

Wavelet shrinkage versus Gaussian spatial filtering of functional MRI data

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Objective

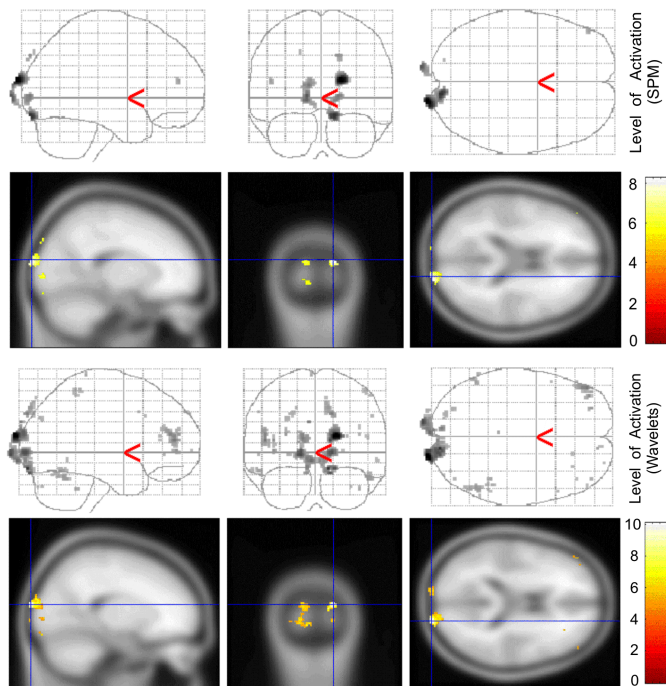
The comparison between wavelet-based simultaneous multiscale denoising/hypothesis testing and single scale Gaussian spatial filtering followed by statistical testing of brain activation maps is carried out for a simple block-type visual paradigm EPI MRI experiment. Probabilistic wavelet shrinkage provides means to consistently combine multiresolution denoising *and* hypothesis testing in a single process. The discrete wavelet transform (DTW) performs scale-varying decomposition of spatial statistic maps, so denoising in the wavelet domain is more adaptive to some spatial features in the true image than applying Gaussian filtering in the spatial domain. DTW also exhibits decorrelating properties, which amounts to mutually independence of the hypothesis tests on the wavelet coefficients and conferring potential benefits in the optimal control of type I error (false positives) [1]. The multiple comparison problem was handled using false discovery rate (FDR) control in wavelet denoising, while familywise error (FWE) control was used for isotropic symmetric Gaussian spatial smoothing required by thresholding the statistical parametric maps with the random field theory (RFT).

Methods

Data analysis in functional neuroimaging entails multiple testing in which a large number of correlated test statistics are evaluated and the resulting summary images assess the evidence for an experimental effect. Spatial smoothing of temporal autocorrelations is a common preprocess step in statistical analysis of functional magnetic resonance imaging (fMRI) data aiming to decrease errors in the estimated standard errors by increasing the effective degrees of freedom df . In addition, smoothing makes df less dependent on the underlying temporal correlation structure and, implicitly, renders statistical inference less problematic [2]. In statistical parametric mapping (SPM) [3], a convolution with a Gaussian kernel is applied before statistical analysis of data. This degrades the image resolution and complicates the statistical inference since the noise can no longer be considered independent. Wavelet-based denoising methods are nonparametric regression estimators that provide means for finding structure in data without imposing a parametric regression model. Algorithmically, DWT is applied to a noisy realization of an image, the wavelet coefficients are thresholded according to soft thresholding nonlinearity, with the threshold selected by the Stein's unbiased risk estimate (SURE), and the inverse DWT of the wavelet retained coefficients are used to estimate the denoised image in the image space [4]. Wavelet shrinkage is optimal for nonparametric regression in the sense of closely approximating the minimax risk if the image is endowed with some prescribed regularity [5].

Results

Full-brain fMRI data originated from one subject performing a visual task in one session of 12 runs of 228 s each in a 1.5 T scanner. Acquisition and reconstruction matrices were 64 x 64, 35 slices, with voxel size (mm) 3.8 x 3.8 x 3.75 at $TR = 3$ s. A flashing checkerboard was presented in blocks of 24 s followed by 24 s of fixation, starting with fixation. All data were subject to some preprocessing: (i) slice timing correction, (ii) realignment (movement correction) with high res T1-based structural image, and (iii) spatial normalization with SPM2 EPI.mnc template. Then the preprocessed data were spatially smoothed with a symmetric isotropic Gaussian kernel having the $FWHM$ (mm) = [6 6 6], followed by statistical inference within SPM2 that yielded the statistical parametric maps (top). Alternatively, the preprocessed data were plugged in WaveLab850 [6] that transferred information of 2D functional neuroimages into 2D wavelet coefficients. A t -test in the wavelet domain was used to detect the coefficients that were significantly different from zero. Their thresholding in the wavelet domain suppressed the noise, while preserving the sharp structure in the neighborhood of the rapidly varying spatial components when shifting back to the spatial domain by the inverse DWT (bottom). The results were overlaid on the high res T1.mnc template in SPM2.



Brain activation images obtained by: Spatial smoothing and statistical inference in spatial domain (top); Wavelet shrinkage (bottom).

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Conclusion

Wavelets provide orthonormal bases for MRA and decorrelation of nonstationary, scaling, scale-invariant, and fractal processes in time, space, or both, which is the case in neuroimaging. A kernel much larger than the spatial extent of brain sources precludes evidence for significant local activation. Scale-varying wavelet-based methods for hypothesis testing of brain activation maps circumvent the need to specify a priori the size of signals expected and, therefore, the optimal choice of smoothing kernel required by spatial smoothing. The SURE shrinkage achieves the best reconstruction of signals both in terms of noise suppression and sharp structure preservation in the neighborhood of highly-variable spatial components. Wavelet-based methods are likely to provide an overall richer characterization of distributed brain activation.

References

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