Machine-learned Regularization and Polygonization of Building Segmentation Masks

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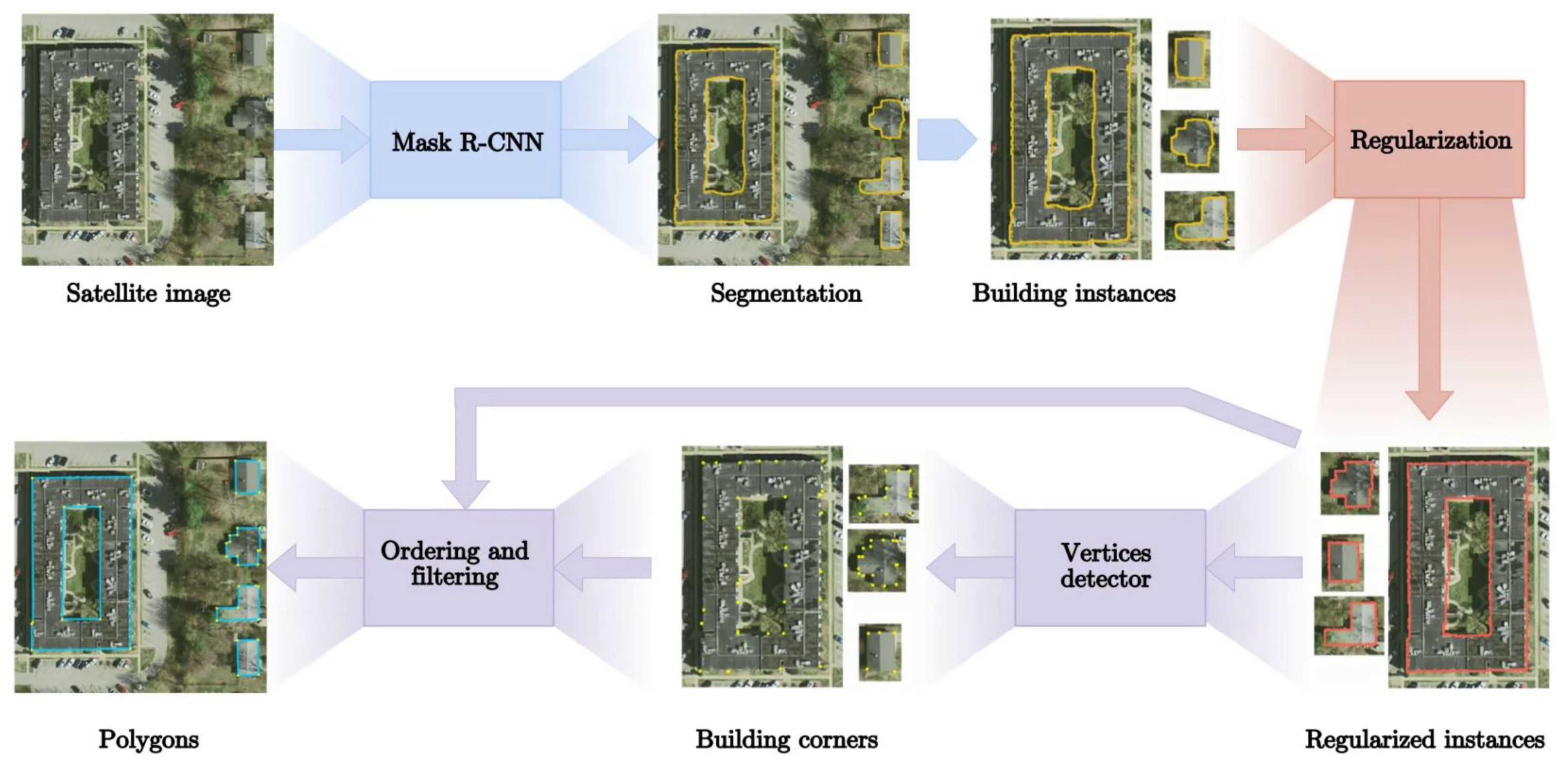
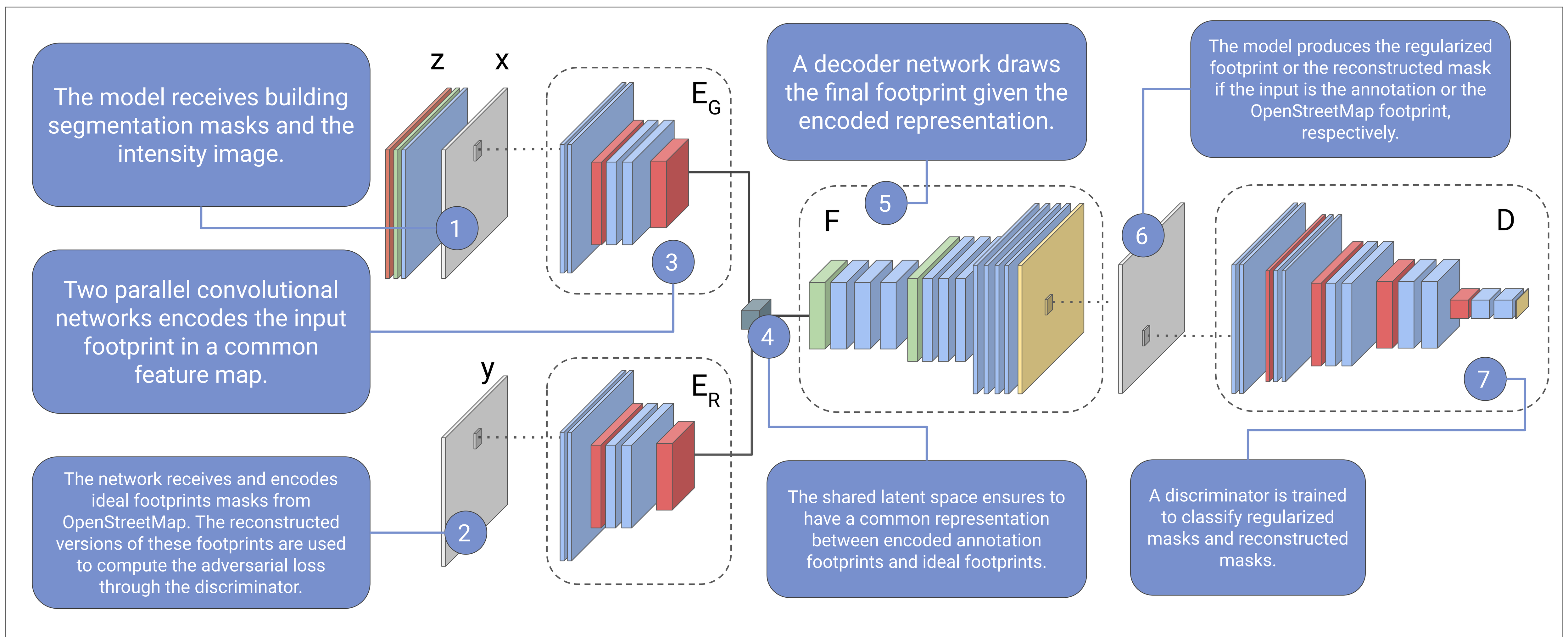


Abstract

We propose a Deep Learning pipeline for automatic regularization and polygonization of building segmentation masks. Taking an image as input, we first predict building segmentation maps exploiting a generic instance segmentation network. A regularization network is then involved to perform a refinement of building boundaries to make them more realistic. Finally, we exploit a CNN adapted to predict sparse outcomes corresponding to building corners out of regularized building segmentation results. Experiments on three building segmentation datasets demonstrate that the proposed method is not only capable of obtaining accurate results, but also of producing visually pleasing building outlines parameterized as polygons.

Regularization



Objective

Our objective contains three types of terms:

- **Adversarial loss** to force the autoencoder to produce regularized masks that look like ideal footprints. While the discriminator learns to classify regularized and reconstructed footprints the encoder-decoder network is trained to fool the discriminator in order to produce more realistic footprints.
- **Regularized losses** to further improve the footprint regularization exploiting the building image. We use two losses called *Potts loss* [3] and *Normalized Cut loss* [2, 3].

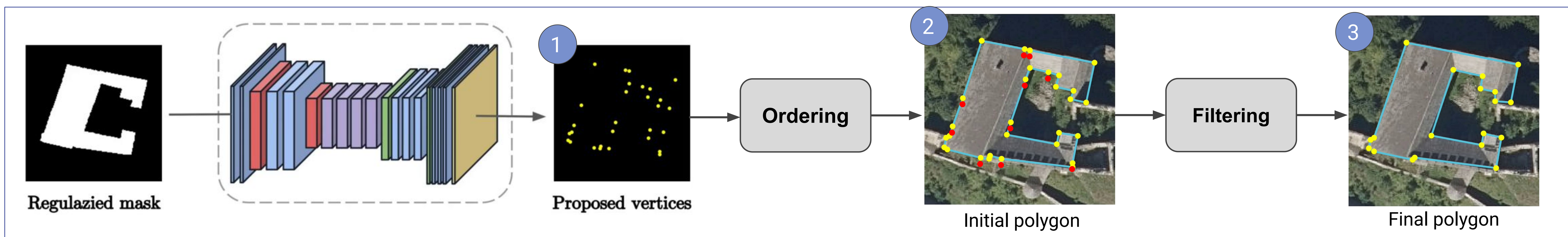
$$\mathcal{L}_{potts}(G) = \sum_k cut(\Omega_k, \Omega/\Omega_k) = \sum_k S^{k\intercal} W (1 - S^k)$$

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

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

- **Reconstruction losses** to obtain building footprint as close as possible to the input annotation. In this case, *binary cross entropy loss* is simply used.

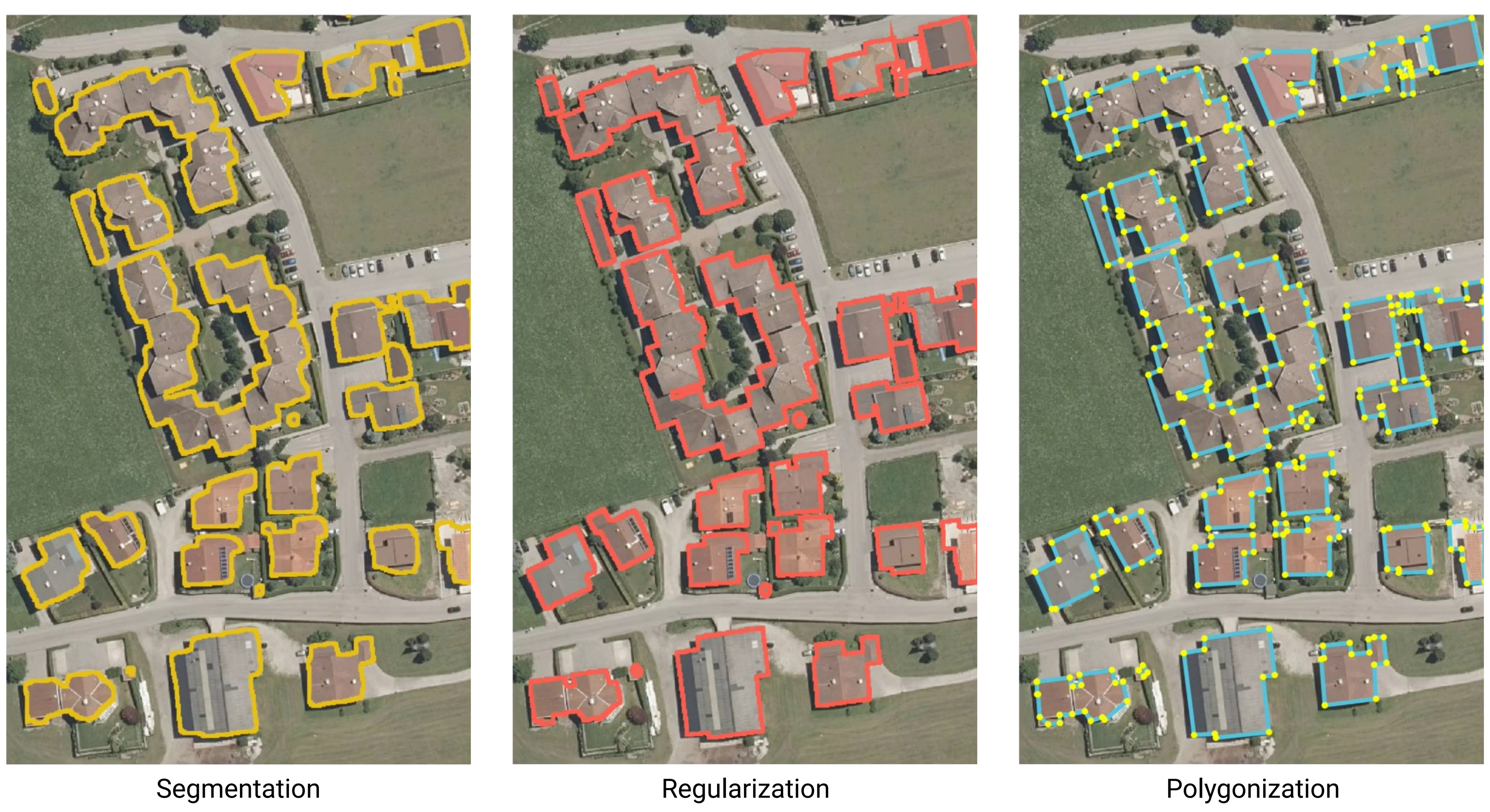
Polygonization



Polygon extraction steps:

1. given the regularized building footprint, a CNN model detects all the building corners candidates (yellow vertices).
2. The vertices are then sorted to produce a valid set of polygon coordinates. Redundant corners which lie too close to a building edge are filtered (in red).
3. Final result.

Results



	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
Mask R-CNN	*Zorzi et al.*	Ours	72.13	13.82	92.57	4.80
Mask R-CNN	Ours	Ours	74.23	14.51	94.12	4.75

Contacts and References

[1] S. Zorzi and F. Fraundorfer, "Regularization of Building Boundaries in Satellite Images using Adversarial and Regularized Losses," IEEE International Geoscience and Remote Sensing Symposium (IGARSS),2019.
[2] Tang, Meng, et al. "Normalized Cut Loss for Weakly-supervised CNN Segmentation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.
[3] Tang, Meng, et al. "On Regularized Losses for Weakly-supervised CNN Segmentation." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

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