Representing Anatomical Trees by Denoising Diffusion of Implicit Neural Fields

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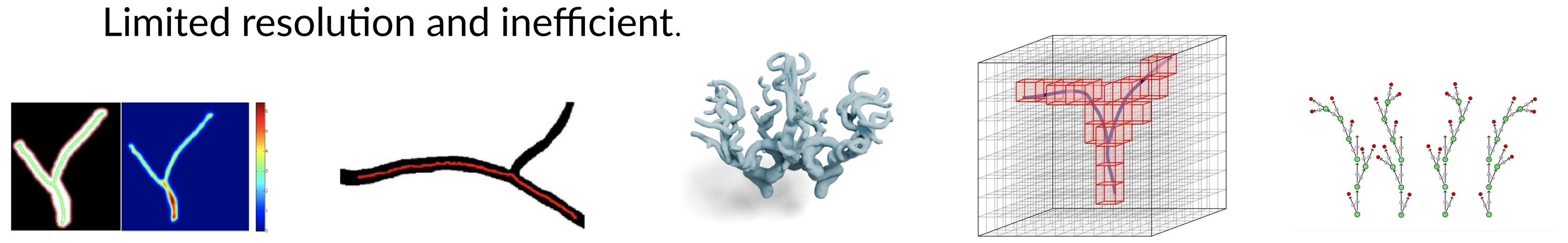
Motivation

- Anatomical trees are **ubiquitous**, *eg.*, brain vessels and airways
  - Important for clinical diagnosis and surgical planning.
- Difficult to represent
  - Varying and **complex topology and geometry**.
- Traditional medical imaging methods
  - **Limited resolution and inefficient**.



(a) Medial Axis [5]   (b) Minimal Paths [2]   (c) Meshes [8]   (d) Voxel-grids [9]   (e) L-System [3]

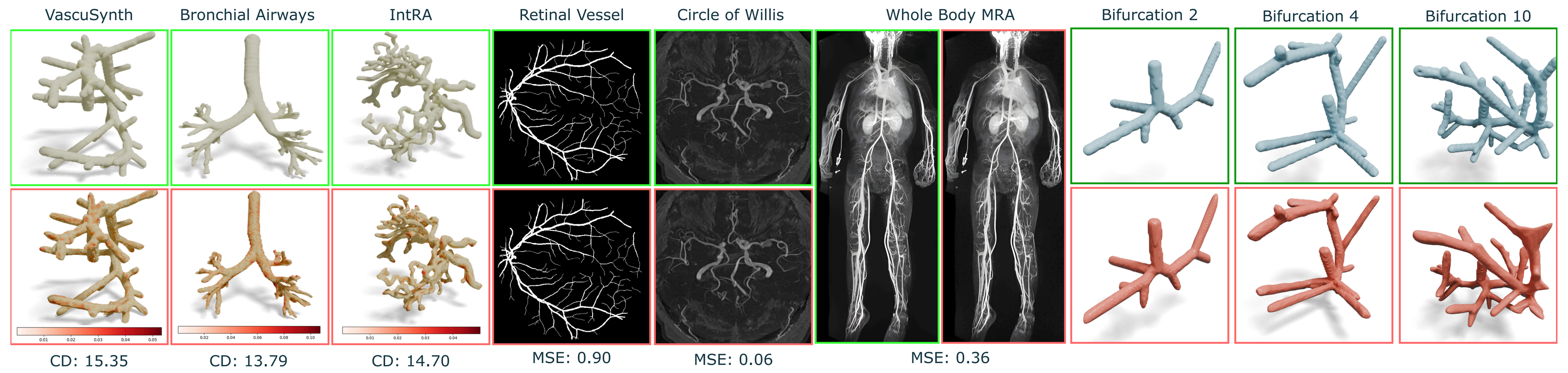
Goal

Represent anatomical trees accurately and efficiently using implicit neural representations (INRs), and learn a distribution of trees using denoising diffusion on the space of INRs.

Contributions

- First work to represent complex anatomical trees with INRs.
- First work to utilize INRs for segmenting tree-structure from medical images.
- First work to perform diffusion on the space of INR-represented trees for learning tree distributions and generating plausible novel trees with complex topology.
- Demonstrate adaptability across trees of different dimensions, complexities, and anatomy.
- Qualitatively and quantitatively evaluate representation compactness and reconstruction accuracy at high resolutions.

Versatility across modalities (2D/3D/CT/MRI), organs & complexities



Quantitative Results

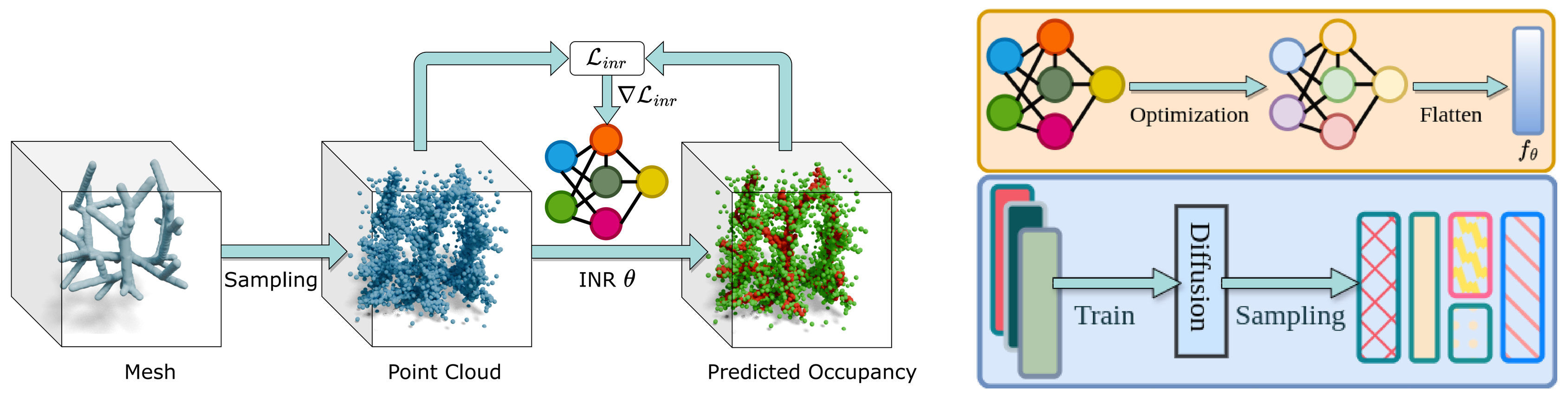
Modality	Rel. Error (%)	Input Size (MB)	INR Size (MB)
DRIVE (RGB) [7]	0.018	$0.37_{\pm 0.0055}$	$0.066_{\downarrow \times 5.60}$
DRIVE (Mask) [7]	1.204	$0.02_{\pm 0.0013}$	$0.003_{\downarrow \times 6.60}$
BraTS [4]	0.039	$68.11_{\pm 0.00}$	$0.753_{\downarrow \times 90.45}$
HAN-Seg [6]	5.627	$12.1_{\pm 1.55}$	$0.630_{\downarrow \times 19.20}$

Representing tree structures across medical imaging modalities with INRs.

Metric	Value
MMD ↓	$13.36_{\pm 8.37}$
COV ↑	$0.46_{\pm 0.11}$
1−NNA (%) ↓	$87.49_{\pm 8.99}$

Novel tree generation on VascuSynth dataset.

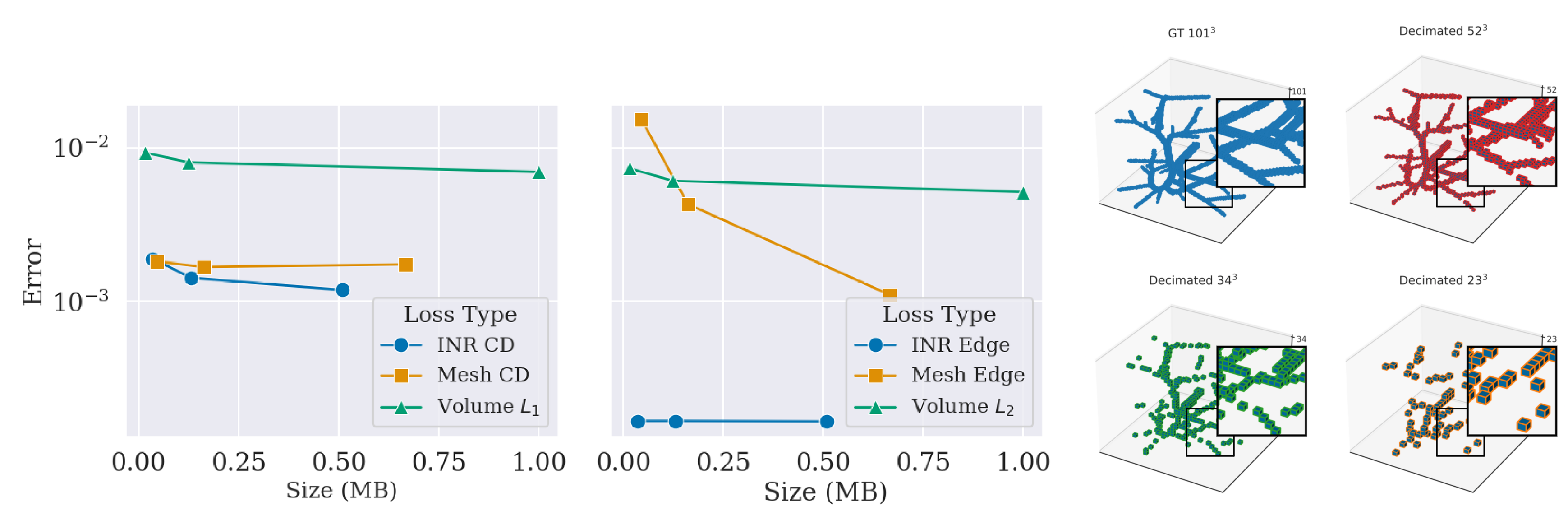
Methodology



(a) Stage 1: Per-Instance Optimization   (b) (Top) Stage 1, (Bottom) Stage 2

(a) Given a 3D mesh, optimize an INR for occupancy (*i.e.*, inside/outside). (b) Model diffusion process on flattened vectors of optimized INRs to learn the data distribution, and sample novel INRs during the reverse diffusion process.

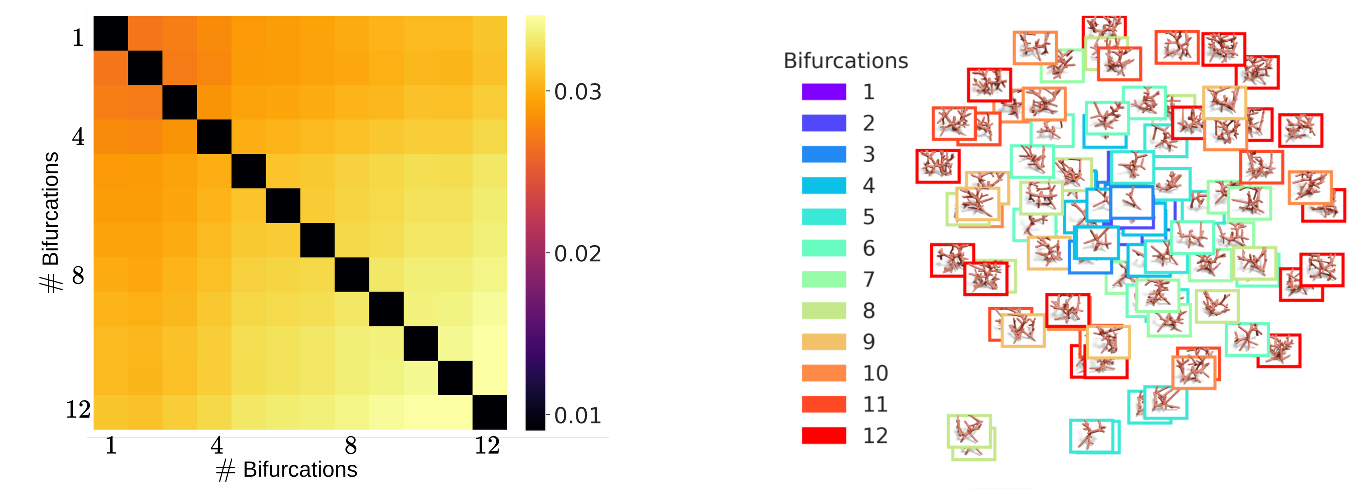
Compression *vs* Reconstruction Accuracy of INRs/Meshes/Volumes



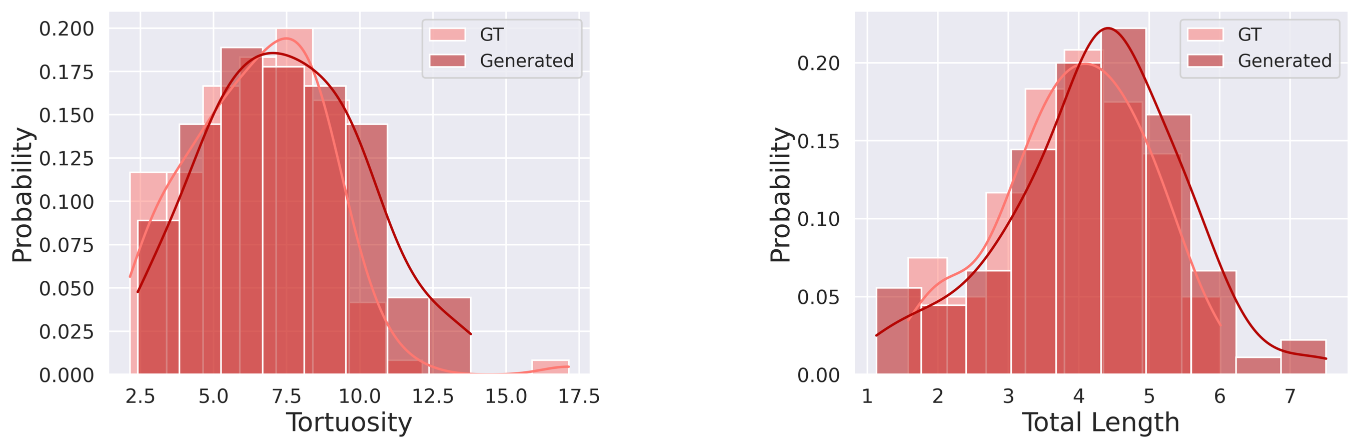
(a)   (b)

(a) For approx. the same memory space, meshes and volumes have higher reconstruction error *w.r.t* INRs. (b) Notice the disconnected components in low-res volumes.

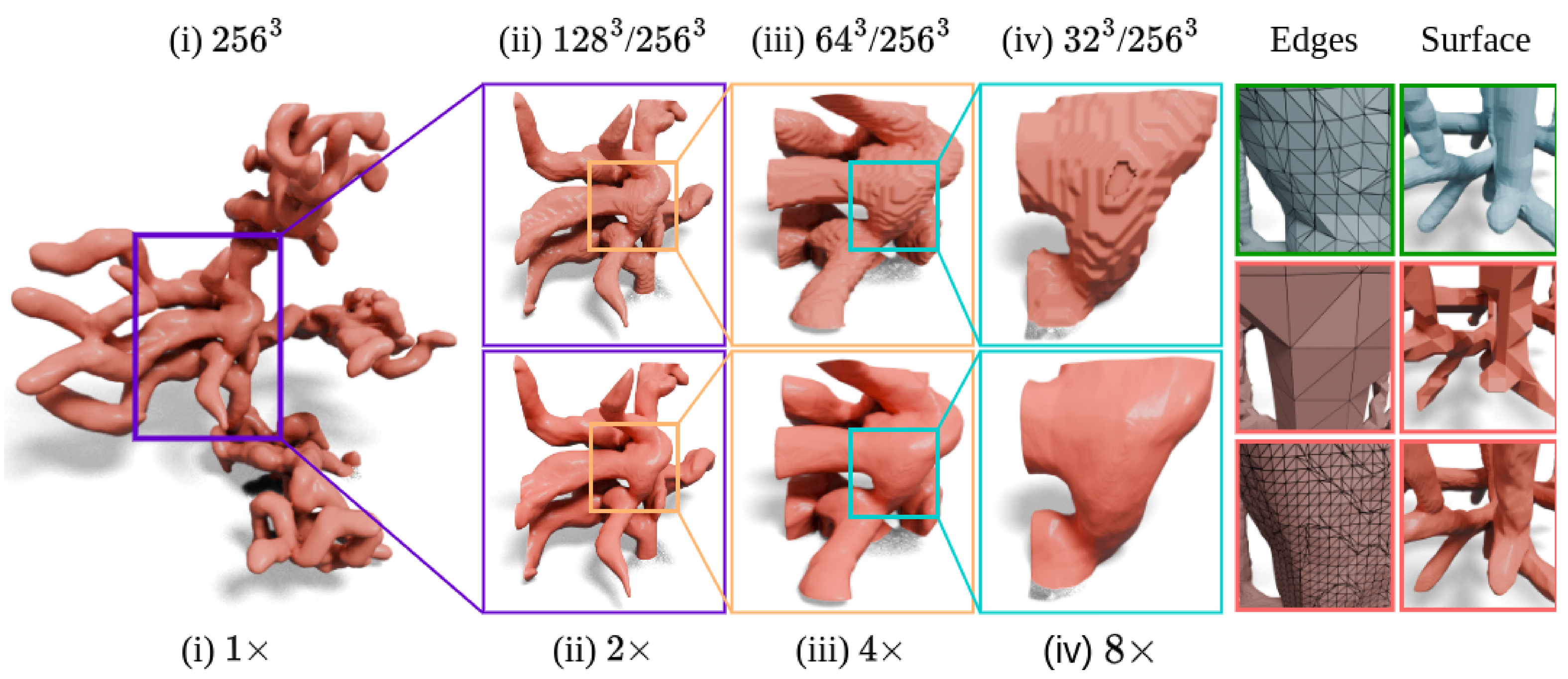
Tree Statistics: Do INRs have an understanding of the underlying signal?



(a) L_2 between INRs of trees with similar bifurcations   (b) T-SNE plot of the space of trees represented as INRs



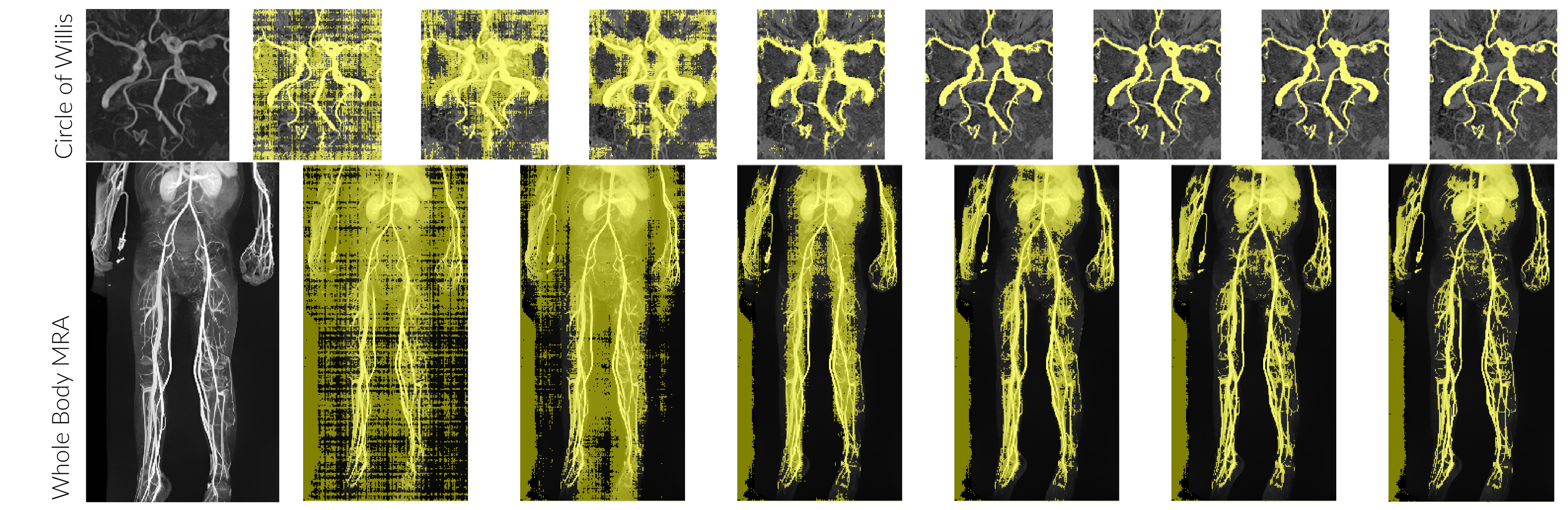
Arbitrary Resolution: Volumetric grids *vs* INRs



(a)   (b)

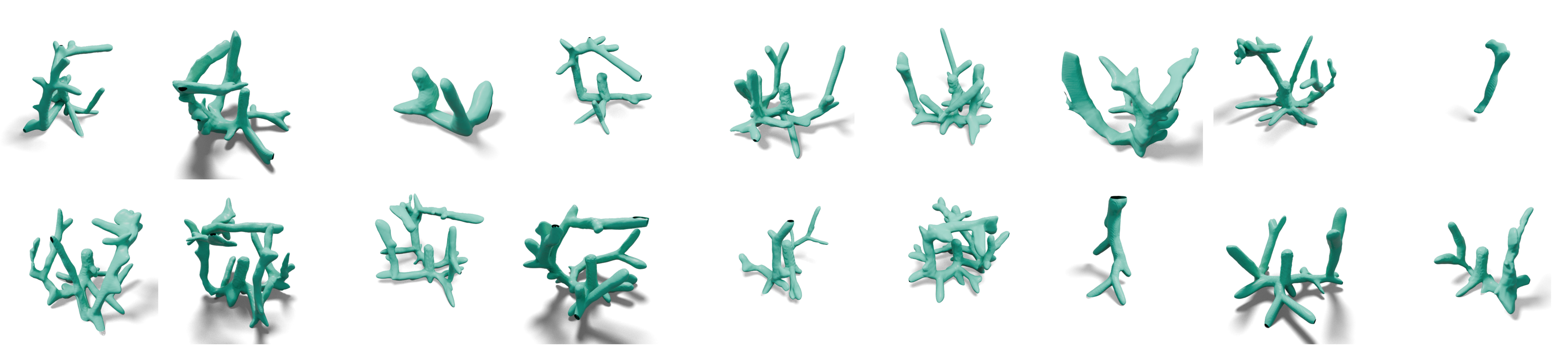
(a) Comparison of 2x, 4x, and 8x zoom. (b) Zoomed-in regions of a mesh reconstructed from INRs and ground truth at different mesh resolutions.

INR-based Image Segmentation



Similar to Mumford-Shah based segmentation [1], we use a piecewise-constant version of the INR to perform segmentation during optimization.

Tree Synthesis using Denoising Diffusion



References

[1] Chan, T.F., et al.: Active contours without edges. IEEE Transactions on image processing **10**(2), 266–277 (2001)
[2] Li, H., et al.: Vessels as 4-D curves: Global minimal 4-D paths to extract 3-D tubular surfaces and centerlines. IEEE TMI **26**(9), 1213–1223 (2007)
[3] Lindenmayer, A., et al.: Mathematical models for cellular interactions in development I. filaments with one-sided inputs. Journal of theoretical biology **18**(3), 280–299 (1968)
[4] Menze, B.H., et al.: The multimodal brain tumor image segmentation benchmark (BRATS). IEEE TMI **34**(10), 1993–2024 (2014)
[5] Pizaine, G., et al.: Implicit medial representation for vessel segmentation. In: Medical Imaging 2011: Image Processing. vol. 7962, pp. 1184–1190. SPIE (2011)
[6] Podobnik, G., et al.: HaN-Seg: The head and neck organ-at-risk CT and MR segmentation dataset. Medical physics **50**(3), 1917–1927 (2023)
[7] Staal, J., et al.: Ridge-based vessel segmentation in color images of the retina. IEEE TMI **23**(4), 501–509 (2004)
[8] Yang, X., et al.: IntrA: 3D intracranial aneurysm dataset for deep learning. In: CVPR (2020)
[9] Zhao, M., et al.: Tree-LSTM: using LSTM to encode memory in anatomical tree prediction from 3D images. In: MICCAI Workshop (MLMI). pp. 637–645. Springer (2019)