Simulation-Based Segmentation of Blood Vessels in Cerebral 3D OCTA Images

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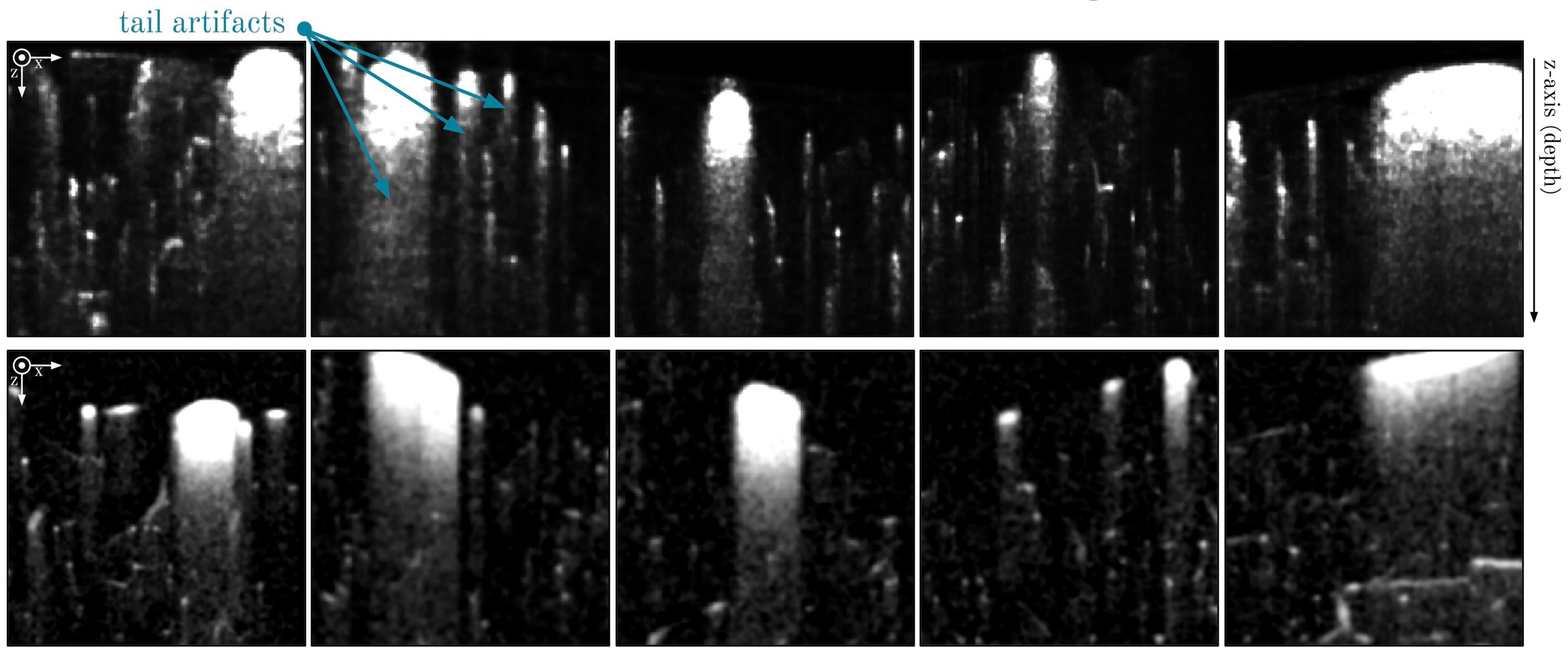
Motivation & Contributions:

Segmentation of blood vessels in murine cerebral 3D OCTA images is **foundational for *in vivo* quantitative analysis of the effects of neurovascular disorders**, such as stroke or Alzheimer's, on the vascular network.

3D OCTA images are plagued by artifacts and generally have a low signal-to-noise ratio. Therefore, **no large manually annotated datasets** necessary for precise segmentation exist to this date. Further, **high variability in OCTA image characteristics** limits the use of annotated data from different OCT setups.

We propose a **synthesis pipeline** that can be adapted to the 3D OCTA data at hand with little effort to **generate a vast amount of synthetic data** with matching ground truth labels. By utilizing our generated synthetic data to train an off-the-shelf deep learning-based segmentation network, we demonstrate **accurate, annotation-free segmentation performance on real cerebral 3D OCTA images**.

Exemplary Generated Synthetic Images:



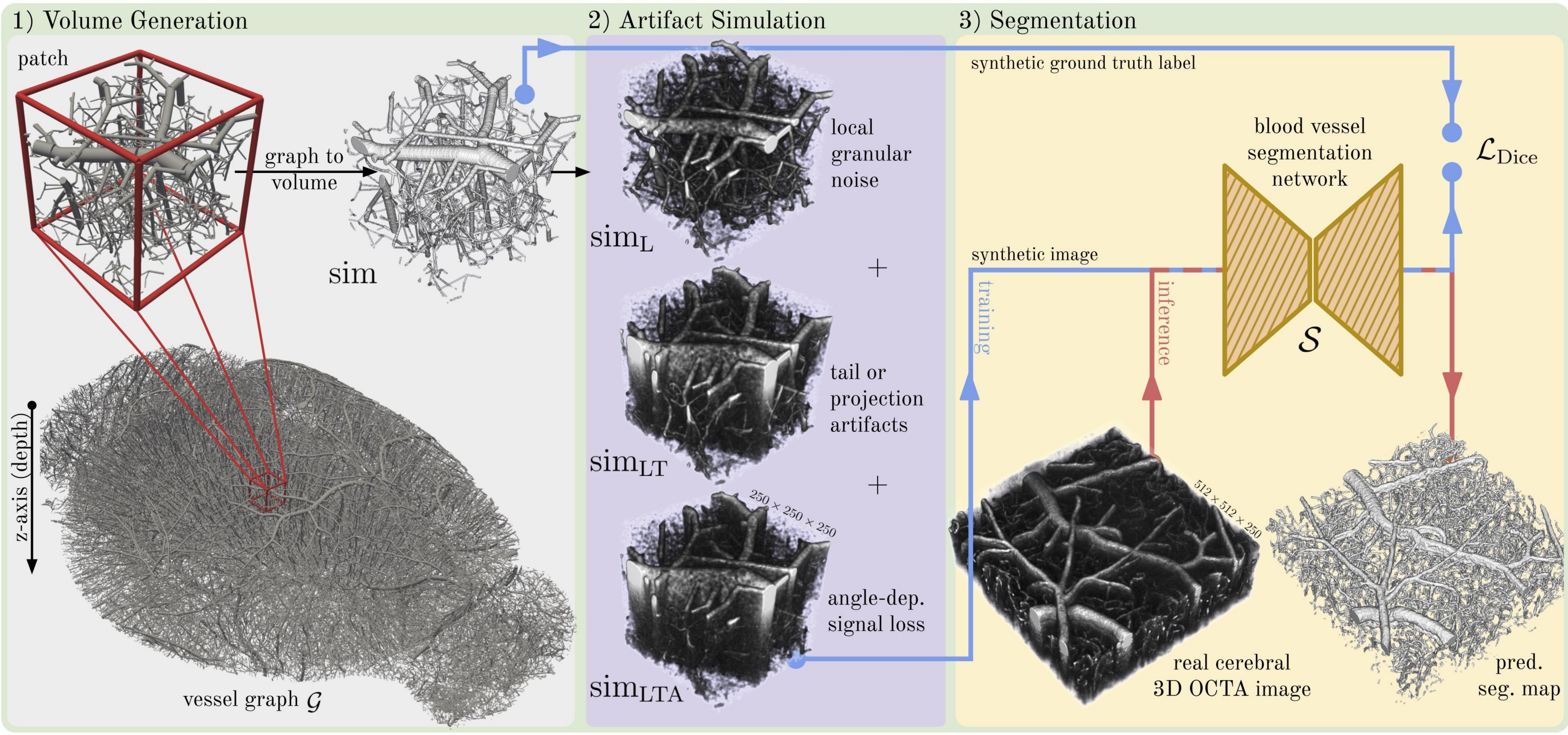
Slices of real (top) and synthetic (bottom) cerebral 3D OCTA images. We accurately match 3D OCTA-specific artifacts, resulting in synthetic images almost indistinguishable from real images.

Method:

1) Volume Generation: Extract patches from vessel graphs and transform them into a vast amount of voxelized volumes.

2) Artifact Simulation: Transform volumes into synthetic cerebral 3D OCTA images by simulating the most dominant image acquisition artifacts.

3) Segmentation: Utilize synthetic cerebral 3D OCTA images paired with their matching ground truth labels to train a segmentation network.



Overview of our proposed synthesis pipeline and its three stages: Volume generation, artifact simulation, and segmentation.

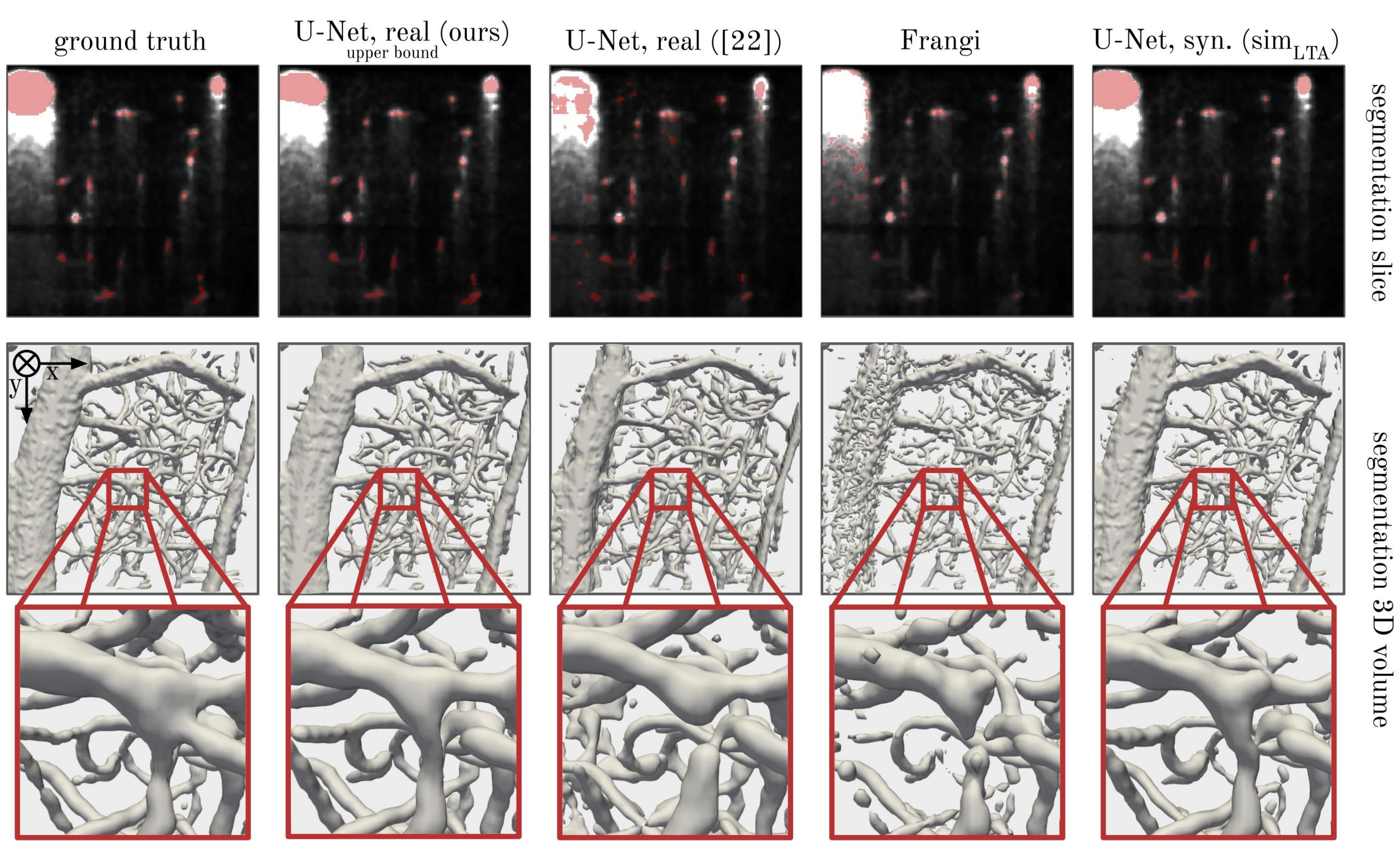
Experiments & Results:

We outperform traditional techniques and deep learning methods trained on real manually annotated data from a different OCT system while almost matching the performance of the upper bound. We differentiate between performance on small and large vessels.

	Method	Data	all Dice ↑	all clDice ↑	small Dice ↑	small clDice ↑	large Dice ↑	large clDice ↑
a	3D U-Net	real (ours)*	79.46±0.18	85.29±0.16	74.31±0.08	87.86±0.12	82.54±0.25	70.93±0.21
	3D U-Net	real ([22])	54.13±1.37	65.41±1.09	52.78±0.90	67.57±1.16	55.07±2.17	48.50±1.39
b	Frangi	-	40.84±0.00	53.13±0.00	58.52±0.00	65.96±0.00	19.57±0.00	30.95±0.00
	Otsu	-	50.62±0.00	33.47±0.00	42.99±0.00	49.34±0.00	51.63±0.00	11.20±0.00
c	3D U-Net	syn. ($\mathrm{sim_{LTA}}$)	74.83±0.23	80.92±0.13	66.90±0.16	81.27±0.14	80.66±0.36	69.19±0.31
d	3D U-Net	syn. (sim)	50.85±0.88	29.98±1.15	54.26±1.77	62.63±2.01	47.33±1.27	9.87±0.99
	3D U-Net	syn. ($\mathrm{sim_L}$)	52.68±1.18	46.15±2.15	56.67±0.99	61.34±1.13	47.61±1.59	28.77±2.39
	3D U-Net	syn. ($\mathrm{sim_{LT}}$)	70.38±0.43	72.80±0.73	57.50±0.93	73.60±0.53	79.81±0.30	59.48±0.75
e	3D U-Net	syn. ($\mathrm{sim_{LTAC}}$)	74.46±0.19	80.84±0.19	66.50±0.21	80.75±0.11	80.33±0.41	69.55±0.75
f	3D U-Net	syn. ($\mathrm{sim^{SAT}_{LTA}}$)	60.00±1.28	74.48±1.10	66.77±0.53	80.88±0.19	51.84±3.86	52.92±1.82

*Upper bound trained on our annotated images. Annotating 2 training volumes consumed ~2 months.

a) U-Net trained on real, manually annotated data, b) traditional techniques, c) U-Net trained on our synthetic 3D OCTA data, d) ablation on simulated artifacts, e) ablation on curvature, f) ablation on vessel graphs.



Qualitative results. The U-Net trained on our synthetic data (right) accurately segments cerebral vasculature, eliminating the need for a time-consuming manual annotation process.

Keywords: OCT Angiography · Blood Vessels · Synthetic Data · Simulation · Cerebral Vasculature · 3D Segmentation