3D point clouds change detection:

From supervised to unsupervised deep learning methods

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Change detection in urban areas

Google Earth Timelapse (Google, Landsat, Copernicus)

Wikipedia

Change detection in geosciences

NEWS

Cliff collapse on Greece's 'shipwreck beach' injures tourists

NEWS

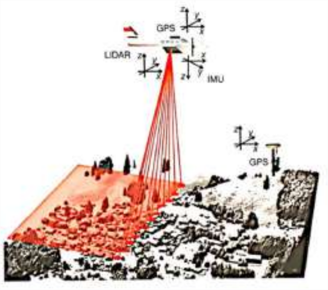
Thorpeness cliff erosion: Warning to avoid part of beach

- → Coastal cliffs ∼ **52% of the global shoreline** *(Young and Carilli 2019)*
- → Cliff erosion likely to **increase** with sea level rise *(Allan et al. 2021)*
- → **Endangering** population and infrastructure

3D point clouds

Data description

Laser Scanning: LiDAR



Lebègue et al. 2020

Photogrammetry

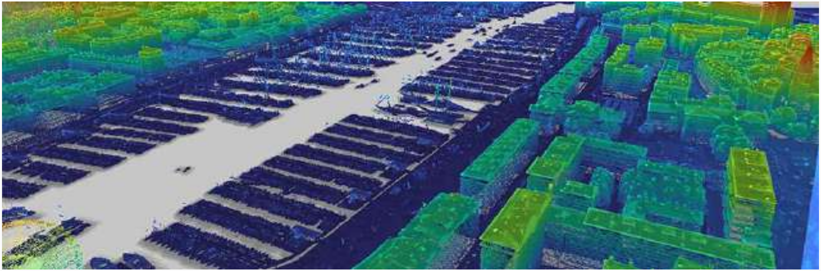
J. Vallet

Terrestrial, aerial or satellites acquisitions.

More and more 3D data available...

Lebègue et al. 2020

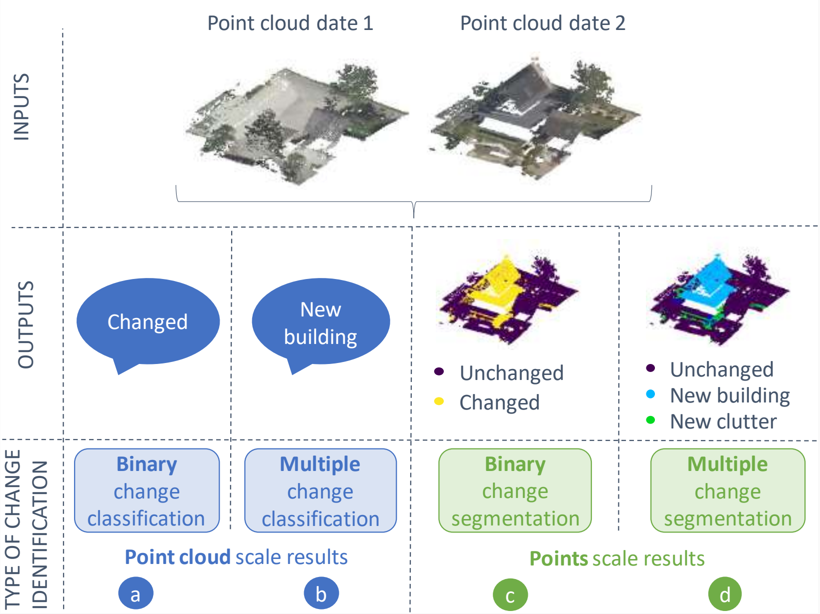
https://www.intelligence-airbusds.com/



https://www.ign.fr/institut/lidar-hd-vers-une-nouvelle-cartographie-3d-du-territoire

3D change detection

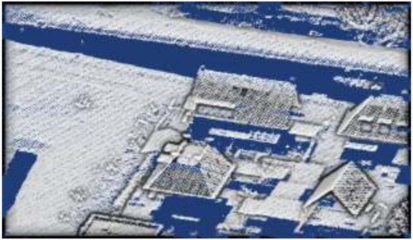
Change detection into 3D point clouds?



3D point clouds for change detection

Date 1

Date 2



3D point clouds for change detection

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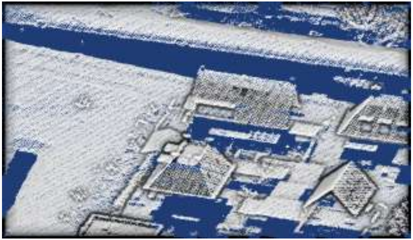
Date 2



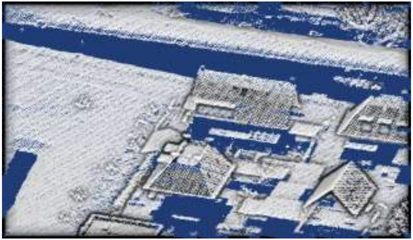
- Sparse
- Unordered

Unlike 2D images:

3D point clouds for change detection

Date 1

Date 2



- Sparse
- Unordered

$\Big\}$ Raw PCs $\neq$ matrices

Unlike 2D images:

3D point clouds for change detection

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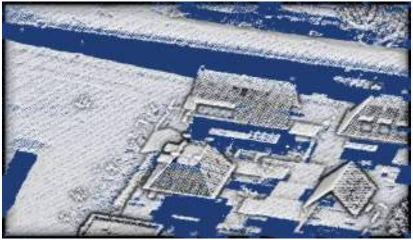


$\left.\begin{array}{l}\bullet\ \text{Sparse}\\ \bullet\ \text{Unordered}\end{array}\right\}$ Raw PCs $\neq$ matrices

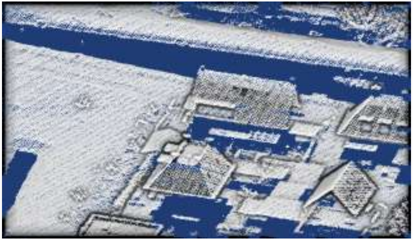
Unlike 2D images:

- No direct comparison possible

3D point clouds for change detection

Date 1

Date 2



- Sparse
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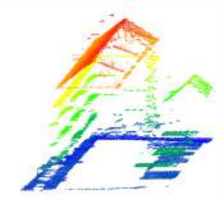
$\Big\}$ Raw PCs $\neq$ matrices

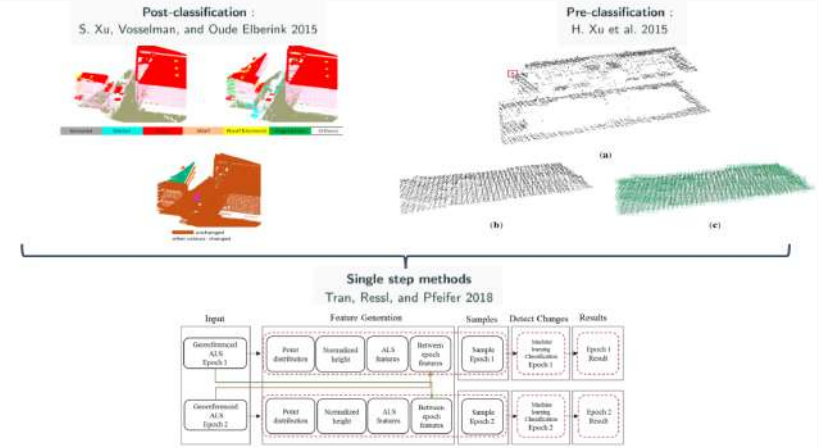


Unlike 2D images:

- No direct comparison possible
- Different hidden parts in each point cloud

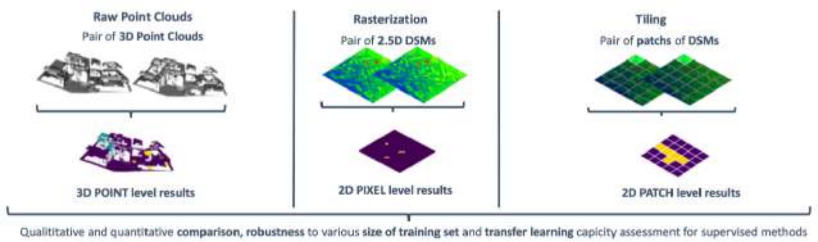
Related works

Related Works – Using raw 3D point clouds



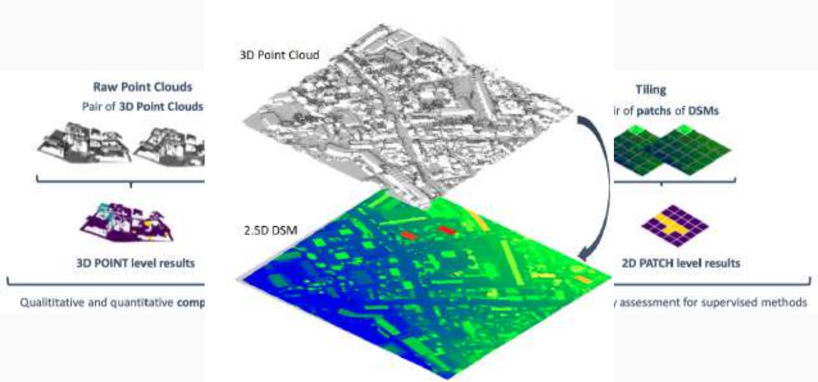
⇒ **No deep learning** based method for **3D point clouds change detection and categorization**

Benchmark of methods for change detection



Iris de Gélis et al. (2021b). "Change Detection in Urban Point Clouds: An Experimental Comparison with Simulated 3D Datasets". In: *Remote Sensing* 13.13, p. 2629

Benchmark of methods for change detection



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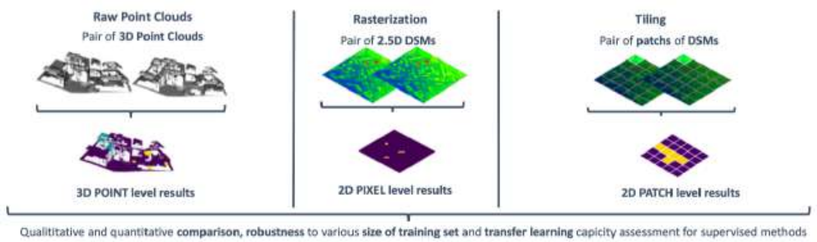
Benchmark of methods for change detection



⇒ Majority of methods only focus on **DSMs** : loss of information

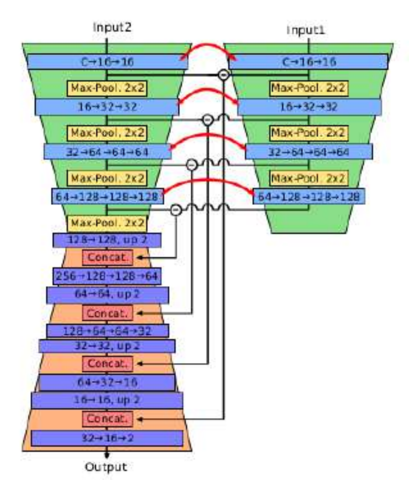
⇒ **Deep learning** method on produce a binary per 2D patch results

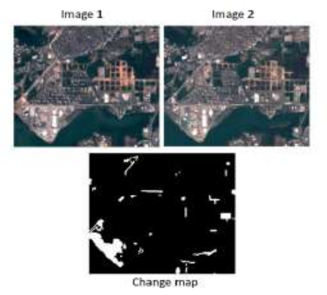
⇒ Existing **traditional methods** scores can be **largely improved**

Iris de Gélis et al. (2021b). "Change Detection in Urban Point Clouds: An Experimental Comparison with Simulated 3D Datasets". In: *Remote Sensing* 13.13, p. 2629

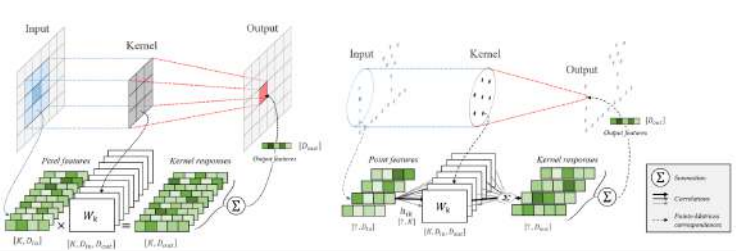
Our proposition using deep learning

Fully Convolutional Siamese Network with difference





2D Convolution **3D Kernel Point Convolution**



Thomas et al. 2019

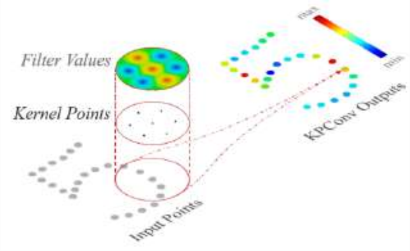
Convolution by a kernel function g at a point $x \in \mathbb{R}^3$:

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

- x_i points from $\mathcal{P} \in \mathbb{R}^{N \times 3}$
- f_i corresponding features from $\mathcal{F} \in \mathbb{R}^{N \times D}$
- $\mathcal{N}_i = \{x_i \in \mathcal{P} \mid \|x_i - x\| \leq R\}$ with $R \in \mathbb{R}$
- g: kernel function defined inside $\mathcal{B}_R^3 = \{y \in \mathbb{R}^3 \mid \|y\| \leq R\}$

3D point clouds Semantic Segmentation : KPConv

2D change detection | 3D segmentation | Our contribution



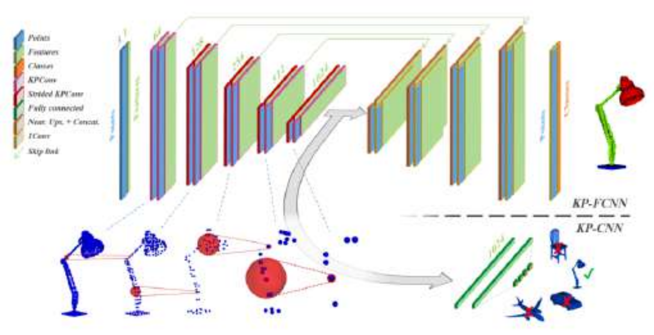
Thomas et al. 2019

Kernel function g applies weights to different areas :

$$g(y_i) = \sum_{k<K} h(y_i, \widetilde{x}_k) W_k$$

- $\widetilde{x}_k$: Kernel Point (k<K)
- W_k : Weight matrices $\{W_k | k < K\} \subset \mathbb{R}^{D_{in} \times D_{out}}$
- h : Correlation function: $h(y_i, \widetilde{x}_k) = max(0, 1 - \frac{\|y_i - \widetilde{x}_k\|}{\sigma})$
- σ : influence distance of kernel points

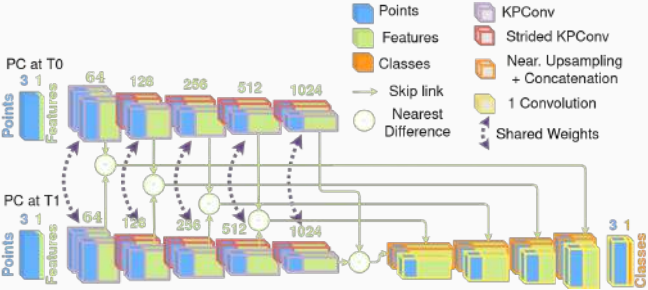
3D point clouds Semantic Segmentation : KPConv



Thomas et al. 2019

⇒ Network that looks like traditional 2D images CNN

Siamese Kernel Point Convolution Network



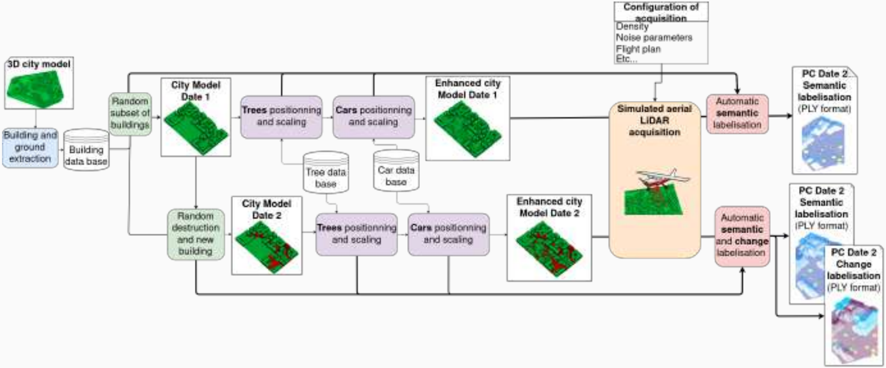
de Gélis et al. 2021a

→ Nearest point feature difference: $\ominus$ between the older PC $\mathcal{P}_0$ and its corresponding features in $\mathcal{F}_0$ and the newer PC $\mathcal{P}_1$ and its features $\mathcal{F}_1$

$$(\mathcal{P}_0, \mathcal{F}_0) \ominus (\mathcal{P}_1, \mathcal{F}_1) = f_{1i} - f_{0j|j=\arg\min(\|x_{\mathbf{1}i} - x_{\mathbf{0}j}\|)}$$

Application to urban environment

Urb3DCD - Simulator for 3D PCs in urban environment



→ **Automatic annotation** of PCs

→ Configuration of acquisition given by the user

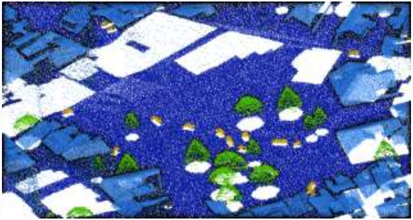
→ **8 different classes**: unchanged, new building, demolition, new vegetation, vegetation loss, vegetation growth, mobile objects

→ Mono-date semantic labels also available

Simulated pair of point clouds

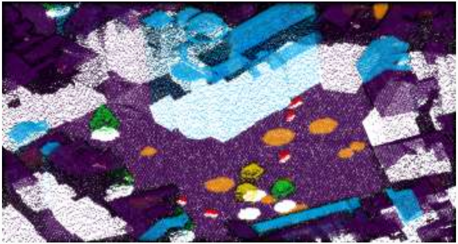
● Ground ● Building ● Vegetation ● Mobile Objects

Date 1



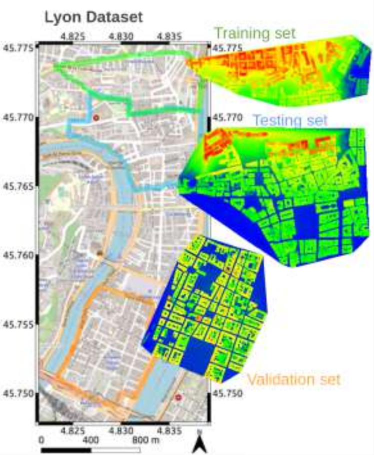
Date 2

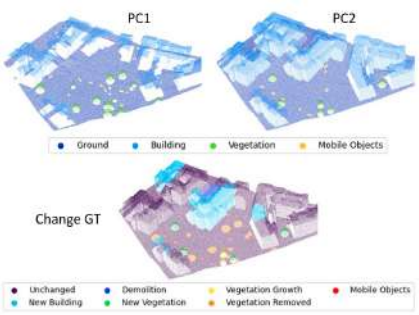
Labelling according to the change



● Unchanged ● New Building ● Demolition ● New Vegetation
● Vegetation Growth ● Vegetation Removed ● Mobile Objects

Urban 3D Point Clouds Changes Dataset





Parameters	Sub-datasets LiDAR low res. Urb3DCD-1	MS Urb3DCD-2
Amount of training pairs	10	10
Density (points/m²)	0.5	0.5 / 10
Noise range across track (°)	0.01	0.2 / 0.01
Noise range along track (°)	0	0.2 / 0
Noise scan direction (m)	0.05	1 / 0.05
Scan angle (°)	-20 to 20	-20 to 20
Overlapping (%)	10	10

⇒ This dataset is publicly available:
https://ieee-dataport.org/open-access/urb3dcd-urban-point-clouds-simulated-dataset-3d-change-detection

Learning strategies

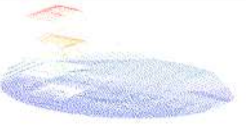
→ Cylindrical inputs for remote sensing large point clouds: $R = 25 \times dl_0$ (dl_0 input subsampling cell size)

→ Unbalanced classes: Input cylinders chosen thanks to a weighted random drawing

→ Loss: SGD with momentum (0.98) to minimize a point-wise weighted negative log likelihood loss

→ Data augmentation:

- Random rotation around vertical axis
- Point scale random Gaussian noise

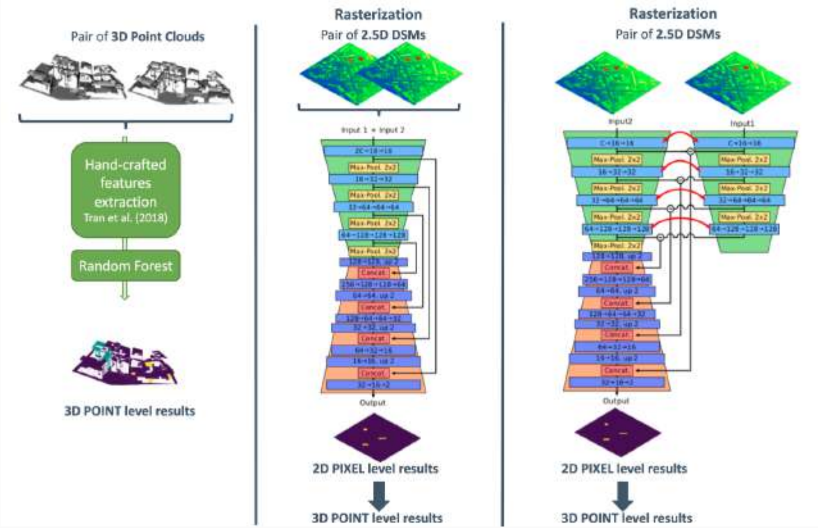


First cylinder

Second cylinder

Experimental Protocol

RF | DSM-FC-EF | DSM-Siamese



Tran et al. 2018 | Daudt et al. 2018 Zhang et al. 2019 | Daudt et al. 2018 Zhang et al. 2019

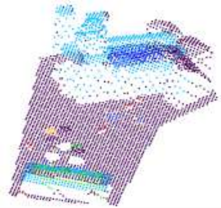
Urb3DCD – LiDAR low density – Qualitative results

(a) PC1

(b) PC2

(c) GT

- Ground
- Building
- Vegetation
- Mobile Objects



(d) RF

(e) DSM-FC-EF

(f) Pseudo-Siamese KPConv

- Unchanged
- New Building
- Demolition
- New Vegetation
- Vegetation Growth
- Missing Vegetation
- Mobile Objects

Urb3DCD – LiDAR low density – Quantitative results

Method	mAcc	$mIoU_{ch}$
Siamese KPConv	90.03 ± 0.69	81.54 ± 1.00
Pseudo-Siamese KPConv	$\mathbf{93.98} \pm 1.26$	$\mathbf{83.77} \pm 1.20$
DSM-Siamese	80.91 ± 5.29	57.41 ± 3.77
DSM-Pseudo-Siamese	75.17 ± 10.03	55.30 ± 8.17
DSM-FC-EF	81.47 ± 0.55	56.98 ± 0.79
RF	65.82 ± 0.05	52.37 ± 0.10

$\Rightarrow$ Large increase of performance with our (Pseudo-)Siamese KPConv

$\Rightarrow$ High results on harder classes (vegetation growth, mobile object)

Urb3DCD – Multi-Sensor – Qualitative results

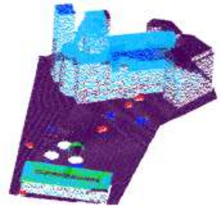


● Ground ● Building ● Vegetation ● Mobile Objects

(a) PC1

(b) PC2

(c) GT



(d) RF

(e) DSM-FC-EF

(f) Pseudo-Siamese KPConv

● Unchanged ● New Building ● Demolition ● New Vegetation
● Vegetation Growth ● Missing Vegetation ● Mobile Objects

Urb3DCD – Multi-Sensor – Quantitative results

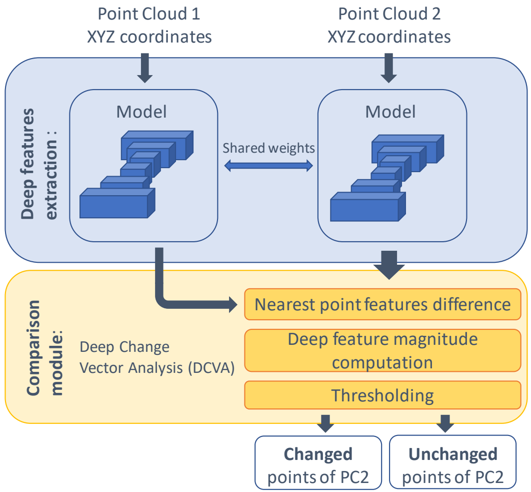
Method	mAcc	mIoU$_{ch}$
Siamese KPConv	58.19 $\pm$ 8.51	36.75 $\pm$ 5.46
Pseudo-Siamese KPConv	**89.74** $\pm$ 1.19	**75.59** $\pm$ 0.67
DSM-Siamese	69.91 $\pm$ 6.18	49.14 $\pm$ 4.92
DSM-Pseudo-Siamese	66.50 $\pm$ 10.82	46.60 $\pm$ 10.13
DSM-FC-EF	81.25 $\pm$ 1.86	55.59 $\pm$ 1.84
RF Tran et al. 2018	62.20 $\pm$ 0.02	46.81 $\pm$ 0.01

$\Rightarrow$ Unshared weights version of our network is better for multi-sensor dataset

What if no annotations are available?

Unsupervised learning and self-supervised learning

Idea: Find indirect strategies for the network to learn discriminating features



Inspired from unsupervised 2D change detection: Saha, Bovolo, et al. 2019

Supervised Semantic Segmentation Training

⇒ Use annex dataset: Supervised Semantic Segmentation Training (SSST)

Hessigheim 3D (H3D) ALS dataset (Kölle et al. 2021)

Self-Supervised Learning

⇒ Use different sub-tasks: Self-Supervised Learning (SSL)

Inspired from unsupervised 2D change detection between SAR and optical data:

Saha, Ebel, et al. 2021

Self-Supervised Learning

$\Rightarrow$ Use different sub-tasks: Self-Supervised Learning (SSL)

Based on two assumptions:

- Changes occur very few

Self-Supervised Learning

$\Rightarrow$ Use different sub-tasks: Self-Supervised Learning (SSL)

Based on two assumptions:

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- PCs properties : point distribution never similar

Self-Supervised Learning

$\Rightarrow$ Use different sub-tasks: Self-Supervised Learning (SSL)

Based on two assumptions:

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Training alternatively with the following losses:

- $\mathcal{L}_{1,2}$: **Temporal consistency** loss: enforce similar predictions for tiles at similar places

Self-Supervised Learning

$\Rightarrow$ Use different sub-tasks: Self-Supervised Learning (SSL)

Based on two assumptions:

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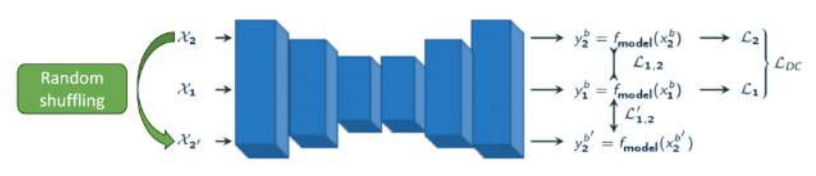
Training alternatively with the following losses:

- $\mathcal{L}_{1,2}$: **Temporal consistency** loss: enforce similar predictions for tiles at similar places
- $\mathcal{L}'_{1,2}$: **Contrastive** loss: enforce dissimilar features for tiles different places

$\Rightarrow$ Use different sub-tasks: Self-Supervised Learning (SSL)



Based on two assumptions:

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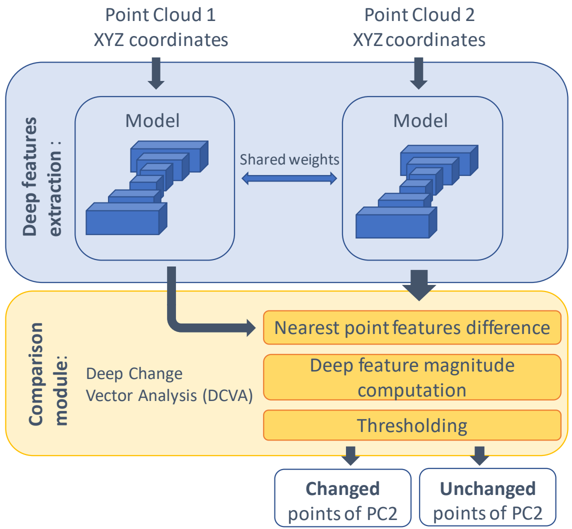
Training alternatively with the following losses:

- $\mathcal{L}_{1,2}$: **Temporal consistency** loss: enforce similar predictions for tiles at similar places
- $\mathcal{L}'_{1,2}$: **Contrastive** loss: enforce dissimilar features for tiles different places
- $\mathcal{L}_{DC}$: **Deep Clustering** loss: force the network to learn discriminative features

Self-Supervised learning

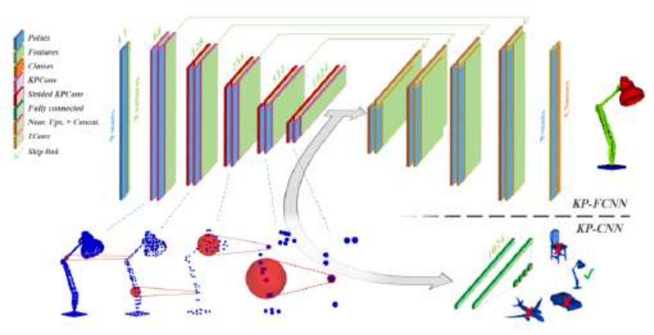
Algorithm 1 Self-supervised training of the backbone

Initialize KP-FCNN weights
for $e \leftarrow 1$ to $\mathcal{E}$ **do**
  Sample $\mathcal{B}$ tiles from $\mathcal{P}_{\mathbf{1}}$, denoted as $\mathcal{X}_{\mathbf{1}}$
  Obtain corresponding $\mathcal{B}$ tiles from $\mathcal{P}_{\mathbf{2}}$, denoted as $\mathcal{X}_{\mathbf{2}}$
  Obtain $\mathcal{X}'_{\mathbf{2}}$ as random shuffling of $\mathcal{X}_{\mathbf{2}}$
  for $i \leftarrow 0$ to $\mathcal{I} - 1$ **do**
    for $b \in \mathcal{B}$ **do**
      $y^b_{\mathbf{1}} = f_{\textbf{KP-FCNN}}(x^b_{\mathbf{1}})$
      $y^b_{\mathbf{2}} = f_{\textbf{KP-FCNN}}(x^b_{\mathbf{2}})$
      $y^{b'}_{\mathbf{2}} = f_{\textbf{KP-FCNN}}(x^{b'}_{\mathbf{2}})$
    Compute the weights W_k considering $y^b_{\mathbf{1}}$ and $y^b_{\mathbf{2}}$
    Calculate weighted deep clustering losses $\mathcal{L}_{\mathbf{1}}$ and $\mathcal{L}_{\mathbf{2}}$
    Calculate temporal consistency loss $\mathcal{L}_{\mathbf{1},\mathbf{2}}$
    Calculate contrastive loss $\mathcal{L}'_{\mathbf{1},\mathbf{2}}$
    if i mod $3 = 0$ **then**
      Use $\mathcal{L}_{DC} = \frac{\mathcal{L}_{\mathbf{1}} + \mathcal{L}_{\mathbf{2}}}{\mathbf{2}}$ to modulate KP-FCNN weights
    else if i mod $3 = 1$ **then**
      Use $\mathcal{L}_{\mathbf{1},\mathbf{2}}$ to modulate KP-FCNN weights
    else
      Use $\mathcal{L}'_{\mathbf{1},\mathbf{2}}$ to modulate KP-FCNN weights


Point Cloud 1
XYZ coordinates
Point Cloud 2
XYZ coordinates
Deep features extraction :
Model
Shared weights
Model
Comparison module:
Deep Change Vector Analysis (DCVA)
Nearest point features difference
Deep feature magnitude computation
Thresholding
Changed points of PC2
Unchanged points of PC2

DCVA - Experimental settings

- Backbone model: KP-FCNN (Thomas et al. 2019)



DCVA - Experimental settings

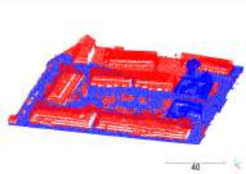
- Backbone model: KP-FCNN (Thomas et al. 2019)
- Dataset for the experimentation: Actueel Hoogtebestand Nederland (AHN)

- Backbone model: KP-FCNN (Thomas et al. 2019)
- Dataset for the experimentation: Actueel Hoogtebestand Nederland (AHN)
  - → Manual annotation of the test set.

AHN 3

AHN 4

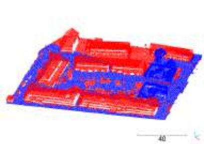
Ground Truth



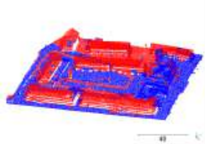
DCVA - Results

a) AHN3 data (time 1)

b) AHN4 data (time 2)



c) Ground truth



d) SSL-DCVA results

		IoU	
	mAcc	Unchange	Change
SSL-DCVA	**85.20**	**78.91**	**69.38**
SSST-DCVA	81.88	70.02	63.85
Siam. KPConv transfer **(de Gélis et al. 2021a)**	79.29	77.89	58.89
M3C2 **(Lague et al. 2013)**	51.77	3.66	39.90
Siam. KPConv (supervised) **(de Gélis et al. 2021a)**	97.08	95.39	92.95

Conclusion

Conclusions

- End-to-end **deep learning** method for **change detection and categorization on raw 3D point clouds**
- Application to **urban** and **geoscience** environment
  - *Urban application*: **Simulator** of **multi-temporal** urban **3D PCs** with **automatic annotation**
  - *Urban application*: IoU on classes of change: $\sim$ **+ 30 %** compared to RF with hand-crafted features (machine learning method)
- **Unsupervised binary change detection**: self-supervised learning
- **Nowadays works**:

  $\rightarrow$ Unsupervised change detection with multi-class results

Bibliographie i

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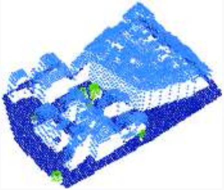
Thank you for your attention

Urb3DCD – LiDAR low density – Qualitative results : Occlusions

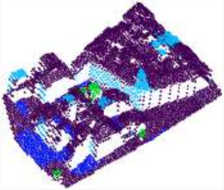


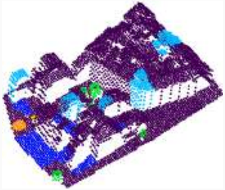
● Ground ● Building ● Vegetation ● Mobile Objects

(a) PC1

(b) PC2

(c) GT





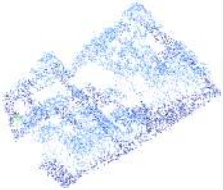
(d) RF

(e) DSM-FC-EF

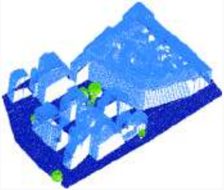
(f) Pseudo-Siamese KPConv

● Unchanged ● New Building ● Demolition ● New Vegetation
● Vegetation Growth ● Missing Vegetation ● Mobile Objects

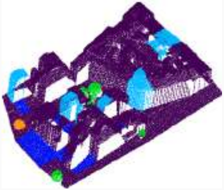
Urb3DCD – Multi-Sensor – Qualitative results : Occlusions



(a) PC1

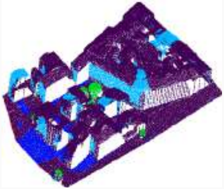


(b) PC2

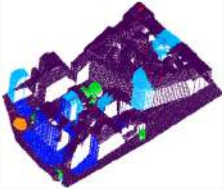


(c) GT

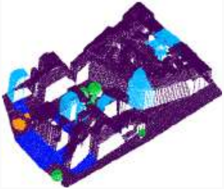
Ground · Building · Vegetation · Mobile Objects



(d) RF



(e) DSM-FC-EF



(f) Pseudo-Siamese KPConv

Unchanged · New Building · Demolition · New Vegetation
Vegetation Growth · Missing Vegetation · Mobile Objects