TRACKING OF AXONAL BUNDLES IN DIFFUSION MRI BRAIN IMAGES

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Abstract: The aim of this work is to design tracking algorithm which will be able to track brain axonal bundles in diffusion weighted MRI data. Estimation of anisotropic diffusion profile inside voxels was performed by diffusion tensor imaging model (DTI). Tracing is based on the 4th order Runge-Kutta method. Algorithm is implemented in the MATLAB computing environment and is tested on real data biological phantom.

Keywords: Diffusion MRI, tractography, diffusion tensor imaging, DTI, Runge-Kutta method, deterministic tracking algorithm

1. INTRODUCTION

Magnetic resonance imaging method (MRI) sensitized for diffusion motion is called diffusion-weighted MRI (DW-MRI). We can achieve information about histological architecture of the brain tissue in vivo by this approach. On the base of the DW-MRI, we are able to not only distinguish grey and white matter, but even the white matter structure. White matter consists of the axon bundles which functionally connect specific parts of the brain [1]. The aim of tractography is to create a map of these connections throughout the brain. This knowledge can be useful during brain surgical interventions, for evaluating tumorous tissue etc. [2].

2. METHODS

2.1. DIFFUSION TENSOR IMAGING (DTI)

Estimation of the direction of the diffusion motion within voxel is the objective of the tensor model. Fiber propagation is related to diffusion direction because molecule diffusive motion follows the fiber. Diffusion in white matter is anisotropic, while gray matter disposes with isotropic diffusion profile. Anisotropic diffusion is characterized by ellipsoid in DTI, Figure 1. Orientation and size of the ellipsoid are fully described by diffusion tensor which is related to the ellipsoid as shows equation (1) where eigenvaules λ_1, λ_2 and λ_3 characterize the lengths of major semi-axes and eigenvectors $\boldsymbol{v}_1$, $\boldsymbol{v}_2$ and $\boldsymbol{v}_3$ their orientation in space [1]. Vector belonging to the longest axis λ_1 (the 1st eigenvector $\boldsymbol{v}_1$) can be seen as the prevailing direction of diffusion as far as the direction of fiber propagation.

$$\begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{xy} & D_{yy} & D_{yz} \\ D_{xz} & D_{yz} & D_{zz} \end{pmatrix} = \begin{pmatrix} v_{1x} & v_{2x} & v_{3x} \\ v_{1y} & v_{2y} & v_{3y} \\ v_{1z} & v_{2z} & v_{3z} \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix} \begin{pmatrix} v_{1x} & v_{1y} & v_{1z} \\ v_{2x} & v_{2y} & v_{2z} \\ v_{3x} & v_{3y} & v_{3z} \end{pmatrix} \quad (1)$$

Fractional anisotropy (FA) is the coefficient related to the shape of the diffusion ellipsoid. FA reflects whether the ellipsoid is anisotropic or not. Higher FA value means that diffusion is more anisotropic, FA=0 means isotropic diffusion. We can get FA coefficient by following equation (2) [1].

$$FA = \sqrt{\frac{1}{2}} \frac{\sqrt{(\lambda_1 - \lambda_2) + (\lambda_2 - \lambda_3) + (\lambda_3 - \lambda_1)}}{\sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}} \quad (2)$$

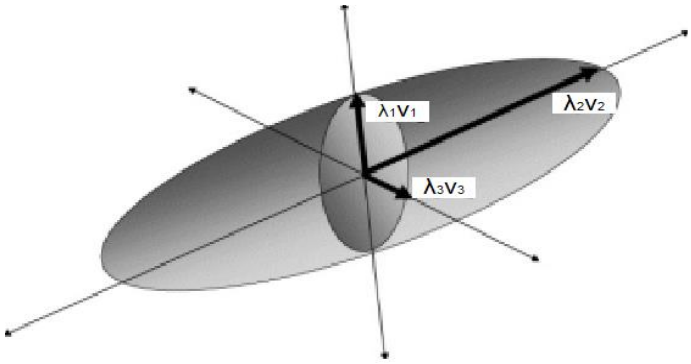

Figure 1: Diffusion ellipsoid [1]

2.2. RUNGE-KUTTA METHOD

Diffusion tensor model provides the map of the 1st eigenvectors, it means that there is information about the direction of diffusion for every voxel. We can understand this map as the vector field or visualization of unknown differential equation whose solution can be estimated e.g. with the Runge-Kutta method [3]. We used 4th order of this method (usage of 4 auxiliary points), which provides small computation error but acceptable computation time increase.

To describe 4th order Runge-Kutta method (Figure 2), vectors v_i and v_{i+1} represent the vectors in starting and auxiliary points, Δk is a step size. To reach the $\mathbf{p_{i+1}}$ point, we follow the equation (3).

$$p_{i+1} = p_i + \frac{1}{6}\Delta k(\vec{v}_i + 2\vec{v}^{1}_{i+1} + 2\vec{v}^{2}_{i+1} + \vec{v}^{3}_{i+1}) \quad (3)$$

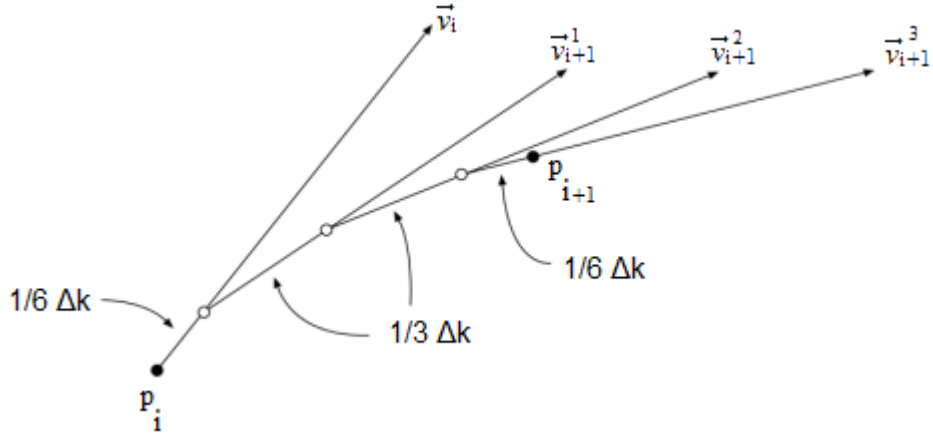

Figure 2: 4th order Runge-Kutta algorithm [3]

2.3. DATA ACQUISITION AND PARAMETER SETTINGS

The algorithm was tested on biological phantom [4]. Golden standard of the phantom is shown in Figure 3(a). Diffusion data were acquired with these parameters: size of the voxel is 3x3x3 mm, b-value equals to 2000 s/mm^2. Data were acquired from 130 gradient directions with gradient-echo scanning sequence. Step size Δk for Runge-Kutta method is the constant, set to 1mm. Trilinear interpolation was used for vector value computation in positions out of the gridded data. It was necessary to define terminating criteria (FA, angle deviation and step size). We fixed the threshold for

FA value to 0.1, maximum angle deviation was set to 45°. Tracing was also stopped when the size of the vector between last and previous point was smaller than 10^{-4}.

3. RESULTS

In the Figure 3(b) is the best achieved trajectory. As you can see, the trajectory deviates from the main direction. This is expected situation rising from the fact that DTI model is not capable to estimate more than one direction of fiber propagation inside one voxel. In this task, algorithm deals well with crossing fibers in the bottom part of trajectory. On the other hand, Figure 3(c) shows unsuccessful tracking.

Figure 3: a) Golden standard [4], b) and c) results of tracking

4. CONCLUSION

Designed algorithm is able to track simple straight fiber with no crossing parts. However, it gives disappointing results for tracts specified by seed point situated near the border of the fiber, Figure 3(c). Algorithm suffers from too early termination. Solution is in process, we assume problem would be solved by special form of interpolation. FA value is high within the fibers, whether in the voxels outside of bundles isotropic diffusion occurs. According to this fact, data would be included to the interpolation algorithm with different weights depending on the value of FA in the voxel. Weighting would be based on FA value with dependency on some sigmoid function. This approach should cause the algorithm more stable in the direction of fiber propagation. However, computational issue appears with using weighted interpolation for tracking large brain data. Tracking of the fiber shown in Figure 3(b) with use of trilinear interpolation is easy to compute and takes few seconds. Current version of weighted interpolation prolongs computation time approximately 10 times.

REFERENCES

[1] MORI, Susumu and J-Donald TOURNIER. Introduction to diffusion tensor imaging: and higher order models. 2nd edition. Oxford: Elsevier, 2014, 126 p, ISBN: 978-0-12-398398-5.

[2] CICCARELLI, Olga, Marco CATANI, Heidi JOHANSEN-BERG et al. Diffusion-based tractography in neurological disorders: concepts, applications, and future developments. *The Lancet Neurology*. 2008, vol. 7, issue 8, p. 270-280. DOI: 10.4018/978-a 1-59904-016.ch011

[3] JOY, Kenneth. Numerical Methods for Particle Tracing in Vector Fields. *On-Line Visualization Notes*, University of California Davis, Davis, CA, 2007. Available from: http://web.cs.ucdavis.edu/~ma/ECS177/papers/particle_tracing.pdf

[4] POUPON, C., RIEUL, B., KEZELE, I et al. New diffusion phantoms dedicated to the study and validation of high-angular-resolution diffusion imaging (HARDI) models. *Magnetic Resonance in Medicine*, 2008, vol. 60, issue 6, p. 1276-1283. DOI: 10.1002/mrm.21789