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2nd Workshop and Challenge on Computer Vision in the Built Environment
for the Design, Construction, and Operation of Buildings

Floor layer-based kernels and pillars of points (FLKPP): 3D building model reconstruction

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CONTENT

1 Background

2 Key methods

3 Results

4 Conclusion

1 **Background**

2 Key methods

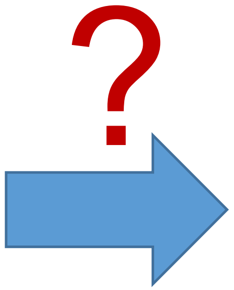
3 Results

4 Conclusion

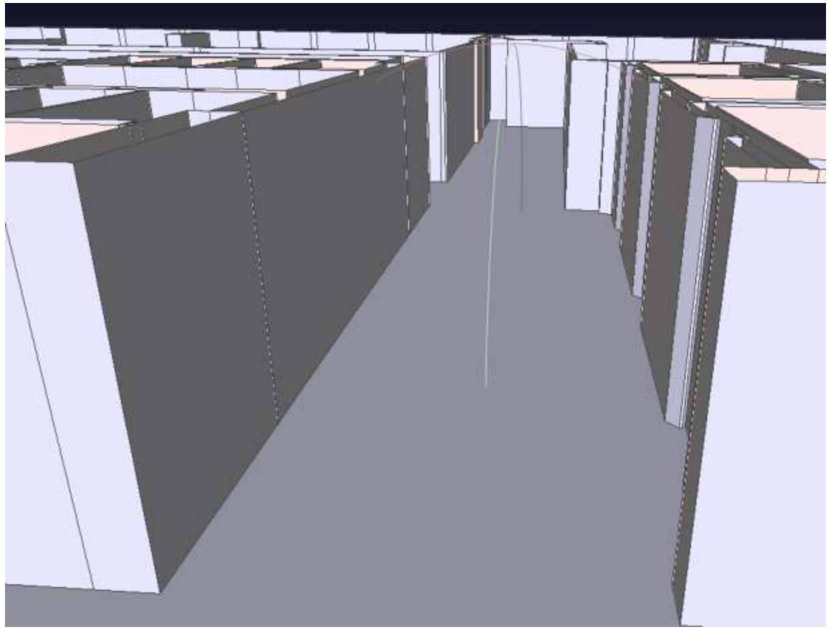
1.1 Background

- Automatic Building Information Model (BIM) and City Information Model (CIM) reconstruction
  - can help free repetitive manual modelling work, (Wu et al. 2021)
  - attracting attentions both from architecture, engineering, construction, and computer science.

3D point cloud



3D BIM

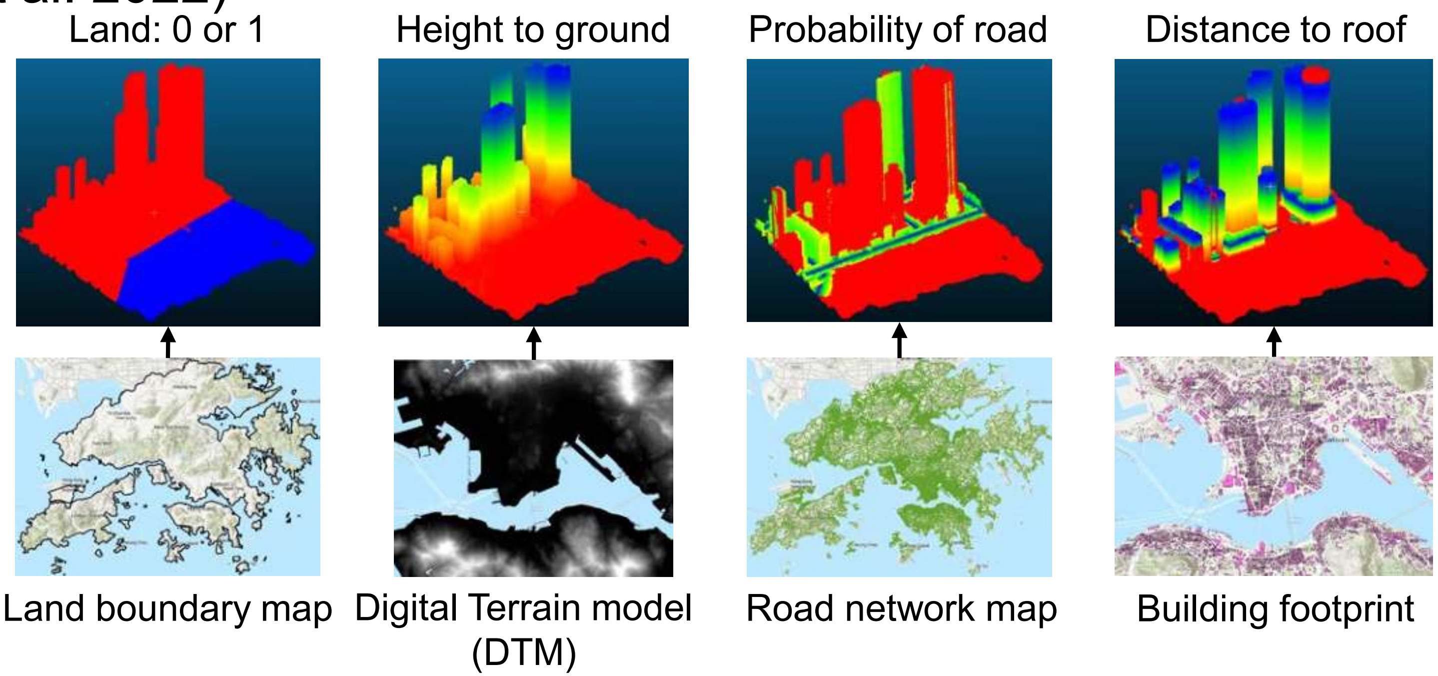


- Accurate geometric information and textured appearance
- But less semantic and instantiated

- More useful in building and facility management
- But requires high-cost manual modelling

1.2 Our recent interests

- Rich features from different sources may boost the performance of computer vision in the urban and built environment. (Li et al. 2022)



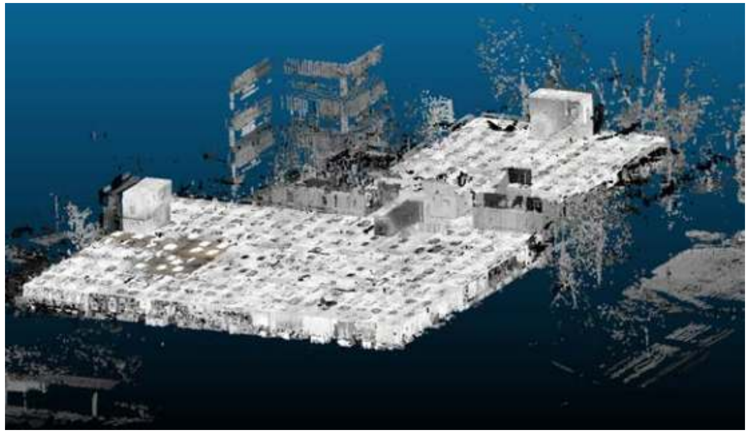
KPConv (Thomas et al. 2019)

Feature	Ground	Terrain	Building	Vehicle	Vegetation	Water	Facility	mIoU
Color + xyz	0.51	0.18	0.88	0.16	0.77	0.84	0.24	0.51
Color + xyz + land + ground + roof + road	0.54	0.24	0.91	0.28	0.76	0.88	0.26	0.56

Similarly, is feature enrichment of point cloud still helpful for automatic building model reconstruction in the built environment?

1.3 Scan-to-BIM Challenge

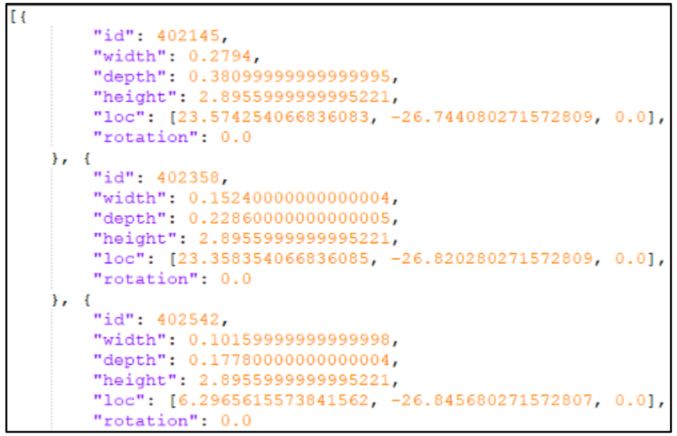
- Fully understand **the relationship mapping** between point cloud and ground truth of training set,
- To **automatically reconstruct** the walls, doors, and columns of the test set.



Training dataset: point cloud

Mapping

Extract



```
[{
        "id": 402145,
        "width": 0.2794,
        "depth": 0.38099999999999995,
        "height": 2.8955999999995221,
        "loc": [23.574254066836083, -26.744080271572809, 0.0],
        "rotation": 0.0
    }, {
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        "depth": 0.22860000000000005,
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        "width": 0.10159999999999998,
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        "height": 2.8955999999995221,
        "loc": [6.2965615573841562, -26.845680271572807, 0.0],
        "rotation": 0.0
```
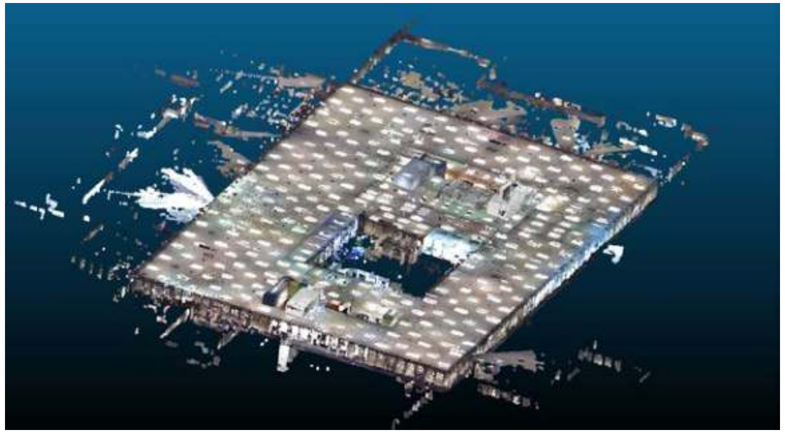


Ground truth: Walls, columns, and doors



Test dataset: point cloud

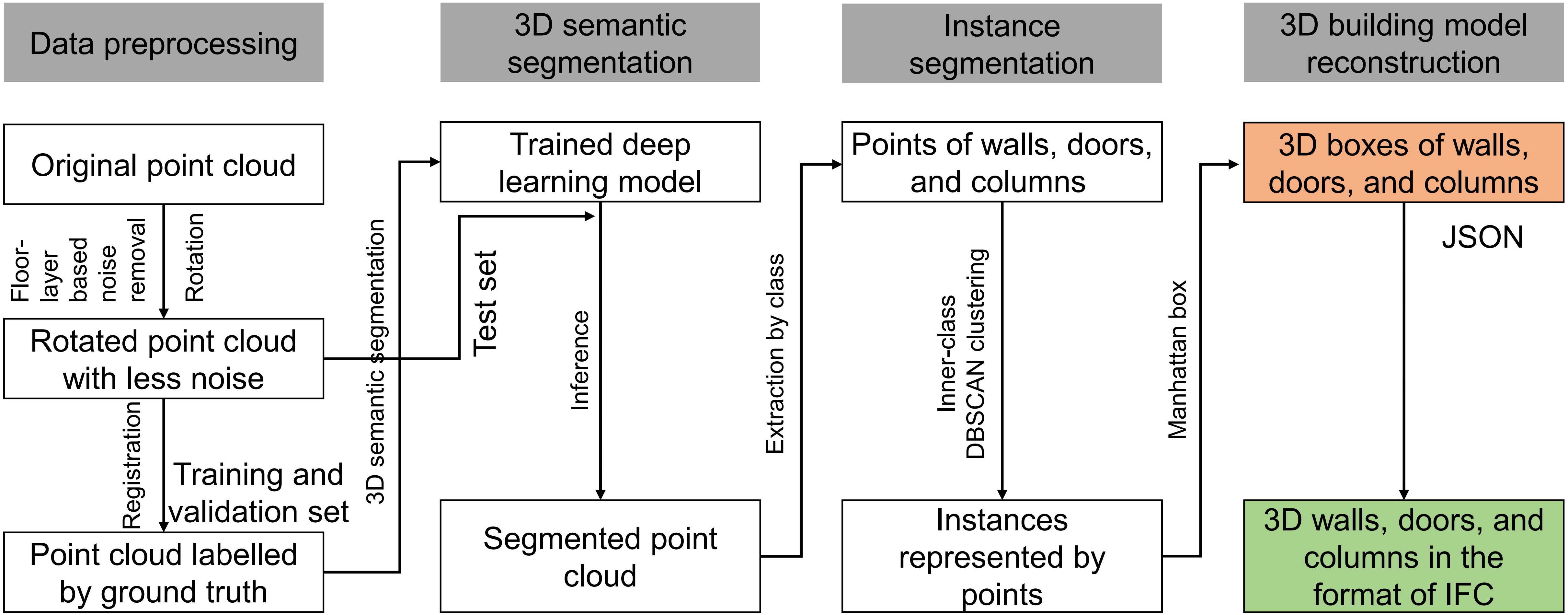
Patterns of the relationship mapping

What, where, and how?

?

Automatic detected result

2.1 Experimental design



2.1.1 Data pre-processing

☐ Floor-layer based noise removal

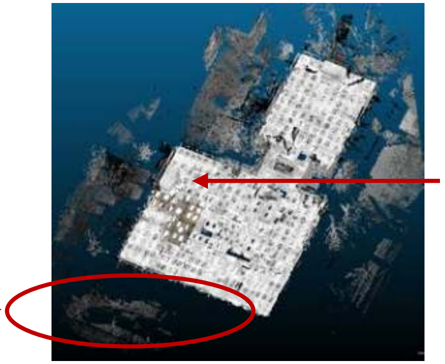
Observation

Some floors have big holes due to tripods and occlusion, while ceilings are more complete and no obstruction.

A heuristic algorithm (Xue 2022)

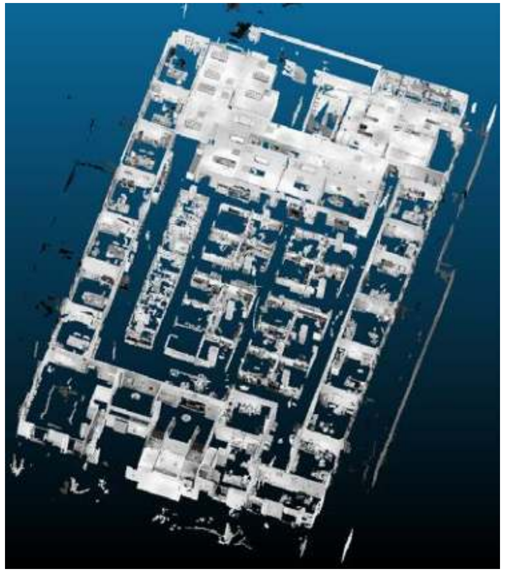
Aim:

- ✓ Control the class balance;
- ✓ Remove outdoor noise.



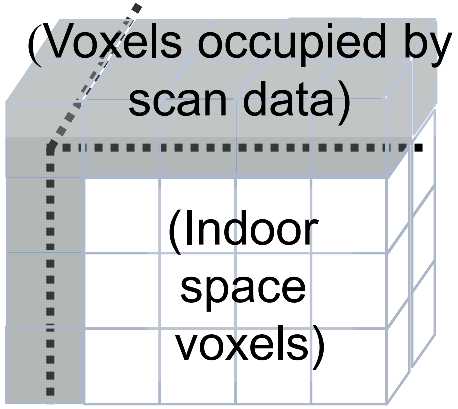
Ceilings are <u>not wanted.</u>

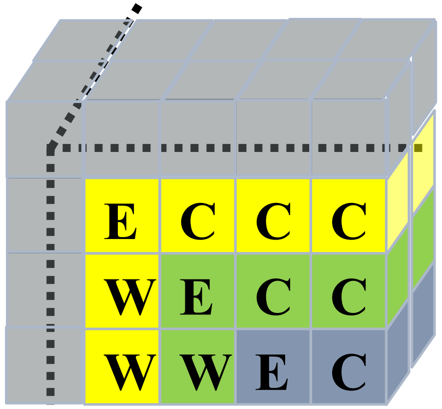
Head-level room layer x
Three floor layers (x, x+1 m, x-1 m)



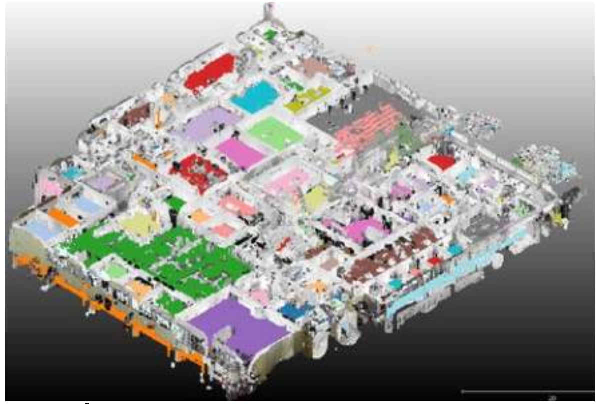
Result

Point cloud without outdoor noise and ceiling and ground parts.





1. Space voxels
(closer to **E**dge, **C**eiling, **W**alls)

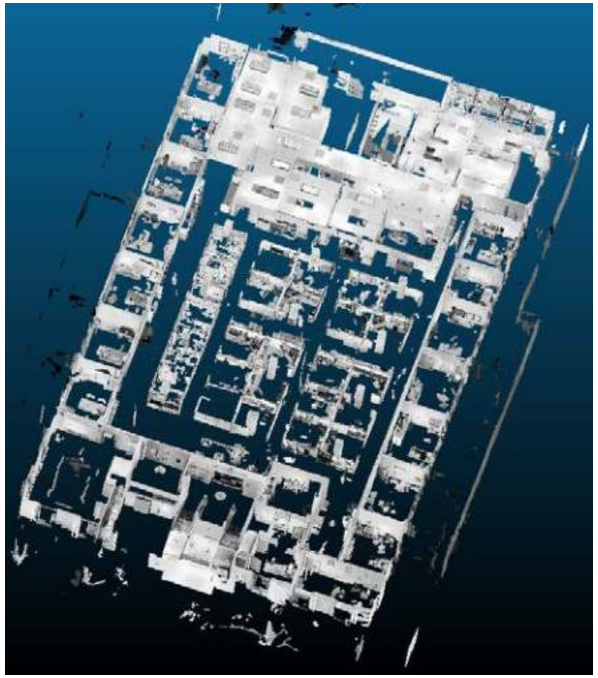


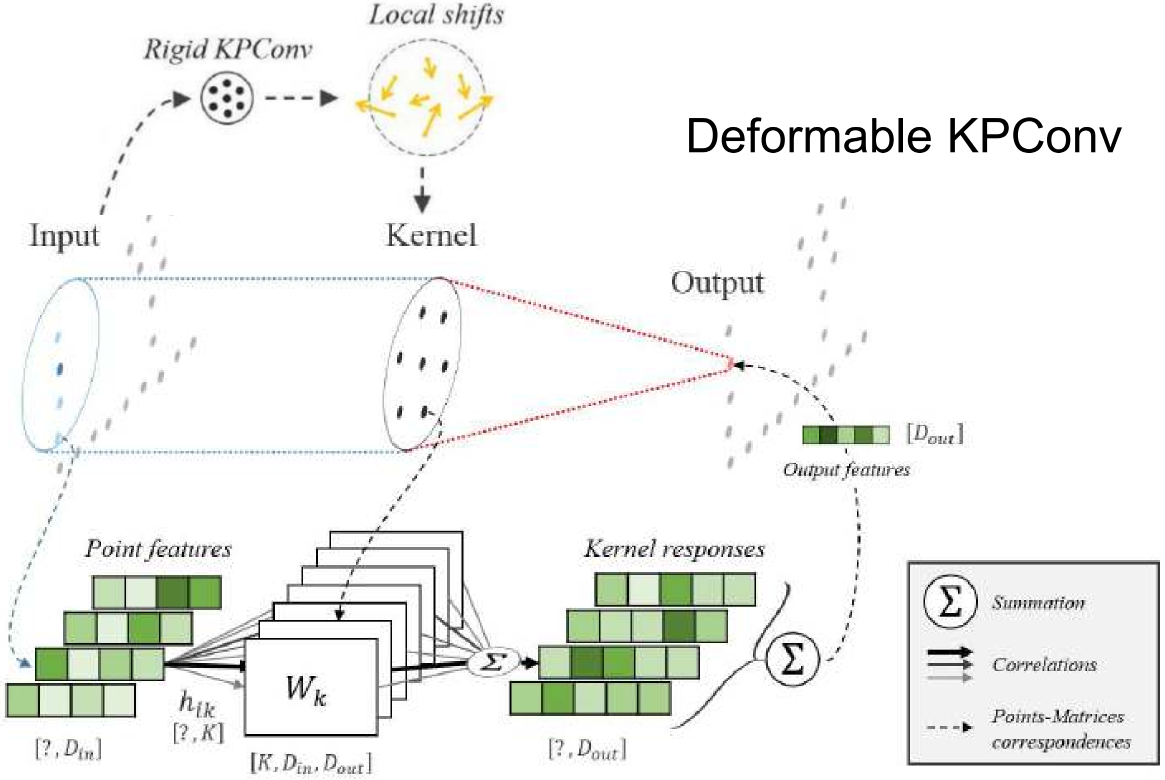
2. Room clustering

2.1.2 3D semantic segmentation

- **KPConv:** Point-level semantic segmentation
- Segment the input point cloud into four groups: Wall, door, column, and others.

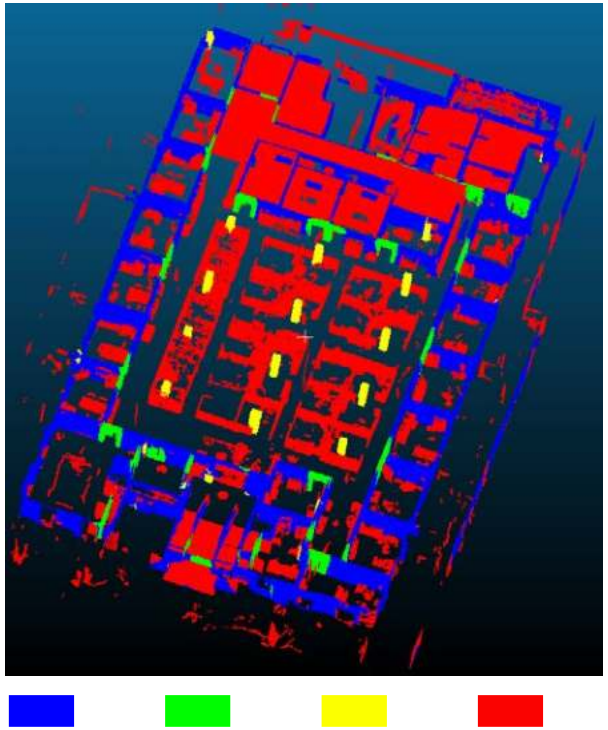
Input





(Thomas et al. 2019)

Output



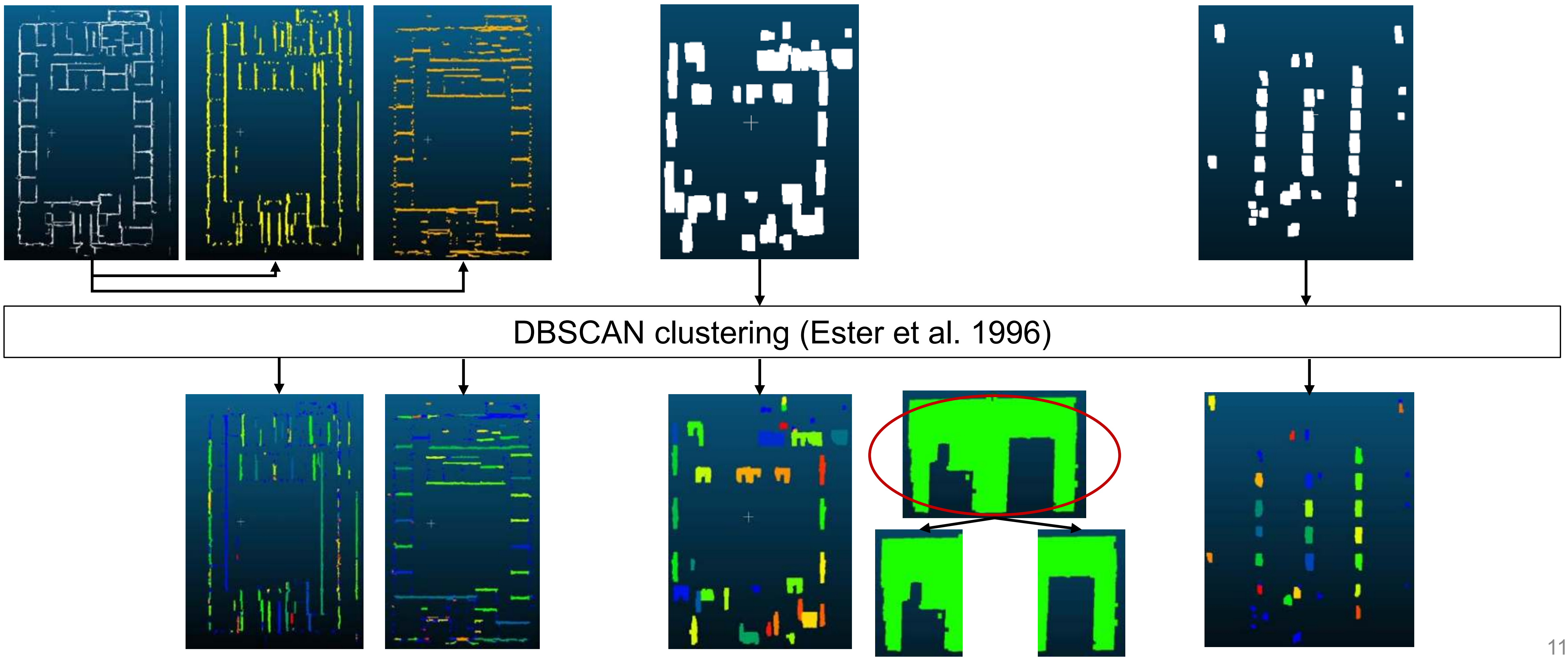
Wall Door Column Others

2.1.3 Instance segmentation

- **DBSCAN based clustering**

✓ **Wall** ✓ **Door** ✓ **Column**

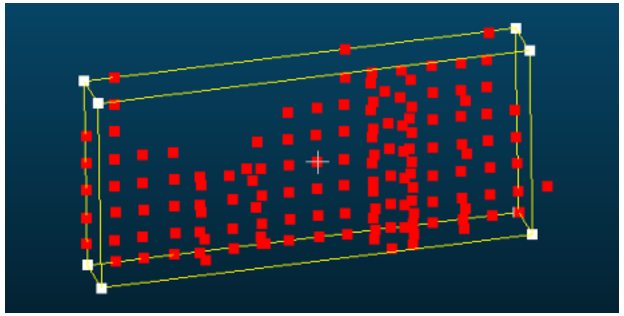
◆ Split walls according to normal



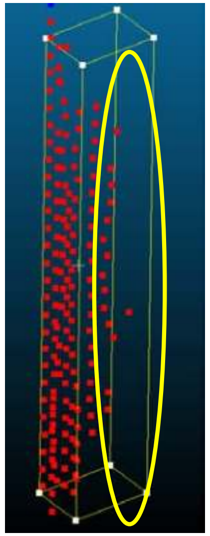
2.1.4 3D building model generation

☐ Manhattan box + BIM generation

Manhattan box with repairments



Wall



Column

Door

JSON file generation

```
""" Columns.
    Have only one location point and 3D measures:
        Width - X,
        Depth - Y,
        Height - Z.
    Rotation parameter is used to rotation the structure around Z-axis."""
```

```
""" Doors.
    The same schema as the one above."""
```

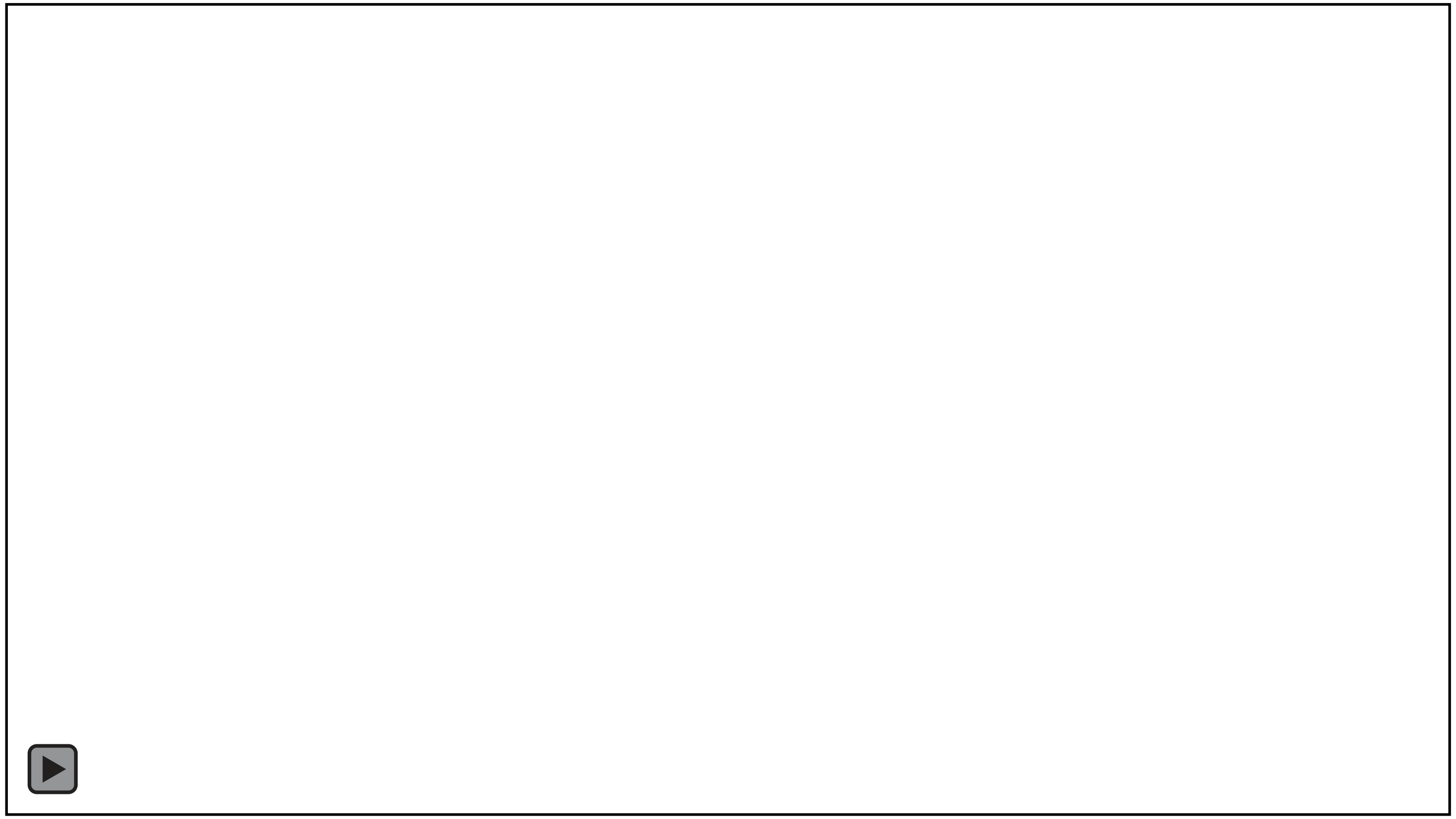
```
""" Walls.
    Consists of the two points and width, height dimensions.


       •-------------•
      /|            /|          z    y
     / |           / |          |   /
    /  |          /  |  height  |  / width (around ep-st vector)
   •-------------• --•          | /
   |  /          |  /           |/
   | st----------|-ep           •----------x
   |/            |/                  length (ep-st)
   •-------------•


    Height measure for both points is assumed to be the same.
"""
```

IFC file generation for BIM

```
ISO-10303-21;
HEADER;
FILE_DESCRIPTION(('ViewDefinition [CoordinationView]'),'2;1');
FILE_NAME('','2022-06-18T10:38:15',(),(),'IfcOpenShell 0.6.0b0','IfcOp
FILE_SCHEMA(('IFC4'));
ENDSEC;
DATA;
#1=IFCSIUNIT(*,.LENGTHUNIT.,.MILLI.,.METRE.);
#2=IFCSIUNIT(*,.PLANEANGLEUNIT.,$,.RADIAN.);
#3=IFCDIMENSIONALEXPONENTS(0,0,0,0,0,0,0);
#4=IFCMEASUREWITHUNIT(IFCAREAMEASURE(0.017453293),#2);
#5=IFCCONVERSIONBASEDUNIT(#3,.PLANEANGLEUNIT.,'degree',#4);
#6=IFCUNITASSIGNMENT((#1,#5));
#7=IFCCARTESIANPOINT((0.,0.,0.));
#8=IFCAXIS2PLACEMENT3D(#7,$,$);
#9=IFCGEOMETRICREPRESENTATIONCONTEXT($,'Model',3,1.E-05,#8,$);
#10=IFCPROJECT($,$,$,$,$,$,$,(#9),#6);
#11=IFCGEOMETRICREPRESENTATIONSUBCONTEXT('Body','Model',*,*,*,*,#9,$,.
#12=IFCSHAPEREPRESENTATION(#11,'Body','Brep',(#15));
#13=IFCPRODUCTDEFINITIONSHAPE($,$,(#12));
#14=IFCCLOSEDSHELL((#22,#29,#36,#43,#50,#57));
#15=IFCFACETEDBREP(#14);
#16=IFCPOLYLOOP((#17,#18,#19,#20));
#17=IFCCARTESIANPOINT((-1.21559416021844,1.20324344652382,0.149706574
#18=IFCCARTESIANPOINT((-1.62665337952797,1.20396717049907,0.149706574
#19=IFCCARTESIANPOINT((-1.62592709403133,1.61648127732798,0.149706574
#20=IFCCARTESIANPOINT((-1.2148678747218,1.61575755335272,0.14970657462
#21=IFCFACEOUTERBOUND(#16,.T.);
#22=IFCFACE((#21));
#23=IFCPOLYLOOP((#24,#25,#26,#27));
#24=IFCCARTESIANPOINT((-1.2148678747218,1.61575755335272,2.75069799505
#25=IFCCARTESIANPOINT((-1.62592709403133,1.61648127732798,2.750697995
#26=IFCCARTESIANPOINT((-1.62665337952797,1.20396717049907,2.750697995
#27=IFCCARTESIANPOINT((-1.21559416021844,1.20324344652382,2.750697995
#28=IFCFACEOUTERBOUND(#23,.T.);
#29=IFCFACE((#28));
#30=IFCPOLYLOOP((#31,#32,#33,#34));
#31=IFCCARTESIANPOINT((-1.62592709403133,1.61648127732798,0.149706574
#32=IFCCARTESIANPOINT((-1.62665337952797,1.20396717049907,0.149706574
#33=IFCCARTESIANPOINT((-1.62665337952797,1.20396717049907,2.750697995
#34=IFCCARTESIANPOINT((-1.62592709403133,1.61648127732798,2.750697995
#35=IFCFACEOUTERBOUND(#30,.T.);
```

2.1.5 Alternative: 3D instance registration

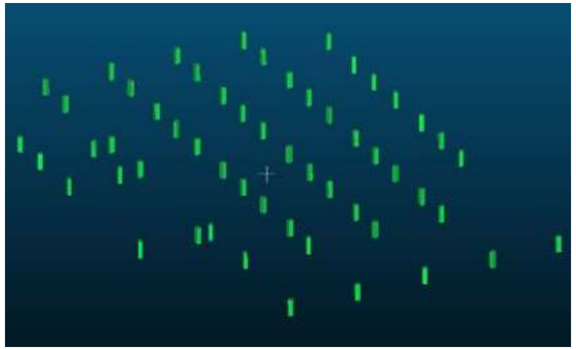
- ☐ **Model-driven instance registration (Xue et al. 2018; 2019)**



Registration process

(To replace 2.1.3 Instance segmentation +2.1.4 Manhattan box generation)

Example Columns

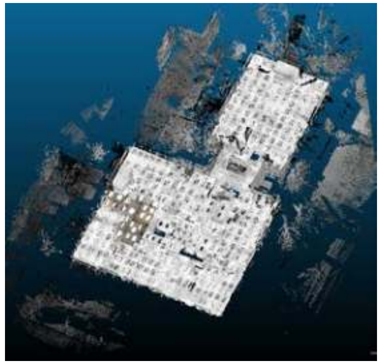


JSON files


```
[
    {
        "model": "data/column/55x45.obj",
        "translation": [
            1.890952463545094 3,
            31.772408610437388,
            1.490614791446266 2
        ],
        "rotation": [
            0,
            0,
            0.0
        ]
    },
    {
        "model": "data/column/55x45.obj",
        "translation": [
            1.8909524635450943,
            31.772408610437388,
            1.4906147914462662
        ],
        "rotation": [
            0,
            0,
            0.0
        ]
    },
    {
        "model": "data/column/55x45.obj",
        "translation": [
            1.8909524635450943,
            31.772408610437388,
            1.4906147914462662
        ],
        "rotation": [
            0,
            0,
            3.025237370123504
        ]
    },
    {
```

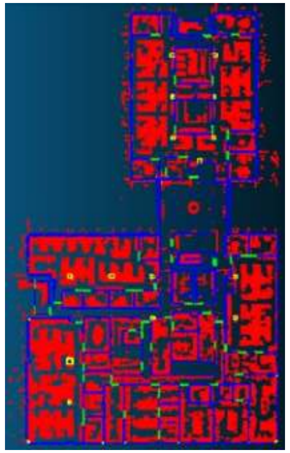
3.1 Results

◆ Preprocessed data



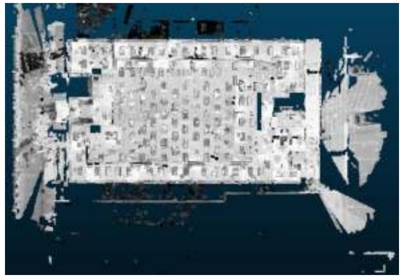
Training and validation sets: Original point cloud

Rotated point cloud with fewer clutters



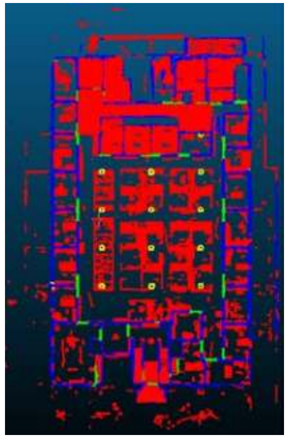
Point cloud labelled by ground truth

◆ Segmented result and metrics



Test set: Original point cloud

Rotated point cloud with fewer clutters



Predicted results

¾ as training set and ¼ as validation set
mIoU computed on validation set

ID	Wall	Door	Column	Others	mIoU
1	0.77	0.55	0.48	0.85	0.67

3D CHALLENGE RESULTS

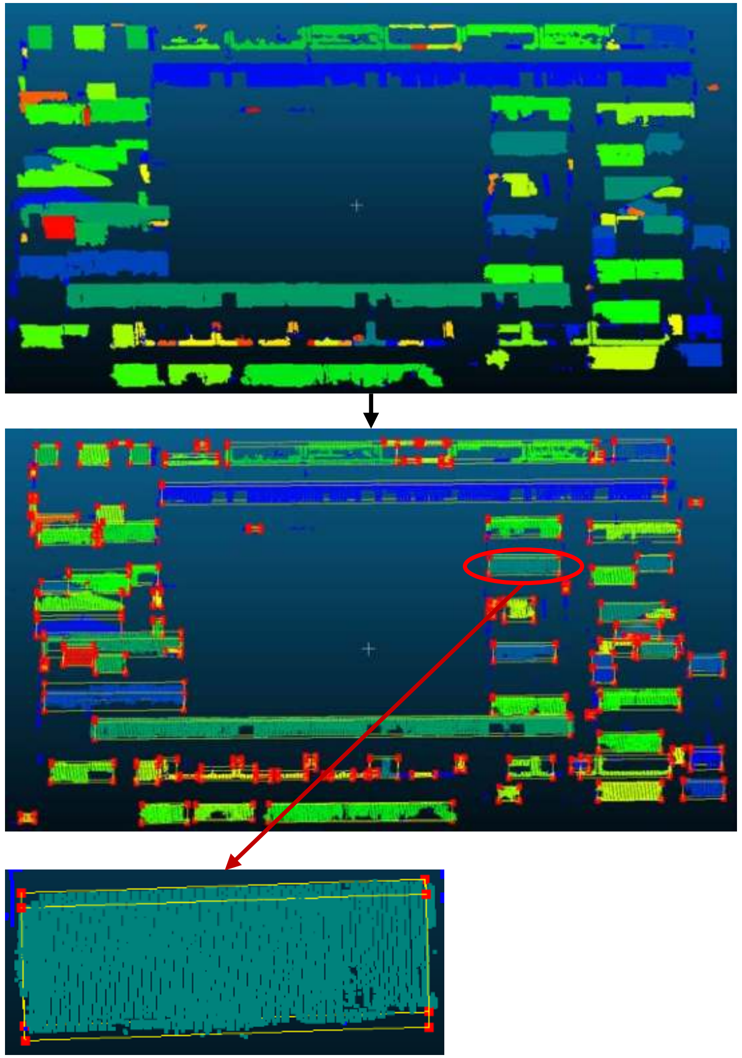
Method Name	Team Members	Affiliation	Average IoU	Columns IoU	Doors IoU	Walls IoU	5cm Average F1	10cm Average F1	20cm Average F1	10cm Columns F1	10cm Doors F1	10cm Walls F1
FLKPP	Yijie Wu, Maosu Li, and Fan Xue	The University of Hong Kong	0.231	0.372	0.230	0.152	0.316	0.454	0.584	0.608	0.367	0.452

Observation: The IoUs in the point and component levels are significantly different.

3.1 Results

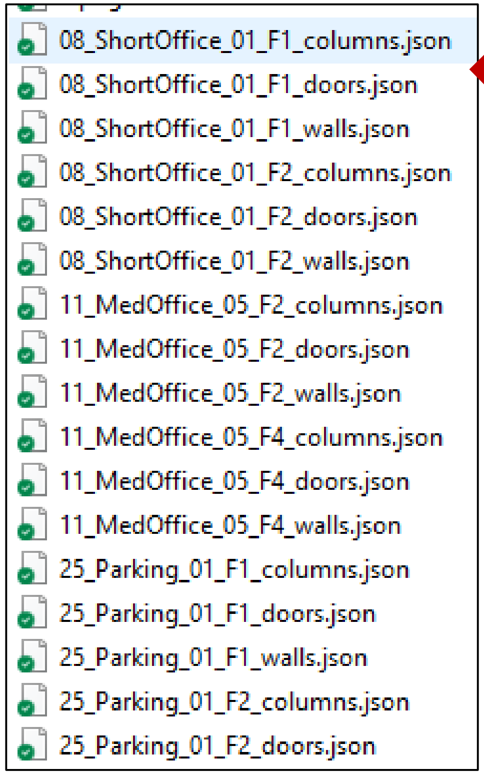
◆ Instance segmentation

✓ Example wall instances

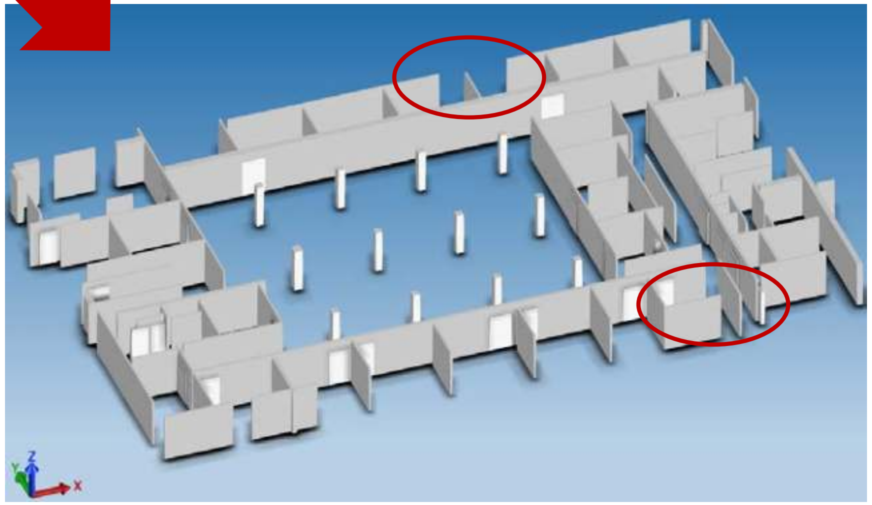


◆ Building model generation

JSON files of walls, columns, and doors



BIM in the format of IFC



Enclosed issue of room

4 Conclusion

❑ Conclusion

- ✓ **The proposed pipeline** utilizes
  - ✓ floor layer-based noise removal
  - ✓ 3D semantic segmentation
  - ✓ DBSCAN clustering, and
  - ✓ Manhattan box-based model generation
- ✓ There still exist amounts of **information loss**
  - ✓ the overall accuracy stay at a low level.

❑ Observation

- ✓ Significantly inconsistent accuracy
  - ✓ between point-wise and component levels
- ✓ Features from other resources
  - ✓ such as prior model library
  - ✓ may improve Scan-to-BIM considerably

❑ Room for improvement

- ✓ **Adaptive thresholds** for instance segmentation
  - ✓ clutter removal and
  - ✓ Occlusion completion
- ✓ Modification and **fine-tuning** of deep learning
- ✓ **Topology repairing**

References

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- Xue, F. (2022). Interpretable segmentation and clustering of rooms in unstructured 3D point cloud using indoor space voxels. (working paper)

Thank you for your attention!

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