Unsupervised Building Extraction Using Snake Model on Optical Imagery and LiDAR Data

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Motivation

Automatic Building Extraction (BE) in urban scenes has become a subject of growing interest in the domain of remote sensing, particularly with the emergence of LiDAR systems since mid-1990s. However, this task is still challenging due to the complexity of building size and shape, as well as of its surrounding environment.
Common issues of existing active contour models (a.k.a. snake models) [1] in BE are:

- Sensitivity to noise and image details;
- Dependence on initial points or training data;
- Weak convergence to building corners;
- Snake's convergence sensitivity to its number of points and weighting parameters.

Motivated by these limitations, we propose an **unsupervised**, **automatic** and **robust** snake model to extract buildings using optical imagery and an unregistered LiDAR dataset, **without manual initial points or training data**.

Keywords: Building extraction, Optical imagery, Airborne LiDAR, Active contour model, Snake model, Polygonization

Four-step Algorithm

a. Registration of optical image with LiDAR data
This approach involves an airborne LiDAR data set, acquired independently of the optical imagery.
This context requires a relevant registration, which has been carried out beforehand [2].

b. BE from LiDAR point cloud (cf. Fig. 2)

c. Proposed snake model
We propose adding a new energy term as a constrained force, calculated based on the similarity between the shape formed by snake points ($\mathbf{x}$) and the projected LiDAR building boundary ($\mathbf{T}B_i$),

$$E_{\text{ShapeSim}}(\mathbf{x}) = 1 - \exp\left(-\frac{d_H^2(\mathbf{x}, \mathbf{T}B_i)}{\delta}\right) \tag{1}$$

d. Improved polygonization
Each building is polygonized into 3 levels of shape: rectangular; Z-, T- or L-shape; U-shape, using the improved method of [3]. The improvement involves using the Minimum Boundary Rectangle (MBR) of the projected LiDAR building boundary points which yields more reliable building orientation.

Proposed Method

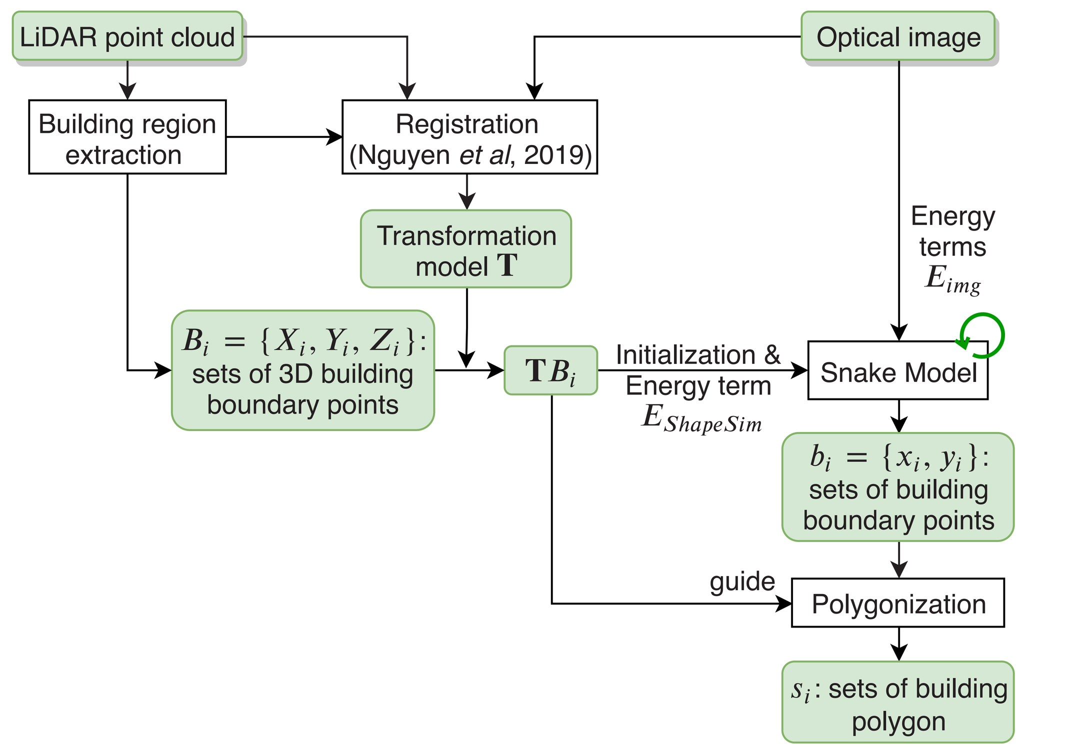

Fig. 1: Flowchart of the proposed method.

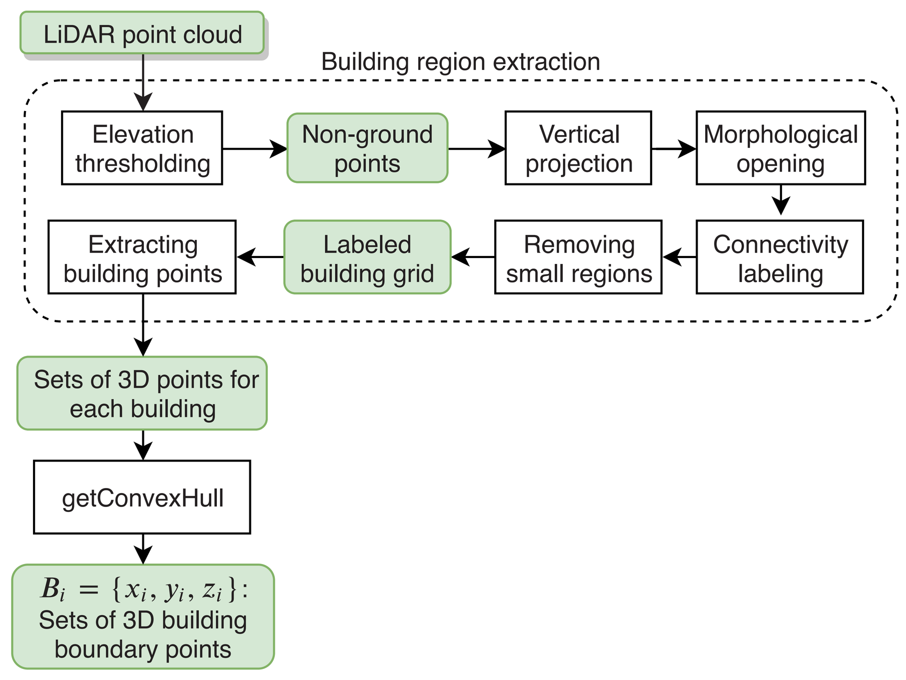

Fig. 2: BE from LiDAR point cloud.

Experimental Results

a. Comparison between snake models

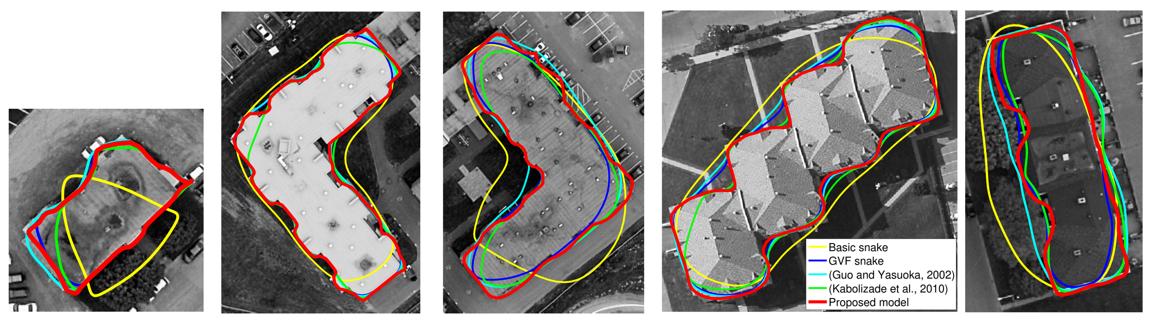

Fig. 3: Snake models on multiple buildings.

Snake models	IoU Mean	IoU Min	IoU Max
Basic snake	61.45%	36.42%	72.61%
GVF snake	88.55%	58.10%	97.57%
(Guo and Yasuoka, 2002)	89.04%	79.85%	96.83%
(Kabolizade et al., 2010)	88.32%	57.68%	97.52%
(Proposed model)	**90.36%**	**74.23%**	**97.74%**

Table 1: Performance of snake models.

b. Result on Quebec City data sets (GSD: 15cm)

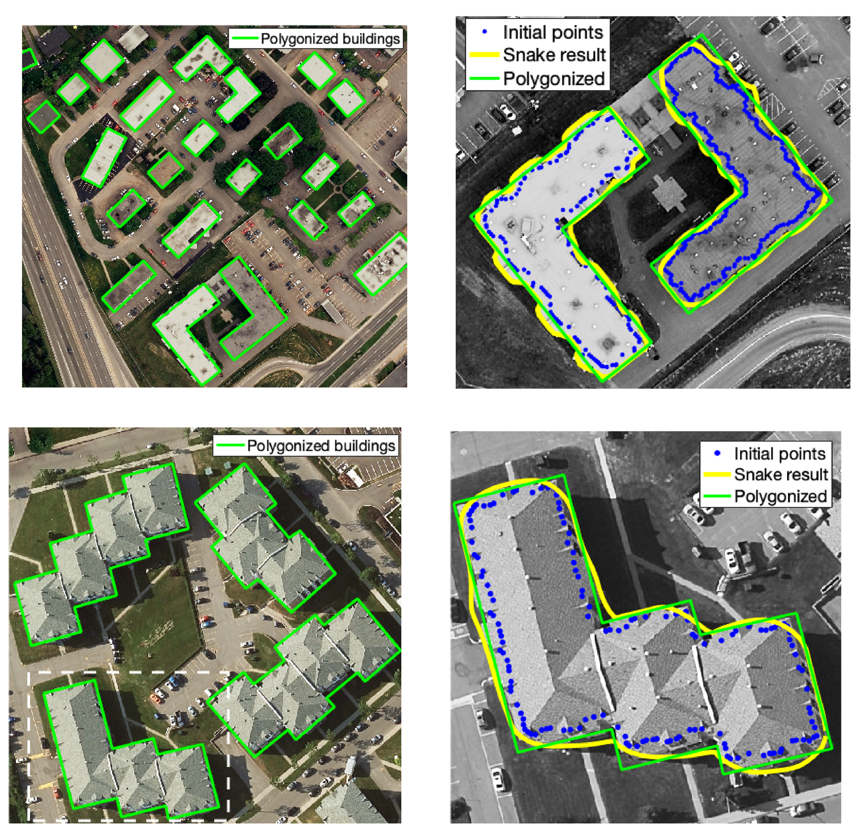

Fig. 4: BE overall result on urban area.

Metric	LiDAR only	Proposed method
IoU	85.51%	91.12%
C_p	87.83%	97.07%
C_r	97.05%	92.88%
EDC	1.48 m	0.89 m
DARE	0.62°	0.81°

$$\text{EDC} = d(C_E, C_R), \quad \text{DARE} = |\theta_E - \theta_R|$$

(E: extracted building, R: ground-truth building.)

Table 2: Average pixel-based BE accuracy metrics.

c. BE result on ISPRS benchmark data sets [4]

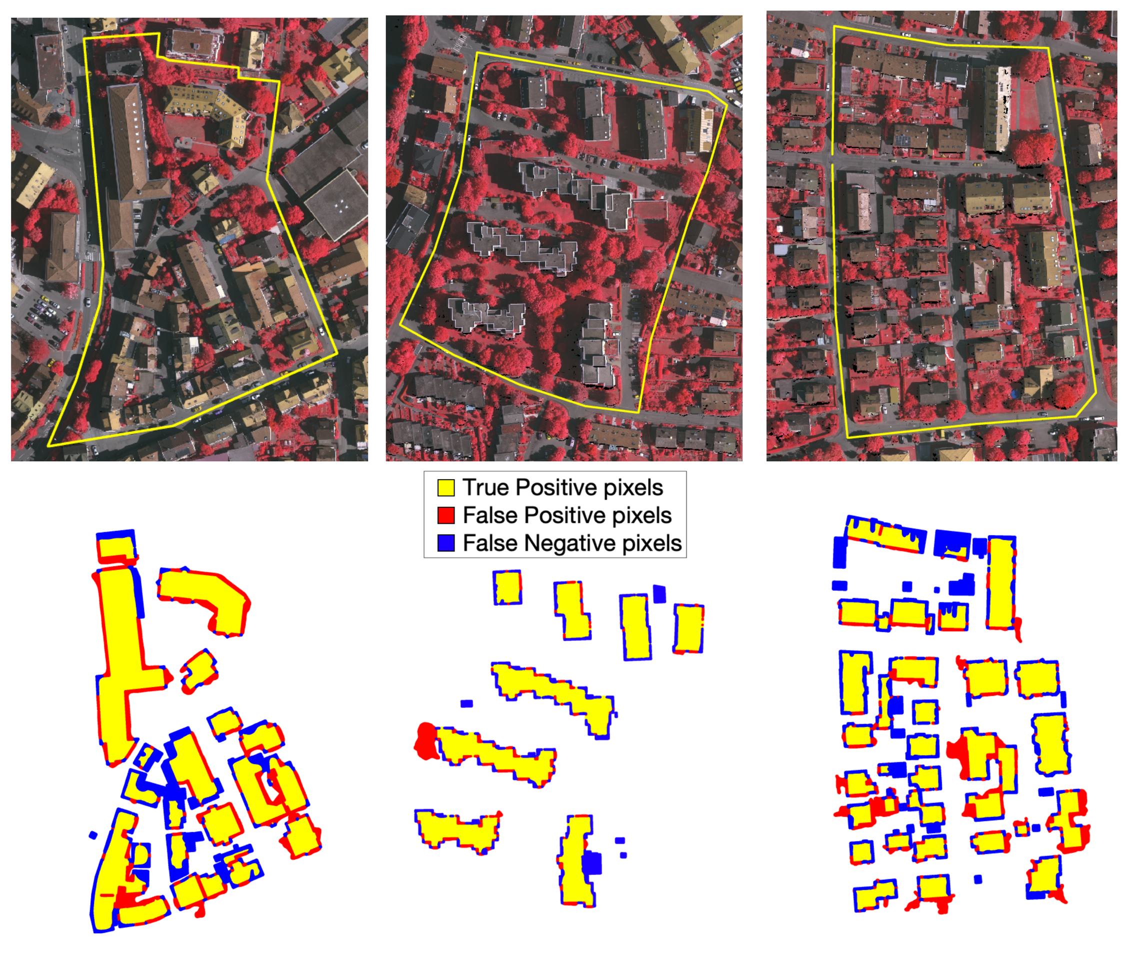

Fig. 5: BE evaluation on 3 test areas.

Area	IoU	C_p	C_r
1	82.27%	89.43%	91.13%
2	87.35%	92.13%	94.39%
3	80.07%	87.21%	90.72%
Avg	83.23%	89.59%	92.08%

$$\text{IoU} = \frac{\mathcal{A}(E \cap R)}{\mathcal{A}(E \cup R)}, \quad C_p = \frac{\mathcal{A}(E \cap R)}{\mathcal{A}(R)}, \quad C_r = \frac{\mathcal{A}(E \cap R)}{\mathcal{A}(E)}$$

Table 3: Pixel-based BE accuracy metrics.

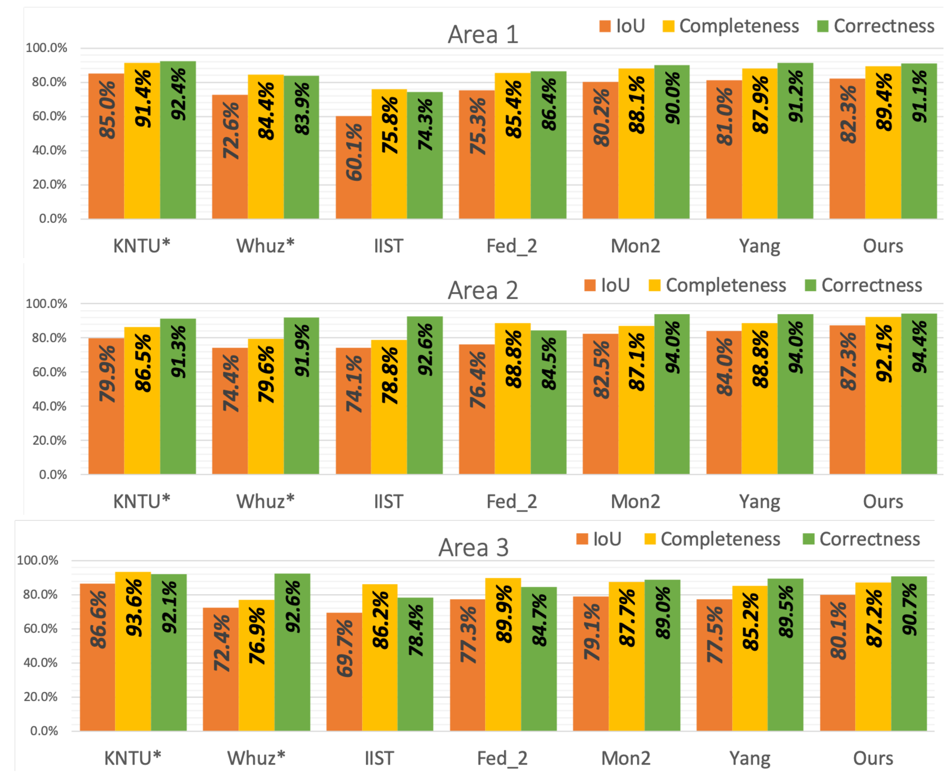

Fig. 6: BE accuracy metrics among methods ('$*$' indicates that a method is supervised).

Conclusion

- ☑ An **unsupervised** and **robust** BE method;
- ☑ Capable of extracting buildings with **varying color** from **complex environments**;
- ☑ **Higher accuracy** than unsupervised methods and **competing accuracy** with supervised ones;
- ☑ Can work with an old LiDAR data set → **cheaper** and **timelier** solution.

Perspectives

- ☐ Automatic snake parametrization based on scene contextualization;
- ☐ Effectiveness of snake model on more complex environments;
- ☐ Polygonization of circular buildings.

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References

[1] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *International journal of computer vision*, vol. 1, no. 4, pp. 321–331, 1988.

[2] T. H. Nguyen, S. Daniel, D. Gueriot, C. Sintes, and J.-M. Le Caillec, "Robust Building-Based Registration of Airborne Lidar Data and Optical Imagery on Urban Scenes," in *IGARSS 2019*, (Yokohama, Japan), IEEE GRSS, July 2019.

[3] M. Dutter, "Generalization of building footprints derived from high resolution remote sensing data," 2007.

[4] M. Cramer, "The DGPF-test on digital airborne camera evaluation–overview and test design," *Photogrammetrie-Fernerkundung-Geoinformation*, vol. 2010, no. 2, pp. 73–82, 2010.