Super resolution reconstruction from differently oriented diffusion tensor datasets

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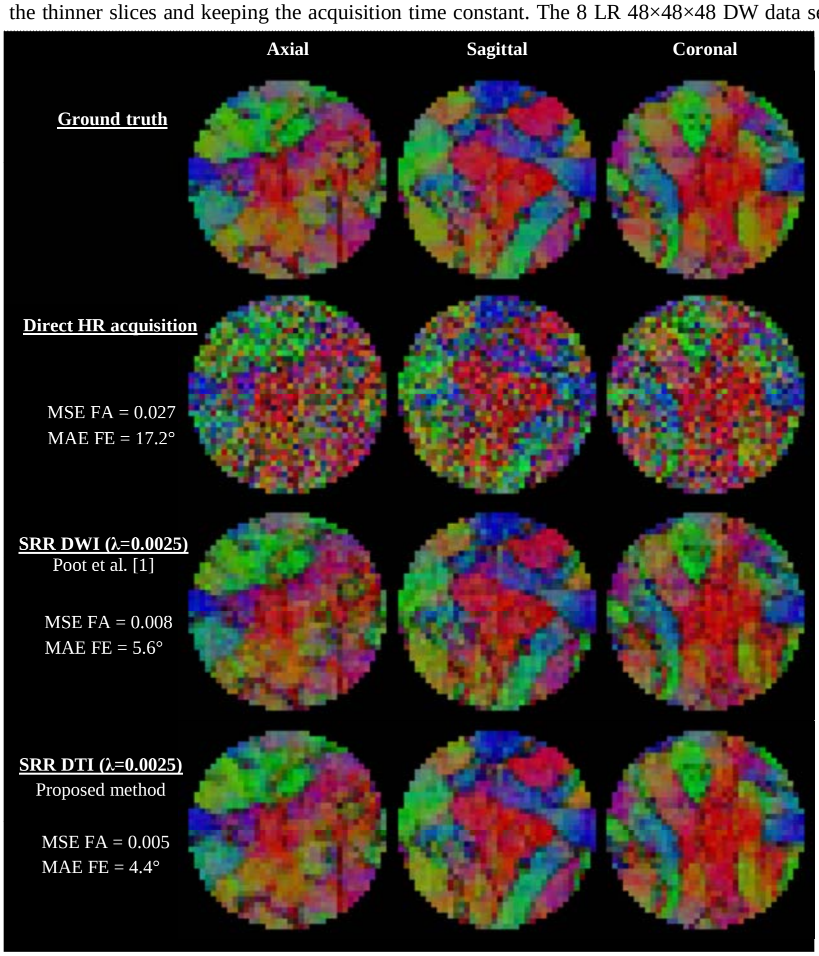
PURPOSE: Diffusion MRI (dMRI) is a noninvasive in vivo imaging modality that measures the diffusion of water molecules. Given that dMRI measures signal loss, it inherently leads to noisy images. Increasing the Signal-to-Noise Ratio (SNR) by averaging, directly increases the scan time, which in turn decreases patient comfort and increases the likelihood of head motion. Therefore, to increase SNR, diffusion weighted (DW) images are acquired with larger voxels, typically 2x2x2 mm^3 to 3x3x3 mm^3 in clinical dMRI. Consequently, due to large partial volume effects, diffusion tensor imaging (DTI) has been limited to the study of unidirectional fiber bundles that are large with respect to the voxel size. Recently, methods have been proposed that improve the trade-off between spatial resolution, SNR and acquisition time [1, 2]. These methods acquire multiple low resolution (LR) DW-images with different slice-directions, and recover the underlying high resolution (HR) DW-images via super-resolution reconstruction techniques. These methods, however, neglect the *q*-space relationship between the different DW-images during the reconstruction. In this work, we propose to integrate the DTI-model into the SRR-model. The use of the DTI-model during the SRR imposes constraints on the solutions of the SRR, making the SRR algorithm more robust. We show, by means of simulations, that SRR benefits from the use of the DTI-model.

METHODS: The proposed method estimates the HR DTI-parameters directly during the reconstruction from the LR DW-images with different arbitrary slice directions, each with a low through-plane resolution, based on the method in [1]. The transformation between the HR DTI-parameters and the LR DW-images is composed of two parts: 1) the diffusion weighting that transforms the HR DTI-parameters to the HR DW-images and 2) a set of affine transformations, which transform the HR DW-images to the LR DW-images with different slice directions. The intensity of a noise free DW-image $\boldsymbol{r}_m$ can be modeled in each voxel $\boldsymbol{k}$ by $\boldsymbol{r}_m(\boldsymbol{k}) = \boldsymbol{r}_0(\boldsymbol{k})e^{-\boldsymbol{g}_m^T\boldsymbol{D}(\boldsymbol{k})\boldsymbol{g}_m b_m}$, where $\boldsymbol{g}_m$ and b_m are the diffusion gradient direction and diffusion weighting factor of the corresponding DW-image $\boldsymbol{r}_m$, respectively, and $\boldsymbol{r}_0$ represents the non-DW signal and $\boldsymbol{D}(\boldsymbol{k})$ the DTI-parameters. The transformation between the HR DW-images $\boldsymbol{r}_m$ and LR DW-images $\boldsymbol{s}_m$ can be represented by: $\boldsymbol{s}_m = \boldsymbol{X}_m\boldsymbol{r}_m + \boldsymbol{e}_m$, where $\boldsymbol{e}_m$ represents the measurement noise and $\boldsymbol{X}_m$ the projection matrix following [1]. Consequently, the relation between the HR DTI-parameters $\boldsymbol{D}$ and the LR DW-images $\boldsymbol{s}_m$ can be written as: $\boldsymbol{s}_m = \boldsymbol{X}_m\boldsymbol{r}_0 e^{-\boldsymbol{g}_m^T\boldsymbol{D}\boldsymbol{g}_m b_m} + \boldsymbol{e}_m$. The HR DTI-parameters $\boldsymbol{D}$ can be estimated by minimizing the mean squared error (MSE) between $\boldsymbol{s}_m$ and $\boldsymbol{X}_m\boldsymbol{r}_0 e^{-\boldsymbol{g}_m^T\boldsymbol{D}\boldsymbol{g}_m b_m}$, which is a nonlinear least squares (NLS) problem: $\widehat{\boldsymbol{D}} = \underset{\boldsymbol{D}}{\operatorname{argmin}}\left\|\boldsymbol{X}\boldsymbol{r}_0 e^{-\boldsymbol{g}^T\boldsymbol{D}\boldsymbol{g}b} - \boldsymbol{s}\right\|_2^2$. Because of the high resolution of the grid of the reconstructed parameters, this problem is badly conditioned or even underdetermined. Hence regularization is required, leading to the following regularized least squares problem: $\widehat{\boldsymbol{D}} = \underset{\boldsymbol{D}}{\operatorname{argmin}}\left\|\boldsymbol{X}\boldsymbol{r}_0 e^{-\boldsymbol{g}^T\boldsymbol{D}\boldsymbol{g}b} - \boldsymbol{s}\right\|_2^2 + \lambda\boldsymbol{R}(\boldsymbol{D})$, where $\boldsymbol{R}(\boldsymbol{D})$ is a penalty function that computes the squared Laplacian of each of the DTI-parameters and of the estimated b=0 s/mm^2 image separately. The weighting factor λ of the regularization is chosen so that the MSE of the solution is minimal. The NLS problem was then solved by using the trust-region Newton method. To evaluate the proposed SRR method we simulated a noiseless 192×192×192 DW data set (1 b=0 s/mm² and 12 b=1200 s/mm²) using the Numerical Fibre Generator [3]. Using affine transformations and the sampling filters described in [1], we obtained a HR 48×48×48 reference DW data set which served as HR ground truth and a collection of 8 LR 48×48×16 DW data sets which served as input for the SRR method. Rician noise was added to the LR data sets, resulting in SNR=20 in the b=0 s/mm² images. The ground truth HR data set was also corrupted with Rician noise, in order to simulate a direct HR acquisition. SNR in the b=0 s/mm² images of the direct HR data set was (20/4)*sqrt(8/4) = 7, taking into account the decreased SNR of the thinner slices and keeping the acquisition time constant. The 8 LR 48×48×48 DW data sets were processed both with the proposed method (SRR DTI, λ=0.0025) and the method from [1] (SRR DWI, λ=0.0025) where first for each diffusion direction a HR DW-image was reconstructed from the corresponding LR DW-images via SRR. These HR DW-images were then used to calculate the HR DTI-parameters. For both methods the optimal λ was chosen, such that the MSE for each method was minimal. To quantify the difference in reconstruction quality, the MSE of the fractional anisotropy (MSE FA) and the median angular error of the first eigenvector (MAE FE) were computed.



RESULTS: The figure on the left shows the direction encoded FA maps constructed from the different data sets in all three orthogonal directions. The direct HR reconstruction suffers from a low SNR, while both the SRR direction encoded FA maps exhibit high SNR, while preserving resolution. This can also be appreciated from the quantitative metrics: MSE FA and MAE FE are much smaller for the SRR outputs than for the direct HR acquisition. The quantitative metrics also show that including the DTI model into the SRR pipeline results in lower MSE FA en MAE FE.

DISCUSSION AND CONCLUSION: A super resolution acquisition and reconstruction method was proposed that directly estimates the DTI-parameters resulting in an improved SNR compared to direct HR acquisitions within the same scan time. It was also shown that the results benefit from including the DTI-model into the super resolution reconstruction model. The promising simulation results encourage us to acquire (pre)clinical data to further validate the proposed technique. Using super resolution techniques in diffusion MRI would enable HR investigation of the brain in clinically feasible scan time. It would also enable us to perform DTI with unprecedented resolution, minimizing the partial volume effects and thereby revealing finer structures.

[1] Poot et al., MRM, in press (doi: 10.1002/mrm.24233)
[2] Scherrer et al., 2012, Media 16 1465–1476
[3] Close et al., 2009, NeuroImage. 47 1288-1300