Diffusion Tensor Visualization with Amira

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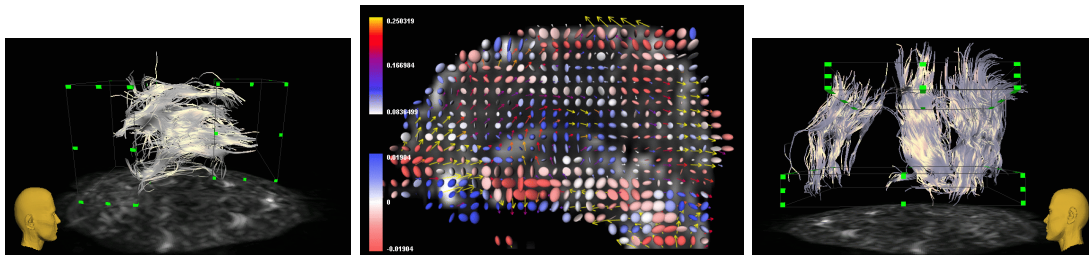
Figure 1: (**left**) fiber tracking posterior to anterior, (**middle**) rate of strain tensor visualization, (**right**) fiber tracking superior to inferior

ABSTRACT

We describe several visualization techniques that where applied to the diffusion tensor data sets provided by the IEEE Visualization challenge 2005. Especially we looked into methods to analyse non-rigid registrations of T_2 weighted image sequences and various display methods for single tensor displays and fiber tracking.

Additional informations to this work can be found on the web at `http://192.148.197.83/IEEEViz05/`. Especially the pages contain captured live demonstrations of the tools that where developed during this work.

Keywords: tensor pattern, fiber tracking, single tensor displays, interactive explorationdiffusion tensor imaging, tensor pattern, fiber tracking

1 INTRODUCTION

The medical interest in diffusion tensor imaging is based on the interest to visualize anatomical structures which are not visible with conventional techniques. Global properties such as the connectivity of brain regions by neuronal fibers in particular local properties of brain tissues under pathological incluences, such as strokes and tumors,. Here we investigated visualization approaches aiming at both targets: fiber tracking and tensor patterns.

2 DATA

We restricted our visualization attempts to one of the two data sets that where provided for the contest of the IEEE Visualization 2005. Our choice was the diffusion tensor data set. This data set was provided as image stacks coded in the DICOM format. They contain two different diffusion tensor data sets from a single patient. One was done with 31, the other with 15 measured gradient direction. Additionally they also contain an image stack without applied gradient. This data set can be recognised by its higher contrast compared to the gradient measurements and we will assume that an MR

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imaging sequence was used that results in a large T_2 weighted component in this stack. This allows us to correct for T_2 image artefacts in the gradient measurements.

3 METHODS

A first step to accurately visualize MR data is adjustment for movements between the data sets, i.e., registration of the data. In particular for diffusion MRI data, where the final tensor image is built from multiple single measurements, image registration is crucial. In this application we analyse two data set which where obtained from the same patient.

We performed rigid and non-rigid registrations on the T_2 weighted images. The rigid registration is performed in order to correct for movements of the patients head position between the two measurements. Non-rigid deformations could be caused by either imaging artefacts or changes in anatomy. Whereas corrections to imaging artefacts would allow to fuse the two data sets later, changes in anatomy are interested in themselfs. They can show for example changes in tumor growths.

In order to analyse the results of the non-rigid registration we used methods borrowed from fluid kinematics. The rate of strain tensor is a symmetric second order tensor which is related to the stress in the material. It can be computed from a displacement vector field that we obtained from the non-rigid registration of the two T_2 weighted image volumes. The metric we used for the automatic registration was a normalized mutual information.

MR imaging does not directly provide diffusion tensor data, but the raw data are given as MR signal loss dependant on certain magnetic field directions. At least six such measurement are required to yield a model of diffusion via a tensor field of order two. Additional measurements are useful to smooth out measurement errors and to increase the signal to noise ratio. A Stejskal-Tanner sequence allows us to obtain the tensor from all gradients at the same time. Westin et al. [2] showed how to compute the diffusion tensor from the gradient measurements. Moreover, these additional measurements are suitable to determine the reliability of the tensor field. In [1] we presented a method on how to assess the properties of an averaged tensor field by statistical means.

Fiber tracking aims to follow neuronal fibers in the human brain and to provide connectivity information. Since the resolution of DTI-MRI is rather low and in the range of about 2mm, it is much too coarse to resolve single physical fibers. Thus, the direction of maximal diffusion is only an averaged information over many ax-

onal fibers. To get an indication of streams of neuronal fibers ranging over many voxels, we may follow the principal direction of diffusion. This approach is facing various difficulties: the process of finding the principal direction is very vulnerable to numerical and data acquisition noise, and it regions with two similar eigenvectors it may change rapidly, leading to unpredictable results. Interpolation of tensor data beyond voxel resolution is an open issue: interpolation methods that work well for scalar data might even lead to interpolated tensor values with negative eigenvalues, an unphysical description of diffusion. When integrating fiber tracks, all these errors accumulate. Nevertheless the resulting images appear to display anatomically known structures, although they need to be interpreted with care. Our visualization is based on the technique of illuminated streamlines and more elaborated methods of fiber tracking that use the full tensor information as in methods of tensor deflection.

Pathological changes in brain tissue influence the diffusion properties as well. Eigenvector streamlines (such as employed for fiber tracking) are influenced as well, but only display a portion of the tensor field, in particular regions of one dominant eigenvector. An alternative is the local inspection of data values by iconic methods incorporating the full tensor quantity, but without connecting them. Choosing ellipsoids as representations of the tensor field is a bad choice since they suffer severely under problems of view occlusion (visual clutter), visual ambiguity and are insufficient to clearly depict small variations of the tensor field. Many alternatives have been developed. Our favorite model are so-called tensor patterns, which is a method to employ Gabor patches to represent the tensor field. This approach is supported by considerations borrowed from vision research and perception theory (see figure 2).
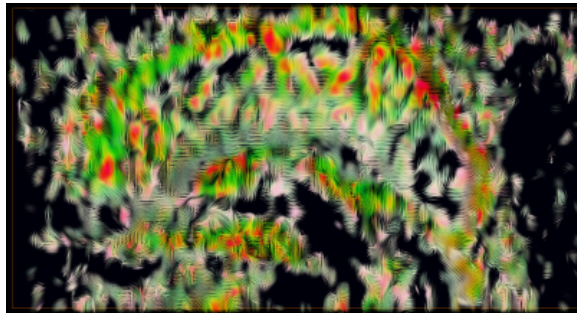

Figure 2: Tensor pattern display

4   RESULTS

All visualizations where performed on a laptop and a workstation both equipped with a NVidia graphics cards for OpenGL hardware acceleration.

The non-rigid registration resulted in a displacement vector field of a mean displacemnt of 1.03 voxel (± 1.07). This indicates that the two data sets sets have very similar T_2 components (see figure 3). Nevertheless we analysed the the spatial distribution of the observed changes which could not be correlated with anatomical features in the data (see figure 4).

The images showing the results of fiber tracking in Figure 1, left and right where obtained by a tensor deflection algorithm with a threshold value of 0.17 for the fractional anisotropy in the data. The user interface provides the means to interactively select sub-sets of lines by either regions of interest or sets of bounding boxes.
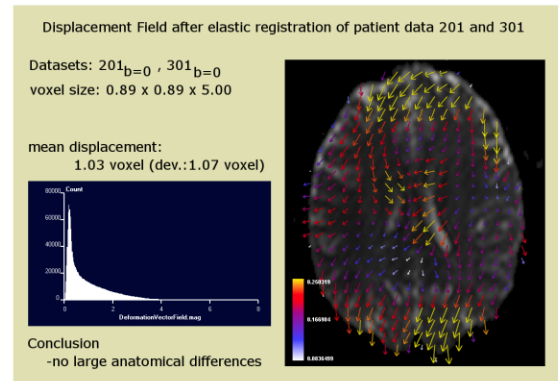

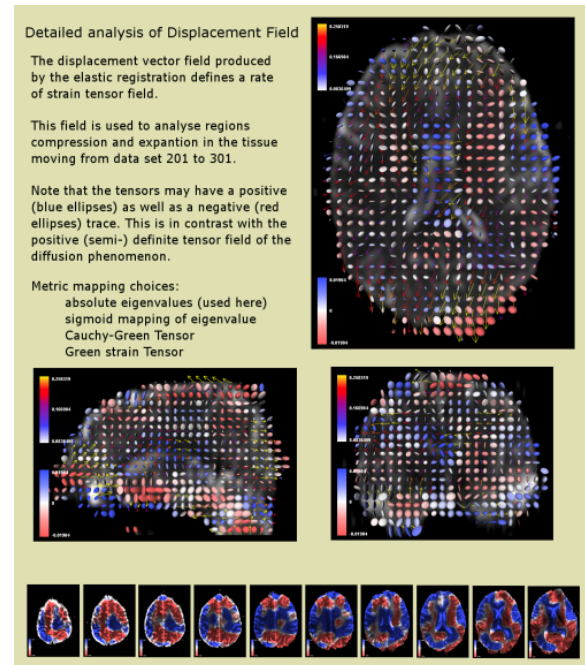Figure 3: Analysis of non-rigid registration of 201 and 301

Figure 4: Spatial variations of non-rigid registration of 201 and 301

REFERENCES

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