NONLINEAR CLASSIFICATION OF EEG DATA FOR SEIZURE DETECTION

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ABSTRACT

We address the problem of classification of EEG recordings for the detection of epileptic seizures. We assume that the EEG measurements can be described by a low dimensional manifold. The geometry of the manifold is typically nonlinear and can be recovered with the Laplacian Eigenmaps method. Our experiments demonstrate that the manifold can reveal the intrinsic structure of the data and that baseline and ictal states are well separated. We use a Kernel Ridge Regression to identify the boundary between ictal and baseline states. We have performed a quantitative evaluation of our new approach using an acute rat model of epilepsy. Our experiments show that our approach outperforms PCA combined with a kernel ridge classifier.

1. INTRODUCTION

Modern electroencephalogram (EEG) systems can record from multiple channels (64 to 128 electrodes) the electrical activity on the scalp. In this paper we address the problem of classification of EEG recordings for the detection of epileptic seizures. The detection of epileptic seizures by clinicians is still often based on the visual inspection of the EEG recordings. Seizures give rise to changes in certain frequencies bands. Recent work has focused on the analysis of the θ (3.5 - 7.5 Hz) and the α (7.5 - 12.5 Hz) rhythms and their relationship to epilepsy. Time-frequency methods, such as the Gabor and wavelet transforms, have been used to detect the onset of seizures [1, 2]. Nonlinear techniques such as the correlation dimension have also been proposed to detect the onset of an epileptic seizure [3]. Correlation dimension provides a measure of the complexity of a system in terms of its intrinsic number of degrees of freedom (the number of parameters needed to describe the state of the system). In [3], it has been shown that the correlation dimension decreases during the ictal (seizure) state. This decrease in dimensionality may be indicative of the synchronization occurring on the neurons during a seizure. Despite the fact that this technique provides an estimate of the intrinsic dimensionality of the data, it is not able to construct a lower dimensional representation of the dataset.

In this work, we consider the D dimensional vector $X(t)$ formed by the measurements on the D electrodes at a given instant t. The dimensionality, D of $X(t)$ is typically of the order of 64 to 128. Classification in such a high dimensional space requires a very large number of training samples [4]. While a large number of microscopic variables are involved in the generation of the EEG signal, many of these variables are coupled and the intrinsic dimensionality of the EEG recording is probably lower than D. In this work, we assume that the measurements $X(t), t = 1, 2, ..., T$ lie on a smooth manifold of dimensionality $d << D$. Each point on that manifold corresponds to a particular set of measurements on the electrodes. Our assumption is that EEG recordings associated with seizure and normal states will lie in different regions of the manifold. Our experiments show that this hypothesis is valid. The goal of this work is to reconstruct the underlying manifold and use it to train a classifier that can discriminate between ictal and normal states.

2. GENERAL OVERVIEW OF THE APPROACH

The main problem attacked in this work is the classification of a EEG recording $X(t)$ at a given time t into one of the two classes: (1) ictal state or (2) baseline state. Our goal is train a classifier using time samples extracted from ictal and baseline states. Formally, we consider the D dimensional vectors $X_b(t)$ for $t = 1, .., T$ of EEG recordings obtained in a baseline state. In a similar manner, let $X_i(t)$ for $t = 1, .., T$ be a set of recordings acquired in the ictal state. Our nonlinear classifier will be trained using the two datasets

$$\mathbf{X}_b = [X_b(1)|...|X_b(T)], \qquad \mathbf{X}_i = [X_i(1)|...|X_i(T)].$$

The EEG vectors $X(t)$ live in $\mathbb{R}^D$. Because of the curse of dimensionality the number of training samples needed to classify in $\mathbb{R}^D$ is extremely large. It becomes critical to reduce the dimensionality prior to classification. The linear subspace reconstructed by Principal Component Analysis (PCA) does not result in high classification accuracy results (as shown in our experiments) with EEG recordings.

We assume that the EEG measurements can be described by a low dimensional manifold. The geometry of the manifold is typically nonlinear and can be recovered with several different techniques. In this work, we use the Laplacian Eigenmap method [5] to reconstruct the underlying manifold from the training samples $\mathbf{X}_b$ and $\mathbf{X}_i$. We can then find the coordinates of any new recording $X(t)$ on the manifold. The dimensionality, d, of the manifold is much smaller than the dimensionality of the ambient space, D, and therefore if we perform the classification directly on the manifold we expect to obtain better performance with the same number of training samples. Our hypothesis is that the manifold can reveal the intrinsic structure of the data and that baseline and ictal states will be well separated. We propose to use a Kernel Ridge Regression to identify the boundary between ictal and baseline states. The classification algorithm is described below.

Classification Algorithm

1) Consider baseline and ictal time series $\mathbf{X}_b, \mathbf{X}_i$ of size $(D \times T)$, and construct $\mathbf{X} = [\mathbf{X}_b|\mathbf{X}_i]$ matrix
2) Construct adjacency matrix, A, from $\mathbf{X}$
   a) $A_{i,j} = \begin{cases} \sum_k W_{k,i} & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$
   b) Weights $W_{i,j} = \exp(-\|X(i) - X(j)\|/(2\sigma^2))$ where $X(i,j)$ are columns i, j of $\mathbf{X}$
   c) Vertices = column k of $\mathbf{X} = X(k)$
   d) Edges defined by k-nearest neighbors
3) Find the Laplacian matrix, L
   a) $L_{i,j} = A_{i,j} - W_{i,j}$
4) Find the eigenvectors $\{\phi_1, ..., \phi_d\}$ of $L\phi_k = \kappa_k A\phi_k$
5) Project the training data on the manifold using (4)
6) Train the Kernel Ridge classifier on the manifold

In the next two sections we describe the reconstruction of the manifold on which the EEG data lie and the classification technique that we apply on the manifold.

3. RECONSTRUCTION OF THE EEG MANIFOLD

We do not have access to a representation of the EEG manifold but we can use the samples to approximate it. We build a graph that should provide a good approximation to the geometry of the manifold. The vertices of the graph are the sample points, $X(t)$ formed by the columns of $\mathbf{X}$, and the edges define the proximity on the underlying manifold. We connect vertices using the k-nearest neighbors approach: the nodes i and j are connected by an edge if i is among the k-nearest neighbors of j. We assign a weight, $W_{i,j}$, to the edge between the nodes i and j. The weights are given by

$$W_{i,j} = \exp(-\|X(t_i) - X(t_j)\|/(2\sigma^2)). \tag{1}$$

Once the connected graph is constructed, we compute the Laplacian, L, on the graph as defined by $L = A - W$, where the adjacency matrix, A, is defined above. We then compute the eigenvectors, $[\phi_1, ..., \phi_D]$ solution to the following eigenvalue problem

$$L\phi_k = \kappa_k A\phi_k, \tag{2}$$

where κ_k is the corresponding eigenvalue. As is explained in [5, 6], the eigenvectors, $\phi_1, ..., \phi_D$, provide the optimal embedding of the manifold. The mapping defined by

$$X \to \Phi(X) = [\phi_1|...|\phi_D]^T(X)$$

preserves the Euclidean distance locally by minimizing the following distortion

$$\sum_{ij} ||\phi_i - \phi_j||^2 W_{ij} = tr(\Phi^T L\Phi). \tag{3}$$

The vector ϕ that minimizes (3) is provided by the lowest non-trivial eigenvalue solution of the generalized eigenproblem in (2). The reduction of dimensionality is achieved by defining the mapping from $\mathbb{R}^D \to \mathbb{R}^d$ as follows

$$X(k) \to \tilde{X}(k) = \text{col } k \text{ of } \tilde{\Phi}(X) = [\phi_1|...|\phi_d]^T(X). \tag{4}$$

4. CLASSIFICATION ON THE MANIFOLD

We project the training data $\mathbf{X}_b$ and $\mathbf{X}_i$ using the mapping defined by (4) and we use the projections $\tilde{\mathbf{X}}_b$ and $\tilde{\mathbf{X}}_i$ to train a Kernel Ridge classifier. A new EEG recording $X(t)$ can be classified by first projecting $X(t)$ on the manifold and using the classifier to determine the status, ictal vs. baseline, of $X(t)$. Note that the mapping (4) is only defined for the training samples, we can extend it by interpolating around the nearest neighbors of $X(t)$ in the training data. We use M-fold cross validation on the set of available training data to estimate the optimal learning parameters for the Kernel Ridge Regression. This method randomly partitions the dataset into $M = 10$ disjoint sets [7]. We used 90% of $\mathbf{X}_b$ and $\mathbf{X}_i$ to train the classifier and the remaining 10% to validate. The estimated outputs label, $\hat{y}$, for an EEG measurement $X(t)$ is given by

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{N} K(\tilde{\mathbf{X}}(t_i), \tilde{X}(t)). \tag{5}$$

We use a Gaussian kernel for K. For the purpose of the cross validation, we define a classification error if a training sample in $\mathbf{X}_b$ is classified as belonging to the ictal class, and viceversa.

5. EXPERIMENTS

In this work several datasets were analyzed, however, due to space constraints only one will be reported here (more experiments can be found in [8]). The EEG data used were collected from an acute rat model of epilepsy with 64 silver electrodes placed on a scalp 8×8 grid. The data were sampled at 2 kHz.

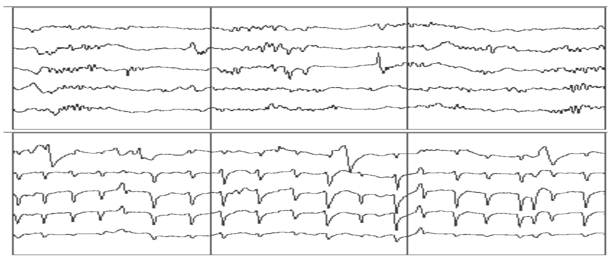

Fig. 1. Top: Five baseline channels, Bottom: Five ictal channels

For the purposes of training information, the EEG recordings have been labeled as baseline and ictal by a neuroscience expert. Two out of the 64 channels were removed due to the presence of artifacts. As a pre-processing step the time series were filtered using a 15^{th} order Chebyshev filter with cutoff frequency of 100 Hz. The selection of this cutoff frequency was based on the maximum bound of frequency rhythms discussed in [1]. Five representative time series from ictal and baseline states are shown in Fig.1.

The set of training data consists of the concatenation of $\mathbf{X}_b$ and $\mathbf{X}_i$ with $T = 1430$, $N = 2T$, and $D = 62$. From this set 90% of the samples were used as a training set and a lower dimensional representation was constructed using either the Laplacian Eigenmaps or PCA. Each class, ictal and baseline, contained the same number of samples. The resulting maps are shown in Fig.3 and Fig.5. In these figures, each of the points on the manifold represent an EEG recording with dimensionality d, at a given time, t. Each color is representative of the class label. The true labels are shown for the ictal and baseline class, gray and black, respectively. A black label where originally it was gray represents a sample in $\mathbf{X}_i$ that has been misclassified, and viceversa for $\mathbf{X}_b$. Note that PCA is unable to partition the data into ictal state and baseline state, whereas the Laplacian Eigenmaps reveals the organization of the dataset into ictal and baseline. We expect therefore, that the classification on the manifold reconstructed by the Laplacian Eigenmaps will outperform the classification based on the projection of the subspace discovered by PCA.

For this dataset the minimum error on cross-validation was obtained by keeping $d = 10$ eigenvectors, and choosing the ridge parameter $\lambda = 0.1$. The width of the Gaussian kernel for the weighted adjacency graph was $\sigma_A = 0.6$, and the width of the Gaussian kernel for the regression was $\sigma_R = 0.05$. We used $k = 5$ nearest neighbors to construct the adjacency graph. The performance of these algorithms was measured by calculating the mean square error.

Figures 4 and 6 show the outcome of the classification for the validation set (10 % of the $N = 2860$ samples) using PCA and the Laplacian Eigenmaps for dimensionality reduction. After using the manifold for reducing dimensionality most of the points are properly labeled. This is not the case when PCA is used to reduce dimensionality; a large number of points are misclassified. Table 1 provides quantitative evaluation of the performance of the classification. For reference purposes we have also included the classification accuracy when the classification is performed directly on the raw data. Clearly, the reduction of dimensionality provided by the Laplacian Eigenmaps results in the optimal performance. This fact can be explained by observing ϕ_2 the first non-trivial eigenvector of L shown in Fig. 2. ϕ_2 behaves as an indicator function on the set of training data: it is positive for the ictal states and negative for the baseline states.

Table 1. Percentage of Classification Accuracy using Gaussian Kernel Ridge Regression

	Baseline Class	Ictal Class	Total
Raw Data	78.32	68.53	73.43
PCA Projection	91.04	64.18	77.61
Laplacian Manifold	98.51	97.01	97.76

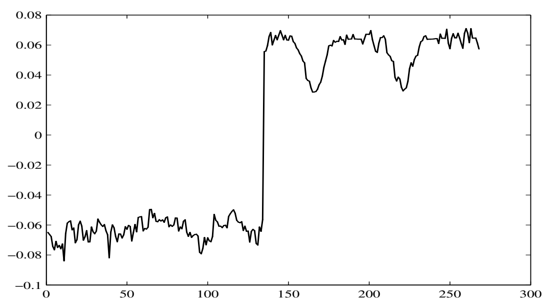

Fig. 2. First non-trivial eigenvector, ϕ_2, of the Laplacian

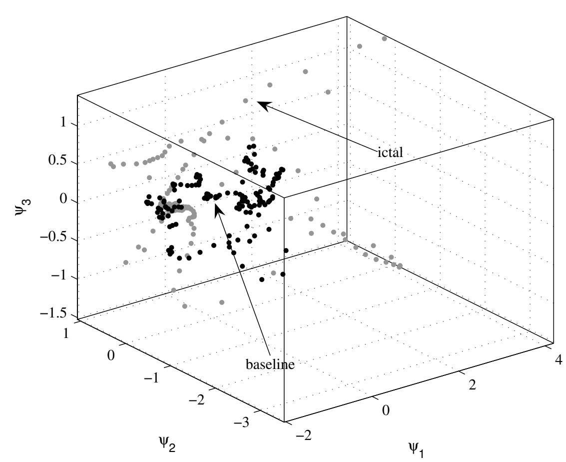

Fig. 3. True labels on the PCA subspace (gray=ictal, black=baseline)

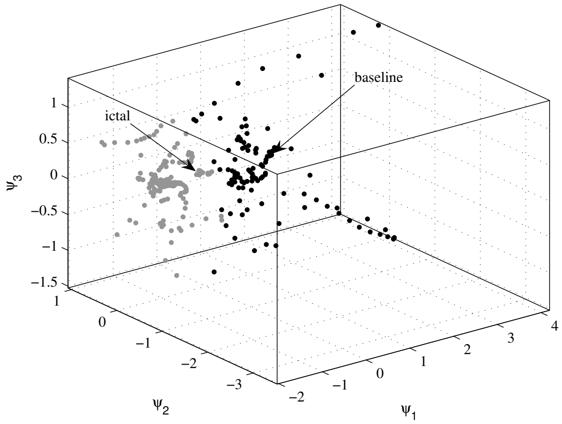

Fig. 4. Result of classification on the PCA subspace

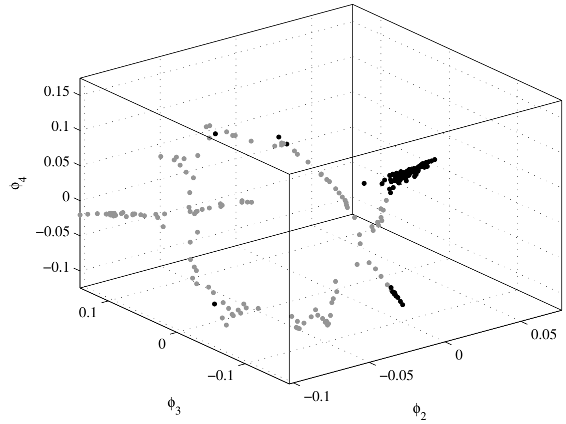

Fig. 6. Result of classification on the manifold

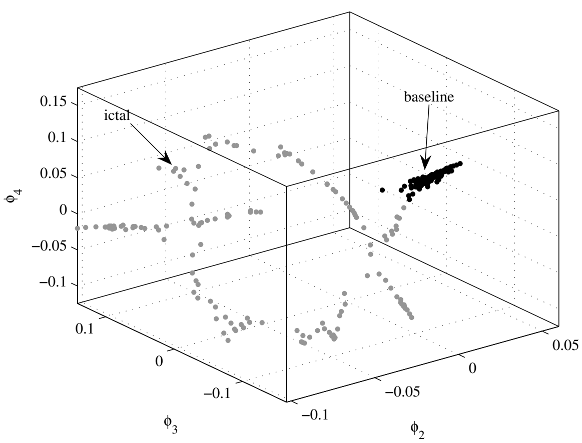

Fig. 5. True labels on the manifold (gray=ictal, black=baseline)

6. CONCLUSION

We have presented in this paper a new approach to classify EEG time series. We have shown that the eigenvectors of the Graph Laplacian provide a natural low dimensional representation for the dataset. The projection of the ictal and baseline states on the manifold are well separated. We have used a kernel ridge classifier to find the optimal boundary between and ictal and baseline states on the manifold. We have performed a quantitative evaluation of our new approach using an acute rat model of epilepsy. Our experiments show that our approach outperforms PCA combined with a kernel ridge classifier. This fact can be seen in the significant increase on the detection accuracy.

7. ACKNOWLEDGEMENTS

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8. REFERENCES

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