The application of consistency constraint in sliding window functional MRI analysis

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Introduction

Sliding window analysis is one of the techniques often used in real-time functional magnetic resonance imaging (fMRI) [1]. In this approach, a fixed number of images (window width, *w*) are used in the analysis throughout the scanning session. For the analysis to keep pace with data acquisition, the number of images is usually kept small to minimize processing time. However, this can affect the overall specificity of the approach, which can lead to a significant number of false positive detection. The sensitivity is also lower as compared to using several data points. Using the receiver operator characteristic (ROC) method [2], we investigate the effectiveness of the consistency constraint introduced in Bagarinao, et al. [3] in improving the detection power of the approach.

Methods

Simulated fMRI data sets were created by adding activation time courses to three series of 100 echo planar images acquired from three subjects in resting condition (no task with eyes closed). The imaging parameters were: TR = 3 s, FOV = 220 mm, slice thickness = 3 mm with 1 mm inter-slice gap, and matrix dimension is 64 x 64 x 30. Simulated fMRI responses emulating a block design with alternating rest and task blocks (10 scans per block) were added to the baseline datasets at designated active regions. Two simulated datasets were created from each baseline dataset corresponding to 1% and 2% activation contrast levels (ACL) [4]. For each simulated dataset, we performed a series of sliding window GLM [5] analysis using different window widths (w = 20, 30, 40, and 50 scans). From the series of generated activation maps, consistency maps [3] were constructed. Consistency constraints using different consistency length λ were applied to the constructed maps. The detection power of both the constraint (λ = 5, 10, 15, 20, 25, and 30 scans) and unconstraint (λ = 1) cases was examined using the ROC method [2].

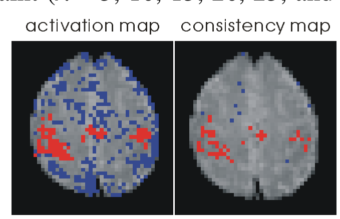

Figure 1

Figure 1. Activation (left) and consistency (right) maps (λ = 20) of a representative slice at n = 82 during sliding window analysis of a simulated data set (ACL = 0.01). Red-colored voxels represent true positives, while blue-colored voxels represent false positives.

Results and Discussion

Figure 1 shows the activation (left panel) and consistency (right panel) maps of a representative slice obtained for p-value equal to 0.1 (red: true positives, blue: false positives). From the figure, the number of false positives was significantly reduced while most of the true positives were retained when a consistency constraint (λ = 20) was applied to the activation map. The plots of the mean of the ROC curves as shown in Fig. 2A within the limited range of false positive fraction (FPF) between 0 and 0.1 for scan n = 81 to 100 also showed that the detection power of the constraint cases (λ = 5, 10, 15, 20, 25, 30) is much improved (higher values) than the unconstraint case (λ = 1). The improvement obtained using consistency constraint is much pronounced when using small window width where the detection power is low as can be seen in Fig. 2B showing the mean of the curves in Fig 2A for different values of w.

The use of consistency constraint reduces both true and false positives (see Fig. 1), thus effectively increasing the applied significance threshold (decreasing p-value). However, the decrease in the number of false positives is more significant when compared to actually changing the p-value of the unconstraint case assuming the same level of true positive fraction (TPF). Similarly, the decrease in the number of true positives is also less for the same FPF value. Thus for the considered range of FPF values, the ROC curves of the constraint cases lie above that of the unconstraint case resulting in the reported higher mean values. The overall effect is an improvement in the detection power of the sliding window approach.

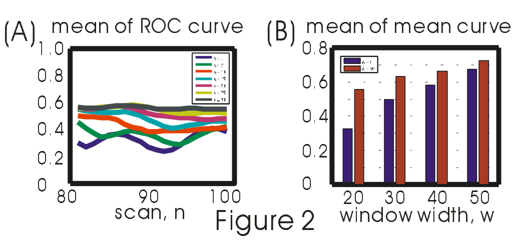

Figure 2

Figure 2. Results of the ROC analysis. Left: Mean of the ROC curves from n = 81 to 100 for different values of λ (window width, w = 20). Right: Mean of the curves shown in (A) for λ = 1 (blue) & 30 (brown) and for different values of w.

Conclusion

Sliding window analysis offers an effective alternative approach to do real-time fMRI. By using smaller window width, analysis time can be reduced to keep pace with data acquisition. This however results to lower overall specificity of the approach resulting to a significant number of false positive detection. From the results presented above, we have shown that consistency constraint can improve the specificity of the sliding window approach without sacrificing its sensitivity. An effective detection power equivalent to using twice the number of scans included in the analysis can also be achieved using consistency constraint. The advantage to real-time fMRI is evident. With consistency constraints, small window width can be used during the analysis to minimize processing time yet achieve a detection power that is equivalent to longer window widths.

References

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