Fast and Motion Robust R2* Reconstruction for functional MRI

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Introduction:
Quantitative images for functional MRI (fMRI) are extremely important to further understand the hemodynamic processes of the BOLD response. In particular R2* maps can be linked to physiological processes such as blood flow, blood volume and metabolic rate of oxygen, all of which participate in the BOLD response. However, traditional methods to reconstruct R2* maps are either computationally time consuming or needed excessive amounts of data. A previous approach used a baseline image and a linear approximation to simplify the problem of estimating both R2* and field map from a single readout to minimizing a quadratic cost function [1]. This is a fast and accurate R2* reconstruction but assumed the initial magnetization M0 was static for all time frames and thus ignored motion during an fMRI experiment. Here, we present a fast reconstruction method that also uses repeated linearizations for speed that reconstructs R2* along with field map and M0, using additional data acquired while waiting for the BOLD contrast.

Theory:
With R2* and off-resonance included, the acquired MR data $\mathbf{y}$ that is needed to reconstruct a slice can be modeled as follows:

$$\mathbf{y} = \mathbf{A}(\mathbf{z})\mathbf{f} + \boldsymbol{\varepsilon}, \text{ with } [\mathbf{A}(\mathbf{z})]_{mn} = \Phi\left(\vec{k}(t_m)\right) e^{-t_m \cdot z_n} e^{-i2\pi\left(\vec{k}(t_m)\cdot\vec{r}_n\right)}, \tag{1}$$

where $\mathbf{A}(\mathbf{z})$ is the system matrix, $\mathbf{z}$ is the complex valued *rate map* with R2* and field map in its real and imaginary parts respectively, $\mathbf{f}$ is the objects initial magnetization M0, $\Phi(\cdot)$ comes from the continuous-to-discrete mapping of the MR signal equation [2,3], $k(t)$ is the k-space trajectory and r is the spatial coordinate. We jointly reconstruct $\mathbf{f}$ and $\mathbf{z}$ using an iterative algorithm for the following regularized optimization problem:

$$\{\hat{\mathbf{f}}, \hat{\mathbf{z}}\} = \arg\min_{\mathbf{f},\mathbf{z}} \frac{1}{2}\left\|\mathbf{y} - \mathbf{A}(\mathbf{z})\mathbf{f}\right\|^2 + \mathrm{R}_1(\mathbf{f}) + \mathrm{R}_2(\mathbf{z}), \tag{2}$$

where $\mathrm{R}_1(\mathbf{f})$ is a quadratic roughness penalty and $\mathrm{R}_2(\mathbf{z})$ is a quadratic roughness penalty that separately penalizes R2* and field map [1]. The cost function in (2) is non-convex which can slow iterative algorithms. To accelerate, suppose we add and subtract a previously acquired reference rate map z_{ref} to the exponent with z in (1) and split it into two exponentials, one with z_{ref} and the other z-z_{ref}. If z_{ref} is close to z, that exponential can be approximated well with its first order Taylor expansion, replacing (2) with:

$$\{\hat{\mathbf{f}}, \hat{\mathbf{z}}\} = \arg\min_{\mathbf{f},\mathbf{z}} \frac{1}{2}\left\|\mathbf{y} - \mathbf{A}(\mathbf{z}_{ref})\mathbf{f} + \mathbf{D}(-\mathbf{t})\mathbf{A}(\mathbf{z}_{ref})\mathbf{D}(\mathbf{f})\mathbf{z}_{ref} - \mathbf{D}(-\mathbf{t})\mathbf{A}(\mathbf{z}_{ref})\mathbf{D}(\mathbf{f})\mathbf{z}\right\|^2 + \mathrm{R}_1(\mathbf{f}) + \mathrm{R}_2(\mathbf{z}), \tag{3}$$

where $\mathbf{D}(\cdot)$ is a diagonal matrix. Using alternating minimization, this problem reduces to quadratic minimizations for both $\mathbf{f}$ and $\mathbf{z}$, which we solve by using fast iterative algorithms [2,3]. We first estimate $\mathbf{f}$ by setting $\mathbf{z} = \mathbf{z}_{ref}$ in (3) and solve, then replace $\mathbf{f}$ with that estimate and estimate $\mathbf{z}$ that is then used to update $\mathbf{z}_{ref}$, repeating until it converges.

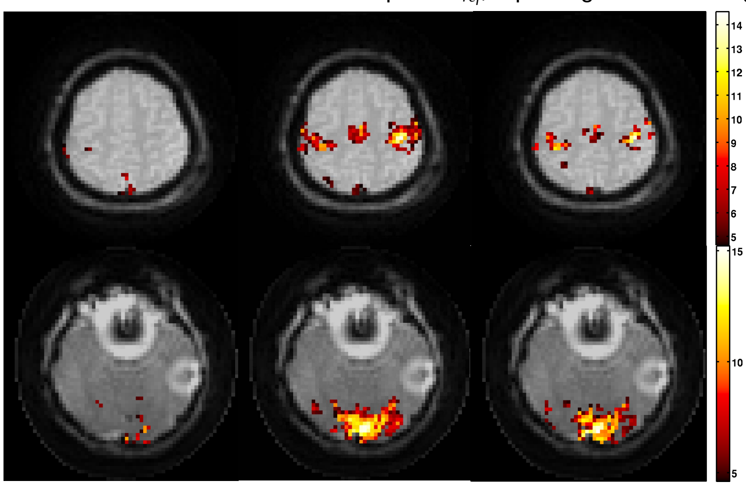

Fig. 1: z-score maps of active areas in the motor (upper) and visual cortex (lower) for $\mathbf{f}$ *(left), R2* (center) and T2*-weighted (right) images*

Methods:
We acquired a 2-echo spiral-out data with TE=4.6ms and 30ms, FOV=22cm, FA=55, TR=1.6s, {# of slices}=24. The TEs were intentionally chosen far apart to minimize correlation between the estimated $\mathbf{z}$ and $\mathbf{f}$ images. The task was a visually cued finger tapping, 20s on 20s off, repeated 5 times. To estimate the initial $\mathbf{z}_{ref}$, we shifted TE of the first time frame by 2ms and estimated the field map from the first echo of the first and second time frames. We estimated R2* using a log linear fit on images reconstructed from both echoes of the second time frame, which was the first time frame of the fMRI experiment. We reconstructed all time frames of the experiment using both the proposed method and conventional T2*-weighted reconstruction of the second echo [3]. All reconstructed volumes were slice-time and motion corrected using FSL 4.0 before being analyzed using GLM.

Results and Discussion:
To solve (3) we ran the alternating minimization 5 times using the iterative algorithm proposed in [2]. It took just under a minute to reconstruct one slice on a 2.6 GHz Intel Xeon. Fig. 1 shows the z-score for voxels above 4.61 for $\mathbf{f}$, R2* and T2*-weighted images, all overlaid on the reconstructed $\mathbf{f}$ for the first time frame. The R2* images seem to boost the overall number of active voxels compared to the T2*-weighted images. This is probably due to the field map and $\mathbf{f}$ being estimated for every time frame, thus correcting for any changes either due to motion or inflow. Inflow effects are evident from the activation in $\mathbf{f}$. For the inferior slices the estimated $\mathbf{f}$ image has piling up around the sinus and ear canals due to large through plane gradients, which requires further investigation.

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References: [1] Olafsson VT *et al*, *IEEE TMI*, 27(9):1177-88, 2008; [2] Sutton BP *et al*, *IEEE TMI*, 22(2):178-88, 2003; [3] Fessler JA *et al*, *IEEE Trans. Sig. Proc.*, 53(9):3393-402, 2005.