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Cartesian 3D-SHORE with Laplacian Regularization

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1 Introduction

The following is a description of the algorithm used to generate submissions to the Sparse Reconstruction Challenge for Diffusion MRI (SPARC dMRI) of the MICCAI 2014 Workshop on Computational Diffusion MRI. A total of three submissions were generated for the challenge \#1 using the three-shells datasets with 20, 30, and 60 gradients per shells ($b$-values of 1000, 2000, and 3000 \text{ s/mm}^2). We pre-processed the data using a 3D Non-Local Means denoising \cite{1} on each DWIs separately.

2 Method description

We used the 3D-SHORE Cartesian basis \cite{2} with a Tikhonov regularization on the Laplacian to fit the dMRI signal. We solve the optimisation problem \( \min_x \frac{1}{2} \| E - \Phi \cdot c \|_2^2 + \frac{\lambda}{2} \| R \cdot c \|_2^2 \) where \( E \) is the normalized diffusion signal, \( \Phi \) is the system matrix of size (number of q-points)$\times$(number of basis elements) (eq. 23 in \cite{2}), \( c \) is the coefficient vector and \( R \) is the regularization matrix. We recast this optimization problem as a Quadratic Program and constrained the reconstructed signal at \( q = 0 \) to be 1. We note that the present technique makes no attempt to promote sparsity on the coefficient vector.

For all datasets, we used \( \lambda = 0.005 \) and a maximal radial order \( (N_{\text{max}}) \) of 8 for the 30 and 60 gradients per shell datasets and 6 for the 20 gradients per shell dataset in the construction of \( \Phi \).

From the fitted coefficients \( c \), we analytically compute the \( s^{th} \) order “radial moment” of the propagator \( \int_0^\infty P(r u) r^{2+s} \text{d} r \) (eq. 33 in \cite{2}). For example, Tuch’s diffusion ODF (dODF) corresponds to \( s = -2 \) and the classical dODF to \( s = 0 \). The ODFs are computed on a sphere of 5780 points with \( s = 2 \), promoting sharp angular profiles. The maxima extraction is performed discretely on min-max normalized ODFs and points with a relative amplitude \( \geq 0.5 \) that are maximal inside a 25° neighbourhood are considered as true maxima.

The signal estimation is obtained by \( E_{\text{est}} = \Phi \cdot c \) where \( \Phi \) is a new system matrix computed from the desired q-points coordinates.

Figure 1: ODFs estimated from the 3-shells with 60 gradients directions per shell dataset.

References
