Multiclass motor imagery classification for BCI application

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Multiclass Motor Imagery Classification for BCI Application

Md. Mamun or Rashid
Department of Biomedical Engineering,
Khulna University of Engineering & Technology
Khulna-9203, Bangladesh
mamunbme@yahoo.com

Mohiuddin Ahmad
Department of Electrical and Electronic Engineering,
Khulna University of Engineering & Technology
Khulna-9203, Bangladesh
mohiuddin.ahmad@gmail.com

***Abstract*— Motor Imagery (MI) is now highly adapted to control machine or computer by interfacing with brain or mind. This paper proposes a method to differentiate left, right and feet motor imagery movement according to two and three class classification using statistical features of the EEG signal of the subjects. For this purpose the collected EEG signals of three subjects are segmented and feed to discrete wavelet transform (DWT). DWT decomposes each EEG segmented signal to collect the relevant features. ANN classifies the three left, right and feet movement class trials data. Classification accuracy varies with respect to subject. This straightforward method can be used to design a well-organized BCI system with better accuracy.**

Keywords—motor imagery; discrete wavelet transform; neural network; brain machine interface; statistical feature.

I. Introduction

In broad aspects of MI, MI is specially supervised and efficient procedure for the patients who suffer from Motor neuron diseases (MNDs). MNDs are neurological disorders that affect mostly motor neurons; that command over the voluntary muscles of the body. MI is also consulted for the paralyzed patients or if the motor neurons are dead because of disease or accident.

Among many accomplished research studies, authors [1] developed a method to decompose the EEG signal using short time Fourier transform with CSP and SVM for better classification accuracy. Results verified that single channel EEG signals taken from both sensorimotor and forehead areas can classify four class motor imagery movement. Authors in [2] used CSP for feature extraction and FDA for dimension reduction of the feature vectors. Finally SVM classifies the four class motor imagery movement individually from the rest position. Authors in [3] classify left hand, right hand, feet and tongue, a multi-class imagery movement based on ERD and sample entropy using SVM classifier. Researchers in [4] introduced a method to distinguish between simple and compound limb motor imagery with help of CSP and SVM. They adopted ERSP, PSE and spatial distribution coefficient method to prove the comparison. In [5] researchers used SVM, LDA and KNN classifiers to multiclass motor imagery using two different datasets. In [6] authors proposed FBCSP algorithm to separate multiclass motor imagery and evaluates performance in terms of kappa value. Researchers in [7] introduced a new technique to collect MRICs automatically and differentiate three class LH, RH and foot imagery data. In [8], authors used 22 electrodes over the scalp and multi-class discrimination accomplished using ICA and CSP algorithm. In [9] authors proposed Biomimetic Pattern Recognition (BPR) for 2 class motor imagery classification and compares performance between SVM and LDA. In [10], authors proposed wavelet-CSP algorithm with ICA to improve the classification rate of SVM in terms of kappa value.

In this work, we propose an easy method of classifying multiclass EEG MI signal and with acceptable accuracy rate.

The rest of this paper is arranged as follows: Section II describes materials and proposed method. Section III illustrates the results and discussion is in section IV. Finally section V concludes the paper.

II. Materials & Proposed Methodology

A. EEG Data Collection & Dataset Description

This research work exploits a publicly available dataset [11]. Many subjects perform two class and three class motor imagery functions during data acquisition. In our works three class data for three subjects (A, B, C) are used. Fourteen electrodes have been placed over the subject's sensorimotor area for data acquisition as shown in Fig. 1. All three subjects imagine left hand (LH), right hand (RH) and both feet (FT) movement on different days for several sessions. Subjects are requested to sit in front of a computer desk and to imagine as the cue indicated. Motor imagery task starts after the trigger and continuous to 3-10 seconds and ends each trial followed by 2 seconds of short break.

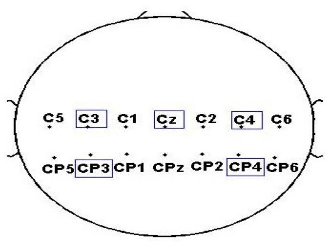

Fig. 1. Fourteen electrode placement for data acquisition.

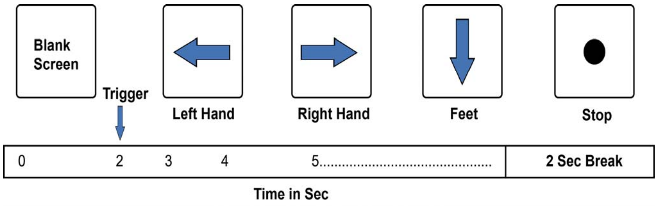

Fig. 2. Block diagram of the experimental paradigm for data acquisition.

The whole experimental procedure with corresponding time is shown in Fig. 2 above as given in [11].

B. Experimental Flowchart and Channel Selection

The complete experimental working flow is shown in Fig. 3 below. First and foremost is to record the motor imagery data from subjects and all subjects are required to perform imagery task well for better results. Recorded signal then segmented according trials and decomposed using DWT to collect statistical characteristics for each signal. These feature vectors afterwards provided to NN to evaluate the classification accuracy of the proposed method.

EEG signals from the subjects are recorded using two devices of g.tec and Neuroscan devices. Among the 14 electrodes 5 electrodes data are recorded for 3 class motor imagery movement. Those 5 electrodes are indicated in figure-1 in square box. But further for our research purpose most significant channels, channels C3 and C4 are taken from both hemispheres.

C. Feature Extraction using DWT

DWT is a prominent tool for EEG signal decomposition to the required level depending on the dominant frequency. In our work db4 wavelet is used to perform level 5 decomposition of each EEG segment. Wavelet toolbox provides 12 statistical characteristics, 5 are chosen as features. In Fig. 4, approximate coefficient is A5 and detail coefficients D1, D2, D3, D4 and D5 are shown, which are outcome by consecutive low pass and high pass filtering to level 5. Each EEG segment DWT decomposes into increasingly finer detail based on two sets of basic functions [12] as follows:

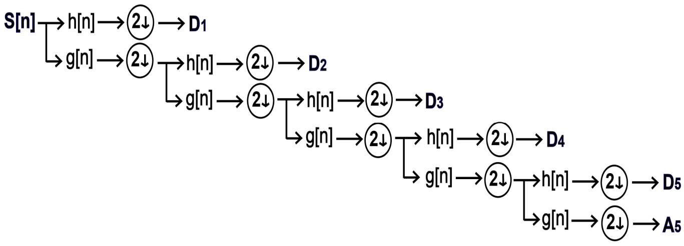

Fig. 4. Motor imagery EEG signal decomposition using db 4 wavelet.

$$S(t)=\sum_k 2^{j_0/2} a_{j_0}(k)\phi\left(2^{j_0}t-k\right)+\sum_{j=j_0}^{\infty}\sum_k 2^{j/2} d_j(k)\psi\left(2^j t-k\right) \quad (1)$$

Where $\varphi(t)$ and $\psi(t)$ are the basic scaling and mother wavelet function respectively.

$$a_j(k)=\int_{-\infty}^{\infty} 2^{j/2} x(t)\varphi\left(2^j t-k\right)dt \quad (2)$$

$$d_j(k)=\int_{-\infty}^{\infty} 2^{j/2} x(t)\psi\left(2^j t-k\right)dt \quad (3)$$

Here $a_j(k)$ and $d_j(k)$ are the approximation and detail coefficients of wavelet respectively. In equation (1), the first summation is an approximation of $S(t)$ and second term sums more detail component [12].

D. NN Design

Depending on the input feature vectors and on the number of class of the classifier ANN is designed. So 5 input and 3 output for the corresponding input and output class respectively is used in the NN. While using 2 classes, 2 target vectors are used for the corresponding 2 class classification. In the Fig. 5 designed NN is shown with input, hidden and output layer. 5-45 neurons in the hidden layer are tried, but better results using 10-15 neurons. Trials number varies with respect to the subject; subject A completes 270 trials, 90 trials for each class. Subject B performs 174 trials, 58 for each class and subject C imagines 180 trials, 60 trials for each class.

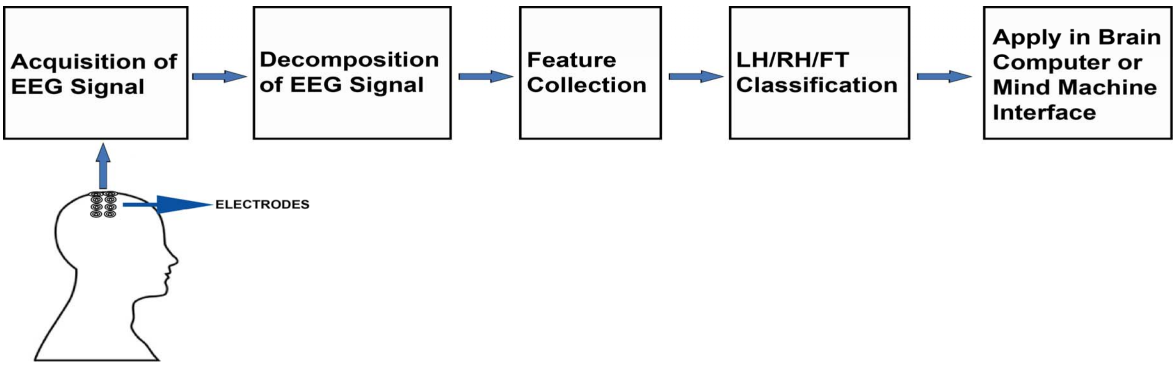

Fig. 3. Block diagram of the multiclass motor imagery classification for BCI application.

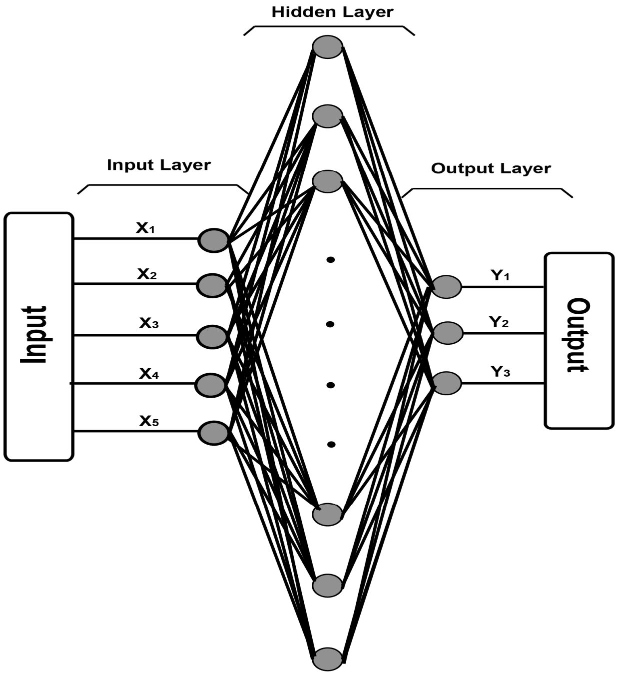

Fig. 5. NN design for 3 class MI classification.

III. Result

A. DWT Decomposition Result

All trials from all subjects are decomposed through DWT and 5 statiscal parameters of these EEG segments are collected to create feature vectors for NN. Five statistical parameters are mean, median, standard deviation, median absolute deviation and mean absolute deviation of the each EEG signal or trial. Fig. 6, Fig. 7, and Fig. 8. depicts the decomposition of LH, RH and FT trials of subject A respectively.

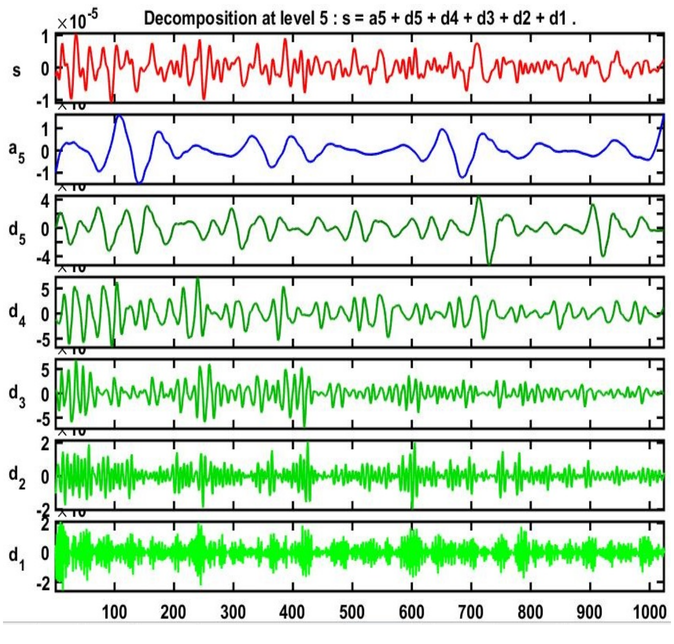

Fig. 6. Decomposition of LH imagery signal of subject A.

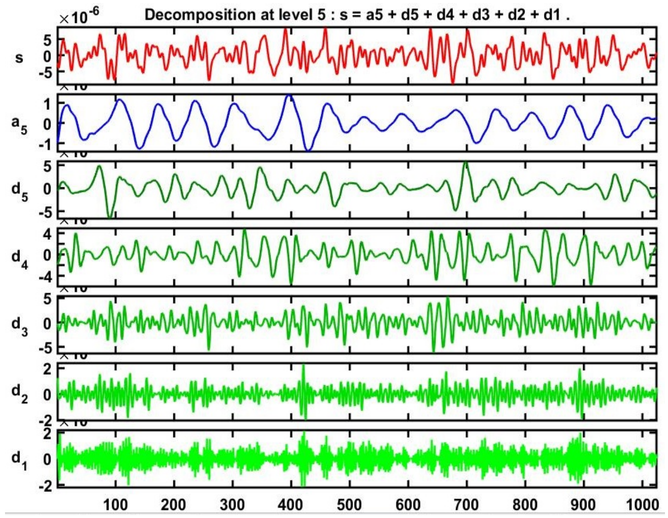

Fig. 7. Decomposition of RH imagery signal of subject A.

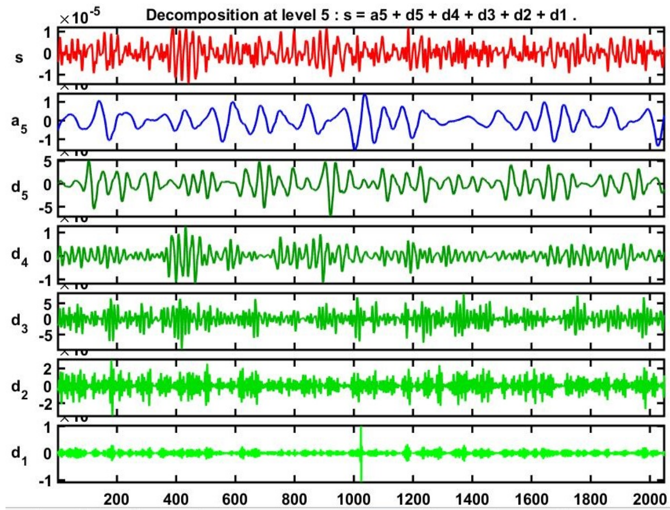

Fig. 8. Decomposition of FT imagery signal of subject A.

B. NN Classification Result

Feature vectors are given to NN subject wise and 70% of them are counted for training, 15% for testing and 15% are for validation. Resulting, such as for subject A; 188, 41 and 41 trials are for 3 class and 126, 27, 27 trials for 2 class are randomly distributed for training, testing and validation respectively. Confusion matrixes are listed in Table I and Table II, and classification accuracies are shown in Table III.

TABLE I. Confusion matrix for LH and RH classification

Subject A		Subject B		Subject C	
LH	**RH**	**LH**	**RH**	**LH**	**RH**
61 33.9%	20 11.1%	39 33.6%	21 18.1%	60 50.0%	0 0.0%
29 16.1%	70 38.9%	19 16.4%	37 31.9%	0 0.0%	60 50.0%

TABLE II. CONFUSION MATRIX FOR LH, RH AND FT CLASSIFICATION

Subject A			Subject B			Subject C		
LH	**RH**	**FT**	**LH**	**RH**	**FT**	**LH**	**RH**	**FT**
57 21.1%	18 6.7%	0 0.0%	37 21.3%	21 12.1%	21 12.1%	60 33.3%	0 0.0%	2 1.1%
32 11.9%	55 20.4%	2 0.7%	15 8.6%	29 16.7%	2 1.1%	0 0.0%	57 31.7%	2 1.1%
1 0.4%	17 6.3%	88 32.6%	6 3.4%	8 4.6%	35 20.1%	0 0.0%	3 1.7%	56 31.1%

TABLE III. CLASSIFICATION RESULTS FOR LH-RH AND LH-RH-FT CLASS

Subject	LH-RH Classification		LH-RH-FT Classification	
	Accurately classified	**Misclassified**	**Accurately classified**	**Misclassified**
A	72.8%	27.2%	74.1%	25.9%
B	65.5%	34.5%	58.0%	42.0%
C	100.0%	0.0%	96.1%	3.9%

Table I and Table II represents the confusion matrix for two and three class respectively for all subjects. In 2 classes classification trials are divided as class wise to 50% and for 3 classes to 33.3%. So in Table I for subject A, 33.9% (61) trials are correctly classified from 50% (90) trials for LH and 38.9% (70) trials are accurately discriminate from 50% (90) trials for RH. Best results come for subject C with 50% (60) trials out of 50% (60). In Table II for subject A, from 33.3% (90) trials, correctly separated 21.1% (57), 20.4% (55) and 32.6% (88) trials for LH, RH and FT respectively.

C. Regression Plot

Regression plot illustrates the connection between outputs and targets. In Fig. 9, Fig. 10 and Fig. 11, regression plot for individual subjects are depicted with their corresponding R values. R value indicates that how closely related outputs and targets. If the value is 1 proves they are closely related or if 0 then randomly related. In the figure inside the square box, the dash line represents the best fit position and solid line as in Fig. 9, the blow line shows the original fits of the data. Circles portray the distribution of the data. Subject C indicates the best regression value for all R=0.94, nearly 1 and subject B shows regression value for all R=0.45, close to 0.50. So subject C's data best fits and finally results maximum classification accuracy. Here regression plots are drawn for LF, RH and FT (3 class data) feature vectors for subject A, B and C.

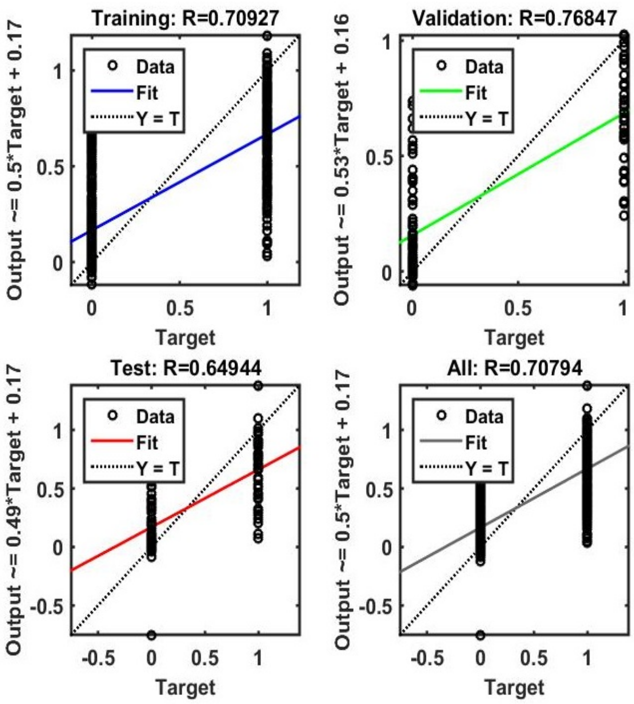

Fig. 9. Regression curve of a random trial of subject A.

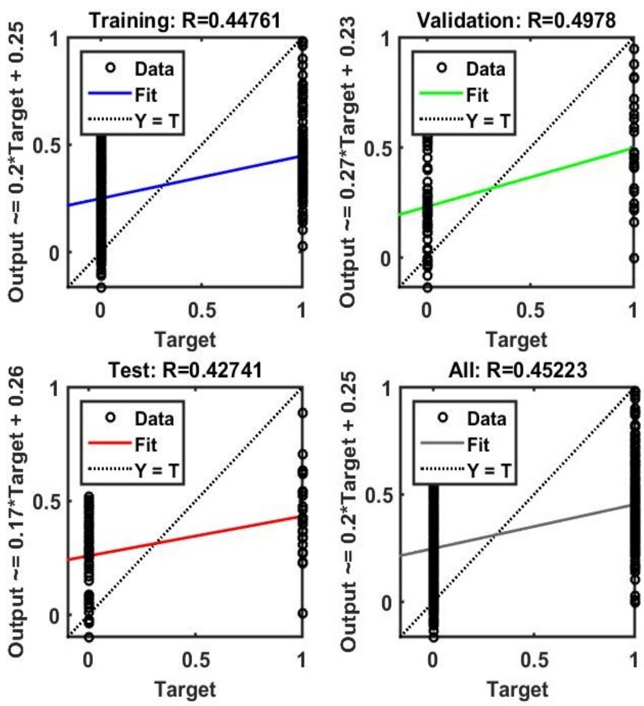

Fig. 10. Regression curve of a random trial of subject B.

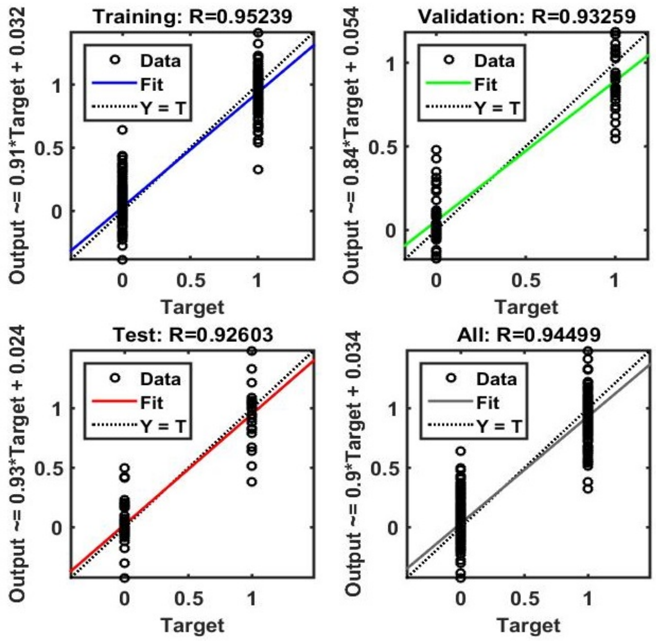

Fig. 11. Regression curve of a random trial of subject C.

IV. Discussion

Classification results prove that using DWT MATLAB toolbox for feature extraction and NN classifier it is possible to classify 3 class motor imagery movement (LH/RH/FT) utilizing statistical features of the EEG signal. Among three subjects classification results, dataset for subject C shows best seperation accuracy, for 2 class (LH/RH) and 3 class accuracy is 100% and 96.% respectively. But dataset of subject B shows average accuracy results for both 2 and 3 classes. Now after analyzing and comparing the regression plot and R value of the subject B's and C's dataset, plots shows data unfited for B's dataset and well fited for subject C's dataset. R values for B's is 0.50 (approximately) and for subject C's is above 0.90. So if the datasets of subject's B and A fits well as subject's C then classification results would be better for all subjects. However our proposed method can be used to classify 3 class motor imagery movement with precise accuracy as subject C for various BCI application. Accuracy rate varies ± 4% for all class except subject C's 2 class accuracy rate which shows 100 % always.

In Table IV below, we have presented a comparison table where we juxtapose our research work with other relevant studies and research works with related important information.

V. Conclusion

Left hand, right hand and feet classification is the mostly used in the BCI application to execute primary command using neural activity. To perform elementary task with perfectness it is very necessary to discriminate between those orders from cerebral cortex. This research work proves that our proposed method is able to LH/RH/FT motor imagery signal with acceptable accuracy. So this procedure can be applied to design an efficient BCI system to differentiate multiclass or three class neural activities.

TABLE IV. COMPARISION WITH RELEVENT STUDIES

Authors	**Data Set**	**Electrodes**	**Class**	**Subjects**	**Methods**	**Performance**
Sheng Ge [1]	Dataset IIIa, BCI competition	C3, Cz, C4, Fp1, Fpz, Fp2,	4	K3, K6 and L1	CSP and STFT, SVM	Fp2 - 73.4, 78.3, 75.2 C4 - 71.3, 88.1, 71.2
Aarathi Kumar [2]	BCI competition IV	---	4		CSP and SVM	Overall accuracy 91.11%.
Deng Wang [3]	Dataset IIa BCI competition IV	C3, Cz , C4	4	9 subjects	ICA and SVM	S1-71.43, S2-67.50, S3-64.29, S4-57.50, S5-87.86, S6-58.93, S7-85.71, S8-79.29, S9-73.93.
Weibo Yi [4]	Author's	C3, Cz, C4	Multiclass	10 subjects	CSP and SVM	Highest accuracy 84% Mean accuracy 70%.
Ridha Djemal [5]	IIa, BCI competition IV IVa, BCI competition III	C3, Cz, C4	3	9 subjects 4 subjects	FFT, AR and SVM, LDA and KNN Classifier	For IIa: 86.06%; For IVa: 93.3%
Zheng Yang Chin [6]	Dataset IIa BCI Competition IV	---	4	9 subjects	FBCSP	Mean Kappa values ranges 0.31-0.57
Bangyan Zhou [7]	Dataset IIa BCI Competition IV	---	3	9 subjects	ICA and SVM	Highest accuracy 86.96% and average accuracy 67.64%.
M Naeem [8]	---	C3, C4, Cz, CP1, CP2, CPz	4	8 subjects	ICA and CSP	Classification accuracies between 33% and 84%
Yan Wu [9]	Five datasets, BCI Competition and Author's	C3, Cz, C4	2	---	CSP and Biomimetic Pattern Recognition, LIBSVM	SVM – average 82.33 % LDA – average 80.43 % BPR – average 85.56 %
BAI Xiaoping [10]	Data sets from BCI Competition IV	C3, Cz, C4	4	9 subjects	Wavelet-CSP with ICA and SVM	Average kappa coefficient of 0.68
Yijun Wang [13]	---	C3, C4	3	5 subjects	CSP and LDA Classifier	Average online 79.48% and offline 85.00%
Proposed Method	Data sets provided by the Dr. Cichocki's Lab [11]	C3, C4	3	3 subjects	DWT and NN	2 class: Highest 100% and average: 79.43%. 3 class: Highest 96.1% and average: 76.06%.

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