Controlled Denoising for fMRI using Adaptive Overcomplete Dictionaries

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Introduction: Overcomplete dictionaries (OCD) have been used successfully with Compressed sensing (CS) for image reconstruction [1] and parameter mapping [2]. Chen et.al. [3] showed that by using an overcomplete dictionary (OCD), better sparse representations and by extension better denoising with sparsity based denoising algorithms (SBD)) of images, are possible. Recently, a new algorithm called the KSVD algorithm [4] adapted an initial OCD to the data to increase sparsity. If compressed sensing (CS) is to be applied in fMRI, care must be taken to assure denoising of intrinsic noise while not altering the physiological noise. We propose to use the KSVD algorithm in conjunction with parallel imaging (PI) for fMRI and control the level of denoising using knowledge of the intrinsic noise and the g-factor estimated using the pseudo Replica method.

Figure 2: fMRI activation maps zoomed in to show the visual and motor cortex →

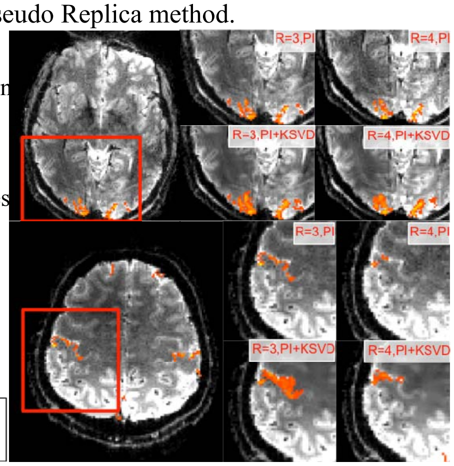


Figure 1: Reconstruction pipeline. The dotted lines indicate the denoising modules added to the PI pipeline.

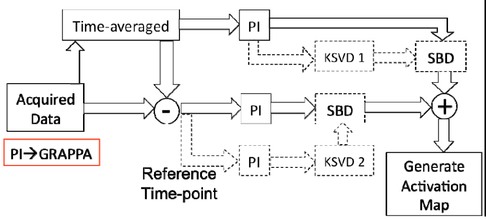
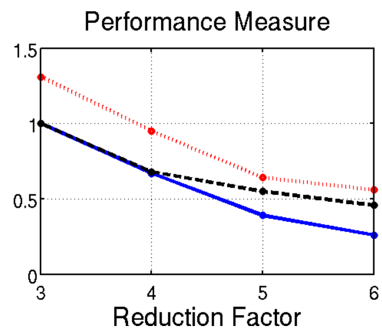


Figure 3: Plot of Δ_e(blue solid line) and Δ_a(black dashed line – PI, red dotted line – PI+KSVD



Methodology: Figure 1 depicts the algorithm pipeline used to reconstruct the fMRI time-series. The average image is denoised with a SBD-algorithm using an adapted OCD from $KSVD_1$ and the difference images are denoised using a different adapted OCD from $KSVD_2$. The difference is then added to the mean after denoising. Similar to [5] the adapted OCD's are applied over smaller image patches thereby spatially localizing the denoising. This is especially advantageous because of the spatially varying noise due to the g-factor from the PI reconstruction. fMRI time series were generated separately using PI and PI+KSVD and then analyzed using the simple students t-score test. The FWHM of the t-score for unactivated pixels together with the mean t-score of the activated pixels indicate the level of separation between the activated and unactivated t-score distributions.

$$\sigma_t^2 = \sigma_{Phys}^2 + g^2 R \sigma_{Int}^2 \quad (1)$$

$$\Delta_e(R) = \frac{g(R_{ref})}{g(R)}\sqrt{\frac{R_{ref}}{R}} \quad (2)$$

$$\Delta_a(R) = \frac{tscore(R)}{tscore(R_{ref})} \quad (3)$$

Results: fMRI studies were performed on a 7T magnet with a 16-channel headcoil. The fMRI acquisition used a PE undersampled multi-slice GE-EPI (echo time/T_R = 16/3000msec) with a 1.5x1.5x1.5mm^3 resolution covering the whole brain (reconstructed with GRAPPA to a 128x128x72 matrix). Separately and sequentially fMRI runs were also obtained with reduction factors of 3, 4, 5 and 6 (with uniform 1D undersampling along PE direction) (5 min duration). The fMRI paradigm consisted of an 8Hz flickering checkerboard and simultaneous finger tapping for periods of 30sec ON/OFF. For the KSVD, the initial OCD was the discreet cosine transform with an overcomplete factor of 16. The patch size used was 5x5 with complete overlapping. The Orthogonal Matching Pursuits algorithm was used as the SBD algorithm. Figure 2 shows the fMRI activation maps for two slices covering the visual and motor cortex respectively. Table 1 shows the FWHM and t-score means for PI and PI+KSVD.

	R=3		R=4		R=5	
	FWHM (Unactivated Pixels)	Mean t-score (Activated Pixels	FWHM (Unactivated Pixels)	Mean t-score (Activated Pixels	FWHM (Unactivated Pixels)	Mean t-score (Activated Pixels
PI	2.9	4.31	2.89	2.94	2.83	2.36
PI+KSVD	2.93	5.66	3.09	4.09	2.84	2.74

Table 1: FWHM & mean t-score for different reduction factors. ROI to calculate mean t-score is choosen around visual and motor cortex.

Conclusion and Discussion: PI+KSVD show better activation maps (Fig. 2) with increased separation between the activated and unactivated distributions (Table 1). The temporal noise (σ_t) in the fMRI signal is composed of physiological (σ_{Phys}) and intrinsic noise (σ_{Int}) (eq.1). By combining PI+KSVD denoising the contribution from $g^2 R \sigma_{Int}^2$ is reduced. Applications that will benefit from this type of noise filtering are scenarios when either the g-factor or the intrinsic noise is a significant contributor to the temporal noise (R=3 & R=4, Fig. 3). This is the case for high resolution imaging, highly accelerated imaging or accelerated imaging with only few receiver coils. Further analysis needs to be done to test the algorithm for resolution loss, but visually there is no apparent resolution loss as suggested in [1]. The algorithm will in the future be tested for resting-state fMRI where physiological noise is the signal and for diffusion weighting imaging which typically has low SNR.

Reference: [1]R.Ortazo, D.Sodickson, ISMRM 2010; [2] MRM,64,pp:1114-1120; [3] SIAM Review,43(1),pp:129-159; [4]IEEE TSP,54(11),pp:4311-4322; [5] IEEE TIP,15(12),pp-3736-3745.

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