Bayesian Variable Selection in fMRI

B. McEvoy[1], and R. Nandy[1,2]

[1]Biostatistics, UCLA, Los Angeles, CA, United States, [2]Psychology, UCLA, Los Angeles, CA, United States

Introduction

Analysis of functional magnetic resonance image (fMRI) data is characterized by a two step process[1]. The first step applies a univariate statistical model to each voxel and produces a test statistic to summarize the effect. In the second step test statistics are thresholded and the surviving voxels are declared active. This paradigm, though informative, performs these steps as independent processes. In other words, the statistical model is run independent of the thresholding process. We propose to unite these steps under one coherent framework. We achieve this by exploiting characteristics of the Bayesian variable selection technique Stochastic Search Variable Selection (SSVS)[3]. The appeal of this framework is it permits the inclusion of prior information on hypothesized effect and avoids sensitivity and specificity issues introduced by the thresholding[3]. By incorporating the threshold in the model activation maps are provide sharp contrast between activation regions.

Methods

The hallmark feature of SSVS is a mixture prior on the regression parameters. The mixing is controlled by a voxel activation indicator γ, where if the parameter estimate surpasses a threshold, the probability in favor of activation increases. Posterior inferences are on these indicators, $P(\gamma \mid \mathbf{y})$, which is the probability the voxels exceeds a threshold. Like SPM, our inferences are based on the spatial distribution of $P(\gamma \mid \mathbf{y})$ over all voxels[1]. Prior information in the form of hypothesized activation regions and/or anatomical information can seamlessly enter the model and are substantively easy to specify. Anatomical information can be incorporated through segmentation maps

This framework can be extended to evaluate custom contrasts. In addition, an analytical solution for $P(\gamma \mid \mathbf{y})$ is provided which makes this method computational efficient[4]. Hence, MCMC sampling is not required.

Results

We evaluate SSVS on a simple motor task. Results are contrasted with SPM. We evaluate SSVS by with an anatomical prior (AP) and not including anatomical prior (NAP). We assume a priori that 5% of voxels are effected by the activation paradigm. This prior is specified uniform over the image. The threshold in the SSVS model was set to 3 times the standard error of the parameter estimate. Results for a single slice are given in Figure 1. Panel (a) corresponds to SSVS AP, panel (b) to SSVS NAP, and panel (c) is SPM test statistics thresholded at +/- 3. All three activation maps locate the same general regions, however, SSVS NAP and SPM are more similar. One the contrary, SSVS AP is less noisy and activation regions are more local. Note that SSVS activation maps provide sharp contrast between regions with high posterior support for activation (red) and low activation (blue).

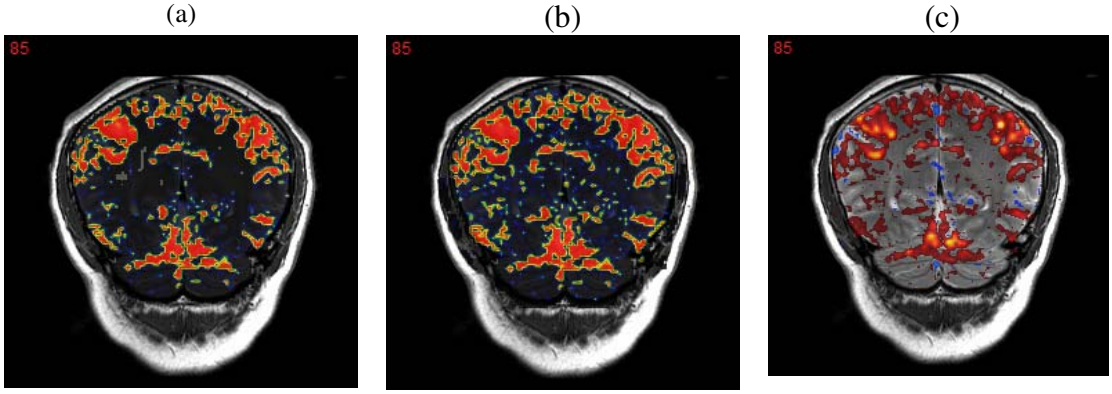

Figure 1. Activation map from motor experiment on a single slice. Panel (a) is SSVS AP, panel (b) is SSVS NAP, and panel (c) is SPM test statistics thresholded at +/- 3. SSVS panels define the posterior the voxel is active.

Conclusion

We propose an alternative way of framing the fMRI analysis based on SSVS. This framework is based on the same linear model and produces activation similar to SPM, however affords the research numerous advantages it. That is, prior information can be seamlessly incorporated into the analysis and circumvents the thresholding issue in the classical framework.

References

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