Anisotropic Smoothing of Diffusion Tensor Images

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Introduction

Diffusion tensor imaging (DTI) has emerged as a primary technique capable of non-invasively characterizing structural integrity and connectivity of neuronal fibers in the brain white matter. It has been found, however, image noise has a detrimental impact on this capability by inducing biased estimate of diffusion anisotropy (1) and errors in connection pathways (2). To improve the accuracy of tissue structural characterization, we have developed an anisotropic smoothing technique for denoising DTI data. This technique is briefly described below, followed by a demonstration of initial results obtained with phantom and in vivo DTI data of the human brain.

Methods

1. The smoothing algorithm. The anisotropic smoothing technique we developed is based on the concept of diffusion filtering proposed in (3), but extends it to denoise multi-channel data. The smoothing involves an iterative process with the following governing equation:

$$I_{n+1}(x,y,z,c) = I_n(x,y,z,c) + \Delta t \bullet \mathrm{div}(\mathbf{T}(x,y,z)*\mathbf{G}_c(x,y,z))$$

Where $I(x,y,z,c)$ is the intensity of the image from channel c at location (x,y,z), n is iteration number, Δt is time step size, **T** is a structure tensor, and **G** is an intensity gradient vector. Smoothing anisotropy is provided by the structure tensor **T**, which determines the direction and magnitude of smoothing. To construct the structure tensor, the intensity gradient vector $\mathbf{G}_c$ is first computed for each data channel. A gradient tensor is then obtained by taking the principal components of the gradient vectors from all data channels. The structure tensor **T** is derived by rescaling the eigenvalues of the gradient tensor such that the ellipsoid representing the structure tensor is “inverse” to that representing the gradient tensor. Thus, the eigenvalue of the structure tensor is small along the direction of large gradient, and large along the direction of small gradient. The structure tensor constructed as such will allow smoothing along the direction of low intensity gradient preferentially to that of high gradient. For smoothing diffusion tensor data, a common structure tensor **T** is constructed from diffusion weighted images acquired in all directions, and smoothing is performed individually for each diffusion weighting direction.

2. Experiments with phantom data. The smoothing algorithm was tested with a computer phantom constructed from in vivo diffusion parameters. The phantom consisted of multiple layers of “fiber” sets with different orientations. Fig. 1a shows two neighboring layers, with different colors denoting different fiber orientations (black denotes isotropic region). The phantom data were noise free but Gaussian noise was added at standard deviation (SD) of 0.05, 0.10 and 0.15 respectively. The noisy phantom data were smoothed for up to 60 iterations, and four regions of interest near “fiber” boundaries, as illustrated in Fig. 1a, were chosen to evaluate the effect of smoothing. The smoothing effect was evaluated by the dot product between the main (i.e., highest diffusivity) eigenvector in noise free data and that in smoothed data, and the increment in fractional anisotropy (FA) in smoothed data.

3. Experiments with in vivo human DTI data. DTI data from a healthy human subject were acquired at 3T GE signa scanner, generating a dataset of 128x128x34 voxels at spatial resolution of 2x2x4 mm^3. Eight scans were acquired and averaged to yield a dataset with high SNR, which was corrupted with Gaussian noise at SD=0.10 for smoothing tests. A region of interest as shown in Fig. 2a was selected for up to 60 iterations of smoothing.

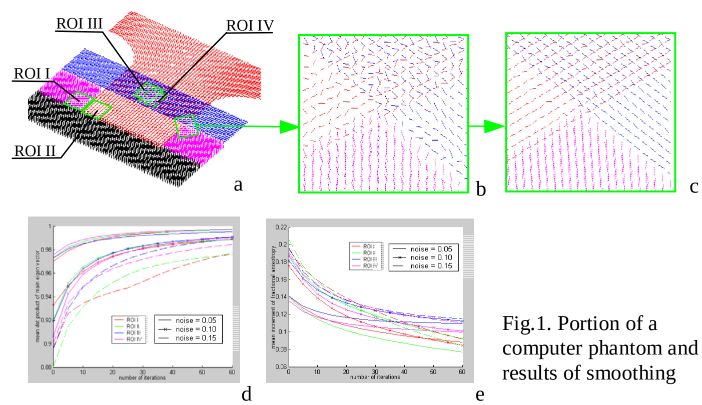

Fig.1. Portion of a computer phantom and results of smoothing

Results

Fig. 1b and 1c show the main eigenvectors in the region indicated in Fig. 1a, corrupted with Gaussian noise at SD=0.1 and after 60 iterations of smoothing respectively. It can be seen that the direction of main eigenvectors was largely restored, and no blurring near the “fiber” boundaries occurred. Variation of dot product of main eigenvectors and increment in FA with the number of iterations are plotted in Fig. 1d and 1e respectively. It is shown that the dot product increases and increment in FA (due to noise) decreases with smoothing; smoothing at 20-30 iterations can reduce most of the noise effect on main eigenvector and FA. Fig. 2b, 2c and 2d respectively show the main eigenvectors in the boxed region in Fig. 2a, with added Gaussian noise at SD=0.1, and smoothed with 30 iterations. It can be seen that smoothing can restore the main eigen directions significantly for the in vivo human DTI data.

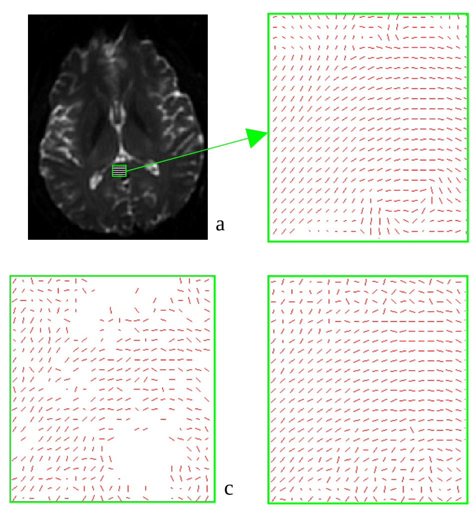

Fig.2. Results of smoothing in vivo human DTI data

Discussion and Conclusion

The restoration of direction information and preservation of structure boundaries impose special constraints on noise reduction techniques for DTI data. Linear smoothing techniques are inadequate in general. Efforts have been made in non-linear smoothing (4), but the method reported restricts smoothing near edges. Our anisotropic smoothing technique allows smoothing both in homogeneous regions and near structure boundaries (but with direction preference), thus extending the non-linear smoothing method in (4). As DTI data typically contain a large amount of tissue boundaries, such an extension may improve DTI smoothing significantly.

Acknowledgements

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