Anisotropic Kernel Smoothing of DTI Data

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Introduction

DTI measures, such as FA, trace and the eigenvector orientations, are very sensitive to noise. As the spatial resolution of DTI applications is increased, these noise effects are increased. Therefore, it is desirable to use image processing methods, such as regularization or smoothing, that will reduce noise effects while preserving the structural organization of DT field. Typical isotropic smoothing methods are effective for increasing SNR. However, isotropic smoothing also reduces the high spatial frequency image content and blurs the image features. The diffusion tensor describes a Gaussian distribution that tends to be oriented preferentially in the direction of white matter structures. Thus, we implemented an anisotropic Gaussian kernel smoothing method based on the diffusion tensor for preserving structural features while significantly reducing the noise.

Theory

Anisotropic Gaussian kernel based on tensor $\overline{D}$ is a formulated as $K_t(r) = \dfrac{exp(-r\overline{D}^{-1}r / 4t)}{(4\pi t)^{n/2}(det\,\overline{D})^{1/2}}$, where D is diffusion tensor and t is a parameter that governs the extent of the diffusion, i.e. smoothing. This kernel has a bigger bandwidth along the major eigen vector direction and a smaller bandwidth along the minor axis. The Gaussian smoothing is a process of convolution of image I and the Gaussian kernel $K_t(r)$, i.e., $K_t(r) \otimes I$ and the convolution in practical computation requires a limited t for a prescribed discrete window size, if a larger smoothing kernel is desired, the kernel convolution may be iterated to increase the effective t. Their mathematical relationship is: $K_{\sqrt{nt}} = K_t \otimes K_t \otimes K_t \ldots \otimes K_t$ *(n times)*

Methods

<u>*Data and gold standard images*</u>: A single-shot spin echo EPI sequence with diffusion-tensor encoding (12 directions, b=1000s/mm^2) , was used to get 9 sets (identical slice locations, voxels = 0.93x0.93x3.0mm interpolated to 0.9375~1mm quasi isotropic, 34 slices, 24 cm FOV) of DTI data from a single subject. Image misregistraion between DW images and data sets was corrected using affine image registration software(AIR; bishopw.loni.ucla.edu/AIR5/). “Gold standard” FA and principal eigen vector images were obtained by averaging all 9 sets of diffusion weighted images.

<u>*Isotropic versus Anisotropic Kernel Smoothing*</u>: Both anisotropic kernel smoothing and isotropic Gaussian kernel, which was provided by $K_t(r)$ with $\overline{D} = I$ (identity matrix), were applied to DW images of each DTI set. $\overline{D}$ in the kernel is normalized by the major eigenvalues to regularize a kernel size regardless of diffusion amplitudes (e.g., the filter bandwidth will be spatially invariant). Different effective kernel widths were investigated by iterating up to 32 times with $t = 0.2$. The FA and major eigenvector-maps were evaluated at each level of smoothing. Error and variance were obtained by calculating

$Error(iteration) = \left\langle |\,goldstandard\ \ FA - < FA_{\ iteration,\ i} >| \right\rangle$,

$Variance(iteration) = \left\langle |\,FA_{\ iteration, i} - < FA_{\ iteration,\ i} >|^2 \right\rangle$, *i=consecutive data set, 1…9*. The dot product of major eigenvectors from smoothed data and gold standard data in the region of high anisotropy (FA > 0.3) was also calculated to observe the effect on the directional field by Gaussian kernel convolution. Based on these three comparison methodologies, a cost function in the sense of variational principle was made to optimize t in anisotropic Gaussian kernel.

Results

The global minimum error was achieved at the 2nd iteration with the anisotropic kernel (72 % reduction) and at the 1st iteration using the isotropic kernel (39 % reduction). The error using anisotropic Gaussian kernel was always smaller than isotropic kernel at the same t and with increased iterations. The error was substantially smaller in anisotropic white matter regions with the anisotropic kernel and this difference increased with iterations. With respect to reducing the variance, the isotropic Gaussian kernel performed slightly better. The eigenvector dot product analysis showed that the eigenvector direction was better preserved using the anisotropic kernel. Based on the analysis of error, variance and principal eigenvector alignment, a cost function,

$f = \alpha \cdot error^2 + \beta \cdot variance + \delta \cdot 10^{-3}\,dot\ \ product^{-1}$ (10^{-3} was used for a scaling factor to be compatible with squared error and variance), was used to find the optimum iteration to be 3 in the case of $\alpha = 1, \beta = 1, \delta = 1$ [Fig A], if the variance reduction wants to be more emphasized, β should be increased. For instance, if $\beta = 5$, then the optimum iteration would be 8.

Discussion and Conclusions

3D anisotropic kernel smoothing based upon the tensor shape was found to preserve structural information while reducing noise. For example, compared to the original image [Fig. B], the anisotropically smoothed image [Fig. C] is markedly less noisy. While the isotrorpically smoothed image [Fig. D] is also less noisy than the original image, it shows considerably more blurring than Fig.C. The optimal parameters (e.g., iterations) are likely to depend upon the specific application and initial noise level. This approach may ultimately be useful for DTI studies at higher spatial resolution, which may suffer from impaired SNR.

Reference

Chung M.et al, 2003, UW Dept of Stats Technical Report No.1081

Fig A

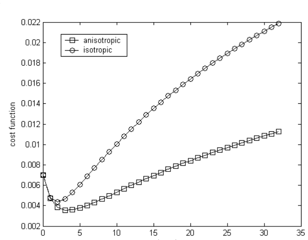

Fig B

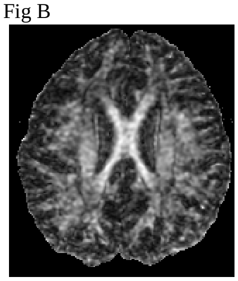

Fig C

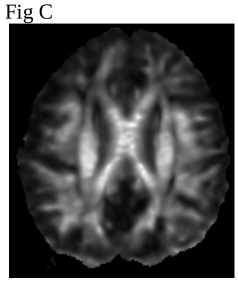

Fig D