Machine-learned Regularization and Polygonization of Building Segmentation Masks

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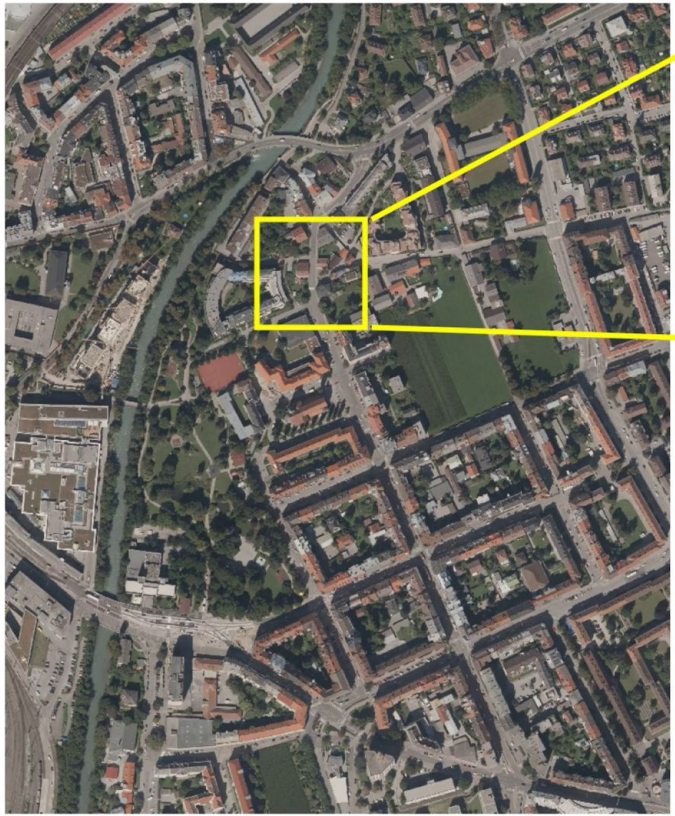
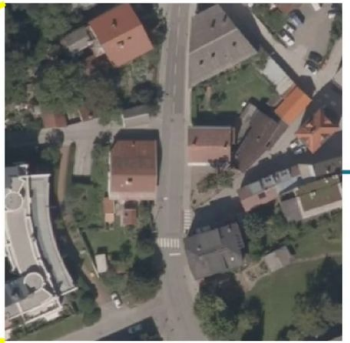
Buildings Detection and Segmentation in Satellite Images



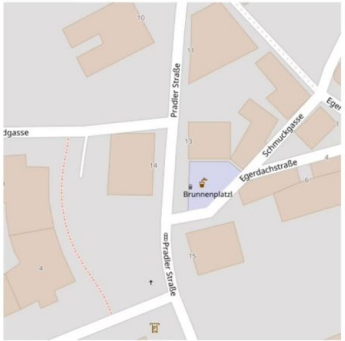
Innsbruck19, Inria Dataset



Aerial/Satellite image

CNN

Segmentation



OSM layer

Mask Regularization and Polygonization

Segmentation

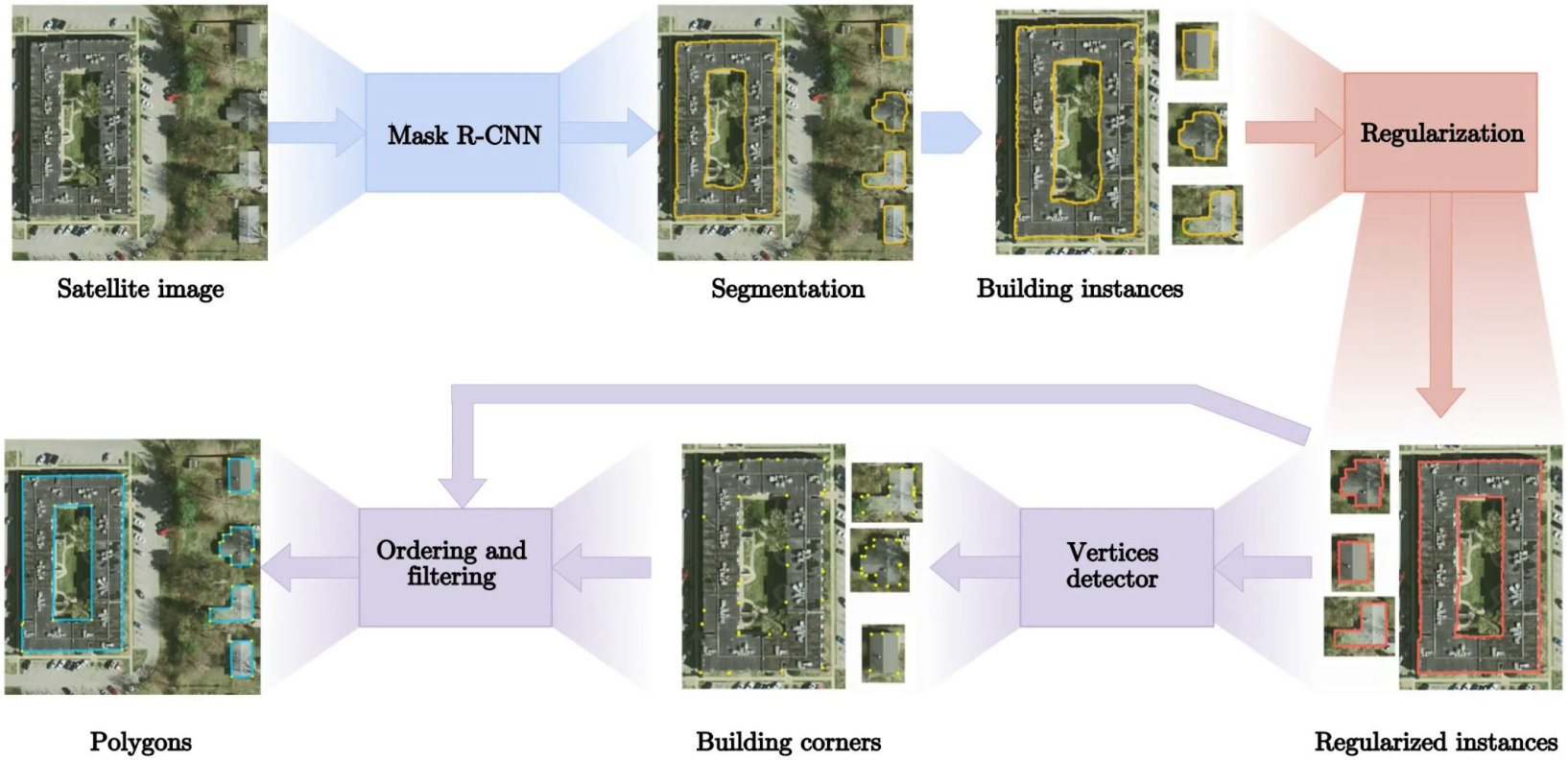
Mask Regularization and Polygonization

Regularization

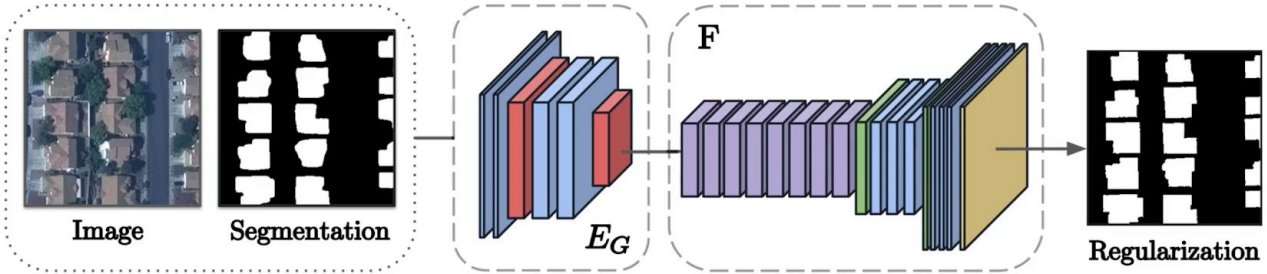
Mask Regularization and Polygonization

Masks to Polygons

Building Extraction Workflow

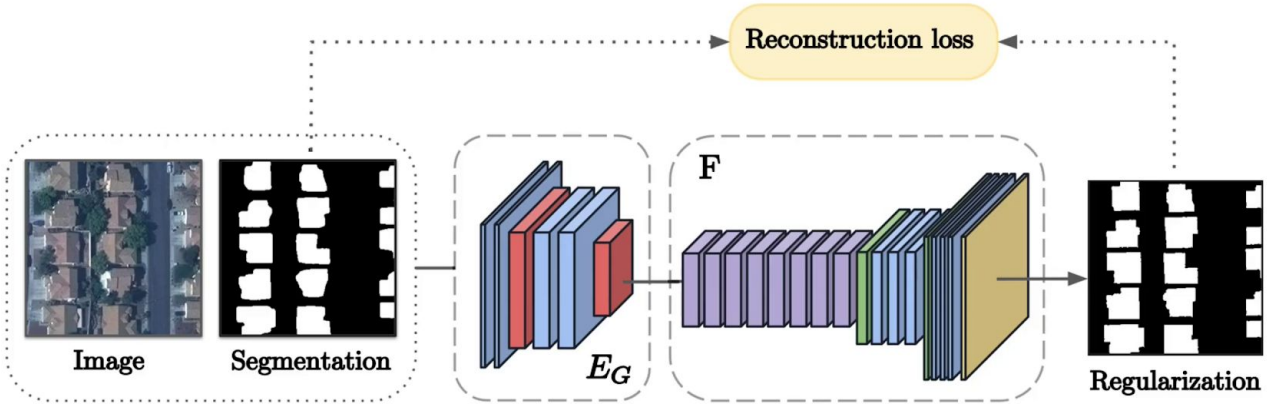


Regularization network

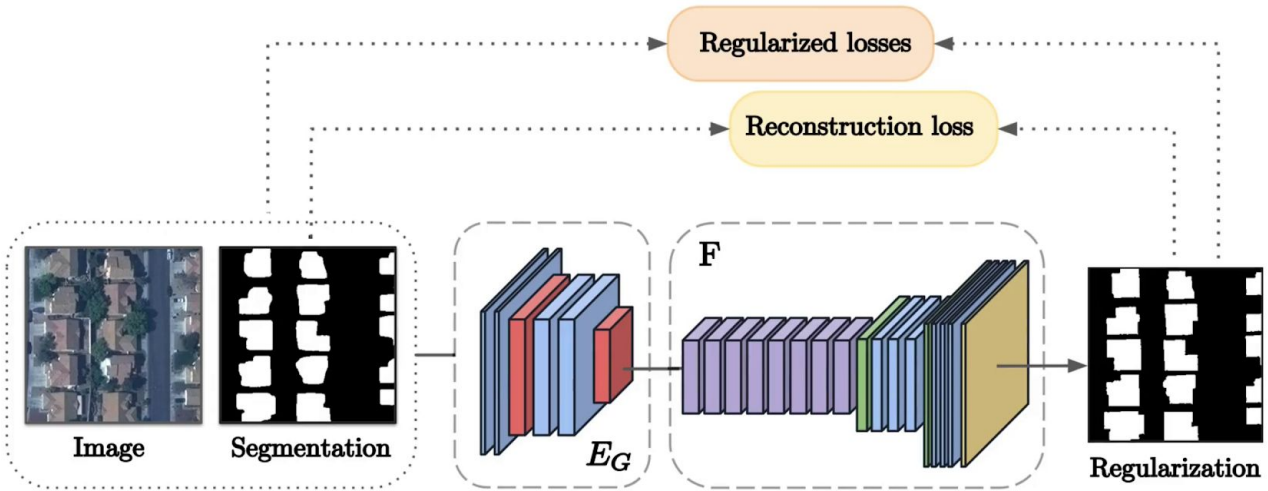


S. Zorzi, F. Fraundorfer. "Regularization of Building Boundaries in Satellite Images using Adversarial and Regularized Losses" IGARSS 2019 IEEE

Regularization network



Regularization network



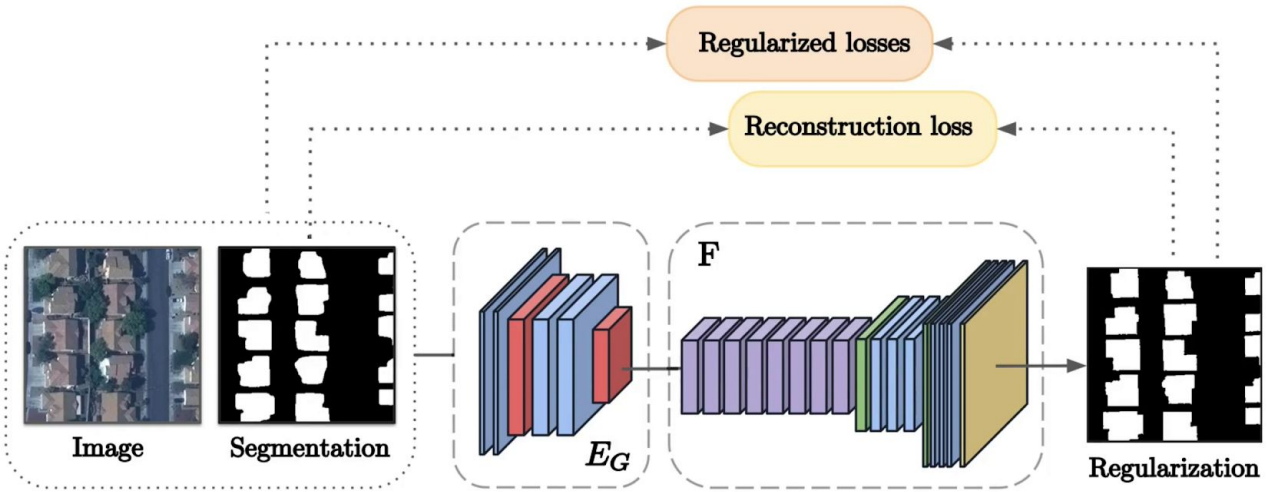
$$\mathcal{L}_{potts}(G) = \sum_k cut(\Omega_k, \Omega/\Omega_k) = \sum_k S^{k\intercal} W (1 - S^k)$$

$$w_{ij} = e^{\frac{-||F(i)-F(j)||_2^2}{\sigma_I^2}} \cdot e^{\frac{-||X(i)-X(j)||_2^2}{\sigma_X^2}}$$

Segmentation Reg. losses effect

Tang, Meng, et al. "On Regularized Losses for Weakly-Supervised CNN Segmentation.", ECCV 2018

Regularization network



$$\mathcal{L}_{ncut}(G) = \sum_k \frac{cut(\Omega_k, \Omega/\Omega_k)}{assoc(\Omega_k/\Omega)} = \sum_k \frac{S^{k\intercal} W (1 - S^k)}{1^\intercal W S^k}$$

$$w_{ij} = e^{\frac{-||F(i)-F(j)||_2^2}{\sigma_I^2}} \cdot e^{\frac{-||X(i)-X(j)||_2^2}{\sigma_X^2}}$$

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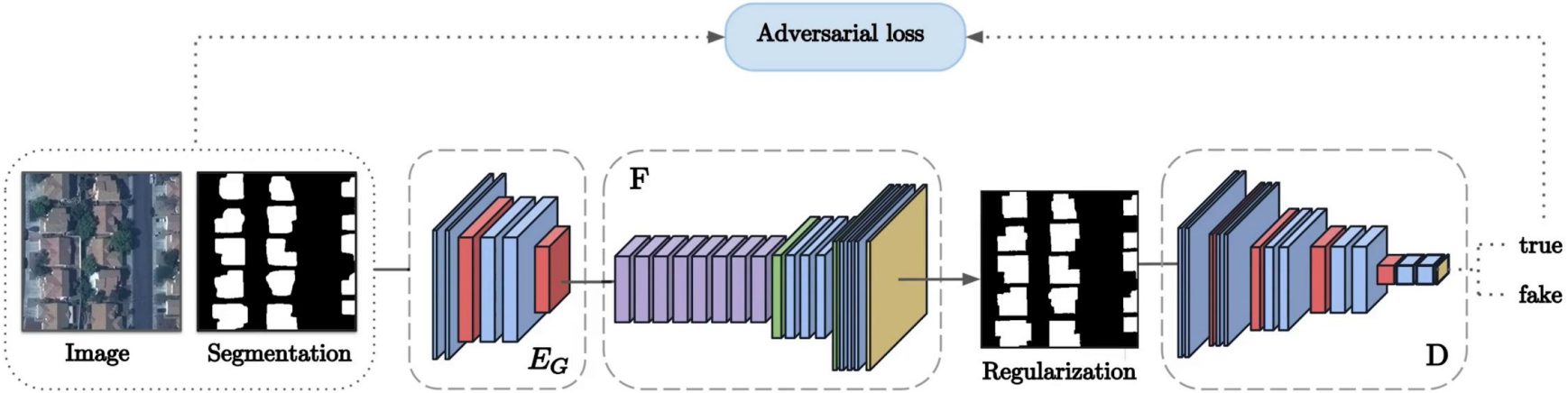
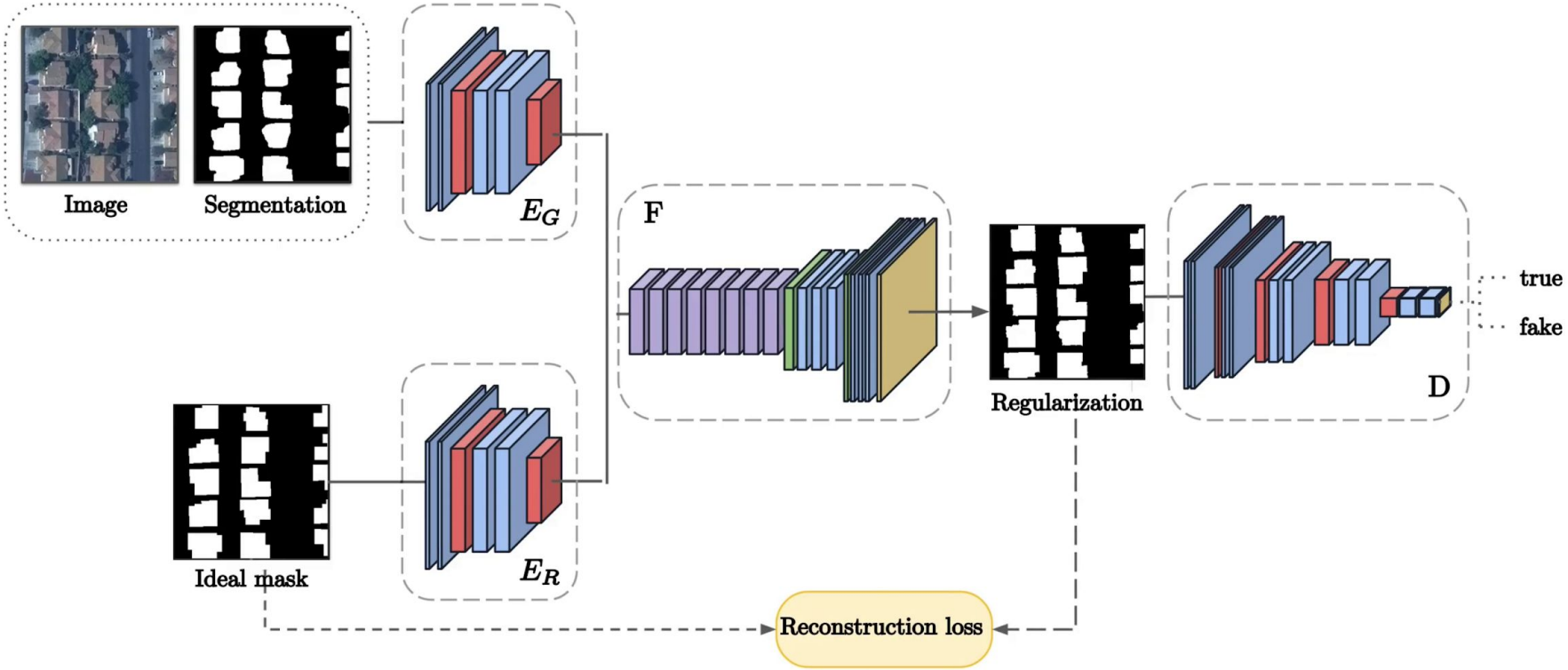
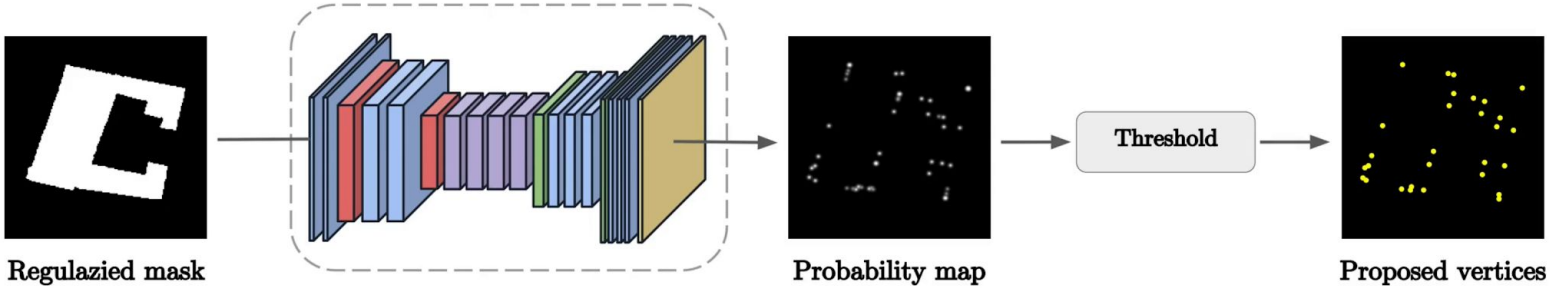


Regularization network



Polygonization



Polygonization

Regularization and corner proposals

Polygonization

Initial polygon

Polygon = [[240, 112], [420, 147], [442, 152], [713, 204], [678, 371], [612, 357], [625, 322], [551, 305], [564, 257], [520, 244], [442, 226], [424, 274], [362, 454], [345, 506], [555, 546], [564, 498], [643, 511], [621, 625], [621, 642], [323, 607], [275, 594], [271, 607], [236, 603], [96, 568], [83, 559], [91, 519], [105, 511], [118, 471], [161, 353]]

Polygonization

Final polygon

Polygon = [[240, 112], ~~[420, 147]~~, ~~[442, 152]~~, [713, 204], [678, 371], [612, 357], [625, 322], [551, 305], [564, 257], ~~[520, 244]~~, [442, 226], ~~[424, 274]~~, ~~[362, 454]~~, [345, 506], [555, 546], [564, 498], [643, 511], ~~[621, 625]~~, ~~[621, 642]~~, ~~[323, 607]~~, [275, 594], [271, 607], ~~[236, 603]~~, [96, 568], [83, 559], [91, 519], [105, 511], ~~[118, 471]~~, ~~[161, 353]~~]

Experiments

R2U-Net Segmentation

	INRIA											
	Bellingham		Bloomington		Innsbruck		San Francisco		Tyrol		Overall	
	IoU	Acc	IoU	Acc	IoU	Acc	IoU	Acc	IoU	Acc	IoU	Acc
R2UNet	70.30	**97.04**	72.94	**97.40**	**73.48**	**96.85**	**76.29**	**91.85**	75.92	**97.84**	**74.57**	**96.20**
Zorzi *et al.* [7]	63.90	96.37	63.65	96.51	60.20	95.23	55.97	84.60	65.56	96.88	59.81	93.92
Ours	**70.36**	96.99	**73.01**	97.36	73.34	96.77	75.88	91.55	**76.15**	**97.84**	74.40	96.10

	SpaceNet											
	Jacksonville				Tampa				Overall			
	IoU		Acc		IoU		Acc		IoU		Acc	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
R2UNet	**72.85**	7.077	**96.54**	1.105	**70.74**	6.056	**94.90**	1.219	**71.80**	6.670	**95.75**	1.406
Zorzi *et al.* [7]	59.17	5.348	94.73	1.693	57.99	6.892	92.58	2.317	58.58	6.197	93.65	2.296
Ours	70.90	7.551	96.29	1.169	69.04	6.587	**94.90**	1.286	69.97	7.146	95.50	1.463

Dataset			CrowdAI			
Method			IoU		Acc	
Baseline	**Regularization**	**Polygonization**	μ	σ	μ	σ
R2U-Net	-	-	80.44	16.10	95.86	5.20
R2U-Net	*Zorzi et al.*	-	76.95	15.34	94.75	5.47
R2U-Net	Ours	-	79.87	15.93	95.57	5.28
R2U-Net	*Zorzi et al.*	Ours	76.67	13.37	94.62	5.14
R2U-Net	Ours	Ours	80.03	14.24	95.55	5.09
Mask R-CNN	-	-	73.22	17.84	94.38	4.77
Mask R-CNN	*Zorzi et al.*	-	71.72	17.32	93.88	4.82
Mask R-CNN	Ours	-	73.57	17.65	94.34	4.74
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Mask R-CNN	Ours	Ours	74.23	14.51	94.12	4.75

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TU Graz

Thank You!

Stefano Zorzi

Ksenia Bittner

Friedrich Fraundorfer