Rigid Head Motion Correction for DTI Using Non-Linear Conjugate Gradient

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Introduction In multi-shot sequences, rigid body motion can be normally corrected by acquiring a low resolution navigator images to estimate the amount of rotation and translation for each interleaf. However, for a multi-shot diffusion-weighted imaging (DWI) acquisition, simply correcting the rotation and translation of the image itself may not be sufficient. Patient motion does not only affect image registration from shot to shot, but it also changes the diffusion encoding gradients. As a result, each interleaf will have a different diffusion weighting due to the altered gradient direction with respect to patient frame of reference. In this case, it is not feasible to reconstruct the diffusion-weighted images directly. We propose to use a non-linear reconstruction algorithm to estimate diffusion tensors instead of reconstructing the images. In this study, we investigate the use of Non-Linear Conjugate Gradient Algorithm (NLCG) for rigid head motion correction in DTI.



Figure 1 - Low resolution navigator images obtained from the spiral in part for each interleaf before (first row) and after (second row) registration are shown. The Pearson Correlation Coefficient is used as a measure of similarity between the navigator and the template image. It can be seen that correlation coefficient is significantly lower (3^{rd} interleaf) for k-space data that is corrupted by motion. Using thresholding, the k-space data corresponding to those interleaves with decreased correlation coefficient are removed.



Figure 2 – Results of computer simulations using SENSE and NLCG. For the case when there is no simulated motion, the performances of both methods are similar. In the case of very large motion, the artifacts resulting from altered diffusion encoding gradient direction are successfully removed by the application of NLCG. **Materials and Methods** Application of diffusion encoding gradients before readout results in a signal attenuation given by the well known expression $S=S_0exp(-bD)$. Here, **D** represents the diffusion tensor and **b** is determined by the applied diffusion encoding direction and strength. If there is rotational rigid body motion, the diffusion encoding direction changes. Assuming **R** to be the relative rotation matrix with respect to a template, the new diffusion encoding matrix in this case is given by **b'** = **R b R**^T. Thus, for an interleaved sequence, rotational motion between each shot causes each readout to obtain a different diffusion encoding. This makes it impossible to reconstruct individual diffusion weighted images that are used in regular tensor estimation schemes. Hence, a non-linear optimization scheme has to be used that takes the altered diffusion encoding into account. In this study, we used NLCG algorithm to solve for diffusion tensors from complex & arbitrary k-space data.

In our motion correction algorithm, we used a spin-echo sequence with a spiral in & out readout. In this sequence, the spiral in part is used to get a low resolution navigator image for each interleaf and the spiral out part makes up one interleaf of the final high resolution image. The low resolution navigator images are used for finding the relative rotation and translation between interleaves. The coil sensitivities are also obtained from these low resolution navigator images. Since DTI is very sensitive to bulk motion, the k-space data obtained at the time of subject motion will be highly corrupted (Figure 1). In this case, our registration routine is used to detect and throw out this corrupted k-space data. Parallel imaging is used to compensate for the undersampling that is caused by this operation.

To illustrate the performance of our method, two sets of experiments were carried out: 1) **Computer simulations** were performed using a high SNR data set with 256x256 matrix size. Images with no motion, medium motion (30^0 rotation) and very large motion (60^0 rotation) were simulated and the corresponding k-space data were obtained for each. The motion corrected FA maps were reconstructed with (using NLCG) and without (using SENSE & linear least-squares tensor estimation) diffusion encoding direction correction. 2) *In vivo* studies were carried out using our spiral in & out sequence with TR/TE=3000/61 ms, 6 diffusion gradient directions [($1 \ 1 \ 0$]^T, ($1 \ 0 \ 1$)^T, ($-1 \ 1 \ 0$)^T, ($1 \ 0 \ 1$)^T, ($1 \ 0 \ -1$)^T], NEX=2, matrix size = 128x128, navigator matrix size = 32 x 32, 8 interleaves. The subject was asked to perform rigid

head motion with different ranges. An additional reference scan was also obtained where the subject was asked to stay stationary. FA maps obtained with and without correction were compared.

Results and Discussion Results of our computer simulations are given in Figure 2. For the case with no simulated motion, the performance of our method is comparable to the conventional tensor estimation. For $+-30^{\circ}$ motion, the results are still similar whereas for motion with $+-60^{\circ}$ range, NLCG performs better than SENSE.

The results for in-vivo experiments are shown in Figure 3. The results for SENSE and NLCG are comparable for the case with no subject motion. For small and medium motion case, the amount of change in diffusion encoding direction induced by

motion is not significant. Thus, the results obtained with and without diffusion encoding direction correction are comparable. This is also the case for the data set with large motion. In this case, the artifacts in the image are mainly caused by the aliasing resulting from the elimination of corrupted data and rotational motion. On the other hand, for all degrees of motion, NLCG performs better visualization of the lateral ventricles. However, for both computer simulations and *in vivo* studies, the FA maps obtained by NLCG are relatively more noisy compared to those obtained with SENSE.

Conclusion A motion correction scheme for DTI using NLCG is presented. The proposed scheme successfully removes the rigid head motion related artifacts. Compared to the motion correction scheme where the change in diffusion encoding direction is omitted, our method provides improvements. A limitation of our algorithm is its sensitivity to inconsistent data such as noise, artifacts resulting from misregistration and inaccurate estimation of coil sensitivities. This limitation can be alleviated up to a certain degree using preconditioning and regularization. **References** [1] Bammer et al, MRM, in press [2] Liu et al, MRM, 54:1412:22, 2005 **Acknowledgements** This work was supported in part by the NIH (1R01EB002711), the Center of Advanced MR Technology at Stanford (P41RR09784), Lucas Foundation and Oak Foundation.



Figure 3 – In-vivo results for different degrees of motion including no motion, small motion $(+.3^{\circ} \text{ rotation})$, medium motion $(+.7^{\circ} \text{ rotation})$ and large motion $(+.30^{\circ} \text{ rotation})$. Due to the non-linear random phase accrued by each spiral arm phase correction is necessary. Application of motion correction significantly improves image quality.