

Change detection in 3D point clouds based on deep learning

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Motivation

Context:

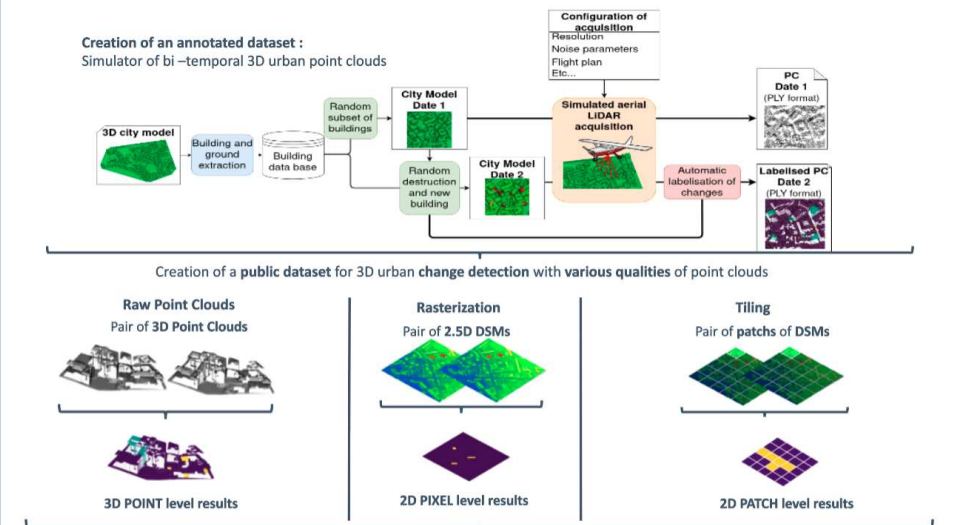
- From 2022, CO3D mission is set to map the globe in 3D. Temporal monitoring of zones of interest to track potential changes.
- 3D Point Clouds (PCs)** acquired by LiDAR sensor or photogrammetry process are becoming more common for **earth observation**.

Objectives: Explore and propose a solution for **change detection and characterization** over raw 3D PCs using **deep learning**.

Challenges:

- 3D PCs characteristics:** sparse, unordered, contain hidden parts, no matrix storage without loss of information
- Change detection:** unchanged objects have different point distribution
- Deep learning:** usual convolution used for 2D images are not applicable

State-of-the-art: 3D change detection and characterization [1]



Qualitative and quantitative comparison, robustness to various size of training set and transfer learning capacity assessment for supervised methods

Conclusion of state-of-the-art methods benchmark:

- Most of studies only focus on Digital Surface Models (DSMs) implying a loss of information
- No deep learning methods** for change detection directly on **raw 3D PCs**
- Existing **traditional methods scores can be largely improved**

Convolution for 3D PCs: 3D KPConv [2]

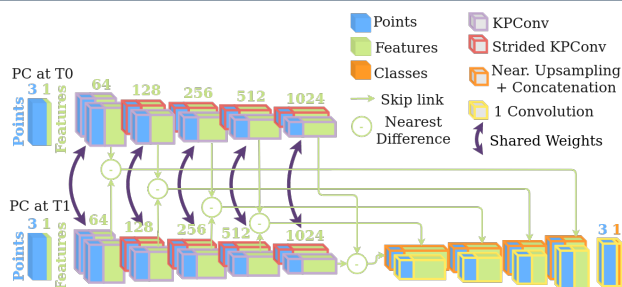
3D Kernel Point Convolution

Convolution by a kernel function g at a point $x \in R^3$:

$$(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_i} g(x_i - x) f_i$$

- x_i points from $\mathcal{P} \in R^{N \times 3}$ and corresponding feature f_i from $\mathcal{F} \in R^{N \times D}$
- $\mathcal{N}_i = \{x_i \in \mathcal{P} \mid \|x_i - x\| \leq r\}$ with $r \in R$
- Kernel function g : applies weights to different areas inside a ball $B_r^3 = \{y \in R^3 \mid \|y\| \leq r\}$ thanks to kernel points

Siamese Kernel Point Convolution Network [3]



Conclusions and Future Works

Outcomes:

- Creation of a public dataset made of annotated urban PCs for change detection and characterization
- Development of **Siamese Kernel Point Convolution Network** to address change detection and characterization in a single step
- Improvement** of about **20%** of the mean per class IoU compared to random forest method with hand-crafted features

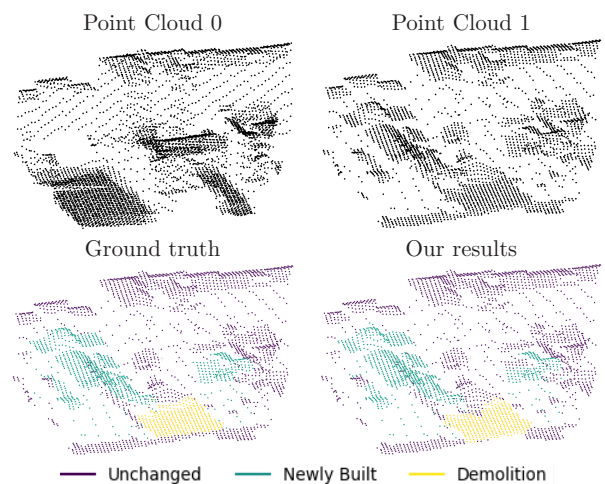
Perspectives:

- Test on real datasets not only in urban context (cliffs, ...)
- Focus on **self-supervised** methods in order to get rid of time-consuming data annotation

Results

Results over a simulated urban dataset composed of challenging low resolution PCs:

	mAcc	mIoU	mIoU over classes of change
RF [4]	91.14	74.53	63.41
Ours	96.24	93.27	90.22



References

- [1] Iris de Gélis, Sébastien Lefèvre, and Thomas Corpetti. Change detection in urban point clouds: An experimental comparison with simulated 3d datasets. *Remote Sensing*, 13(13):2629, 2021.
- [2] Hugues Thomas, Charles R Qi, Jean-Emmanuel Deschaud, Beatriz Marcotegui, François Goulette, and Leonidas J Guibas. Kpconv: Flexible and deformable convolution for point clouds. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 6411–6420, 2019.
- [3] Iris de Gélis, Sébastien Lefèvre, and Thomas Corpetti. 3d urban change detection with point cloud siamese networks. *ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 43:879–886, 2021.
- [4] Thi Huong Giang Tran, Camillo Ressel, and Norbert Pfeifer. Integrated change detection and classification in urban areas based on airborne laser scanning point clouds. *Sensors*, 18(2):448, 2018.