Session to Session Transfer Learning Method Using Independent Component Analysis with Regularized Common Spatial Patterns for EEG-MI Signals

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Abstract: *Training the user in Brain-Computer Interface (BCI) systems based on brain signals that recorded using Electroencephalography Motor Imagery (EEG-MI) signal is a time-consuming process and causes tiredness to the trained subject, so transfer learning (subject to subject or session to session) is very useful methods of training that will decrease the number of recorded training trials for the target subject. To record the brain signals, channels or electrodes are used. Increasing channels could increase the classification accuracy but this solution costs a lot of money and there are no guarantees of high classification accuracy. This paper introduces a transfer learning method using only two channels and a few training trials for both feature extraction and classifier training. Our results show that the proposed method Independent Component Analysis with Regularized Common Spatial Pattern (ICA-RCSP) will produce about 70% accuracy for the session to session transfer learning using few training trails. When the proposed method used for transfer subject to subject the accuracy was lower than that for session to session but it still better than other methods.*

Index Terms**— Electroencephalography, Independent component analysis, Motor Imagery signals, Regularized common spatial pattern, Transfer learning.**

I. INTRODUCTION

Brain-Computer Interface (BCI) is a communication protocol enables some disabled people (locked in people) to communicate with the outside world using a computer or other devices. These people have low (or none) motor activities and high mental activity so BCI uses their mental activity to control a computer cursor or a wheelchair. These devices are usually user customized systems (just the target person will use it and no other person) so the target person should be trained to use them. Training people to get a reliable system need either the huge database or very good feature extraction method and classifier. In 2009 Haiping Lu et.al. [1] introduced Regularized Common Spatial Pattern (RCSP) method for transfer subject to subject learning to give more stable results than Common Spatial Pattern (CSP) that introduced by Herbert Ramoser in 2000

[2]. Using multiple subjects to train RCSP reduces the number of training trials and become more stable but they faced a problem which is finding the optimum shrinking parameters for each person. In 2010, Haiping Lu and others proposed a solution for this problem by using Regularized Common Spatial Pattern with Aggregation (RCSP_A) [3]. Rebeca Corralejo et.al., 2011[4] extracted many features using different methods off-line such as (Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), Autoregressive (AR) and Matched Filter (MF)). Then choose the best collection of features using a Genetic algorithm (GA) to be used online. Sumit soman et.al., 2015 [5] used CSP to find the features within the alpha and beta bands (the signal divided into subbands using bandpass filters) to choose which subband gave best results classifiability index is used. Zhichan Tang et.al., 2016 [6] introduce deep learning to extract features and classify them form (2 classes with 28 channels) using raw electroencephalography (EEG) data without any preprocessing. Yousef Rezaei Tabar et.al., 2017 [7] combined Convolutional Neural Network (CNN) and Stacked Auto Encoder (SAE).

Recording big dataset takes time and cause fatigue for the trained person, the features patterns could be changed during the time (improved). Transfer learning is appeared to overcome this problem which means that using data from other people (subject to subject transfer learning) or data from multiple sessions for the same subject (session to session transfer) that will reduce training time by separate it among people or days, respectively, reducing the training time will make the trained subject more comfortable and cause less tiredness [8].

In this paper, we propose a method that gives good results for both (session/session and subject/subject) transfer learning by using Independent Component Analysis (ICA) to separate the mixed sources then applies the signals to RCSP to produce projection matrix that used to extract features from data.

II. DATASETS:

In this paper two different data sets are used, the first one contains data for multiple users with a single recording session and a single user with multiple sessions. The second one contains data for multiple users only. All data recorded for healthy subjects who sat in a comfortable armchair, a trigger appeared on a screen to inform the subject which mental task trial will begin. The first data set is recorded for two classes (Left/Right) hands and three classes (Left hand, Right hand and both feet) while the second one is recorded for three classes only (Left hand, Right hand and Right foot).

A. Dataset I:

This dataset is provided by Dr Cichocki'Lab [9] which is recorded for eight healthy subjects (SUBA_SUBH) using (5 or 6) channels only (C3, CP3, C4, CP4, Cz and CPz) during the Motor Imagery (MI) tasks the subject informed to avoid any eye movement to get as clear as possible signals (without artifacts). Some subjects recorded multiple session each one in the different day (SUBA and SUBC). Two classes are used only either (Left/Right) hands or (hand/foot) so the data with three classes are used as two classes by isolating the data corresponding to the wanted class. Three groups of data are used (Dataset Ia : SUBC, seven sessions each in the different day), (Dataset Ib: SUBC three sessions each in the different day) and the last one is for three different subjects (Dataset Ic: SUBA, SUBB and SUBC).

B. Dataset II:

This dataset is provided by BCI Competition III (Dataset IVa) recorded from 5 healthy subjects labelled as (aa, al, av, aw and ay) using 118 channels and only two classes (Right hand and Right foot)[10].

III. METHODS:

In this section, we listed the methods that we used in this paper.

A. Independent Component Analysis (ICA)[11]:

When brain signals are recorded using Electroencephalogram there is more than one channel to do this job, these signals reach the channels as a mixture, to reveal the interesting information of the original signal Blind Source Signal (BSS) methods are used, one of them is ICA. Which is a method used to separate the mixed signals from unknown sources (original signals). It could be expressed as the weighted sum of the original signals

$$x_j = \sum_{i=1}^{N} a_{ji} S_i \qquad \text{........(1)}$$

$$j = 1 \ldots\ldots M$$

Using matrix notation

$$X = As \qquad \text{.........(2)}$$

Where:

N=Number of sources (original signals)

M=Number of the sensors (received signals)

S= Independent component (original signal)

A: Mixing matrix

X: Time domain signal (received signal)

B. Regularized Common Spatial Pattern (RCSP):

First of all, let us discuss what is CSP [12], CSP is a multichannel analysis used to extract spatial patterns of two classes dataset, these patterns maximize the difference between the classes. The steps of this method are:

1. Find the normalized spatial covariance matrix for each trial of EEG (channel*time) from the training dataset

$$Ec(i) = \frac{EEG * EEG^T}{trace(EEG * EEG^T)} \qquad \text{.....(3)}$$

Where:

(i) refers to the number of trials and c is the class label i.e.1, 2 or L, R.

2. Find the sum of the average Ec for both classes

$$\overline{Ec} = \frac{\sum_{i=1}^{N} Ec(i)}{N} \qquad \text{.......(4)}$$

Where

N=number of trials of c (both classes should have the same number of trials)

3. Find the composite spatial covariance E_{com} which is the sum of both averages(for class 1 and 2)

4. Factored E_{com} as $U\lambda U$ where $U$is the eigenvectors matrix and λ is the diagonal matrix of eigenvalues
5. Find the whitening transformation $P = \sqrt{\lambda^{-1}}\ U^T$
6. S_c=P $\overline{Ec}$ P^T for both classes they share common eigenvectors S_c=B λc B^T where I= $\lambda 1 + \lambda 2$
7. Find the projection matrix W=$(B^TP)^T$
8. Extract features from testing dataset Z=W $EEG_{testing}$ then

$$features = log\left(\frac{var(Z)}{\sum_{i=1}^{Q} var(Z_i)}\right) \qquad ....(5)$$

Where Q is the number of most important pairs of first and last rows of Z.

The drawbacks of CSP are the limited performance when there is a noise (such as eye movements and other artifacts), low number of channels (more channels cost money) or small training dataset. To solve this problem is RCSP introduced in [1] that extracts more efficient spatial filter using a training dataset of more than one subject (population of subjects) and one target subject. Each training subject has a limited number of training trials, while the overall training data set of all training subject will be the summation of all the training data sets. In this algorithm two shrinking parameters (beta and gamma) one for shrinking towards the generic matrix and the other towards the identity matrix both have values between 0 and 1.The algorithm steps are the same as CSP steps but the normalized spatial covariance matrix will be regularized spatial covariance matrix which is

$$REc = \frac{(1-beta)*Ec_{traget}+beta*Ec_{generic}}{(1-beta)*M_{target}+beta*M_{generic}} \qquad ......(6)$$

Where

Ec_{target}: Is the sum of all spatial covariance matrices for the training data set of the target subject.

$Ec_{generic}$: Is the sum of all spatial covariance matrices for the training data set of the other population subjects.

M: Number of training trials of the target subject.

$M_{generic}$: Number of training trials of the other subject of the population.

C. Support Vector Machine (SVM):

To distinguish between classes Classification methods should be applied to the feature vector [13]. SVM is a supervised classifier that will maximize the distance (margins) between the nearest training points (support vectors) by finding the optimal hyperplane to distinguish between two classes as shown in Fig. 1 [14].

D. The Proposed method ICA_RCSP:

MI signals produced from different sources in the brain they reach the scalp as mixed signals then channels read them (each channel read a signal contains information from all original sources). This is the same as the cocktail party problem which is solved by using Blind Source Separation methods such as ICA.

Fig. 2 shows the flowchart of the training phase of ICA_RCSP. The independent component is used as a signal to train the RCSP method. This step isolates the mixed signal to its source signals.

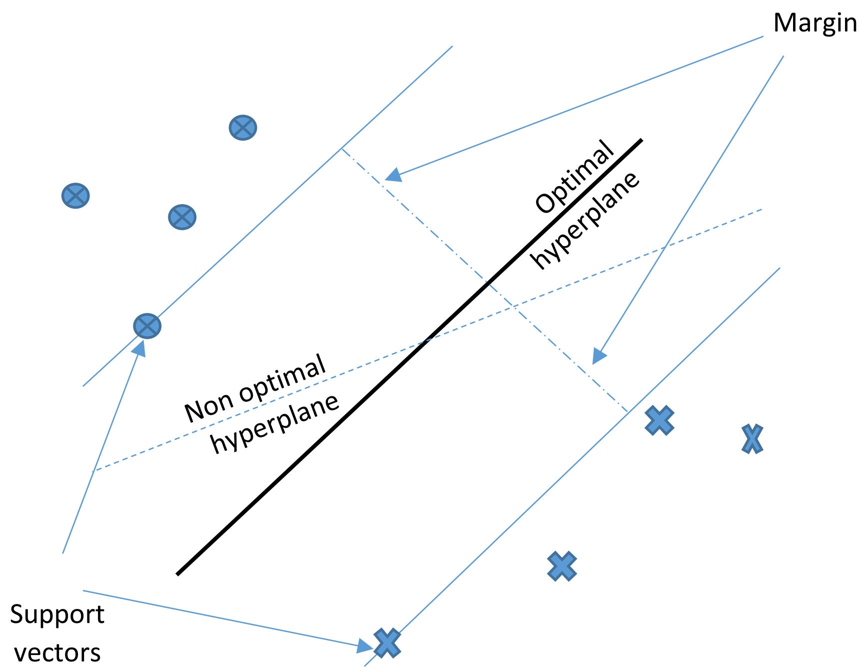

Fig. 1: Support vector machine finds the optimal hyperplane

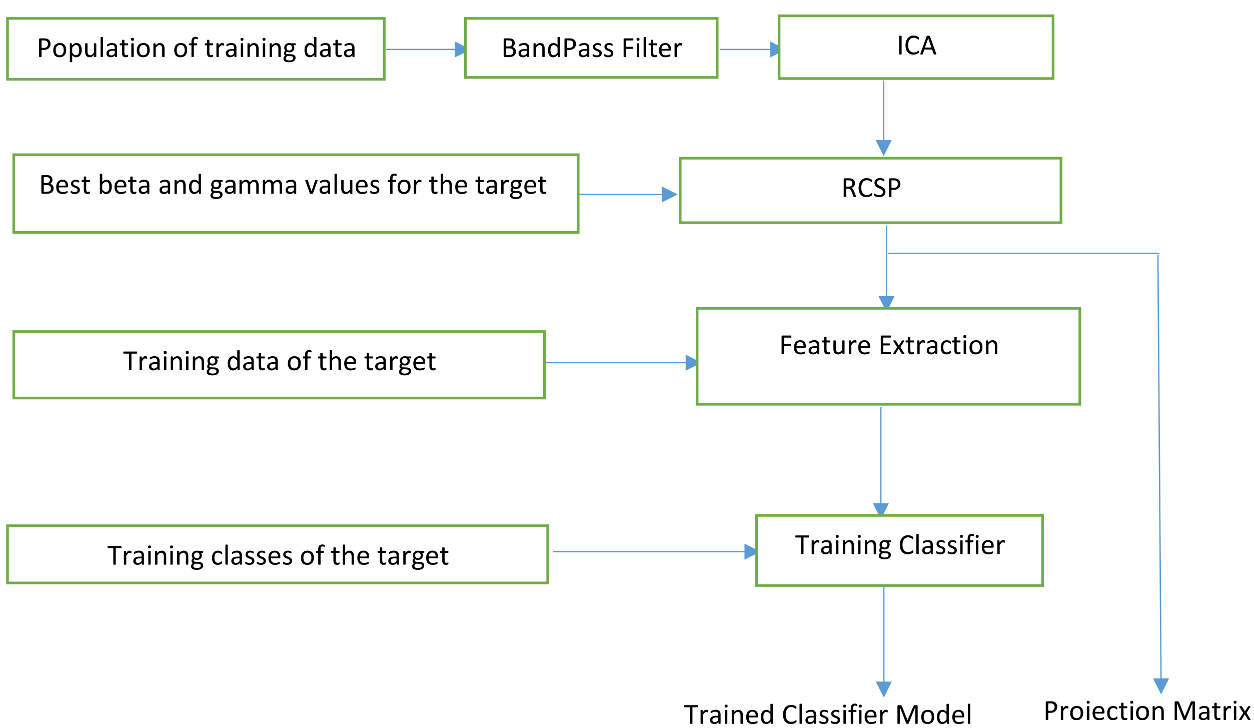

Fig. 2: Flow chart of the training phase of ICA_RCSP

RCSP method is used to transfer learning (session to session or subject to subject) to reduce the number of training trials that recorded for each subject (session).The training data is used to train the SVM classifier model. Fig. 3 shows the testing phase. The projection matrix from the training phase is used to extract features from the testing data of the target, these features applied to the trained classifier model to predict the corresponding class.

IV. EXPERIMENTAL RESULTS:

The recorded data are bandpass filtered in the (alpha-beta) band (7-30) Hz, only two channels (C3 and C4) or(C4 and Cz) are used to extract the features of MI signals for two classes only. The data are separated into testing and training sets the training dataset is used for training both features extraction method and the classifier, and the testing dataset is used to test the classifier model that trained previously.

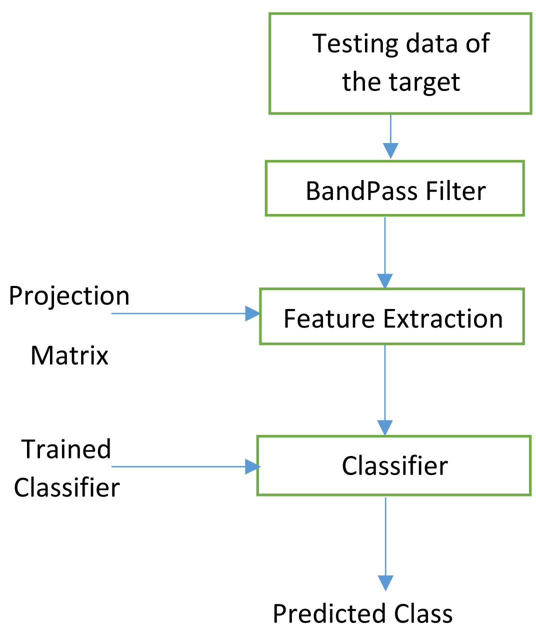

Fig. 3: Flow chart of the testing phase of ICA_RCSP

There is no overlap between them. The linear SVM classifier is used to classify the features that extracted and all results are taken as the average of ten runs to be sure that the values are not recorded by chance. ICA is used to separate the two sources signals (data received from two channels) from their mixed version that reach the channels to produce clearer signals for each source. Session to session transfer learning is used starting from two sessions to seven sessions (i.e. c_day1_2 means two sessions is used day 1 and day 2 the main session is day2). Table I shows the results of ICA_RCSP for different training trials number (M). The average of the classification accuracy is about 71% for 12 training trials for each session (6 trails for each class) see Fig. (4 and 5).

If we focused on the accuracy of the last session only, 20 training trials for each session has the highest accuracy which is 85% but the average accuracy is less than that of M=12. To be noticed the data in this table are recorded for three MI tasks (two hands and both feet) and we separate two classes (Left and Right) hands only to test our proposed method. ICA_RCSP has two subject dependent parameters (beta and gamma) such as RCSP we assumed that both are equal to each other, a simple loop (from 0 to 1 with 0.1 steps) is used to generate them and the pair that gives maximum accuracy is used in training and testing phases. In session to session transfer learning, the sessions should be taken in the same recording order because they are recorded for the same subject in different days so we could not use session 5.

Table I: Accuracy of different number of trails for ICA_RCSP (session to session transfer learning) using Dataset Ia

M Main session	2	4	6	8	10	12	14	16	18	20	30	40	50
c_day1_2	68.2432	68.4932	70.1389	69.2254	67.1429	67.1739	44.8529	67.3881	65.9091	65.3846	64.1667	49.8182	54.3
c_day1_3	64.4068	64.6552	64.0351	63.3929	62.6364	55.5556	41.5094	51.6346	50.9804	50	34.4444	37.5	17.4286
c_day1_4	61.8644	62.931	62.2807	61.6071	60.8182	62.1296	57.9245	60.5769	57.8431	57	40	47.5	40
c_day1_5	53.8961	71.1842	71.4	69.3243	70.6849	82.1528	46.338	78.7143	81.8841	74.5588	66.2698	67.3276	49.5283
c_day1_6	77.551	81.25	82.3404	81.7391	69.2222	83.1818	82.5581	66.1905	76.8293	76.25	74.1429	19.6667	62
c_day1_7	55.9322	64.0517	68.0702	59.5536	67.1818	78.7037	83.3962	83.4615	71.8627	**85.1**	68.8889	27.5	49.4286
Average	63.6489	68.7608	69.7108	67.4737	66.2810	**71.4829**	59.4298	67.9943	67.5514	68.0489	57.9854	41.5520	45.4475
Standard deviation	7.88246 4	6.25756 5	6.48915 7	7.34611 8	3.48148 9	10.5085 8	17.4001 7	10.6491 9	10.6586 4	11.9395 4	15.0800 3	15.6041 3	14.1397 1

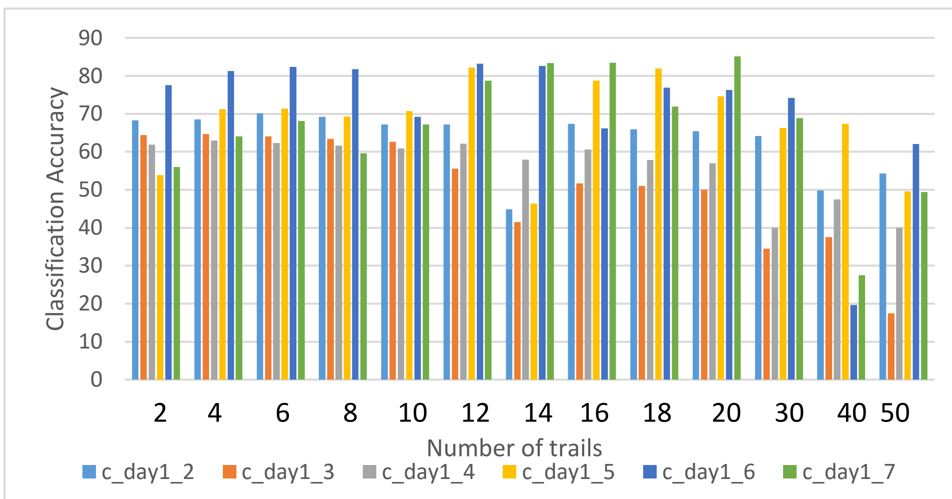

Fig. 4: The Performance of six groups of sessions for different number of trials for ICA_RCSP using Dataset Ia

For example as the main session and session 7 is recorded after session 5 and it is not realistic to use sessions from future for training. Table II and Table III show comparisons among different feature extraction methods and our proposed one using Dataset Ia with (M=20 and M=12) respectively for single training subject with multiple recording sessions. The first row of RCSP and ICA_RCSP are empty because they depend on the previous session and the first one has no previous sessions (RCSP here used for transfer session to session) it is obvious from Fig. (6 and 7) that ICA_RCSP has better classification accuracy for both (M=12 and M=20) and more stable (lower standard deviation) than all other methods except power features.

Table IV shows the results when ICA_RCSP used for the session to session transfer learning using Dataset Ib (three sessions, Hand/Foot classes and all other parameters are fixed (number of channels, classifier type, number of training samples, beta and gamma values)). Although CSP has a higher accuracy it could not consider as stable. CSP is unstable because it has a high standard deviation (see Fig. 8) and it depends on the present session only this is affected by the subject mode in the training and testing sessions. From Tables (I,II and III) ICA_RCSP could produce better accuracy if there are more recorded sessions for SUBC.

Tables (V and VI) shows the results of the subject to subject transfer learning using Dataset Ic and Datatset II. In spite of the low average classification accuracy, the ICA_RCSP still has better results see Fig. (9 and 10). Fig. 11 shows a comparison between the used four methods in both (session to session and subject to subject) transfer learning for the same datasets. Session to session transfer learning gave butter results than subject to subject transfer learning because the features are extracted for the same subject in different sessions.

V. CONCLUSION:

Training a single person in a single session to have big dataset is a very time-consuming process and annoying so transfer session to session learning is used. The modified method is a combination of ICA and RCSP in the training phase to produce a better projection matrix that will extract testing features. Our results show that ICA_RCSP produces high accuracy using only two channels and less than 100 training trials for both sessions to session and subject to subject transfer learning.

The results are taken using two different datasets and two types of classes (Left hand/Right hand) and (Hand/Foot). ICA_RCSP could be used for both (session to session) and (subject to subject) transfer learning.

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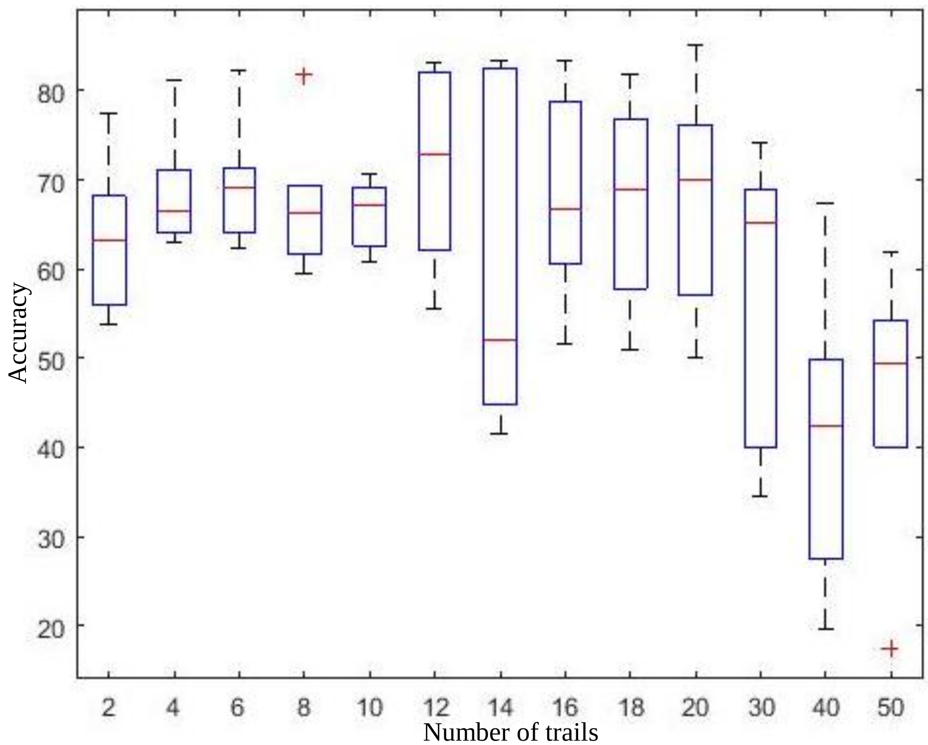

Fig. 5: Statistics of ICA_RCSP method for (Dataset Ia, (session to session transfer learning) for different number of trials)

Table II: Comparison of different feature extraction methods for (Dataset Ia, M=20, (session to session transfer learning))

Main session	Power of alpha and beta	CSP	RCSP	ICA_RCSP
c_day1	49.1667	50.8333		
c_day1_2	53.0769	51.5385	50.3077	65.3846
c_day1_3	49	42	38.7	50
c_day1_4	50	50	44	57
c_day1_5	58.8235	31.6176	83.8235	74.5588
c_day1_6	62.5	87.5	68.625	76.25
c_day1_7	50	82	71.5	85.1
Average	53.22387	56.49849	59.4927	68.0489
Standard deviation	4.964336	19.04735	16.20847	11.93954

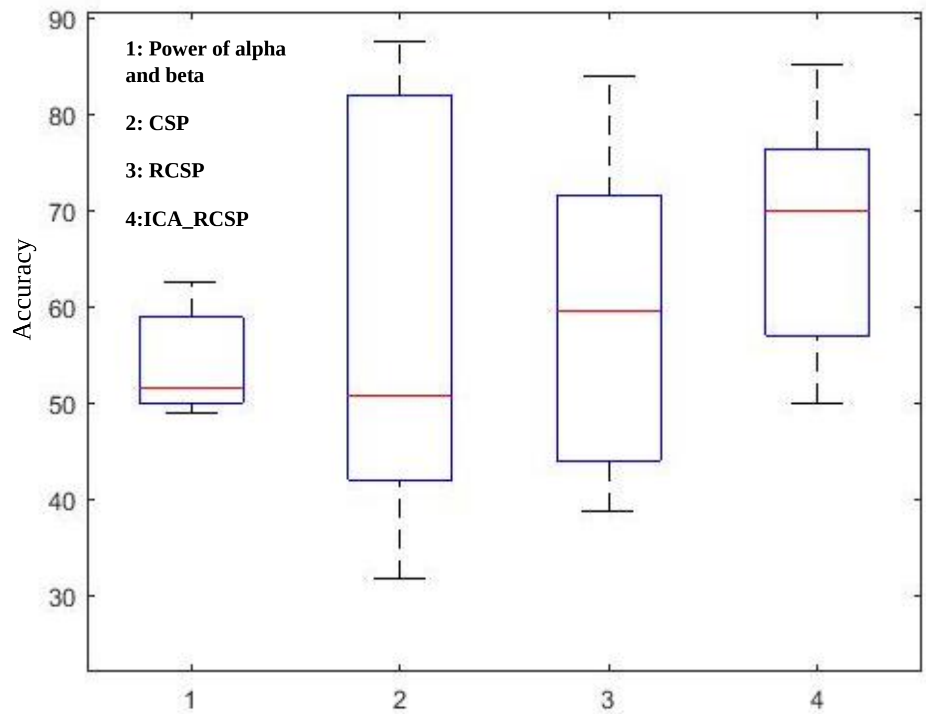

Fig. 6: Statistics of four methods for (Dataset Ia, M=20, (session to session transfer learning))

Table III: Comparison of different feature extraction methods for (Dataset Ia, M=12, (session to session transfer learning)

Main session	Power of alpha and beta	CSP	RCSP	ICA_RCSP
c_day1	47.6563	51.5625		
c_day1_2	54.3478	54.3478	51.5217	67.1739
c_day1_3	37.037	46.2963	58.33333	55.5556
c_day1_4	50	20.3704	45.3704	62.1296
c_day1_5	45.1389	58.3333	83.9583	82.1528
c_day1_6	62.5	85.2273	77.3864	83.1818
c_day1_7	53.7037	88.8889	69.9074	78.7037
Average	50.05481	57.86093	64.41292	71.4829
Standard deviation	7.425942	21.72283	13.82199	10.50858

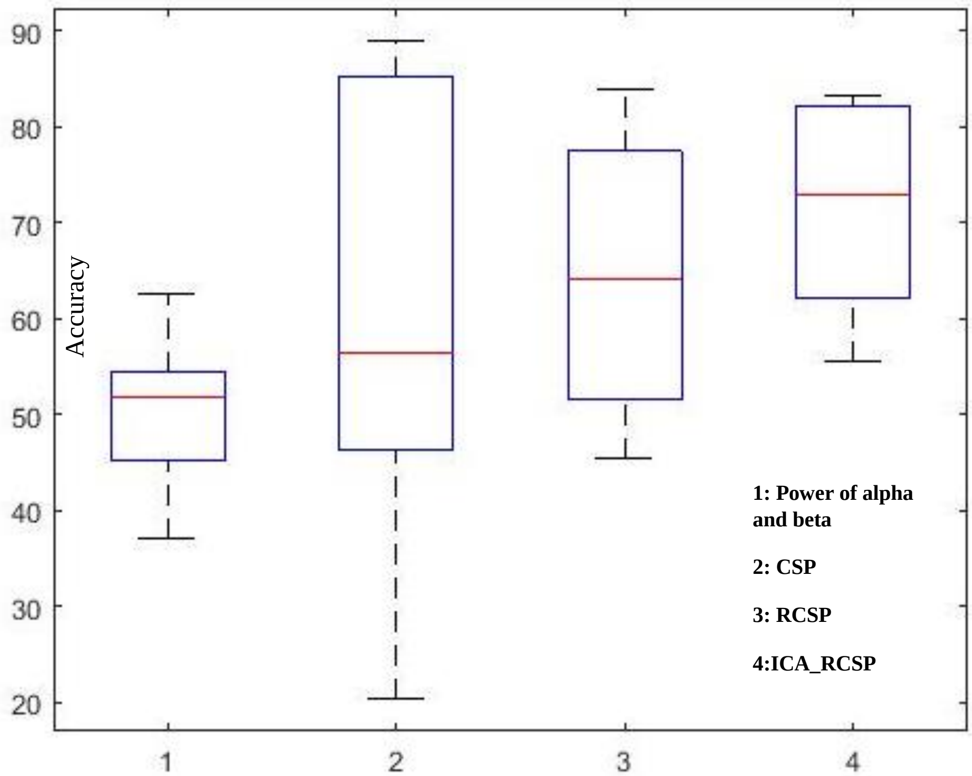

Fig. 7: Statistics of four methods for (Dataset Ia, M=12, (session to session transfer learning))

Table IV: Comparison of different feature extraction methods for (Dataset Ib, M=12 (session to session transfer learning))

Main session	Power of alpha and beta	CSP	RCSP	ICA_RCSP
c1	48.7421	88.0503		
c1_2	58.3333	86.9048	76.7857	78.5714
c1_3	50	76.6667	73.3333	74.4444
Average	52.35847	83.87393	75.0595	76.5079
Standard deviation	4.255941	5.117695	1.7262	2.0635

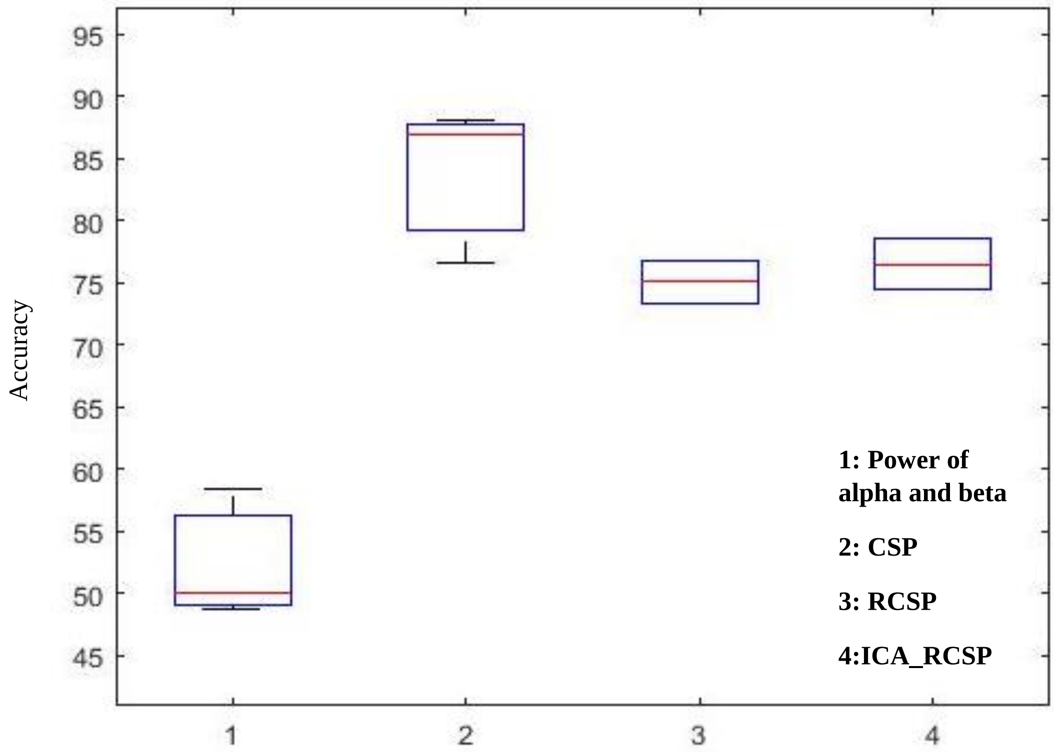

Fig. 8: Statistics of four methods for (Dataset Ib, M=12, (session to session transfer learning))

Table V: Comparison of different feature extraction methods for (Dataset Ic, M=12 (subject to subject transfer learning))

Main subject	Power of alpha and beta	CSP	RCSP	ICA_RCSP
A	50.5952	76.1905	80.5952	82.0238
B	59.6154	79.8077	72.0192	73.0769
C	48.1481	45.3704	50.5556	50
Average	52.78623	67.12287	67.72333	68.3669
Standard deviation	4.931208	15.45204	12.63422	13.49121

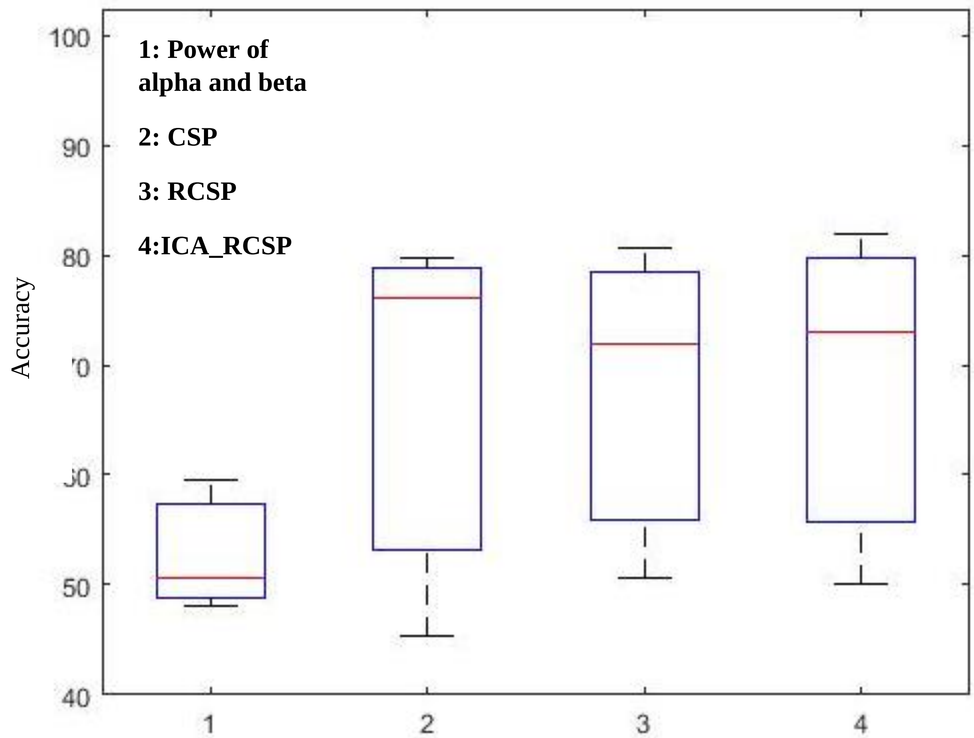

Fig. 9: Statistics of four methods for (Dataset Ic, M=12, (subject to subject transfer Learning))

Table VI: Comparison of different feature extraction methods for (Dataset II, M=12 (subject to subject transfer learning))

Main subject	Power of alpha and beta	CSP	RCSP	ICA_RCSP
aa	44.8718	46.1538	51.2821	50.641
al	62.2642	58.9623	50.9434	52.3585
av	39.1509	55.6604	50.9434	55.6604
aw	43.8679	46.2264	54.2453	57.0755
ay	42.4528	53.7736	50	50
Average	46.5215	52.1553	51.48284	53.14708
Standard deviation	8.10525	5.1460612	1.445841	2.776893

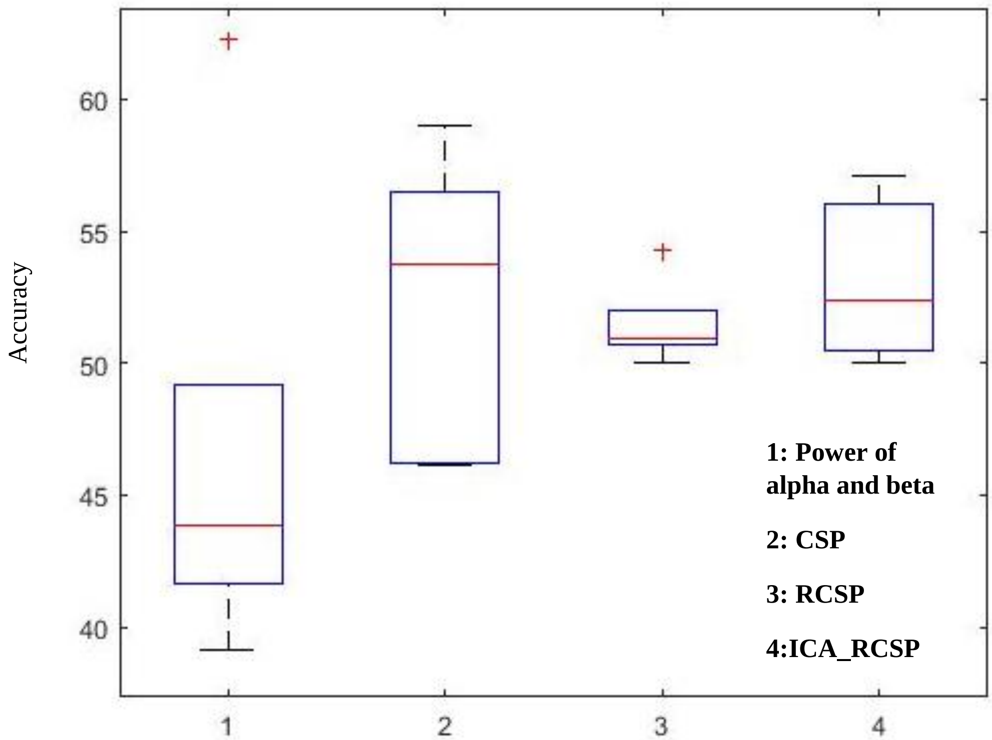

Fig. 10: Statistics of four methods for (Dataset II, M=12, (subject to subject transfer learning))

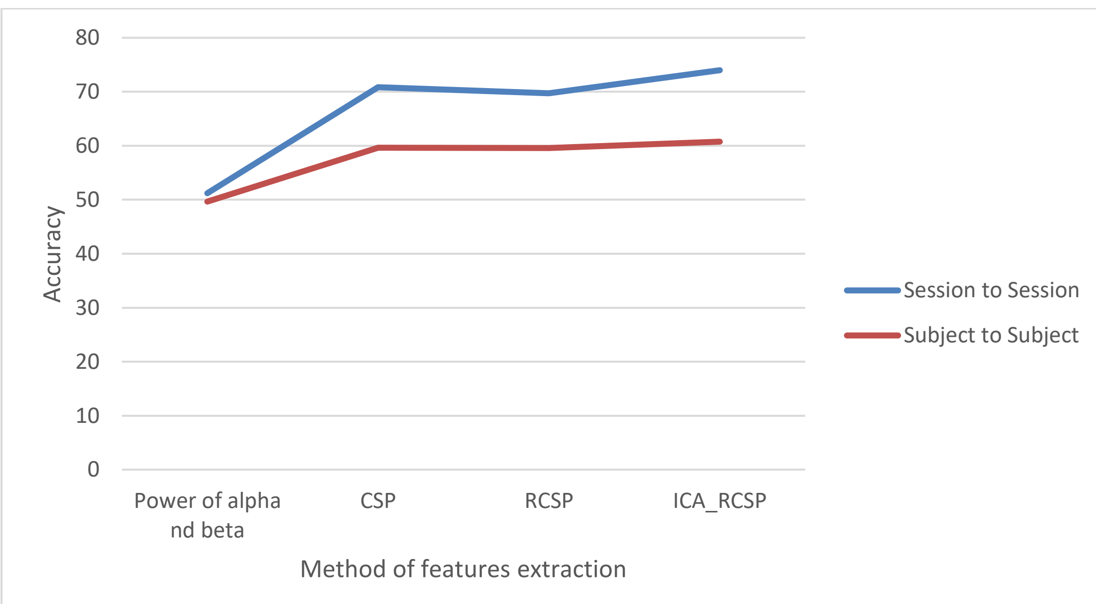

Fig. 11: Comparisons among different methods for (session to session transfer learning and subject to subject transfer learning)