Comparison of Similarity Measures for Driving Diffusion Tensor Registration

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Introduction

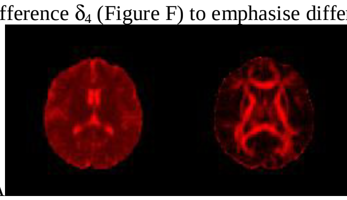
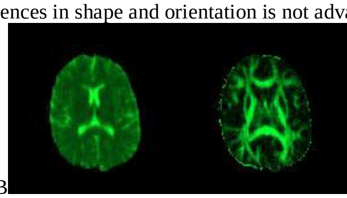
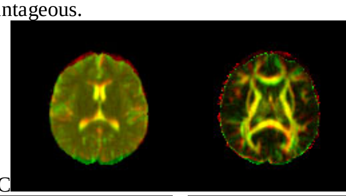
In order to obtain the best possible match between two diffusion tensor (DT) images, it is important to use an appropriate similarity measure to drive the image registration. A numerical measure of similarity is obtained by comparing the data values at corresponding image locations. For scalar images the simplest approach is to use the difference in scalar intensity at corresponding image locations but many others have been proposed that generally produce better results [1]. In the case of DT image matching, a comparative measure of similarity between diffusion tensors is required to drive the registration. Many diffusion tensor similarity measures have been proposed including those that generalise existing scalar measures and those defined specifically for DT images [2]. Alexander et al [3] propose a number of similarity measures for driving DT elastic registration. However, their registration algorithm does not include tensor reorientation in the optimisation and therefore do not match orientations. The simplest kinds of comparisons we can make between DTs are by looking at the difference in modulus (**D**) or relative anisotropy ν_r : $\delta_1(\mathbf{D_1},\mathbf{D_2}) = -|Tr(\mathbf{D_1})/3 - Tr(\mathbf{D_2})/3|$ or $\delta_2(\mathbf{D_1},\mathbf{D_2}) = -|\nu_r(\mathbf{D_1}) - \nu_r(\mathbf{D_2})|$. Similarity measures based on these derived scalar indices do not use the orientational information that is contained in a tensor. We can derive several measures from the full tensor matrix that include orientational information. The tensor difference δ_3 is a Euclidean measure between the nine corresponding elements of the two DTs. For two DTs, $\mathbf{D_1}$ and $\mathbf{D_2}$, $\delta_3(\mathbf{D_1},\mathbf{D_2}) = \sqrt{(\mathbf{D_1}-\mathbf{D_2}):(\mathbf{D_1}-\mathbf{D_2})}$, where the tensor scalar product $\mathbf{D_1} : \mathbf{D_2}$ = Tr($\mathbf{D_1}$ $\mathbf{D_2}$). The tensor difference is sensitive to differences in size, shape and orientation of the two tensors [3] and has proved effective for DT image matching in previous work [3, 4]. It can be normalised, in order to emphasise differences in shape and orientation, in the following way: $\delta_4(\mathbf{D_1},\mathbf{D_2}) = \sqrt{(\mathbf{D_1}-\mathbf{D_2}):(\mathbf{D_1}-\mathbf{D_2})} \big/ \sqrt{Tr(\mathbf{D_1})Tr(\mathbf{D_2})}$. The principal direction difference δ_5 compares the angular separation [4] of the principal DT eigenvectors $\delta_5(\mathbf{D_1},\mathbf{D_2}) = \left(\sqrt{\nu_1\nu_2}\right)^{-1}\left(\sqrt{\nu_1\nu_2} \times \cos^{-1}|\mathbf{e_1}\cdot\mathbf{e_2}|\right)$ where ν_1 and ν_2 are the anisotropies of the two DTs and $\mathbf{e_1}$ and $\mathbf{e_2}$ are their principal eigenvectors. We use a measure of prolateness [5] for ν defined by: $\nu = (\mathrm{Tr}(\mathbf{D}^2))^{-1/2}(\lambda_1-\lambda_2)$ where $\lambda_1 > \lambda_2 > \lambda_3$ are the eigenvalues of the DT. Since the motivation of this work is to determine the best DT similarity measure to drive image registration, it is important to avoid local minima traps. Spurious optima at local minima will not demonstrate the full power of a particular similarity measure.

Methods

In this paper we limit investigation to affine transformations, although the methods we describe can be extended easily to other transformation groups. We sum the voxelwise similarity over the overlapped foreground regions of the transformed source and target images and normalise by the size of the overlap. We consider only an eighth of the voxels (32 x 32 x 42) in order to reduce computation times. We use the Preservation of Principal Direction (PPD) [4] reorientation strategy to compute the transformed source image. In an attempt to find the global minimum, we combine a fast local optimization, Powell's method [6], with a global optimisation technique, Simulated Annealing [6]. We use simulated annealing to optimize the starting point for Powell's method. We call the combined method *gradient annealing* [7]. It does not guarantee to find the global minimum but if the function has many near optimal solutions it should find one. We register three DT-MR brain images (128 x 128 x 42) to a fourth template image and compare the Euclidean distance of fifty-two corresponding landmarks in the warped source and target images for similarity measures δ_1, δ_2, δ_3, δ_4 and δ_5.

Results

In figures A & B, we show the modulus and anisotropy maps in one slice of a source and target volumetric DT-MRI brain image. Figures C-G illustrate the registration results for the five similarity measures. The warped source (red), trace and anisotropy maps, are overlaid on the target maps (green). Comparing the results of the two scalar derived similarity measures, relative anisotropy difference δ_1 (Figure C) and modulus difference δ_2 (Figure D) shows that δ_1 finds a better match than δ_2 for all three registrations. Interestingly, the similarity measures that are sensitive to size, shape and orientation (Figures E-G) do not find as good a match as δ_1. However, Figures E and G illustrate that qualitatively the tensor difference δ_3 and principal direction δ_5 similarity measures are similar to δ_1. However, normalising the tensor difference δ_4 (Figure F) to emphasise differences in shape and orientation is not advantageous.

A

B

C

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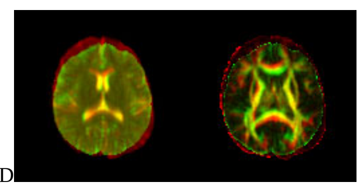

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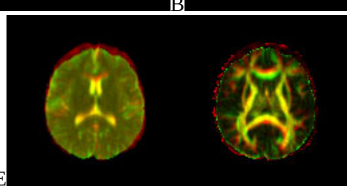
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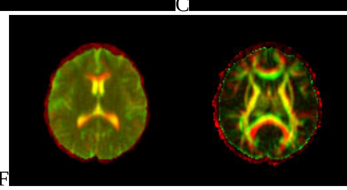
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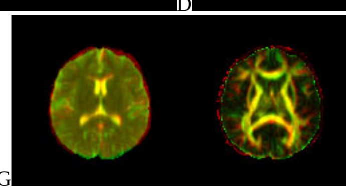

To compare the similarity measures quantitatively we calculated the Euclidean distance between fifty-two corresponding landmarks in the warped source and target images. The mean Euclidean distance for the five similarity measures were 310mm, 353mm, 314mm, 334mm and 341mm, respectively. This suggests that the relative anisotropy difference δ_1 results in the best image match. The tensor difference δ_3 does not perform as well as δ_1 despite the additional orientational information it exploits to guide the DT-MR image registration.

Discussion & Future Work

In this paper we present a comparison of diffusion tensor similarity measures. We would have expected to need similarity measures that are sensitive to all aspects of the diffusion tensor including the size, shape and orientation to exploit the information in DT-MRI fully but these results suggest that δ_1, the scalar derived measure, finds the best image match. However, in one of the three registrations, δ_3 found a better match than δ_1. Previous work [7] has demonstrated the importance of finding the global minimum. Although the gradient annealing method attempts to find the global minimum, it is still possible to get stuck in minima close to the global minima. It would be interesting to repeat the experiment with a slower cooling schedule for a larger number of data sets and for higher-order transformations.

References:

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