MULTI-CHANNEL REGISTRATION OF DIFFUSION TENSOR IMAGES USING DIRECTIONAL INFORMATION

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ABSTRACT

The problem of registering Diffusion Tensor (DT) images is considered. We describe a novel intensity based registration method capable of performing affine and nonlinear registration of multi-channel images such as DT images. We use this method to register 3 dimensional DT images of the human brain based on several channel configurations derived from the DT model. Specifically, we compare the use of channel configurations that include rotationally invariant scalar quantities derived from the DT model against channel configurations that include directional information, such as the elements of the diffusion tensor. Experiments performed with real and simulated data show that the use of the directional information present in the diffusion tensor elements can, in some instances, significantly improve the accuracy of the registration results when compared to methods that use rotationally invariant scalar information.

1. INTRODUCTION

In DT-MRI, local diffusion properties of the tissue being imaged are described via a Gaussian probability density function (pdf) on a voxel by voxel basis. This pdf is entirely characterized by a 3x3 symmetric diffusion tensor, as well as a T_2-weighted amplitude term [1]. From these 7 parameters several other diffusion related quantities can be derived. Some of these are: eigenvectors and eigenvalues of the DT, trace of the DT, diffusion anisotropy measures, etc. Thus, when attempting to register (spatially align) DT images one has several potential choices as to which set of parameters can be used during registration.

In previous work [2] we have shown that the accuracy of registration methods can be increased by including multiple channels (multiple diffusion related quantities) such as trace, anisotropy, and skewness. We showed that the results of registrations based on all three channels is superior to registration based on any single of those channels. The quantities mentioned above, however, are representations of diffusion information that discard directional orientation, they are rotationally invariant. In this paper, we test the hypothesis that the inclusion of all DT parameters during registration provides an additional improvement over multi-channel registration based on rotationally invariant measures.

2. METHODS

2.1. Multi-channel image registration

The goal in image registration is to compute a mapping function $f\colon \mathbf{x} \rightarrow \mathbf{x}'$ that transforms the spatial coordinates $\mathbf{x}$ of a target multi-channel image $\mathbf{T} = \{T_1(\mathbf{x}), ..., T_M(\mathbf{x})\}$ to the spatial coordinates $\mathbf{x}'$ of a source image $\mathbf{S} = \{S_1(\mathbf{x}'), ..., S_N(\mathbf{x}')\}$. For the source and target images to be registered the mapping function f should be chosen in such a way as to maximize some multivariate similarity measure (objective function) between the two images. Mathematically, the image registration problem can be stated as:

$$\max_f I(\mathbf{S}(f(\mathbf{x})), \mathbf{T}(\mathbf{x}), f) \tag{1}$$

where $I(\cdot,\cdot)$ represents the similarity measure or cost function,

$$I(\mathbf{S},\mathbf{T}) = \frac{1}{2} log\left(\frac{|\Sigma_\mathbf{S}||\Sigma_\mathbf{T}|}{|\Sigma|}\right). \tag{2}$$

In equation (2), $|\Sigma|$ is the determinant of joint covariance matrix of multivariate random variables $\mathbf{T}$ and $\mathbf{S}$, given by

$$|\Sigma| = \begin{vmatrix} \Sigma_\mathbf{T} & \Sigma_\mathbf{ST} \\ \Sigma_\mathbf{ST}^T & \Sigma_\mathbf{S} \end{vmatrix}. \tag{3}$$

Equation (2) is the multivariate mutual information for normally distributed multivariate random variables $\mathbf{T}$ and $\mathbf{S}$. Though most real images are not normally distributed, optimizing 2 is equivalent to maximizing the linear correlation coefficient between corresponding channels while minimizing the correlations across channels that do not correspond [2]. Note that optimizing equation (2) is much less computationally expensive than optimizing the general Mutual Information via (M+N)-dimensional estimates of the multivariate joint probability density of the images.

We use the adaptive bases algorithm [3] to model and optimize spatial transformation $f(\mathbf{x})$. The nonlinear transformation has the form:

$$f(\mathbf{x}) = A\mathbf{x} + \mathbf{t} + \sum_{i=1}^{P} \mathbf{c}_i \Phi_i(\mathbf{x}) \tag{4}$$

where A is a 12 parameter affine transformation matrix, $\mathbf{t}$ is a 3D translation vector, and $\mathbf{c}_i$ are the coefficients of radial basis functions Φ_i. Parameters A and $\mathbf{t}$ are optimized first. Optimization is performed using a gradient ascent-type procedure within a multi-resolution approach. The locations of basis functions Φ_i are chosen adaptively, to decrease computation time and increase accuracy.

As explained by Alexander et al. [4], when applying a spatial transformation to a tensor field it is necessary to reorient each tensor according to the local Jacobian of the deformation being applied. If $\mathbf{R}$ is the local rotation being applied to an image coordinate where a diffusion tensor $\mathbf{D}$ exists, the diffusion tensor in that coordinate needs to be rotated by $\mathbf{RDR}^T$. To extract a local rotation matrix given a local Jacobian matrix $\mathbf{F}$ we use the finite strain approach described in [4]:

$$\mathbf{R} = (\mathbf{FF}^T)^{1/2}\mathbf{F}. \tag{5}$$

Tensor reorientation should, in theory, be used continuously throughout any registration procedure. To save in computation time, however, we choose to perform tensor reorientation after affine registration and after the nonlinear registration is complete. We use the underlying assumption that after affine registration most structures in the two images being aligned will have similar orientations. A more aggressive reorientation strategy should, improve the accuracy of registration methods that use directional information.

2.2. Multi-channel configurations

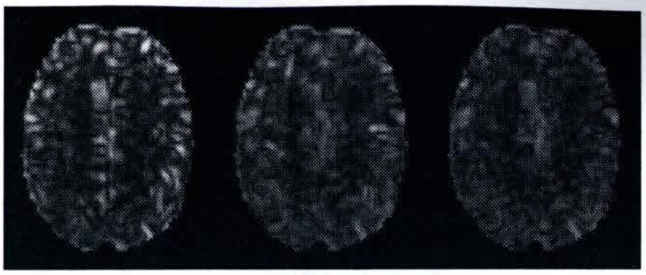
As mentioned earlier, the information content of DT images can be represented several ways. In our experiments we tested the performance of two multi-channel image configurations. One configuration consisted of a 2-channel image with the trace of the tensor in channel 1 and the relative anisotropy in channel 2. This configuration will be referred to henceforth as scalar. The second configuration contained the six unique diffusion tensor elements, as well as the amplitude parameter of the model. This channel combination will be refereed to henceforth as tensor.

2.3. Validation methods

We compared the nonrigid registration results obtained by using the two different approaches in three different experiments. The first experiment consisted of applying 10 known transformations to a reference brain image and trying to recover the same transformation using the two different registration methods. The known transformations were generated randomly by using a linear combination of radial basis functions (the basis function used in generating the known transformations and the basis functions used by the adaptive bases were different). After registration, the error between the known transformation and the transformation recovered via registration can be measured and compared on a voxel by voxel basis.

In a second experiment, we registered 6 DT images of the same subject acquired at different points in the cardiac cycle. Cardiac pulsation is known to cause movement in the brain parenchyma. Thus miss-registrations between images acquired at different points in the cardiac cycle occur. We used the variance of the trace and anisotropy channels at each voxel before and after registration with each method to compare the different approaches.

Finally, we also performed nonlinear registration of DT images of 6 different healthy volunteers to a 7th one. In this case, the true transformations that register each source image to the target image is not known. In addition, we cannot use the assumption that the images should be identical except for noise. Therefore we evaluated the performance of each method visually focusing on regions of interest.



(a) (b) (c)

Fig. 1. Coefficient of variation images of the trace component of a series of cardiac-gated DT MRIs. Part (a): no registration. Part (b): registration using scalar image components. Part (c): registration based in diffusion tensor elements.

3. RESULTS

In the simulation experiments, registration based on the tensor channel combination produced an average voxel error of 0.483 whereas in the scalar channel combination the average voxel error was 0.699. The results were statistically significant using standard Student's T-tests.

In the cardiac gated experiments, the mean of the standard deviation of the relative anisotropy and of the trace of the tensor before registration were 0.0159 and 117.3, re-

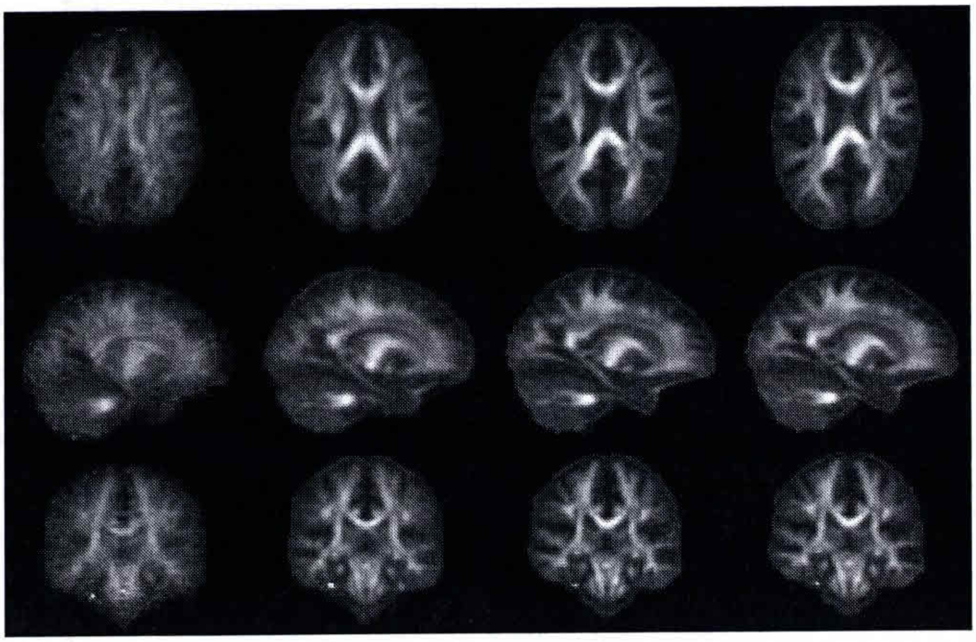


Fig. 2. Average relative anisotropy images of unrelated subjects produced, column-wise from left to right, without registration, after rigid body registration, nonrigid registration using scalar channels, and after nonrigid registration using tensor elements.

spectively. After nonlinear registration using the scalar channel combination these were reduced to 0.0138 and 88.9, respectively. After nonlinear registration using the tensor channel combination, these quantities were further reduced to 0.0131, and 82.8. Again, these differences in mean were statistically significant with a very small significance level ($\alpha \sim 0$).

Figure 1 displays an axial slice of the coefficient of variation of the trace of the diffusion tensor. The location of the slice is near the middle of the brain. Part (a) shows the coefficient of variation before any nonrigid registration. Part (b) shows the coefficient of variation after registration with the scalar channel combination, and part (c) shows the coefficient of variation after registration with the tensor channel combination. The reduction in variability is most visible in the areas of interface between gray matter and cerebrospinal fluid (CSF).

The results of the nonrigid inter-patient registration experiments were visually inspected and, in general, we found that registration using the tensor channel combination failed to produce results that were significantly more accurate than the results obtained using the scalar channel combination. This can be seen in figure 2 which show axial, sagital, and coronal reconstructions of the average fractional anisotropy images obtained with, column-wise from left to right, no registration, with rigid body registration, with nonrigid registration using rotationally invariant components, and finally registration using the tensor elements. The average images show increase in sharpness between the no registration and rigid body registration figures. An increase in sharpness between the rigid body registration figures and the nonrigid registration figures is also noticeable. However, no significant differences can be noticed between the average images obtained using nonrigid registration based on the combination of scalar quantities and the average images obtained using nonrigid registration based on the tensor elements.

One region of the brain where the tensor-based registration seems to have outperformed the scalar based registration is in the area of the pons. This is shown by the slight increase in the sharpness of the average color images produced by the tensor-based registration as compared to the scalar one (figure 3). The images shown in figure 3 are color representations of the direction vector associated with greatest diffusivity, appropriately weighted by an anisotropy index. In this figure, the motor fibers seem to be more distinguishable in the average images produced by the tensor based registration.

An improvement that tensor based registration provides over the scalar channel combination based registration is that it seems to be less prone to produce transformations that tear or fold the image. This seems to be true particularly in sub-cortical regions where a one to one exact correspondence between the images being registered may not exist. Figure 4 contains an example image registration using the scalar channel combination (left image) and the tensor channel combination (right image). Encoded in orange are the regions where the determinant of the jacobian matrix of the transformation produced by the registration procedure

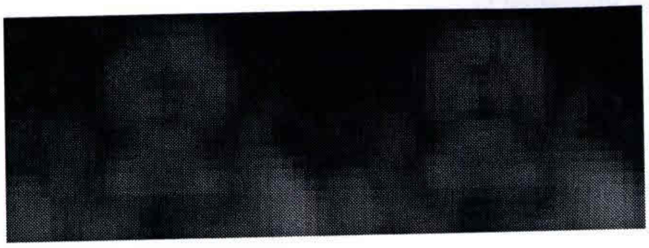


Fig. 3. Color representation of average reconstruction of the pons. Left: average after registration using scalar channels. Right: average after registration with tensor elements.

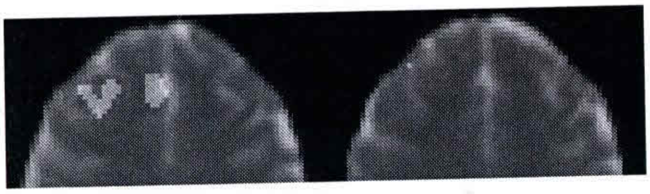


Fig. 4. The trace channel after registration using scalar channels (left) and tensor channels (right). Encoded in orange are regions where the determinant of the jacobian matrix of the transformation resulting from the registration was less than or equal to zero. Registration based on the tensor elements is less likely to produce folding or tearing artifacts.

was less than or equal to zero.

4. DISCUSSION AND CONCLUSIONS

We presented a general method for performing multi-channel based nonrigid registration of DT images. The method uses a multi-channel similarity measure that considers the similarity between same-index image channels as well as the similarity between image channels with different index. Using this method, we registered DT images using several channel combinations so as to identify which channel combinations produce most accurate results. Considering the results from all experiments performed, image registration based on the individual diffusion tensor elements, including also the amplitude image, performed best amongst all options tried.

While the results of the simulation and cardiac-gated DT image registration experiments show improved accuracy when using the tensor channel combination, the results of the inter-subject registrations did not show a significant improvement in accuracy. This is a similar finding to that of Guimond et al. [5], though the methods we used were entirely different. However, tensor based registrations were less likely to produce folding or tearing artifacts when registering images from unrelated subjects.

Thus we conclude that using directional information to register DT images produces an improvement in accuracy over methods that use combinations of rotationally invariant scalar measures when an exact correspondence between a location in the target image and a location in the source image is known to exist. This is the case in the simulated image registration experiments, as well as in intra-subject registrations such as the registration of cardiac-gated DT-MRIs. Our inter-subject registration results did not support the same conclusion. However, because of the lack of a gold standard, our evaluation methods for this experiment were also less reliable.

Our entire software was written in the Interactive Data Language (Research Systems, Inc.) Thus nonrigid free form registration of two 7-channel images with dimensions 128 x 128 x 78 on a Intel Xeon processor running at 2.8MHz can take up to 2.5 days. Registration of two 2-channel images of same dimensions can be performed in 2-3 hours. We are currently in the process of implementing our methods in C, which will reduce computation times significantly. A faster implementation will also allow us to test more aggressive tensor reorientation schemes, which, in theory, should produce more accurate registration results.

We expect that the methods shown here should be useful in characterization and removal of artifacts, e.g., arising from cardiac pulsation, in comparing data obtained from longitudinal and multi-site DTI studies, and in atlas construction from DTI data.

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