Parameter Sensitivity and Uncertainty Visualization in DTI

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Abstract

Diffusion Tensor Imaging is a powerful technique that provides a unique insight into the complex structure of the brain's white matter. However, several sources of uncertainty limit its widespread use. Data and modeling errors arise due to acquisition noise and modeling transformations. Moreover, the sensitivities of the user-defined parameters and region definitions are not usually evaluated, a small change in these parameters can add large variations in the results. Without showing these uncertainties any visualization of DTI data can potentially be misleading. In our work, we develop a visual analytic tool that provides insight into the accumulated uncertainty in the visualization pipeline. The primary goal of this project is to develop an efficient visualization strategy that will assist the end-user in making critical decisions and make fiber tracking analysis less cumbersome and more reliable, a crucial step towards adoption in the neurosurgical workflow.

1. Introduction

Diffusion Tensor Imaging (DTI) is a non-invasive technique that allows the reconstruction of anatomical connections in the brain, i.e., white matter. Despite the potential of these methods, several downsides limit their widespread use. One of the main reasons is the uncertainty present in the results. The acquired data has to go through a complex transformation and visualization pipeline, shown in Figure 1, accumulating uncertainties present at each step. These accumulated uncertainties, affect the data processing, and, subsequently, provide results that can be seen as ad hoc if the variations due to the uncertainty are not considered. In our work, we have developed a visual analytic tool for modeling and visualizing uncertainties individually for each of these stages. Here, we focused on the first three stages of the pipeline, i.e., the uncertainty that arises due to acquisition noise, errors in diffusion modeling, and fiber tracking parameter sensitivities. The developed framework enables users to interactively explore the inherent uncertainties and analyze the parameter sensitivities. These visualizations, in turn, assist users in making critical decisions.

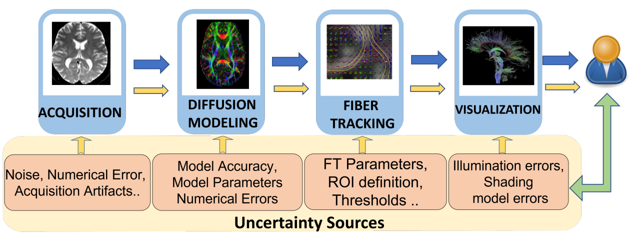

Figure 1: *DTI visualization pipeline with sources of uncertainties.*

2. Noise and modeling uncertainties

We started our uncertainty visualization pipeline by modeling and visualizing uncertainties due to noise and modeling errors. Various approaches have been used to model these uncertainties [KHR*06; BWJ*03; CLH06]. In our previous work, we focus on stochastic methods that simulate sample variations and facilitate the propagation through the pipeline. We chose wild bootstrapping method [Wu86] to estimate and propagate the uncertainty in the data acquisition and diffusion modeling steps. Several authors have used these techniques to model uncertainties in DTI [Jon03; LA05; PB03; VHN*16]. This procedure, however, incurs substantial computational costs and is difficult to be used in an interactive fiber tracking process. To circumvent this problem, we developed a progressive visualization workflow that allows interactive estimation and exploration of fiber tracts and their corresponding uncertainties, as presented in [SHV21]. The developed visualization is shown in Figure 4.

3. Region based parameter sensitivities

After modeling and visualizing uncertainties due to acquisition noise and modeling errors, we next focus on uncertainties due to parameter sensitivities. As discussed, fiber tracking algorithms require several user-defined input parameters that can introduce considerable uncertainty in the result. Out of several user-defined inputs, the most critical one is defining the Region of Interest (ROIs). A very small change in the defined seeding region could result in very high variation in the output, as shown in Figure 2. In these cases, care has to be taken in defining the ROIs. In our work, we have defined several region-based sensitivity features based on the shape, length and connectivity of the fiber tracts to guide the user

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in defining the optimal ROIs. Figure 3 shows the fibers generated from two close by ROIs. The feature map at the bottom left represents the sensitivities based on the shape feature and the defined ROIs which is represented with the blue curve. We have used distance based similarity metric [MVV05] to quantify the similarity in the shape of the fibers originated from the pre-specified neighborhood. For each voxel we calculate the sensitivity features and visualize these sensitivity maps with binned color maps, as shown in the Figure 2. Apart from the shape based sensitivity, another critical feature is the connectivity to the end region. Figure 3 shows the connectivity feature with an overlaid transparent surface on the sensitivity map. The green region in the figure depicts the projection of the end region that represent the area where the fibers are connected to the end region. Having this information helps users in defining the optimal ROI.

4. Visualization and Exploration

In this project, we aim to provide a visual analytics solution for the user to interactively explore the uncertainties and analyze the parameter sensitivities which helps them in making critical decisions. In our system, we have developed techniques to visualize modeling uncertainties and parameter sensitivities. For visualizing the uncertainties due to noise and modeling errors, we developed a progressive visual analytic pipeline that allow the interactive estimation of uncertainty in the tractography [SHV21], as shown in Figure 4. The figure shows the variations of a single fiber based on 100 bootstrap iterations . For analyzing region based parameter sensitivity visualization, we have developed an exploratory visual analytic tool that guide user in defining the optimal region of interest. As explained in section 3, we have calculated several region based sensitivity features. These calculated feature maps are visualized with binned color map to discretely identify the sensitive regions, as shown in Figure 5 a. The number of bins and the values can be interactively adjusted with the slider and the histogram for inspecting further details in the sensitivity features, as shown in Figure 5 b. Based on the computed feature maps, a user can efficiently explore the possibilities for the ROI, represented with a blue curve. The resulting fibers are shown real time in a 3D view (shown in the bottom right). A guiding glyph has been introduced that would guide the user where to extend or compress the regions, based on the sensitivity feature maps, as shown in Figure 5. The length of the glyph encodes the sensitivity feature while the direction corresponds to the normal of the curve. With these exploratory techniques, a user can understand the inherent sensitivities, which could guide them in defining the optimal region of interest.

Figure 2: *Fiber tracts generated from two different regions. Sensitivity maps with the defined ROIs are shown at the bottom left*

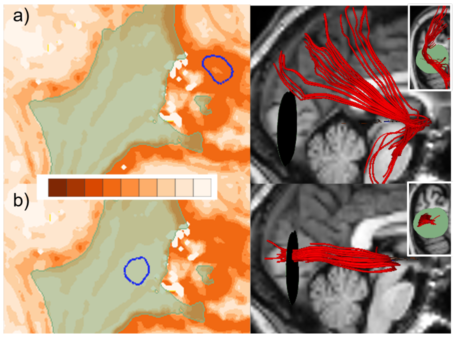

Figure 3: *Left: Sensitivity maps with defined ROIs and the connectivity feature for two cases a and b. Right: The resulting tracts from axial and coronal views*

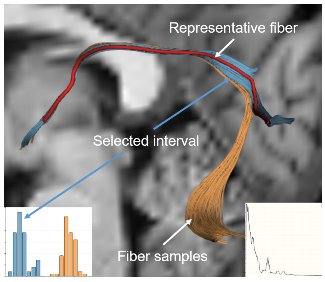

Figure 4: *Visualization of the variation of the single fiber based on 100 bootstrap iterations. Interactive histogram shows the distribution of the fiber samples based on the distances from the representative fiber*

5. Conclusion

In this project, we propose generating a visual analysis solution that allows the interactive estimation and reliable exploration of combined uncertainties and sensitivities in the DTI visualization pipeline. We are aiming to not only visualize the uncertainty of the individual sources, rather providing a way for a user to explore the contribution for each source of uncertainties. The combined uncertainty and sensitivity visualization allows user to understand the inherent uncertainties which can help them in making critical decisions.

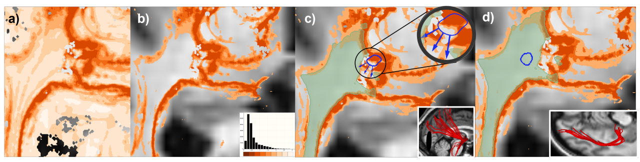

Figure 5: *(a) Colors map visualization of the shape based sensitivity feature. (b) Interaction with slider and histogram (c) defined ROI with guiding glyphs on the sensitivity maps along with the End region projection. The resulting fibers are shown at bottom right. (d) Defined ROI and obtained Optic radiation tract*

Acknowledgments

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