## **DSI 101: Better ODFs for free!**

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Introduction: Diffusion Spectrum Imaging (DSI) is a well established method to recover the diffusion propagator (EAP). However, there has been a lot of debate about Diffusion Spectrum Imaging (DSI)<sup>1</sup> over the course of the last years with the MGH-UCLA Human Connectome Project<sup>2</sup> establishing is as one of their standard diffusion protocol for their tractography and connectomics works and with the discussion between Wedeen and Catani around the conclusions of the recent Science paper by Wedeen<sup>3</sup>. The greatest advantage of DSI is to provide the Ensemble Average Propagator (EAP) easily by solving the signal-propagator Fourier relationship with a grid-like regular sampling of the signal and a Fast Fourier Transform (FFT). DSI remains a heavy diffusion scheme in terms of acquisition time and obtaining the Orientation Distribution Function (ODF) is not direct. As DSI is almost always used as a first step before

tractography and connectomics, it is important to make sure that the ODF is reconstructed as best as possible given this large amount of data. What is really happening in practice when going from the sampled DSI signal to the ODF?

Method: In theory, the EAP, P(R), is obtained by taking the full Fourier transform (FT) of the normalized diffusion signal E(q) and then the ODF,  $\Psi(\varphi, \theta)$  is computed by integration of the EAP over radius  $\mathbf{r}$  in [0, +inf [, where  $\mathbf{q}$  and  $\mathbf{R}$  are 3D vector and  $(\boldsymbol{\varphi}, \boldsymbol{\theta}, \mathbf{r})$  is a spherical parameterization of  $\mathbf{R}$ (Eq.A). In DSI, the signal is sampled in a grid-like fashion inside a truncated q-space defined by  $q_{max}$ (Eq.B). The Fourier integral is then replaced by a discrete FT to compute a discretized EAP (Eq.C). Because of the high b-values used in DSI, the signal can be quite noisy and this noise is especially amplified when we compute the ODF, due to the r<sup>2</sup> weighting. To keep this effect under control, the signal is multiplied by a Kaiser low-pass window K(B) (a Hanning window can be obtained from a Kaiser) (Eq.D). The DSI signal is then often zero padded before the FFT to artificially increase the

$$\begin{split} & \underbrace{\mathbf{A}}_{\Psi(\phi,\theta)} = \int\limits_{\mathbf{r} \in \mathbb{R}} r^2 \left[ \int\limits_{\mathbf{q} \in \mathbb{R}^3} E(\mathbf{q}) e^{-2\pi i \mathbf{q} \cdot \mathbf{R}} \, \mathrm{d} \mathbf{q} \right] \, \mathrm{d} \mathbf{r} \\ & \underbrace{\mathbf{B}}_{\mathbf{r} \in \mathbb{R}} \int\limits_{\|\mathbf{q}\| \leq \mathbf{q}_{\max}} |E(\mathbf{q})| e^{-2\pi i \mathbf{q} \cdot \mathbf{R}} \, \mathrm{d} \mathbf{q} \, \mathrm{d} \mathbf{r} \\ & \underbrace{\mathbf{C}}_{\mathbf{r} \in \mathbb{R}} \int\limits_{\mathbf{r} \in \mathbb{R}} r^2 \, \mathrm{i} \mathrm{FFT} \left[ |E_{DSI}(\mathbf{q})| \right] \, \mathrm{d} \mathbf{r} \\ & \underbrace{\mathbf{D}}_{\mathbf{r} \in \mathbb{R}} \int\limits_{\mathbf{r} \in \mathbb{R}} r^2 \, \mathrm{i} \mathrm{FFT} \left[ Z_G \{ |E_{DSI}(\mathbf{q})| \cdot K(\beta) \} \right] \, \mathrm{d} \mathbf{r} \\ & \underbrace{\mathbf{E}}_{\mathbf{r} \in [\alpha \cdot \lfloor G/2 \rfloor, b \cdot \lfloor G/2 \rfloor]} r^2 \, I_{\phi, \theta} \{ \mathrm{i} \mathrm{FFT} \left[ Z_G \{ |E_{DSI}(\mathbf{q})| \cdot K(\beta) \} \right] \} \end{split}$$

resolution from an 11x11x11 grid (classical DSI acquisition of 515 points in a ball of radius 5 inside an 11x11x11 cube) to a GxGxG grid (operator Z<sub>6</sub>{.}) in Eq.D). Next, the EAP is computed by taking the FFT of this filtered and zero-padded grid-like signal. Before integrating (summing) along the radius, interpolation of this cartesian grid onto a spherical grid is created by discretizing the sphere (therefore,  $(\varphi, \theta)$ ) represents the spherical coordinates of some N points on the sphere) and by discretizing the radius interval  $[0, \mathbf{r}_{max}]$  (here,  $\mathbf{r}_{max} = \mathbf{floor}(\mathbf{0.5 \cdot G})$ ). This operation is represented by  $\mathbf{I}_{\phi,\theta}\{.\}$  in Eq.E. Finally, if we want to obtain accurate ODFs robust to noise but that can also accurately detect fiber crossings, we need to integrate (sum) along a smaller interval than [0, r<sub>max</sub>]. In Eq.E, we choose the generic interval [a·r<sub>max</sub>] ,  $b \cdot r_{max}$  with  $0 \le a < b \le 1$  to be "invariant" to grid size G. However, there is no general consensus as to what one

should use in the literature to maximize the accuracy of the local orientation detected. The two most common configuration of those parameters are (G = 11,  $\beta = 0.0$ , a = 0 and b = 1), motivated directly from the theory (Plain DSI (PDSI)<sup>4</sup>) and ( $\mathbf{G} = 17$ ,  $\boldsymbol{\beta} = 2.5$ ,  $\mathbf{a} = 0.25$  and  $\mathbf{b} = 0.75$ ) (Classical DSI (CDSI)<sup>1</sup>). To analyze the effect of all these parameters  $(\beta, G, a, b)$ , we computed the DSI-ODF with all possible combinations of  $\beta$  in  $\{0, 1, 2, 3, 4\}$ , G in {11, 17, 25, 35, 49, 63}, a in {0.0, 0.1, 0.2, 0.3, 0.4} and b in {0.6, 0.7, 0.8, 0.9, 1.0} for SNR in {5, 10, 15, 20, 30}. We then evaluate the reconstruction with two main metrics, the absolute difference in the number of detected Table 1: Average value of DNC(AE in degree) for the fibers (DNC) and the average Angular Error on fiber orientation (AE).

SNR	PDSI	CDSI	ODSI
5	2.150(18.4)	0.736(19.6)	0.662(21.1)
10	0.849(14.0)	0.536(14.6)	0.516(13.5)
15	0.484(11.9)	0.497(12.9)	0.353(9.3)
20	0.405(10.8)	0.479(12.1)	0.232(7.4)
30	0.348( 9.4)	0.460(11.3)	0.132(5.6)

experiment on the described dataset for a range of SNRs.

Dataset: We use a synthetic phantom of crossing containing equal proportion of angles from 30 to 90 degrees generated in a similar fashion as the ISBI 2013 HARDI reconstruction Challenge phantom<sup>5</sup> using a composite hindered and restricted signal generation model (not classical multi-tensor)<sup>6</sup>. The raw diffusion signal is generated using a classical full Cartesian grid with 515 measurements<sup>1</sup> and bmax=6000 s/mm<sup>2</sup>. We repeated the experiment fifty time with different noise and averaged the results of the metrics for each SNR.

Results: To determine the best parameters for a given SNR, rather than simply looking at the minimum value for a metric, we refine the range of best value and try to disentangle the effect of each parameter sequentially. We believe this approach helps to reduce the generalization error of our "optimal" parameter reconstruction. We also take into account the metric's variance over the repetition as a way to measure the stability of the chosen parameters. We focus mainly on DNC because it is much more representative of overall reconstruction quality (DSI being a model-free technique, the angular error is always quite low when we do detect a maxima). We find that the best parameters for ODSI are ( $\mathbf{G} = 11$ ,  $\boldsymbol{\beta} = 3.0$ ,  $\mathbf{a} = 0.4$  and  $\mathbf{b} = 0.7$ ) for SNR = 5, ( $\mathbf{G} = 63$ ,  $\boldsymbol{\beta} = 1.0$ ,  $\mathbf{a} = 0.4$  and  $\mathbf{b} = 0.7$ ) for SNR = 10, (G = 63,  $\beta = 1.0$ , a = 0.4 and b = 0.9) for SNR = 15, (G = 63,  $\beta = 0.0$ , a = 0.4 and b = 0.9) for SNR = 20 and (G = 63,  $\beta = 0.0$ , a = 0.0, 0.4 and **b** = 1.0) for SNR = 30. As we see in the table 1, ODSI significantly outperforms PDSI and CDSI for both metrics and all SNRs. This is mainly because PDSI captures all the noise in the high radius, resulting in many false positive maxima and CDSI oversmooths the propagator, greatly reducing the minimum angle at which the maximas of two fibers merge together. From the results, we found that synthetic voxel simulated by two more zero-padding always helps but the gain quickly plateaus when the SNR is reasonable (> 10) which motivates G = 35 as a tradeoff tensor (FA=0.8) crossing at 70 between computational efficiency, storage space and reconstruction quality. On the other hand,  $b/\beta$  increase/decrease together as the SNR increases, providing much better results than fixed value. We also show in fig. 1 an example of reconstruction using our ODSI (B), DSI Studio<sup>8</sup> (C) and Diffusion Toolkit<sup>7</sup> (D) on a 70° crossing at SNR = 15. All three reconstruction get a DNC of zero on this voxel but the Studio. D)Diffusion Toolkit. C and AE is 4.6°, 7.5° and 10.4° for B, C and D respectively.

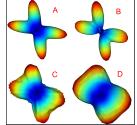


Fig. 1: ODF reconstruction of degree. The signal was corrupted by rician noise (SNR=15). A)Ground Truth. B)ODSI. C)DSI D uses default parameters and max order tesselation.

Discussion: We investigated all the steps necessary to go from the raw DSI signal to the ODF and provided applicable recommendations for these parameters that greatly improve the accuracy of the local orientation detected. These recommendations come "free-of-charge" as they are applicable to all existing DSI data and do not require a significant increase in computation time. We also suggest that the available DSI reconstruction software using the common parameters from the literature (PDSI, CDSI) are sub-optimal and should be revisited.

References: [1] Wedeen et al., MRM, 2005. [2] Setsompop et al., Neuroimage, 2013. [3] Wedeen et al., Science, 2012. [4] Hagmann et al., PLoS ONE, 2007. [5] http://hardi.epfl.ch/static/events/2013\_ISBI/data\_format.html [6] Assaf et al., Neuroimage, 2005. [7] Wang et al., ISMRM 15, 2007. [8] https://sites.google.com/a/labsolver.org/dsi-studio/