Single Step Non-Linear Diffusion Tensor Estimation In the Presence of Microscopic and Macroscopic Motion

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INTRODUCTION – The correction of motion artifacts is an essential prerequisite for reliable DTI. Due to the marked sensitive of diffusion sequences to small motion (e.g. brain pulsation), correction methods have thus far been focused mostly on correcting phase terms resulting from such microscopic motion. Effects on the processed diffusion tensor due to gross subject motion have been considered only in a few studies [1,2] and only in the case of single shot sequences. For a multi-shot sequence, however, the rotational motion might cause each shot to be encoded with a different net diffusion encoding direction. Obviously, individual diffusion weighted images and ultimately the diffusion tensor information will suffer from substantial errors if this effect is not adequately addressed. In this study, we will demonstrate the extent of the confounding effects from microscopic and macroscopic patient motion on DTI data and propose a non-linear approach to solve the diffusion tensor-signal equation for image reconstruction and tensor processing using *Non-Linear Conjugate Gradient* (NL-CG) optimization.

MATERIALS and METHODS – ***(a) Image Reconstruction*:** In the presence of microscopic and macroscopic motion, the obtained k-space data for a multi-shot & multi-coil scan is given by:

$$d_{\gamma,\delta,\xi}(\kappa)=\frac{1}{n_\rho}\sum_{\rho} m(\mathbf{r}_\rho)\, e^{-\sum_{i,l}\left[\mathbf{b}_{\delta,\xi}\right]_{i,l}\left[\mathbf{D}(\mathbf{r}_\rho)\right]_{i,j}} s_{\gamma,\delta,\xi}(\mathbf{r}_\rho)\, e^{-j\mathbf{k}_{\delta,\xi,\kappa}\cdot\mathbf{r}_\rho}$$

where γ stands for the coil number, δ for diffusion weighting direction number, ξ for interleaf number, κ for k-space point within an interleaf, n_ρ for the number of image space points (=N^2), ρ for image space point and i,l for tensor indices (i,l=1,2,3). Here, $m(\mathbf{r}_\rho)$ is the non-diffusion weighted image and $\mathbf{s}_{\gamma,\delta,\xi}(\mathbf{r}_\rho)$ is the coil sensitivity. It is assumed that the arbitrary k-space trajectory $\mathbf{k}_{\delta,\xi,\kappa}$, the non-diffusion weighted image m, coil sensitivities $\mathbf{s}_{\gamma,\delta,\xi}$ and diffusion encoding matrix $\mathbf{b}_{\delta,\xi}$ have been corrected for translational and rotational motion. The coil sensitivities are obtained from the center of a variable density spiral or from an additional spiral-in navigator so that the motion-induced, random phase accrued for each interleaf is already contained in the sensitivity profile as a multiplicative term [3]. Due to the rotational motion, each interleaf will undergo a different diffusion encoding, as given by the ξ-dependence of the exp(-$\mathbf{b}_{\delta,\xi}\mathbf{D}$) term. Therefore, it becomes evident that it is impossible to reconstruct an individual image with uniform diffusion-encoding. Thus, it becomes necessary to estimate the diffusion tensors **D** directly from the unity of all complex k-space data d that were acquired for all diffusion encoding directions. For this, we define a cost function, given by:

$$f(\mathbf{D},m)=\sum_{\gamma,\delta,\xi,\kappa}\left|d_{\gamma,\delta,\xi}(\kappa)-\frac{1}{n_\rho}\sum_{\rho} m(\mathbf{r}_\rho)\, e^{-\sum_{i,l}\left[\mathbf{b}_{\delta,\xi}\right]_{i,l}\left[\mathbf{D}(\mathbf{r}_\rho)\right]_{i,l}} s_{\gamma,\delta,\xi}(\mathbf{r}_\rho)\, e^{-j\mathbf{k}_{\delta,\xi,\kappa}\cdot\mathbf{r}_\rho}\right|^2$$

which will lead to minimum norm estimates of **D** and m by minimizing the discrepancy between the acquired k-space data, d, and the synthesized k-space data under consideration of motion in the diffusion tensor signal equation (right term).

It is important to note that **D** (mm^2/s) and m (a.u.) have different units, which causes them to have different scalings. Thus, preconditioning becomes essential to prevent very slow convergence rates. Specifically, the inverse of a diagonal approximation to the Hessian was used as a preconditioning matrix to speed up convergence and achieve good results. In addition, for NLCG iterations, fast methods that rely on gridding and inverse gridding were used to calculate the steepest descent direction and Hessian of f. In our studies, to speed up the calculations, we replaced the gridding and inverse gridding steps with a faster transfer-function approach [4].

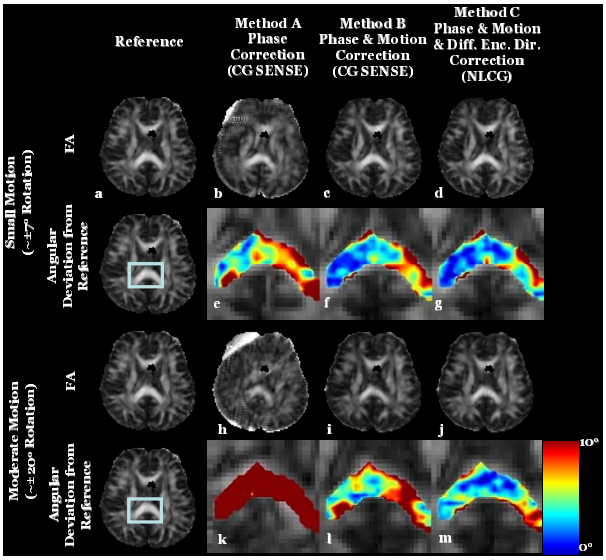

***Figure 1** – The FA maps and angular deviation maps obtained from an in-vivo experiment, reconstructed using the three different reconstruction methods. For both degrees of motion, the FA maps reconstructed with no motion correction show serious motion artifacts (b,h). With the application of motion correction using method B, these artifacts are significantly reduced (c,i). Application of method C gives FA maps of similar quality. However, method C gives more accurate tensor orientations compared to method B, as shown by the lowered angular deviation of the major eigenvectors from the reference orientations (f,g,l,m).*

***(b) Image Acquisition*:** For this study, a diffusion-weighted spin echo spiral in & out sequence was used. The spiral-in part was used to acquire a low resolution navigator image for each interleaf while the spiral-out part was used to acquire individual interleaves for the reconstruction of a final high resolution image. The motion parameters (rotation and translation) and the coil sensitivities were obtained using these low resolution navigators; alternative trajectories, such as interleaved EPI or PROPELLER could be used as well. Reconstructions were performed using 3 methods: **(i)** using an augmented CG-SENSE reconstruction to obtain phase-corrected diffusion-weighted images [3], followed by conventional tensor estimation without any motion correction applied;**(ii)** similar to method (i), but (a) with motion correction applied prior to the augmented CG-SENSE reconstruction, and (b) without considering the change in the effective **b**-matrix as a result from rotation correction the k-space data relative to the encoding gradients; **(iii)** direct estimation of the tensor element maps using NLCG under the consideration of rigid body motion and diffusion-related phase errors. Two datasets were obtained where the subject was asked to perform varying degrees of motion. An additional dataset where each subject was asked to stay stationary was also obtained to determine reference tensor orientations. The scan parameters were as follows: TR/TE=2500/55 ms, six diffusion gradient directions, NEX=4, b-value=800 s/mm^2, matrix size = 128 x 128, navigator matrix size = 32 x 32, 8 interleaves, variable density spiral pitch factor = 3. Two extra scans were obtained with the diffusion-encoding gradients turned off. The performance was evaluated using the angular deviation of the reconstructed major eigenvectors from the reference orientations.

RESULTS – Fig 1 shows the results for in-vivo studies in the presence of mild (~$\pm 7^0$) (b-g) and moderate (~$\pm 20^0$) (h-m) motion. The fractional anisotropy (FA) maps reconstructed without motion correction show significant motion artifacts (b,h). These are significantly removed by the application of motion correction (c,i). The FA maps reconstructed with method C (d,j) have similar quality compared to those reconstructed with method B (c,i). However, the angular deviation maps in the splenium of corpus collosum show that the major eigenvectors reconstructed with method C (g,m) have less deviation from the reference values compared to those reconstructed with method B (f,l). The mean FA in this ROI was also observed to be closer to the reference value for method C compared to method B.

DISCUSSION – A new reconstruction method has been introduced that estimates maps of the diffusion tensor elements in a single step. Its efficacy in simultaneously correcting for both microscopic and macroscopic motion was demonstrated in in-vivo experiments. This generalized mathematical framework can be applied to any trajectory and can be used in conjunction with parallel imaging. The degree of improvement depends on the severity and pattern of motion. Our initial experimental data demonstrate that a considerable improvement in the accuracy of the observed tensor information can be achieved using this novel approach. Such improvement was achieved in the cases of both small and large motion. However, our experiments suggest that small degrees of motion are mostly "swamped" in the noise of tensor estimation. Thus, for small motion we believe that this method will be most effective in studies that utilize a large number of diffusion encoding directions and for DTI data that have high SNR.

References [1] Rohde et al, MRM, 51:103-114, 2004 [2] Andersson et al, Neuroimage, 16:177-199, 2002 [3] Liu et al, MRM, 54:1412-22, 2005 [4] Wajer et al, ISMRM 2001, 767 **Acknowledgements** This work was supported in part by the NIH (2R01EB002711, 1R21EB006860), the Center of Advanced MR Technology at Stanford (P41RR09784), Lucas Foundation and Oak Foundation.