Eigenfunction-Based Coregistration of Diffusion Tensor Images to Anatomical Magnetic Resonance Images

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Abstract To quantitatively study and compare the orientation of white matter fiber tracts, diffusion tensor images (DTIs) of different subject brains must be coregistered into a common coordinate space. We propose a two-step method of coregistration. First, nonlinear distortions are estimated by deforming a subject's DTI into his anatomical magnetic resonance image (MRI). Second, anatomical variability across subjects is removed by warping their anatomical MRIs to a reference MRI. By combining the two estimated deformation fields and reorienting the DTIs, we bring each subject's DTI into the coordinate space of the reference MRI, thereby eliminating anatomical differences between brain images while preserving fiber tract variability.

Introduction A modality of MRI, DT imaging quantitatively measures the diffusion of water molecules in the white matter of the brain [1]. Diffusion is measured along at least six independent directions by applying diffusion-sensitizing gradients that lead to eddy currents and geometric distortions in the acquired image data [2]. For the study of white matter tracts across different individuals or across differing groups of subjects, it is necessary to remove eddy current distortions [2] and coregister DT images into a common coordinate space. DTIs have been coregistered by deforming one image into other by either assuming deformations to be affine [3] or by using higher-order nonrigid deformations, such as elastic deformations [4]. However, higher-order deformations that maximize a similarity criterion may very well remove white matter tract variability between images.

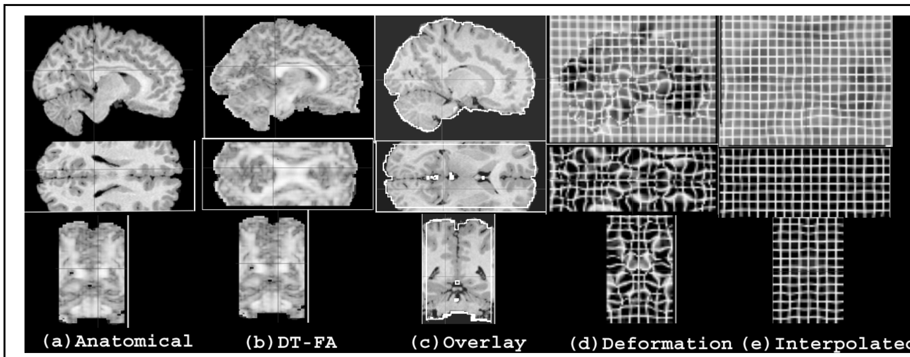
Methods We propose a two-step method for coregistering DT images that will eliminate anatomical differences between images while preserving white matter tract variability across subjects. In the first step, diffusion tensor fractional anisotropy (DT-FA) [5] image is used to estimate a high-order deformation field to warp a subject's DTI into his anatomical MRI using a fluid dynamical model [6] that maximizes mutual information across images. In the second step, the subject's anatomical image is deformed into the coordinate space of an anatomical image chosen as a reference image [6].

<u>Warping by maximizing mutual information</u> The Navier–Stokes partial differential equation (PDE) governing deformation based on fluid dynamics is given as [6]:

$$\mu\nabla^2 v + (\lambda+\mu)\nabla(\nabla\cdot v) + b(u) = 0, \tag{1}$$

where $\nabla^2 = \nabla^T\nabla$ is the Laplacian operator, $(\nabla\cdot v)$ is the divergence operator, μ and λ are the viscosity constants, and $v(x,t)$ is the velocity of the particle at time t and position x in the Eulerian reference frame. To account for differences in pixel intensities in an anatomical MRI and DT-FA image, *b(u)* in Eqn. (1) is estimated such that mutual information across images is increased. The body force b_j acting on the j th pixel in the deformed subject image is evaluated to be: $b_j = \sum_i \left(\frac{W_{\mathbf{t}}(i,j)}{\sigma_{\mathbf{t}}^2} - \frac{W_{\mathbf{s,t}}(i,j)}{\sigma_{\mathbf{s}}^2\sigma_{\mathbf{t}}^2} \right)(t_j - t_i)\left(\nabla T_j - R_{ij}^T \nabla T_i\right)$, with $W_{\mathbf{t}}(i,j) = \left(\frac{\exp\left(\frac{-1}{2}\left(\frac{t_j(h)-t_i(h)}{\sigma_{\mathbf{t}}}\right)^2\right)}{\sum_k \exp\left(\frac{-1}{2}\left(\frac{t_j(h)-t_k(h)}{\sigma_{\mathbf{t}}}\right)^2\right)} \right)$, and $W_{\mathbf{s,t}}(i,j) = \left[\frac{\exp\left[\frac{-1}{2}\left(\left(\frac{s_j(h)-s_i(h)}{\sigma_{\mathbf{s}}}\right)^2 + \left(\frac{t_j(h)-t_i(h)}{\sigma_{\mathbf{t}}}\right)^2\right)\right]}{\sum_k \exp\left[\frac{-1}{2} left(\left(\frac{s_j(h)-s_k(h)}{\sigma_{\mathbf{s}}}\right)^2 + \left(\frac{t_j(h)-t_k(h)}{\sigma_{\mathbf{t}}}\right)^2\right)\right]} \right]$ where s_i, s_j and t_i, t_j are independently selected from the subject's anatomical MR and the DT-FA images, respectively, $\nabla T_j = (\frac{\partial t_j}{\partial x^{(1)}} \frac{\partial t_j}{\partial x^{(2)}} \frac{\partial t_j}{\partial x^{(3)}})^T$ denote the image gradient at the pixel j in the DT-FA image, and let R_{ij} be the rotation matrix which rotates the direction vector d_i into d_j.

<u>Interpolating the deformation field</u> The estimated deformation field tends to remove small structures in the DT-FA image. Thus, to preserve small structures in the DT-FA image and to have a globally smooth deformation field, deformation field estimated along the boundaries of the gray matter and CSF is interpolated across the entire DT-FA image. We propose using the eigen functions [6] of the linear operator in Eqn. (1) for interpolation. The interpolation of the deformation field is carried out by first projecting it on the eigen functions of spatial frequencies up to 10 to estimate the weights and then taking a linear sum of these eigen functions to estimate a smooth deformation field across the entire image.



Results The figure shows (a) anatomical MR image of a subject, (b) DT-FA map coregistered and warped to anatomical image, (c) overlays of the outlines on DT-FA onto anatomical MRI, (d) final estimated deformation field, and (e) interpolated and smoothed deformation field. These results show that final warped DT-FA image preserved small structures, and the outlines of the images match well. Interpolated deformation field is smooth and feasible.

Discussion Our results show that interpolated and Deformed DT-FA image retains important details in white matter structures. Our interpolation method has many advantages: such as eigen function-based interpolation is parameter-independent (except for setting the maximum desired spatial frequency); the estimated deformation field is continuous and differentiable; and maintaining small maximum spatial frequencies produces an estimated deformation field that is globally smooth.

References

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