







Fopology-Preserving Hard Pixel Mining for Tubular Structure Segmentation

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Threshold-based HPM

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Experiments

Quantitative results					
Dataset	Method	Dice	ARE	β -0 Error	β -1 Error
CREMI-A	U-Net	0.9145	0.2337	2.176	23.960
	U-Net + clDice	0.9148	0.2310	2.200	23.552
	U-Net + THPM	0.9007	0.1076	2.016	8.960
	U-Net + PHPM	0.9133	0.2060	2.112	20.352
	U-Net + SHPM	0.9106	0.1042	1.648	7.240
Roads	U-Net	0.7317	0.3191	9.671	28.116
	U-Net + clDice	0.7307	0.3460	9.759	29.676
	U-Net + THPM	0.7242	0.2501	9.062	22.096
	U-Net + PHPM	0.7295	0.3372	8.826	29.232
	U-Net + SHPM	0.7331	0.2381	7.510	20.332
ICAS-d (3D)	U-Net	0.6129	0.0011	5.410	0.000
	U-Net + clDice	0.5867	0.0012	6.440	0.000
	U-Net + THPM	0.6115	0.0011	5.290	0.000
	U-Net + PHPM	0.6059	0.0012	4.590	0.000
	U-Net + SHPM	0.6316	0.0011	4.740	0.000

SPHM demonstrates high superiority on topology-aware metrics while maintaining competitive volumetric accuracy.

	2D Patch (256 × 256)	3D Patch ($128 \times 128 \times 72$)
U-Net	1.61	24.21
U-Net + clDice	2.22	27.40
U-Net + THPM	1.65	24.33
U-Net + PHPM	11.83	718.59
U-Net + SHPM	1.78	26.73

and is more efficient than PHPM.



Model training time for 100 iterations (s)

SHPM has a training speed comparable to original U-Net

Qualitative results on 2D images

The predictions by SPHM have more consistent topology.