Reconstruction of brain neuronal pathways in brain from the diffusion tensor MRI data.

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Abstract. MRI based fiber tracking is a diagnostic method based on the diffusion tensor MRI data, which allows to find pathways of neuronal bundles in brain in vivo. In this work we propose a method of neuronal pathways reconstruction using A-star algorithm, with the possibility to assess its the effectiveness. One of the criteria is the probabilistic search parameter G, defined by a set of diffusion coefficients in a given volume element. The parameter G obtained trajectory correlated to its length has the meaning of entropy and allows to assess reliability of the found path. The proposed method was tested on simulated data with the characteristic behavior of trajectories of the complex variations, different cases of intersection of the beams passing through the intersection without a common voxels, and obtained characteristics of the corresponding probability.

1. Introduction
Magnetic resonance imaging (MRI) became now a powerful diagnostic tool in medicine. Apart visualization of body anatomy, MRI is able to provide information about metabolism, function and connectivity. Monitoring of brain activity with functional MRI opened a new age in neurosciences. Diffusion tensor MRI (DT MRI) [1] allows to track connectivity between different brain regions. The method is based on MRI measurements of local anisotropy of water molecules diffusion. Since myelin shears, covering axons are restricting diffusion of water molecules, the diffusion coefficients along and across axons are different. Assuming that direction of the eigenvector corresponding to the highest eigenvalue is coincides with the local direction of the axonal bundle it is possible to follow the pathway of the axonal bundle [2-4]. However since axon dimensions are much smaller that the resolution of MRI, such method detecting only major fiber track and gives ambitious results in regions of fibers crossing [5-7]. Partial volume averaging and noise contributes also to these errors.

Fiber tracking methods can be roughly divided in two classes – streamline and probabilistic methods [8]. Streamline line methods, like FACT [3] either detecting or not a single pathway fiber tract, while probabilistic methods [9,10] fiber gives different probability for different fiber track pathways. However assessing the reliability of the detected pathways is not possible by these methods. The purpose of this paper was to evaluate the reliability of the detected pathways in order to be able to compare probability of connection between different regions and in different persons.
2. Model description

If the classical A-star algorithm finds the shortest path, our modified algorithm finds the most likely path. To do this, we change one of the search criteria – G function. In this paper, a modified A-star algorithm was implemented in MatLab software package for the analysis of model data. We assumed that each voxel can contain multiple diffusion coefficients in their respective areas by which the cost of the transition at some neighboring voxel.

Define the concept of probability that, based on available data, in this way the real voxel direction coincides with the direction of k:

\[ p_k = \frac{D_k}{\sum_i D_i} \]

where \( D_k \) and \( D_i \) is the diffusion coefficients in the directions of k and i.

The G cost of the transition from the parent to the current j-th cell in the direction of k is defined as:

\[ G_j^k = -\ln \frac{D_k}{\sum_i D_i} \]

The G value for some arbitrary point j in the direction k will consist of the value of its parent cell G and cost of the transition from the current parent. The H function is determined by the Manhattan method, is estimated by the number of the path of elementary steps in the directions x and y, which is needed to reach the end point. Found the path must have a minimum value of G, among others. Function G increases with decreasing probability, that is, the lower the probability of movement in that direction, the more relevant the cost of transition. As we move to target the total value of G trajectory increases. This means that the further we move away from the starting area, the less likely to be in the current point.

3. Results

For simplicity here will be considered a two-dimensional model. Extension to three-dimensional case is straight forward. We define a certain curve in the form of data, represented by the set of directions and the corresponding diffusion coefficients.

![Figure 1](image_url)

**Figure 1.** G-parameters of real and false trajectories.

We define a beam consisting of parallel trajectories with a characteristic curvature. Due to the presence of the isotropic component in each voxel are possible "jumps" between the paths, the results are presented in fig. 1. The smallest value of G corresponds to the highest probability. As you can see, the false path with G = 32 and the actual trajectory with G = 33 realized with almost equal probability. This is due to dependence of the parameter G of the distance, which corresponds to the fact of "the end
point on, the less likely to reach it”. Thus, the parameter G in its current form is not suitable for comparison reconstructed trajectories. To solve this problem we will consider the distance. We introduce a new parameter, which is determined from the following relationship:

$$\beta = \frac{G_{goal}}{h}$$

where $G_{goal}$ is G value of the end point, it is also the path parameter, $h$ - length of the traversed path.

The proposed parameter is essentially a kind of entropy, a measure of the probability of trajectory. We specify a parallel beam paths of the same length and calculate the corresponding $\beta$ parameters (Fig. 2a).

![Figure 2](image)

**Figure 2.** Demonstration of independence of $\beta$ parameter on the length of the trajectory.

The obtained data about the trajectories of the parameters are nearly equal, this means that the data paths are implemented with approximately the same probability. Change the location of relevant end points such that the lengths of the constructed paths were different (Fig. 2b). It is evident that the parameters for the resulting paths are also approximately equal. Thus, does not depend on the distance tracked and is the probability of the fact that, based on available data, the path is found true.

4. Dependence of $\beta$-parameter on the noise

For the model described early (Fig. 2a), we define the target areas on the neighboring trajectories and calculate the corresponding values.

![Figure 3](image)

**Figure 3.** False paths and the corresponding $\beta$ parameters.
Such transitions are possible, but significantly increases the value $\beta$. Comparing with previous results, we find that the implementation of the upper curve (Fig. 3) with a value of $\beta = 2.34$ is less likely than the top of the curve (Fig. 2a), for which $\beta = 1.12$. Thus, the following values can be judged on how this or that found following the real trajectory.

With the increase of noise level jumps between the trajectories become more likely, that is, the cost of such a transition $G$ decreases. Often this causes the accumulation of errors in choosing the direction of the search path tractography methods. When working with the model data is used the value of the signal to noise ratio of 10. Reducing this ratio, we can see how the value changes to "real" (lower value) and "imaginary" (with a high value) of the trajectories (Fig. 4a and Fig. 4b).

![Figure 4](image-url)  
**Figure 4.** The dependence of the $\beta$ parameter for real and imaginary trajectory on the noise.

As can be seen, with increasing level of noise, setting the true trajectory begins to increase, reflecting the fact that it is becoming more difficult to fix the actual path. In second case, the noise decreases with increasing the value, thus increasing the probability of confusion with the actual path of the imaginary.

5. Changes in the degree of anisotropy
In living tissue, due to a number of reasons may be the destruction of the insulating shell pathways, as a consequence, the movement of water molecules is not limited to the barriers, and there are isotropic field. This situation can be modeled by first given a certain trajectory that describes the area of the anisotropy (Fig. 5), and then some of these areas are made isotropic.

![Figure 5](image-url)  
**Figure 5.** Trajectory passing through the anisotropic area.
Through intermediate isotropic field algorithm still builds the path, but it is an increase in the parameter $\beta = 2.72$. Having by some a priori information about the behavior of the beam, we can ask a number of final and initial points along the way and keep track of how the value will vary along the length of the trajectory. Thus, we can not only detect the presence of an isotropic field, but also to localize it. The presence of the intersection of beams within a single voxel can also be reflected by the algorithm as the area through which the increase in the $\beta$ parameter. This kind of analysis of real data provides information about the presence in the study area of any violations shell pathways, or the presence of tumors arise beam intersection. Consequently, the presence of changes in the system can be judged by the change trajectory, or alteration of the characteristic $\beta$ parameter.

Conclusions
In this paper, we proposed a method to reconstruct pathways of the brain with the ability to assess the quality of reconstruction. Proposed likelihood parameter for reconstructed trajectories, allows to compare several pathways. Due to technical limitations, the minimum voxel size is much larger than the thickness of individual axons, thus making it difficult to resolve tracks in the areas of crossing. The proposed method provides a probabilistic assessment of the reconstructing trajectories, and gives possibility to compare them to the likelihood parameter.

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