Model-based super-resolution of diffusion MRI for microstructure imaging

Alexandra Tobisch[1] and Hui Zhang[2]

[1]Department of Medical Physics and Bioengineering, University College London, London, United Kingdom, [2]Department of Computer Science and Centre for Medical Image Computing, University College London, London, United Kingdom

PURPOSE This work develops a super-resolution reconstruction (SRR) technique that constructs isotropic high-resolution (HR) diffusion-weighted images (DWI) from multiple anisotropic low-resolution (LR) acquisitions (Fig 1). Isotropic HR DWIs enable the mapping of tissue microstructure for fine brain structures, such as the subfields of hippocampus. Direct acquisition of such images require prohibitively long imaging time; the SRR approach considered here provides a practical alternative that combines a modest increase in imaging time with intelligent image post-processing. The current SRR technique using this approach [1] considers the LR DWIs acquired for each diffusion-sensitizing gradient separately from the DWIs for the other gradients and produces an isotropic HR DWI independently for each gradient. Such treatment, however, is problematic. DWIs from different gradients are not independent because they are dictated by the same underlying tissue microstructure. This dependency drives the subsequent quantification of tissue microstructure; ignoring it during the reconstruction may prevent its preservation in the reconstructed HR DWIs. The proposed SRR technique addresses this limitation with a model-based strategy [2] that not only maintains the dependency between DWIs from different gradients, but also provides super-resolved parameter maps of the underlying tissue microstructure directly.

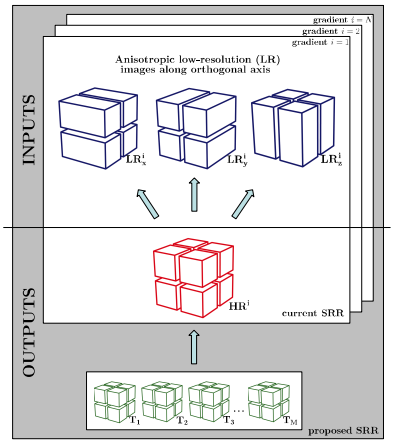

Fig 1: Forward models of the current and the proposed SRR

METHODS Current SRR: Performed separately for each of the *N* diffusion gradients, it reconstructs a HR image **x** from a set of LR images **y** acquired with the same diffusion gradient $\mathbf{g}^i$ (Fig 1). The reconstruction is solved as an inverse problem with a forward model that obtains a set of anisotropic LR images from an isotropic HR image. Proposed SRR: Our approach instead adopts a forward model that predicts the isotropic HR DWIs from all diffusion gradients given an appropriate tissue model, with a set of the tissue parameters $\mathbf{T_m}$, and the imaging protocol **p** (Fig 1). The SRR is performed simultaneously for all diffusion gradients, which directly super-resolves the underlying tissue microstructure represented by all image acquisitions. Tissue model: The choice of tissue model depends on the application. For the present demonstration, we adopt the simple two-compartment ball-and-stick model [5] to relate the underlying tissue microstructure of a voxel to its measured diffusion signal. Implementation: Both techniques are formulated as an optimization problem, which is solved using the steepest gradient descent. Synthetic phantom: We use the ball-and-stick tissue model to synthesize the ground-truth HR diffusion signals for 30 isotropically-distributed gradient directions with b=1000 s/mm^2. We vary two of the model parameters, the volume fraction *f* and the fibre direction **n**, to generate different diffusion signals to create a synthetic phantom that is composed of 8x8x8 voxels of size 1x1x1mm^3 representing a specific underlying microstructure. The input LR images are created by downsampling the HR data and adding different levels of randomly generated noise (SNR of 100, 50 or 20). Synthetic data with an SNR of 20 best simulates real-world diffusion MRI data. Evaluation: We compute the reconstruction error and the voxel-wise root-mean-square error (RMSE) between the ground-truth data and the reconstructed HR to assess the performance of each SRR routine. The procedure is repeated for 20 noise trials and we report the mean and standard deviation of the reconstruction error for each level of noise in the synthetic data.

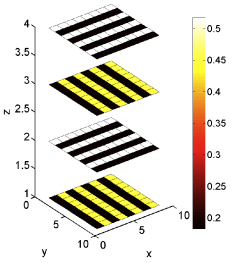

Fig 2: Synthetic phantom: Black voxels mimic grey matter with *f*=0. White and yellow voxels mimic white matter with fibre orientations along the x or y axes, respectively

RESULTS Reconstruction error: The error between the ground-truth and the reconstructed HR image $\mathbf{x}^n$ is shown in Table 1. In comparison with the error values for the initial image $\mathbf{x}^0$ used to start the optimization, these results demonstrate a signal improvement due to the SRR optimization procedure. The proposed SRR produces a smaller error than the SRR by [1]. The difference between their error values increases with decreasing SNR of the synthetic DWI data. Especially for an SNR of 20, the error of the proposed SRR is significantly smaller. RMSE: Fig. 2, a volumetric slice-by-slice presentation of the image data, shows the voxel-wise RMSE values determined between the ground-truth and the reconstructed signal obtained for an SNR of 20 by the current and the proposed SRR. It shows smaller RMSE values for the proposed SRR throughout the phantom. In terms of accuracy and precision, the proposed SRR outperforms the SRR approach in [1]. For SNR of 20, the proposed and the current SRR produce mean reconstruction errors of 1.530 and 18.002, respectively, with associated standard deviations of 0.057 and 0.235.

	NO NOISE		SNR OF 100		SNR OF 50		SNR OF 20	
	SRR_{cur}	SRR_{pro}	SRR_{cur}	SRR_{pro}	SRR_{cur}	SRR_{pro}	SRR_{cur}	SRR_{pro}
$\bar{\mathbf{x}}^0$	60.695	60.695	60.716	60.716	60.956	60.956	61.442	61.442
$\bar{\mathbf{x}}^n$	0.0495	0.0288	0.7614	0.0899	2.9801	0.2627	17.812	1.4456

Table 1: Reconstruction error between ground-truth and either the initial image $\mathbf{x}^0$ or the reconstruction $\mathbf{x}^n$, obtained for data with or without noise

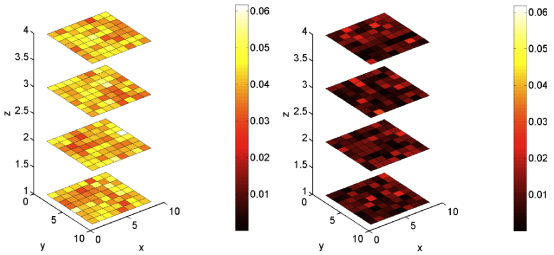

Fig 2: Voxel-wise RMSE between ground-truth and reconstruction obtained for an SNR of 20 by either the SRR by [1] (left) or the proposed SRR (right)

DISCUSSION We show that for simulated DWI data the proposed SRR approach provides better reconstruction results than the SRR technique in [1]. Because the number of tissue model parameters is much smaller than the number of diffusion gradients, the current SRR leads to over fitting. The proposed technique avoids this issue, resulting in improved HR reconstruction. Most importantly, it directly super-resolves the parameters of the underlying tissue microstructure.

CONCLUSION This work presents a novel SRR approach that improves the resolution of synthetic diffusion-weighted images and directly maps the underlying tissue microstructure. Future work will apply the proposed technique to imaging data.

REFERENCE [1] Scherrer B et al. MedIA 2012; [2] Nedjati-Gilani S et al. ISBI 2008; [3] Behrens TE et al. MRM 2003.