Efficient Connectivity-Preserving Instance Segmentation with Supervoxel-Based Loss Function

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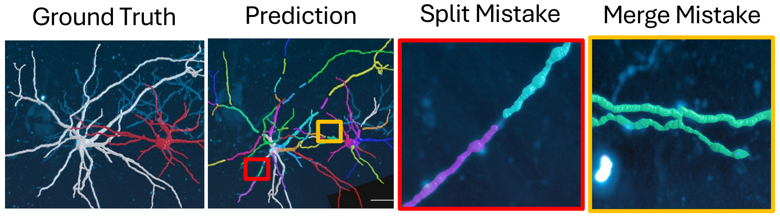
Motivation

Segmentation of curvilinear, filamentous structures continues to pose significant challenges.



Objective: Train topology-aware neural networks that minimize the number of split and merge mistakes.

Overview

We extend simple points from digital topology to supervoxels and train neural networks with connectivity-aware loss.

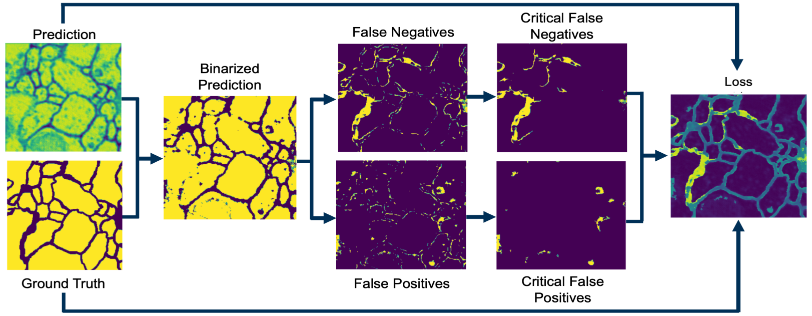


Figure: Visualization of loss computation

Critical Supervoxels

Supervoxels in the false positive and negative mask that change connectivity are *critical*.

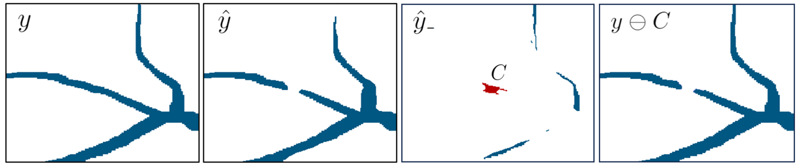


Figure: C is critical because its removal splits the ground truth.

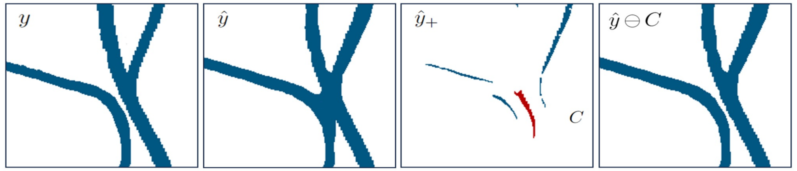


Figure: C is critical because its removal splits the prediction.

Thm: Critical supervoxels can be computed in linear time.

Supervoxel-Based Loss Function

Let $\mathcal{P}(\hat{y}_+)$ and $\mathcal{N}(\hat{y}_-)$ be critical supervoxels from the false positive and negative masks.

$$\mathcal{L}(y,\hat{y}) = (1-\alpha)\mathcal{L}_0(y,\hat{y}) + \alpha\beta \sum_{\mathcal{P}(\hat{y}_+)} L_0(y,\hat{y}) + \alpha(1-\beta) \sum_{\mathcal{N}(\hat{y}_-)} L_0(y,\hat{y})$$

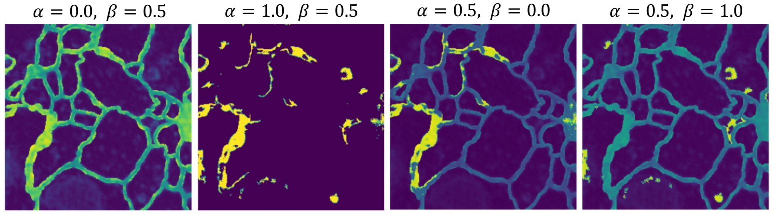


Figure: α controls weight on voxels vs. critical supervoxels and β controls weight on splits vs. merges.

Quantitative Results

Table: Results on 2-d segmentation datasets.

Method	Complexity	Accuracy ↑	Dice ↑	ARI ↑	VOI ↓	Betti Error ↓
DRIVE						
U-Net	$\mathcal{O}(n)$	0.945±0.006	0.749±0.003	0.834±0.041	1.98±0.05	3.64±0.54
DIVE	$\mathcal{O}(n)$	**0.955±0.002**	0.754±0.001	0.841±0.026	1.94±0.13	3.28±0.64
Mosin.	$\mathcal{O}(n)$	0.954±0.005	0.722±0.001	0.887±0.039	1.17±0.03	2.78±0.29
TopoLoss	$\mathcal{O}(n \log n)$	0.952±0.004	0.762±0.004	0.902±0.011	1.08±0.01	1.08±0.27
DMT	$\mathcal{O}(n^2)$	0.955±0.004	0.773±0.004	0.902±0.002	0.88±0.04	**0.87±0.40**
Ours	$\mathcal{O}(n)$	0.953±0.002	**0.809±0.012**	**0.943±0.002**	**0.48±0.01**	0.94±0.27
ISBI12						
U-Net	$\mathcal{O}(n)$	0.968±0.002	0.970±0.005	0.934±0.007	1.37±0.03	2.79±0.27
DIVE	$\mathcal{O}(n)$	0.964±0.004	0.971±0.003	0.943±0.009	1.24±0.03	3.19±0.31
Mosin.	$\mathcal{O}(n)$	0.953±0.006	0.972±0.002	0.931±0.005	0.98±0.04	1.24±0.25
TopoLoss	$\mathcal{O}(n \log n)$	0.963±0.004	0.976±0.004	0.944±0.008	0.78±0.02	0.43±0.10
DMT	$\mathcal{O}(n^2)$	0.959±0.004	0.980±0.003	**0.953±0.005**	**0.67±0.03**	**0.39±0.11**
Ours	$\mathcal{O}(n)$	**0.971±0.002**	**0.983±0.001**	0.934±0.001	0.74±0.03	0.48±0.02

Table: Results on 3-d neuron segmentation dataset.

Method	Complexity	Runtime/Epoch ↓	Splits/Neuron ↓	Edge Accuracy ↑	Normalized ERL ↑
U-Net	$\mathcal{O}(n)$	10.03±0.23 sec	9.86±13.30	0.873±0.087	0.596±0.232
Gornet	$\mathcal{O}(n^2)$	71.62±1.83 sec	3.85±2.58	0.937±0.062	0.664±0.106
clDice	$\mathcal{O}(kn)$	48.55±1.60 sec	3.39±1.52	0.911±0.042	0.701±0.091
MALIS	$\mathcal{O}(n^2)$	50.68±1.58 sec	3.33±0.59	0.917±0.053	0.719±0.098
Ours	$\mathcal{O}(n)$	20.12±1.15 sec	**2.63±1.36**	**0.944±0.043**	**0.784±0.099**

Qualitative Results

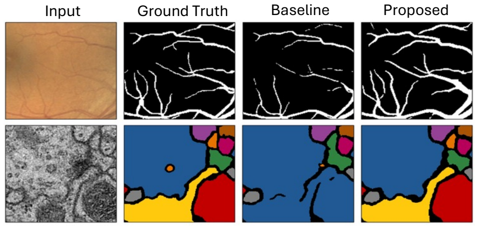


Figure: Results on 2-d segmentation datasets.

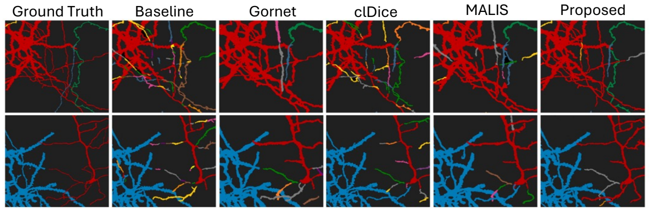


Figure: Results on 3-d neuron segmentation dataset.