# Quantitative Evaluation of 3D Variational Regularized Reconstruction of Undersampled Diffusion Tensor Imaging

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## PURPOSE -

DTI acquisitions take a long time. Undersampling reduces scan time but leads to artifacts with normal reconstruction. Parallel imaging with nonlinear variational constraints has been shown to reduce artifacts in reconstruction of undersampled data [1,2]. However, the effects of nonlinear regularization methods on quantitative evaluation of DTI data are not well studied. Here the quantitative accuracy of a 3D spiral acquisition using 3D second order Total Generalized Variation ( $TGV^2$ ) as a penalty term is evaluated in a simulated atlas-based DTI phantom. Reconstructed values of the FA and principle eigenvector direction were compared for different noise levels.

### **METHODS -**

Digital Phantom: The simulated volume was based on the LONI ICBM DTI-81 Atlas (http://www.loni.ucla.edu/Atlases/). Because the atlas volumes had a low resolution appearance due to averaging over many subjects, resolution inserts were added that had fibers running in all 3 cardinal directions and fiber widths of 1,2,3, and 4 pixels. The phantom was simulated on a 180<sup>3</sup> grid with 32 coils using measured sensitivity maps from a 32 channel head coil and a spiral projection k-space trajectory with 5000 spiral arms [3]. Undersampling (R=4) was done by discarding 75% of the spiral arms. Diffusion acquisition with 2 non-diffusion weighted images and 15 different diffusion directions was simulated. Two different levels of noise were added to the kspace data based on the ratio of the norm of the data to the added noise variance.



**Fig. 1** – FA difference-from-truth maps (a,b,f,g) and color FA maps (c,d,h,i) from gridding and TGV<sup>2</sup> reconstructions with both SNR levels. Color FA maps are compared to truth (e). FA difference maps from TGV<sup>2</sup> (f,g) were lower than those of gridding (a,b) at both SNR levels especially in the white matter. Note the high difference in the corpus callosum (red arrow). Color FA maps from TGV<sup>2</sup> (h,i) were closer to truth (i) than those of gridding (c,d) at both SNR levels. Note the near absence of the genu in the gridding map (d, yellow arrow) while it is present in the TGV<sup>2</sup> map (I, yellow arrow) and close to the same structure in the truth color FA map (e).

Image reconstruction: For TGV<sup>2</sup> constrained reconstruction, the following optimization problem has to be solved for each individual diffusion encoding direction *i*:

$$\min_{u_i} \frac{1}{2} \|F(u_i) - k_i\|_2^2 + \alpha \cdot TGV^2(u_i)$$

In this equation  $u_i$  is a reconstructed 3D volume of images from a single diffusion-encoding direction,  $k_i$  is the corresponding 3D spiral k-space data,  $TGV^2()$  is the penalty functional,  $\alpha$  is a regularization parameter, and F is the undersampled non-Cartesian sampling operator that also includes information about the sensitivities. The value of the regularization parameter was chosen empirically and remained constant for all investigated data sets. For comparison, reconstructions were also obtained using conventional regridding with density compensation [4].

<u>Analysis</u>: FA maps and principle eigenvector maps were computed from each volume. The difference in FA from each map with the ground truth was computed as well as the angular difference of the principle eigenvector. Computations were performed only over those pixels containing white matter tissue as defined by the LONI ICBM DTI-81 white matter mask.

### **RESULTS –**

FA maps from images reconstructed with  $TGV^2$  were quantitatively superior to gridding reconstruction results at both levels of SNR tested (**Fig. 1 a,b,f,g**) especially in the white matter. A similar trend was observed in the color FA maps (**Fig. 1 c,d,h,i**). Histograms of the difference of the FA (**Fig. 2a**) and the angular difference of the principal eigenvector (**Fig. 2b**) over the white matter regions (as segmented by the LONI atlas) show that  $TGV^2$  has less error in both metrics at both SNR levels. The most striking difference is in the FA where  $TGV^2$  at the lower SNR had lower error than gridding at the higher SNR level.

#### b Angular Diff of Principle Eigenvector from FA difference from truth r 10<sup>4</sup> truth (degrees) 14000 Gridding 12000 High SNR Low SNR 10000 8000 TGV<sup>2</sup> High SNR 6000 Low SNR 4000 2000 2222 0.2 0.3 0.4 0 10 20 Error Histograms of pixels in the white matter 30 0.1 40

**Fig. 2** – Histograms of the difference of the FA from truth (a) and the angular difference of the principle eigenvector from truth (b) from the gridding data (red) and  $\text{TGV}^2$  (blue) at both SNR levels computed over the pre-segmented white matter regions.  $\text{TGV}^2$  quantitatively outperforms gridding in both metrics at both levels of SNR.

### **DISCUSSION and CONCLUSIONS -**

Non-linear variational constraints have demonstrated improved image quality in parallel imaging enhanced data. However, the penalty term imposes some smoothness criteria on the data which may operate differently depending on the diffusion-encoding direction. Thus, an atlas-based DTI simulation tested  $TGV^2$  reconstruction against gridding in the computation of parametric DTI maps. FA and principal eigenvector maps computed from the  $TGV^2$  reconstruction had less artifacts and were quantitatively better than gridding results with the same level of undersampling (R=4) for both levels of SNR tested. In addition, the sharp edges of the resolution inserts were preserved with  $TGV^2$  indicating no loss of resolution in the constrained reconstructions. This suggests  $TGV^2$  could be used to help reduce lengthy 3D DTI protocols.

### **REFERENCES** –

[1] Block et al., MRM 57: 1086-98 (2007), [2] Knoll et al., MRM 65: 480-91 (2011), [3] O'Halloran et al. MRM: in press (2012), [4] Zwart et al., MRM 67:701-10 (2012).

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