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Semi-supervised Segmentation of Mitochondria from Electron Microscopy Images using Spatial Continuity

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Background

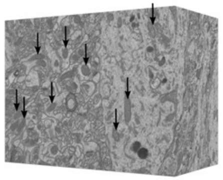


Figure 1. EM image stack from EPFL dataset

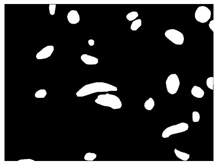


Figure 2. Segmentation results of one image slice

- Figure.1 is originally from ref. [1].
- Accurate segmentation of electron microscopy (EM) images is essential for underlying morphology analysis.
- Manual annotation of 3D EM images is laborious.
- We aim to build deep learning models requiring limited labels.

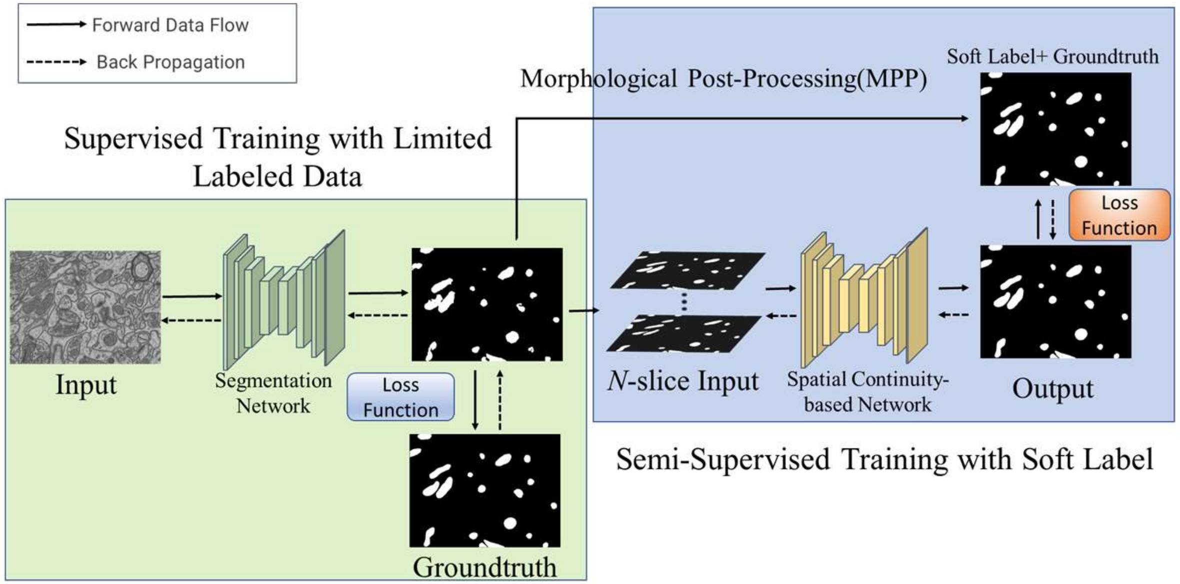
Key Contributions

We propose a semi-supervised segmentation method:

- In the first stage, we train a segmentation network (2D U-Net) using labeled images in a supervised manner.
- In the second stage, we train a a spatial continuity-based model (SCM) using unlabeled images.
    - Develop a morphological post-processing (MPP) for segmentation refinement of unlabeled images.
    - The SCM takes raw segmentation results as input and use the refined segmentation results as training target.
- We use the random piecewise affine transformation for augmentation.

MPP and SCM

- The MPP module is proposed to obtain the training targets for unlabeled image slices during the second training stage.
- The MPP module includes a spatial continuity-based operator across Z axis at each single XY location to remove segmentation noise.
- To incorporate a full 3D morphological operation on XYZ axes, we propose a spatial continuity-based models.
    - We use the segmentation results obtained from MPP as training targets for the unlabeled images
    - We also use the labeled image slices in this stage to regularize the unsupervised training.
    - The SCM is implemented as a neural network which uses the raw segmentation mask of labeled and unlabeled image slice and its adjacent masks as N-channels input, and output fine segmentation result of the middle slice.

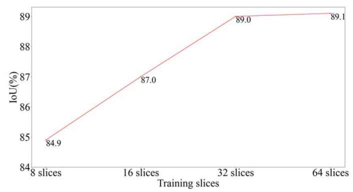


Qualitative results on EPFL dataset

Methods	Labels	Dice (%)	IoU (%)
Lucchi [1]	165	86.7	75.7
Peng [3]	165	90.8	83.4
2D U-Net [2]	165	91.4	84.4
3D U-Net [4]	165	93.5	87.7
Xiao [6]	165	94.7	90.0
Yuan [7]	165	**94.8**	**90.1**
Ours	**32**	94.2	89.0

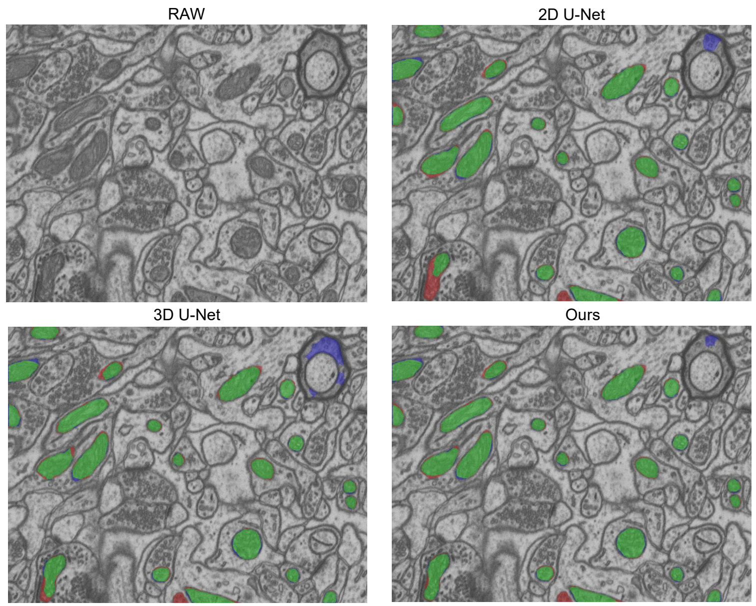
Ablation experiments

Affine	MPP	SCM	Dice (%)	IoU (%)
-	-	-	90.5	82.6
✓	-	-	92.5	86.9
✓	✓	-	93.6	88.0
✓	✓	✓	94.2	89.0



Performance of using different number of labeled slices

Quantitative results on EPFL dataset



Green: true positive (TP) Red: false negative (FN) Blue: false positive (FP)

[1] A. Lucchi, CVPR,2013

https://github.com/cbmi-group/MPP

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