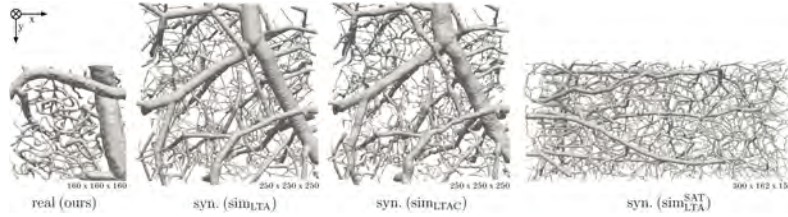
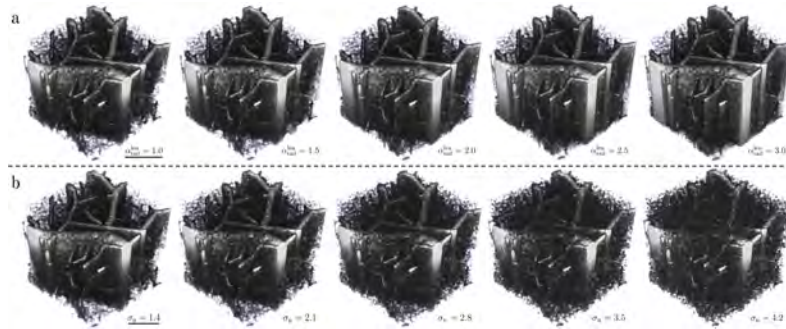


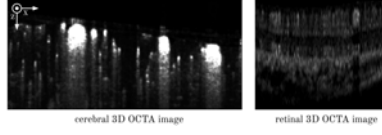
## Supplementary Material



**Fig. 6.** Comparison of ground truth labels. All labels have a similar voxel size of approximately  $2 \mu\text{m}$ . We compare manual annotations (left) to the ground truth labels of synthetic datasets used in our experiments. Direct comparison leads to the conclusion that capillaries appear inflated in our manual annotations, indicating an annotator-specific bias. We would like to highlight the effect of elastic deformation on curvature ( $\text{sim}_{\text{LTAC}}$ ) and the morphological differences between labels arising from synthetic arterial trees ( $\text{sim}_{\text{LTA}}^{\text{SAT}}$ ) and vascular corrosion casts ( $\text{sim}_{\text{LTA}}$ ). Modifications to ground truth labels were solely made in the experiment on curvature ( $\text{sim}_{\text{LTAC}}$ ).



**Fig. 7.** Effect of adjusting simulation parameters. The length of projection artifacts can, *e.g.*, be increased to account for other beam geometries or the absence of external contrast agents by increasing the tail length factor  $\alpha_{\text{tail}}^{\text{len}}$  (first row), while modifying  $\sigma_n$  (second row) adjusts the intensity of local granular noise patterns. This flexibility enables us to cope with high variability in OCT system design and acquisition protocols.



**Fig. 8.** Slices of a cerebral and a retinal 3D OCTA image. The images differ not only drastically in underlying blood vessel morphology but also in general characteristics, such as signal-to-noise ratio, FOV, and voxel size. The depicted retinal 3D OCTA image originates from the OCTA-500 dataset [1].

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### Algorithm 1 Pseudocode: cerebral 3D OCTA artifact simulation

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**Require:** voxelized volume  $I$ , metadata  $I_{\text{meta}}$ , upper radius threshold  $r_{\text{max}}$ , radius threshold microvessels  $r_{\text{micro}}$ , angle delta scaling factor  $\gamma_{\Delta}$ , lambda intensity  $\lambda_{\text{int}}$ , tail length factor  $\alpha_{\text{tail}}^{\text{len}}$ , tail intensity factor  $\alpha_{\text{tail}}^{\text{int}}$ , tail noise mean  $\mu_{\text{tail}}$ , tail noise std  $\sigma_{\text{tail}}$ , granular noise mean  $\mu_{\text{n}}$ , granular noise std  $\sigma_{\text{n}}$ , smoothing sigma  $\sigma_{\text{s}}$ , lower int. threshold  $i_{\text{min}}$ , upper int. threshold  $i_{\text{max}}$

- 1:  $I' \leftarrow \text{ZEROSLIKE}(I)$  // Initialize output volume
- 2: **for all** voxels  $(v_{\text{int}}, v_{\text{id}})$  in  $I$  **do** // Loop over voxels given by intensity & ID
- 3:   **if**  $v_{\text{int}}$  is 0 **then**
- 4:     **continue** // Ignore empty space
- 5:    $\theta_z, r \leftarrow I_{\text{meta}}[v_{\text{id}}]$  // Retrieve angle & radius from metadata
- 6:   // Estimate intensity component contributed by vessel radius
- 7:    $v_{\text{int}}^{\text{rad}} \leftarrow \text{SCALE}(\text{CLIP}(r, 0, r_{\text{max}}))$  // Clip with  $(0, r_{\text{max}})$  & scale to  $[0, 1]$
- 8:   // Estimate intensity component contributed by angle between vessel & z-axis
- 9:    $v_{\text{int}}^{\text{micro}} \leftarrow \text{SCALE}(\text{EXPDECAY}(90^\circ - \theta_z))$  // Exponential signal decay & scale to  $[0, 1]$
- 10:    $v_{\text{int}}^{\text{macro}} \leftarrow \text{SIGMOID}(\gamma_{\Delta} \cdot (r - r_{\text{micro}}))$  // Soft thresholding
- 11:    $v_{\text{int}}^{\text{ang}} \leftarrow \text{MAX}(v_{\text{int}}^{\text{micro}}, v_{\text{int}}^{\text{macro}})$  // Signal decay just has an effect on microvessels
- 12:    $v_{\text{int}} \leftarrow \lambda_{\text{int}} \cdot v_{\text{int}}^{\text{ang}} + v_{\text{int}}^{\text{rad}}$  // Update voxel intensity
- 13:   **if**  $\text{OCCUPANCYBELOW}(I, v_{\text{id}})$  **is not 0 then** // Check if voxel not in lower vessel wall
- 14:      $I'[v_{\text{id}}] \leftarrow v_{\text{int}}$
- 15:     **continue** // Do not model tail artifacts
- 16:   // Model projection/tail artifacts
- 17:    $l_{\text{tail}} \leftarrow \alpha_{\text{tail}}^{\text{len}} \cdot v_{\text{int}}^{\text{rad}}$  // Determine tail length
- 18:    $t \leftarrow \text{GEOMPROG}(v_{\text{int}} \cdot \alpha_{\text{tail}}^{\text{int}}, 0, l_{\text{tail}})$  // Model tail as sequence with geom. progression
- 19:    $t \leftarrow t + \text{GAUSSIANNOISE}(\mu_{\text{tail}}, \sigma_{\text{tail}})$  // Add random Gaussian noise to tails
- 20:    $I' \leftarrow I' + \text{CLIP}(t, 0, v_{\text{int}})$  // Add clipped tail to output volume
- 21: // Model local granular noise patterns
- 22:  $I' \leftarrow I' + \text{GAUSSIANNOISE}(\mu_{\text{n}}, \sigma_{\text{n}})$
- 23:  $I' \leftarrow \text{GAUSSIANSMOOTHING}(I', \sigma_{\text{s}})$
- 24:  $I' \leftarrow \text{SCALE}(\text{CLIP}(I', i_{\text{min}}, i_{\text{max}}))$  // Clip with  $(i_{\text{min}}, i_{\text{max}})$  & scale to  $[0, 1]$
- 25: **return**  $I'$  // Return synthetic cerebral 3D OCTA image

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## References

1. Li, Mingchao, et al. "OCTA-500: a retinal dataset for optical coherence tomography angiography study." *Medical Image Analysis* 93 (2024): 103092.