

Activation Spread due to Local Low-Rank Denoising in SMS-EPI Task-Based fMRI Data

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DENOISING NORDIC LOCAL LOW-RANK

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Impact

Low-rank denoising in fMRI improves sensitivity, but may also produce false positive activation spread. Understanding the effect of low-rank denoising can help researchers more accurately identify activation regions to interpret brain activity.

Synopsis

Motivation: Locally low-rank (LLR) denoising methods improve SNR in fMRI but can spread signal and alter the t-statistics, potentially causing false positive activation regions.

Goals: This study investigates how LLR denoising influences a known activation area, and compares the performance of SVHT and OptShrink within the NORDIC process.

Approach: Simulated fMRI data with known activation and modified experimental task-based SMS-EPI data are denoised with LLR methods, using NORDIC for computing patch rank and SVHT/OptShrink to shrink singular values.

Results: Denoising improved sensitivity to task signal but spread activation regions further than the ground truth. OptShrink achieved higher sensitivity and lower noise variance than SVHT.

Introduction

Low-rank denoising is a promising way to increase the signal-to-noise ratio (SNR) of fMRI images. In particular, locally-low-rank (LLR) methods exploit the redundant signal within small patches of the volume over time. Techniques such as NORDIC PCA¹ and MPPCA² determine the rank threshold that separates signal singular values from those dominated by thermal noise. After denoising, one generates activation maps by thresholding the t-statistics of the voxel time series. While denoising improves SNR, it can also artificially spread activation areas, raising concerns about false positives introduced by LLR methods. Through simulations, we demonstrate that LLR denoising increases the t-values, and applying the same statistical threshold used on the original noisy data produces false positive activation spread. Finally, we use augmented experiment data to compare the denoising effects of SVHT and OptShrink³ within the NORDIC denoising process.

Methods

[Figure 1](#) outlines the simulation pipeline. We constructed a 90×90×60 volume with 150 time points and a known activation area. Patchwise denoising was applied using a patch size of 5×5×5, stride 4, and patch averaging. Thresholded t-statistics were compared to the true added activation to determine false positive activation.

We compared two singular value shrinkage methods: singular value hard thresholding (SVHT), used in NORDIC, and OptShrink³. SVHT reconstructs each patch's Casorati matrix using the original singular values above a threshold, but noise can persist in those components. OptShrink, another random matrix theory-based denoising method, estimates and shrinks the remaining signal singular components based on its noise estimate, maximizing the SNR. OptShrink achieves more thermal noise suppression than SVHT³.

We also acquired task-based fMRI data with four runs of a flashing checkerboard and finger-tapping task. Data were collected on a 3T GE Signa MR750 scanner using Blipped-CAIPI SMS-EPI⁴ (multislice factor 6, 6/8ths partial Fourier, 32-channel NOVA head coil). The coil images were reconstructed using Slice-GRAPPA⁴ and coil-combined to a complex image using sensitivity maps computed by PISCO⁵. A noise-only scan was used to determine the g-factor scaling for variance normalization, as done in NORDIC. This ensures the noise is spatially uniform. To assess NORDIC denoising with thermal noise-limited data, we generated low SNR, augmented experiment data by adding simulated white Gaussian noise to the normalized images. The volume was denoised patchwise (6×6×6 patch, stride 4). Finally, we computed the t-statistics using a GLM with the HRF task waveform, polynomial trends, and bias terms.

Results

In the simulated data, the true activation region is concealed by noise and cannot be detected, but denoising improves SNR and signal recovery ([Fig. 2](#)). However, LLR denoising also introduces false positive activation. After denoising, t-values increase even outside of the true activation region ([Fig. 3a](#)), so applying the same statistical threshold to noisy and LLR denoised data yields false activation. The ROC curves in [Fig. 3b](#) demonstrate improved true positive activation detection after denoising. For a given false positive rate, OptShrink also achieves a slightly higher true positive rate than SVHT.

In the low SNR experiment, OptShrink achieved lower noise variance than SVHT ([Fig. 4b](#)). The activation maps after both denoising methods appear similar but show broader activation areas compared to the low SNR data ([Fig. 5b](#)). The lower time series plots in [Fig. 5c](#) highlight voxels identified as active post-denoising. Increased t-values result from reduced variance via denoising, signal spread, or a combination. The reported β values represent estimated coefficients for the task-related BOLD waveform. In the lower plot, β doubles after denoising, consistent with spreading of the regressor signal across the patch. Thus, LLR denoising may artificially increase t-scores when activation signal is present in the patch, expanding activation regions.

Discussion

The original NORDIC study¹ was evaluated on higher resolution datasets dominated by thermal noise, whereas the experiment data in the current study may be more limited by physiological fluctuations. Consequently, denoising the original data did not substantially increase the t-map activation areas as reported in¹ ([Fig. 5b](#)). To address this limitation, we generated low SNR, augmented experimental data. While studies have shown that t-statistics increase following

NORDIC⁶, further work is needed to analyze the spread of activation regions due to low-rank effects. Distinguishing false positive signals in experimental data without ground truth activation regions is challenging, but careful selections of patch size and rank thresholds may help minimize signal spread within patches. Future work should also assess how LLR denoising alters the t-statistic distribution and affects the degrees of freedom, which may require changes to statistical thresholds. Understanding these influences is essential for developing more accurate thresholds and improving the identification of true activation.

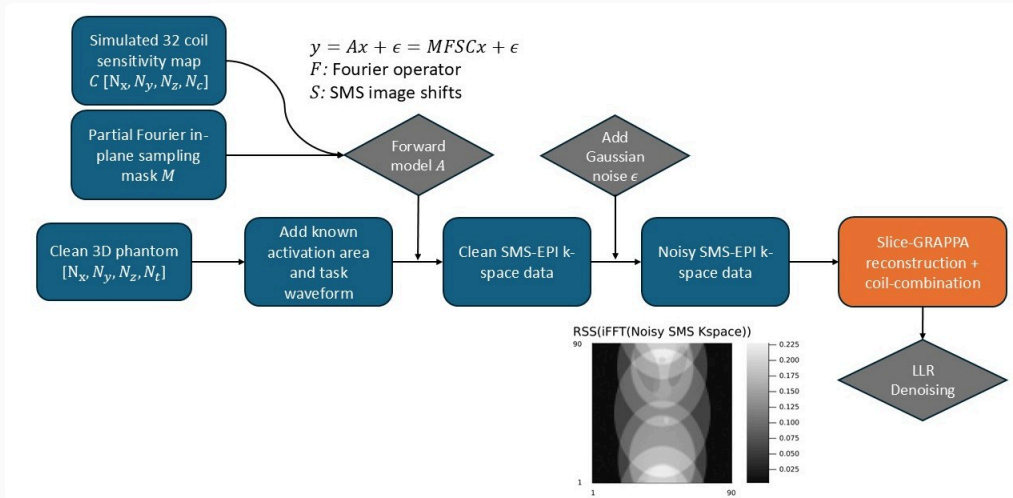
Acknowledgements

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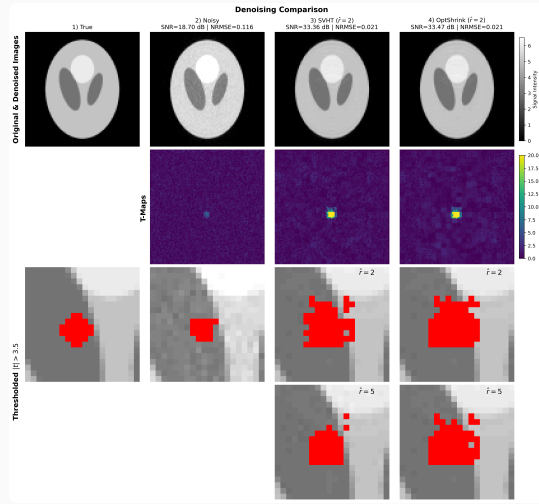
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Figures and Tables



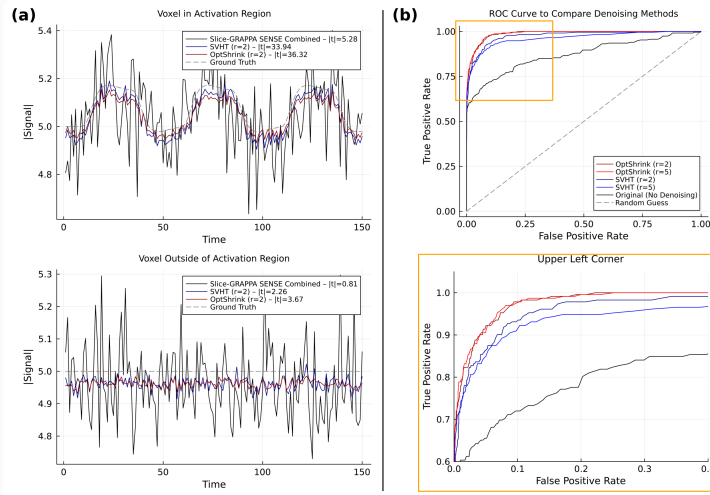
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Figure 1: Simulation procedure. A forward model simulating SMS data with simulated coil sensitivity maps and in-plane partial Fourier sampling is applied to a 3D phantom. Complex white Gaussian noise is added to k-space. Then, Slice-GRAPPA is used to reconstruct a volume time series. LLR denoising is applied using either SVHT or OptShrink as the singular value shrinkage operator, with rank thresholds of 2 and 5 chosen to represent the true local rank in a signal patch and an overestimate, respectively.



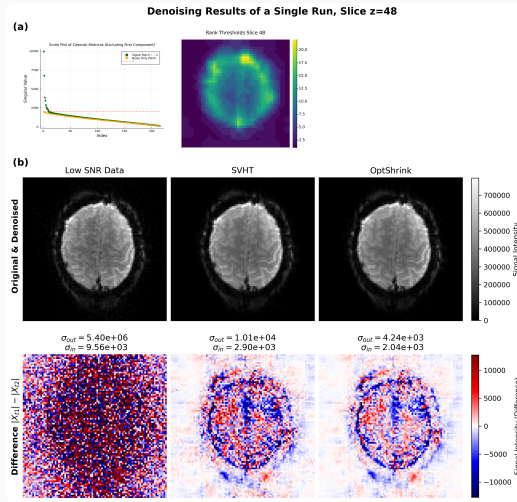
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Figure 2: Denoising results on simulation data. The first column contains the clean image and activation area. The second column shows the image after Slice-GRAPPA reconstruction and its t -map. The third and fourth columns compare SVHT and OptShrink with the same rank threshold. Thresholding at the same statistical significance as the noisy data causes false positive activation spreading (bottom two rows). Activation regions vary with the patch size and stride used during denoising.



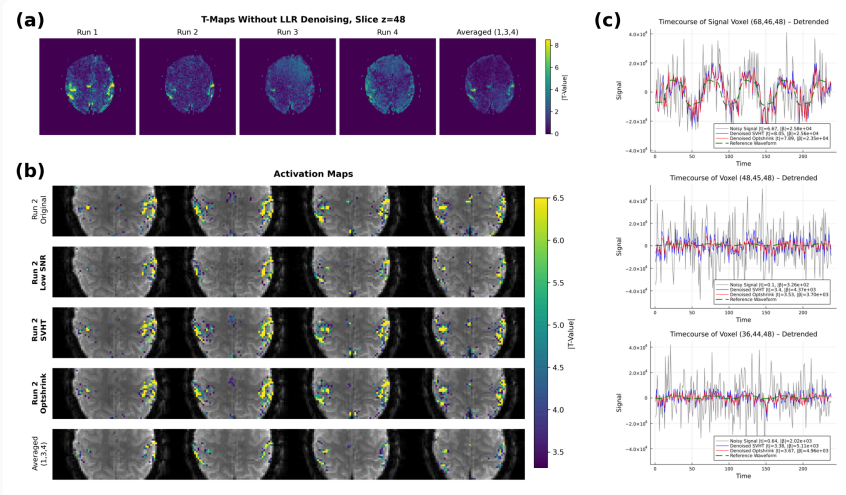
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Figure 3: Analysis of false positive activation in simulated data. a) Time series of voxels within and outside of the true activation region. T -scores increase after denoising, causing voxels to be misclassified as activation as shown in the lower plot. b) ROC curves compare denoising methods in terms of their false positive detection rate. While the original noisy data is unable to recover the true positive signal, denoising improves the detection and OptShrink slightly outperforms SVHT.



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Figure 4: NORDIC denoising results using SVHT and OptShrink. a) Scree plot of representative patches inside and outside of the brain. NORDIC-computed rank thresholds are shown for individual patches across the slice. b) Denoised images demonstrate reduced thermal noise. Difference images between consecutive time points present spatial noise information. As expected, noise variance is higher near the center. OptShrink achieves lower noise standard deviation than SVHT within and outside of the brain.



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Figure 5: a) T-maps from all runs. b) Activation regions in four slices of run 2 are shown for the original, low SNR, and LLR denoised images, and compared to an averaged t-map at a threshold of $|t| = 3.3$ (voxelwise $p < 0.001$, uncorrected). c) Time series from three voxels in run 2. The top shows an active voxel and the middle/bottom show inactive voxels before denoising. The lower examples demonstrate cases where LLR denoising may have led to artificial activation, indicated by increased β values.