A Simulation Tool for Evaluating Fiber Tractography Algorithms

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Abstract. Diffusion-Tensor Magnetic Resonance Imaging is a popular imaging modality for reconstructing the nerve fiber structure in the brain. In recent years many fiber tracking algorithms have been proposed, but little research has been done comparing them and evaluating their suitability for pathological neuroanatomy. We present a modeling tool for designing normal and abnormal neuroanatomical features and for synthesizing diffusion tensor imaging data from it in order to compare fiber tractography algorithms. Initial results indicate that our modeling techniques make it easy to simulate DTI data sets for healthy and pathological brain anatomy. We compared three simple fiber tractography algorithms using our synthesized data and we obtained similar results as reported in the literature for more basic artificial DTI data sets.

Keywords: fiber tractography, diffusion tensor imaging, simulation tool, soft object, isosurface

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1. Introduction

Diffusion-Tensor Magnetic Resonance Imaging (DTI) is used to measure the intrinsic properties of water diffusion in the brain by an orientation invariant quantity, the diffusion tensor [1,2]. DTI has been successfully applied to research various neurological diseases such as Multiple Sclerosis [3], Fragile X Syndrome, a common form of hereditary mental retardation [4], and periventricular leukomalacia (PVL), the principal form of brain injury in the premature infant [5]. Researchers from the Human Motor Control Laboratory of the University of Auckland, with whom we collaborate, currently examine the neural control of movement and in particular the recovery of hand function following a stroke. This involves the development and validation of techniques for reconstructing the nerve fibre tracts in the brain from DTI data.

The reconstruction of fibre tracts is achieved by using the fact that water diffusion within fibre tracts is high in the fibre direction and low transverse to it. Due to errors (noise) in the DTI data and because of its low resolution advanced mathematical models must be employed in order to find the fibre tract with the highest probability of being correct. Previously suggested solutions include statistical models [6], which make use of the assumption that sudden changes in fibre tract direction are most likely due to errors (noise) in the data, curvature minimising schemes [7], which are based on the observation that the fibre tracts in a healthy brain usually follow a path with a minimum curvature, physically-based models [2,8], and general ordinary differential equation solvers incorporating empirical data [9]. However, no mathematical model exists which takes into account the degradation of nerve fibres (axons) after a subcortical stroke. We are currently in the process of developing novel fiber tractography algorithms which are capable for tracking nerve fibre tracts through stroke affected brain regions where diffusion anisotropy information is often misleading due to Wallerian Degeneration [10,11].

While many different techniques have been suggested for tracking nerve fiber tracts, few researchers have evaluated the quality and error sensitivity of these methods and their suitability for pathological brain DTI data. Lazar and Alexander have compared fibre tracking algorithms for tensor fields with linear, radial and circular major eigenvector fields [12].
In this paper we introduce a novel framework for modelling arbitrarily shaped virtual nerve fiber tracts and the surrounding anatomical structures and for synthesizing DTI data sets from them. The framework makes it possible to quantitatively compare nerve fiber tracking algorithms and to evaluate their sensitivity to noise and other measurement errors introduced during the imaging process. The modeling technique used in our framework can also be used to model abnormal brain anatomy and consequently will make it possible to compare the suitability of different nerve tracking algorithms for pathological brain DTI data sets.

2. A Framework for Simulating DTI Data

In order to quantitatively compare fiber tracking algorithms synthetic tensor fields are required. We reconstruct synthetic tensor fields by modeling nerve fiber tracts using B-Splines and other anatomical structures using a soft object modeling technique. Using typical diffusion values for these tissue types obtained from the literature we are then able to reconstruct a DTI data set to which noise can be added in order to simulate the errors introduced during the magnetic resonance imaging process.

2.1 Modeling of Virtual Nerve Fiber Tracts

We have developed an interactive user interface which allows the modeling of fiber tract trajectories by B-Spline curves [13]. Virtual nerve fiber tracts are created by fitting a cylindrical surface around the curve as illustrated in figure 1. The water diffusion within a fiber tract is characterized by a high diffusion in the direction of the fiber tract and a low diffusion transverse to it. In order to incorporate these directional differences during the synthesis of the tensor field we require a reference frame for the B-Spline curve trajectory. We follow the approach by Bloomenthal which in contrast to Frenet frames is also defined for straight curve segments [14]. In addition Bloomenthal's approach results in a reference frame with a low torsion which corresponds to our observation that nerve fiber tracts do not twist. Our observations are obtained from visualizing nerve fiber tracts from DTI data sets of a healthy volunteer. Unfortunately we are not aware of any study which investigates the changes in the spatial arrangement of individual nerve fibers over an entire fiber tract.
The three axes of the reference frame define the principal diffusion directions. The tangent vector is associated with the maximum diffusion value and indicates the direction of the pathway. Since different types of fiber tracts have different ranges of typical diffusivities [15] the user can specify the principal diffusivities accordingly.

Fig. 1. The trajectory of a virtual nerve fiber tract is a cubic B-Spline curve (left). Using a low torsion reference frame we can fit a cylinder around it which defines the thickness of the fiber tract (right).

2.2 Modeling of Anatomical Structures Using Soft Objects

Fluid filled compartments and pathological structures, such as tumors and stroke affected regions, are defined using a soft object modeling (implicit surface modeling) technique originally proposed by Wyvill et al. [16]. Objects are represented by skeletal primitives and a density field, which equals one on the primitive and smoothly decreases to zero at a distance of *R* (the radius of influence) from the primitive. The soft object is then defined as the field's 0.5-isosurface, which is efficiently computed using a surface tracking algorithm similar to that proposed by Wyvill et al. [16]. More complex objects can be assembled by summing up the field functions of all primitives

We have implemented four simple primitives: "Soft Balls" are defined by a centre point and a constant radius of influence. "Soft Cylinders" are defined by a line segment, represented by its endpoints, and a constant radius of influence. A "Soft Cone" is defined similarly, but has one radius for each endpoint. Finally "Soft Tubes" are described by Catmull-Rom splines defined by *n* control points. The user can define different radii for the control points of the spline which makes it possible to represent various tubular structures. In order to compute the distance function and radius of influence we approximate the spline by a polyline and then use similar computations as for the "Soft Cone". A fiber tract can also be converted to a soft object by interpreting its B-Spline trajectory as a skeleton.

Primitives can be combined by adding and subtracting density fields. The gradient of the density field of a soft object can be used as a force field in order to modify the structure of a fiber tract (e.g. for simulating a growing tumor). While soft objects are easy to use it is usually challenging to model a particular shape exactly. The reason for this is that when adding or subtracting fields it is difficult to predict where the isosurface of the resulting field will be. However, this drawback is not a disadvantage for our project since we are interested in modeling the topology of neuroanatomical structures rather than their exact shape. More control over the precise object boundary can be achieved by scaling the density field of a primitive [17].

2.3 Computation of Synthetic DTI Data

In order to create a simulated DTI data set the user has to specify the number and spacing of sample points. For each sample point inside a fiber tract the closest curve point to it is computed. We then determine the reference frame at that point and the tract's principal diffusivities as described in subsection 2.1 and compute the diffusion tensor at that point. If a point is inside several tracts the corresponding tensors are summed up. If a point is inside a soft object we use the diffusion tensor values characterizing the structure represented by the soft object. For example, if the soft object represents a fluid filled compartment a high isotropic diffusion for all sample points inside of it is used. A sample point not included in any structure is deemed to lie in a gray matter region and an isotropic diffusion tensor with a low mean diffusivity as reported in the literature is defined.

To make the synthetic diffusion tensor data more realistic, complex Gaussian normal noise with zero mean and the standard deviation corresponding to the desired signal-to-noise ratio (SNR) is added to the real and imaginary channels of the ideal signal for every sample point. The procedure of adding noise to a synthetic tensor field is the reverse of the process for DTI data acquisition as suggested by Skare et al. [18].

In order to evaluate the tracking results for a user defined set of seed points it is necessary to define what constitutes a correct solution. We choose as correct solution the B-Spline curve defining the trajectory of the nerve fiber tract and translate it linearly with respect to its reference frame such that it passes through the given seed point. The results are quantified using three error metrics [19].

3. Results

The simulation framework was implemented in C/C++ using the OpenGL, GLU and GLUT libraries in order to gain platform independence. An object-oriented design makes it easy to add new fiber tracking methods or different types of tensor fields such as real DTI data or fields obtained using different simulation techniques. Using the B-Spline and soft object modeling technique we found that it is easy to rapidly synthesize DTI data sets corresponding to simulated healthy and pathological brain anatomy.
We have implemented three simple fiber tracking methods, streamlines, tensor lines [20] and tensor deflection [21], and compared them using simulated DTI data sets for different scenarios. An example with two crossing fiber tracts and a large fluid filled compartment is shown in figure 2. We found that overall the tensor deflection method gives the best tracking results for both low and high signal-to-noise ratios.

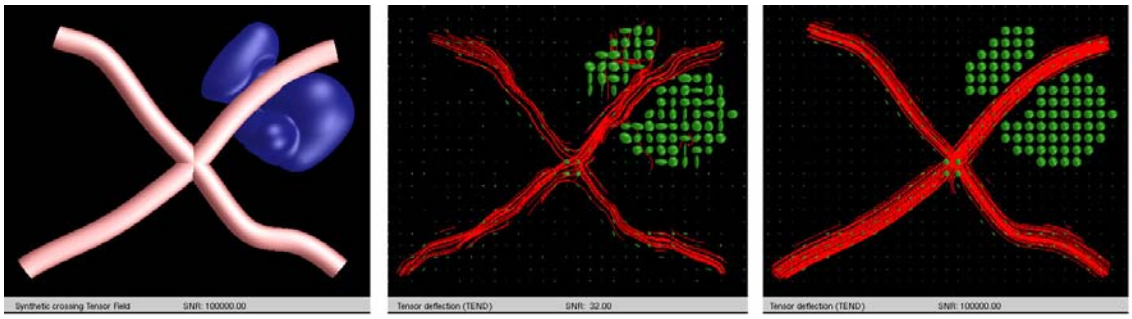

Fig. 2. Two fiber tracts and a fluid filled compartment (left) and the resulting DTI data sets with signal-to-noise ratios of 32 (middle) and 100000 (right). Nerve fiber tracts computed using the tensor deflection method are shown in red.

4. Conclusion

We have introduced a framework for simulating DTI data and for testing and analyzing fiber tractography algorithms. Our tool allows the user to define virtual nerve fiber tracts by B-Spline curves, which specify the direction of the pathway, and a radius which specifies the thickness of the tract. Other healthy and pathological anatomical structures can be designed using a soft object modeling technique.
A DTI data set is synthesized by computing for each sample point typical diffusion values according to the tissue properties at that point. Complex Gaussian normal noise with zero mean and the standard deviation corresponding to a user-defined SNR is added.
We have used our framework to analyze and compare three fiber tracking techniques and we found that overall the tensor deflection methods performs best, whereas the streamline method fails completely for crossing fiber tract topologies. In future work we want to investigate more advanced fiber tracking algorithms and evaluate them for simulated neurodegenerative diseases and pathological DTI data.

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