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Dimensionality Reduction of Brain Imaging Data Using Graph Signal Processing.

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ABSTRACT

Mind imaging information, for example, EEG or MEG is high-dimensional spatiotemporal estimations that normally require dimensionality decrease before being utilized for further investigation or applications. This paper introduces another dimensionality decrease technique in view of the late chart signal preparing hypothesis. In particular, we concentrate on an errand to order the cerebrum imaging signals recording the cortical exercises in light of visual boosts. We propose to utilize the resting-state estimations (i.e., before onset of the boost) of the subjects to manufacture a network chart. The diagram Laplacian and Graph-Based Filtering (GBF) are then connected to take in the low-dimensional straight subspace for the errand state estimations.

Keywords: Brain imaging, Dimension reduction, Graph based filtering, Graph signal processing.

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INTRODUCTION

Automatic analysis of brain imaging data is an important topic in both neuroscience and brain computer interface (BCI) technology. In many cases, the task is to find the spatiotemporal neural signature of a task, by performing classification on cortical activations evoked by different stimuli [1, 2]. Common brian imaging techniques are Electroencephalography (EEG) and Magnetoencephalography (MEG). In particular, MEG measures the magnetic fields produced by electrical activity in the brain via extremely sensitive sensors distributed across the scalp. These measurements are highdimensional spatiotemporal data. For instance, in our experiments, we use a recumbent Elekta MEG scanner with 306 sensors to record the brain activity for 1100 milliseconds. Furthermore, the measurements are degraded by various types of noise (e.g., sensor noise, ambient magnetic field noise, etc.) and the overall noise is difficult to model (potentially non-Gaussian). The high-dimensionality and noise limit both the speed and accuracy of the signal analysis, that may result in unreliable signature modeling for classification. The high-dimensionality of these signals also increases the complexity of the classifier. Combination of a complex classifier and availability of few data samples (due to time, cost, or study limitations) can easily lead to an overfit model. Thus, for a reliable study of brain imaging data, there is a need for a robust dimensionality reduction method that ensures inclusion of task-related information in the transformation process.

Dimensionality reduction transforms the data in the highdimensional space to a space of fewer dimensions with a linear or nonlinear method. The commonly employed PCA is a classical approach to perform a linear mapping of the data in a way that the variance of the data in the low-dimensional representation is maximized. In addition to PCA, methods such as linear discriminant analysis (LDA), locality preserving projections (LPP), marginal Fisher analysis (MFA), and their numerous variants also serve as linear methods of dimension reduction (see [3] for details). Many nonlinear methods have also been proposed for dimensionality reduction. Self-organizing maps and other neural network-based approaches set up nonlinear optimization problems to learn the low dimensional manifolds (e.g., autoencoder [4]). Laplacian eigenmaps (LE) [5] and diffusion maps [6] capture the geometric structure of manifold to help map the data points into a lower dimensional space.

In this work, we propose to apply the recent graph signal processing theory [7] and a graph based filtering algorithm (GBF) for dimensionality reduction, and investigate techniques to construct the connectivity graph suitable for brain imaging. Compared with existing dimensionality reduction approaches, the distinctiveness of the GBF-based approach is that it can use the underlying graph model (if exists) as side information to help reduce the dimensionality in a more robust manner. We hypothesize that when the measurements are degraded and noisy, the side information (modeled as graph) may contain more accurate correlation information than the measurements. Thus, by leveraging the graph, we may learn a more accurate low-dimensional subspace. This is different from previous work that uses *solely* the measurements to learn the low-dimensional subspace / manifold (e.g., PCA, Laplacian eigenmaps).

Therefore, here we propose to perform connectivity analysis on the resting-state brain imaging signals (i.e., when a subject is not performing an explicit task). Then, we compute the graph Laplacian of this resting-state connectivity graph, and use its dominant eigenvectors to form the low-dimensional subspace. Subsequently, we project the noisy task-state measurements (evoked by visual stimuli) to this low-dimensional subspace to reduce the dimensionality of the signals. The reduced-dimensional signals are then subject to a SVM classifier to assess their inclusion of task-related discriminative information.

This work is inspired by [8], which uses GBF to learn a “normal” linear subspace for anomaly detection in wireless sensor networks. In [8], measurements that are deviated from the normal subspace are deemed to be abnormal. GBF has also been shown to be useful in image compression [9] and temperature data [10]. A few signal features motivated by graph signal processing have been proposed [11, 12]. In [13], graph Fourier transform is applied to decompose brain signals into low, medium, and high frequency components for analysis of functional brain networks properties. Our work focuses on linear dimensionality reduction and directly uses a few projections onto the graph Laplacian eigenvectors as the feature. We investigate the usefulness of this approach in a supervised classification task of brain image signals. The proposed GBF-based approach is also different from Laplacian eigenmaps [5]. Laplacian eigenmaps use *solely* the measurements to learn the low-dimensional manifold. There is no notion of side information in Laplacian eigenmaps. The idea and mechanism to produce low-dimensional representations is also different.

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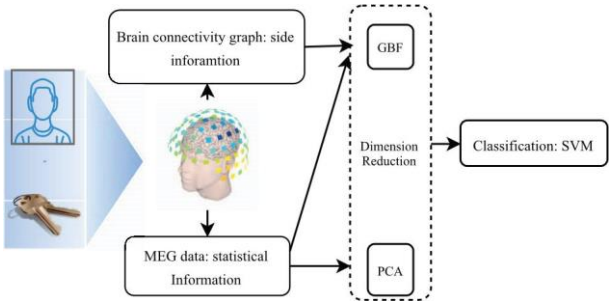

Fig. 1: MEG experimental setup for application of dimensionality reduction.

SET UP OF THE EXPERIMENT

In order to systematically evaluate performance of different techniques in dimensionality reduction, we use two sets of data, synthetic and real MEG data.

In our synthetic data, we generate spatiotemporal signals with both Gaussian and non-Gaussian noise. The synthetic signal H_t therefore consists of two components, signal S_t and noise N_t:

$$H_t = S_t + N_t \qquad (1)$$

where S_t is the signal vector and N_t is the noise vector, H_t, S_t, and N_t are defined in R^m.

We generate S_t based on the graph information. The graph consists of m nodes, with each pair of nodes with a probability of p to be connected together. The edge weights between different nodes are drew from 0 to 1 with uniform distribution, that are represented in an $m \times m$ symmetric adjacency matrix W. We then perform decomposition of the Laplacian matrix L (details in Section 3) to reach eigenvectors $f_i \in R^m$. We assume S_t is generated as follows:

$$S_t = \beta \sum_{i=1}^{\lfloor k/2 \rfloor} a_{t,i} f_i + \gamma \sum_{i=\lfloor k/2 \rfloor + 1}^{k} a_{t,i} f_i \qquad (2)$$

where β and γ are the scalar weight for components, f_i is the i-th eigenvector of L, k is the number of eigenvectors used to generate signal, and $a_{t,i} (1 \le i \le k)$ is a uniform random variable in range $[0,1]$ [14]. For the sake of the binary classification scheme, we change the values of β and γ to produce different classes.

For noise component, we generate three kinds of noise: white noise with Gaussian distribution, white noise with uniform distribution, and sparse white noise. For sparse white noise, we randomly choose $e\%$ nodes among m nodes and add uniformly distributed noise to their respective signal to reach the final high dimensional data H_t. The final data consists of n temporal samples: $[H_1, H_2, \ldots H_n]$.

In addition to the synthetic data, we propose a experiment of classifying the MEG signals recording the brain activities in response to two categories of visual stimuli: face and object. There are 16 subjects in the experiment. As depicted in Figure 1, MEG signals from 306 sensors have been recorded as 16 subjects were randomly exposed to 320 face images and 192 non-face images. The recording started 100ms before the stimuli presentation and continued for 1 second after the presentation of the stimuli (i.e. 1100ms in total). Each stimuli was presented for 300ms at the center of the screen and the subjects were instructed to look at each stimuli with minimal movement. There were no (behavioral) responses required by the subjects.

We apply PCA, LDA, LE and our GBF to reduce the dimensionality of these two set of data and use SVM to classify whether the subject views faces or objects. The performance is judged by the classification accuracy.

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GBF-BASED DIMENSIONALITY REDUCTION

We propose to apply GBF for dimensionality reduction with three steps: pre-processing, decomposition and projection.

In(the pre)-processing step, we need to construct the graph

G N,ε,W based on the application or data itself. In the graph *G*, *N* represents the nodes or sensors in the graph and *ε* represents the edges connecting the nodes. Based on the graph *G*, we can calculate the adjacency matrix *W*, which shows edge weights between different nodes. There are many ways to compute *W*. Here is a commonly-used method:

$$w_{i,j} = exp(-\frac{(1-\|\rho(i,j)\|_1)^2}{2\sigma_1^2}) \cdot exp(-\frac{d(i,j)^2}{2\sigma_2^2}) \qquad (3)$$

where *ρ*(*i,j*) = *ci,j/*(√*ci,icj,j*) is the correlation()∈coefficient[01] using elements of the covariance matrix *C*. *d i,j* , represents the normalized Euclidean distance between sensor *i* and *j*. *σ*1 and *σ*2 are exponential decay rates [8]. Later, we also describe other techniques to determine *W* suitable for brain imaging data.

In the decomposition step, we first calculate the normalized Laplacian matrix *L* by L = I− $D^{-\frac{1}{2}}$WD$^{-\frac{1}{2}}$, where D is the diagonal degree matrix of $D_{ii} = \sum_{.i} w_{ii}$. Then we decompose *L* using L =(U)**Λ**U^T where U is the matrix consisting of eigenvectors u*l* *l*=1,...,*N* and the diagonal elements in **Λ** are related eigenvalues. The cut - off frequency is found by sorting the eigenvalues from higher to lower. The eigenvectors whose eigenvalues are larger than the cut-off frequency are used for building the subspace.

In the projection step, original data is projected onto the subspace to obtain the lower dimensional data.

EVALUATION ON SYNTHETIC DATA

In this section, we compare the performance of GBF, PCA and LDA on dimensionality reduction of noisy synthetic data. We use a binary SVM classifier on the output of each method, and compare the results in different cases of noise. We here show that GBF is more robust than other compared techniques, especially when the signal noise is non-Gaussian.

We use the synthetic data model in Section 2 to generate $n = 300$ data samples for each class with $m = 100$ nodes in the graph where each pair has a probability $p = 0.3$ connecting together. For signal part, we use top $k = 8$ eigenvectors of L as signal generating components and set $\beta_1 = 4$, $\gamma_1 = 2.5$ for one data class and $\beta_2 = 2.5$, $\gamma_2 = 4$ for the other. For noise component, all three types of noise have mean $\mu = 0$ and variance $\sigma^2 = 1/6$. We then apply GBF, PCA and LDA on the synthetic data to decrease

	Gaussian noise	White uniform noise	Sparse white noise
GBF	0.8564	0.8718	0.8744
PCA	0.8641	0.8564	0.8590
LDA	0.8385	0.8436	0.8333
Orignal	0.8692	0.8718	0.8564

Table 1: Classification accuracy with synthetic data

the dimensionality from $m = 100$ to 8. As for the GBF, we use (3) with parameters $\sigma_1 = 0.2$ and $\sigma_2 = 0.9$ to estimate the adjacency matrix W. We perform 10-fold cross validation and compare the SVM classifier performance. Table 1 presents the classification accuracy using each technique with $SNR = 25dB$ for white noise and $SNR = 25dB, e\% = 5\%$ for sparse white noise. Based on these results, in

existence of Gaussian noise, PCA performs better. It is because Gaussian data has no higher order statistics beyond variance. Thus, PCA is efficient to model Gaussian data. However, when it comes to the non-Gaussian noise, GBF performs better than any other methods.

We further analyze the robustness of GBF under different levels of signal to noise ratio (SNR = $10dB$ to SNR = $60dB$) for the white noise. Figure 2(a) indicates that as the SNR increases (i.e. more than 25dB), GBF outperforms the other two methods, and even has better performance than the original data. We also assess the performance under different percentages of noise (SNR = $25dB$, e = 1% to e = 50%) for the sparse white noise. The second set of results illustrated in Figure 2(b) indicate that GBF mostly performs either better or as good as PCA with different levels of sparsity in the noise. After analysis of the synthetic data, we proceed to use real MEG data for final evaluation, in the Section 6.

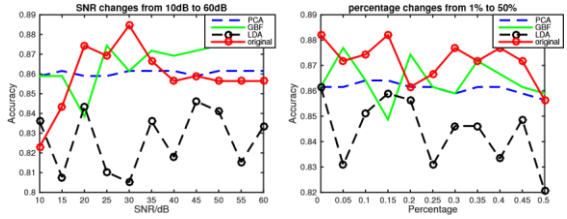

Fig. 2: Comparison of classification accuracy: (a) White noise (uniform distribution) with SNR from 10dB to 60dB. (b) Sparse white noise with SNR=25dB and the ratio of noisy nodes from 1% to 50%.

BRAIN CONNECTIVITY ANALYSIS

In application of GBF to brain signal processing, one of the most important problems is to find a suitable connectivity graph. Our brain can be considered as a complex network [15] which is so complex that the sophisticated analysis techniques are needed. Neuroscientists have suggested three different brain connectivities: structural connectivity, functional connectivity and effective connectivity, which can be used as the graph for GBF. Structural connectivity describes the physical connections in the brain. Functional connectivity quantifies functional dependencies between different brain regions. Effective connectivity presents directed influence or causal relationship between neuronal system components [16]. In this paper, we investigate four different connectivity analysis to build the graph for GBF: three functional connectivity analysis and one effective connectivity analysis. In each case, we analyze the restingstate recordings (measurements before the onset of the stimulus) to build the connectivity graph, and we use this resting-state connectivity graph to model the task-state measurements (after the onset of the stimulus). Given the resting-state sensor measurements (time-series signals) at two spatially=1-separated2 brain regions: *X* and *Y* written as *xt* and *yt* for *t* , ,..,*T*, we discuss how to compute the edge weight *wx,y*.

Correlation connectivity

Correlation is a basic estimation for statistical dependency for function connectivity [17]. We consider the correlation coefficient between *X* and *Y* as the edge between these two regions:

$$w_{x,y} = \frac{\sum_{t=1}^{T}(x_t - \bar{x})(y_t - \bar{y})}{(T-1)s_x s_y} = \frac{\sum_{t=1}^{T}(x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^{T}(x_t - \bar{x})^2 \sum_{t=1}^{T}(y_t - \bar{y})^2}}$$

(4)

where x^- and y^- are the sample mean of *X* and *Y* . *sx* and *sy* are sample standard deviation of *X* and *Y* .

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Coherence connectivity

Coherence connectivity is a functional connectivity, quantifying oscillatory interdependency between different brain regions. It is the frequency domain analog of the cross-correlation coefficient. Given two series of signals $x(t)$, $y(t)$ and a frequency f, the first step is to spectrally decompose the signal at target f to obtain the instantaneous phase at each time point [18]. After band-pass filtering each signal between $f \pm 5Hz$, the convolution of $f(t)$ with a Morlet wavelet centered at frequency f provides the instantaneous phase at time t. Thus, the two signals can be represented as: $x = A_x(t)e^{j\varphi_x(t)}$ and $y = A_y(t)e^{j\varphi_y(t)}$, where $A_x(t)$ and $A_y(t)$ are amplitudes. $\varphi_x(t)$ and $\varphi_y(t)$ are the phase for X and Y at time t. Then the coherence connectivity edge is calculated as below:

$$w_{x,y} = \left| \frac{\frac{1}{T}\sum_{t=1}^{T} A_x(t)A_y(t)e^{j[\phi_x(t)-\phi_y(t)]}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} A_x(t)^2} \cdot \sqrt{\frac{1}{T}\sum_{t=1}^{T} A_y(t)^2}} \right|$$

Phase locking value (PLV) connectivity

The phase locking analysis applied to MEG has been described in several articles [19] [20]. The PLV is a measure of the phase synchrony between two time-series signals at a given frequency. Compared with coherence connectivity, PLV separates the amplitude effects from the consistency of the phase difference [19]. So the previous calculation procedure are the same as coherence connectivity. After we get $x = A_x(t)e^{j\varphi_x(t)}$ and $y = A_y(t)e^{j\varphi_y(t)}$, the PLV connectivity edge between region X and Y is then defined as timeaveraged value:

$$w_{x,y} = \left| \frac{\frac{1}{T}\sum_{t=1}^{T} 1 \times 1 e^{j[\phi_x(t)-\phi_y(t)]}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} 1^2} \cdot \sqrt{\frac{1}{T}\sum_{t=1}^{T} 1^2}} \right| = \frac{1}{T}\left| \sum_{t=1}^{T} e^{j[\phi_x(t)-\phi_y(t)]} \right| \quad (6)$$

Granger causality connectivity

Granger Causality captures the causality relationship between two regions in both directions and at different frequencies, which inspects directed interactions of neural assemblies. The Granger causality, at each frequency, is defined by the ratio of predicted power to total power [21]. To show the prediction of the signal from one region by taking into consideration the past of the signal of the other region, univariate and bivariate AR models are fitted to the regions X and Y. For univariate AR model, the prediction error depends only on the past of the own signal [22]:

$$\sum_{k=0}^{m} a_{1k}x(t-k) = u_1(t)$$
$$\sum_{k=0}^{m} b_{1k}y(t-k) = v_1(t) \quad (7)$$

For bivariate AR model, the prediction of a signal is based on the past of its own and also on the past of the other signal:

$$\sum_{k=0}^{m} a_{2k}x(t-k) + \sum_{k=1}^{m} c_{2k}y(t-k) = u_2(t)$$
$$\sum_{k=0}^{m} b_{2k}x(t-k) + \sum_{k=1}^{m} d_{2k}y(t-k) = v_2(t) \quad (8)$$

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In both cases, the u_1,u_2,v_1,v_2 are the temporally uncorrelated residual errors. a_1,b_1,a_2,b_2,c_2,d_2 are model coefficients. The accuracy of prediction is expressed by the variance of the prediction errors:

$$\Sigma_{X|X_-} = var(u_1), \Sigma_{Y|Y_-} = var(v_1) \quad (9)$$

$$\Sigma_{X|X_-,Y_-} = var(u_2), \Sigma_{Y|Y_-,X_-} = var(v_2)$$

The Granger causality of Y to X and X to Y as measures of linear feedback between two signals are defined by [23]:

$$GC_{Y\to X} = ln\frac{\Sigma_{X|X_-}}{\Sigma_{X|X_-,Y_-}}$$
$$GC_{X\to Y} = ln\frac{\Sigma_{Y|Y_-}}{\Sigma_{Y|Y_-,X_-}} \quad (10)$$

PCA	0.6688	21
LDA	0.6690	1
LE	0.6296	21
Original	0.6708	306

Because GBF requires symmetric matrix as adjacency matrix, we compute the maximum value of both terms as the final Granger causality connectivity edge for the strength of interaction:

$$w_{x,y} = max(GC_{Y\to X}, GC_{X\to Y}) \quad (11)$$

EVALUATION ON MEG DATA

We test our algorithm with real MEG data from the experiment described in Section 2. First, we test all types of connectivity graphs, generated with resting state measurements (100ms before the stimuli appears), listed in Section 5 for GBF on the real data and find the one with the best performance which will be applied in the subsequent experiments. Then we compare the dimension reduction performance among different algorithms: GBF, PCA, LDA and LE. We use a MATLAB open source toolbox *BrainStorm* to compute the connectivity graphs [24]

.

Method	Accuracy	Data Dimension
GBF(GCC)	0.6800	21

Table 2: Classification accuracy with MEG data

Comparison between different graphs

In this experiment, we only apply GBF with different kinds of connectivity graph on the brain signal data to reduce its dimension. We use the brain signal data from 96ms to 110ms after the stimuli appears for the experiment. We choose 96ms to 110ms because cortical activities in this duration have been shown to contain rich discriminative information [2]. We use a 20ms-long sliding window for one time accuracy calculation, average the data over time and obtain a 306 dimensions vector. Step length is 1ms.

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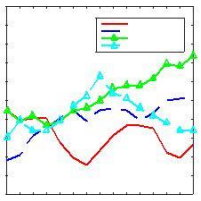

Fig. 3: Comparison of different connectivity graphs for GBF

Figure 3 shows that GBF with Granger Causality connectivity (GCC) topology gives the best overall performance. Therefore, we choose this connectivity as our graph in the following experiment.

Comparison of GBF, PCA and LDA

In this experiment, we use a 20ms-long window (average the data over time and obtain a 306 dimensions vector), set the step length to 1ms. GBF, PCA, LDA and LE are applied to decrease the dimension. We also compare the results with the one without dimension reduction. For classification, we apply SVM as the classifier and average the accuracy over time as the final results. We use 10-fold cross validation and report the average classification accuracy. According to Table 2, the performance of GBF is better than PCA when the dimensionality is reduced from 306 to 21.

CONCLUSION

Graph-based filtering (GBF) is a promising signal processing technique when the data at hand can be modeled as a graph. The graphbased representation of cortical processes has been studied in both functional and structural connectivity graphs. In this work we therefore proposed and evaluated application of GBF dimensionality reduction on brain imaging data. Based on our experimental results on synthetic data and MEG data and in different levels of noise, GBF can maintain more information in the process of dimensionality reduction, due to the use of graph-based side information. This is more evident when the signal contains non-Gaussian noise, such as the brain imaging data. In our future steps we aim to address the complexity of GBF and its employment in real-time applications.

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