Analysis of the spatial specificity of canonical correlation analysis in fMRI

R. R. Nandy[1], D. Cordes[1]

[1]Department of Radiology, University of Washington, Seattle, Wa, United States

Introduction

The importance of multivariate statistical methods has been realized in fMRI in recent years as they are more proficient in detecting brain activations in a noisy and sensitive environment. One such popular method is canonical correlation analysis (CCA), where instead of looking at the single voxel timecourse, the joint timecourses of a group of neighboring voxels are investigated [1]. The value of a suitable test statistic is used as a measure of activation. It is customary to assign the value to the center voxel. However, this is a choice of convenience and the method is prone to false activations as activations tend to bleed to the neighboring voxels of a voxel with strong activation. To rectify this deficiency an adaptive method has been proposed recently which is dynamic in nature and increases spatial specificity [2]. Although, in principle, the adaptive method should be a significant improvement over the conventional assignment scheme, an in depth analysis is necessary to validate such claims. Here, we apply the conventional CCA and the adaptive method to pseudo-real datasets with certain features which are expected to be detrimental to the conventional assignment scheme. If the adaptive CCA indeed performs better than the conventional scheme, it will serve as a validation of the improvements. We will also apply the adaptive method to a real dataset, where a strong bleeding effect is suspected.

Theory and methods

Suppose $X^{(1)}$ and $X^{(2)}$ (known as canonical variates) are two random vectors with n_1 and n_2 components respectively. In CCA, we look for the linear combinations $Y=\alpha^T X^{(1)}$ and $Z=\beta^T X^{(2)}$ so that their correlation coefficient (ρ) is maximum [1] and this gives the first canonical correlation ρ_1. The process is then repeated in the spaces orthogonal to the selected linear combinations and this gives the other canonical correlations $\rho_2,\ldots,\rho_n$, where n is $\min(n_1,n_2)$. In an fMRI setup, the vector $X^{(1)}$ stands for the observed signals at neighboring voxels and $X^{(2)}$ stands for the basis functions of a finite dimensional Fourier signal subspace with same periodicity as that of the paradigm for the task. The likelihood ratio test statistic $\Lambda=[0.5(n_1+n_2+3)-N]\Sigma(1-r_i^2)$ is the appropriate test statistic in this context. Here N is the number of observations (timeframes). The problem is to decide on the voxel to which the significance value of the test statistic will be assigned. A conventional choice is the center voxel among the collection of voxels taken for CCA. However, in the event of a highly localized activation, this method could possibly detect its neighboring region as active as well. One possible alternative is to assign the activation to the most dominant voxel among the set of nine voxels used for CCA. This scheme is not perfect either, as a truly active voxel may be left out when all its neighbors are more active. These considerations lead to a recently proposed new assignment scheme. In this adaptive scheme, p-values are assigned as measures of activation dynamically to the voxels so that the values get updated periodically. A detailed description of this method is presented in the appropriate reference [2].

Here we use pseudo-real data to investigate the effectiveness of this new assignment scheme. We first identify a highly active 9×6 region in a slice of the brain, while the subject performs a periodic phoneme-matching task. We then choose significantly smaller subsets of this region with different shapes. For each voxel in such a subset, we replace the active state timecourse with the resting state timecourse for the same voxel acquired during a resting state scan with identical scanning protocols within the same scanning session. Ideally, any fMRI post-processing method applied to the modified data should not detect the voxels within the subset as active, but by construction, conventional CCA is likely to detect these voxels as active. In the results section, we will observe if CCA indeed incorrectly detects these voxels as active and also if the adaptive scheme can successfully rectify the problem.

Results

In Figure 1, we have provided a map of relative CNR for the chosen 9×6 region with high activation. In Figure 2, we show the cross-shaped subset, where we replace the active state timecourses with the corresponding resting state timecourses. In Figure 3, we provide the activation map using conventional CCA for the modified data. Activation is measured as the negative logarithm of the p-value for the corresponding test statistic. As suspected, the activation values are incorrectly depicted to be high also on the voxels of the cross. In Figure 4, we have shown the activation map for the adaptive scheme. This map accurately exhibits the lack of any strong activation on the cross. This immediately validates the claim that the adaptive assignment scheme is a vast improvement over the conventional assignment scheme. Similar results were obtained from subsets with different shapes, but are not presented here as they do not provide any further insight. It should be noted that in the figures (Figures 1-4), brighter voxels correspond to higher values. Finally, in Figure 5, we present the activation maps at a p-value threshold of 10^{-8} (unadjusted) for the entire slice of interest using the two different schemes without modifying the data. As expected, the map using the adaptive scheme exhibits no obvious bleeding artifact and has an increased specificity. It in fact picks up a voxel missed by conventional CCA.

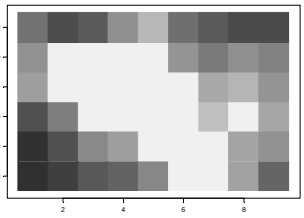

Figure 1.

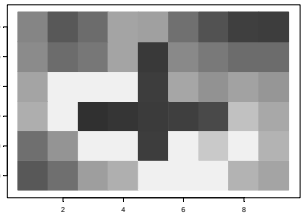

Figure 2.

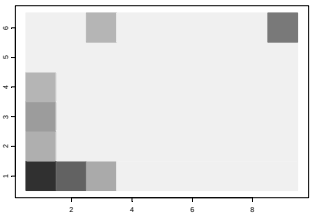

Figure 3.

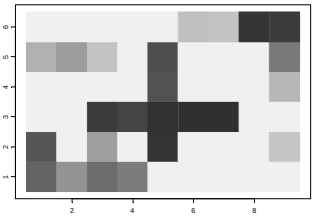

Figure 4.

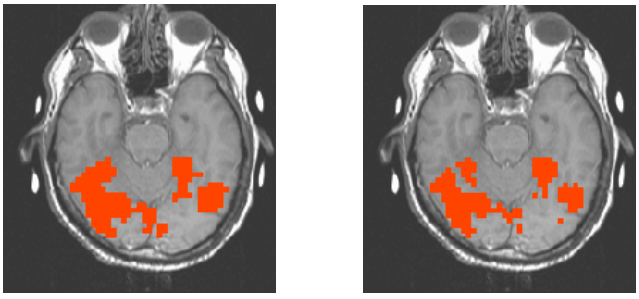

Figure 5. Comparison of functional maps at the same threshold using conventional CCA (left) and adaptive CCA (right) for the same slice. It is obvious that the adaptive CCA rectifies the bleeding effect the conventional method is prone to. Also it picks up activation at a voxel which was missed by the conventional method.

References

1. Friman O., Cedefamn J., et al, Magn. Res. Med. 45, 323-330 (2001).
2. Nandy R., Green C., Cordes D. Proceedings ISMRM, 489 (2003).