

A Multi-Resolution watershed-based approach for the segmentation of Diffusion Tensor Images

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INTRODUCTION: The analysis and visualisation of Diffusion Tensor Images (DTI) still remains a big challenge. The investigation is exploratory in nature and one has to deal with complex data: *tensors*, *fiber tracts*, *bundles*. This quickly leads to clutter problems in visualisation but also in analysis. Clustering techniques have been used to group individual fiber tracts into coherent bundles. However, these methods deal with derived structures from the tensor field, i.e., do not use directly the full tensor information; therefore they are very sensitive to the used fiber tracking method. An alternative is the direct segmentation of the tensor field in volumetric regions. Some interesting approaches have been proposed recently. However, they often do not allow a full segmentation of the data, i.e. they segment one object at a time. Furthermore, they have a multitude of parameters to be set to achieve the desired result and have limited user interaction, preventing the added value of clinical users' expert knowledge in segmentation. In this paper, a new framework for the **multi-resolution** analysis of DTI is proposed. Based on fast and greedy **watersheds** operating on a multi-scale representation of a DTI image, a **hierarchical** depiction of a DTI image is determined conveying a global-to-local view of the structure of the analyzed tissue.

METHODS: Figure 1 depicts the stages involved in the creation of a hierarchical representation of the data. Given an input DTI, a **scale-space** representation is constructed [1], by successive blurring of the DTI image. When increasing the scale, details disappear while main fibrous tissue structures can still be recovered.

At each scale a **watershed** transform [2] is applied, providing a fast and simple partitioning of the data. We use the **Log-Euclidean gradient** magnitude as a general measure defining region borders.

By **linking** several regions across scales [3], we infer a meaningful hierarchical representation of the data. This linking tree can be used for a "region focusing" process (see Figure 2), where a simplified region at a selection scale is formed by merging the regions at the lower representation scale. This selection scale determines how simplified the data is for inspection.

In this scale stack, a connectivity graph $G(n_i, e_j)$ can be built where: - each node n_i holds the Log-Euclidean mean tensor representing basin i ; - each edge e_j holds the Log-Euclidean distance between each neighboring basin. In this graph a simple region growing algorithm can be applied, quickly grouping similar and connected basins. These can then be 'focused' to the lowest representation scale.

RESULTS: Employing an isotropic Gaussian kernel in a real brain dataset, as in Figure 3, fails to deliver an appropriate high level selection scale for the automatic segmentation of the larger structures. Brain tissue, i.e., white matter, manifests itself in DTI images as anisotropic structures. In the isotropic scale space these structures of interest successively disappear. Nevertheless, with a semi-automatic segmentation we can get meaningful results easily. The multi-resolution representation of the data allows the segmentation of different structures, of different sizes, at different resolutions.

CONCLUSION: In a semi automatic manner, a hierarchical representation of the data is assembled providing a new way to visualize and interact with this type of data. This multi-resolution partitioning of the data is versatile enough to allow a semi-automatic segmentation of the structures of interest by combining the several building blocks. Future work will study the use of anisotropic kernels based on the diffusion tensor at each voxel so to improve the inference of tissue's structure adaptively. The proposed hierarchical methodology is also relevant for HARDI given its close analytic connection to DTI.

REFERENCES: [1]: Florack et al, CVPR 2008; [2]: Rittner et al, IEEE Computer Society 2008; [3]: Dam et al, MICCAI 2000.

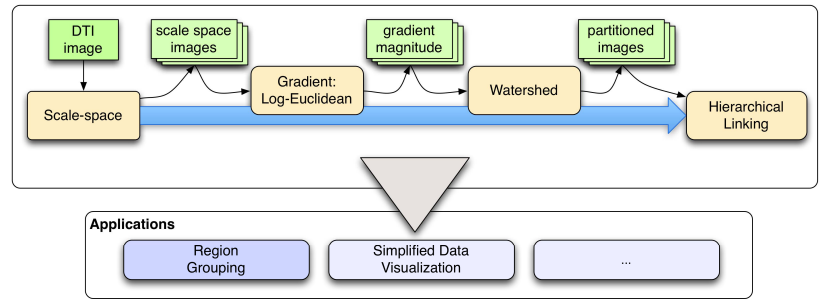


Figure 1. Global gist of the hierarchical segmentation.

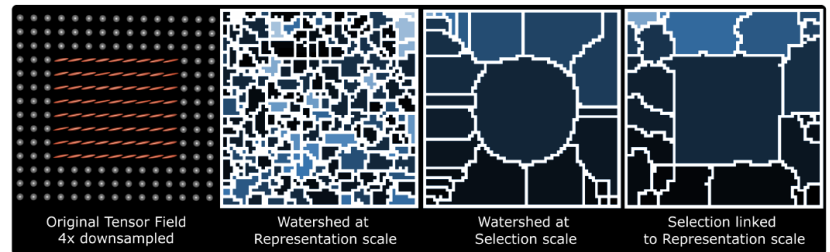


Figure 2. Region focusing across scales. Following the linking tree from the **selection scale** to the **representation scale**, fine detail is obtained; last image shows the regions at the selection scale represented with basins of the lower representation scale.

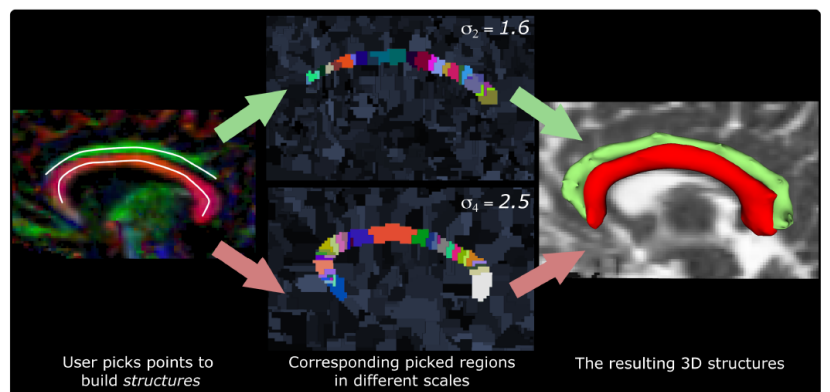


Figure 3. A $128 \times 64 \times 64$ DTI brain image. The user chooses a selection scale, by inspecting the level of simplification provided by a scale. Then he selects points in his segmentation task (Left), the correspondent basins in the respective Selection Scale are highlighted (Middle). Similar regions are collected by a region grouping algorithm, which are then focused into the representation scale. A smooth isosurface wraps the grouped similar connected regions (Right).