Improved SNR in Diffusion Spectrum Imaging with Statistical Reconstruction

J. P. HALDAR[1], V. J. WEDEEN[2], M. NEZAMZADEH[3], G. DAI[2], N. SCHUFF[3], AND Z-P. LIANG[1]

[1]ELECTRICAL AND COMPUTER ENGINEERING, UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN, URBANA, IL, UNITED STATES, [2]RADIOLOGY, MGH MARTINOS CENTER FOR BIOMEDICAL IMAGING, HARVARD MEDICAL SCHOOL, CHARLESTOWN, MA, UNITED STATES, [3]RADIOLOGY, UNIVERSITY OF CALIFORNIA SAN FRANCISCO, SAN FRANCISCO, CA, UNITED STATES

INTRODUCTION

The diffusion spectrum imaging (DSI) technique [1] can map the probability density of the average relative spin displacement in a voxel, and has a unique capability to resolve complex intravoxel diffusion heterogeneity. This capacity is important because the voxel sizes in typical MRI experiments are large with respect to the diffusion scale, and the signal within each voxel can represent many distinct diffusional environments. There are two important practical limitations of DSI. First, because a large number of data samples need to be collected to sufficiently cover (k, q)-space, the imaging time is inherently long. In standard implementations of DSI, a total of 515 different diffusion-weighted images are acquired; even with fast EPI pulse sequences, a full DSI experiment can take more than 25 minutes. Second, DSI data has very low signal-to-noise ratio (SNR), particularly for images encoded with heavy diffusion weightings. This is especially problematic because low SNR further limits our ability to improve resolution and imaging speed. As a result, *in vivo* DSI studies are typically acquired with relatively large voxel sizes in the range of 3-4 mm along each dimension, and still suffer from limited SNR.

THEORY AND METHODS

This paper proposes a new method to address the SNR problem, utilizing a specially-designed robust statistical reconstruction algorithm that performs adaptive spatial-spectral filtering. In particular, we reconstruct the set of diffusion weighted images using the following quasi-Bayesian optimality criterion that implicitly incorporates shared line-sites [2]:

$$\left\{\hat{\boldsymbol{\rho}}_1, \hat{\boldsymbol{\rho}}_2, \ldots \hat{\boldsymbol{\rho}}_Q\right\} = \underset{\{\boldsymbol{\rho}_1, \boldsymbol{\rho}_2, \ldots \boldsymbol{\rho}_Q\}}{\arg\min} \left\{ \left[\sum_{q=1}^{Q} w_q \left\| \mathbf{F}\boldsymbol{\rho}_q - \mathbf{d}_q \right\|_2^2 \right] + \lambda \sum_{n=1}^{N} \sum_{\substack{m\in\Omega_n \\ m>n}} \Psi\left(\sqrt{\sum_{q=1}^{Q} w_q^{\,2} \left| \rho_{q,n} - \rho_{q,m} \right|^2} \right) \right\}$$

where the $\boldsymbol{\rho}_q$ vectors represent the diffusion weighted images (with the different diffusion weightings indexed by q), the $\mathbf{d}_q$ are the corresponding vectors of k-space data, $\mathbf{F}$ is the Fourier imaging operator, the w_q are weighting coefficients, λ is a regularization parameter, and $\Psi(\cdot)$ is a cost functional related to Huber's minimax robust estimator [3]. The first term in this equation imposes that the final reconstructions are close to being data-consistent. The second term imposes a quasi-Bayesian feature-preserving joint smoothness prior on the reconstructions. This prior is designed to leverage the correlation that exists in DSI data to remove noise while preserving structural features.

The above optimization problem is solved using a half-quadratic regularization procedure [4]. This iterative scheme is globally convergent due to the convex structure of the optimality criterion, so reconstruction results are not sensitive to the initialization of the algorithm. In addition, the properties of the resulting reconstructions can be characterized using the spatial response function, as described in [5]. It is also worth pointing out that the proposed algorithm reconstructs images directly from the acquired k-space data, which allows us to accommodate non-Cartesian k-space trajectories and parallel imaging in a statistically optimal way.

RESULTS

Figure 2 shows the results of applying the proposed reconstruction technique to a mouse brain dataset in which 12 different diffusion weightings were acquired. As can be seen, the proposed method can match the SNR of an image with 4 averages, while preserving high-resolution spatial features. Figure 3 shows the result of applying the proposed method to a human brain DSI dataset. Tractography was generated using [6]. In this example, a 1 cm spherical seed volume was placed over a mesial temporal region of interest (red ball). After applying the spatial-spectral filtering, the connections of the cingulum bundle (green central curve) and fornix (small green-orange curve) are well-demonstrated.

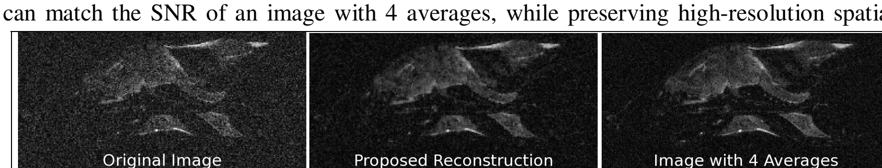

Figure 1. Images to illustrate noise reduction performance.

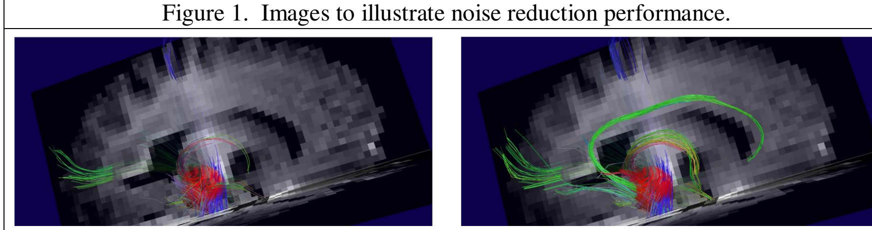

Figure 2. Tractography generated from standard image reconstruction (left) and from improved reconstruction using the proposed method (right).

CONCLUSION

This paper addresses the limited SNR problem inherent to high-resolution DSI, using a statistical reconstruction method with feature-preserving filtering capabilities. The proposed method allows new structures to be revealed within DSI data that were previously hidden by noise, and can enable faster and/or higher-resolution experiments. We expect that these improvements will benefit the precision of fiber tracking as well as the sensitivity of DSI to detect degeneration of small nerve fibers.

REFERENCES

[1] V. Wedeen , *Magn Reson Med* 2005;54:1377-1386.
[2] S. Geman, *IEEE Trans PAMI* 1984;6:721-741.
[3] P. Huber, *Robust Statistics*, New York: John Wiley & Sons, 1981.
[4] M. Nikolova, *IEEE Trans Imag Proc* 2007;16:1623-1627.
[5] J. Haldar, *Magn Reson Med*, Accepted.
[6] R. Wang, *ISMRM* 2007, 3720.