Ground-truth and Data Synthesis of Simulated DW-MRI Brain Data Sets for Quantitative Evaluation of Estimated Fiber Orientations

Establishment of simulation ground-truth

A 28-year-old right-handed male volunteer without any history of neurological disease was scanned on a GE 3T HDxt scanner (General Electric, Milwaukee, WI, USA), equipped with an 8-channel head coil. The subject signed an informed consent form for which the imaging protocol was approved by the Institutional Review Board of the University of Southern California.

A DW data set was acquired by a twice-refocused pulsed-gradient spin-echo (PGSE) sequence with TE/TR = 83.4 ms/16100 ms, acquisition matrix = 128x128, ASSET acceleration factor of 2, voxel size = 2.4x2.4x2.4 mm, 60 contiguous slices, 150 diffusion gradient directions with diffusion-weighting $b = 1000 \text{s/mm}^2$, and 10 non-diffusion weighted volumes. The acquisition took approximately 43 minutes.

Without eddy-current or motion correction the diffusion data set was processed by the probabilistic multi-fiber “ball and stick” method implemented in the program ‘bedpostx’, a part of the diffusion toolbox in the FMRIB Software Library (FSL v5.0.2.2; http://www.fmrib.ox.ac.uk/fsl; Behrens et al., 2003; Smith et al., 2004). Up to three fibers were estimated per voxel. To reduce the possibility of false minor fibers resulting from data over-fitting, a threshold of 0.1 was applied to second and third fiber volume fractions. Images of number of fibers/voxel were inspected to ensure known crossing regions (as explored later in Sect. 3.5) retained 2 or 3 fibers after thresholding.

Our synthetic DW data sets are derived from the fiber volume fractions ($f_1, f_2, f_3$) and orientations ($v_1, v_2, v_3$) estimated for each voxel and output by ‘bedpostx’. Because of differences between the “ball and stick” model and our data synthesis equation, Eq. (1), the isotropic compartment fraction ($f_0$) was not used. Instead, the fiber fractions were normalized ($\sum_{k=1}^{3} f_k = 1$) and $f_0$ was iteratively determined per voxel: beginning with $f_0 = 0$, $f_0$ was gradually increased until the generalized fractional anisotropy (GFA) (Tuch, 2004) of the synthetic data reduced to within 0.00005 of the GFA of the corresponding in-vivo data.

Anatomical T1-weighted SPGR images (TE/TR = 2.856 ms/7 ms) were acquired with a voxel size of 1x1x1 mm. The anatomical volume was registered to the mean non-diffusion weighted volume and subsequently segmented into white-matter (WM), gray-matter (GM) and cerebrospinal fluid (CSF) using default options in SPM (SPM v8; http://www.fil.ion.ucl.ac.uk/spm; Friston et al., 1995). The high-resolution tissue probability maps were then down-sampled by linear interpolation to the resolution of the DW data, and each voxel was classified as WM, GM, or CSF according to its most probable tissue type.

Diffusion-weighted data synthesis

Diffusion-weighted data were synthesized according to a multi-tensor model (Alexander et al., 2001; Tuch et al., 2002) accommodating three crossing fibers per voxel in addition to a free-diffusion compartment. For any given voxel the signal model is:

$$S(b, g_j) = S_0 f_0 \exp(-bD_0) + (1 - f_0) \sum_{k=1}^{3} f_k \exp(-b g_j^T D_k g_j)$$

(1)

where $S_0$ simulates T2-weighting, $f_0$ and $D_0$ are the volume fraction and diffusivity, respectively, of the isotropic free-diffusion compartment, $f_k$ and $D_k$ are the volume fraction and diffusion tensor, respectively, of the $k^{th}$ fiber in

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The diffusion-weighted data was inspected for eddy-current and motion related artifacts, and only minor artifacts were found. Even so, we evaluated eddy-current correction but the post-processing caused smoothing of the data which we considered detrimental to resolving crossing-fibers.
the voxel, $b$ is the diffusion-weighting, and $g_j$ is a unit vector representing the $j^{th}$ gradient direction. Altogether the volume fractions satisfy $f_0 + (1-f_0)\sum_{k=1}^{3} f_k = 1$.

Each fiber’s diffusion tensor, $D_k$, was computed by rotating a default single tensor, $D_x$. That is $D_k = R_x(v_k)D_xR_x(v_k)^T$, where $v$ is a vector defining the desired fiber orientation, $R_x(v)$ is the rotation matrix that aligns the vector $x = [1 0 0]^T$ oriented along the $x$-axis to $v$, and $D_x$ is the single-fiber tensor model with diffusivities in orthogonal directions given by $\lambda_{1,2,3}$.

\[
R_x(v) = \frac{(x+v)(x+v)^T}{(x^Tv + 1)} - I
\]  
(2)

\[
D_x = \begin{bmatrix}
\lambda_1 & 0 & 0 \\
0 & \lambda_2 & 0 \\
0 & 0 & \lambda_3
\end{bmatrix}
\]  
(3)

Complex Gaussian noise was added to the synthesized signal, $S$, to achieve a Rician distribution of noisy magnitude diffusion data (Gudbjartsson and Patz, 1995):

\[
E(b, g_j) = \sqrt{\left( S(b, g_j) + \frac{n_1}{\sqrt{2}} \right)^2 + \left( \frac{n_2}{\sqrt{2}} \right)^2}
\]  
(4)

where $n_1$ and $n_2$ are independent and identically distributed Gaussian random variables with zero mean and standard deviation $\sigma_n = \mu_{S_0}/SNR$, in which $\mu_{S_0}$ is the mean signal from a homogeneous white-matter region of the $S_0$ non-diffusion weighted image, and $SNR$ is the desired signal-to-noise ratio of the magnitude image, $E$.

References


