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Brain Fibre Tracking Improved by Diffusion Tensor Similarity using Non-Euclidean Distances

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Abstract—Fibre tracking is a non-invasive technique based on Diffusion Tensor Imaging (DTI) that provides useful information about biological anatomy and connectivity. In this paper, we propose a new fibre tracking algorithm, named TAS (Tracking by Angle and Similarity), which is able to overcome the shortfalls of existing algorithms by considering not only the main diffusion directions, but also the similarity of diffusion tensors using non-Euclidean distances. Quantitative comparison is carried out through a collection of simulation experiments using statistics of diffusion tensor anisotropy and volume, and tracking errors. Fibre tracking in Corpus Callosum from a healthy human brain dataset is presented.

Index Terms—Diffusion Tensor Imaging, Fibre Tracking, Non-Euclidean Distance, Similarity

I. INTRODUCTION

Diffusion Tensor Imaging is a technology which uses Diffusion-Weighted Magnetic Resonance Imaging (DWI or DW-MRI) data to describe the movement of water molecules in biological tissues. The movement of water molecules in tissue is restricted by structures and objects such as macromolecules, fibres walls and membranes [1] [2] [3] [4]. Therefore, by analyzing the behavior of water molecules in images, we have the opportunity to study the detailed structures in body tissues, *in vivo*, in a non-invasive way [5]. A DTI-based fibre tracking technology, tractography, is able to provide useful information on micro structure for research and diagnosis.

A. DTI

1) *Diffusion Tensor*: In DTI, the diffusion tensor model at each voxel can be represented as a 3×3 symmetric positive semi-definite real matrix $\mathbf{D}$ [6]. This tensor may be diagonalised at each voxel using $\mathbf{v}_i = (v_{ix}, v_{iy}, v_{iz})^T$, $i = 1, 2, 3$, the orthonormal eigenvectors and $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$, the three eigenvalues. The eigenvalues are used to describe the strength of the movement of water molecules along the direction of their corresponding eigenvectors. By convention, we take λ_1 to be the maximum diffusivity over all directions. In voxels with a single dominant fibre orientation, $\mathbf{v}_1$ (the principal eigenvector) is believed to be aligned with this fibre orientation.

2) *The Diffusion Tensor Ellipsoid*: Using the properties of the eigensystem, we may visualise the diffusion tensor as an

ellipsoid, in which the eigenvectors define the directions of the principal axes and the eigenvalues define the ellipsoidal radii.

Diffusion is considered as isotropic when the eigenvalues are nearly equal ($\lambda_1 \approx \lambda_2 \approx \lambda_3$), and as anisotropic when the eigenvalues are significantly different in magnitude (e.g. $\lambda_1 > \lambda_2 \approx \lambda_3$).

Fig. 1: The eigensystems in voxels represent the direction and extent of water molecule movement in the voxels. Images based on [7].

3) *Fractional Anisotropy (FA) Map*: Fractional Anisotropy (FA) is one of the most commonly used measures to describe the degree of the anisotropy of a diffusion process. FA is defined by:

$$FA = \frac{\sqrt{3[(\lambda_1 - MD)^2 + (\lambda_2 - MD)^2 + (\lambda_3 - MD)^2]}}{\sqrt{2(\lambda_1^2 + \lambda_2^2 + \lambda_3^2)}}, \quad (1)$$

where MD is the average of the eigenvalues of $\mathbf{D}$: $MD = (\lambda_1 + \lambda_2 + \lambda_3)/3$.

FA value ranges from 0 for complete isotropy to 1 for a linear anisotropy. FA maps are intuitive to interpret when used with brain images, as white matter is rendered white (close to linear) and grey matter is rendered dark (close to isotropy).

B. Fibre Tracking and Approaches

DTI provides information on the extent of diffusion anisotropy and its orientation, which can be used to generate a 3D vector field [5]. By tracking the flows defined by the vector field, we are able to reconstruct fibre tissues inside human body, e.g. the structural connections in brain or in muscle bundles, at a microscopic level. There are two main methods of doing DTI fibre tracking, the deterministic method and the probabilistic method [8]. Deterministic approaches are techniques based on line propagation algorithms that use

local tensor information for each step of the propagation [9]. Probabilistic method generates all possible trajectories of fibre pathway according to Probability Density Function (PDF) [10]. We focus on deterministic method in this paper.

As one of the most popular deterministic fibre tracking algorithms, FACT stands for Fibre Assignment by Continuous Tracking. This algorithm was proposed by Mori et al in 1999 [11] [12]. FACT follows the local fibre orientation in each voxel with no interpolation.

C. FACT Algorithm

1) *Implementation*: FACT (Fibre Assignment by Continuous Tracking) is a classic deterministic streamline tracking algorithm. The key idea of FACT algorithm is that the fibre trajectory starts from the center of a seeding voxel and travels following the direction of the main principal eigenvector in each voxel to until the terminating conditions are fulfilled. It introduced the concept of voxel boundary, so the fibre is able to enter the voxel at one boundary, travel along its principal eigenvector and then leave through a different boundary and enter the next voxel continuously. Therefore the path of a fibre can be defined as a set of points on voxel boundaries, which will not be disturbed by the relatively discrete voxels and produces an unbroken path that is the most close to the direction of the eigenvectors in those voxels it passed by [11] [12]. Please refer to the left of Fig. 2.

Fig. 2: Left: A voxel space is represented by a black rectangle; a block gray arrow indicates its main direction V ; a thin arrow line, which is parallel with the main direction, is a tracing trajectory that goes into the voxel space from P_{in} and leaves it from P_{out} . Right: The principal eigenvector in voxel 1 points in a direction in between voxel 2 and voxel 3, but is a bit closer to voxel 2. However, the eigenvalue of voxel 1 is very similar to that of voxel 3.

2) *Problem of FACT*: A shortcoming of FACT is that it uses only the principal eigenvector of each voxel rather than full information about the diffusion tensor. This will cause a problem in some particular scenarios. Consider the situation on the right in Fig. 2. The principal eigenvector in voxel 1 points in a direction between voxel 2 and voxel 3. In fact, it is slightly closer to voxel 2. However, the diffusion tensor of voxel 1 is more similar to that of voxel 3, which can be told from the shape of voxels' ellipsoids. In this case, should the fibre go from voxel 1 to voxel 2 or to voxel 3?

Thus, as an improvement, we try to introduce the tensor similarity to participate the decision of tracking path. The performance comparison between this new method and FACT is implemented by using artificial and real data.

II. AN IMPROVED TRACKING ALGORITHM

A. Methodology

In this paper, we propose a tracking algorithm, TAS (Tracking by Angle and Similarity), which works by analyzing the diffusion direction and the diffusion tensor similarity (using a non-Euclidean distance function) between adjacent DTI voxels. While doing fibre tracking along the main direction in the diffusion tensor of current voxel, we give a tolerance angle θ ($0^\circ \leq \theta \leq 45^\circ$), therefore more potential succeeding voxels may included. We compare the similarity of these candidates with the current voxel, and choose the candidate that has the most similar diffusion tensor to the current voxel.

B. Similarity Map

TAS relies on a similarity map to decide tracking path. For each voxel in a DTI data cube, there is an accompanying data structure that is used to record the main direction difference and diffusion tensor similarity between this voxel and its neighbours.

1) *Direction*: The *angle* difference between the main diffusion direction of this voxel and the offset vector of all its adjacent neighbours is determined by:

$$angle = \arccos\left(\frac{\mathbf{V}_0 \cdot \mathbf{V}_{offset}}{\|\mathbf{V}_0\| \|\mathbf{V}_{offset}\|}\right), \quad (2)$$

where $\mathbf{V}_0$ represents the principal eigenvector of the diffusion tensor at a specific voxel and $\mathbf{V}_{offset}$ represents the offset vector of its neighbours.

2) *Euclidean and non-Euclidean Distance*: There are many proposed distances between diffusion tensors. The most common approach is Euclidean distance. However, as diffusion tensors are symmetric positive semi-definite real matrices, which form a non-Euclidean space. One potential problem of using Euclidean distance is when extrapolating beyond the data, non-positive semi-definite estimates may be obtained [13] [14]. In this practice, we will use both Euclidean distance and various non-Euclidean distances (see TABLE I) to estimate the similarity between the tensors in adjacent voxels and observe their performance.

Name	Form
Euclidean	$\ \mathbf{D}_i - \mathbf{D}_j\ $
Log-Euclidean	$\ \log(\mathbf{D}_i) - \log(\mathbf{D}_j)\ $
Riemannian	$\ \log(\mathbf{D}_i^{-1/2} \mathbf{D}_j \mathbf{D}_i^{-1/2})\ $
Cholesky	$\ \text{chol}(\mathbf{D}_i) - \text{chol}(\mathbf{D}_j)\ $
Root Euclidean	$\ \mathbf{D}_i^{1/2} - \mathbf{D}_j^{1/2}\ $
Procrustes size-and-shape	$\inf_{R \in O(k)} \ \mathbf{L}_i - \mathbf{L}_j R\ $

TABLE I: Definitions of the distances between diffusion tensor $\mathbf{D}$. Note that $\|X\| = \sqrt{\text{trace}(X^T X)}$.

3) *Implementation*: From the description above, we can assume that the lower the *angle* value, the higher the chance the streamline will continue along the principal eigenvector direction at each voxel; and the shorter the *distance*, the more similar the tensors will be in voxels along a streamline.

While proceeding fibre tracking, we start from a seed voxel, give an adjustable tolerance angle along its principal eigenvector, find potential candidates within neighbour voxels according to the *angle* values, and then select the most similar adjacent voxel among those candidates according to the *distance* values. Connectivity will be determined by a certain strategy. Same as FACT, tracking needs to be performed in both directions starting from the seed voxel, until terminating conditions are met, e.g. FA value is smaller than a threshold, or fibre tuning angle is greater than a threshold.

C. Algorithm of TAS

Input: A DTI dataset, where each data unit contains the diffusion tensor matrix at that voxel; A set of seed voxels within the DTI dataset, where fibre tracking starts.

- 1) Start from a seed voxel X_0 with FA value greater than threshold T_1 (e.g. $T_1 = 0.2$) and explore a fibre along the both sides of its principal eigenvector V_0 ;
- 2) Take V_0 at X_0 as the current fibre searching direction and voxel;
- 3) Calculate the angles θ between V_0 and the offset vectors V_{offset} , which are the centre connections from V_0 to each adjacent voxel respectively, then sort the results according to ascending order, refer to equation 2;
- 4) Find out the adjacent voxels whose θ is less than the tolerance threshold T_2 (e.g. $T_2=35^\circ$);
- 5) Compare the diffusion tensor similarity between X_0 and the adjacent voxels found in step 4 by calculating the distance (e.g. log-Euclidean, root-Euclidean, Riemannian, and so on, refer to TABLE I);
- 6) Find the most similar neighbour voxel X_n to the current voxel along the fibre, if there is no satisfied succeeding voxel found, go to step 11;
- 7) Check the FA in X_n , if it is less than the threshold T_1 , go to step 11;
- 8) Calculate the inner product of V_0 and the principal eigenvector V_n in X_n , swap the sign of V_n if the result is negative;
- 9) Check the turning angle between V_0 and V_n , if it is greater than threshold T_3 (e.g. $T_3=70^\circ$), go to step 11;
- 10) Assign X_n to X_0 , assign V_n to V_0 , go to step 2;
- 11) Restart searching from the original seed point X_0 , swap the sign of principal eigenvector V_0 at X_0 , perform tracking in reverse direction from step 2 again. If tracking has been completed for both directions of the seed voxel, go to step 12;
- 12) Combine the tracking results of both directions from seed point together to produce a fibre coordinate chain. Perform 3D curve smoothing and generate a property table of this fibre;
- 13) If all seed voxels have been processed, stop, otherwise go to step 1.

Output: Visual image and properties (e.g. length, coordinates, etc) of each fibre that found by running above tracking algorithm.

III. RESULTS

A. Artificial DTI Data Study

In order to compare the tracking results of the classic FACT algorithm and our algorithm TAS, we created a set of artificial diffusion tensor data that may be used to simulate different scenarios. Each tensor unit, a voxel, is visualized as an ellipsoid. Its directions are limited to a two dimensional space to simplify the visualisation.

We are interested in the tracking performance for FACT and TAS at the boundary of two different biological tissues. For this purpose, we design a 10 by 10 voxel matrix. Half of the matrix is filled by voxels with higher anisotropy and another half is occupied by lower anisotropy voxels. The difference in main directions of the voxels within each half matrix are 56° , 36° and 0° in models 1, 2, and 3, respectively. Fig. 3 shows the main direction relationships between the two half matrices in each model, and Fig. 4 is a visualized sample artificial tensor matrix. The thin stick on each ellipsoid points to its main direction. The main directions of the voxels in upper group are approximately along a normalized vector direction $(0.5, 1, 0)$, their eigenvalues are around $(0.005, 0.003, 0.002)$; while the main directions of the voxels in lower group are approximately along a normalized vector direction $(1, 0.5, 0)$, their eigenvalues are nearly $(0.009, 0.0025, 0.0018)$. By adjusting the main directions and shapes of ellipsoids, we are able to simulate different scenarios and observe results.

Fig. 3: Three matrix models of the main direction relationship between the two half matrix. Left: model 1; Middle: model 2; Right: model 3.

In order to make the artificial data looks more natural, for each diffusion tensor $\mathbf{D}$, we apply a random noise variance, which is generated by $\mathbf{D}_n = (\Delta + X)(\Delta + X)^T$, where $\mathbf{D}_n$ is a diffusion tensor with noise applied, $\Delta = chol(\mathbf{D})$, X is a random matrix with i.i.d. entry $N(0, \sigma^2)$ [13].

Fig. 4: A 10×10 artificial voxel matrix sample for model 2 with random noise ($\sigma^2 = 0.002$) applied. The thin stick on each ellipsoid points to its main direction.

1) *Visual Comparison of Tracking Algorithms*: After performing fibre tracking algorithms on the artificial tensor matrix, a set of comparing results are shown in Fig. 5. In this

experiment, we chose the 5 lower voxels at the 1st left column in the artificial matrix as the seed points. We can observe that TAS fibres in this example stay within the lower tissue more often than FACT fibres for all three models.

Fig. 5: The results of algorithm comparison between FACT and TAS-Root. The noise parameter is set to $\sigma^2 = 0.002$ in model 2 for these results.

From the results we can tell in some situations, for example, at the boundary of different biological tissues, FACT will lead a fibre to the next voxel along the principal directions without considering whatever the diffusion tensors are; while TAS will decide the next voxel on the fibre based on the balance of similarities and directions. In this case, we believe TAS is able to get better results.

2) *Quantitative Comparison of Tracking Algorithms:* In order to quantitatively compare the tracking performance among algorithms, we generated 20 artificial tensor matrices for each of the three models and at 6 different noise levels ($\sigma^2=0.001$ to $\sigma^2=0.006$). The noise will influence not only the principal eigenvector, but also the shape of tensor voxels. Fig. 6 shows the effects while various noise level applied on tensor matrix.

Fig. 6: Different level noise variances applied on artificial matrix.

The experiment was undertaken as follows:

- 1) Fix the underlying model (0° , 36° or 56° angle between main diffusion direction in lower and upper voxels) and noise level $\sigma^2 = [0.001, 0.002, \dots, 0.006]$.
- 2) Generate 20 tensor matrix samples for each combination.
- 3) Track fibres in each sample from seed voxel (1,1) (bottom left corner) to (1,5) (top left of lower tissue) by using each of the seven proposed algorithms (FACT, TAS-Euclidean, TAS-Log Euclidean, TAS-Riemannian, TAS-Cholesky, TAS-Root Euclidean and TAS-Procrustes).
- 4) Record four statistics for each fibre generated.
- 5) For each model, noise level, seed voxel and algorithm, take mean of each of the four statistics over the 20 samples.

The four statistics recorded for each fibre are:

- 1) Percentage of fibres crossing the boundary between tissues (i.e., having voxels with y-coordinate > 5),
- 2) Length of fibre before the tissue crossing (number of pixels before first pixel with y-coordinate > 5),
- 3) Standard deviation of FA of DT along voxels in the fibre,
- 4) Standard deviation of volume of DT along voxels in the fibre.

The first two statistics are used to evaluate the performance of TAS against FACT in terms of fibres staying within a tissue group and in terms of having fibres of the appropriate length. Recall that the width of the synthetic data arrays is 10, so we should expect fibres staying within the tissue to have length around 10. The second two statistics are used to evaluate how well a cell-by-cell similarity rule maintains globally more consistent fibres.

By analyzing the experiment results, we can tell from the statistics that compare to TAS, FACT has very high chance of leading fibre to cross boundary; for those seeds close to boundary, TAS has more stability of keeping fibres to stay in the lower tissue group; compare to FACT, TAS fibres have lower std FA and std volume values, which means a better global consistency; among those non-Euclidean distances, the performance of Log-Euclidean and Riemannian are similar, while the Root Euclidean is slightly better (Fig. 7). We also notice that higher level noises affect the results of TAS more than that of FACT (Fig. 8) and the tracking performance of TAS and FACT is relevant similar in model 3, where identical main tensor direction in both tissue groups (Fig. 9).

B. Real DTI Application

We compare the FACT algorithm to the TAS-Root algorithm also by using real data. The original real DWI data of a healthy human brain is provided by QMC Nottingham using Philips Intera Achieva 3T MRI system. The data matrix size is $224 \times 224 \times 52$, voxel size is $1.0 \times 1.0 \times 2.0$ mm, with a 224 mm field of view, diffusion encoding in 32 directions, and with diffusion gradient strengths set at b values of 0 and 1000 s/mm^2 . We then convert this raw DWI data into corresponding DTI data. Fig. 10 shows one DTI slice from this dataset. The figure includes an FA map and a RGB colored v1 map. In the FA map, darker dots are close to isotropy and brighter dots are

Fig. 7: Comparison of FACT and the six TAS algorithms with different metrics for model 2 with noise parameter $\sigma^2 = 0.002$. The algorithms are compared for each seed voxel in terms of: (a) proportion of fibres that leave tissue 1, (b) mean length of fibres within tissue 1, (c) mean standard deviation of FA along fibres, and (d) mean standard deviation of ellipsoid volume along fibres.

Fig. 8: Comparison of FACT and TAS-Root for crossing and length metrics across a range of noise levels in Model 2.

close to linear. In the RGB v1 map, the RGB color channels at each voxel is determined by the directional components of its principal eigenvector (v1) along x-axis, y-axis and z-axis, respectively.

For the experiment with real data, the seed voxels are determined by assigning a Region of Interest (ROI) along the coronal plane around the junction of Corticospinal fibers and Corpus Callosum area (the green rectangle area shown in Fig. 10). This region was chosen because the fibres in the white matter are known to curve around the Corpus Callosum from the left to right hemispheres. When tissue fibres have a curvature that is relatively large compared to the resolution

Fig. 9: Comparison of FACT and TAS-Root at noise level $\sigma^2 = 0.002$ for crossing and length metrics in the three models.

of the instrument, we have a situation in which the principal eigenvector in each voxel along the fibre will point along the tangent of the curve into the grey matter rather than towards the next voxel in the fibre. We can picture this as in Fig. 11. This is similar to the situation we studied in the synthetic data.

Fig. 10: A DTI slice of a human brain along coronal plane. The figure includes an FA map (left) and a RGB colored v1 map (right). A ROI around the junction of Corticospinal fibers and Corpus Callosum area is indicated in green rectangle.

Fig. 11: The fibres of the corpus callosum connect the left and right hemispheres (green arrow), but due to the curvature of the tissue, the principle eigenvectors point outside the tissue and into the surrounding grey matter (orange arrow).

We then applied FACT and TAS-Root to do fibre tracking. Fig. 12 shows a visual comparison of the results. We observe that the FACT algorithm fibres stop at the region of higher curvature in the Corpus Callosum (top arrow in (a)), whereas the

TAS-Root fibres are able to continue to the right hemisphere (top arrow in (b)). Note that neither algorithm incorrectly continues fibres that have followed the Corticospinal fibres, which are not connected physically in this slice (bottom arrows in (a) and (b)).

(a) Tracking results within human brain by using FACT.

(b) TAS with Root Euclidean distance.

Fig. 12: Tracking results within real human brain data by using FACT and TAS-Root.

Finally, we do the tracking experiments in a larger ROI where the location is around the Corpus Callosum area in human brain by using FACT and TAS-Root. We use a software tools ITK-SNAP to help assigning the ROI. An FA map of human brain can be loaded in advance as background. Then we are able to assign the ROI slice by slice according to the FA map accurately. The red area in Fig. 13 is the ROI around Corpus Callosum we assigned by using ITK-SNAP.

Fig. 13: The area in red color is the ROI we chose, where is around the Corpus Callosum in human brain.

After doing fibre tracking, Fig. 14 are the visualization results by using FACT and TAS-Root algorithms. We can see approximately 2000 fibres tracked based on the ROI around Corpus Callosum. Compare to FACT, TAS is able to track more comprehensive fibres, particularly in the Anterior and Mid-Anterior Cingulus bundle (zone 1) and the Brainstem (zone 2), both indicated in side view, and in the Inferior Occipitofrontal Fasciculus (zone 3 and 4) regions, indicated in top view.

IV. CONCLUSION

We have developed a DTI fibre tracking algorithm, TAS, which considers not only the main direction, but also the similarity of diffusion tensors using non-Euclidean distances. Comparing to an existing deterministic tracking algorithm FACT, TAS has the capability of avoiding possible misleading tracking at special areas, e.g. near the boundary between different tissues. The results can be demonstrated visually and quantitatively by using artificial and real diffusion tensor data. Various distance measurement algorithms have been practiced. We conclude that TAS may produce more comprehensive

Fig. 14: Tracking results using FACT (left) and TAS-Root (right) around Corpus Callosum. Bottom left: coronal view; top left: sagittal view; right: axial view.

fibres and achieve lower std FA. For the results in large amount fibres tracking, std volume is lower too.

Further work involves testing tolerance options to obtain reasonable patterns for different biological tissues; exploring the possibility of working as a probabilistic tracking method by designing a suitable PDF; comparing tracking results with anatomy knowledge to verify the accuracy; applying to brain disease diagnostic [15] and muscle structure analysis [16].

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