Alcoholic EEG Analysis Using Riemann Geometry Based Framework

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***Abstract*—Brain functioning is severely affected in long-term alcoholics. This degradation is reflected in Electroencephalographic signals(EEG) which are electrical signals in the brain generated due to the firing of neurons. These signals can be used to understand the changes in the brain of an alcoholic. In this work, Riemann geometry based classification framework is used to study changes in interdependencies across various brain regions in alcoholics. Publicly available data of 50 subjects(25 alcoholics, 25 control) with 10 trials each are used in this work. Spatial covariance matrices for empirically chosen channels are input to two classification scenarios. In the first scenario, covariance matrices are used as features to "Minimum Distance to Mean classifier with geodesic filtering(fgMDM)" on the manifold. The highest mean accuracy obtained is 82.8% for the channel set of AF2 & P6. In the second scenario, the covariance matrices are mapped to tangent space and the resultant tangent vectors are used as features for Support Vector Machine with Radial Basis Function kernel. In this scenario, the highest mean accuracy obtained is 87.6% for the channel set FP1 & PO1. Both scenarios indicate significant changes across frontal lobe in comparison to the posterior lobes of the brain, in alcoholics. Changes in covariance matrices for the EEG, when the same stimulus is provided, indicate changes in brain functioning, consistent with alcoholism. Hence, Riemann geometry is a promising framework to study changes in brain region inter-dependencies, for subjects exposed to different brain-altering situations.**

***Index Terms*—Electroencephalographic Signals, Alcoholic, Riemann Geometry, Tangent Space**

I. Introduction

Electroencephalographic signals (EEG) are utilized in analysis of brain function. These signals carry characteristics corresponding to the state of the brain. EEG has been used in diagnosing neurological disorders like epilepsy [1] and Parkinson's disease [2] as well as analyzing mental health issues like depression [3]. For brain Machine Interface, EEG provides a non-invasive means of analyzing Brain function [4]. In addition to these, understanding the emotions of a person [5], analyzing the effects of meditation [6] and detecting the different sleep stages [7] in a person can be carried out using EEG.

EEG signals can be divided into various frequency components, here called as brain waves [8]. Frequencies in the range (0-60Hz) are most informative in all analysis. This range is further divided into five bands mainly: Delta(0-4Hz), Theta(4-8Hz), Alpha(8-14Hz), Beta(14-30Hz) and Gamma(30-60Hz). Deep sleep mainly consists of delta waves. Theta waves are usually found during drowsiness and are also associated with intuition. When a person is relaxed with eyes open, mainly alpha waves are generated in the brain. Beta waves become predominant when a person is performing a focused mental activity. Perception and REM (Rapid Eye Movement) sleep involve Gamma waves.

Long-term alcohol abuse has a negative impact on health. Apart from liver damage, brain gets affected with alcohol abuse [9]. Negative effects of alcohol on brain include memory lapse, disruption in growth of new cells and blackouts. Many alcoholics have thiamine deficiency which could lead to serious neurological disorders like WernickeKorsakoff syndrome [10]. In addition, structural changes like actual shrinkage of brain and loss of neuronal connection [11] can occur in the brain.

Studies have shown that EEG of alcoholics have higher power in some of the brain waves (mainly Theta [12] and Beta [13]). Along with the power of EEG waves, coherence is also used to distinguish alcoholics and control [14]. Support Vector Machine was used with features such as approximate entropy, sample entropy, Largest Lyapunov Exponent and Higher Order Spectra to result in an accuracy of 91.7% [15]. In the work by [16], Horizontal visibility graph entropy (HVGE) feature reported an accuracy of 87.5% using three HVGE features and 95.8% using 13-dimension HVGE. Hybrid features involving raw signal with derived features were explored in [17] resulting in an accuracy of 88%.

Many studies in literature are limited to analyzing EEG signals with respect to frequency compositions (statistical features) and non-linear dynamical frameworks (chaos feature) [12]–[15], [17]. The spatial inter-dependencies of different brain regions are not taken into account in these studies. However, covariance matrices of the channels of the EEG capture information on the spatial inter-dependencies of the brain regions. In this work, Riemann Geometry (RG) is utilized for classification of covariance matrices of different channels of alcoholics and control. To the best of the authors' knowledge, Riemann Geometry has not been used before for analysis of alcoholic EEG. Here two scenarios of classification framework are carried out, one being the classification of covariance matrices of the EEG in Riemannian manifold and the other being the classification of tangent vectors, corresponding to the covariance matrices in the manifold, in the tangent space.

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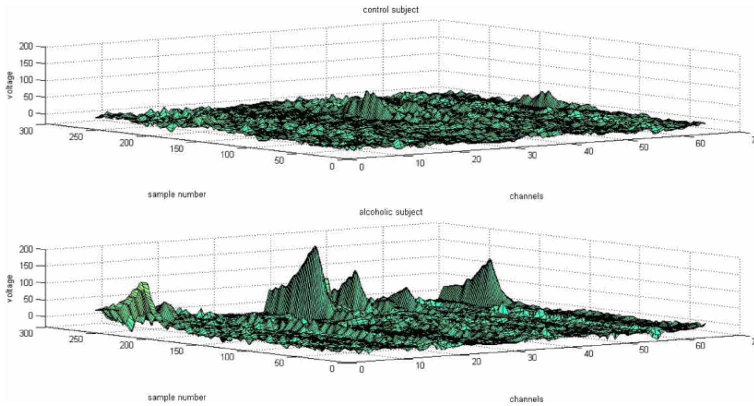

Fig. 1. Sample plot of control and alcoholic EEG data

II. Data Description

UCI Machine Learning repository [18] was utilized for obtaining the data for this work. The database consists of 10 trials of 1 second EEG of alcoholics and control who were shown a single stimulus S1 (1980 Snodgrass and Vanderwart picture set - picture of objects). EEG was sampled at 256 Hz. The data consisted of 64 electrodes of which two were EOG electrodes and one reference. For this work EOG and reference electrodes were not considered. Here, 50 subjects (25 alcoholics and 25 control) with each subject containing 10 trials were used. Total of 500 time series are considered in this work. Fig.1 shows a sample plot of alcoholic and control data.

III. Proposed Methodology

The block diagram of the proposed methodology is shown in Fig.2. The EEG signals are used to calculate the covariance matrices of channel combination that are empirically chosen. In scenario 1, these covariance matrices are given as features to an extended version of "Minimum Distance to Mean" classifier for classification. Here, the classification is carried out in the Riemannian manifold. In scenario 2, these covariance matrices are mapped on to tangent space of a reference covariance matrix, which is the mean covariance matrix of the training data. After mapping, the tangent vectors are used as features to support vector machine with radial basis function kernel for classification. A 7-fold cross validation is carried out.

A. Riemann Manifold

A topological space, which resembles Euclidean space locally is known as manifold [19]. A continuous map exists from the open subset of the manifold to the open subset of Euclidean space. If this map is differentiable, the manifold has the structure of a differential manifold. Differential manifolds are those manifolds where notions used in multi-variable calculus can be defined [20]. Smooth manifolds are those where the transition maps are smooth [19]. At every point on the smooth manifold, there exists a linear space that defines the velocity of the curves passing through it. Riemann Manifold [20], M, can now be defined as a smooth manifold equipped with inner products on the linear space at each point. Riemannian metric is the collection of all inner products defined on the vector space associated with each point on the manifold. Earth is an example of Riemann Manifold. The distance between any two points on the Earth is a curve on the manifold. The shortest smooth curve between two points on the manifold is known as geodesics [20].

The vector space associated with each point on the smooth manifold is known as Tangent Space [20]. There exists mapping of points from Riemann Manifold to its tangent Space and vice versa. For a reference point p on the Riemannian Manifold M, there exists Tangent Space T_pM, and let v be the tangent vector in the Tangent Space. The exponential map $Exp_p : T_pM \rightarrow M$, maps the tangent vector v from Tangent space to the manifold. The mapping from a point on the manifold to the tangent vector v is known as logarithmic map, $Log_p : M \rightarrow T_pM$.

For a symmetric matrix, if its eigenvalues are all positive, then that matrix is known as a positive definite matrix. A space symmetric positive definite (SPD) matrix forms a differential manifold, specifically Riemannian manifold [21]. Each SPD matrix m xm can be viewed as a point on the manifold of dimension $\frac{m(m+1)}{2}$. The distance between two SPD matrices S_1 and S_2 can be calculated as [21]:

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

where λ_i are the real eigen values of $S_1^{-1}S_2$.

The exponential and logarithmic map can be calculated for N number of SPD matrices, $S_i, i = 1, 2..., N$ on the manifold at the reference point (SPD matrix) S_{ref}as [21]:

Logarithmic map:

$$T_i = Log_{S_{ref}}(S_i) = S_{ref}^{1/2} logm(S_{ref}^{-1/2} S_i S_{ref}^{-1/2}) S_{ref}^{1/2} \tag{2}$$

Exponential map:

$$S_i = Exp_{S_{ref}}(T_i) = S_{ref}^{1/2} expm(S_{ref}^{-1/2} T_i S_{ref}^{-1/2}) S_{ref}^{1/2} \tag{3}$$

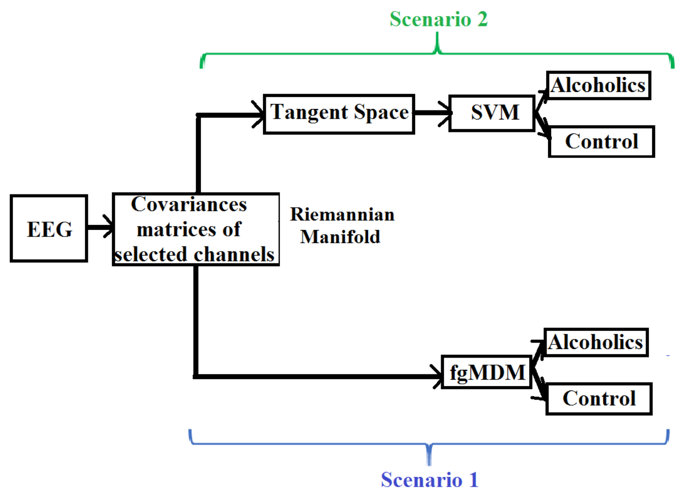

Fig. 2. Block diagram of the proposed methodology

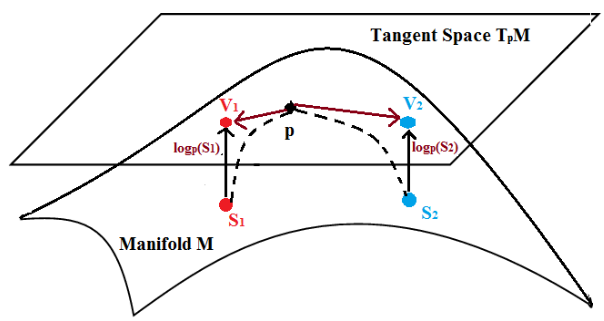

Fig. 3. Example of Riemann manifold and tangent space at point p of the manifold. S_1 and S_2 are two points on the manifold that are mapped to tangent space as tangent vectors V_1 and V_2 respectively.

where logm(.) and expm(.) denote the logarithm and the exponential of a matrix. $T_i, i = 1, 2, ...N$ are tangent vectors on the tangent space of S_{ref}.
In multichannel EEG analysis, covariance matrices provide information about the variances along each channel and between channels. Covariance matrix is SPD matrix and hence form a Riemannian manifold. For each subject, covariance matrix can be calculated and using these covariance matrices a reference covariance matrix is calculated. This matrix is the Riemannian mean (geometric mean) of all covariance matrices. Using this reference matrix, the covariance matrices can be mapped to tangent space for using machine learning algorithms such as support vector machine. If machine learning algorithms such as minimum distance to mean classifier are to be applied on the manifold itself, then the distance measure used should be Riemannian distance.

B. Classifiers

In this work, two classifiers are considered for classifying the covariance matrices, namely, Minimum Distance to Mean classifier with geodesic filtering that operates on the manifold and support vector machine that operates on the tangent space.

1) Minimum Distance to Mean classifier with geodesic filtering on the manifold: Minimum Distance to Mean (MDM) classifier calculates the distances of the test covariance matrices to the Riemannian mean of each class and the class label is assigned corresponding to the class to which the test data has minimum distance. Fisher geodesic discriminant analysis, which is an extension of Fisher Linear Discriminant Analysis to the tangent space, is used to obtain a set of filters which are applied to MDM classifier to obtain Minimum Distance to Mean classifier with geodesic filtering (fgMDM) [22].

2) Support vector Machine on Tangent Space: Tangent Spaces are Euclidean spaces and hence Support Vector Machine (SVM) can be used on tangent vectors without any modification [23]. SVM works on the principle that if data cannot be linearly separated in the present dimension, then data can be separated by projecting onto higher dimension. For projection onto higher dimensions, kernels are used. In this work, radial basis function kernel is used for classification.
7-fold cross validation is carried out.

IV. Results & Discussion

In this experiment, Riemannian geometry was used to classify the spatial covariance matrices of EEG of alcoholic and control subjects. 50 subjects (25 from alcoholics group and 25 from controls group) were used in this study. Each EEG recording was for 1 second and contained 61 EEG channels.

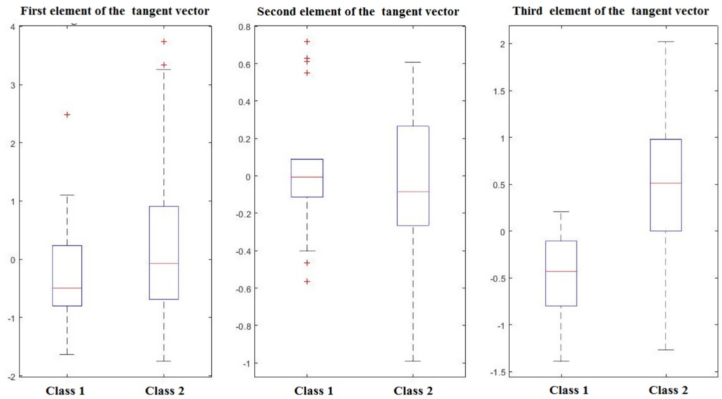

Fig. 4. Boxplot of the three elements of tangent vectors

The signals were sampled at 256 Hz. A 10-fold classification was carried out to obtain the resultant mean accuracy of the classification framework.

Empirical channel selection was carried out for the proposed classification framework. Initially pairs of all channels were used to determine empirically those channels that showed distinct characteristics of the two classes,that is, the channel pairs that showed altered inter-dependencies in the alcoholics. Only those pairs of channels that resulted in highest classification accuracies were chosen. Channel pairs of "FP1" & "PO1', "AF2" & "P6" and "CP3" & "P1" resulted in the highest mean accuracies. This shows that these pairs of channels have distinct covariance matrices of the two classes which can be exploited to distinguish alcoholic EEG from control. The channel pair "FP1" and "FC6" performed worst in classification with least mean accuracy of 60.4% for scenario 1 and 32% for scenario 2 which indicate that the inter-dependencies between these two channels do not contain sufficient information to distinguish alcoholics from controls.

Scenario 1: The covariance matrices of the EEG data (of selected channels) were calculated and directly given as features to Minimum Distance to Mean classifier with geodesic filtering (fgMDM) for classification. The covariance matrices are points on the Riemannian manifold and the fgMDM classifier resulted in the highest mean accuracy of 82.8% for the channels pair "AF2" & "P6" as seen from the Table.I. It is also observed that the channel pairs "FP1" & "PO1" and "CP3" & "P1" resulted in mean accuracies of 78% and 76.4% respectively. When we use all three pairs together to calculate the covariance matrix and give them to the classifier, the mean accuracy decreases. Hence, only pairs of channels resulted in distinct covariance matrices of the two classes and not the combination.

TABLE I

CLASSIFICATION ACCURACIES OF TWO SCENARIOS FOR CHANNEL COMBINATIONS

Channels	fgMDM (%) (Manifold)	SVM (%) (Tangent space)
FP1 & PO1	78	87.6
AF2 & P6	82.5	80
CP3 & P1	76.4	80
CP3,P1,AF2,P6,FP1,PO1	60	69.6
FP1 & FC6	60.4	32

Scenario 2: The covariance matrices of the selected channels of EEG data were computed and instead of performing classification in the Riemannian manifold, these matrices were mapped onto the tangent space of the reference covariance matrix. The reference covariance matrix was calculated as the geometric mean of the covariance matrices of the training data. The same reference matrix was used to map the test data. Once the covariance matrices were mapped onto the tangent space using logarithm map, these matrices were now in the form of tangent vectors in the tangent space. These vectors were then used as feature vectors to support vector machine with radial basis function kernel for classification into two classes. The boxplot of the three elements of tangent vectors are shown in Fig.4. As observed from Table.I, the channels pair "FP1" & "PO1" resulted in the mean accuracy of 87.6%, while the channel pairs "AF2" & "P6" and "CP3" & "P1" both gave 80% mean accuracy.

TABLE II

CONFUSION MATRIX OF (A)"AF2" & "P6" USING FGMDM IN THE MANIFOLD FOR 1 FOLD OF CROSS VALIDATION. (B) "FP1" & "PO1" USING SVM IN TANGENT SPACE FOR 1 FOLD OF CROSS VALIDATION. ABBREVIATIONS: SUB = SUBJECT; TR = TRIALS; TS= TIME SERIES; ALCO = ALCOHOLIC; CONTR =CONTROL

	Alcoholic	Control	Alcoholic	Control
Alco	**4** (4 sub*10 tr = 40 ts)	**0**	**3** (3 sub*10 tr = 30 ts)	**0**
Contr	**1** (1 sub*10 tr = 10 ts)	**2** (2 sub*10 tr = 20 ts)	**1** (1 sub*10 tr = 10 ts)	**4** (4 sub*10 tr = 40 ts)
F-score	0.8889	0.8	0.8571	0.8889

This work analyzes the interdependency of the selected channels and how they vary between alcoholics and controls. The maximum accuracy achieved was 87.6% in the tangent space which is comparable to the accuracy obtained by [16] using

Horizontal visibility graph using 3 HVGE features. With 13-dimension HVGE features, the accuracy was 8% higher at the cost of higher complexity. [15] and [17] have higher accuracy than current work by 4%and 0.5% but they use features that don't utilize the interdependency information between channels. Hence, Riemann geometry can be used to utilize the channel interdependencies for classification of alcoholics and control.

An important perspective of using covariance matrices as the feature is that changes in channel interdependency indicate changes in brain structure or function. This indicates that alcohol affects the brain functioning and hence results in changes in covariance matrices of the two classes.

It is observed that the channel pair "FP1" & "PO1" were responsible for the maximum mean accuracy of 87.6%. "FP1" electrode captures information from Prefrontal cortex, specifically fronto-polar area 10(FPA10). This region is innervated by the Anterior Cingulate Cortex (ACC). In the study by [24], it has been seen that binge alcoholics develop thinning of ACC while Parieto-Occipital Sulcus (region near "PO1" electrode placement) is unaffected. This thinning of ACC affects functioning of FPA10 which in turn is reflected in the EEG obtained at "FP1". Thus the channel pair "FP1" & "PO1" provide significant difference in the characteristics of alcoholics from control.

V. Conclusion

In order to understand differences in spatial inter-dependencies among brain regions, the utility of Riemann geometry has been illustrated. Riemann geometry framework based classification has been described to distinguish between EEG from "alcoholics" versus "Controls". EEG channel pairs were empirically chosen and their respective covariance matrices were computed. Two scenarios of classification framework were carried out. In the first scenario, the calculated covariance matrices were given as features to fgMDM classifier for classification in the manifold. Maximum mean accuracy of 82.8% was obtained with covariance matrices of channel pair "AF2" & "P6". In the second scenario, the calculated covariance matrices were mapped into tangent space using logarithm mapping and converted to tangent vectors. These vectors were then used as features for the SVM classifier with radial basis function kernel. Here, it was observed that a maximum mean accuracy of 87.6% was obtained for the channel pair "FP1" & "PO1". The significant changes in inter-dependencies across frontal and posterior lobes, evident in the classification performance, illustrates the promise in Riemann geometry based framework for studying subjects who have been exposed to brain altering situation.

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