

Cardiac Diffusion Tensor Imaging Registration

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Introduction

Diffusion tensor imaging (DTI) [2] allows the visualization of diffusion of water in tissue. For the last decade, this powerful imaging technique has been mainly applied in neurological studies where fiber tracts can be analyzed revealing white matter connectivity. Extensive work on DTI brain registration was developed with the goal of providing physicians a tool for monitoring degenerative brain diseases (intra-subject registration) and finding statistical differences between different populations (inter-subject registration). Cardiac DTI registration is an ongoing subject of research. DTI provides a means to characterize cardiac fiber architecture, resulting in a better understanding of the electrical and mechanical behavior of the heart. Cardiac pathologies can be identified through DTI, where myocardium structural remodeling may be observed. The first attempts to create a statistical atlas of the cardiac fiber [7] and use cardiac DTI for clinical applications [5, 9] have recently been presented. However, in-vivo cardiac DTI is challenging due to the signal attenuation resulting from the heart motion. Efforts are being made in order to work towards in-vivo DTI [6, 8].

Aim

In this paper we focus on registering ex-vivo cardiac DTI using affine transformations and comparing five different similarity measures: (1) Relative anisotropy (v_1): $\delta 1(\mathbf{D}_1, \mathbf{D}_2) = -|Tr(\mathbf{D}_1)/3 - Tr(\mathbf{D}_2)/3|$. (2) Modulus difference: $\delta 2(\mathbf{D}_1, \mathbf{D}_2) = -|v_r(\mathbf{D}_1) - v_r(\mathbf{D}_2)|$. (3) Tensor difference: $\delta 3(\mathbf{D}_1, \mathbf{D}_2) = ((\mathbf{D}_1 - \mathbf{D}_2) : (\mathbf{D}_1 - \mathbf{D}_2))^{1/2}$ where $\mathbf{D}_1 : \mathbf{D}_2 = Tr(\mathbf{D}_1 \mathbf{D}_2)$. (4) Normalized tensor difference: $\delta 4(\mathbf{D}_1, \mathbf{D}_2) = ((\mathbf{D}_1 - \mathbf{D}_2) : (\mathbf{D}_1 - \mathbf{D}_2))^{1/2} / (Tr(\mathbf{D}_1)Tr(\mathbf{D}_2))^{1/2}$. (5) Principal direction difference: $\delta 5(\mathbf{D}_1, \mathbf{D}_2) = (v_1 v_2)^{-1/2} ((v_1 v_2)^{1/2} \times \cos^{-1} |e_1 \oplus e_2|)$. v_1 and v_2 are the anisotropies and e_1 and e_2 are the principal eigenvectors of the two tensors. We compared similarity measures based on derived scalar indices which do not use orientation information (1, 2) and measures that are sensitive to the full tensor (3, 4, 5).

Methods

(1) **Ex-vivo scans** DTI data of 6 Wistar rat hearts were measured at 6.3T (Bruker BioSpec, Germany) (FOV=32x16x16 mm³, matrix size = 128x64x64, spatial resolution = 250 μm/pixel, TR/TE = 1000/25 ms, NSA = 1). Diffusion weighting parameters: gradient separation time $\Delta = 14$ ms, gradient duration $\delta = 6$ ms, b-values ≈ 900 s mm⁻². Diffusion was measured in 10 different directions.

(2) **DTI Registration** The images obtained were preprocessed using MATLAB routines developed with the purpose of extracting the raw diffusion tensor and filtering the background noise. In this paper we present the results of inter-subject registration of five subjects (sources) to a reference image (target). The registration was performed using an algorithm, which matches the tensor orientation to find the registration transformation, originally developed by Curran et al. [3] for brain registration. The source was warped into alignment with the target by applying a transformation that matches tensor size, shape and orientation most closely. Affine transformations and the Preservation of the Principal Direction (PPD) reorientation strategy were used to align the images [1]. Registration was performed with global optimization using gradient annealing [3]: Powell's local optimization combined with Simulated Annealing global optimization.

Results

For illustrative purposes, mid-ventricular short-axis views of the diffusion tensor for the source and the target images are shown in Fig. 1. The color code shows the principal eigenvector directions: x (red), y (green) and z (blue). Fig. 2 shows the overlaid anisotropy maps of the target (red) with the warped source (green) images computed for the five different similarity measures. The yellow regions correspond to the areas where the images are well aligned. Visual inspection of the anisotropy maps revealed that the principal direction difference was the best similarity measure (highlighted in red in Fig. 2).

In order to describe quantitatively the results of the registration, we compared the Euclidean distance of three manually selected anatomical landmarks (L1:apex, L2:posterior and L3:anterior papillary muscles) in the warped and target images for the five similarity measures described above. The mean Euclidean distances obtained were, in descending order of accuracy, 0.90 mm (principal direction), 0.92 mm (normalized tensor difference), 0.96 mm (tensor difference), 1.26 mm (relative anisotropy difference) and 2.02 mm (modulus difference).

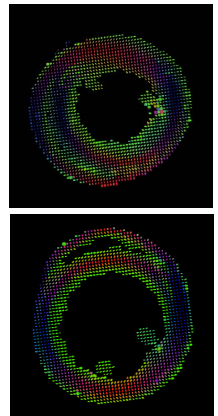


Fig. 1: DTI of source (top) and target (bottom).

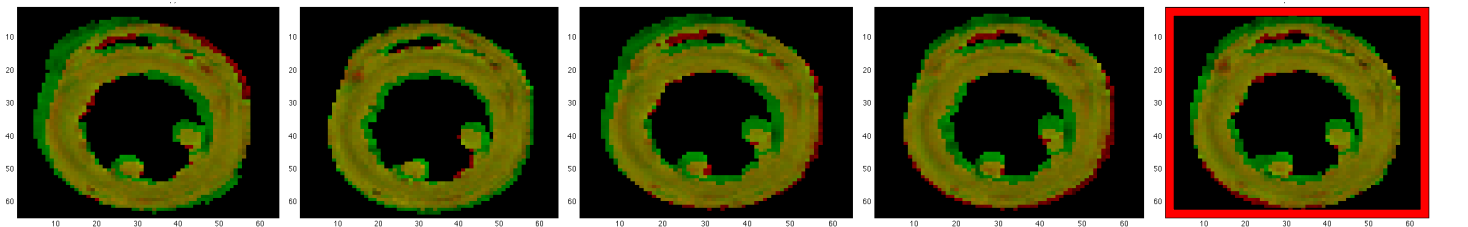


Fig. 2: From the left to the right: anisotropy maps of the five overlaid images of the target and warped images for the five similarity measures (best result in red).

Discussion and Future Work

We have successfully registered cardiac DTI and compared five different similarity measures. Results indicate that the principal direction difference is superior to the other similarity measures, followed by the normalized tensor difference and tensor difference. For cardiac DTI registration, measures sensitive to the full tensor perform better than scalar derived measures in agreement with [10] and contrary to the results obtained by [4] for brain DTI registration. We plan to extend the algorithm to use elastic transformations for improvement of cardiac DTI image registration.

References

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