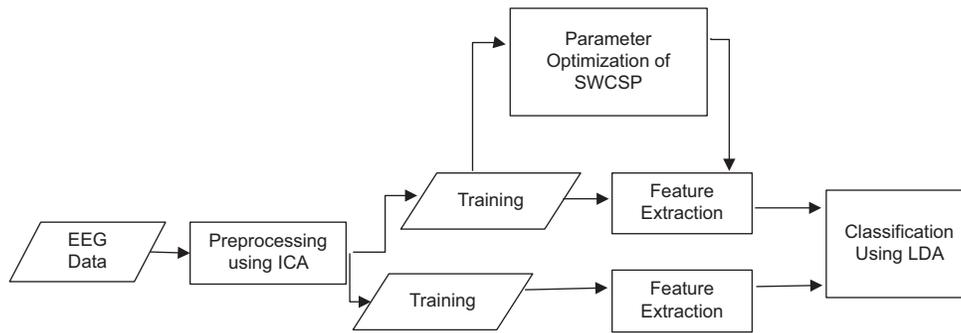


Fig. 1. A block diagram representing the proposed optimized spectrally weighted common spatial patterns.

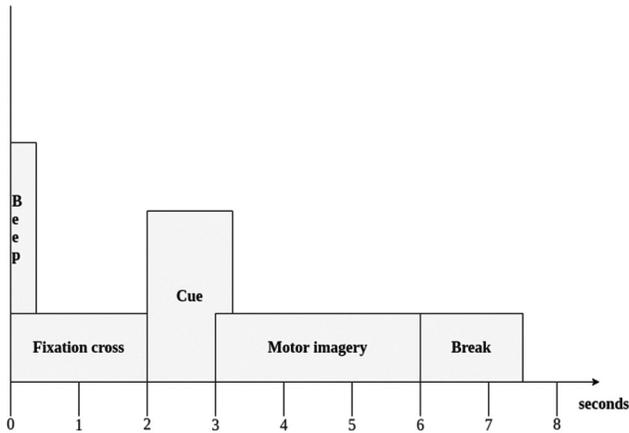


Fig. 2. Timing of dataset 2a from BCI Competition IV (Liu, et al., 2017).

human subject, by placing electrodes, as shown in Fig. 2. The acquired signals are prone to huge quantities of noise, which is eliminated in the next stage of preprocessing before these are fed to the feature extraction stage. Overall performance of a BCI system can be enhanced by the selection and execution of a combination of algorithms to implement preprocessing, feature extraction, and classification stages.

CSP and its variants are widely used feature extraction technique using spatial filtering to enhance the discriminability of two classes (Zhang, et al., 2015, 2018; Kirar and Agrawal, 2016, pp. 14–21). Their performance is limited as they manually establish frequency bands for successfully discriminating between two classes of tasks, as explained in Section 2C.

In this work, the performance of the feature extraction stage of BCI implementation is enhanced, by identifying and optimizing parameters of SWCSP, which is a popularly used variant of CSP. It focuses on the performance of the feature extraction component of the EEG-based BCI system, as it has a direct bearing on the overall performance of a BCI system. Spatial and spectral parameters are optimized and the prior filter band of SWCSP is varied to improve feature extraction. The performance of the proposed approach is measured by executing it on a benchmark dataset and compared with reported literature.

A. Related Work

In recent years, many EEG signal feature extraction and feature classification techniques are proposed by the

researchers. In this part, recent studies on feature extraction from EEG signal are briefly discussed.

Alam, Ibrahimy, and Motakabber, 2021, have employed the power spectral density to extract features on the basis of frequency transformation to enhance the classification accuracy. However, they have used dataset 2b of BCI Competition IV, which is only a two-class MI of the left and right movement. In our study, four-class MI of the left and right hand besides foot and tongue movement is considered, for more effective BCI.

The authors in Rashid, et al., 2020, have reviewed many popular BCI applications and analyzed methods used for feature extraction, classification, and evaluated their performance. They have opined that most of the current BCI applications are at a nascent stage, adoption of common BCI framework by the research community, and commercialization of BCI technology, which can enhance its acceptance and popularity in near future. They have also reported that CSP and its variants such as common spatial-spectral patterns and regularized CSP are popularly used feature extraction methods.

Other BCI researchers have experimented with and proposed several alternative methods to implement BCIs, which widely vary from simple binary capabilities (Wolpaw, McFarland, and Vaughan, 2000), to state-of-art applications such as Talk Assist (Kennedy, et al., 2000). This has enabled patients suffering from a neurological disorder to compose words by contributing a limited input, for useful communication with the outside world by controlling external devices. They have recommended improvements in learning during training phase of the BCI model and identification of reliable techniques for meaningful implementation of the BCI model.

A wide number of studies in the past have focused on improving methodologies to implement various stages of BCI implementations. The data acquired in EEG-based BCIs are bulky and contain a lot of artifacts. Various preprocessing methods can be used to identify and remove noise. Multichannel EEG signals are non-stationary and non-linear; hence, information of interest has to be identified efficiently (She, et al., 2017). They have proposed a novel method of identifying intrinsic mode functions that contain information of interest. This has increased classification accuracy, but only for some of the subjects, leaving scope for further improvement in the future work.

Feature extraction methods can be used for reducing the number of features in a dataset, which summarizes most of

the information contained in the original set of features, by selecting task-specific features from EEG signals in spectral and spatial domains (Tan, et al., 2017). It identifies important features of the data using spectral methods such as Fourier transform, wavelet transform (Lemm, et al., 2005), and spatial methods like common spatial pattern (Selim, et al., 2018) (Yang and Wu, 2014). The authors in Tan, et al., 2017, have proposed EEG classification by fusing multiple features in an orchestrated way to enhance accuracy. This approach has additional computational overheads as multiple Siuly and Li, 2012, have proposed a cross-correlation-based feature extraction method for two-class MI signal recognition. They have reported an improvement in classification accuracy by 7.40%, by evaluating it on benchmark datasets of BCI Competition III. However, a two-class classification is not enough for implementing a useful BCI.

In the classification stage, classifier algorithms are used for assigning classes to the features extracted from the previous stage. The designers of a multiclass classification BCI system choose an appropriate classifier for attaining a requisite level of efficiency (Padfield, et al., 2019). Various classifiers such as artificial neural network, linear discriminant analysis (LDA), fuzzy logic, K-nearest neighbor algorithm, and support vector machine may be employed for the classification of the selected features. However, their classification accuracy attainment is not at the desired level.

The authors in Nguyen, et al., 2018, introduced a new model of BCI consisting of feature extraction and fuzzy classification to handle uncertainty, noise, and outliers in EEG data. They have used a common spatial pattern algorithm to extract discriminant features from multiclass data. They have reported performance attained using different popularly used algorithms, which are used in this study to compare the performance of the proposed approach.

It is analyzed from the study of the related work that CSP and its variant SWCSP are widely used feature extraction techniques. Hence, the authors in this work have focused on improving performance by optimizing its parameters. The efficiency gained at the feature extraction stage will be reflected by an increase in classification accuracy achieved using the proposed approach.

II. METHODOLOGY

The effectiveness of the proposed approach is verified by implementing preprocessing, feature extraction, and classification stages of an EEG-based BCI system. In this study, MATLAB-based open-source toolkit BCILAB is used for the development, testing, and evaluation of new BCI methods (Kothe and Makeig, 2013).

A. EEG Dataset

An EEG-based BCI system analyzes signals fetched by electrodes positioned according to the standard international 10–20 system of EEG, as shown in Fig. 3, on designated parts of the scalp (Costantini, et al., 2009).

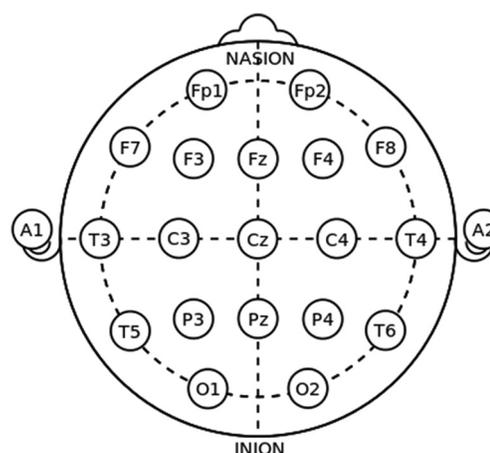


Fig. 3. International 10–20 system of electrode placement (Tangermann, et al., 2012).

In this work, benchmark dataset 2a of BCI Competition IV (Brunner, et al., 2008) is used. This dataset is publicly accessible and is vastly used by the research community to validate signal processing and classification methods for BCIs. It consists of trials of spontaneous EEG activity recorded from nine healthy subjects. One part is labeled, which is used for training and another part is unlabeled, which is used as test data. It contains 22 EEG Ag/AgCl channels besides three electrooculography (EOG) channels and the left mastoid acts as a reference while executing one of the four stipulated MI tasks. Each subject performs one training session and another test session. Each of the two sessions consists of six runs and each of the runs has 48 trials consisting of 12 trials for every four MI classes. The subject is shown a cue on the screen for performing the MI tasks of the left, right hands, both feet, or tongue movement (Tangermann, et al., 2012). Every trial starts with a short warning sound with a fixation cross, which is shown on a computer screen. It is followed by a small arrow signaling the subject to begin the execution of a corresponding MI task. The arrow sign switches back to the sign of fixation cross after 1.25 s and the MI task is continued for 6 s, after which the signaling fixation cross fades away from the screen. Then, there is a short break turning the screen black again. The experiment duration for each trial was 8 s, as shown in timing Fig. 2. Each subject's data set consisted of a training set and an evaluation set. The signals fetched in the above trials are sampled at 250 Hz, followed by bandpass filtering between 0.5 and 100 Hz. The noise from the power line is suppressed using a 50 Hz notch filter, whereas EOG channels are used for ensuing artifact processing (Mannan, et al., 2018).

B. Preprocessing

EEG signals detected at electrodes positioned on different parts of the scalp, are overlapping, and have some superfluous and misleading information. The signals are then preprocessed to boost the signal-to-noise ratio by removing artifacts. In this work, independent component analysis (ICA) is used to isolate the artifacts inbuilt in the signals acquired from several electrodes. ICA applies a variable representing

the “unmixing” matrix of weights (W). It is multiplied by the matrix of scalp data for creating a matrix of independent component activities. In this work, EEGLAB, which is a MATLAB-based toolkit, is used for implementing the Infomax ICA algorithm, as it is a popularly used technique for the decomposition of mixed signals.

C. Feature Extraction

The obtained preprocessed signals are then applied feature extraction method to the preprocessed EEG signals. In this work, a variant of CSP is used to extract features, while optimizing its parameters to enhance the performance of the BCI system.

CSP

It is a popularly used method of feature extraction using spatial filtering for increasing the discriminability of two classes (Zhang, et al., 2015, 2018; Kirar and Agrawal, 2016, pp. 14–21). It establishes linear subspaces in such a way that the variance in one projected class is enhanced to a maximum value while reducing the variance in another class to a minimum value (Ramoser, Muller-Gerking, and Pfurtscheller, 2000). The optimum spatial filters are identified by combined diagonalization of the covariance matrices corresponding to each of the two classes of EEG signals. The covariance matrix of EEG signal E, from each trial, is calculated as:

$$C = \frac{E_{N*T} E_{N*T}^T}{\text{trace}(E_{N*TE_{N*T}^T})} \quad (1)$$

Where, E_{N*T} represents the EEG signal of the trial, N represents number of channels, T denotes number of points in the EEG signal in the trial, and $\text{trace}(X)$ is the sum of diagonal values in matrix X. The sum of the covariance matrix for class i of the subject is:

$$C_i = \sum_{m=1}^M C(i, m) \quad (2)$$

In CSP, the frequency band for successfully discriminating two tasks is manually established. Another variant of CSP called SWCSP was proposed to avoid repeated experiments to find this frequency band (Park, Lee, and Kim, 2014).

Spectrally weighted common spatial pattern (SWCSP)

Feature extraction from the signals preprocessed in the earlier stage is done using SWCSP (Tomioka et al., 2006) (YÜKSEL, 2016). It is employed for extracting the weighted CSP features by using the subject-specific spectral and temporal spectral filters for establishing distinction between various MI tasks. The SWCSP transforms domain of time to frequency and performs optimization of spatial filters by using CSP and spectral filters by Fisher’s criterion sequentially and iteratively. The most relevant channels are selected, and irrelevant ones are rejected from extracted SWCSP features. It uses an iterative algorithm to calculate optimum values of the spatial filter and spectral coefficients. It determines a feature vector with J columns as

$$\varphi_j(X, \omega, B_j) = \log \omega_j^T X B_j B_j^T X^T \omega_j \quad (3)$$

Where, $\omega_j \in R^N$ is the spatial filter vector and $B_j \in R^{T \times T}$ linear temporal filter. It contains the spectral filter coefficients for

localized MI signal in frequency domain optimization of spatial filter (ω_j). Let U be Fourier transformation matrix where

$$U = \frac{1}{\sqrt{Te}} \frac{2\pi kl}{T} \in C^{T \times T} \quad (4)$$

$$UU^T = I_{T \times T} \quad (5)$$

Inserting UU^T into the equation generates a sensor covariance matrix as:

$$\sum^c B = \{XUU^T B_j B_j^T UU^T X^T\}^c \quad (6)$$

Here,

$$U^T B_j B_j^T U = \text{diag}(\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_T) \quad (7)$$

is a diagonal matrix including spectral weights α_i and $\{\}^c$ in Equation 6 represents the expected value within Class c.

$XU \in C^{N \times T}$ represents the Fourier transformed input signal and $X_i \in C^N$ represents i^{th} frequency component. The cross-spectrum matrix based on α_i is represented as

$$\sum(\alpha) = \sum_{i=1}^T \alpha_i V_k^c \in R^{N \times N} \quad (8)$$

The α coefficients are calculated by following the optimization function solved with Fisher discriminant analyses (FDAs)

$$\alpha_{opt} = \max \frac{s(\omega, \alpha)^1 - s(\omega, \alpha)^2}{\text{var}(s(\omega, \alpha)^1) + \text{var}(s(\omega, \alpha)^2)} \quad (9)$$

where ($\alpha_i \geq 0$)

$$s(\omega, \alpha)^c = \sum_{i=1}^T \alpha_i \omega^T V_k \omega \quad (10)$$

in which c represents the class label. Both spatial and spectral coefficients are updated alternately at each optimization step. Generalization of spectrum information of the task is represented in the following equation:

$$\alpha_k^{(c)} = \alpha_k^{(c)opt q} \cdot \beta_k^p \text{ where } (c \in 1, 2, 3, 4) \quad (11)$$

Where, $\beta_{k=1}^T$ represents the prior information of the spectrum specific to the problem. The values of p and q parameters are dependent on data, preprocessing, and prior information. Hence, their optimal values can be chosen using cross-validation. Finally, the classifier is executed on all SWCSP features in different time intervals to allocate a class to the features.

Optimized spectrally weighted common spatial pattern (OSWCSP)

In this work, spatial and spectral filter parameters of SWCSP are identified and iteratively optimized to improve its performance, as shown in Fig. 1. The signals were pre-filtered in a particular frequency band subject wise, as shown in Table I, to attain better performance. The increase in its performance is reflected in the accuracy of classification of the features extracted using SWCSP. Hyperparameter (m) represents a count of spatial filters used for constructing it. All possible values of m were considered and the best value of m giving the highest accuracy is selected. The spectral filter optimization in SWCSP is done by changing hyperparameters (p and q), whereas the prior filter band is varied from subject to subject. Since optimal values of the

TABLE I
CLASSIFICATION ACCURACY ON DATASET 2A

Subject	Frequency range from	to	P	q	Accuracy
1	9	32	0	0.1	0.826
2	7	30	0	1.0	0.621
3	7	28	0	0.1	0.893
4	7	30	0	0.1	0.539
5	9	32	0	1.0	0.513
6	9	32	0	0.1	0.57
7	7	28	0	0.1	0.795
8	7	28	0	0.1	0.886
9	7	28	0	0.1	0.886
Mean	7	28	0	0.1	0.705

spatial, as well as the spectral filters, are interdependent, we have employed an iterative method that begins from the basic CSP method for spatial filters and updates one fixing the other alternately, as shown in Fig. 1.

D. Classification

In this work, LDA is used as a classifier as it is reported to offer higher classification accuracy in many MI-based BCIs (Lotte, et al., 2007) (Resalat and Saba, 2016) (Bashashati, et al., 2007). LDA is a technique of dimensional reduction, which is often used for classification based on supervised learning. It classifies a recorded set of observations into pre-configured classes, by finding the combination of a linear feature to establish a distinction between signal classes. It starts with the calculation of interclass variance, which represents separability between different classes. It then calculates the intraclass variance, which is the distance between the mean and sample of each class, and finally calculates a lower-dimensional space, such that interclass variance is maximized and intraclass variance is minimized (Kołodziej, Majkowski, and Rak, 2012).

III. RESULTS AND DISCUSSION

To measure the performance of the proposed approach, MI-based BCI system consisting of signal preprocessing, feature extraction, and feature classification was carried out using MATLAB R2015a. ICA was employed for preprocessing to isolate and discard artifacts from the experimental dataset. The proposed method of OSWCSP was executed for implementing the feature extraction phase of BCI, whereas the LDA method was employed for the classification of these signals into corresponding MI tasks. Experiments were conducted to verify the performance of OSWCSP while optimizing its parameters. Various extensions of CSP were also chosen and their performance was compared with that of the OSWCSP. The proposed approach was executed on the publicly available dataset 2a of BCI Competition IV which has EEG recordings from nine subjects whereas they performed MI tasks. This benchmark dataset consists of 288 trials per session, having 72 trials whereas subjects performed MI tasks of each of four classes. The recorded EEG signals were processed using ICA for removing undesired artifacts, whereas features were extracted using the proposed method of OSWCSP, and

LDA was used for classification. The overall efficiency of the system using the proposed feature extraction approach was calculated in terms of classification accuracy for each of the subjects. In the proposed approach of OSWCSP, values of three hyperparameters (m , p , and q) were optimized to improve overall classification accuracy. The improved value of classification accuracy was attained at $m = 3$, $p = 0$, and $q = 0.1$ for subjects 1, 3, 4, 6, 7, 8, and 9, whereas $q = 1.0$ for subjects 2 and 5. We have used 5-fold cross-validation to achieve a bias-variance trade-off. The k is assigned a value of 5, as it is not prone to high bias or variance. In each cycle, the dataset is shuffled randomly and split into five groups. The 5-fold cross-validation procedure is executed as follows:

- The dataset is shuffled randomly
- Data sample is partitioned into five subsets
- For $i = 1-5$
 - Train the classification algorithm on all samples except belonging to fold i
 - Test the classifier on a sample of fold i
 - Calculate the percentage P_i of correctly classified sample
- Classification accuracy is calculated as

$$E = \frac{\sum_{i=1}^k P_i}{5} \quad (12)$$

in which the data sample is partitioned into five subsets. Iteratively, one of the subsets is used as a testing dataset whereas the remaining subsets are treated as training datasets. Then, the model is fitted to a training set and evaluated on the test dataset, and the average accuracy attained in five such cycles is calculated.

We have optimized the spatial projection, by applying a bandpass filtering dataset for each subject, from 7 to 34 Hz, and CSP projection with $m = 3$. Patterns corresponding to each of the four classes are calculated on the complete dataset, for eliminating unrelated frequency bands. Spectral filtering is applied on spatially filtered datasets using SWCSP, which has parameters p and q as given in Equation 11, required for tailoring the feature extraction method to specific data. The scaling factors of the spectral filter are selected for each subject using the grid search method, which consists of coarse and fine grid search methods. In coarse grid search, we selected a wide frequency band, which is then narrowed down using fine grid search. The other hyperparameters p and q are varied in the range $[0, 1]$. It attained the best classification accuracy at $m = 3$ whereas p and q were varied in a range of 0 and 1. The performance of the proposed optimization is evaluated on the classification of the benchmark dataset, which is then compared with other approaches evaluated on the same benchmark dataset. The performance comparison in terms of classification accuracy, which is the number of correct predictions divided by the total number of predictions, is shown in Table I and Fig. 4.

Classification accuracy attained for all subjects 1, 2, 3, 5, 6, 7, and 8 is higher than the result reported in (Nguyen, et al., 2018). The efficacy of the proposed feature extraction technique is also evident from an improvement in average

TABLE II
COMPARISON OF CLASSIFICATION ACCURACY RATES WITH EXISTING TECHNIQUES
IN NGUYEN, et.al., 2018

Subject	LDA	NB	KNN	Ensemble	SVM	FLS	(OSWCSP for feature extraction and LDA for classification)
1	0.722	0.639	0.670	0.594	0.688	0.719	0.826
2	0.444	0.493	0.455	0.465	0.483	0.531	0.621
3	0.781	0.757	0.747	0.726	0.760	0.764	0.893
4	0.632	0.632	0.504	0.590	0.618	0.667	0.539
5	0.403	0.399	0.358	0.399	0.413	0.392	0.513
6	0.403	0.438	0.399	0.351	0.410	0.424	0.57
7	0.788	0.705	0.674	0.656	0.778	0.773	0.795
8	0.785	0.802	0.760	0.708	0.816	0.802	0.886
9	0.767	0.785	0.726	0.750	0.792	0.816	0.705
Mean	0.636	0.628	0.588	0.582	0.640	0.650	0.706

TABLE III
CONFUSION MATRIX AVERAGED FOR ALL SUBJECTS

Predicted class ▶	Left	Right	Foot	Tongue
Actual class ▼				
Left	0.85	0.09	0.02	0.04
Right	0.07	0.88	0.03	0.02
Foot	0.09	0.08	0.77	0.06
Tongue	0.07	0.06	0.08	0.79

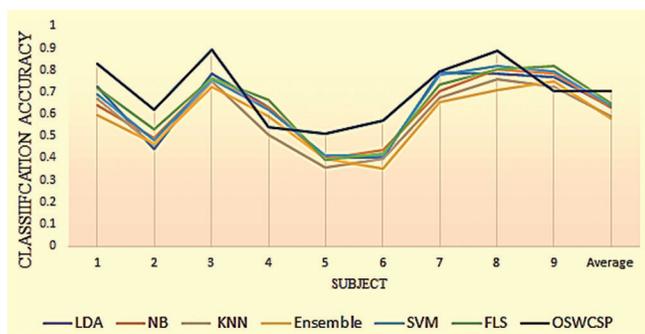


Fig. 4. Classification accuracy.

classification accuracy to 70.6%, as shown in Table II. The confusion matrix of the results is shown in Table III, which depicts correct and incorrect predictions, broken down by class of left hand, right hand, feet, and tongue MI task.

IV. CONCLUSION

In this work, the optimized SWCSP approach is proposed for feature extraction from multiclass MI EEG signals. In preprocessing stage, ICA is used for removing artifacts from acquired EEG signals. The next stage of feature extraction is implemented by the proposed OSWCSP method, whereas its parameters are varied to search for their optimal values using the grid search method. The selected features are then input to the LDA classifier. The performance of the proposed approach was evaluated on dataset 2a from BCI Competition IV, which is used as a benchmark by many in the reported literature, using a 5-fold cross-validation process yielding improved performance. The proposed approach yields an average classification accuracy of 0.706, which is better than the accuracy attained using

other approaches executed on the same benchmark dataset, as reported in the literature. It has the potential to enhance the robustness and reliability of future EEG-based BCI systems for rehabilitation. The challenge is now to test the efficacy of the proposed approach in a real online BCI system.

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