Trajectory-Based Method for Nerve Bundle Tracking in Diffusion Tensor MR Data

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Abstract

Tracking Fiber tracts in coherently organized brain white matter is an open research problem. Simple methods that only rely on following the preferred eigenvector of the tensor field become unstable, especially when entering complex regions. A method is applied to clinical data, utilizing a novel algorithm, inspired from mechanical projectile trajectory leaded by various mechanical forces. The forces (propellant force, viscosity and friction), each correspond to certain leading parameters such as anisotropy, eigenvectors/values of the diffusion tensor and curvature of bending. The method is compared with a similar existing method by means of 2D simulated data and sample results are presented to demonstrate the connectivity between brain regions using clinical data.

Introduction

Diffusion tensor imaging is a relatively new MRI (Magnetic Resonance Imaging) modality [1],
In which the measurement made at each voxel of a 3D-image array is a tensor describing the local water diffusion behavior. Water diffusion in gray matter is isotropic whereas in white matter which consists of tracts of aligned fibers, diffusion is restricted in directions normal to the fiber cell walls. This characteristic has made the DTMR (Diffusion tensor magnetic resonance) data, a strong indicator of white matter fibers orientation. If the provided data was in resolution of individual fibers, a simple algorithm would follow the main diffusion direction and produce streamlines based on particular seeds. Unfortunately, the resolution of current MRI systems is not enough, so a selected voxel would be composed of different-oriented fibers which results to an ambiguous resultant diffusion direction. This phenomenon is called *partial voluming*.

Based on the facts above, a robust algorithm is needed to follow fiber tracts that could conquer the complex regions.

Proposed Method

Preprocessing: The DTMR data used is acquired from the brain tissue of healthy man, provided in 5 sets. Each set has 18 slices and there are 12 gradients for each slice, achieved in different non-orthogonal directions in order to extract the tensor with a reasonable SNR ratio.

a) Noise Reduction: DTMR data is acquired based on measurement of small signal loss due to spin immigration to regions with different phase. This makes the diffusion imaging an inherently noisy procedure. Since diffusion images will undergo mathematical calculations, the noise reduction procedure is different from simple smoothing of conceptual images. The method used for noise reduction is based on simulation of thermal diffusion [2].

b) Distortion Correction: Then the images were corrected for distortions due to eddy current using the algorithm adapted by Ghanei, Soltanian-zadeh [3] and then the 5 sets were averaged to increase the SNR ratio. Diffusion tensor was then calculated for each voxel.

Processing: A mechanical trajectory is found for a particle, beginning from a particular seed and moving trough the vector field. Firstly, the propellant force is defined, (1).

$$F_t = FA_t \times E_{1,t} \tag{1}$$

Where $E_{1,t}$ is the principal eigen vector of the current tensor. FA_t is the Fractional anisotropy [4] of the point 't'. Acceleration is defined by (2). The term $b_t \times v_t$ corresponds to viscosity of the region. The last term ($f_s \times v_t / |v_t|$) is a friction coefficient (f_s), multiplied by the velocity unit vector. Viscosity plays a significant role when the seed is growing (3).

$$a_t = \frac{F_t - b_t \times v_t - f_s\left(v_t / |v_t|\right)}{m} \tag{2}$$

The term ($\frac{E_{1,t} \cdot v_t}{|E_{1,t}||v_t|}$) returns the direction difference between $E_{1,t}$ and v_t. Viscosity (b_t) is defined in a way that satisfies the conditions in Tab.1.

$$b_t = b_0 \times \frac{E_{1,t} \cdot v_t}{|E_{1,t}||v_t|} \times FA_t \tag{3}$$

After defining the parameters, displacement and velocity vectors for new points can be calculated iteratively (4, 5). The step-size $(step)$ is chosen small enough so that choosing a smaller one would not change the result.

$$X_{t+1} = 0.5a_t(step)^2 + v_t(step) + X_t \quad , \quad v_{t+1} = a_t(step) + v_t \qquad (4, 5)$$

Tab.1. Viscosity in different conditions and its effect on the fiber path.

Condition		Result
FA	Field	
High FA	Curvatures	High velocity avoids following curvatures due to centrifugal force. In such conditions, direction of $E_{1,t}$ and v_t become different. A relatively high viscosity is produced which makes the velocity decrease.
High FA	Straight vectors	Direction of $E_{1,t}$ and v_t are similar. A relatively low viscosity is produced. Velocity increases and vector field will be passed fast.
Low FA	Curvatures	In such a condition, the propellant force decreases, because low FA vectors are not reliable enough. Two cases are most probable for this condition: 1- If the algorithm has entered the gray matter regions, the term of friction stops the algorithm. 2- If the algorithm has encountered a single noisy voxel in a high FA region, initial velocity will help the algorithm to pass the voxel, (noting that the viscosity is low). On the other hand the direction of the noisy voxel would not be considered because it would not affect the force. (Fig1)
Low FA	Straight vectors	Like the last case, If the algorithm has encountered a single noisy voxel in a high FA region, initial velocity will help the algorithm to pass the voxel, and if it is in gray matter, friction stops it. In addition, low FA vectors in a straight manner are more probable to be related to a nerve fiber than low FA vectors with random directions. This condition is satisfied too, because in this case viscosity comes to its minimum value and lets the algorithm pas through such a region.

In many previous methods, stability of the fiber path in complex regions is guaranteed only by applying a limitation on curvature of the path [5] or using a combination of previous and next displacement vectors [6]. In other words, existing methods avoid the path from ambiguous and sudden direction changes, using the *path history*. According to (5), it is clear that here, the velocity of the projectile is used as the avoiding history. Velocity of the projectile at the time it arrives to a complex region, avoids it to follow unreliable low-radius curvatures.

Results

In Fig.1, the new method and the method in [6] are applied to simulated data. For clarity, 2D data is used. The colored path is related to new method and the blue thin path is produced by last method. It is seen that entering complex regions is much more affective on last method than ours. The method is applied to clinical data and some anatomical parts visible in Fig.2

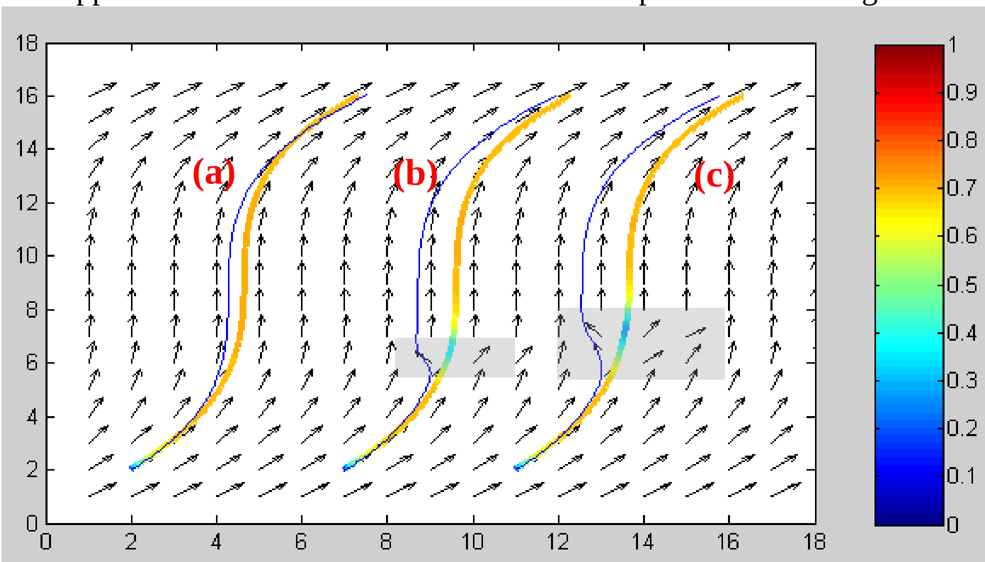

Fig.1. the effect of complex regions on an existing method and the new method, is shown. in (a) no complexity is seen and both the methods pass a similar way. In (b), a small complexity (in the size of gray cube shown), is applied to the field which is effective on the last method. In (c) a bigger complexity is shown, which is more effective on the last method. The velocity of the path is shown in the color bar. As it is clear, in the complex region, the propellant force has decreased.

Discussion

A novel method for tracking nerve bundles was introduced. The main attempt was avoiding mistakes and ambiguities when following a nerve bundle in complex regions. In must of the methods, instability is reduced by means of using the positions and the characteristics of the fiber path in last moments which we call it the *path history*. The history of the path corresponds to just few last points in previous methods, but in this approach we used the velocity of the projectile as the history (which in the integration of all last moments) and it improvement the results.

Conclusion

MRDT data is capable of indicating white matter nerve fiber orientation. But some deficiencies like the resolution and SNR of MRI systems cause the necessity of robust algorithms. In this study, a novel method based on trajectory of a mass affected by diffusion features was presented.

For future work, some other features like stochastic parameters of local tensors could be modeled by mechanical forces and become added to the algorithm effectively.

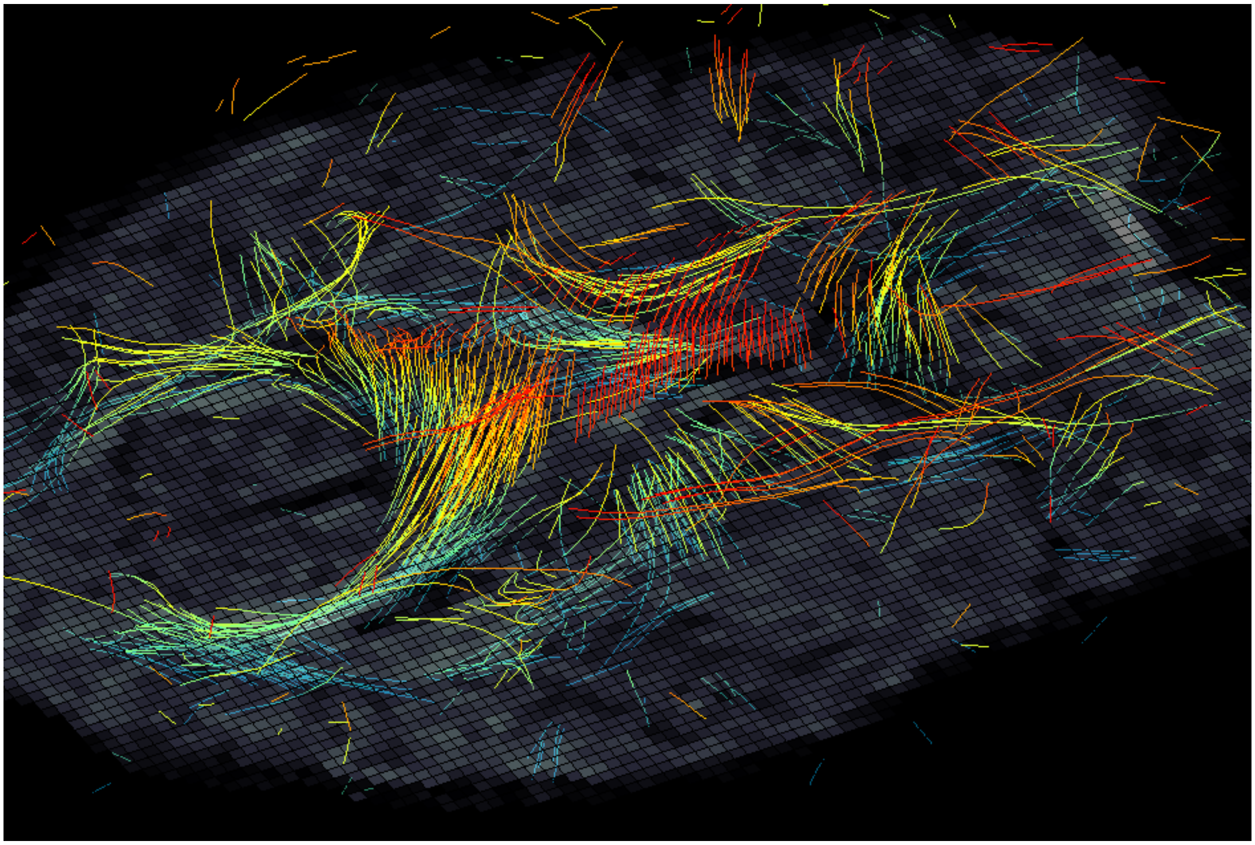

Fig. 2. Fibers growing from particular seeds are demonstrated. Color spectrum indicates the slice number; fibers in upper slices are shown in red and fibers at bottom are in blue. for better visualization, a T2-weighted image of brain is also shown transparently in the position of ninth slice.

References

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