

1 Introduction

We present a technique for visualizing the differences between two diffusion tensor MR (DT-MRI) volumes. Our technique registers two DT-MRI's and then produces a 3D model that allows a user to simultaneously view structure in each volume. The geometric model is based on an earlier one developed to visually represent a single volume with a carefully chosen set of streamtubes [6,7]. In the new model, we choose corresponding tubes in both volumes and show how they differ as a way to display the differences between the volumes. Saturation is used to indicate the magnitude of the difference between corresponding points on streamtubes. Streamtubes follow the orientation of the principal eigenvector of the diffusion tensor at each point in the volume. The cross-section at each point of the streamtube is an ellipse determined by the second and third eigenvectors and eigenvalues of the diffusion tensor.

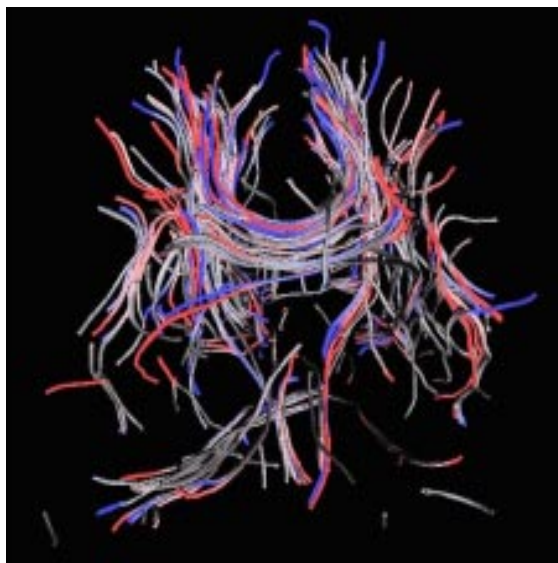
We apply the method to four cases. In the first, we show how the choice of integration method can change the streamtubes by comparing streamtubes generated with different integration methods. In the second case, we show difference models for two volumes that are identical except for noise. In the third case we show differences between two volumes acquired from the same human subject but at different orientations.

2 Methods

The technique used to generate the difference models presented in this paper consists of four steps. First, two DT-MRIs are resampled to the same isotropic resolution. The resampling is done using tricubic interpolation of each of the six diffusion tensor components. Basser *et al.* showed that such component-wise interpolation was sufficient in several experiments [1].

Next, the two volume data sets are registered semi-automatically using the gradient based methods described in [2] to align T2-weighted images. This approach works best when the difference in orientation between the two images is small enough that most voxels need move less than eight voxels. Therefore, an initial estimate of the transformation matrix is applied to one of the original images, and this image is then used by the automatic image registration program. Once the transformation matrix is calculated, it is applied to one of the DT-MRI volumes. It's important to realize that the diffusion tensors must also undergo a transformation to reflect the change in coordinates. To achieve this, we apply the linear transform to the diffusion tensor.

Once the volumes are aligned, the third step is to generate corresponding streamtubes in each image. We first generate a model for one of the volumes. This is described in more detail in [6,7]. A streamtube is analogous to the streamline in fluid flow visualization. It follows the principal direction of water diffusion. This is accomplished by integrating the principal eigenvector field (as discussed in [1]) both forward and backward starting at a particular point. Currently, one sample is within each voxel where the T2-weighted image is greater than three times the noise level is chosen as a starting point. Streamtubes that are similar to previously generated streamtubes are culled, as are short streamtubes and streamtubes with low average linear anisotropy (less than 0.2). The numerical integration is carried out by either Euler, Runge-Kutta, or Adams integration using Numerical Algorithms Group or Numerical Methods software. Diffusion tensor values at non-grid coordinates are found by tricubic interpolation of the six component values.



(A) RK vs. Euler



(B) Adams vs. RK

Figure 1: Frontal view of streamtube difference images of human brain data. For reference, note that the large left-to-right bundle of tubes near the center is the corpus callosum and the ascending connections from that bundle the corona radiata. (A) is a difference image between a model generated with Runge-Kutta (in blue) and Euler (in red) integration. (B) is a difference image between Adams (in blue) and Runge-Kutta (in red) integration. Note that (B) is almost entirely gray, in contrast with the color in (A), indicating that the Adams and Runge-Kutta integration schemes produce paths that are much more similar to each other than to paths generated by Euler integration.

With the seed points for the representative tubes for one volume, we generate corresponding tubes in the second volume. The second and third eigenvectors of the diffusion tensor at each sampled point

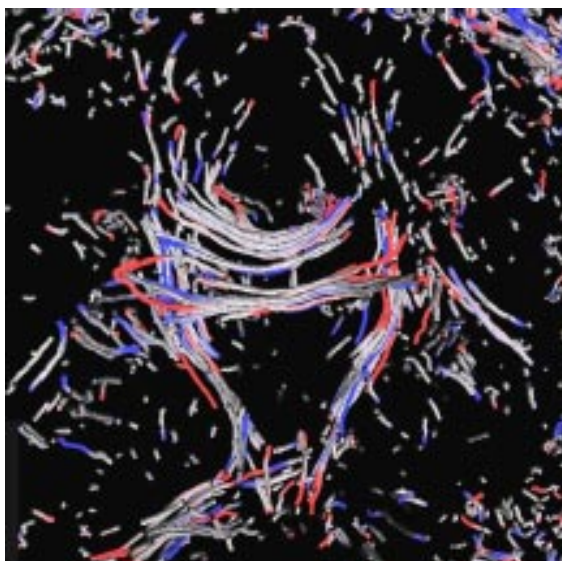


Figure 2: A streamtube difference image of the data used in figure 1 with noise added. Two new brain DT-MRI's were generated. Note the differences in streamtubes caused by the noise.

of a streamtube is stored as well as that point's distance to its corresponding streamtube in the other data set. The distance is defined to be the minimum distance between the current point and all points on the other streamtube.

The fourth and final step is the rendering of the difference model. Each streamtube is rendered as a tube. At each sampled point of the tube the second and third eigenvectors are used to construct an elliptical cross-section. The color assigned to each point on the cross-section is defined to be $(max_d - d)/max_d$, where d is the distance found and stored in the previous step and max_d is an arbitrary constant (we used ten voxels) representing the maximum voxel distance that can be represented. The elliptical cross-sections are stitched together to produce a continuous tube and output as a VRML mesh file, which can then be viewed in standard viewing applications.

3 Results and Discussion

The first type of comparisons we examined were comparisons between numerical integration algorithms. Figure [1] shows that results can vary depending on the integration scheme chosen.

We then used the same integration techniques to compare different DT-MRI's. First, we assessed the effect of noise on our technique. Figure [2] suggests that our technique is moderately sensitive to noise in the two images. We then evaluated the effect alignment has on our technique in Figure [3]. The significant amounts of gray are consistent with data collected from the same subject. The color that is present may be due to noise, to inaccuracies in the registration, or to thresholding, which can turn very small changes in the tensor into large changes in the location of a threshold.

Streamtubes are well suited for showing changes in the orientation of the principal direction of diffusion, but poorly suited for depicting changes in anisotropy. While the second and third eigenvectors are encoded in a streamtube, it is difficult to determine by sight the differences in these values between corresponding streamtubes by sight.

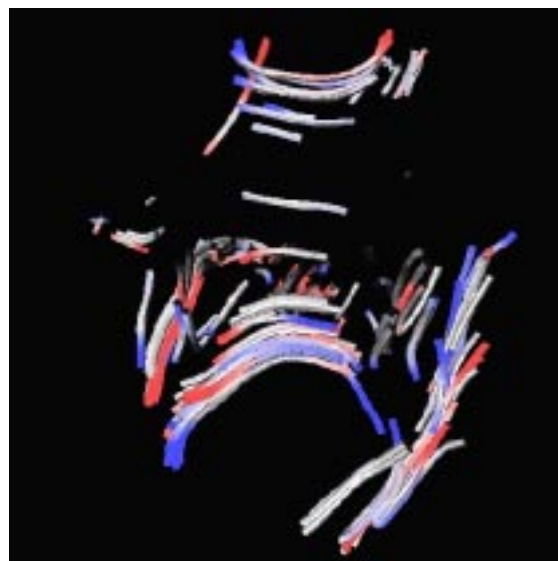


Figure 3: A different image between two acquisitions of the same brain. The acquisitions were taken at different orientation and the datasets registered before the different image was created.

4 Conclusions

This extended abstract describes a method designed to help investigators visualize differences between DT-MRI's. Despite some limitations, the images show differences that are difficult to see as well contextually using other methods.

Acknowledgments

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