

Fast Feature-Based Multi-Scale Registration of HARDI Data Using Fourth Order Tensors

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INTRODUCTION: Diffusion Weighted Magnetic Resonance Imaging (DW-MRI) affords an unprecedented insight into the microstructures of brain tissues. However, second order tensor which is commonly used to approximate the diffusivity profile of each acquired voxel is known to fail to capture fiber-crossings. One-third to two-thirds of imaging voxels in the human brain's white matter are thought to contain multiple fiber bundle crossings [1], in which case the second order model breaks down. Of the approaches proposed to solve this problem, Fourth Order Tensors (FOTs) give elegant mathematical properties akin to that of the second order tensors. Recent formulation of FOT imposes positivity on the estimates to ensure soundness in a physical sense - a property not often found in more general higher order tensor approximations [2]. Employing FOTs, we propose a fast feature-based multi-scale registration algorithm for whole brain HARDI data. Our registration algorithm requires a low computation cost - 5 minutes to register a pair of 128x128x80 images at 2mm isotropic resolution - making it practically feasible for clinical applications. Our methods involve three major components: 1) Generation of FOT-based features, 2) Hierarchical correspondence matching, 3) Dense deformation field estimation, and 4) Retransformation.

METHODS:

[Features] Fourth order tensors represent the diffusion function $d(\mathbf{g})$ using the standard notation of quartic forms: $d(\mathbf{g}) = \sum_{i+j+k+l=4} D_{i,j,k,l} g_1^i g_2^j g_3^k g_3^l$ where $\mathbf{g} = [g_1, g_2, g_3]^T$ is the magnetic field gradient direction. There are 15 unique diffusion coefficients $D_{i,j,k,l}$ in contrast to 6 in the case of second order tensors. A regularized symmetric positive definite parameterization of the coefficients can be found in [3]. In our algorithm, features extracted from these coefficients include: 1) **Generalized Trace:** $\langle \mathbf{D} \rangle = (D_{4,0,0,0} + D_{0,4,0,0} + D_{0,0,4,0} + (D_{2,2,0,0} + D_{2,0,2,0} + D_{0,2,2,0})/3)/5$, which measures the extent of diffusivity. 2) **Generalized Anisotropy:** $5/4 \times \sqrt{\text{dist}^2(\mathbf{D}, \mathbf{D}_{\text{iso}}) / \text{dist}^2(\mathbf{D}, \mathbf{D}_0)}$, where \mathbf{D}_{iso} has all components equal to zero except $D_{4,0,0,0} = D_{0,4,0,0} = D_{0,0,4,0} = 0.5D_{2,2,0,0} = 0.5D_{2,0,2,0} = 0.5D_{0,2,2,0} = \langle \mathbf{D} \rangle$, and \mathbf{D}_0 is a zero fourth order tensor. The definition of the distance $\text{dist}^2(\dots)$ is relatively lengthy and hence not included here; it can be found in [3]. 3) **Regional Trace:** $\langle \mathbf{D}_{\text{mean}} \rangle$, where \mathbf{D}_{mean} is a regional mean tensor obtained by averaging the tensor in a local neighborhood. 4) **Regional Variance:** $\sqrt{\sum_z \text{dist}^2(\mathbf{D}(\mathbf{z}), \mathbf{D}_{\text{mean}})} / \langle \mathbf{D}_{\text{mean}} \rangle$. 5) **Edges of Generalized Trace and Generalized Anisotropy Maps:** Edge maps computed from the statistical maps by applying a 3D Canny edge detector - important for characterizing and ensuring proper alignment of ventricular and white-matter boundaries. **[Correspondence matching]** The above-mentioned features are collected into a feature vector for each voxel as its structural signature for correspondence matching. The following strategies are employed for robust matching: 1) **Automatic hierarchical landmark selection:** A salient-feature priority scheme where automatic landmarks are progressively selected in decreasing saliency (according to the feature vector distinctiveness of a voxel) to participate in guiding the registration, 2) **Soft-correspondence:** where we allow all possible candidate correspondence points (with sufficient feature vector similarity to a current landmark point) to be given respective weights, so that in the end we can come to a deformation target location based on a final, more informed, weighted decision. 3) **TPS-Interpolation:** A hierarchical thin-plate spline (TPS) [4] interpolation strategy, where we ensure well-behaving transformation to properly preserve biologically meaningful topology, first for the prominent major structures and then for the finer minor structures. More description of these strategies can be found in [5]. **[Retransformation]** We use the method presented in [3] and [4] for retransforming the fourth order tensors.

MATERIALS: 6 adult subjects were scanned using an EPI sequence with b values 1000s/mm² and 3000s/mm² applied in 120 non-collinear directions (NEX=1). Reference scans with $b = 0$ were also obtained. 80 contiguous slices with slice thickness of 2mm covered a field of view (FOV) of 256 x 256mm² with an isotropic voxel size of 2mm.

RESULTS: [Registration Accuracy] Selecting one image (from the set of images acquired with $b=1000\text{s/mm}^2$) as the template, we registered the other 5 images onto the template and measured the registration consistency by computing the normalized scalar products of the diffusion anisotropy maps of the aligned images with respect to that of the mean image generated by the aligned images. Our method gives a high average value of 0.92 (the highest possible value is 1), and is significantly better compared to affine registration (paired t -test, $p < 0.001$). **[Noise Robustness]** We evaluated the performance of our algorithm with respect to noise by performing the same registration process on the set of images acquired using $b=3000\text{s/mm}^2$. Despite the decreased SNR, registration performance of our method, as measured by the normalized scalar product, does not show statistically significant degradation (paired t -test, $p=0.89$).

REFERENCES: [1] Behrens et al., NeuroImage, 2007. [2] Barmpoutis et al., NeuroImage, 2009. [3] Barmpoutis et al., MICCAI, 2007. [4] Barmpoutis et al., MICCAI 2009.

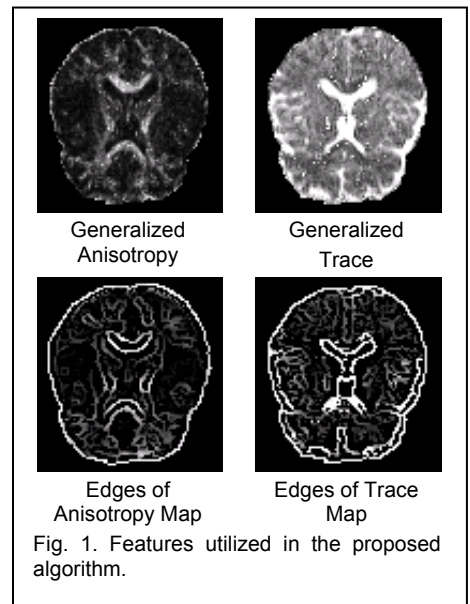


Fig. 1. Features utilized in the proposed algorithm.