

Accelerated motion-robust non-Cartesian multi-shot diffusion-weighted imaging with reconstruction in the image space

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Purpose: To achieve high-resolution diffusion-weighted imaging (DWI) with short duration acquisition and robustness to patient motion.

In [1, 2], high resolution (HR) dense k-space sampling of a DW image was achieved with a series of anisotropically oversampled acquisitions (so-called "shots"), which amounts to sampling k-space in a non-Cartesian manner, and by reconstruction in the image space. It was shown to provide a theoretical 8x acceleration at equal SNR compared to conventional sampling [1]. However, in [1, 2], each DWI was reconstructed separately. First, an isotropic HR gradient image could not be reconstructed if one of its shots was corrupted by intra-scan motion, even if other shots for this gradient were successfully acquired. Second, the fact that the DWIs constitute different views of the same anatomy was ignored. DW images are coupled, and this correlation of information can be leveraged by introducing in the reconstruction the knowledge of the local tissue microstructure. We propose to describe the tissue microstructure at a voxel with a diffusion compartment imaging (DCI) tissue model (e.g., Multi-tensor model, NODDI, DIAMOND) that provides a model-based description of the signal attenuation for any diffusion gradient orientation and strength. This tissue model also enables model-based generation of the non-acquired shots. We propose a novel non-Cartesian multi-shot DWI technique that simultaneously achieves HR reconstruction and DCI model estimation (Simultaneous multi-shot high-resolution Reconstruction and diffusion compartment imaging, SHORTCUT). It enables reconstruction from shots with different subsets of gradients, providing increased robustness to patient motion and potential for acceleration.

Method. SHORTCUT is formalized as a joint probabilistic model synthesized in Fig. 1. Specifically, the simultaneous estimation of HR images \mathbf{x} and of DCI model parameters \mathbf{t} (see Fig. 1) is performed according to the maximum a posteriori principle, by maximizing:

$\hat{\mathbf{x}}_{\text{MAP}}, \hat{\mathbf{t}}_{\text{MAP}} = \arg \max_{\mathbf{x}, \mathbf{t}} p(\mathbf{x}, \mathbf{t} | \mathbf{y}) = \arg \max_{\mathbf{x}, \mathbf{t}} p(\mathbf{y} | \mathbf{x}, \mathbf{t}) p(\mathbf{x} | \mathbf{t}) p(\mathbf{t})$ (1). The likelihood $p(\mathbf{y} | \mathbf{x}, \mathbf{t})$ relates to the HR reconstruction (HRR) and, assuming conditional independence, decomposes

into: $p(\mathbf{y} | \mathbf{x}, \mathbf{t}) \propto \prod_{g=1, \dots, G} \prod_{k=1, \dots, K_g} p(\mathbf{y}_{g,k} | \mathbf{x}_g, \mathbf{t}) \prod_{k=K_g+1, \dots, K} p(\mathbf{t} | \mathbf{x}_g, \mathbf{y}_{g,k})$. The term $p(\mathbf{y}_{g,k} | \mathbf{x}_g, \mathbf{t})$ incorporates an image generation model that describes how observed shots constitute an observation of the unknown \mathbf{x} (see [1],[2]). The term $p(\mathbf{t} | \mathbf{x}_g, \mathbf{y}_{g,k})$ describes the agreement (to maximize) between one HR image \mathbf{x}_g and the signal arising from the DCI model for the unobserved k^{th} shot of the gradient g . The term $p(\mathbf{x} | \mathbf{t})$ describes the agreement between all the DW images \mathbf{x} and the HR signal modeled by the DCI model with parameters \mathbf{t} , and relates to the DCI model estimation. Finally, the term $p(\mathbf{t})$ enables incorporation of a regularization prior that exploits spatial homogeneity of DCI parameters. The maximization (Eq. 1) is performed with a relaxation approach which iteratively maximizes for \mathbf{x} and \mathbf{t} , resulting in a novel algorithm that iteratively achieves 1) DCI tissue model estimation; 2) generation of the DWIs for the unobserved shots; and 3) HRR. The algorithm is initialized by computing the mean of the observed LR shots.

First, we performed numerical simulations to demonstrate the effectiveness of coupling DCI model estimation and HRR. We considered a numerical phantom composed of 1000 tensors crossing with various angles (Fig 2d) and synthesized the DW signal corrupted with Rician noise (SNR=20dB on $b=0$) for three anisotropic orthogonal shots (1x1x2mm³). We compared HRR (1x1x1mm³) alone as performed in [1, 2] to simultaneous SHORTCUT with DTI and to SHORTCUT with the DIAMOND[3] DCI tissue model. Second, we acquired three orthogonal DW scans (axial, sagittal, coronal) of a healthy volunteer (Siemens 3T Trio, 32-channel head coil, FOV=220mm, matrix=176x176, resolution=1.25x1.25x2mm³, 68 gradients each). We compared HRR alone [1, 2] to SHORTCUT-DIAMOND. Finally, we investigated the impact of discarding an increasing number M of shots. This was achieved by assessing, for each M , the average relative error between DIAMOND model parameters estimated with full gradient sampling to DIAMOND model parameters estimated over 20 repetitions of M shots randomly discarded.

Results. We experimentally observed convergence of the SHORTCUT algorithm (Fig. 1a, 1b). Fig. 1c reports the reconstruction accuracy (PSNR) of each DW image with the noise-free DW images. It shows that while SHORTCUT-DTI provides generally a higher PSNR than HRR alone (Fig. 1c ii,iii), the over-simplistic DTI tissue model can negatively impact the reconstruction (Fig. 3c iii,iv). In contrast, SHORTCUT-DIAMOND always provides the best results. Fig. 2 qualitatively shows that the mean of the LR shots is blurred and the HRR alone highly impacted by noise. In contrast, SHORTCUT-DIAMOND provides a regularized solution that preserves edges, qualitatively leading to a better HRR. Fig. 3 shows the average relative error of two DIAMOND parameters (compartment FA and fraction of isotropic diffusion) in two ROIs for increasing number of discarded shots over the 204 shots acquired. The relative error in cFA is low, while the fraction of isotropic diffusion is more impacted. A relative error lower than 10% is ensured for both parameters when a maximum of 40 gradients (i.e., 20% of the shots) is discarded.

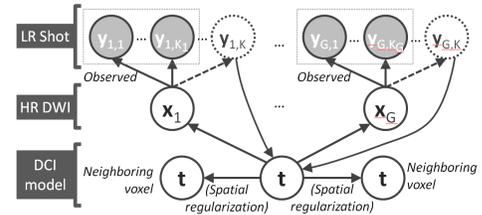
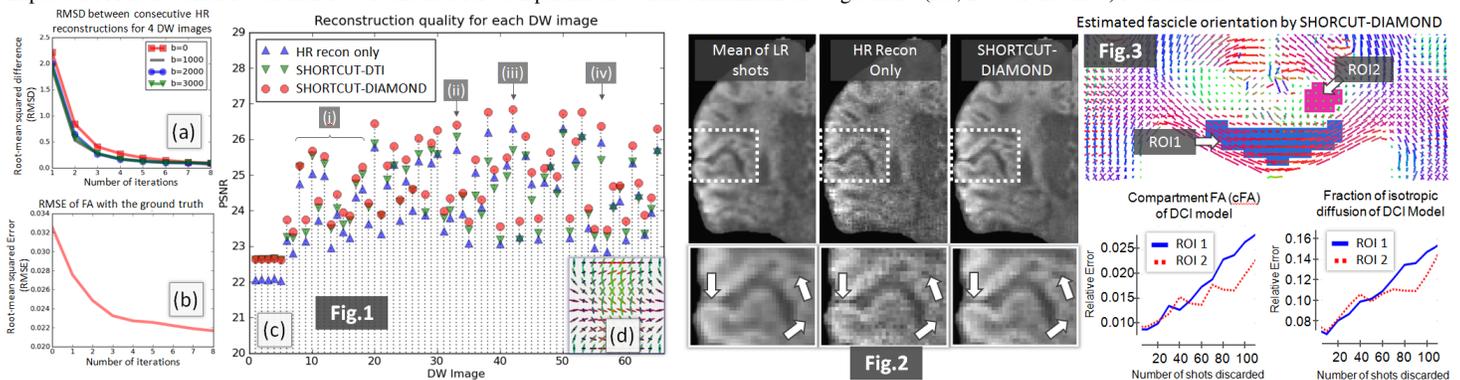


Fig.1 Graphical representation of the SHORTCUT model in which we consider that some gradients may not be acquired in all shots. K : Number of shots; G : number of unique diffusion gradients; $\mathbf{y} = (\mathbf{y}_{1,1}, \dots, \mathbf{y}_{1,K}, \dots, \mathbf{y}_{G,1}, \dots, \mathbf{y}_{G,K})$: set of KG shots in which only $(\mathbf{y}_{1,1}, \dots, \mathbf{y}_{1,K_1}, \dots, \mathbf{y}_{G,1}, \dots, \mathbf{y}_{G,K_G})$ have been actually acquired; \mathbf{t} : parameters of a general DCI model; $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_{KG})$: HR DW images we aim to recover.

Discussion and Conclusion. Our technique only requires a conventional EPI sequence and, in contrast to segmented EPI, performs model-based image HR reconstruction in the image space (instead of k-space). In contrast to segmented EPI, SHORTCUT benefits from higher SNR measurements due to the larger voxel size for each shot. We showed that combining HRR and DCI model estimation provides better results than HRR alone. However, incorporating an over-simplistic tissue model (DTI) can substantially impact the reconstruction. We showed that the error when shots are not acquired (e.g., due to motion or to accelerate the acquisition) can be quantified. **References.** [1] Scherrer, B. et al., Med Image Anal, 2012, 16(7): p. 1465-1476 [2] Poot, D.H., et al., Magn Reson Med, 2013, 69(1): p. 103-113 [3] Scherrer, B., et al., MICCAI, 2013, 16: p. 518-526.