

Compressed Sensing Enabled Ultra-High Resolution Optogenetic Functional Magnetic Resonance Imaging (ofMRI)

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Introduction: Optogenetic functional magnetic resonance imaging (ofMRI) [1, 2] is a powerful new technology that enables precise control of brain circuit elements while monitoring its causal output. To bring ofMRI to its full potential, it is essential to achieve high-spatial resolution with minimal distortions.

Method: To achieve this goal, we developed a compressed sensing (CS) [3, 4] enabled high-resolution, passband b-SSFP fMRI [5, 6] approach obtaining an ultra-high spatial resolution of $210 \times 210 \times 500 \mu\text{m}^3$, and $3.5 \times 3.5 \times 1.6 \text{ cm}^3$ FOV, while avoiding any significant image distortion or signal dropout. For rapid imaging, 3D stack-of-spiral readout was used with 9.3732 ms excitation repetition time (TR) and 10 interleaves. Without the additional speedup enabled by CS algorithms, this will normally allow $500 \times 500 \times 500 \mu\text{m}^3$ spatial resolution to be obtained with a 3 s temporal resolution. Utilizing the compressed sensing algorithm, data was under-sampled by a factor of 3 where 10 interleaves were randomly selected from a total of

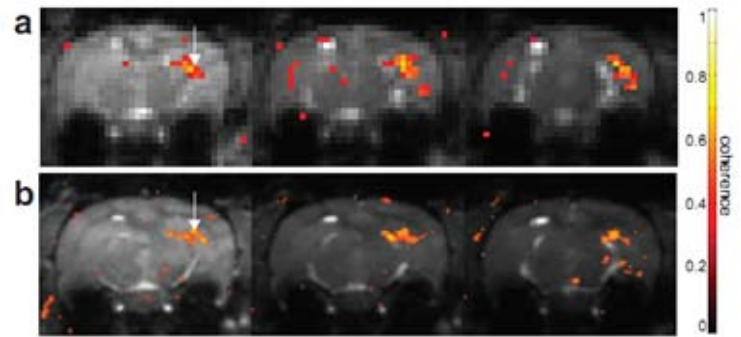


Figure 1: Compressed sensing ofMRI achieves approximately 6 times voxel volume reduction with same scan time. a, Nyquist rate, fully sampled, gridding reconstructed, and analyzed ofMRI activation map results in 0.5 mm isotropic resolution with 3 s scan time/frame. **b,** Under-sampled, gridding reconstructed, and analyzed ofMRI activation map results in approximately 200 μm in plane, 500 μm through-plane resolution with the same 3 s scan time/frame. white arrow: optical stim. site.

	w/o parallelization	w/ parallelization
Time to compute DCT across 3 dimensions	100s	20s (GPU)
Time to compute NFFT for 4160 images	60s	30s (CPU)
Matrix multiplication (892448x130 with 130x130)	300s	2s (GPU)

Table 1: Speed of algorithm components, w/ and w/o parallelization.

	Total Variation ($\lambda_1 = 10^{-3}, \lambda_2 = 10^{-4}$)	Total Variation with DCT ($\lambda_1 = 10^{-3}, \lambda_2 = 10^{-4}, \lambda_3 = 10^{-3}, \lambda_4 = 10^{-4}$)	Total Variation with DCT ($\lambda_1 = 10^{-3}, \lambda_2 = 10^{-4}, \lambda_3 = 10^{-2}, \lambda_4 = 10^{-3}$)
Reconstruction time	2 days	15 hours	3 hours
Rate of convergence	>500 iterations	145 iterations	30 iterations

Table 2: Speed and rate of convergence of different cost functions. λ_1 and λ_2 are L1 norm weighting parameters of temporal and spatial TV. λ_3 and λ_4 are L1 norm weighting parameters of temporal and spatial DCT, respectively.

implemented to speed up the reconstruction.

Result: Figure 1 compares CS reconstructed under-sampled high-resolution images (Fig. 1b) with conventional gridding reconstructed fully-sampled low-resolution images (Fig. 1a). High-quality, high-resolution 4D images are reconstructed with the proposed CS approach where the activations are faithfully captured in high-resolution (Fig. 1). Table 1 compares the processing time improvement with parallelization. Table 2 shows that the cost functions with DCT and TV converge faster than the cost functions with only TV. In addition, if the DCT is weighted more than TV, the cost function converges even faster.

Conclusion: With compressed sensing enabled, high-resolution ofMRI images can be reconstructed with significantly less data and scan time compared to the conventional method. More importantly, the high-resolution ofMRI images conserve activity of the brain from the stimulation.

References: 1. Lee, et al., Nature 2010, 2. Lee, Front. Neuroinform. 2011, 3. Candes and Wakin, IEEE Signal Processing Magazine, 2008, 4. Lustig et al., MRM 2007, 5. Lee et al., MRM 2008, 6. Lee, Int. J. Imag. Syst. Tech. 2010,

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Backtracking line search algorithm was used for the optimization. Graphic processing unit (GPU) and central processing unit (CPU) based parallelizations are