fMRI detection of Asperger's Disorder using support vector machine classification

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Introduction

Recently, a resting state functional MRI study [1] reported that subjects with Asperger's disorder showed decreased functional connectivity between nodes in the default mode network [2]. In the present work, we develop a machine learning algorithm using Support Vector Machines (SVM) to classify subjects with Asperger's disorder from normal subjects in a more objective and automated manner.

Methods

Written informed consent as approved by the Emory University IRB was obtained for all subjects prior to enrollment in the study. Resting-state fMRI scan data was collected from 7 subjects with Asperger's disorder and 17 normal (healthy control) subjects on a 3T Siemens Trio scanner. Acquisition parameters : FOV 22cm, matrix size 64x64, in-plane resolution 3.4x3.4 mm, 10 contiguous 5-mm thick axial slices, TR 750ms, TE 35ms, flip angle 50 degree, total scan time 3.5 minutes, 280 volumes collected. For each patient, a correlation map was generated by computing the correlation between the time series of each voxel and that of a seed voxel taken from the posterior cingulate cortex (MNI: -2, -51, 17). The correlation values were normalized using Fisher z-transformation, and the resulting z-maps were transformed into MNI space using SPM [4]. Different combinations of preprocessing methods were then applied prior to performing SVM training: 1) taking absolute correlation values, 2) smoothing with a Gaussian kernel with FWHM of 6 voxels, 3) spatial masking of correlation values to include only regions in the default mode network. The processed correlation maps were then used to train an SVM model, using a linear kernel in libSVM [3] and 3dSVM in AFNI [5,6]. Leave-one-out cross-validation (LOOCV) was then performed to estimate the classification performance for each combination of the preprocessing choices. Weight vector maps were generated in each case.

Results

The resultant classification accuracy values for each combination of the preprocessing methods are presented in Table 1, with the highest classification accuracy using all three preprocessing methods, with only one misclassification.
Figure 1 shows an example of the weight vector map for one preprocessing combination (number 5). The top 10% of the positive weights are superimposed on normalized brain data as shown in the figure. It should be noted that significant classification weights appear to occur in regions associated with the default mode network (i.e. posterior cingulate cortex, medial prefrontal cortex and lateral parietal cortex).

	Preprocessing Combinations							
Preprocessing Step	1	2	3	4	5	6	7	8
Absolute correlation		✔			✔	✔		✔
Spatial smoothing			✔		✔		✔	✔
Default mode network mask				✔		✔	✔	✔
Prediction Accuracy	**79 %**	**83 %**	**66 %**	**79 %**	**92 %**	**83 %**	**75 %**	**96 %**

Table 1. Prediction results from different combinations of preprocessing methods.

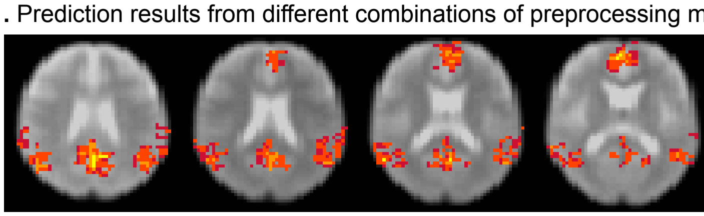

Figure 1. Weight vector maps for four slices (z=2 to z=5), and the top 10% of positive weights have been displayed.

Conclusion

We have successfully demonstrated a machine learning algorithm using SVM to classify subjects with Asperger's disorder from normal subjects. In the cross-validation, we observed very high accuracy (96%, combination 8) using a combination of preprocessing methods that included use of an absolute correlation map, spatial smoothing, and spatial masking of the default mode network; as well as a comparably high classification accuracy without using a spatial mask (92%, combination 5). Future work will extend our method to the use of regression to relate the clinical severity of autism to the fMRI resting state functional connectivity measures.

References

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