

Supplementary materials for “Serial section microscopy image inpainting guided by axial optical flow”

1 Experiments

1.1 Dataset and metric

To comprehensively estimate the network performance by evaluating its contribution to segmentation work and designing stability experiment, we introduce another **EPFL Dataset**¹. It provides an image stack with 1065 serial sections of size 2048×1536 . This dataset is collected from the CA1 hippocampus region of a mouse brain. The dataset is acquired by FIB-SEM and the resolution of each voxel is approximately $5 \times 5 \times 5$ nm.

The common segmentation map assessment metrics consist of VOI (Variation of Information) [3] and ARAND (Adapted Rand Error) [4]. VOI calculates the sum of two conditional entropies of the predicted and the ground truth segmentation maps, while ARAND measures the similarity between the predicted segmentation maps and the ground truth segmentation maps based on the cluster to which randomly selected pixels belong.

1.2 Further Comparison on Segmentation Results

To demonstrate the rationality of FlowInpaint’s inpainted results, we further perform neural segmentation tasks on them. Here, we adopt a random walker-based image segmentation method [2] to generate the segmentation maps of the inpainted results. The quantitative and visual comparison results of inpainted images in segmentation tasks on the CREMI dataset are presented in Table 1 and Figure 1. From these segmentation maps, we can tell that the generated textures that violate the trend of structural changes and blurry content that affects image feature extraction would lead to imprecise neural segmentation results. However, our method has already addressed the aforementioned issues during the scheme design. Thus FlowInpaint’s results can well enhance the accuracy of subsequent work to some extent.

1.3 Stability Analysis

1.3.1 Stability on Contrast. In real-world scenarios, low contrast is often introduced during the imaging process and affects the recognition of structure information. We simulate the neighboring images I_{i-1}^{con} under different contrast ratios by adjusting the brightness (B) and the haze (H) level of the original image I_{i-1} as follows:

$$I_{i-1}^{con} = I_{i-1} \times (1 - H) + 255 \times B \times H. \quad (1)$$

A lower brightness (B) value corresponds to a darker image, whereas a higher haze (H) level value indicates lower clarity. We set the brightness (B) between 0.6~1 and the haze (H) between 0.4~0.8 based on the contrast variation in the real world, and Table 2 summarizes the quantitative results. The change in contrast does not alter the relative intensity relationship between pixels, thus having little impact on optical flow estimation. Actually, FlowInpaint

Table 1: Inpainting results on neuron segmentation task. ↑ means higher is better. ↓ means lower is better.

Method	Metric					
	CREMIA		CREMIB		CREMIC	
	VOI↓	ARAND↓	VOI↓	ARAND↓	VOI↓	ARAND↓
PEN-NET	1.887	0.468	2.779	0.563	2.131	0.511
AOT-GAN	1.569	0.413	2.473	0.559	2.033	0.504
CCPGAN	1.175	0.218	1.292	0.369	1.183	0.355
SSF-Restoration	1.098	0.214	1.174	0.361	1.171	0.312
Ours	1.073	0.194	1.168	0.357	1.164	0.305

Table 2: Stability Studies on contrast. ↑ means higher is better. ↓ means lower is better.

H(haze)	Metric	B(brightness)				
		0.6	0.7	0.8	0.9	1.0
0.2	PSNR↑	29.992	30.108	30.186	30.327	30.748
	SSIM↑	0.911	0.916	0.920	0.925	0.930
	FSIM↑	0.946	0.947	0.949	0.950	0.950
	FID↓	8.111	8.030	7.971	7.859	7.806
0.4	PSNR↑	29.779	29.943	30.032	30.152	30.201
	SSIM↑	0.904	0.910	0.914	0.918	0.921
	FSIM↑	0.945	0.947	0.948	0.948	0.948
	FID↓	8.190	8.116	7.968	7.892	7.825
0.6	PSNR↑	29.546	29.642	29.793	29.588	29.622
	SSIM↑	0.898	0.902	0.905	0.908	0.911
	FSIM↑	0.944	0.945	0.946	0.946	0.946
	FID↓	8.411	8.265	8.183	8.073	8.003

achieves nearly the same high-quality restoration results in different combinations of brightness and haze, which can also be derived from Figure 2.

1.3.2 Stability on Axial Resolution. The thickness of tissue sections determines the resolution along the sectioning direction (axial resolution). Typically, the common axial resolution of serial sections ranges from 30 to 70 nm, and the appearance of FIB-SIM allows for the improvement of resolution to 5~10 nm [1]. To test the stability of FlowInpaint under different axial resolutions, we simulate the axial resolution by adjusting the section interval among the EPFL image stacks, whose raw section interval is 5nm. We train the FlowInpaint on the data of $5 \times 5 \times 50$ nm³ resolution, and apply it on all testing data of $5 \times 5 \times 20 \sim 70$ nm³ resolution, which is shown in Table 3. With the reduction of axial resolution, the transformation of biological structures along the axial direction becomes larger and more difficult to estimate. When the axial resolution ranges from 20 to 60 nm, FlowInpaint generates acceptable recovered results.

¹Dataset available at <https://www.epfl.ch/labs/cvlab/data/data-em/>

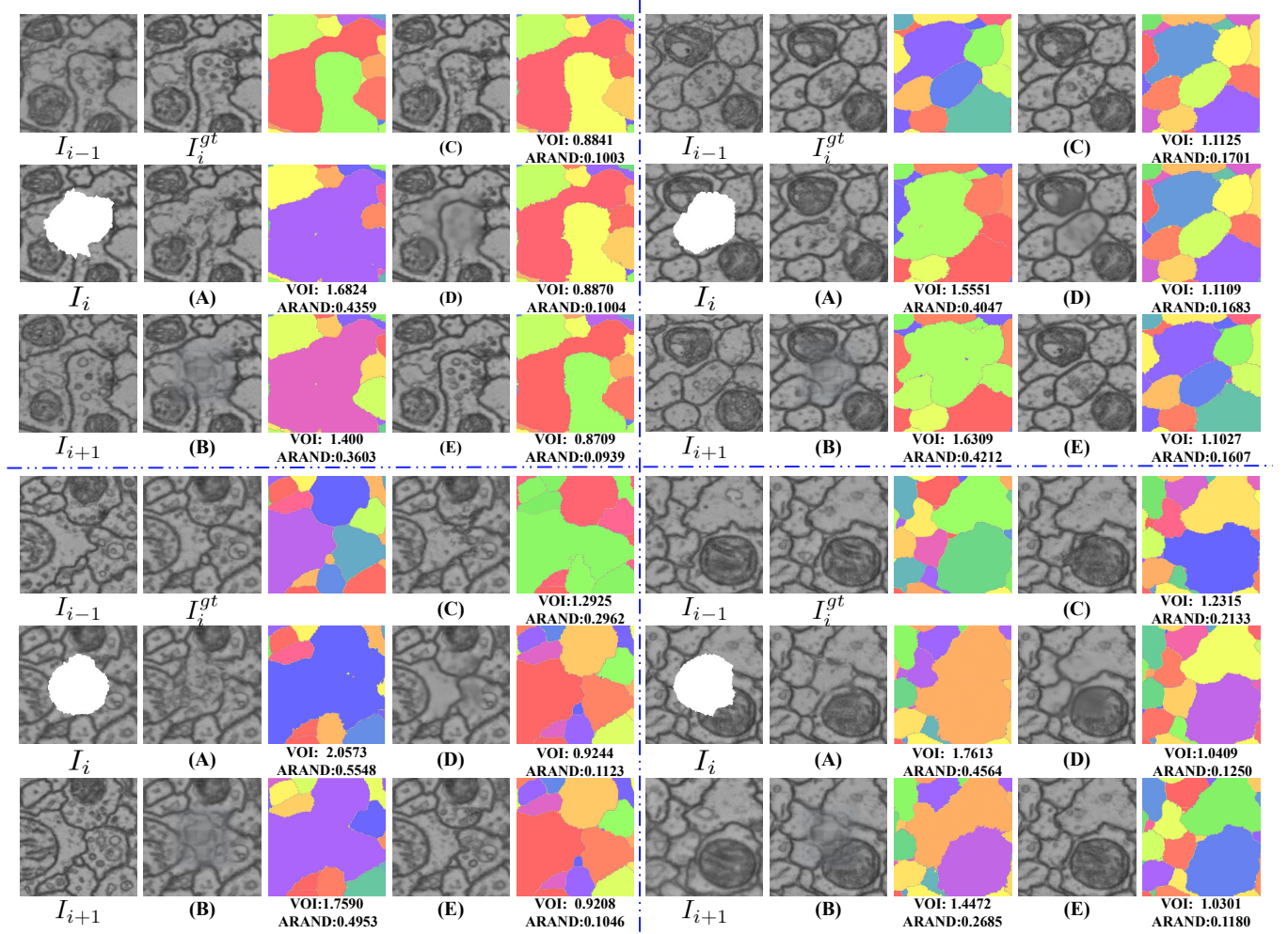


Figure 1: The neuron segmentation maps of inpainted results. (A) PEN-Net, (B) AOT-GAN, (C) CCPGAN, (D) SSF-Restoration, and (E) Ours.

Table 3: Stability Studies on axial resolution (nm^3). \uparrow means higher is better. \downarrow means lower is better.

Resolution(nm^3)	$5 \times 5 \times 20$	$5 \times 5 \times 30$	$5 \times 5 \times 40$
SSIM \uparrow	0.886	0.867	0.850
PSNR \uparrow	28.404	27.747	27.248
FSIM \uparrow	0.941	0.938	0.935
FID \downarrow	10.321	10.884	11.085
Resolution(nm^3)	$5 \times 5 \times 50$	$5 \times 5 \times 60$	$5 \times 5 \times 70$
SSIM \uparrow	0.832	0.804	0.778
PSNR \uparrow	26.762	26.086	25.556
FSIM \uparrow	0.932	0.929	0.927
FID \downarrow	12.555	13.567	16.684

References

- [1] TD Ambegoda, Julien NP Martel, J Adamcik, M Cook, and Richard HR Hahnloser. 2017. Estimation of Z-thickness and XY-anisotropy of electron microscopy images using Gaussian processes. *Journal of Neuroinformatics and Neuroimaging* 2, 2 (2017), 15–22.
- [2] Lorenzo Cerrone, Alexander Zeilmann, and Fred A Hamprecht. 2019. End-to-end learned random walker for seeded image segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 12559–12568.
- [3] Marina Meilă. 2003. Comparing clusterings by the variation of information. In *Learning Theory and Kernel Machines: 16th Annual Conference on Learning Theory and 7th Kernel Workshop, COLT/Kernel 2003, Washington, DC, USA, August 24–27, 2003. Proceedings*. Springer, 173–187.
- [4] Ranjith Unnikrishnan, Caroline Pantofaru, and Martial Hebert. 2007. Toward objective evaluation of image segmentation algorithms. *IEEE transactions on pattern analysis and machine intelligence* 29, 6 (2007), 929–944.

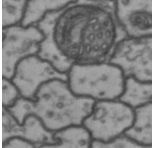
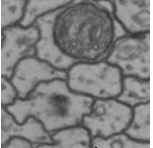
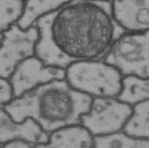
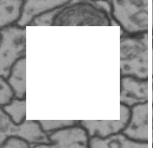
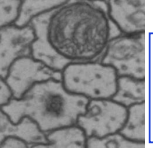
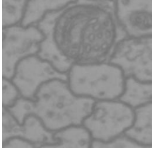
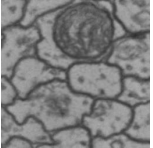
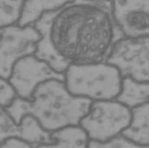
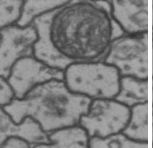
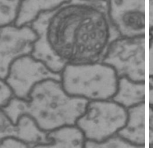
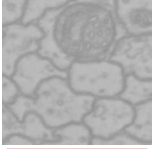
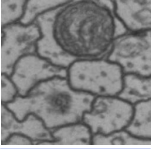
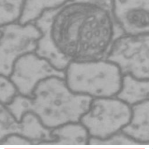
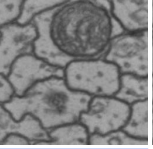
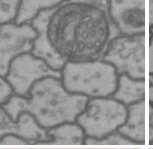
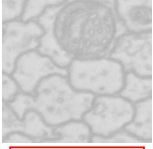
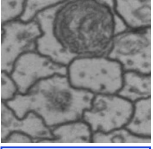
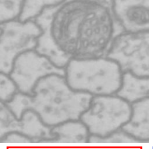
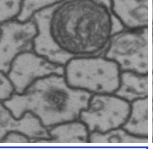
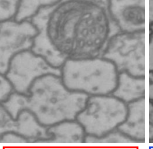
					PSNR=30.575 SSIM=0.953 FSIM=0.956 FID=12.991
I_{i-1}	I_i^{gt}	I_{i+1}	I_i	Ours	
					
B=0.6; S=0.6	PSNR=29.256 SSIM=0.921 FSIM=0.952 FID=14.531	B=0.6; S=0.4	PSNR=29.396 SSIM=0.928 FSIM=0.953 FID=14.414	B=0.6; S=0.2	PSNR=29.472 SSIM=0.931 FSIM=0.954 FID=14.201
					
B=0.8; S=0.6	PSNR=30.263 SSIM=0.937 FSIM=0.953 FID=14.342	B=0.8; S=0.4	PSNR=30.433 SSIM=0.942 FSIM=0.953 FID=14.209	B=0.8; S=0.2	PSNR=30.529 SSIM=0.946 FSIM=0.954 FID=14.012
					
B=1; S=0.6	PSNR=30.374 SSIM=0.940 FSIM=0.954 FID=14.238	B=1; S=0.4	PSNR=30.476 SSIM=0.944 FSIM=0.954 FID=13.947	B=1; S=0.2	PSNR=30.543 SSIM=0.947 FSIM=0.955 FID=13.372

Figure 2: The example under different contrast ratios, B represents brightness and S represents the degree of spray.