High Performance Multi-class Motor Imagery EEG Classification

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Abstract: Use of Motor Imagery (MI) in Electroencephalography (EEG) for real-life Brain Computer Interface applications require high performance algorithms that are both accurate as well as less computationally intensive. Common Spatial Pattern (CSP) and Filter Bank Common Spatial Pattern (FBSP) based methods of feature extraction for MI-classification has been shown very promising. In this paper we have advanced this frontier to present a new efficient approach whose variants out compete in accuracy (in terms of kappa values) with the existing approaches with the same or smaller feature set. We have demonstrated that use of one mu band and three beta sub-bands is very ideal both from the point-of-view of accuracy as well as computational complexity. We have been able to achieve the best reported kappa value of 0.67 for Dataset 2a of BCI Competition IV using our approach with a feature vector of length 64 directly composed out of FBCSP transformed data samples without the need of further feature selection. The feature vector of size 32 directly composed from FBCSP data is enough to outcompete existing approaches with regard to kappa value achievement. In this paper we also have systematically reported experiments with different classifiers including kNN, SVM, LDA, Ensemble, ANN and ANFIS and different lengths of feature vectors. SVM has been reported as the best classifier followed by the LDA.

1 INTRODUCTION

Motor Imagery (MI) based Electroencephalography (EEG) signals processing for the brain computer interface (BCI) systems is one of the most progressing technologies of current times. It's numerous applications, extended to medical and non-medical fields have concerned substantial attention over the recent times and it is growing at an exponential rate (Meisheri, 2018).

In order to develop a BCI system for MI tasks, a pre-processing scheme is mandatory because the EEG signals captured from the brain are random and noisy (Xie, 2018). Signal pre-processing incorporates artefacts removal such as noise and eye blinks in case of MI data, selection of the appropriate channels band-pass filtering of the signals. Numerous signal pre-processing techniques have been developed for MI tasks. (Cheng, 2004) addressed Common Average Referencing (CAR) to de-noise the EEG signals by averaging the signals across all the channels. Band-pass filtering is also proposed by different authors such as (Osalusi, 2018) and (Xie, 2018) for preprocessing of EEG signals. It is usually done to obtain the information only from the required band for further processing.

For features extraction from the raw EEG signals, there are many methodologies proposed in the literature which includes Common Spatial Patterns (CSP) (Nguyen, 2018), Power Spectral Density (PSD) (Amjed, 2014), Discrete Wavelet Transforms (DWT) (Osalusi, 2018) etc. CSP is the most commonly used technique, which computes Spatial Patterns in EEG before extracting features for MI classification. CSP calculates the filters, which maximizes the difference between two classes of the MI brain activities (Nguyen, 2018), in terms of variance. It was first introduced for two-class hand movement imagination and then further refined for four class patterns. (Abbas, 2018) Presented Filter Bank Common Spatial Patterns (FBCSP) in which EEG data filtered into multiple frequency bands is feed to CSP. Extracted features in CSP domain are then used to compose the feature vector. Fusion of spectral and temporal features has also been utilized by (W.Abbas, 2018) in the context of FBCSP approach. Dimensionality reduction technique, Principal Component Analysis (PCA), has also been used in the literature (Lotte, 2018) for MI-EEG classification.

Numerous approaches for classification have been proposed which include k-nearest neighbor (KNN), support vector machine (SVM), linear discriminant

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analysis (LDA), Nave Bayes classifier (NBC), AdaBoost ensemble learning, fuzzy logic and adaptive neuro-fuzzy systems (Meisheri, 2018), (Nguyen, 2018), (Baghli, 2014). Classification techniques like artificial neural networks (ANN) and Deep learning approaches have also been tested for EEG data classification in recent times (W. Abbas, 2018).

A high performance FBCSP-based technique for feature extraction is proposed for 4-class MI-EEG which has been tested with multiple classifiers. We use only four filters for preprocessing as compared to other FBCSP approaches such as (Xie, 2018) and (Miao, 2017), which incorporates 9 bands in preprocessing. Employing less number of bands (if the accuracy is not compromised) provides opportunity to yield a smaller features vector for classification. We incorporate sensorimotor rhythms from mu and beta ranges in our approach but use one band for mu and three sub-bands for beta. These approaches also computes other statistical parameters for feature selection such as Band power, Time domain parameters and Mutual information. This adds on computational complexity of the algorithm. We have composed our feature vector directly from the FBCSP transformed data as we are keeping our number of sub-bands just four. This produces a feature vector of size 64 which compares well with other FBCSP approaches also performing statistical feature extraction like (Abbas, 2017) with 88 features, (Abbas, 2018) with 60 features and (Miao, 2017) with 162 features.

Our approach based on FBCSP method is more optimal with regard to accuracy, size of feature vector and computational complexity. CSP-based 4-class MI-EEG classification approach like that of (Raza, 2016) has achieved a good kappa value of 0.58 but has used a bank of 10 filters. Other methodologies using CSP approach such as (Meisheri, 2018) and (Nguyen, 2017) does have low feature vector size but faces the disadvantage of low classification accuracy. In our FBCSP approach, we managed to just outperform other existing approaches in terms of Kappa value with feature vector size of 32 (Variant 2). This offers the advantage of low computational complexity as we are using only 4 bands. With a feature vector of size 64 (Variant 1), our approach leads other approach by high margin in accuracy and is still computationally light compared to many other approaches. With regard to classification we will present results with different classifiers and show that SVM performs the best.

Rest of the paper is organized as follows: complete workflow architecture of the proposed methodology is addressed in Section II. Section III encapsulates the experimental paradigm with detailed discussion on the obtained results. Finally, the conclusion of this paper is incorporated in Section IV.

2 PROPOSED METHODOLOGY

Detailed work flow of the proposed MI-EEG data classification methodology is presented in this section. Fig. 1 summarizes the complete work flow architecture with three different variants. The first variant (variant-1) all the FBCSP coefficients for classification. Second variant (Variant-2) corresponds to using half of the features discussed in the next section and third approach (Variant-3) also performs feature reduction. We will highlight these differences in the description of each variant. Further computation of secondary features after applying FBCSP could also be done as in (Abbas, 2018) but our goal is to just explore how many bands are optimal to utilize directly for classification.

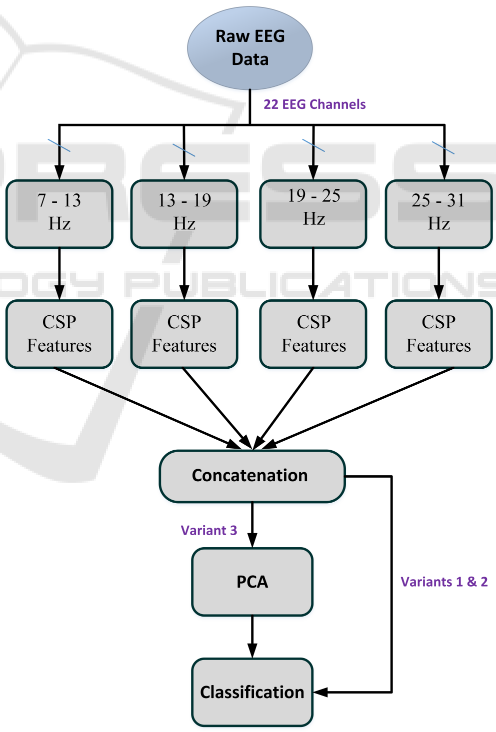

Figure 1: Proposed Methodology work flow.

2.1 Pre-processing

The brain oscillations for MI based BCI systems, the EEG signals carry the sensorimotor rhythms in the frequency band of 7-13 Hz (mu) and 13-30 Hz (beta) (Nguyen, 2018). The raw EEG data is pre-processed by developing four separate band pass filters as per

Nyquist Criteria, depicted in Fig. 1. The band pass frequency for band 1 is $7-13$ Hz, band 2 acquires $13-19$ Hz, band 3 contains $19-25$ Hz and $25-31$ Hz is band 4. We have divided Beta band in three sub-bands as the frequency range in beta band is large. These frequency bands also provide the advantage of artifacts rejection such as noise and eye blinks. Using these bands in beta and mu rhythm produces adequate feature for MI classification (Mahmood,, 2017).

2.2 Feature Extraction

Common Spatial Patterns (CSP) technique is utilized for feature extraction from the pre-processed EEG data. EEG classification performed by different authors in the literature such as (Mahmood, 2017), (Abbas, 2018) implies that CSP is an effective approach for extracting features in EEG data classification. CSP discriminates the EEG signals by decomposing them into spatial patterns that increase the differences between two separate classes. The main goal of applying CSP is to maximize the variance for one class of EEG signals and decreases for the other ones. We are using one vs rest approach of CSP by breaking the multi-class problem to k binary classes.

The four classes of pre-processed EEG data X1;X2;X3; and X4 indicates an N x G matrix where N represents the number of EEG channels and G corresponds to number of data samples. The process of the algorithm for multi-class CSP described in (Mahmood, 2017) is as follows. The normalized spatial covariance C is presented as :

$$C_k = \frac{X_k^i X_k iT}{trace(X_k^i X_k iT)} \tag{1}$$

where X_k^{iT} is the matrix transpose of X_k^i for k $=1,2,3,4$. Accumulating the all four spatial covariance matrices as:

$$C = \sum_{k=1}^{4} C_k \tag{2}$$

and covariance matrices for disjoint trials $C^{'}$ are given as:

$$C_k^{'} = \sum_{j \neq k} C_j \tag{3}$$

where $j = 1,2,3,4$. Matrix factorization o C is done by eigenvalue decomposition

$$C = U_0 \Lambda U_0^T \tag{4}$$

Here, Λ is the square matrix of order N containing the diagonal elements as eigenvalues and U_0 corresponds to the matrix of eigenvectors. The data whitening process is performed as:

$$P = \Lambda^{-1/2} U_0^T \tag{5}$$

where P is the whitening matrix. The Covariance matrices C_k and $C_k^{'}$ are whitened to compute intermediate matrices S_k and $S_k^{'}$.

$$S_k = P C_k P^T \tag{6}$$

$$S_k^{'} = P C_k^{'} P^T \tag{7}$$

Both of these matrices share common eigenvectors and sum of the eigenvalue matrices of both results to Identity. Consequently, the maximum eigenvalue for S_k will acquire minimum eigenvalue for $S_k^{'}$ and vice versa. Therefore, maximizing the variance between S_k and $S_k^{'}$ by the transformation of matrix X_k onto eigenvector space. The matrix projection for each of the class is computed as

$$W_k = U_k^T P \tag{8}$$

where U_k^T is the matirix of eigenvectors. The first and last m rows of W_k are obtained to develop a $2m \times N$ spatial filter W_{kS} which is utilized to spatially filter X_k^i.

$$Z_k = W_{kS} X_k^i \tag{9}$$

The W_{kS} for four classes ($k = 1-4$) are concatenated resulting in one spatial filter W_S of order $N \times 8m$. The band-passed filtered signals $x_{band}(x_1, x_2, x_3, x_4)$ of order $N \times T$ for each trial are spatially filtered and the log variance of these signals is computed as feature vectors having the order of 1 $\times$ $8m$.

$$F_{band} = \frac{log\left[diag(W_S^T x_{band} x_{band}^T W_S)\right]}{trace(W_S^T x_{band} x_{band}^T W_S)} \tag{10}$$

(Nguyen, 2018) then selects first two and last two rows of these feature vectors. We applied multi-class CSP algorithm discussed in (Nguyen, 2018) for four classes. Instead of feeding the whole EEG data to CSP as in (Nguyen, 2018), we have divided the signal into 4 bands and then performed CSP transformation on each band. Total of 64 features are obtained in the same fashion by selecting the first and last two rows respectively in each band by equation (10). These 64 data samples are directly utilized for classification in the first variant of our approach (Variant-1). In order to reduce the computational complexity of the proposed algorithm, and considering the fact that maximum correlation and covariance lies in the first and last row of the CSP transformed matrix, we choose just the first and last row from the final spatial filter (10), which corresponds to 8 features for each band. This yields our second variant (Variant-2) having a feature vector containing total of 32 features.

Table 1: Accuracy(%) of different classifiers for 32 features proposed in our approach.

Subject	kNN	SVM	LDA	Ensemble	ANN	ANFIS
1	60.4	60.8	58.6	65.3	73.1	46.6
2	54.9	52.8	51.0	68.1	58.4	37.5
3	79.2	80.7	79.5	86.8	38.0	55.6
4	48.3	78.5	72.5	52.4	72.8	36.8
5	46.2	62.5	60.8	65.6	96.7	35.7
6	42.0	70.5	68.7	47.9	70.9	40.6
7	78.5	79.2	80.9	90.2	70.4	40.2
8	76.4	83.4	73.3	86.8	69.3	58.0
9	63.2	84.0	85.4	69.1	72.8	59.8
Mean	61.1	72.5	70.6	69.6	66.2	45.7

Table 2: Accuracy(%) of different classifiers for 16 features proposed in our approach with PCA.

Subject	kNN	SVM	LDA	Ensemble	ANFIS
1	64.2	66.0	62.5	65.2	25.7
2	50.7	56.3	57.3	56.6	19.4
3	79.2	86.8	85.1	86.1	29.5
4	45.8	49.7	52.1	51.4	33.0
5	48.3	54.2	55.6	55.6	24.0
6	43.1	44.8	41.0	42.0	29.2
7	78.8	86.1	86.5	86.0	45.1
8	75.0	78.8	78.1	78.5	33.0
9	60.4	64.2	62.5	61.8	52.4
Mean	51.9	65.5	64.5	64.8	33.0

2.3 Feature Reduction

Principal Component Analysis (PCA) is a known method for feature reduction. Although, we have selected a very small number of EEG feature vectors as compared to different algorithms discussed in the literature such as (Abbas and Khan, 2018), (Abbas, 2018) and (Nguyen, 2018), PCA described in (Lotte, 2018) is also applied in one variant of our approach to see it's effectivity. 32 features obtained in the previous section are further reduced to 16 features (Variant-3).

2.4 Classification

After feature extracting process, the next step is to utilize these features for signal classification. In order to classify EEG signals, numerous classifiers have been addressed in the literature (Meisheri, 2018). In this paper, we are using built-in tools of MATLAB for kNN, SVM, LDA, Neuro Fuzzy and Ensemble learning classifiers. SVM is used as weak classifier to develop the ensemble learning scheme and parameter setting kept the default in all the classifier tools. In case of binary classification algorithms, we incorporate One Vs Rest approach by encapsulating K binary classifiers. Results obtained by these classifiers are addressed in next section.

3 RESULTS AND DISCUSSION

3.1 Dataset

The EEG Dataset we are using for classification in this project is dataset 2a of BCI Competition IV (Tangermann, 2012). The dataset comprises of MI based EEG data from 9 different subjects. It contains 4 different motor imagery tasks, where the class 1 corresponds to imagination of left hand movement, class 2 relates to the movement of right hand, both feet are associated with class 3 and tongue to class 4. The recordings were made for total of 288 trails using 25 electrodes (22 EEG and 3 EoG). Signal sampling frequency is 250 Hz and all the data is filtered in the band of 0.5-100 Hz. An notch filter of the frequency of 50 Hz was applied to suppress the noise.

Table 3: Mean Kappa coefficient comparison with different techniques.

Method	Year	Feature Extraction	Feature Selection	Features Used	Mean Kappa Value	Accuracy (%)
(Guan, 2019) *et al.*	2019	Riemannian Geometry	SJGDA	-	0.60	70.0
(Xie, 2018) *et al.*	2018	Filter Bank ELM-TS-RE	MIBIF	-	0.62	71.5
(Meisheri,2018) *et al.*	2018	CSP with Fano's inequality	Nil	-	0.38	53.5
(W. Abbas) *et al.*	2018	FBCSP	FFTEM	-	0.61	70.7
(Nguyen, 2018) *et al.*	2018	CSP	Nil	16	0.53	64.7
(Abbas, 2018) *et al.*	2018	FBCSP	BP &TDP	60	0.59	69.2
(Abbas, 2017) *et al.*	2017	HALS-NNMF	BP &TDP	88	0.62	71.5
(Miao, 2017) *et al.*	2017	FBCSP	STFSCSP	162	0.53	64.7
(Raza, 2016) *et al.*	2016	CSP	Nil	-	0.58	68.5
(Ang, 2012) *et al.*	2012	FBCSP	MIBIF	-	0.59	69.2
Proposed (Variant-3)	-	FBCSP	PCA	16	0.54	65.5
Proposed (Variant-2)	-	FBCSP	Nil	32	**0.63**	**72.5**
Proposed (Variant-1)	-	FBCSP	Nil	64	**0.67**	**75.2**

3.2 Experimental Paradigm

Experiment is performed on dataset 2a of BCI competition IV. All 22 EEG channels are used for classification. Each trial is 7.5 seconds long with 250 Hz sampling rate. Besides all the challenges discussed previously, choosing an optimized time window for classification is also the requirement. We are using a time window of 1s which ranges from 4s to 5s in each trial for training data and 0.5 s window ranging from 2.5s to 3s in case of testing data for all the subjects.

3.3 Performance Evaluation

In order to evaluate the effectiveness of the proposed algorithm, metrics to address the classification performance is the Accuracy defined by (Nguyen, 2018).

Table1 addresses the percent classification Accuracy of evaluation data for all 9 subjects with different classifiers. 32 CSP features are utilized for these classification results. The last row of the table represents the average Accuracy of all the subjects. Classification results presented in Table1 shows that SVM is the most suitable classifier for proposed method. In order to further reduce the computational complexity of the classifiers, one variant of our approach uses Principal Component Analysis (PCA) algorithm. Total of 32 features obtained by CSP are further reduced to 16 features. Table 2 envelops the percent classification Accuracy of all the subjects for evaluation data after applying PCA algorithm with mean Accuracy as well.

Another metric used in the literature for performance evaluation of different BCI classification algorithms is the Cohen's Kappa coefficient (Nguyen, 2018). Average Kappa value of all nine subjects obtained by the proposed classification methodology is compared with different MI classification techniques in TABLE 3. We have included the size of feature set of existing approaches where available and computed the Kappa coefficient from stated classification accuracies where Kappa value was not provided. "-" sign in the table indicates that no exact feature size was mentioned in the paper. The highest Kappa value obtained in proposed method is achieved by SVM classifier, so we have mentioned it in comparison with different number of features. If we choose first two and last two rows from CSP (Nguyen, 2018), we obtain 16 features for each class and there will be total of 64 CSP features. This tends to improve the classification Accuracy to 75% by SVM. Kappa value in this table demonstrates that the proposed methodology provides the best classification results among all the listed techniques.

3.4 Analysis and Discussion

Classification results of the methodologies in the literature address that dataset we are using in this study is one of the most strenuous EEG data to classify. Results comparison in terms of classification Accuracy score as well as for Kappa value with different techniques has witnessed the effectiveness of the proposed classification algorithm. Accuracy in case of cross validation for all the subjects of the dataset and for separate testing of evaluation data has shown that the proposed method attained best results for SVM classification as we achieved 75.2 % mean accuracy corresponding to the Kappa value of 0.67 on testing dataset for 64 features. 72.5 % Accuracy with Kappa value of 0.63 is achieved using 32 features only. Our results are the best compared to all methods listed in Table 3. Performance of ANN and Deep learning approaches can be further improved but these methods require large amount of data and high computational cost. Secondly, the results comparison with different techniques which have been proposed in recent times, has shown that the proposed method comes up with best results for Kappa value as well as for classification accuracy. Additionally, proposed technique gain the dominance over other listed techniques is computational cost. We have achieved better results for less number of features as compared to other methods.

4 CONCLUSION

A method for classifying MI signals of EEG for BCI systems has been proposed in this paper and results have been compared with different state of the art algorithms. Proposed methodology presented in this paper encapsulates 4 band-pass filters for preprocessing. FBCSP algorithm is developed as feature extraction technique to classify EEG signals for 4-class motor imagery. Many classification algorithms have been tested on our methodology with feature set of different lengths where SVM has produced best classification results among all the listed approaches. Results are compared with some latest techniques of the literature witnessing that the proposed methodology addressed best results among all the listed techniques. We have came with the conclusion that using a very less number of CSP features extracted from only *mu* and *beta* rhythms can provide a reliable feature extraction source for multi class EEG data classification. Since we have utilized the CSP features of a limited number for classification task by a computationally very inexpensive classification technique, the proposed algorithm can be applied for on-line classification of MI tasks in real-time BCI applications.

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