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Dictionary-Based Oscillating Steady State fMRI Reconstruction

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Synopsis

Oscillating steady state (OSS) imaging is a new fMRI acquisition method that substantially improves SNR by exploiting a large and oscillating signal. However, the oscillation nature of the signal leads to an increased number of acquisitions. To improve the temporal resolution and address the nonlinearity of the OSS signal, we propose a novel dictionary-based regularization method for OSS reconstruction to reconstruct dramatically undersampled (e.g. R = 12) data. The proposed method leads to better image quality than CG-SENSE and does not require any temporal filtering like low-rank methods, therefore the undersampling directly leads to an improved fMRI temporal resolution. The high SNR advantage of OSS is also well preserved.

Introduction

OSS imaging exploits a unique and large signal source and offers 2 to 3 times higher SNR compared to standard T2* weighted GRE BOLD imaging. The signal oscillates with a periodicity dictated by a quadratic phase cycling. A basic OSS approach would acquire and combine multiple images with different phase increments for fMRI analysis, which would compromise the temporal resolution. To improve temporal resolution, we sparsely sample the k-space and use regularizers for the under-determined reconstruction problem. Previously we introduced a patch-tensor low-n-rank regularizer to account for the reproducibility of OSS signals. However, the signals are not very low-rank along the fast repetition dimension as shown in Fig. 1. Low-rank models fit data to linear subspaces, whereas OSS signals have nonlinear features. Inspired by parameter estimation methods for MR fingerprinting [1,2], we propose a nonlinear dimension reduction approach that uses a physics-based dictionary as a regularizer. The fast repetition images are accurately modeled with only three parameters, so we are able to accelerate the acquisition by a factor of 12 and maintain the high SNR of OSS without any spatial or temporal smoothing.

Methods

OSS fMRI data has two time dimensions due to the acquisition pattern.The oscillation dimension is called "fast time" (t_f), and the dimension corresponding to the fMRI time course is called "slow time" (t_s). We model the fast time dimension with parameters m_0, T_2, and Δf in a voxel-by-voxel manner, where m_0 captures the signal magnitude, T_2 accounts for the tissue properties, and Δf denotes off-resonance frequency due to B_0 field inhomogeneity. We exclude T_1 because the dominant effect is an approximate scaling on the apparent m_0. (See Fig. 2)

The proposed reconstruction problem that incorporates the OSS signal model is:

$$\hat{\mathbf{X}}_s = \underset{\mathbf{X}_s \in \mathbb{C}^{N_x \times N_x \times N_f}}{\operatorname{argmin}} \ \frac{1}{2} \| \ulcorner\ (\mathbf{X}) - \mathbf{y}_s \|_2^2 + \tilde{} \sum_{x,y,t_s} R(\mathbf{X}[x,y,:]), \quad s = 1, \ldots, N_s,$$

$$R(\mathbf{v}) = \min_{m_0, T_2, \Delta f} \|\mathbf{v} - m_0 \Phi(T_2, \Delta f)\|_2^2,$$

where $\mathbf{X}_s \in \mathbb{C}^{N_x \times N_y \times N_f}$ represents the images at the sth of N_s time points to be recovered from limited k-space measurements $\mathbf{y}_s$, $\ulcorner\ (\cdot)$ is a linear operator presenting the MRI physicsconsisting of the non-uniform Fourier transform and coil sensitivities,and $\mathbf{v} \in \mathbb{C}^{N_f}$ is a vector of fast-time image values for one particular voxel. The fast-time signal model is denoted $\Phi(T_2, \Delta f) \in \mathbb{C}^{N_f}$. The regularization parameter~ was selected based on the condition number of the system matrix. We alternate between updating the image $\mathbf{X}$ and the dictionary based regularizer. The minimization of the parametric prior is a nonlinear estimation problem, and we solve it using the variable-projection method [3] and a signal dictionary. Specifically, we construct the dictionary with signals generated from a discretized range of parameters T_2, Δ_f using Bloch simulations, and estimate the 3 parameters through grid search. The $\mathbf{X}_s$ update is a quadratic least-squares problem solved by the conjugate gradient method and is easily parallelized across temporal frames. We sampled the data with randomized variable-density (VD) spirals and pseudo-random golden-angle rotations between consecutive interleaves and frames. The retrospective undersamplinggives an acceleration factor of 6 compared to fully sampled uniform-density spirals. For prospective undersampling, we acquired only 8% of the fully measurements. The data were collected on a 3T GE MR750 scanner with FOV = 22 cm, matrix size = 168, slice thickness = 2.5 mm. The OSS parameters are TR = 15 ms, nc = 10, TE = min, $t_f = 10$ and flip angle = 10°. The human functional task is flashing-checkerboard visual stimulus with left and right stimulus.

Results

As shown in Fig. 3, the image structures are preserved, and the activation pattern is very similar to the mostly sampled reference, which indicates a very accurate signal modeling and recovery. The tSNR maps and time course are also comparable to the mostly sampled case, which is impressive given that we are not performing temporal smoothing. The model is able to provide good activations and clean time courses with more aggressive undersampling and provide a factor of 12 acceleration, demonstrated by the prospectively undersampled reconstruction results in Fig. 4.

Conclusion

We present a new dictionary-based reconstruction framework for OSS fMRI that uses its unique signal model and enables nonlinear representations of the data. With this accurate modeling, the method can recover detailed structures and functional activities in fMRI images with only 8% of the fully sampled data. The reconstruction doesn't introduce any spatial or temporal blur, and the high SNR advantage of OSS is also well preserved. Furthermore, the dictionary model can be easily extended to include a dictionary built with T2* variations.

Acknowledgements

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References

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Figures

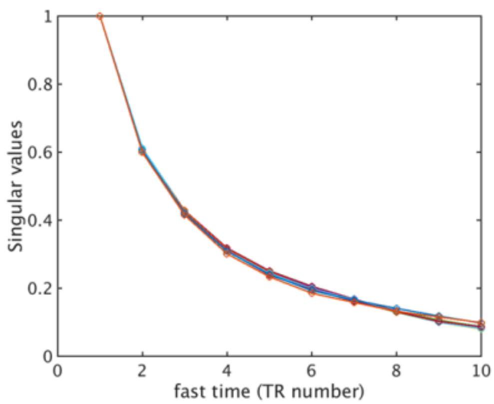

Fig. 1. The normalized singular values of 30 pairs of 10 fast time images showing that the OSS signal is not very low-rank along the fast time dimension. This motivates us to model the signal in a nonlinear way.

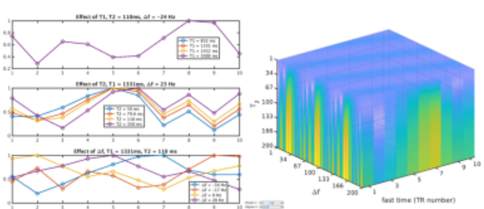

Fig. 2. The left figure presents how T1, T2, and Δf affects the OSS signal by plotting the normalized signal magnitude. We can see that the effect of T1 is only a scaling factor to the signal. Therefore, our dictionary (visualization given on the right) is built with parameters T2 and Δf, with T2 changing from 11 to 210 ms, and Δf from -99 to 100 Hz. Note that the OSS is periodic with shifts in frequency. We use a larger range which helps improve the reconstruction performance.

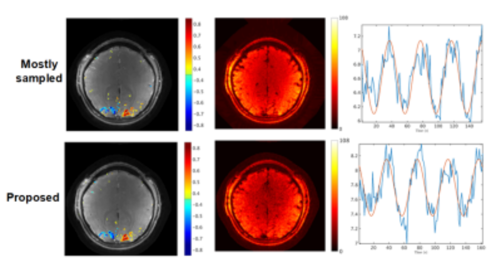

Fig. 3. Functional results including activation maps, temporal SNR maps, and time courses in a 2-pixel ROI. The images were reconstructed using retrospectively undersampled data with a factor of 6 acceleration compared to fully sampled k-space. The spatial resolution is 1.3 mm, and the temporal resolution is 1.35 s (TR $\times$ $n_c \times$ # of VD interleaves = 15 ms $\times$ 10 $\times$ 9). The reconstruction took 2 iterations for the conjugate gradient update, and 6 outer iterations for the alternating minimization. The model almost fully recovered the activations and maintained the high tSNR.

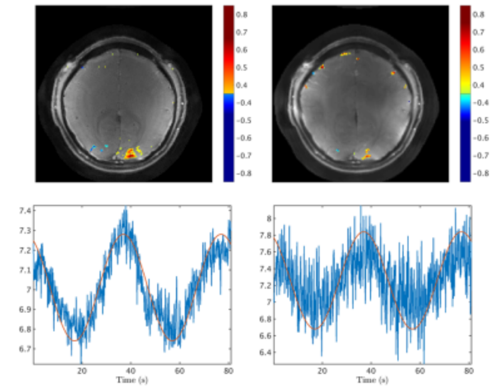

Fig. 4. The functional signals reconstructed using prospectively undersampled data with a factor of 16 acceleration. The spatial resolution is 1.3 mm, and the temporal resolution is 150 ms (TR $\times$ n_c = 15 ms $\times$ 10). Same numbers of inner and outer iterations were chosen as the retrospective experiment, while the regularizer parameter˜ was increased.

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