Reducing Effects of Drift in fMRI Data Using Joint Reconstruction of R2* and Field Maps

V. Olafsson[1], M. Ulfarsson[1], J. A. Fessler[1], and D. C. Noll[2]

[1]EECS, University of Michigan, Ann Arbor, MI, United States, [2]BME, University of Michigan, Ann Arbor, MI, United States

Introduction

In blood oxygenation level dependent (BOLD) functional MRI (fMRI), linear signal drifts are often seen in the time series. These drifts are nuisance parameters that are either regressed or filtered out when performing the functional analysis. The largest sources are believed to be scanner instability such as B0 drift and physiological noise and motion [1]. B0 drift also causes drift in off-resonance that can be measured by estimating field maps for all time frames in fMRI data. The field maps can then be used in off-resonance corrected reconstructions to correct for these temporal changes. We recently proposed a method for jointly reconstructing R2* and field maps from single shot k-space data [2]. These field drift corrected R2* estimates should be less sensitive to B0 drifts. Here we investigate the reduction in drift in R2* maps from this reconstruction and compare it to results from conventional BOLD-weighted fMRI analysis.

Joint Reconstruction of Dynamic R2* and field maps

The joint reconstruction [2] is based on estimating R2* and field map for each time frame by repeated refinements using linear approximations. For an fMRI study, time frame j of acquired k-space data $\mathbf{y}_j$ can be modeled as follows:

$$\mathbf{y}_j = \mathbf{s}(\mathbf{z}_j) + \boldsymbol{\varepsilon}_j, \text{ with } [\mathbf{s}(\mathbf{z}_j)]_m = \sum_{n=1}^{N} f(r_n) e^{-t_m z_j(r_n)} e^{-i2\pi(k(t_m)\cdot r_n)} \text{ and } \mathbf{z}_j = \boldsymbol{\alpha}_j + i\boldsymbol{\beta}_j, \quad (1)$$

where $\boldsymbol{\alpha}_j$ and $\boldsymbol{\beta}_j$ are R2* map and field map respectively, $\mathbf{s}(\cdot)$ is the discrete MR signal equation and $\boldsymbol{\varepsilon}_j$ is iid Gaussian noise. Assume we have a previous estimate $\hat{\mathbf{z}}_j^{(l-1)}$, which is the *l-1* refinement of $\mathbf{z}_j$. By adding and subtracting $\hat{\mathbf{z}}_j^{(l-1)}$ in the exponent of $e^{-t_m z_j(r_n)}$ in $\mathbf{s}(\mathbf{z}_j)$ and by using a linear approximation on the resulting $e^{-t_m(z_j(r_n)-\hat{z}_j^{(l-1)}(r_n))}$, the MR signal can be approximated as follows:

$$[\mathbf{s}(\mathbf{z}_j)]_m \approx [\mathbf{s}(\hat{\mathbf{z}}_j^{(l-1)})]_m + \sum_{n=1}^{N} f(r_n) e^{-t_m \hat{z}_j^{(l-1)}(r_n)} (-t_m)(z_j(r_n) - \hat{z}_j^{(l-1)}(r_n)) e^{-i2\pi(k(t_m)\cdot r_n)} = [\mathbf{s}(\hat{\mathbf{z}}_j^{(l-1)})]_m + [\mathbf{A}(\hat{\mathbf{z}}_j^{(l-1)}) \cdot (\mathbf{z}_j - \hat{\mathbf{z}}_j^{(l-1)})]_m. \quad (2)$$

Using this in (1) we can now estimate $\hat{z}_j^{(l)}(r_n)$ by minimizing a penalized likelihood:

$$\hat{\mathbf{z}}_j^{(l)} = \arg\min\left\{\frac{1}{2}\left\|\tilde{\mathbf{y}}_j - \mathbf{A}(\hat{\mathbf{z}}_j^{(l-1)})\mathbf{z}_j\right\|^2 + \mathrm{R}(\mathbf{z}_j)\right\}, \text{ where } \tilde{\mathbf{y}}_j = \mathbf{y}_j - \mathbf{s}(\hat{\mathbf{z}}_j^{(l-1)}) + \mathbf{A}(\hat{\mathbf{z}}_j^{(l-1)})\hat{\mathbf{z}}_j^{(l-1)}. \quad (3)$$

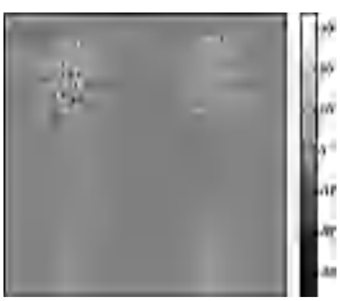

Fig.1: T-statistic maps of the drift (Top) and activation (Bottom) for BOLD (Left) and R2* (Right).

This is repeated for $l = 1,\ldots,L$ where $\hat{\mathbf{z}}_j^{(L)} = \hat{\mathbf{z}}_j = \hat{\mathbf{z}}_{j+1}^{(0)}$. To start the algorithm, we need to find $\hat{\mathbf{z}}_1^{(0)}$ and $\hat{\mathbf{f}}$, which can be reconstructed from multi-echo data (see Methods). This algorithm returns $\hat{\mathbf{z}}_j$ for all time frames whose real part is the off-resonance corrected R2* map for time frame *j*.

Methods

We collected an fMRI dataset with TR/TE = 750/30ms, 240 time frames and 10 oblique slices. The task was a block designed visually cued bilateral finger tapping OFF/ON = 15sec/15sec repeated 5 times. The first and second time frames were used for the conventional estimation of initial field map [3] and the second to fifth frame were collected with different TE's to estimate initial R2*. These maps formed $\hat{\mathbf{z}}_1^{(0)}$ which was used along with (1) to find $\hat{\mathbf{f}}$ using data from the first five frames by iterative reconstruction algorithm with a roughness penalty [4]. Using this, $\hat{\mathbf{z}}_j$ was reconstructed using (3) for j=6,…,240 with L=2. Off-resonance corrected T2*-weighted images for the BOLD analysis were also reconstructed for the same time frames, where only the initial field map was used. A GLM model was fitted to the time series from both reconstructions with baseline, linear drift and activation as regressors. A non-central t-statistic map was then constructed for all the effects. For the comparison we chose the second lowest slice that included the visual cortex.

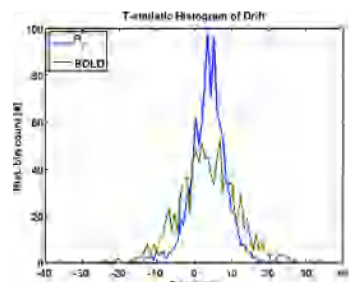

Fig.2: Histograms of the T-statistics for the linear drifts. Results from both BOLD and R2*

Results and Discussion

Fig.1 shows the t-statistic maps of the slice for the drift and activation effects for both reconstructions. No motion correction was used so the t-statistics were masked to exclude brain edges. Fig.1 shows the drift effect being larger compared to the activation effect for both reconstructions, where the visual activation is barely visible in both cases. However, for the BOLD reconstructed data the drift effect is proportionally greater relative to the activation effect than for the R2* reconstruction. This indicates that by jointly estimating field map along with R2* the effect size of the linear drift is reduced considerably. This is shown further in Fig.2 which compares the histograms of the drift effect t-statistics for both reconstructions. It shows that the histogram for the R2* reconstruction is much narrower (STD = 4.75 vs. 7.92) then for the BOLD analysis. In both cases the drift not eliminated, which needs further investigation.

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