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Screening of autism spectrum disorder based on task-free fMRI using tensor decomposition approach

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Abstract

In recent decades, autism spectrum disorder (ASD) has displyed an incremental prevalence rate. Due to unavailability of a definite cure, the early diagnosis of the disorder is of high significance. There are evidences suggesting the dimcriminatable differences between resting state networks of people who suffer from the disorder and healthy individuals. This distinguishability allows for utilization of fMRI imaging to perform as a good instrument for identification autism spectrum disorder. In this paper, a tensor decomposition method for diagnosis of autism form fMRI images is presented. The selected dataset for testing the performance of the proposed algorithm is ABIDE1. All site of the ABIDE1 are used for training the algorithm which is a challenging problem in fMRI data analyzing. Our proposed method successfully achieves the classification performance of about 60% for all site analysis.

Keywords: Autism spectrum disorder, Tensor decomposition, ABIDE.

1. Introduction

Autism spectrum disorder (ASD) is a neuro-developmental disorder that affects person's social communication skills and behavior. Prevalence Of ASD displays an incremental trend with 1 in 59 children diagnosed with the disorder, according to Centers for Disease Control and Prevention [1]. It inflicts heavy financial costs on governments [2] and adverses childrens' potential thrive opportunities

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by effectively influencing their social skills and causing misinterpretation of behavior and intentions [3, 4, 5, 6].

Similar to many neurological dysfunctions such as ADHD, Alzheimer's and schizophrenia, unavailability of definite cure makes the assessment of the disorder in its early stages a highly significant task. Taking into account the fact that symptoms of ASD in many cases can be observed in 12 to 18 months from birth and diagnosed reliably by the age of 2 [7], early identification can remarkably reduce the progression of the disease.

Some of the widely used traditional methods for diagnosis of ASD requires clinical in-person contact which involves the subject undergoing behavioral interviews and performing tasks that help the examiner measure their social skills [8].

The emergence of new of neuroimaging techniques has provided researchers with opportunities for approaching the neuro-developmental disorders more effectively. Of special interest is functional magnetic resonance imaging (fMRI) leverages blood oxygenation level to provide means for revealing activity in different areas of the brain. This can in turn be used for unraveling the underlying mechanisms behind certain brain functionalities and developing an understanding of how neuropsychiatric illnesses affects them. The relative adequacy of fMRI in terms of spatial resolution and non-invasivity, makes it a proper neuroimaging method for acquisition of brain activity data of awake human subjects. Resting state fMRI (rs-fMRI) which is used to study the activity of the brain during a task-negative state, has been shown to contain valuable data for diagnosing ASD [9, 10], as it holds information on functional brain networks that can be exploited to identify the subjects who suffer from the neurological disorder.

1.1. Statement of problem

Analysis of neuroimaging data, especially for the purpose of identification of neurological disorders, can be a data demanding process and challenging to deal with for many researchers who lack access to medical imaging equipments. Autism Brain Imaging Data Exchange [11] is one of the most well-known data-sets that addresses this problem. To overcome the abovementioned challenge, ABIDE provides researchers with large scale multi-site recordings of resting state fMRI data taken from healthy control subjects and patients diagnosed with ASD from around the globe. Exploitation of these massive amounts of inherently complex data requires employment of proper methods and algorithms that are able to extract meaningful information and patterns from them. Towards this purpose, many researchers has made efforts to put their knowledge form other relevant fields to use. Well known examples include methods that tackle the problem by leveraging machine learning and neural network based approaches [12].

Despite all the success that these methods have been able to achieve, especially in recent decade, they exhibit shortcomings that can be considered as their main disadvantages. As a start point, excessive need for large amounts of data in order for the classifier to gain the capability to distinguish the right class among the different categories can be mentioned. This in turn leads to high computation power requirements and makes the model prone to over-fitting which increases the unreliability of the discriminator. Lack of convenient support for generalization is also a drawback for these methods.

Tensors methods on the other hand, emphasize on properly addressing many of the drawbacks of these commonly used methods. Their enhanced interpretability, relatively low computational demands, high precision and less demand for data to reach the same accuracy levels are making them into competitive rivals for the previously mentioned methods.

In this work, we propose an algorithm based on tensor decomposition, an expression scheme for multidimensional data by means of mathematical operations and a set of often simple data containers,

for classification of ASD from resting state fMRI data, using ABIDE dataset as training data source.

1.2. A brief review of other methods existing in the literature

Taking into consideration the remarkable potential of brain imaging data, many has investigated the possibility of applying machine learning [13] and deep learning [14, 15] techniques to medical and neural imaging and in particular, magnetic resonance based imaging [16, 17].

In [18], authors use deep-auto encoder and hidden Markov model for investigation of underlying functional dynamics in rs-fMRI and using it as basis for identification of Mild Cognitive Impairment. [19] uses an auto-encoder with convolutional layers to predict relapse in heavy smoker subjects using fMRI data. A handful of machine learning techniques such as probabilistic independent component analysis (PICA) and sparse auto-encoders (SAE) on predefined brain regions are employed in [20] and a support vector machine (SVM) is applied for discrimination of ASD and healthy subjects.

Noteworthy attempts have also been made in neural network community regarding the related topics. [21] Combines feed-forward convolutional and long short-term memory (LSTM) recurrent deep networks for consideration of both spatial and temporal in diagnosis of ADHD.

In recent years, the priorly discussed advantages of tensor methods has motivated many to consider encouraging researchers to migrate from conventional neural networks to more interpretable tensor based methods by elaborating on tensor methods with special attention to application of these methods in machine learning and classification problems [22, 23] and by providing walkthroughs and examples on how neural networks can be equipped to deal with massive high dimensional data [24]. Similarly, [25] focuses on demonstrating the utilization of tensors as data structures in neural networks (known as tensor networks) and tensor decomposition as tools for alternative representations of data. Accordingly, many works exhibit successful employment of decomposition in various types of neural data [26] and for classification of neurological diseases such as Alzheimer's disease (AD) [27].

Aside from tensor networks, tensors are also used in functional connectivity based methods that try to approach the problem by inspecting the connections among different networks of the brain. [28] uses high order functional connectivity networks to capture the effect of interaction of multiple brain regions which can contribute to better diagnosis of ASD. Closely related, writers of [29] propose using tensor methods and tensor decomposition to account for dynamic nature of functional connectivity networks over time within the scope of neuroimaging. In [30] performance of various models of tensor decomposition on fMRI recordings for classification of neurodevelopmental disorders are explored.

2. Basics of tensor decomposition

In this section, we are going to present some basics of tensor decomposition that are needed in presented method. At first, it is necessary to define n-mode tensor-matrix multiplication. Then, a theorem is presented that supports the possibility of the method.

Definition 2.1. *[31] Let $\mathcal{A} \in \mathbf{R}^{I_1 \times \cdot \times I_N}$ and $\mathcal{F} \in \mathbf{R}^{I_n \times J_n}$. Then the n-mode tensor-matrix product of $\mathcal{A}$ and $\mathcal{F}$ is denoted by $\mathcal{A} \times_n \mathcal{F}$, and is defined as follows:*

$$(\mathcal{A} \times_n \mathcal{F})(i_1, \cdots, i_{n-1}, j_n, i_{n+1}, \cdots, i_N) = \sum_{i_n=1}^{I_N} \mathcal{A}(i_1, \cdots, i_N)\mathcal{F}(j_n, i_n).$$

Theorem 2.2. *(HOSVD) [32]. A n-th order tensor $\mathcal{A} \in \mathbf{R}^{I_1 \times \cdot \times I_N}$ can be written as the following product:*

$$\mathcal{A} = \rho \times_1 A^{(1)} \times_2 A^{(2)} \cdots \times_N A^{(N)},$$

where $A^{(1)} \in \mathbf{R}^{I_1 \times I_1}$, $A^{(2)} \in \mathbf{R}^{I_2 \times I_2}$, $\cdots$, $A^{(N)} \in \mathbf{R}^{I_N \times I_N}$, *and* ρ *is a real tensor of the same dimensions as* $\mathcal{A}$.

3. Tensor classification algorithm for Multi-site ABIDE

Structural and resting state functional MRI data from a total number of 1063 subjects consisting of 510 individuals diagnosed with ASD and 553 healthy controls from 16 international data acquisition centers comprise the data-set used in this work. Imaging data of 63 individuals was randomly selected and reserved for evaluation of the performance of the model and the rest of the data-set was used as training data.

Applied preprocessing steps were as the following. Exclusion of five initial samples, Fourier interpolation for slice timing correction, head motion correction, despiking of the signal for truncating abnormally large spikes, normalization of intensity values of volumes with a single mean-based normalization factor, a Gaussian kernel of full-width half maximum 6 mm for spatial smoothing, a band-pass filter of 0.01-0.1 Hz for temporal filtering, registration of fMRI recordings to subjects' structural images, nonlinear (FNIRT) and linear (FLIRT) registration to normalize the subjects' acquisitions to MNI152 atlas, motion outlier removal by evaluation of confound matrix with 6 motion parameters and nuisance signal removal by regressing out non-neural signals of white matter and cerebrospinal fluid. The preprocessed data used in this work, obtained by applying the abovementioned pipeline was provided by Connectomes Project [33]. After the preprocessing pipeline, five functional connectivity map matrices for each subject was constructed using 200 regions of interest (ROI) of the whole brain fMRI atlas, presented and evaluated in [34] and on the basis of five different similarity measurement methods, each encoding a representation of functional connectivity information. Five similarity measurement methods include correlation and partial correlation [35], co-variance and inverse co-variance (a.k.a precision) [36] and tangent [37].

Groups of 5 functional connectivity matrices are then divided into two categories of control and ASD diagnosed subjects, for each of which, obtained connectivity matrices of each individual are concatenated to build higher order tensors. These resulting tensors are then decomposed by applying higher-order singular value decomposition (HOSVD) [lose the full name if mentioned on Preliminaries] [add more technical description if see fit]. These decomposed tensors comprise the basis for differentiation of ASD patients from healthy individuals.

In order for the model to make predictions about the previously unobserved individuals, the same preprocessing steps are executed on the fresh sample and the resulting connectivity matrix is compared against the obtained basis matrices by performing their inner product.

The final prediction is determined by applying a majority voting along the output results of each basis models.

In summary, the training and classification procedures of the proposed method can be expressed as the following

4. Obtained results

Our evaluations of HOSVD on ABIDE data-set show roughly 7% improvement over SVM method. In Table 1 and Table 2 the obtained results of SVM method and HOSVD method are reported respectivly.

As you can see in Table 1 and Table 2, the SVM method has a major problem in predicting positive class and actually all of its predictions are the negative class. On the other hand, the trend of changing accuracy of the HOSVD method by changing the number of basis is shown in Figure 1.

Algorithm 1 Classification by HOSVD

1: **procedure** TRAINING
2: Sort the training fMRI data into two tensors with two labels, 'ASD' and 'Control'.
3: Compute the HOSVD of the tensors.
4: Compute and store the normalized basis matrices for two classes.
5: **procedure** TEST
6: Normalize the unknown fMRI.
7: Compute sum of inner product of the normalized fMRI image and the normalized basis of each classes.
8: Assign the label of the maximum sum of the products as the label of unknown fMRI.

Table 1: Evaluation results of SVM.

	Actual Positive	Actual Negative
Predicted Positive	0	0
Predicted Negative	33.86	29.14
Accuracy	53.2 %	

Table 2: Evaluation results of HOSVD.

	Actual Positive	Actual Negative
Predicted Positive	14.92	15.66
Predicted Negative	9.32	23.14
Accuracy	60.4 %	

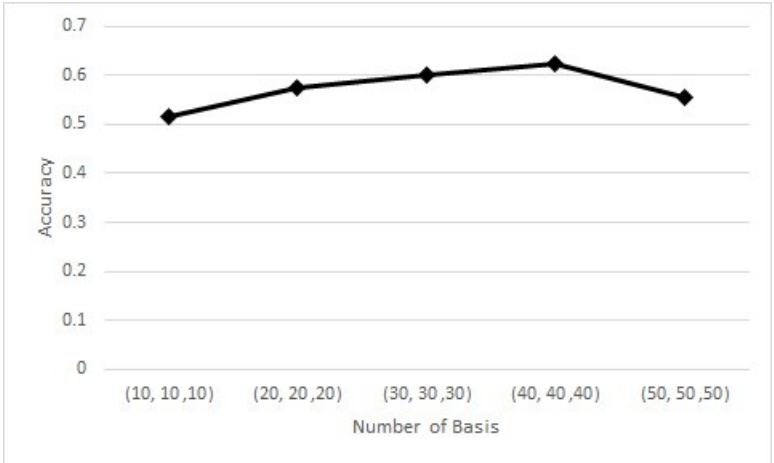

Figure 1: Average accuracy obtained by different numbers of basis for HOSVD method.

For this method to be able to properly differentiate between the two classes of subjects, a search for the proper values of its three parameters [better to mention them] is required, whereas HOSVD does not require any parameter optimization and can be applied to the problem in an out-of-the-box manner.

Another notable fact is extendability of the proposed HOSVD method for employment on huge amounts of data. In such scenarios, utilization of SVM is computationally infeasible as the execution time for the training procedure increases superlinearly [38]. In contrast, HOSVD does not impose any limitation on the size of the dataset [32], which when considered with the intrinsically space-intensive nature of neuroimaging data, especially fMRI data, can become a very desirable attribute.

5. Discussion and conclusion

In this work, we proposed an algorithm for classification of ASD using resting state fMRI data through construction of multiple types of functional connectivity networks and by applying tensor decomposition HOSVD. Our algorithm shows acceptable enhancement on accuracy and substantial improvement on f1 score due to significant reduction of false positives in comparison to SVM. Moreover, we have been able to achieve this classification accuracy and lower the false positive detection rate without any parameter optimization which would be a necessity with the SVM. On a broader perspective, taking advantage of tensor methods can allow for better generalizability and interpretability of the model, making the training computationally less expensive and reducing the amount of data required for gaining the same classification accuracies which are appealing advantages, especially in the field of neuroimaging.

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