Diffusion Spectrum Imaging from Undersampled Data Using Tensor Fitting

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TARGET AUDIENCE: Scientists involved with acquisition schemes and reconstruction methods for diffusion MRI.

PURPOSE: The purpose is to accelerate the acquisition of full diffusion spectra. Commonly, a Gaussian probability distribution is assumed such that only a few samples in q-space are enough to reconstruct the Ensemble Average Propagator (EAP). But, in many occasions the Gaussian assumption is not true, and a full diffusion spectrum[1] is needed, which requires a long acquisition time[2]. In order to accelerate it, it has been proposed to use undersampling in a Compressed Sensing (CS) framework[3-6]. Nevertheless, CS requires random sampling and is only well suited for high resolution images (many samples), and since diffusion imaging is typically low resolution in the diffusion dimensions, it is difficult to achieve high acceleration factors. In this work we propose a simple modification which allows CS to work much better. The idea is to fit a tensor or multi-tensor model to the undersampled data and to work with the differences between the actual data and the model. The hypothesis is that the non-Gaussian EAP can be reasonably approximated by Gaussians.

METHODS: Single and Multi-tensor models, Pm(q), were fit to the acquired undersampled data, P(q), in q-space. We propose to reconstruct the difference of the EAP, pd(r), that fits to the q-space acquired differences Pd(q) = P(q) – Pm (q). The method uses CS (assuming a sparse pd(r)). So, the minimization problem turns to:

$$\min \mathrm{p_d} \ \|\mathrm{SFp_d(r)} - \mathrm{P_d(q)}\|_{\ell 2}^2 + \ \lambda \, \|\, \Psi \, \mathrm{p_d(r)}\|_{\ell 1} \qquad (1)$$

Where S is the sampling pattern; F the Fourier transform; and Ψ a sparsifying domain. The weight λ was manually adjusted to optimize the reconstruction. We used the regular CS reconstruction as reference for the comparison:

$$\min \mathrm{p} \ \|\mathrm{SFp(r)} - \mathrm{P(q)}\|_{\ell 2}^2 + \ \lambda \, \|\, \Psi \, \mathrm{p(r)}\|_{\ell 1}. \qquad (2)$$

Simulated data was generated as follows: (a) For one fiber we used a mix of Gaussians with the same orientation to simulate a non-Gaussian distribution; (b) For the two fibers case we use a mix of Gaussians for each orientation. Since the data is simulated we have the ground truth for evaluating the method. In the CS algorithms we use the canonical domain as the sparse domain. The data was 4-fold undersampled and tests were done in a noise-free scenario.

RESULTS: As can be seen in the figures, the proposed method is able to better reconstruct the non-Gaussian EAP forone and two fibers. We also measured the performance by the RMSE, given in the table, which agrees with the visual information from figures.

METHOD \ RMSE [%]	(A) 1 Fib – Gaussian	(B) 1 Fib - nGaussian	(C) 2 Fib - nGaussian
DSI-CS	0.14	0.3487	0.7771
PROPOSAL	**0**	**0.0363**	**0.6566**

Table 1- Comparison between our proposal and DSI-CS for (A) 1 Gaussian fiber (B) 1 non-Gaussian fiber and (C) 2 non-Gaussian fibers.

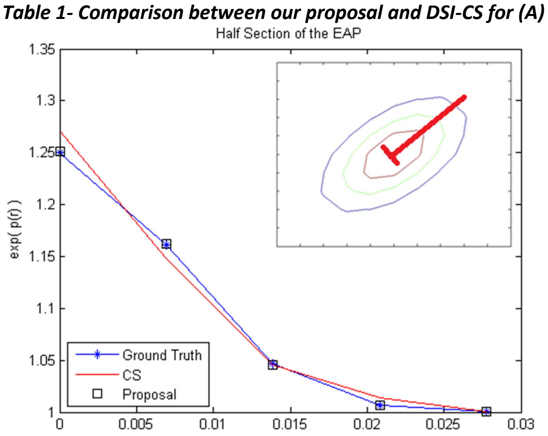

Figure 1- Reconstruction of a single fiber and visualization of a single slice (red line from the fiber simulation above the graph).

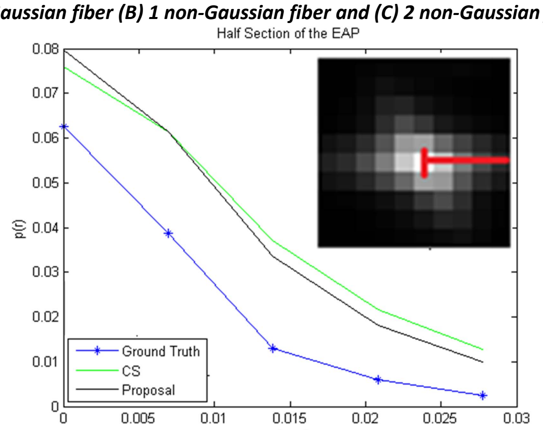

Figure 2- Reconstruction of 2 nG-fibers and visualization of a single slice (red line from the simulation above the graph).

DISCUSSION: The simple idea to fit a tensor model to the data allows for much better reconstructions of undersampled data. The novelty of this idea is that the tensor is fit to randomly sampled data. The sampling pattern can be any and is not restricted to the simple versions of same magnitude of the b-value, or a more structured sampling such as shells or multi shells. One difficulty with the proposed methods is that it requires fitting multi-tensor models which is not easy, particularly if one does not know how many fibers are in the voxel. But even in that case, it is possible to treat the data radially, in other words, fitting a Gaussian model to each angular projection (or radial line in q-space).

CONCLUSION: We have proposed a novel idea to reconstruct full diffusion spectrum images from undersampled data, using the a-priori knowledge that the EAP resembles a Gaussian distribution, although it is not. This method consists on working with the differences between the acquired data and a fitted tensor model. We presented a variant of the DSI-CS formulation which improves the quality of the image reconstruction in comparison with the traditional DSI-CS.

REFERENCES: [1] Wedeen, MRM 2005 [2] Assemhal, MIA 2011 [3] Candes, IEEE S&P 2008 [4] Menzel, et al, ISMRM 2011 [5] Paquette, MRM 2014 [6] Merlet, MICCAI 2010