

# Noise Reduction in Accelerated Diffusion Spectrum Imaging Through Integration of SENSE Reconstruction into Joint Reconstruction in Combination with q-Space Compressed Sensing

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**Target Audience:** Scientists and physicians working with diffusion imaging or with other protocols that involve several parallel imaging acquisitions of the same anatomical structure.

**Purpose:** Diffusion MRI acquisitions consist of a series of diffusion weighted images (DWIs) of the same anatomical structure. Usually, all DWIs are reconstructed independently, without exploiting the prior knowledge of the structural similarity between DWIs. Incorporating such prior knowledge for the purpose of SNR enhancement, Haldar *et al.*<sup>1</sup> proposed a smoothing but edge-preserving joint reconstruction of all DWIs. For acceleration of diffusion spectrum imaging (DSI)<sup>2</sup>, Menzel *et al.*<sup>3</sup> proposed compressed sensing (CS) reconstruction of randomly undersampled q-space data, leveraging the assumption of transform-domain sparsity of the data in diffusion-encoding q-space. Sperl *et al.*<sup>4</sup> demonstrated an increase in image quality through the combination of these two prior knowledge approaches. Parallel imaging using sensitivity encoding (SENSE)<sup>5,6</sup> is an image acquisition/reconstruction approach which, in the context of diffusion MRI, so far is limited to independent reconstruction of each DWI without using their commonalities. In the present work, we incorporate the SENSE reconstruction of k-space-undersampled multicoil diffusion MRI data as the encoding operator in joint reconstruction, yielding “joint SENSE reconstruction” (JSR), in combination with q-space compressed sensing, further improving image quality.

**Methods:** In SENSE reconstruction<sup>5,6</sup> of the images, each DWI  $I_n$  is obtained from the undersampled multicoil k-space data  $d_n$  by solving  $E I_n = d_n$ . The encoding operator  $E$  is given by  $E = U F C$ , where  $C$  represents the weighting of the spatial signal distribution  $I_n$  by the spatial coil sensitivity profiles,  $F$  is the Fourier transform, and  $U$  is the k-space undersampling operator. Assuming complex-valued Gaussian noise in k-space, a least-squares solution is sought. Joint image reconstruction, originally elaborated<sup>1</sup> for Fourier encoding, i.e. for  $E = F$ , incorporates a regularization term  $R(I_1, I_2, \dots, I_N)$  over all DWIs into the joint reconstruction of the DWIs, yielding

$$(\hat{I}_1, \hat{I}_2, \dots, \hat{I}_N) = \underset{(I_1, I_2, \dots, I_N)}{\operatorname{argmin}} \sum_{n=1}^N (\alpha_n^2 \|E I_n - d_n\|_2^2) + R(I_1, I_2, \dots, I_N)$$

with scalar data-consistency adjustment parameters  $\alpha_n$ . With an appropriate regularization  $R$  which models smoothness and common edges in the DWIs, joint reconstruction is performed iteratively, using, for instance, a multiplicative half-quadratic algorithm.<sup>1</sup> This formulation implies calculating finite differences between neighboring voxels and modeling the edges in the anatomical structure explicitly by line-process values. We modify the original formulation of the data consistency term by using the SENSE operator  $E = U F C$  instead of the Fourier transform  $E = F$  within the joint reconstruction framework, and by using k-space data  $d_n$  from all coils.

In case of an accelerated DSI acquisition, i.e. for randomly undersampled q-space, CS reconstruction is performed on the jointly reconstructed DWIs. For every image voxel, the q-space signals  $y_n$  are used to estimate the reciprocal r-space data by solving  $\min_x \|A x - y\|_2 + \lambda \|\Psi x\|_1$  with  $A = M F$  (undersampling operator and Fourier transform) and  $\Psi$  a sparsifying transform. A solution can be obtained using standard iterative shrinkage/thresholding algorithms (ISTA).<sup>8</sup> The reconstructed signal  $x$  can be used to compute orientation distribution functions and fiber tracts,<sup>7</sup> or  $F^{-1} x$  is used to fit diffusion and kurtosis tensors.<sup>9</sup>

Accelerated DSI experiments were performed on healthy volunteers using a 3T GE MR750 MR scanner (GE Healthcare, Waukesha, WI, USA), equipped with a 32-channel head coil (TE=116.8ms, TR=1700ms, 96x96, FOV= 240x240x27.5mm, slice=2.5mm, ASSET factor 2). The q-space size was an 11x11x11-cube with under-sampling factor R=4 (Gaussian density weighting<sup>3</sup>) and  $b_{\max}=3,000$  s/mm<sup>2</sup>. DWIs were reconstructed using standard SENSE reconstruction and JSR. Subsequently, diffusion and kurtosis tensors were fitted using weighted linear least squares<sup>10</sup> based on the undersampled and on the CS-reconstructed ( $\Psi$  total variation) q-space data.

**Results:** Fig. 1 depicts mean kurtosis for the different reconstruction methods (standard SENSE and the proposed JSR with and without CS). Independent from each other, both advanced methods (JSR and CS) improved the image quality in terms of SNR while preserving anatomical structures. Moreover, their combination yielded superior results.

**Discussion and Conclusion:** Joint SENSE reconstruction takes advantage of sensitivity encoding using multiple-coil systems as well as of the structural similarity between DWIs within one single image reconstruction framework, improving SNR. CS in q-space in combination with JSR further improves image quality.

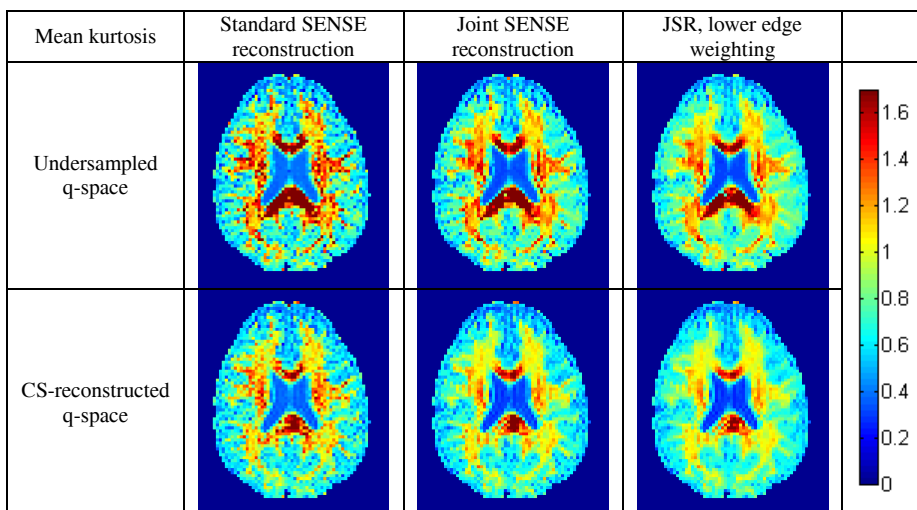


Fig. 1: Comparison of mean kurtosis for different reconstruction methods.

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