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Towards Quantification of the Brain’s Sheet Structure in Diffusion MRI Data

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Abstract— The recent hypothesis on the occurrence of sheet structure in the brain has posed many questions to the diffusion MRI (dMRI) community as to whether this structure actually exists and can be measured with dMRI. In this work, we exploit the capability of the discrete Lie bracket to infer information on the existence of sheet structure in real dMRI data.

I. INTRODUCTION

The question whether our brain’s structure is best reflected by a three-dimensional Manhattan street grid or by the intricate streets of Victorian London added three Science publications to the dMRI literature [1-3]. Wedeen et al. [1,3] analyzed adjacency and crossings between cerebral fiber pathways of the brain using diffusion spectrum imaging (DSI) and tractography, and proposed that cerebral white matter pathways form parallel sheets of interwoven paths. Catani et al. [2] concluded that the grid pattern is most likely an artifact, biased by the limited angular resolution of DSI.

We believe that in order to accept or reject the sheet structure conjecture, more extensive quantitative analyses are needed. Previous work [5] focused on evaluating the discrete Lie bracket as a tool to quantitatively assess the presence of sheet structure in simulated vector fields. In this work, we extend this approach to real dMRI data.

II. THEORY AND METHODS

A. Lie bracket theory

The Lie bracket [\(V, W\)]\(_{p}\) is a measure of the deviation from \(p\) when trying to move around in an infinitesimal loop along the integral curves of the fields \(V\) and \(W\) (Fig. 1). If and only if \([V, W] = 0\), the vector fields form a sheet at \(p\) [6]. The Lie bracket can be approximated by various difference vectors \(r\) according to

\[ r_p(h_1, h_2) = h_1 h_2 [V, W]_{p} + (\Delta h, h_2), \]

where \(h_1\) and \(h_2\) are walking distances and \(\Delta h\) is an error term that scales with \(h_1\) and \(h_2\). See references [5,7] for details.

B. Implementation and experiments

Starting from point \(p\) in the data, we assign two fiber orientation distribution function (fODF) peaks [4] as representative members of vector fields \(V\) and \(W\).

III. RESULTS AND DISCUSSION

We use nearest neighbor streamline tractography using steps of size \(\Delta h\) to find the difference vectors. Each difference vector is based on 4 consecutive tractography paths \(\Delta h\) (Fig. 1) of up to \(h_{\text{max}} = 6\Delta h\). At each streamline step the local vectors are assigned to one of the fields based on their cosine similarity with the vectors at the previous position. Tracts passing through voxels with only one peak are ignored. Subsequently, \([V, W]_{p}\) is calculated as an indicator of sheet structure in a simulated dMRI dataset that was known to represent a sheet [5,8] and in high resolution mouse brain data.

IV. CONCLUSION

In this work we extend the analysis of the Lie bracket normal component as a tool for the detection of sheet structure in artificial vector fields, to vector fields derived from diffusion MRI data. We have shown that spatial resolution and the curvature influence the ability to detect sheet structures. We present preliminary but promising results of a high resolution mouse brain, which shows the presence of a sheet formed by two main fODF peaks, with a diffusion tensor imaging (DTI) geometry map.

REFERENCES


Fig. 1 Walking loop with \((\Phi^p_x + \Phi^p_y)\) to the end point. Difference vector \(r_p\) approximates \([V, W]_{p}\) [5].

Fig. 2 Diffusion data generated from vector fields \(V = (1,0,0)\) and \(W = (0,1,0)\) [7] defined on domain \([-10 \text{mm}, 10 \text{mm}]^3\) with 1 mm voxel size and the curvature in point \(p\). These have zero Lie bracket by design and are locally tangent to the surface \(x(y) = 0.5 \cos^2 \pi \cdot y\), \(h_{\text{max}} = 2.5 \text{ mm}\) and \(\Delta h = 1 \text{ mm}\). For \(\kappa > 2\), \([V, W]_{p}\) deviates significantly from 0. The number of paths used (numbers above each graph) is lower for higher \(\kappa\), partially causing the increased standard deviation.

Fig. 3 Mouse brain dMRI data with \(b = 4000 \text{ s/mm}^2\), measured with 120 different directions and 112 images, voxel size 0.043 mm isotropic. (a) Direction encoded fractional anisotropy map. (b) \([V, W]_{p}\) between two largest fODF peaks, with \(\Delta h = 0.043 \text{ mm}\) and \(h_{\text{max}} = 5\). The blue location shows a region with low \([V, W]_{p}\), the yellow location one with noisy \([V, W]_{p}\) (c) The corresponding DTI geometry map.

These authors contributed equally to this work.

In this work we consider the difference vectors \((\Phi^p_x \cdot \Phi^p_y + \Phi^p_y \cdot \Phi^p_z)\) (\(p\), \(p\) = \(\Phi^p_x \cdot \Phi^p_y \cdot \Phi^p_z \cdot \Phi^p_z\)) (\(p\)), and \((\Phi^p_x \cdot \Phi^p_y \cdot \Phi^p_z)\) (\(p\) = \(\Phi^p_x \cdot \Phi^p_z\)) (\(p\)), where the flow operator \(\Phi^p\) (\(p\)) denotes moving a distance \(s\) along the integral curve of vector field \(X\) starting from point \(p\).