A new high-dimensional machine learning approach for identifying Alzheimer Disease from MRI structural images

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Objectives

Valid and reliable methods for differentiating persons with early Alzheimer's Disease (AD) from cognitively normal (CN persons are lacking. Many classification methodologies for structural MRI images, one possible approach to identifying persons with early AD, are based on a severe reduction of the feature space [1, 2]. In the present study, we propose a new classification method for structural MRI images (sMRI), based on penalized logistic regression combined with a high dimensional image warping technique[3], that uses voxels as input features. To demonstrate this method we classified a subset of images from a set of **Alzheimer Disease Neuroimaging Initiative** (ADNI) cognitive normal (CN) and AD participants.

Methods

We downloaded sMRI data from 98 subjects (49 CN and 49 AD) website matched by age and sex from the **ADNI** imaging database[4]. The images were segmented using the SPM8 new segment routines and normalized to an elderly population template using the software package advanced normalization tools (ANTS). Modulated grey matter (GM) and white matter (WM) volume maps were generated by multiplying the respective segmented tissue classes with the Jacobian determinants from the normalization. The classification was performed using the GLMNET library implementation of the L_2 penalized logistic regression which is based on coordinate-wise descent optimization techniques[5, 6]. The selection of the regularization parameter is performed by nested 10-fold cross-validation to avoid upward bias in estimation of accuracies. The results were evaluated using overall accuracy, sensitivity and specificity for classifying AD.

Results

Our methodology shows high levels of accuracy, sensitivity and specificity when automatically classifying sMRI images of CN subjects and AD patients. The highest levels of accuracy, sensitivity, and specificity were achieved for the GM volume maps with values of 85.7%, 82.9% and 90%, respectively, while for WM volume maps the values were slightly lower at 81.1%, 80.6%, and 82.5%. The grey matter discriminative maps (Figure 1-left column) show excellent localization to temporal lobe structures including the hippocampus, parahippocampal gyrus, entorhinal cortex, fusiform gyrus, and inferior and middle temporal gyri. Other areas include bilateral basal ganglia, thalami, posterior parietal cortex, frontal, and cerebellar areas. The white matter discriminative maps (Figure 1- right panel) localize to temporal lobe white matter areas associated with the hippocampus, parahippocampul gyrus, inferior and middle temporal gyri. Additional areas include the anterior commissure, splenium and body of the corpus callosum, forniceal columns, external capsule and bilateral parietal and occipital white matter regions.

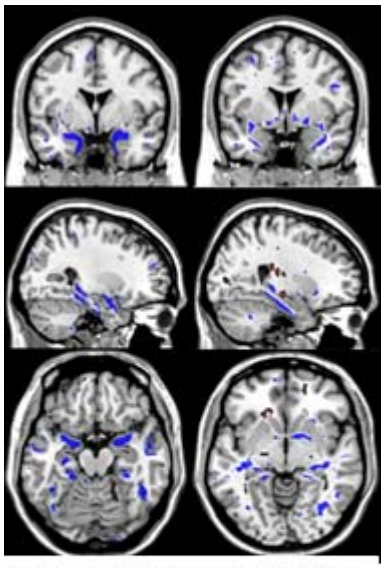

Figure - Discriminative maps built using grey matter and white matter volumetric information are shown in the left and right columns respectively. Maps were generated by averaging the weight maps obtained across 10 repetitions of the computations.

Conclusion

A voxel-wise classification methodology for automatic classification of sMRI images based on the combination of the L_2 penalized logistic regression and high dimensional image warping may be useful for differentiating persons with AD from CN. Both grey matter and white matter tissues carry useful information for this discrimination of AD patients from CN subjects using structural MRI brain data. This method may prove valuable for both diagnostic purposes as well as identifying subjects for future intervention trials.

References

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