Supplementary Material for FreeCOS: Self-Supervised Learning from Fractals and Unlabeled Images for Curvilinear Object Segmentation

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1. Additional Visualization Results of Generated Fractal Curvilinear Object

Figure. 1 shows some exemplar fractals generated by the parametric Fractal L-systems with various intensities, angles, lengths, and widths. These fractals are used as synthetic curvilinear objects X_{frac} and integrated into the target unlabeled images by our FFS module.

2. Visualization of Additional Segmentation Results

We illustrate some segmentation results based on our method in Figures. 2, 3 and 4.

Figure. 2 shows that our FreeCOS has the ability to achieve satisfactory vessel segmentation performance even when the background is noisy and contain confusing artifacts.

Figures. 3 and 4 illustrate the qualitative results on the STARE and CrackTree datasets. The retinal and crack datasets have curvilinear objects with various widths, tiny branches, tortuosity shapes, and ambiguous boundaries which bring huge challenging. Results in Figures 3 and 4 show that without annotated data for training, our self-supervised method can still achieve satisfactory results.

3. Generalization Performance of Self-Supervised Methods

FreeCOS (the last row of Table. 1) has been trained on DRIVE and STARE as our method does not require clean background images as SSVS and DARL. FreeCOS achieves excellent performance than other self-supervised methods [2, 1]. In comparison, SSVS and DARL are unable to train the segmentation model on DRIVE and STARE, greatly limiting its performance and application scenario. We also compare the generalization performance of FreeCOS in Table. 1. Our method (trained on XCAD) also achieves better performance than previous self-supervised methods, indicating that our method is not only easier to use in different applications, but also has good generalization performance.

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	Methods	DRIVE			STARE		
		Dice	Pr.	IoU	Dice	Pr.	IoU
Self-supervised	SSVS [2]	0.469	0.549	0.314	0.450	0.490	0.311
	DARL [1]	0.525	0.617	0.372	0.508	0.537	0.368
	Ours (trained on XCAD)	0.547	**0.753**	0.378	0.621	0.547	0.453
	Ours	**0.648**	0.550	**0.482**	**0.713**	**0.657**	**0.556**

Table 1. Quantitative generalization evaluation of FreeCOS compared with different methods on the retinal dataset.

Figure 1. Visualization of exemplar fractals.

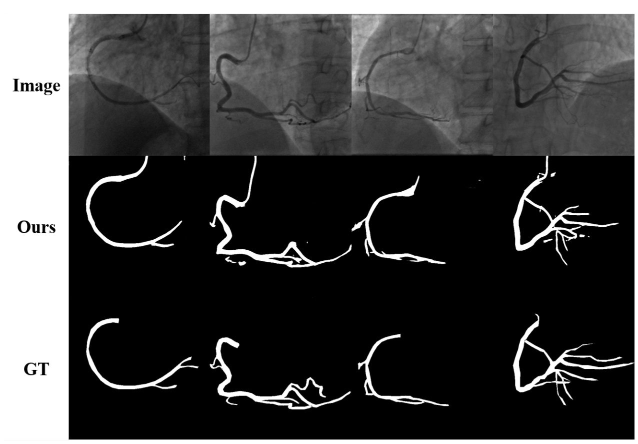

Figure 2. The visualization segmentation results of the coronary dataset XCAD.

Figure 3. The visualization segmentation results of the retinal dataset STARE.

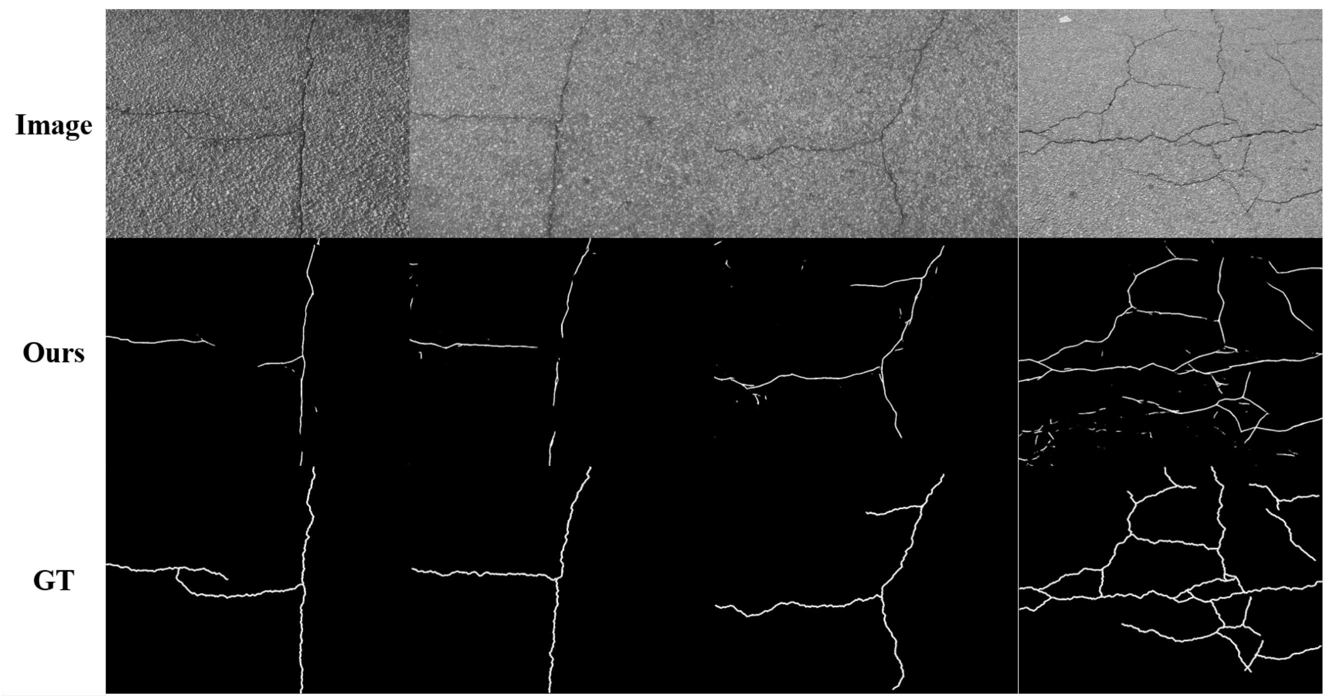

Figure 4. The visualization segmentation results of the crack dataset CrackTree.

References

[1] Boah Kim, Yujin Oh, and Jong Chul Ye. Diffusion adversarial representation learning for self-supervised vessel segmentation. In *International Conference on Learning Representations*, 2022. 1

[2] Yuxin Ma, Yang Hua, Hanming Deng, Tao Song, Hao Wang, Zhengui Xue, Heng Cao, Ruhui Ma, and Haibing Guan. Self-supervised vessel segmentation via adversarial learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 7536–7545, 2021. 1