Inter-channel Covariance Matrices Based Analyses of EEG Baselines

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***Abstract*—Electroencephalographic (EEG) signals are used to assess neurological disorders as well as different states of the brain. The choice of EEG baseline in any analysis is crucial as the two EEG baselines (Eyes Open and Eyes Closed) have differences in connectivity and power levels. The work proposes the use of inter-channel covariance matrices of multi-channel EEG to differentiate the two baselines. Two avenues of approach are explored using: (1) Tangent Vectors of Riemannian Manifold and (2) Covariance matrix properties such as Eigen Values, Eigen Vectors, Spectral Radius and the coefficients of Characteristic Polynomial. K-nearest neighbors, Ensemble of Decision Tree classifier with Bagging and Support Vector Machines are used in both scenarios with 10-fold cross-validation repeated 10 times. Tangent Vectors, Eigen Values, Spectral Radius, coefficients of Characteristic Polynomial and Eigen Vectors result in a mean performance of 80.78%, 95.56%,95.05%, 95.15% and 94.5% respectively. Changes in the inter-dependencies of the considered brain regions are captured more effectively by the covariance matrix properties than by the direct use of covariance matrices. These analyses clearly show that the two baselines have different inter-dependencies of the considered brain regions. The properties of covariance matrices prove to be effective in exploiting these differences to distinguish the baselines.**

***Index Terms*—EEG baselines, Covariance Matrix, Riemannian Manifold, Eigen Value Decomposition, Classification**

I. Introduction

Electrical signals generated in the brain are captured on the scalp as Electroencephalographic (EEG) signals. These signals provide insight into the brain function and are used to analyze the states of the brain and its neurological abnormalities. EEG signals are analyzed mainly in the range of 0 - 60 Hz and can be further divided into sub-bands, namely, Delta (0-4Hz), Theta (4-8Hz), Alpha (8-14Hz), Beta (14-30Hz) and Gamma (30-60Hz).

EEG baselines are considered as the lowest levels of brain activity that can be acquired in an experimental set up. There are two types of baselines : Eyes Open and Eyes Closed. This work addresses the differences in EEG rest conditions (baselines) and not whether the subject closed or opened his eyes. During Eyes Open baseline, the subject is asked to fixate on a point and stay relaxed. In Eyes Closed baseline, the subject has to close his eyes and relax. EEG baselines show topographical as well as connectivity differences in EEG [1] and hence the choice of EEG baseline is vital in an experiment. Most visual BCI paradigms rely on oculomotor functions such as visual P300 [2]. The eyes closed visual BCI is mainly applicable in the medical scenarios. Patients with neuro-degenerative diseases, however, lose motor function resulting in oculomotor dysfunctions (in late-stage ALS or completely locked-in state patients). Hence, conventional BCI systems are of inutile use to these patients. This necessitates the need for BCI that can perform under Eyes Closed condition and hence understanding the characteristic differences of the two baselines is required. Additionally, these baselines have differences cognitive, emotional and motor processes associated with them [3]. Hence, they provide different measures of baselines especially when visual stimuli based analyses are carried out. Thus, it is necessary to understand the differences between the two baselines and characteristics that distinguish them. There are works that have compared the effect of using the two baselines for the task considered. For instance, Mesut et al. [4] compared the effectiveness of using Eyes Open and Eyes Closed baselines to distinguish Alzheimer's from Healthy subjects using Permutation entropy and it was observed that Eyes Open baseline provided higher distinguishing characteristics than Eyes Closed. In biometric based person identification, it was observed by Zhang et al. [5] that Eyes Open based analysis resulted in a higher performance than Eyes Closed analysis. This necessitates the need to distinguish the two baselines and the importance of using the optimal baseline for experiments.

There are several works [6]–[8] assessing the differences in the eye state but it is to be noted here that EEG baselines - Eyes Open and Eyes Closed - are different from the state of the eyes being open or closed. Barry et al. [3] analyzed the two baselines and found that they differ in power levels and topography. This difference was further studied by Ling et al. [9] using autoregressive models and it was found that higher power levels were observed in the Eyes Closed baseline. Differentiating the baselines based on changes in the functional connectivity of the brain was studied by Bo et al. [1] using graph based approaches. A statistical feature analysis of the two baselines by Gopan K et al. [10] showed that the combination of Kurtosis, Interquartile Range and Median Absolute Deviation resulted in a mean performance of 77.92% in distinguishing the two baselines. Gopan K et al. [11] found that the source distributions of the two baselines are different and can be exploited to distinguish the baselines, resulting in a mean performance of 86.54%. LSTM and CNN based analyses of the baselines carried out by Gao et al. [12] resulted in mean performances of 85.88% and 90.5% respectively.

Covariance matrix based analyses, especially Riemannian

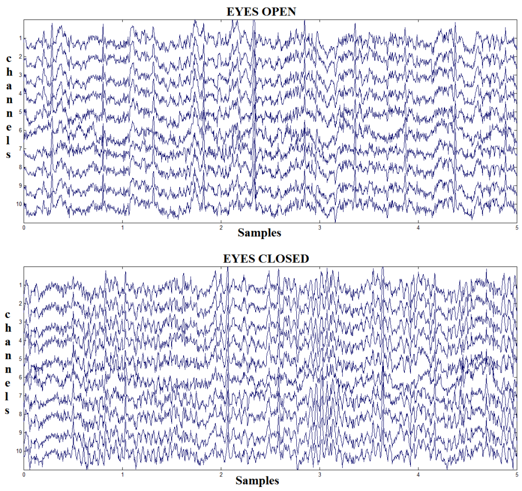

Fig. 1. Representative plots showing sample EEG data from 10 channels of 9500 samples.

Geometry, have been used in multiple classification scenarios such as motor imagery classification [13], sleep stage classification [14] and in distinguishing alcoholic EEG from control [15]. Since topographical and connectivity differences were observed in the two EEG baselines, using features that exploit the changes in the inter-dependencies of the various brain regions could provide the required distinct characteristics to distinguish the two baselines. The present work proposes the use of inter-channel covariance matrices obtained from multi-channel EEG to distinguish the two baselines using two different approaches, namely, (1) Riemannian Geometry and (2) Covariance matrix properties. The use of covariance matrices captures the spatial inter-dependencies of different brain regions and this information is exploited in this work to classify the two EEG baselines. To the authors' knowledge, this is the first time a Riemannian Geometry based analysis and a covariance matrix properties based analysis are being carried out to distinguish the EEG baselines. Additionally, use of coefficients of Characteristic Polynomial as features for classification are exploited for the first time in this scenario. The work also explores the use of Spectral Radius (Largest Eigen Value) to distinguish the baselines instead of using all Eigen Values.

II. Data Description

Physionet "EEG Motor Movement/Imagery Dataset" [16], [17]is used in this work where EEG is recorded using BCI2000. 64-channel EEG from 109 subjects were recorded for Eyes Open and Eyes Closed Baselines, each for a duration of one minute with sampling rate of 160 samples per second. Apart from this, EEG for four different tasks were also recorded. For this work only Baseline EEGs are considered and 9500 samples were obtained for each baseline run. Fig. 1 shows sample EEG for each baseline.

III. Proposed Methodology

Analyzing the changes in the different regions of the brain could provide substantial information to enable effective classification of EEG signals. Spatial covariance matrix can be used to exploit the changes in the inter-dependencies of the different brain regions as the elements of the covariance matrix provide information on how much a signal varies over time and the relative variation of two signals over time. Hence, inter-dependencies of brain regions can be related to spatial covariance matrix computed from EEG.

Two types of analysis of covariance matrix can be carried out:(1) Analysis using Riemannian Geometry and (2) Analysis using covariance matrix properties after Eigen Value Decomposition. The block diagram of the proposed method is shown in Fig.2.

The raw EEG are initially band-limited to 60 Hz with high pass filter's cut off being 1 Hz. A notch filter is utilized to remove power line noise at 60 Hz. Covariance matrices are calculated for various combinations of channels. In the first approach, the covariance matrices are mapped onto the Tangent Space of a reference covariance matrix (geometric mean of all covariance matrices in the training set). The obtained Tangent Vectors are used as the features forming Feature Set 1. In the second approach, the covariance matrices undergo Eigen Value Decomposition resulting in Eigen Values and Eigen Vectors forming Feature Sets 2 and 3 respectively. Apart from this, Spectral Radius, which is the largest Eigen Value, is considered as Feature Set 4 and coefficients of Characteristic Polynomial form Feature Set 5. Each feature set is then separately analyzed using three different classifiers for classification. 10-fold cross validation is repeated 10 times.

A. Riemannian Manifold

A smooth manifold where every point has an associated inner product on the linear space is known as Riemannian manifold and this is the space of symmetric positive definite(SPD) matrices [18]. The distance between any two points on the Riemannian manifold is a curve and can be calculated as [13] :

$$\delta(S_1, S_2) = \sqrt{\sum_{i=1}^{m} log^2 \lambda_i} \qquad (1)$$

where S_1 and S_2 are two points (SPD matrices) on the Riemannian manifold, and λ_is are the real Eigen Values of $S_1^{-1}S_2$. Each point on the manifold has an associated vector space known as Tangent Space where Euclidean measures are valid [18]. To analyze the points on the manifold using Euclidean measures based techniques, these points are often mapped to the tangent space of a reference point on the manifold. The reference point is often calculated as the geometric mean of all the points on the manifold. The mapping of points from the manifold to the Tangent Space is known as logarithmic mapping.

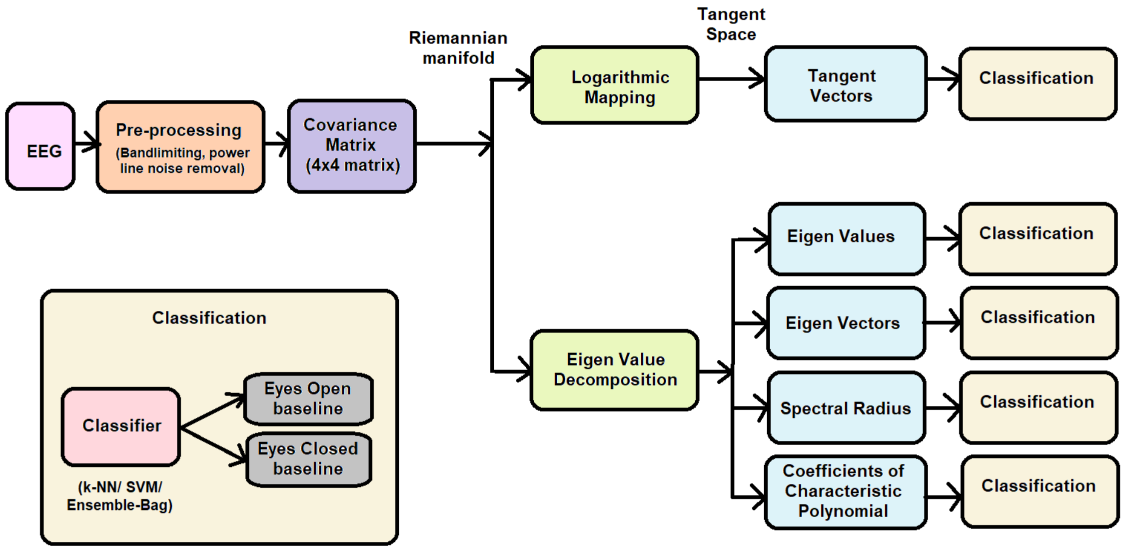

Fig. 2. Proposed Methodology.

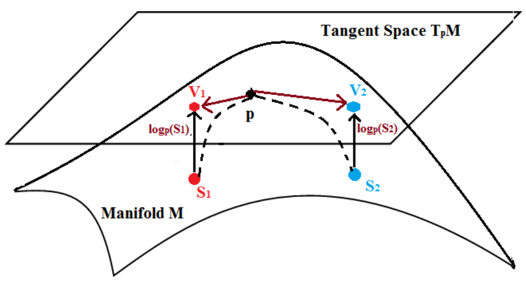

Fig. 3. Riemannian manifold. M is the Riemannian manifold with S_1 and S_2 being two points on the manifold. These points are SPD matrices. P is the reference point, which is another SPD matrix calculated as the geometric mean of the points on the manifold. $T_P M$ is the tangent space associated with P. S_1 and S_2 are mapped to $T_P M$ using logarithmic mapping $log_P(S_1)$ and $log_P(S_2)$ forming tangent vectors V_1 and V_2 respectively.

Logarithmic map for i^{th} point S_i on the manifold to the Tangent Space of the reference point P is calculated as [13]:

$$Log_P(S_i) = P^{1/2} logm(P^{-1/2} S_i P^{-1/2}) P^{1/2} \qquad (2)$$

A visual illustration of the manifold is shown in Fig. 3.

B. Covariance Matrix Properties

A different approach to analyze covariance matrix would be to exploit the matrix properties using Eigen Space based analysis. Features used here are :

1) Eigen Values & Eigen Vectors: Eigen Value Decomposition can be interpreted as transformation of the EEG signals to a space of independent components which have associated variance in directions orthogonal to one other. This decomposition captures the magnitude and the orientation of the maximum to the minimum variances when the dependencies of the electrodes considered are eliminated. The Eigen Value Decomposition results in Eigen Values and Eigen Vectors, which are the magnitude of variation and the direction of variation respectively [19].

2) Spectral Radius: The maximum Eigen Value is the Spectral Radius [19]. This represents the magnitude of the largest variation and hence provides the maximum information about the structure of the signal.

3) Characteristic polynomial: This polynomial has Eigen Values as its root [19]. The coefficients of this polynomial are utilized as a feature vector. The coefficients encapsulate information regarding variations in the brain activations taking into account individual regional variations and the variations associated with the dependencies of the various brain regions considered. This can be interpreted as information pertaining to differential variance.

C. Classifiers

Three different classifiers are considered in classifying the different feature sets, namely, K-nearest Neighbors, Ensemble with bagging and Support Vector Machines.

1) K-Nearest Neighbors (K-NN) : k-NN classifiers are non-parametric classifiers and hence except for the number of neighbors "k" to be considered to assign the label, no other parameters need to be estimated [20]. When a test feature vector is presented, the k-NN initially identifies the "k" nearest neighbors of the test vector from training vectors using a distance measure. The class label of the test vector is then assigned based on the class of the majority of the "k" neighbors. In this work Euclidean distance measure is chosen and experimentally k=4 is found to be optimal.

2) Ensemble - Bagging: Several weak classifiers, namely Decision Trees, are combined to form an ensemble of classifier with a performance higher than that of the individual classifier. Bootstrap aggregating [21] eliminates over-fitting as well as reduces variance. In bootstrapping, small samples are repeatedly sampled with replacement from a single large sample. The classifiers are then trained on bootstrap samples which are very large in number. The final prediction is the averaged prediction of the weak classifiers. The hyperparameter optimization, with cross-validation, has found minimum leaf size to be 3 at a learning rate of 0.0023 with maximum splits allowed being 12.

3) Support Vector Machines (SVM): SVM fit a decision surface to separate classes such that the distance between the points from each class that is closest to the decision surface is maximized [22]. Linear kernel provides a linear decision surface. To separate linearly non-separable classes, data can be mapped to higher dimensions using kernel functions such as Radial Basis Functions (RBF), Polynomial and Quadratic. These kernel functions can be used to obtain non-linear decision surfaces. In this work both Linear and RBF kernels are explored and it is observed that Linear kernels provide higher performances. Hence, all performance metrics are reported for Linear kernels.

IV. Results & Discussion

In this experiment covariance matrix based analyses are carried out using two different approaches to distinguish the EEG baselines. EEG from 109 subjects are used in this work. Each recording contains one minute (9500 samples) of 64-channel EEG data. 10-fold cross validation is carried out 10 times.

Channel selection is carried out experimentally starting with all combinations of pairs of channels. 2x2, 3x3, 4x4 and 5x5 covariance matrices are analyzed for various combinations of all the EEG channels using cross-validation. It is observed that the combination of channels C5, AF7, FP2 and C1 results in the highest mean performance. Further increase in the size of covariance matrices does not yield any improvement in performance. Hence, for this work 4x4 covariance matrices are calculated with channels C5, AF7, FP2 and C1.

Two approaches to analyze covariance matrices are carried out in this work. In the first approach, the covariance matrices are converted into Tangent Vectors and used as features. The test data use the same reference point as the training data to map the points on the manifold into Tangent Vectors. It can be observed from Table I that SVM classifier distinguishes the baselines with a mean performance of 80.78%. In the second approach, covariance matrix properties are used after Eigen Value Decomposition. Here four feature sets are analyzed, namely, Eigen Values, Eigen Vectors, Spectral Radius and coefficients of Characteristic Polynomial. Ensemble classifier distinguishes the baselines with a peak mean performance of more than 90% for all the feature sets in this approach.

Eigen Values, Spectral Radius and coefficients of Characteristic Polynomial result in peak mean performances of 95.56%, 95.05% and 95.15% respectively. Table II shows the confusion matrices of these three feature sets for a single fold of 10-fold cross validation. It can be observed that misclassification occurs only for Eyes Closed baseline for all three feature sets. Apart from accuracy, other performance metrics such as Cohen's Kappa [23], Mathews Correlation Coefficient [24] and F-score [25] are also calculated and shown in Table III.

TABLE I
Mean classification accuracies(in %) of pre-processed EEG covariance matrices of channels C5, AF7, FP2 & C1 for 10-fold cross-validation repeated 10 times.

Features	k-NN k=4	Ensemble Bagging	SVM
Vectors in Tangent Space	68.33 $\pm$1.41	76.03 $\pm$1.49	80.78 $\pm$0.95
Eigen Values	85.25 $\pm$1.65	**95.56 $\pm$1.45**	63.22 $\pm$1.56
Eigen Vectors	84.16 $\pm$2.75	94.5 $\pm$1.74	75.49 $\pm$1.63
Spectral Radius	84.78 $\pm$1.99	**95.05 $\pm$1.16**	58.85 $\pm$2.17
Characteristic Polynomial Coefficients	83.32 $\pm$1.01	**95.15 $\pm$1.61**	59.61 $\pm$1.42

The changes in the inter-dependencies of the different regions of the brain are analyzed in this work. Analysis of covariance matrices as Tangent Vectors have resulted in a peak performance of about 3% more than the statistical properties based features analysis [10] but about 6% less than source distribution based analysis [11]. All the feature sets in covariance matrix properties based analysis have about 5%-18% more peak mean accuracy than all previous works, clearly indicating that the two baselines have differences in the inter-dependencies of the brain regions, specifically, those associated with channels C5, AF7, FP2 and C1.

In Tangent vector based analysis, the whole covariance matrix provides information on how the EEG of a channel is associated with the EEG of another channel over a period of time. Finer details like mutually uncorrelated variances (Eigen Values) and the corresponding topographical distributions (Eigen Vectors) are not explicitly obtained using covariance matrix (Tangent Vectors) directly as features. Thus, it can be observed that the finer details of covariance matrices provide the distinguishing characteristics of the EEG classes considered for enhanced classification performance. This could be the reason for the lower performance of the Tangent Vector based analysis. Additionally, during testing phase it is noted that the tangent vector based analysis takes 3 seconds longer for classification of a single input than covariance matrix properties based analysis(1.2 second for a single input). This could be due to the computational time required for logarithmic mapping.

TABLE II
Confusion matrices for one fold of cross validation of classification for best performing features with Ensemble-Bag classifier.

	Eigen Values			**Spectral Radius**			**Charactristic Polynomial**	
	Eyes Open	**Eyes Closed**		**Eyes Open**	**Eyes Closed**		**Eyes Open**	**Eyes Closed**
Eyes Open	12	0		10	0		13	0
Eyes Closed	1	9		1	11		1	8

The analysis clearly implies a change in the inter-dependencies of the brain regions. In a study by Kan et al. [26],

TABLE III
MEAN ACCURACY, COHEN'S KAPPA, MATHEWS CORRELATION COEFFICIENT AND F-SCORE FOR CLASSIFICATION WITH VARIOUS BEST PERFORMING FEATURES WITH ENSEMBLE BAG CLASSIFIER.

	Mean Accuracy (%)	**Cohen's Kappa**	**MCC**	**F-Score**
Eigen Values	95.56	0.9	0.91	0.95
Spectral Radius	95.05	0.88	0.89	0.95
Characteristic Polynomial	95.15	0.91	0.91	0.95

in Euthymic (emotionally well) subjects, it was observed that during Eyes Open state, the electrodes Fp1 and Fp2 showed higher power values for Delta, Theta, and Beta frequencies. C3 and C4 provided the lowest power among all channels for Eyes Open and Eyes Closed states. Occipital and Parietal regions too showed changes in power in both Eyes Open and Eyes Closed states. It must be noted that the quadruplet of channels in the present work belongs to (1) areas having Baseline and (2) areas having lowest power values for both Eyes Open and Eyes Closed Baselines. Hence, FP2 as well as AF7 (which is adjacent to Fp1) reflects the high power levels for Eyes Open state while C5 and C1, which are on either side of C3, have the lowest power values in both Eyes Open and Eyes Closed states. Thus, the inter-dependencies in the brain regions associated with C5, C1, FP2 and AF7 are altered in the two baseline states.

V. CONCLUSION

The differences in the inter-dependencies in the regions of the brain in EEG baselines are presented here using the covariance matrix based analyses. Two approaches of analysis are carried out: (1) Tangent Vectors based analysis and (2) Covariance Matrix properties based analysis. While Tangent vectors of the covariance matrices of C5, AF7, Fp2 and C1 give good performance, the best performance of more than 95% is observed when Eigen Values, Spectral Radius and coefficient of Characteristic Polynomial of covariance matrix are considered. This depicts a difference in the relative brain activation of the frontal and the central regions of the brain. The obtained high performance shows that the two baselines have different characteristics even at the level of changes in the brain activations of various regions and hence appropriate choice of EEG baselines needs to be chosen for the experiments.

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