

# Spherical Deconvolution on single shell and multishell combined with denoising

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## I. INTRODUCTION

We tested some classical deconvolution methods for the Sparse Reconstruction Challenge for Diffusion MRI (SPARC dMRI) of the MICCAI 2014 Workshop on Computational Diffusion MRI. We used the Constrained Spherical Deconvolution (CSD) [1] and the Sharpening Deconvolution Transform (SDT) [2] with two denoising algorithms : the Non Local Means (NLM) [3] and the Non Local Spatial and Angular Matching (NLSAM) [4] techniques. The aim was to test regular methods combined with denoising algorithms that do not take explicit advantage of sparse regularization.

Both the CSD and SDT were used on the multishell data and the 20, 30 and 60 gradients datasets with a b-value of 2000. The methods were run on the unprocessed datasets as well as on the NLM and NLSAM processed datasets, for a total of 36 submissions.

## II. METHOD DESCRIPTION

The CSD is a constrained deconvolution method working directly on the signal while the SDT deconvolves a diffusion orientation distribution function (ODF). Both methods assume that the sharper fiber ODF is formed by the convolution of a single fiber response function  $R$  and the signal or the diffusion ODF. Using the SDT and recovering the fiber ODF  $\psi_{SDT}$  enables sharper and tighter crossings than the diffusion ODF  $\psi_{QBI}$  would initially permit.

The NLM denoising method works in the image space by finding similar neighbors for each voxels. Those similar neighbors are then used to reweight each voxel according to a spatial similarity metric in order to reduce the noise.

The NLSAM denoising algorithm works in both the image domain and the angular domain. Its aim is to first find a common basis through dictionary learning to jointly denoise all of the diffusion weighted images together, which share the same underlying physical structure.

Angular neighboring gradients directions on the sphere are then jointly denoised to further enhance the angular structure and refine the denoising. Gradients directions that are close on the sphere share structure as well as angular information, which can be used to estimate the real signal value. Eq. 1 finds the dictionary  $\mathbf{D}$  and the coefficients  $\alpha$  used to denoise the raw data  $\mathbf{x}_i$ . Local patches are reorganized as  $i$  columns for the optimization and  $\lambda$  is a regularization parameter to control the sparsity of  $\alpha$ .

$$\min_{\mathbf{D}, \alpha} \frac{1}{n} \sum_{i=1}^n \left( \frac{1}{2} \|\mathbf{x}_i - \mathbf{D}\alpha_i\|_2^2 + \lambda \|\alpha_i\|_1 \right) \quad (1)$$

## III. LIST OF USED PARAMETERS

We used spherical harmonics of order 4 for the 20 gradients directions, order 6 for the 30 gradients directions and order 8 on the multishell and 60 gradients directions datasets for both the SDT and the CSD. The response function  $R$  were set to  $(\lambda_1 = 30, \lambda_2 = 2) \times 10^{-4}$  for the CSD and a ratio of  $\lambda_1/\lambda_2$  was used for the SDT. For the NLM and NLSAM method, we estimated the standard

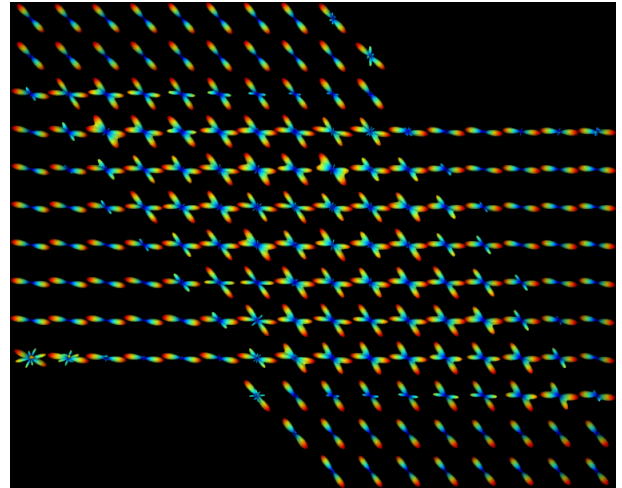


Fig. 1. CSD with NLSAM denoising on the multishell data. The 60 gradients directions dataset was used for the reconstruction.

deviation of the noise from the data itself and used a patch size of  $3 \times 3 \times 3$ . Other values were in the same range as in [3], [4]

To estimate the signal values at the required points, we simulated a multitensor model using the response function from the voxels identified as containing only one fiber. For the isotropic compartment, the mean signal on each shell was computed, then a mono-exponential decay model was fitted to extrapolate the signal for higher b-values.

## REFERENCES

- [1] J.-D. Tournier, F. Calamante, and A. Connelly, "Robust determination of the fibre orientation distribution in diffusion MRI: Non-negativity constrained super-resolved spherical deconvolution," *NeuroImage*, 2007.
- [2] M. Descoteaux, R. Deriche, T. R. Knösche, and A. Anwander, "Deterministic and probabilistic tractography based on complex fibre orientation distributions," *IEEE transactions on medical imaging*, 2009.
- [3] M. Descoteaux, N. Wiest-Daesslé, S. Prima, C. Barillot, and R. Deriche, "Impact of Rician adapted Non-Local Means filtering on HARDI," 2008.
- [4] S. St-Jean, P. Coupé, and M. Descoteaux, "Non Local Spatial and Angular Matching : a new denoising technique for diffusion MRI," in *ISMRM'14*.