Dictionary-Based Oscillating Steady State fMRI Reconstruction

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Declaration of Financial Interests or Relationships

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I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.
Oscillating Steady-State Imaging (OSSI)\(^1\)

A new fMRI acquisition method exploits a large, oscillating signal compared to GRE

- 2 times higher SNR
- high-resolution fMRI

\(^1\)Guo and Noll, ISMRM, 2018 #5441, 2019 #1170
Need for k-Space Undersampling

RF phase cycling with cycle length $n_c$, OSSI signal oscillates with period $n_c \times TR$

- $n_c = 10$ times more images would compromise temporal resolution
- short $TR = 15$ ms limits single-shot spatial resolution
Need for Nonlinear Dimension Reduction

Not very low-rank along fast time\(^2\), linear subspace model may not help much

1 slow-time image set = 10 fast-time images

- nonlinearity of the OSSI signal
- dimension reduction for undersampling

\(^2\)Guo and Noll, ISMRM, 2018 #3531
OSSI Manifold Model

RF, gradients, tissue properties → MR Physics Bloch Eqn Nonlinear → transverse magnetization $X$ → encoding $A$ → k-space measurements $y$
OSSI Manifold Model

- RF, gradients, tissue properties
- MR Physics
  - Bloch Eqn
  - Nonlinear
- Transverse magnetization $X$
- Encoding $A$
- K-space measurements $y$
OSSI Manifold Model

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low-rank
OSSI Manifold Model

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low-rank
OSSI Manifold Model

RF, gradients, tissue properties → MR Physics Block Eqn Nonlinear → transverse magnetization $X$ → encoding $A$ → k-space measurements $y$

low-rank
OSSI Manifold Model

- RF, gradients, tissue properties
- MR Physics: Bloch Eqn, Nonlinear
- Transverse magnetization $X$
- Encoding $A$
- k-space measurements $y$

Low-rank
OSSI Manifold Model

$\text{RF, gradients, tissue properties} \rightarrow \text{MR Physics Bloch Eqn Nonlinear} \rightarrow \text{transverse magnetization } X \rightarrow \text{encoding } \mathcal{A} \rightarrow \text{k-space measurements } y$

$m_0 \Phi(T_1, T_2, \Delta f)$
Parameterization of OSSl Signal

$m_0 \Phi(T_1, T_2, \Delta f)$

MR Physics
Bloch Eqn
Nonlinear

10 fast time points

Magntitude vs TR Number
Parameterization of OSS1 Signal

\[ m_0 \Phi(K_1, T_2, \Delta f) \]

MR Physics

Bloch Eqn

Nonlinear

10 fast time points
Parameterization of OSSI Signal

- $m_0$ signal magnitude
- $T_2$ tissue properties
- $\Delta f$ off-resonance frequency

$\Phi(T_2, \Delta f)$

MR Physics
Bloch Eqn
Nonlinear

- effectively 3 physical parameters $\Rightarrow$ 10 time points
- nonlinear dimension reduction

10 fast time points
Voxel-Wise Near Manifold Regularizer

- One slow-time image set $\mathbf{X} \in \mathbb{C}^{N_x \times N_y \times n_c}$, $n_c = 10$

- Voxel-wise

  $\mathbf{v} = \mathbf{X}[i, j, :] \in \mathbb{C}^{n_c}$ is a vector of 10 fast-time image values
Voxel-Wise Near Manifold Regularizer

Problem formulation for one slow-time image set $X \in \mathbb{C}^{N_x \times N_y \times n_c}$,

$$\hat{X} = \arg\min_X \frac{1}{2} \|A(X) - y\|_2^2 + \beta \sum_{i,j} R(X[i, j, :]),$$

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

- $A(\cdot)$ is the encoding operator,
- $y$ denotes undersampled k-space measurements,
- $\beta$ is the regularization parameter.
$$R(v) = \min_{m_0, T_2, \Delta f} \| v - m_0 \Phi(T_2, \Delta f) \|_2^2$$

- $$\{ m_0 \Phi(T_2, \Delta f) \in \mathbb{C}^{10} : m_0 \in \mathbb{C}, T_2, \Delta f \in \mathbb{R} \}$$
\[ R(v) = \min_{m_0, T_2, \Delta f} \| v - m_0 \Phi(T_2, \Delta f) \|^2 \]

- nonlinear least square \(\Rightarrow\) dictionary fitting via VARPRO\(^3\)

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\(^3\)Golub and Pereyra, Inverse problems, 2003
MR Physics Based Reconstruction

\[ \hat{X} = \arg \min_X \frac{1}{2} \| A(X) - y \|_2^2 + \beta \sum_{i,j} R(X[i,j,:]) , \]

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

- alternating minimization
- \( X \) update → the conjugate gradient method
- regularizer update → dictionary fitting
- easily parallelized for all slow-time points
2D Human Retrospective Undersampling

- acceleration factor 12, NRMSD 5.6%, spatial resolution = 1.3 mm
2D Human Prospective Undersampling

- acceleration factor 12, spatial resolution = 1.3 mm, temporal resolution = 150 ms
Dictionary-Based Oscillating Steady State fMRI Reconstruction

- MR physics based signal model for reconstruction as a voxel-wise parametric regularizer
- Nonlinear dimension reduction for OSSI
- Acceleration factor of 12 with NRMSD 5.6%
- No spatial or temporal smoothing
- Joint undersampled reconstruction and parameter estimation
Future Work

- More accurate parameterization, $T_2$ or $T_2^*$
- More exploration of the manifold
- Combine with other regularizers (for both undersampled reconstruction and parameter estimation)
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