Exploration of algorithms for extracting wireframe models from man-made urban linear object point clouds

P5 presentation

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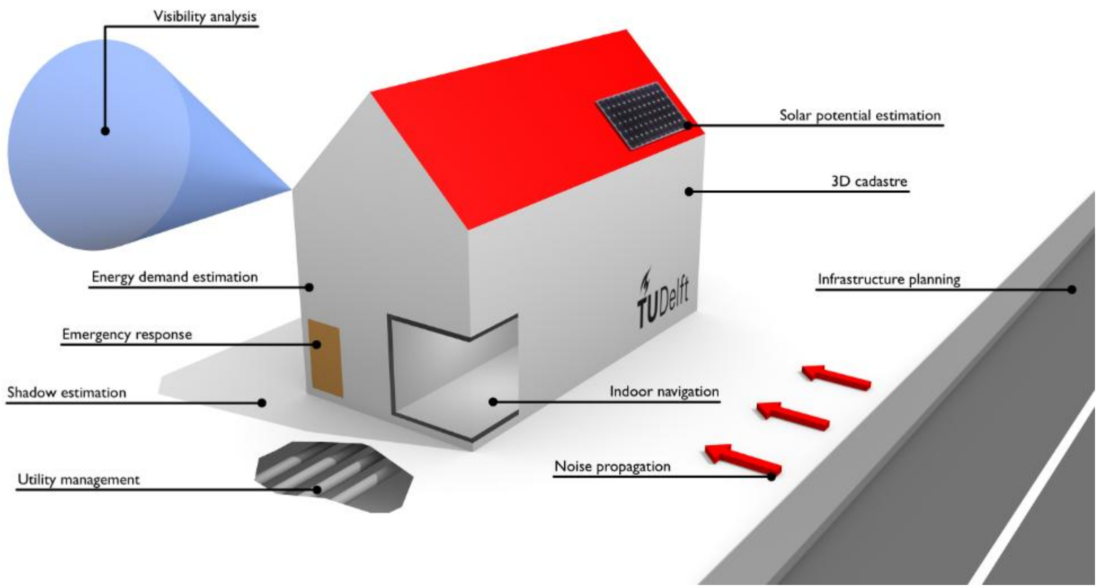
First supervisor: Hugo Ledoux
Second supervisor: Weixiao Gao

Content

Background

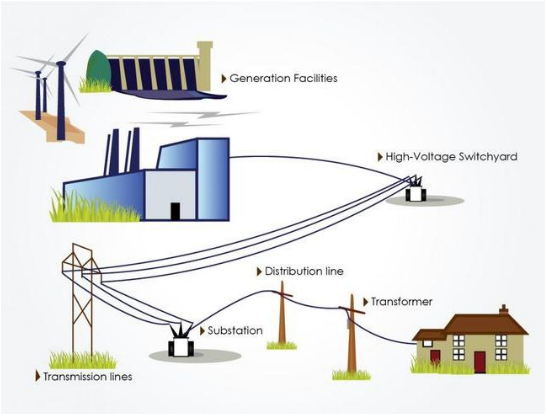
Background

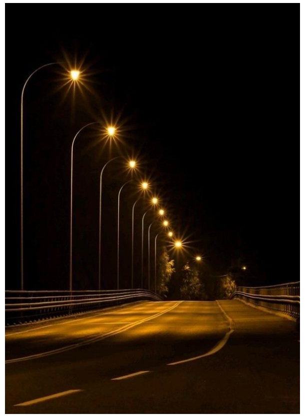


Applications that 3D models can be applied in. [Biljecki et al., 2015]

Buildings and trees

Man-made urban linear objects (power lines, pylons, street lamps)





Applications that involved man-made urban linear objects (electricity supply, transportation illumination)

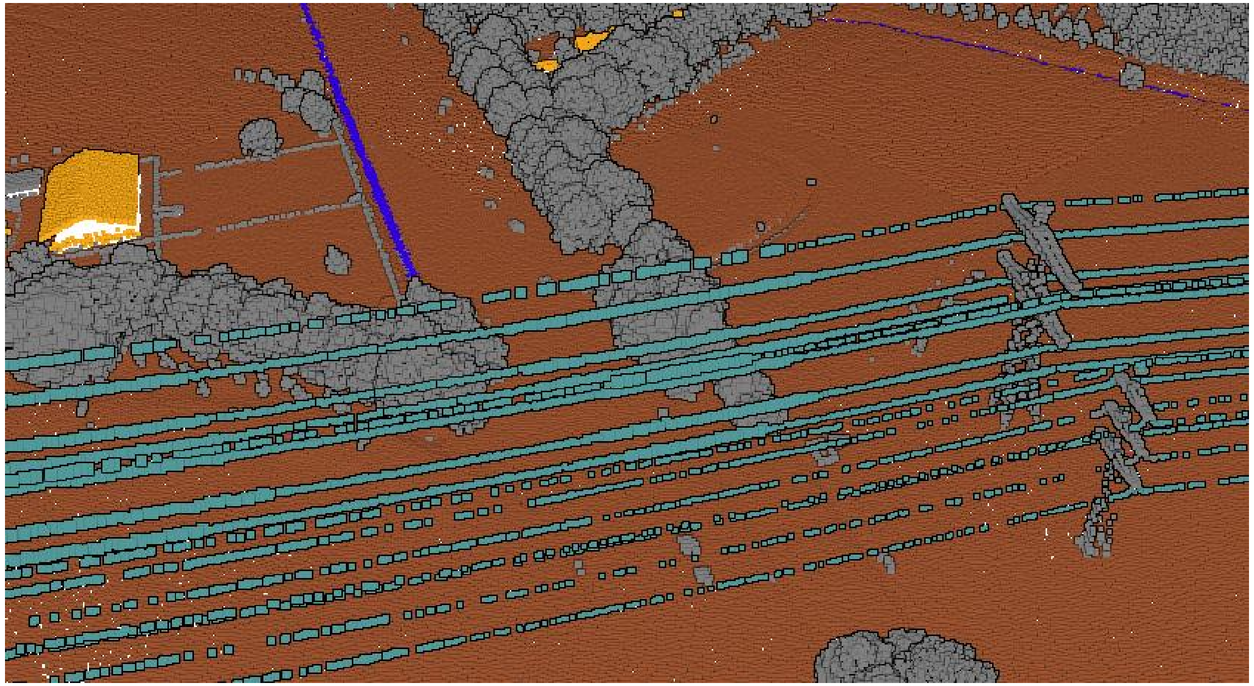
Background

Manual reconstruction

Manual reconstruction for multiple objects in urban environment is time consuming.

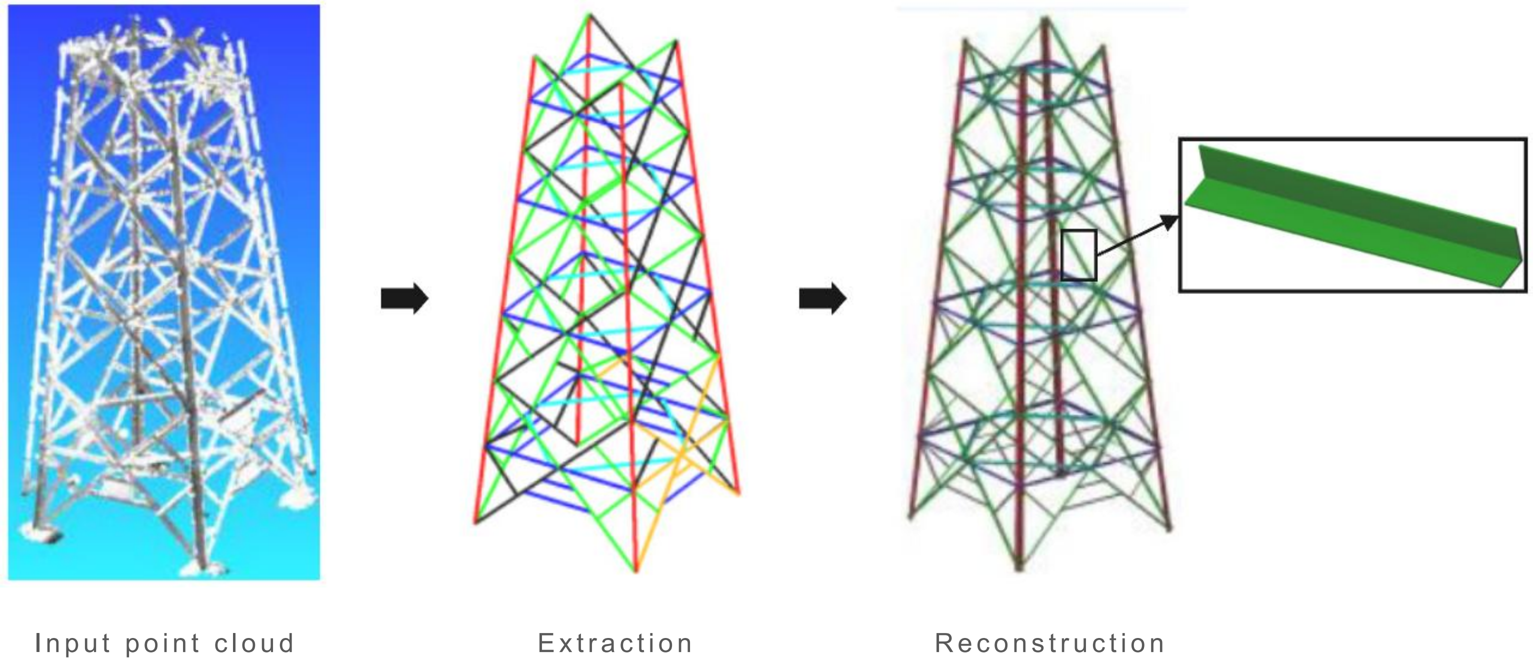
Automated reconstruction from point clouds

- Less labor-intensive
- Convenient for collection
- Suitable for 3D processing



Automated reconstruction from point clouds

Background



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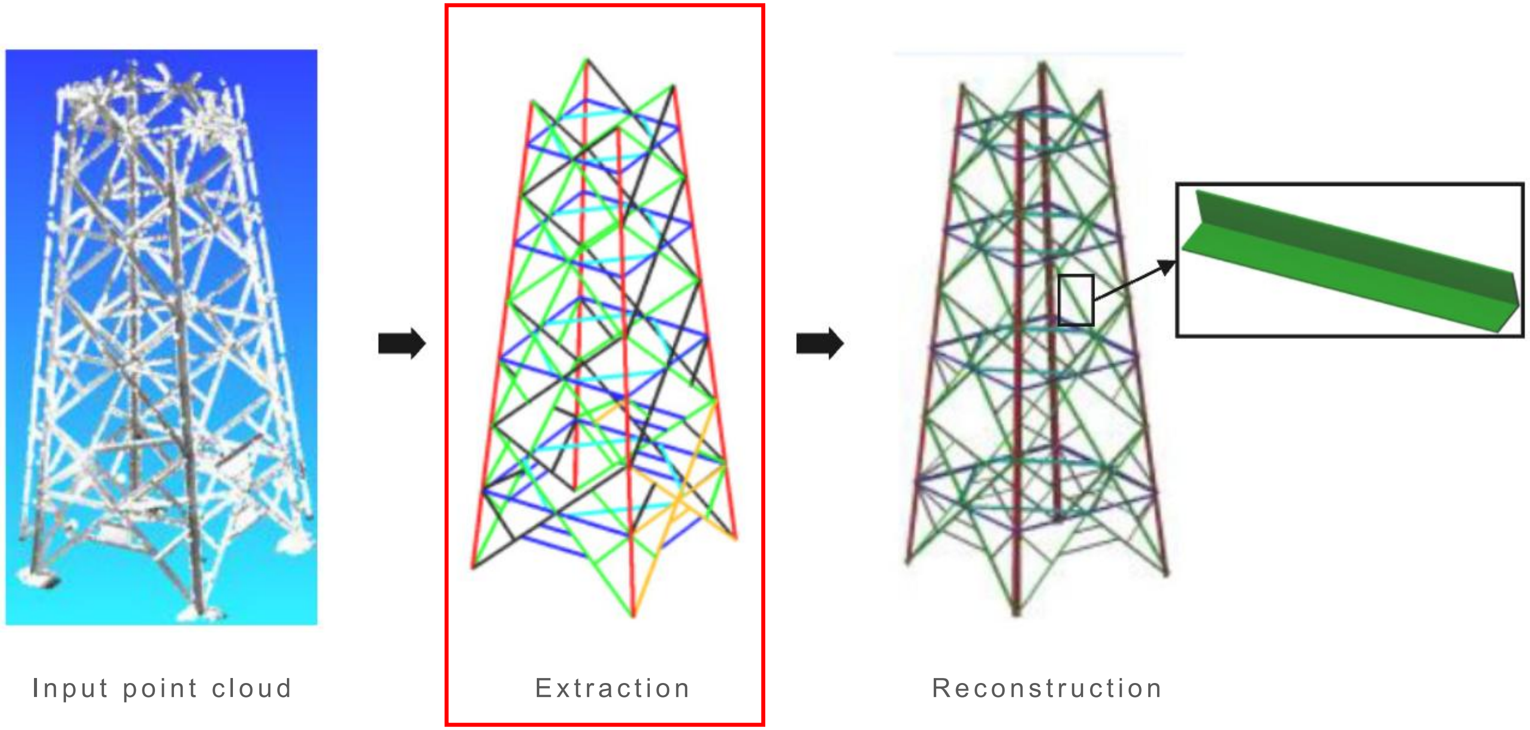

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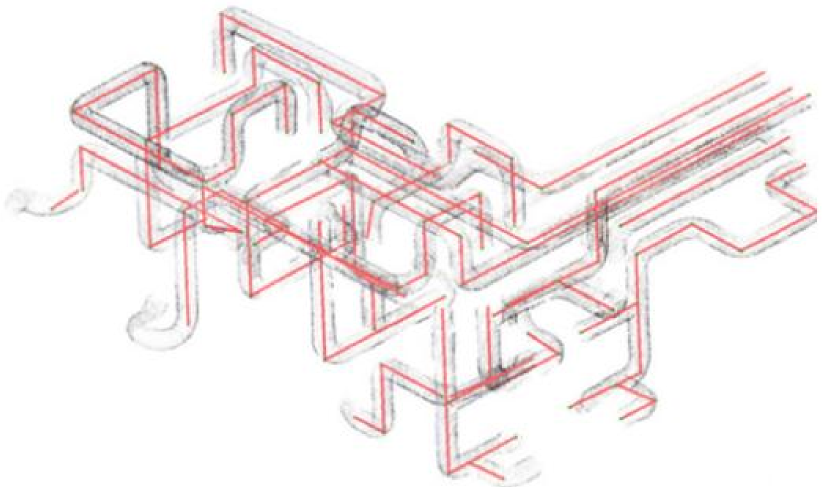
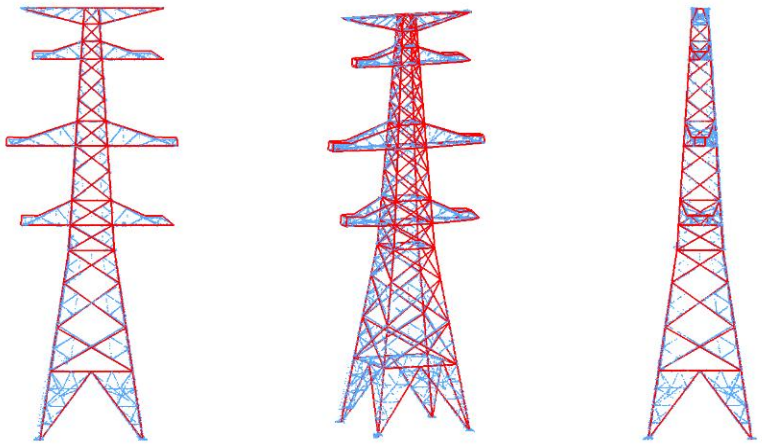
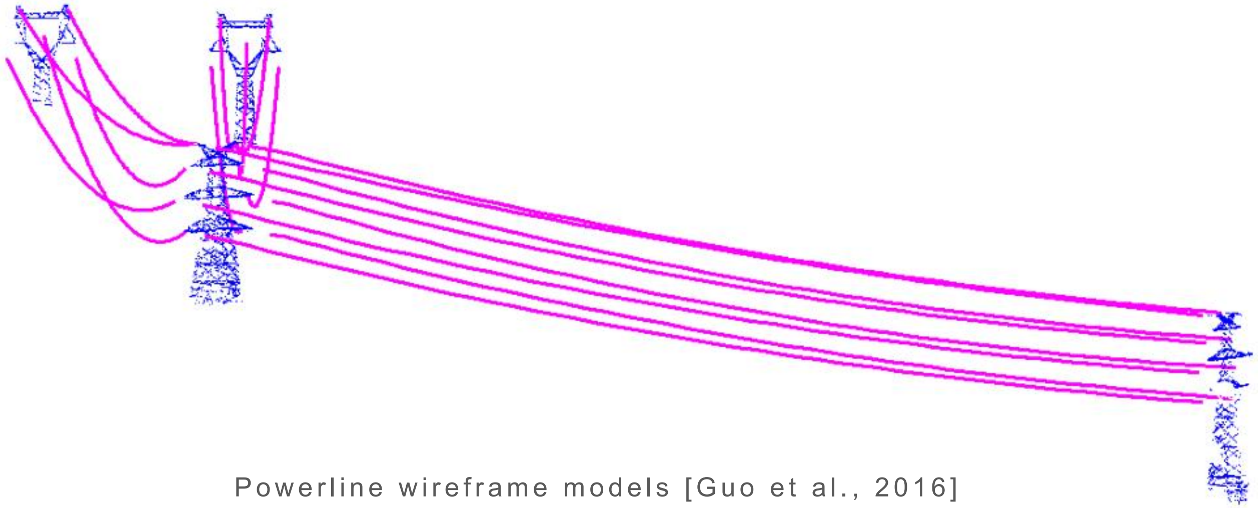


Industrial pipeline wireframe models [Jin and Lee, 2019]

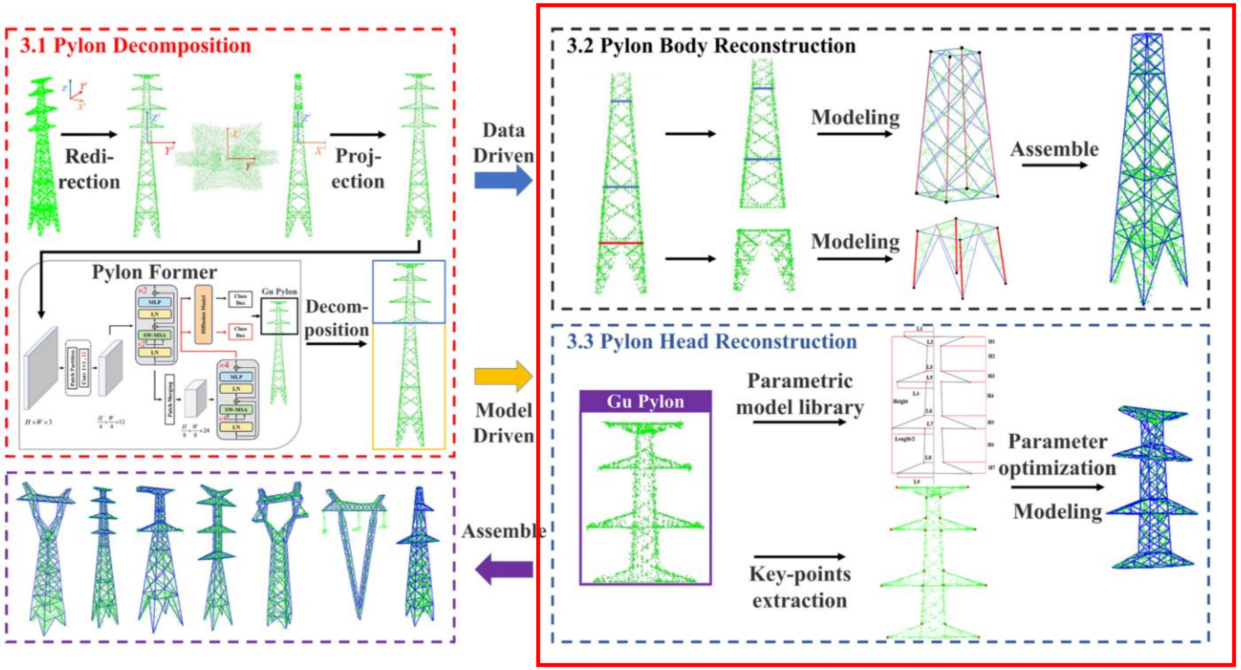


Pylon wireframe models [Jin and Lee, 2019]

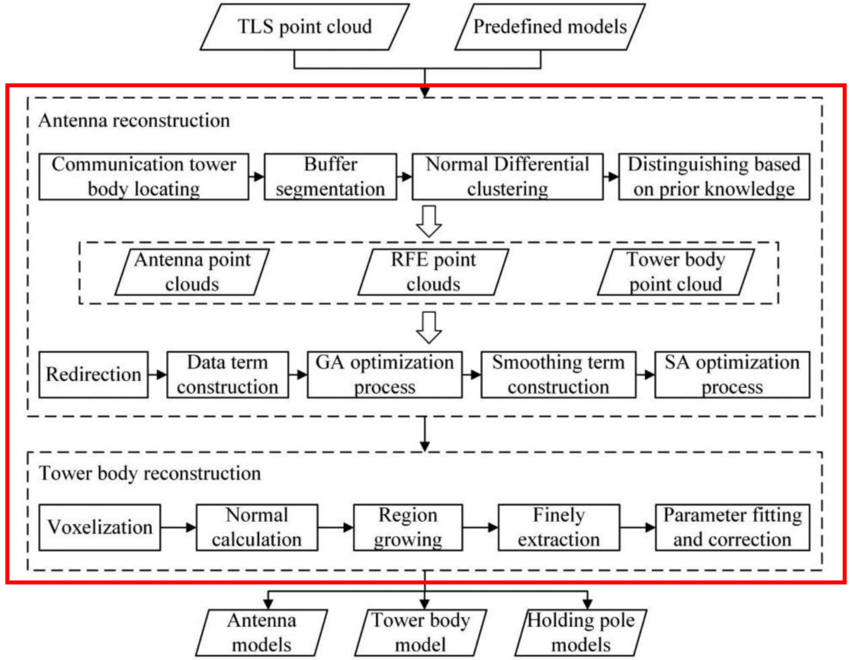


Powerline wireframe models [Guo et al., 2016]

Background



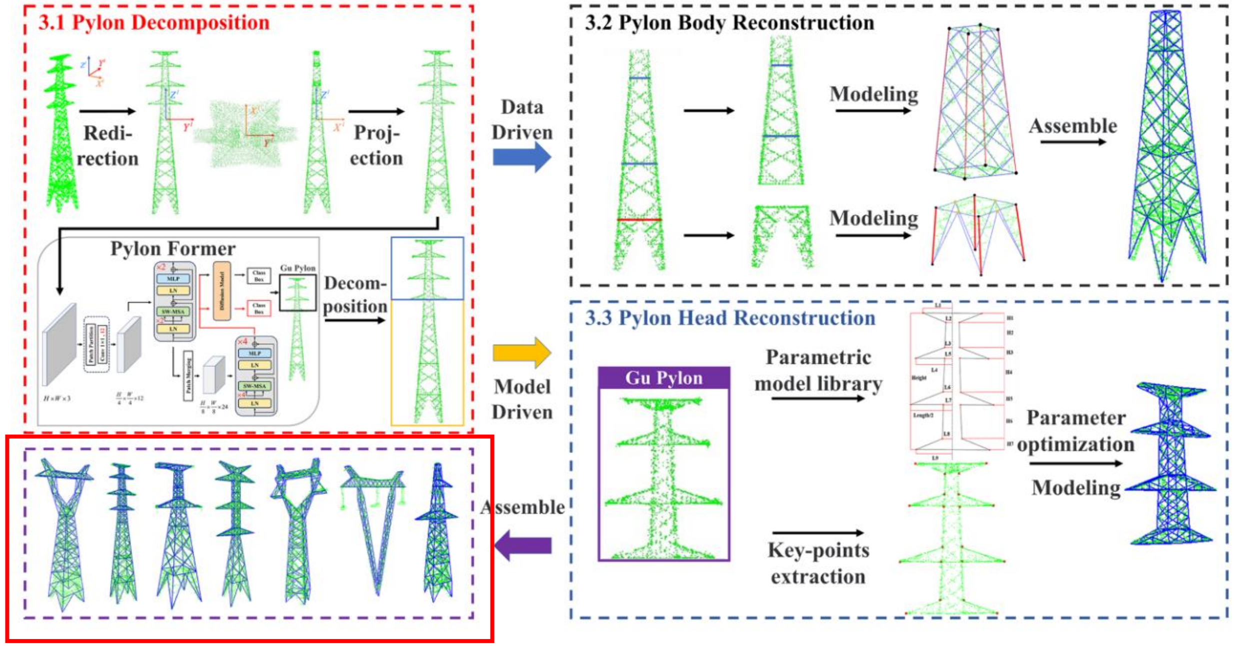
Methodology [Wu et al., 2025]



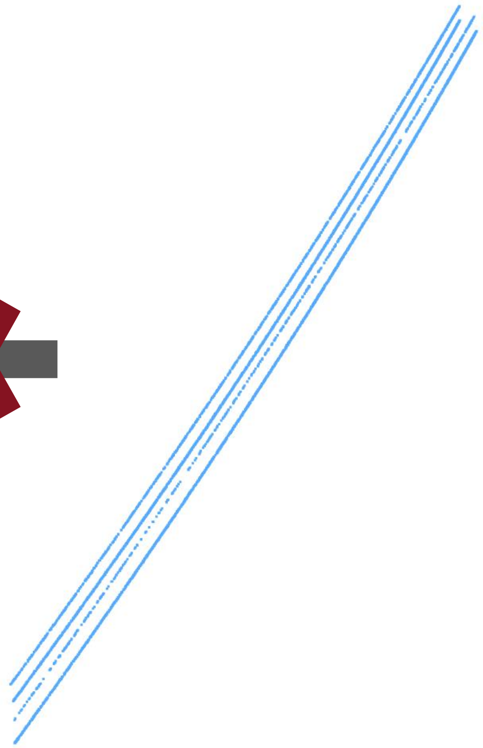
Methodology [Qiao et al., 2024]

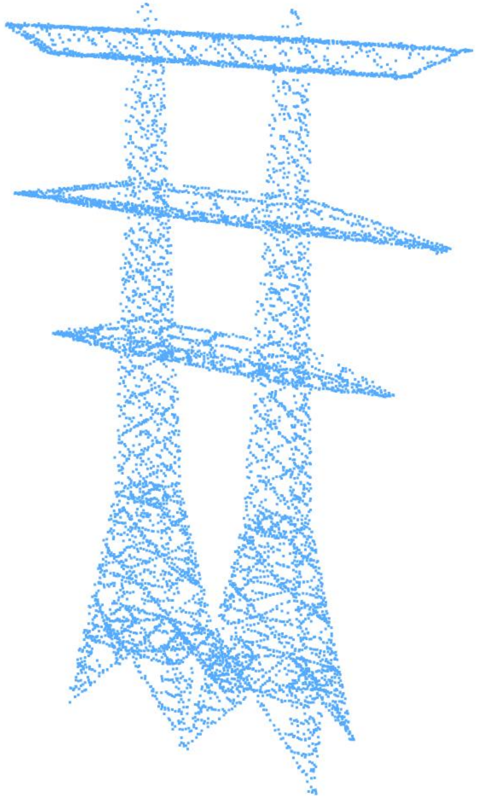
Background

Generalization ability



Methodology [Wu et al., 2025]





powerline

multi-body pylon

Research focus

Research focus

Research Objective:

*To explore algorithms with **generalization ability** for extracting wireframe models from isolated man-made urban linear object point clouds.*

An algorithm with generalization ability should be:

Type-agnostic:

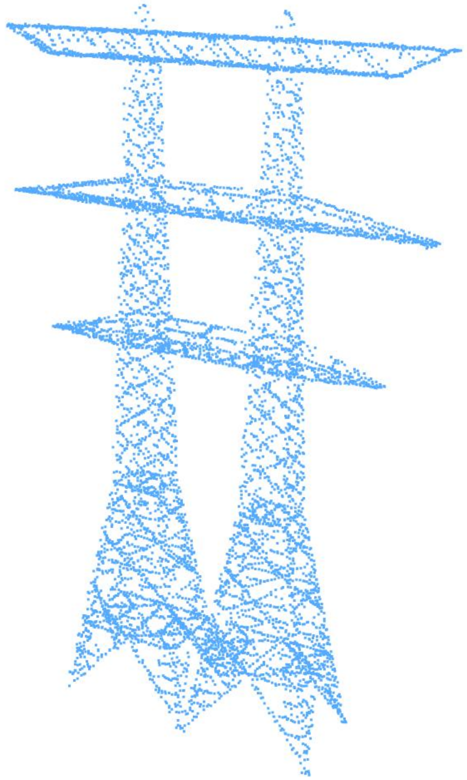
No prior assumptions about one specific type of man-made urban linear objects.

Data-driven:

No pre-defined model libraries, such as pre-defined parametric model for pylons.

Holistic-pipeline:

Input object should not be processed in seperate parts.



isolated point cloud

Research focus

Main research question:

Is it possible to extract wireframe models from point clouds of man-made urban linear objects with an algorithm that has generalization ability?

Sub research question:

Is there any algorithm that gives or has the potential to give promising extraction results of the wireframe models of man-made urban linear objects?

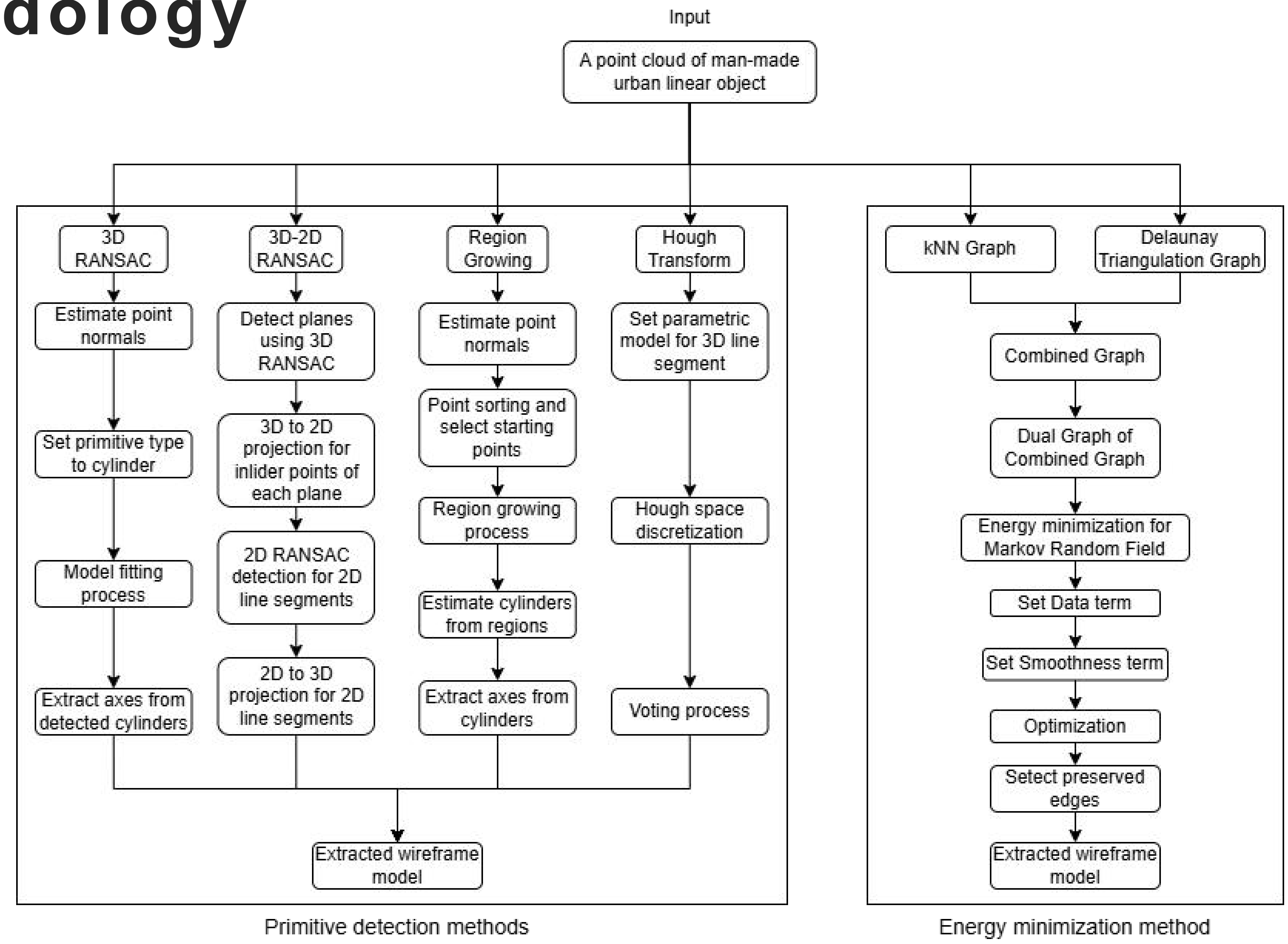
Methodology

Methodology

- **Primitive detection method**
  - **Model fitting-based methods:** RANSAC, Hough transform
  - **Region growing-based method:** Normal-based region growing

- **Energy minimization methods**
  - Energy minimization for Markov Random Fields (MRF)

Methodology



Methodology

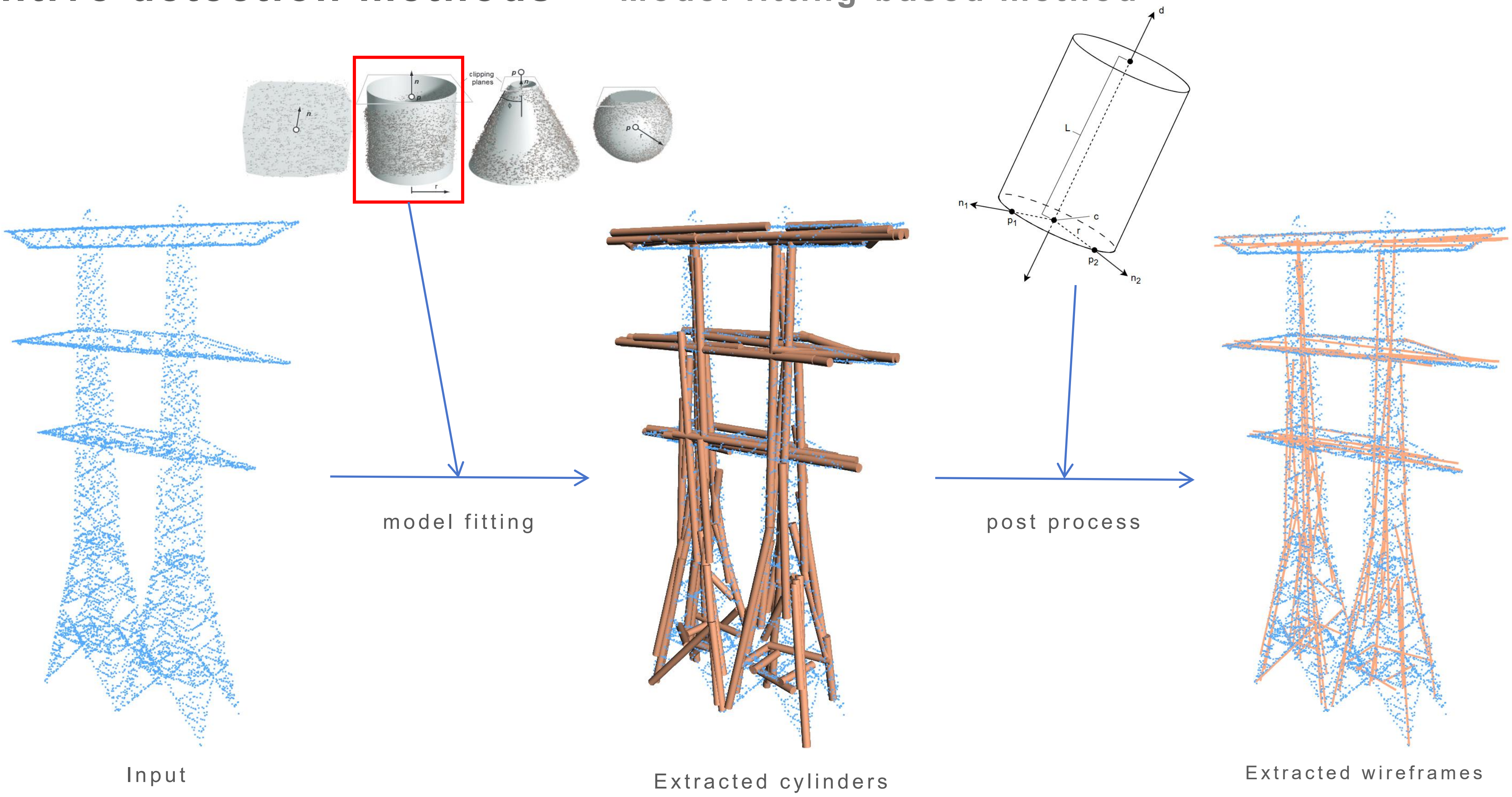
Primitive detection methods

Model fitting-based methods: RANSAC, Hough transform

Region growing-based method: Normal-based region growing

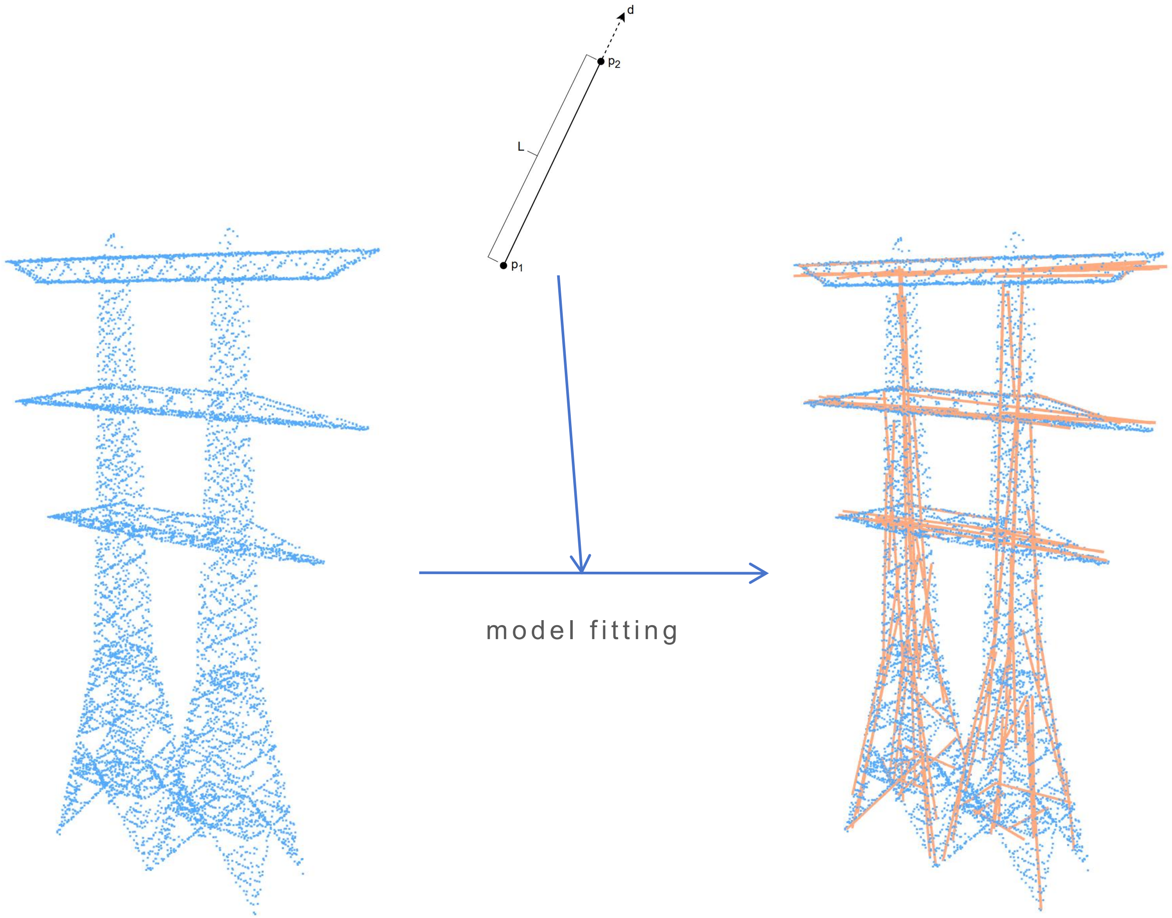
Methodology

Primitive detection methods -- Model fitting-based method



Methodology

Primitive detection methods -- Model fitting-based method

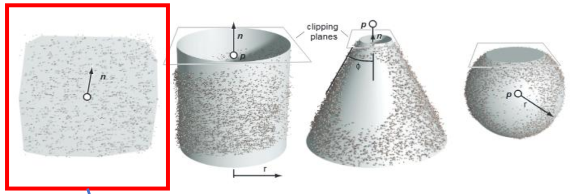


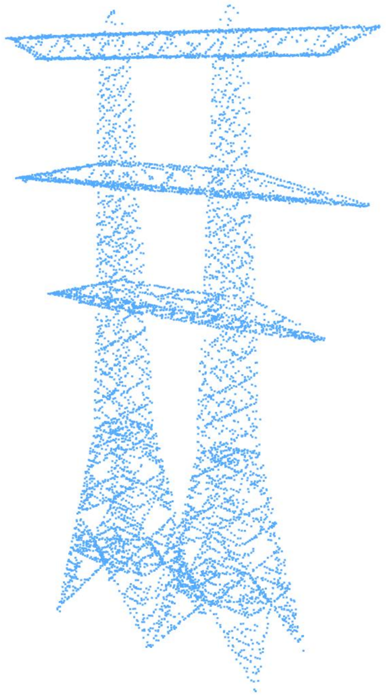
Input

Extracted wireframes

Methodology

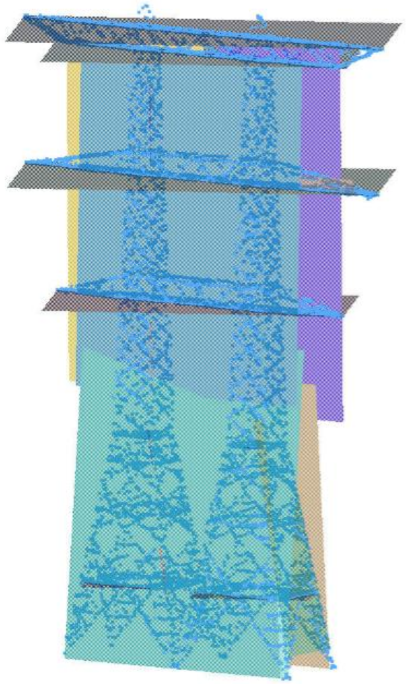
Primitive detection methods -- Model fitting-based method





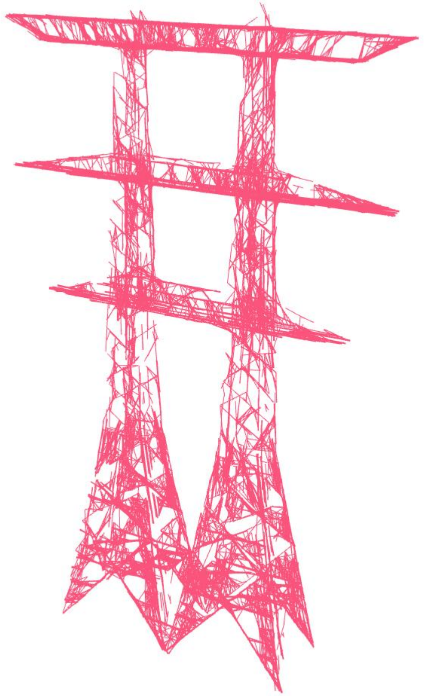
Input

model fitting 1:
3D plane detection



Extracted planes

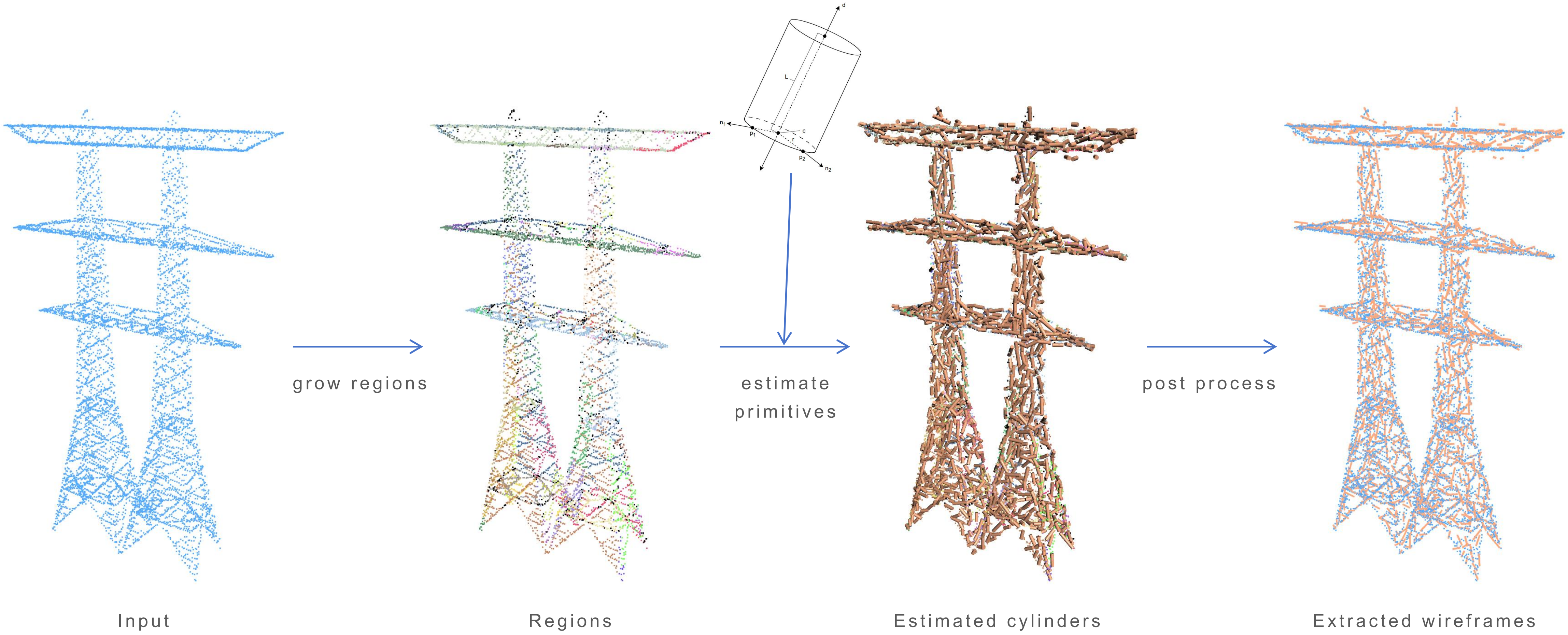
model fitting 2:
2D line detection
+ reprojection



Extracted wireframes

Methodology

Primitive detection methods -- Region growing-based method

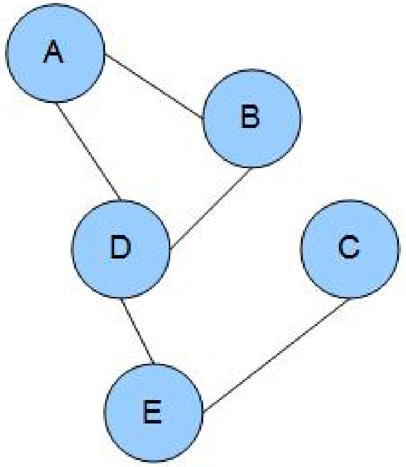


Methodology

Energy minimization method

Energy minimization for Markov Random Fields (MRF)

Labeling process with two labels:



$$G = \langle V, E \rangle$$

Minimize $E(x)$, where

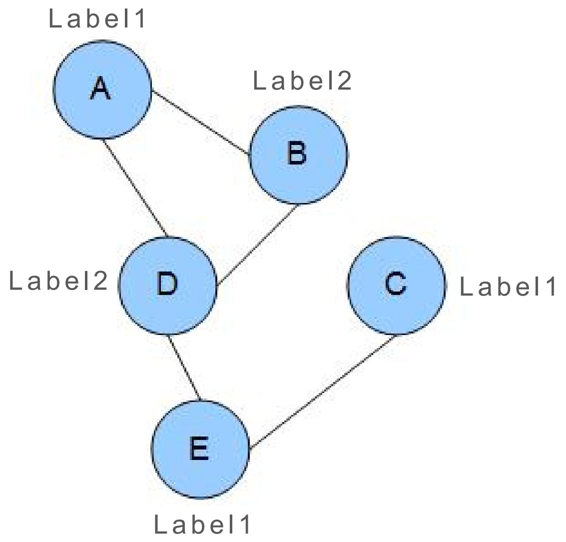
$$E(x) = D(x) + \lambda V(x)$$

Data term

$$D(x) = \sum_{i=1}^{n} D(x_i)$$

Pairwise term

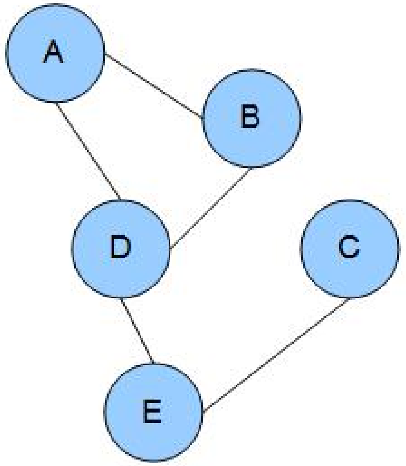
$$V(x) = \sum_{i=1}^{n-1} \sum_{j>i}^{n} V(x_i, x_j)$$



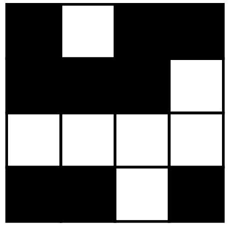
Methodology

Energy minimization method

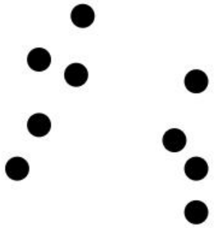
Energy minimization for Markov Random Fields (MRF)



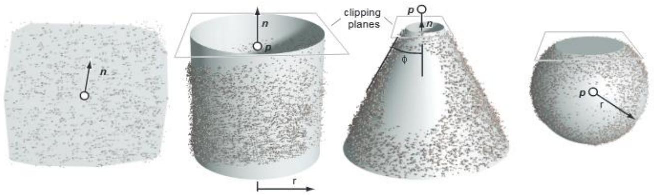
$$G = \langle V, E \rangle$$



Pixels



Points



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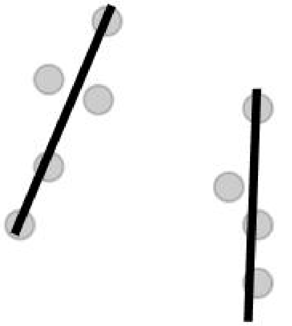
Geometric primitives

Methodology

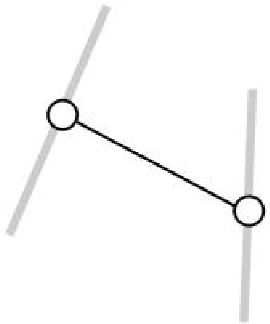
Energy minimization method

Energy minimization for Markov Random Fields (MRF)

Labeling process with two labels (preserved or removed):



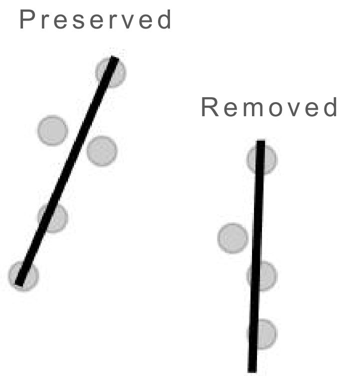
Nodes: wireframes



Edges: spatial relationship between wireframes

Minimize $E(x)$, where

$$E(x) = D(x) + \lambda V(x)$$

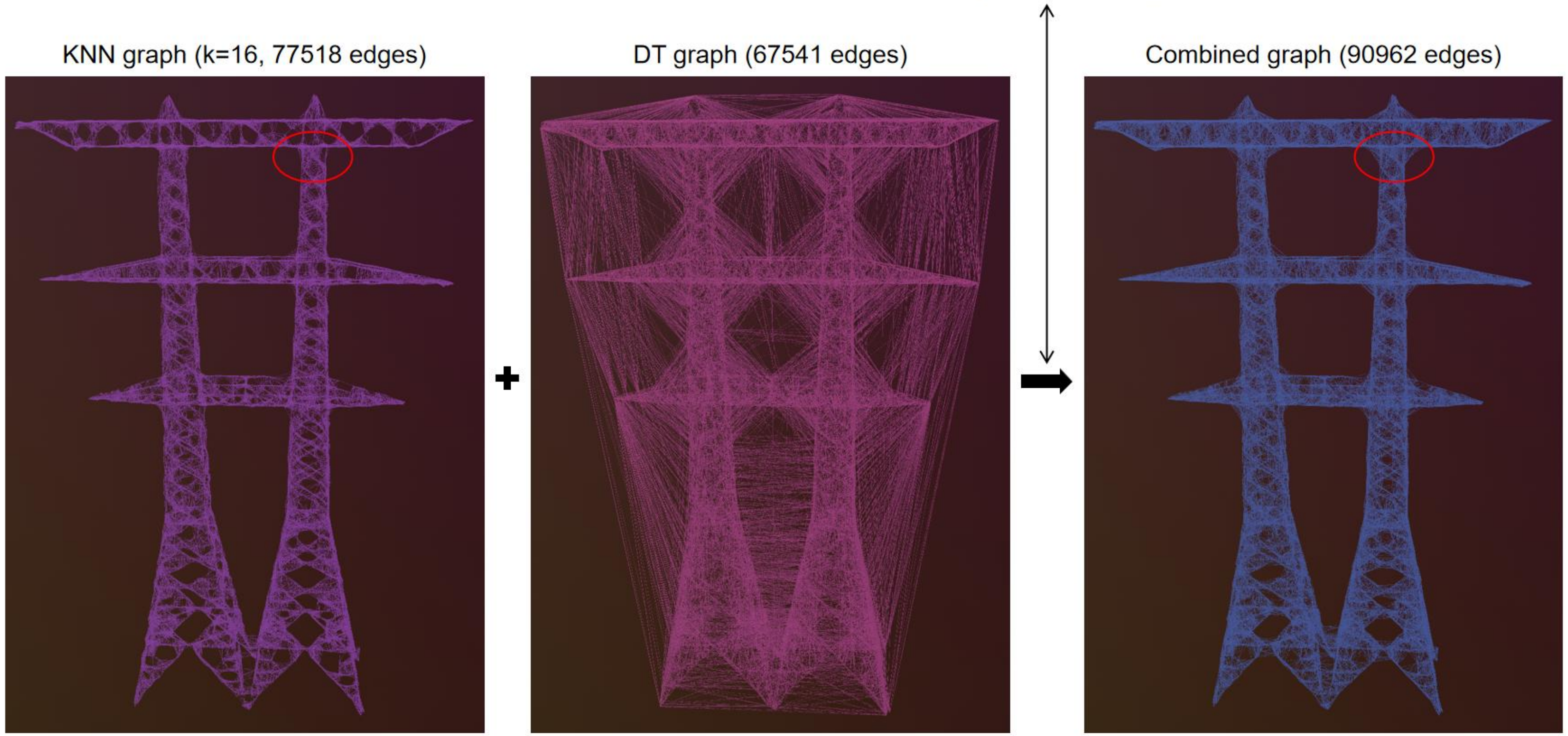


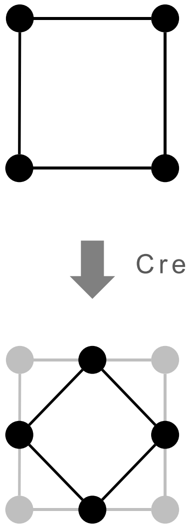
$$G = \langle V, E \rangle$$

Methodology

Energy minimization method

Energy minimization for Markov Random Fields (MRF)





Methodology

Energy minimization method

Energy minimization for Markov Random Fields (MRF)

Energy function

$$E(x) = D(x) + \lambda V(x)$$

Data term

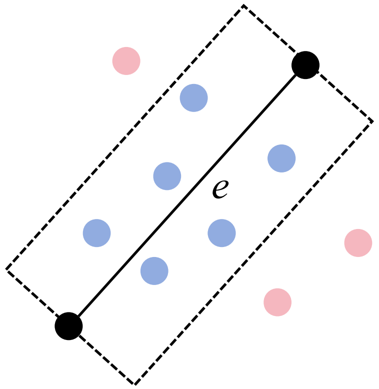
$$D(x) = I(x) \cdot L(x)$$

Pairwise term

$$V(x) = \sum_{i=1}^{n-1} \sum_{j>i}^{n} w(x_i, x_j) \cdot V(x_i, x_j)$$

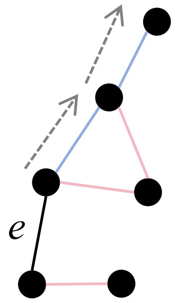
Inlier probability term

$$I(x) = \sum_{i=1}^{x_i} p(x_i)$$



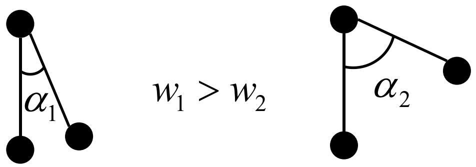
Edge length term

$$L(x) = \frac{L_e}{L_{tol}}$$



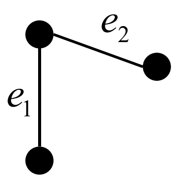
Weight function

$$w(x_i, x_j) = \sum_{i \neq j}^{x_i, x_j} (\cos^{10}(\alpha_{x_i, x_j})),$$



Label penalty function

$$V(x_i,\ x_j) = \begin{cases} 0 & l_{x_i} = l_{x_j} \\ 1 & l_{x_i} \neq l_{x_j} \end{cases},$$



$$l_{e_1} = l_{e_2} \rightarrow V(e_1, e_2) = 0,$$

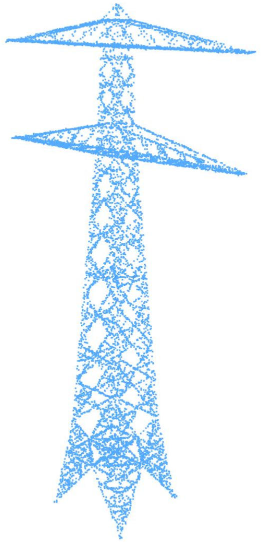
$$l_{e_1} \neq l_{e_2} \rightarrow V(e_1, e_2) = 1$$

Experiments

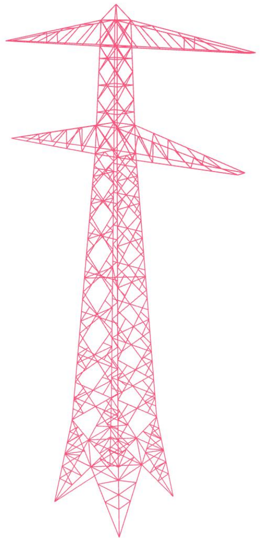
Experiments

Dataset creation

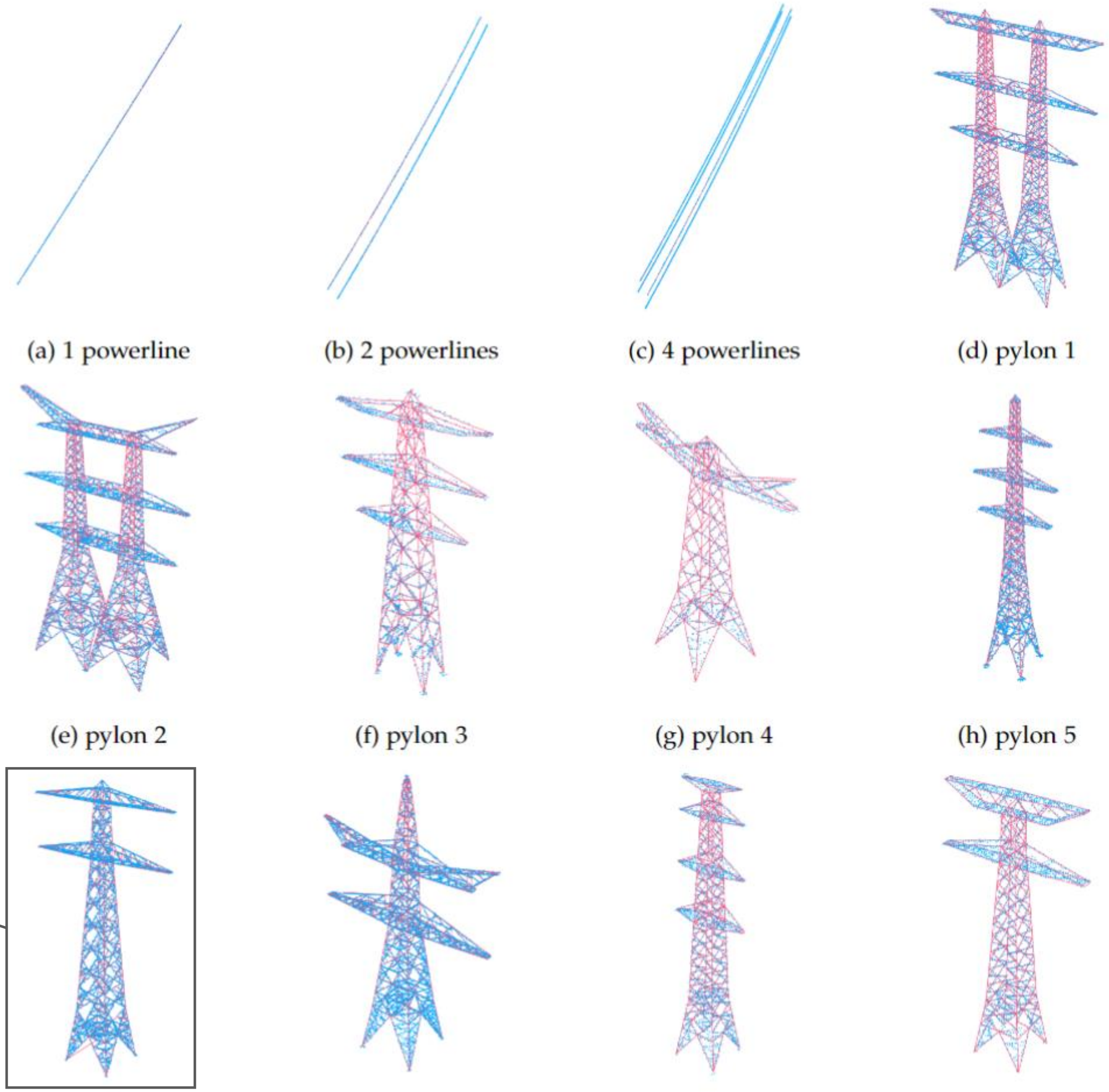
- 12 objects:
  - 3 powerlines
  - 9 pylons.
- Each object:
  - Point cloud from AHN5
  - Manually extracted wireframe model



Point cloud



Manually extracted wireframe model



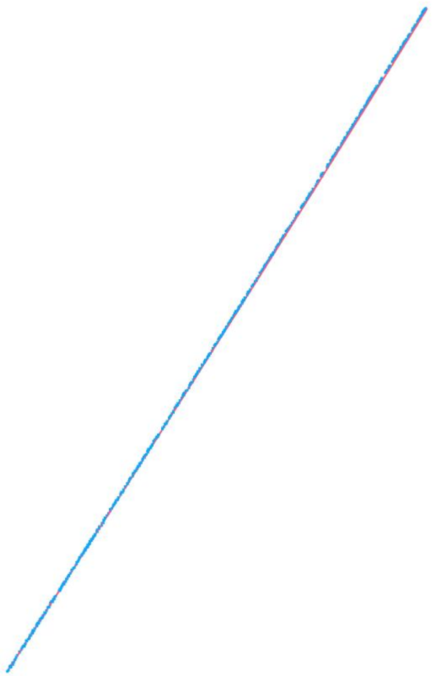
(a) 1 powerline (b) 2 powerlines (c) 4 powerlines (d) pylon 1

(e) pylon 2 (f) pylon 3 (g) pylon 4 (h) pylon 5

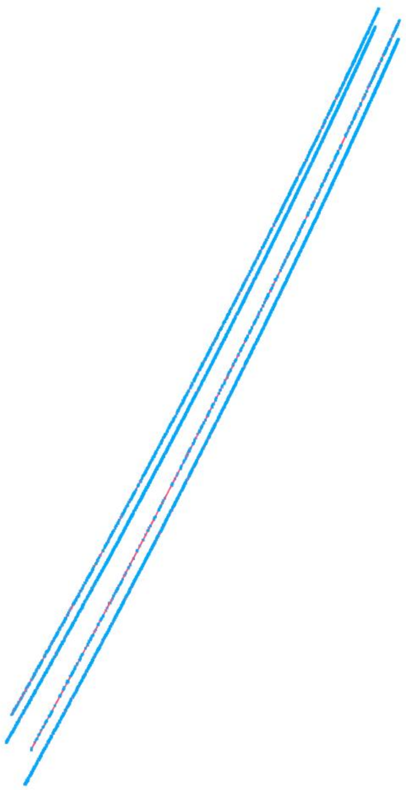
(i) pylon 6 (j) pylon 7 (k) pylon 8 (l) pylon 9

Experiments

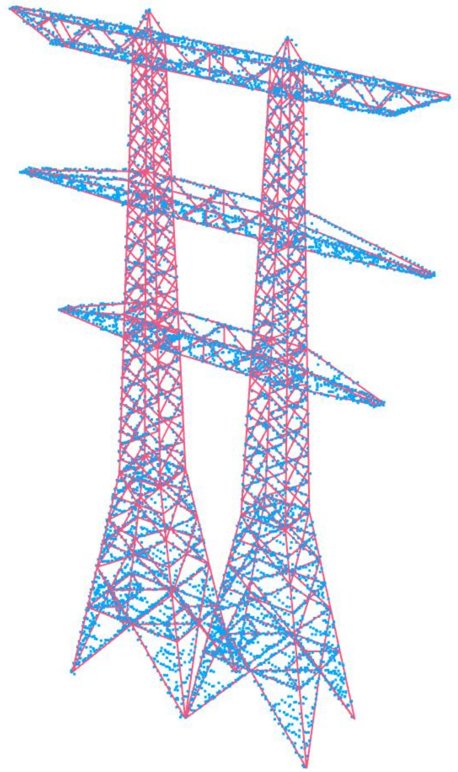
Test cases



Simple case: 1 powerline



Medium case: 4 powerlines

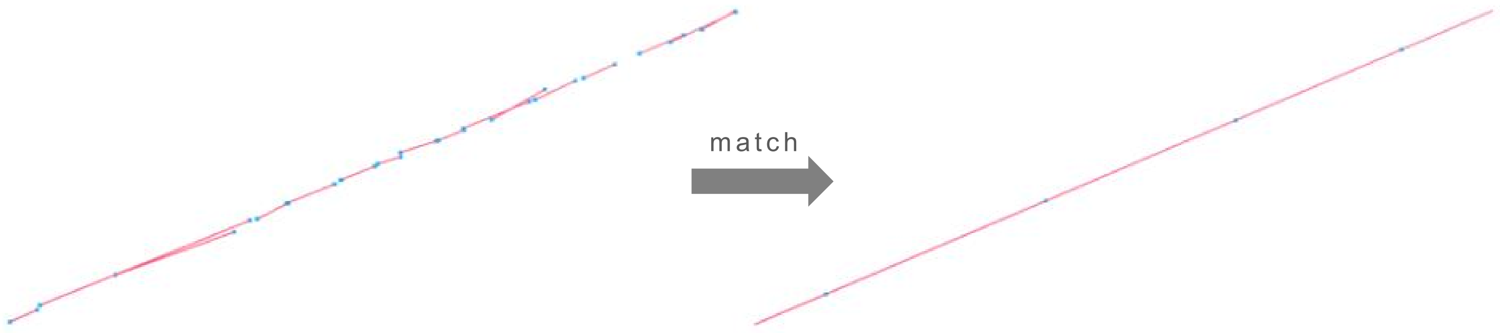


Difficult case: pylon 1

Experiments

Analysis method

For each ground truth 3D line segment and extracted 3D line segments:



(a) Extracted wireframe model

(b) Ground truth wireframe model

For all extracted 3D line segments:

$$\text{Unmatched rate} = \frac{M_{unmatched}}{M_{total}}$$

For each matched group:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}$$

Experiments

3D RANSAC results

Point cloud	Input points	Leftover points	Leftover rate (%)
1 powerline	538	79	14.7
4 powerlines	6439	624	9.7
pylon 1	8947	3774	42.2

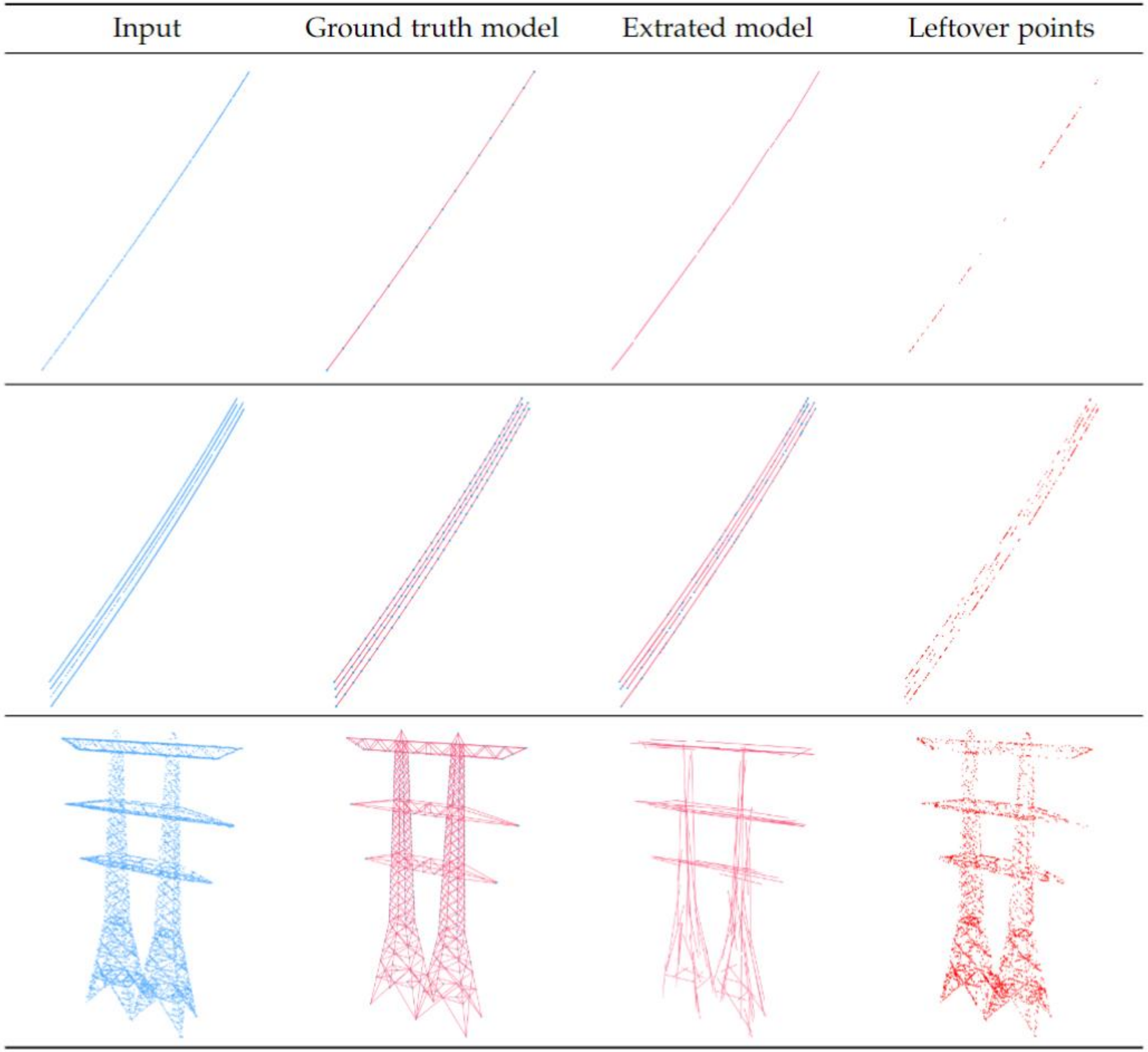
Leftover rate

Point cloud	M_{total}	$M_{unmatched}$	Unmatched rate (%)
1 powerline	22	4	18.2
4 powerlines	62	16	25.8
pylon 1	97	35	36.1

Unmatched rate

Point cloud	Min	Max	Mean	Median	Std dev.	RMSE
1 powerline	0.325	2.238	1.106	0.991	0.707	1.313
4 powerlines	0.091	3.496	1.000	0.914	0.605	1.169
pylon 1	1.443	89.679	55.368	55.072	29.105	62.551

Angle deviation analysis



Experiments

3D-2D RANSAC results

Point cloud	Input points	Leftover points	Leftover rate (%)
1 powerline	538	9/125/134	24.9
4 powerlines	6439	18/1297/1315	20.4
pylon 1	8947	27/1172/1199	13.4

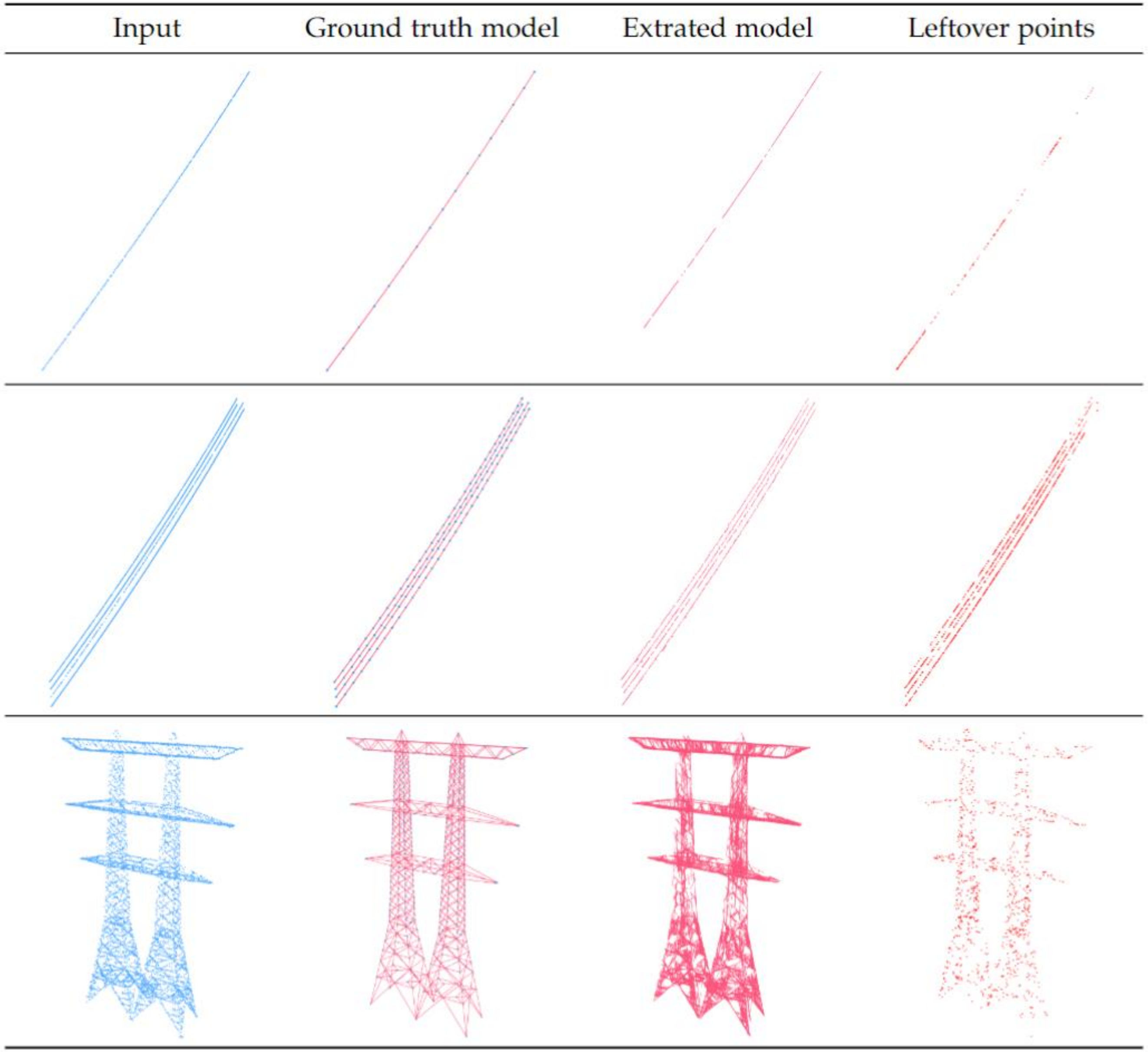
Leftover rate (for leftover points: 3D plane detection / 2D line detection / overall leftover)

Point cloud	M_{total}	$M_{unmatched}$	Unmatched rate (%)
1 powerline	30714	643	2.1
4 powerlines	60947	28933	47.5
pylon 1	31228	7030	22.5

Unmatched rate

Point cloud	Min	Max	Mean	Median	Std dev.	RMSE
1 powerline	0.167	1.874	0.777	0.547	0.494	0.921
4 powerlines	0.113	4.808	1.383	1.253	0.747	1.571
pylon 1	0.346	89.987	51.514	51.668	20.994	55.628

Angle deviation analysis



Experiments

Region growing results

Point cloud	Input points	Leftover points	Leftover rate (%)
1 powerline	538	6	1.1
4 powerlines	6439	205	3.2
pylon 1	8947	179	2.0

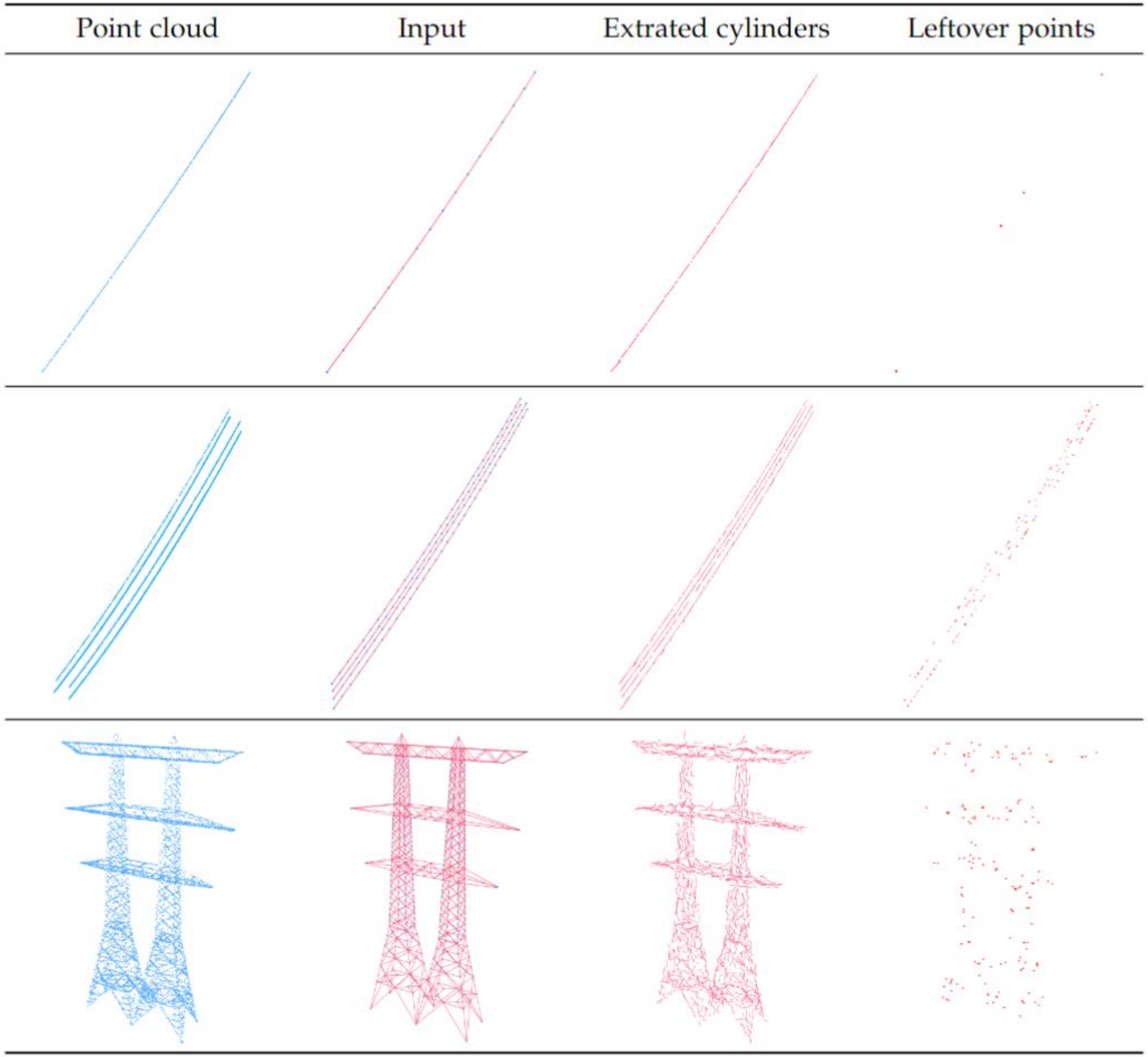
Leftover rate

Point cloud	M_{total}	$M_{unmatched}$	Unmatched rate (%)
1 powerline	81	28	34.6
4 powerlines	1040	520	50.0
pylon 1	1443	1018	70.5

Unmatched rate

Point cloud	Min	Max	Mean	Median	Std dev.	RMSE
1 powerline	0.876	3.955	2.645	2.956	0.983	2.822
4 powerlines	0.310	31.696	7.132	6.250	5.216	8.835
pylon 1	0.984	89.969	52.282	51.756	23.459	57.304

Angle deviation analysis



Experiments

Hough transform results

Point cloud	Input points	Leftover points	Leftover rate (%)
1 powerline	538	16	3.0
4 powerlines	6439	63	1.0
pylon 1	8947	2077	23.2

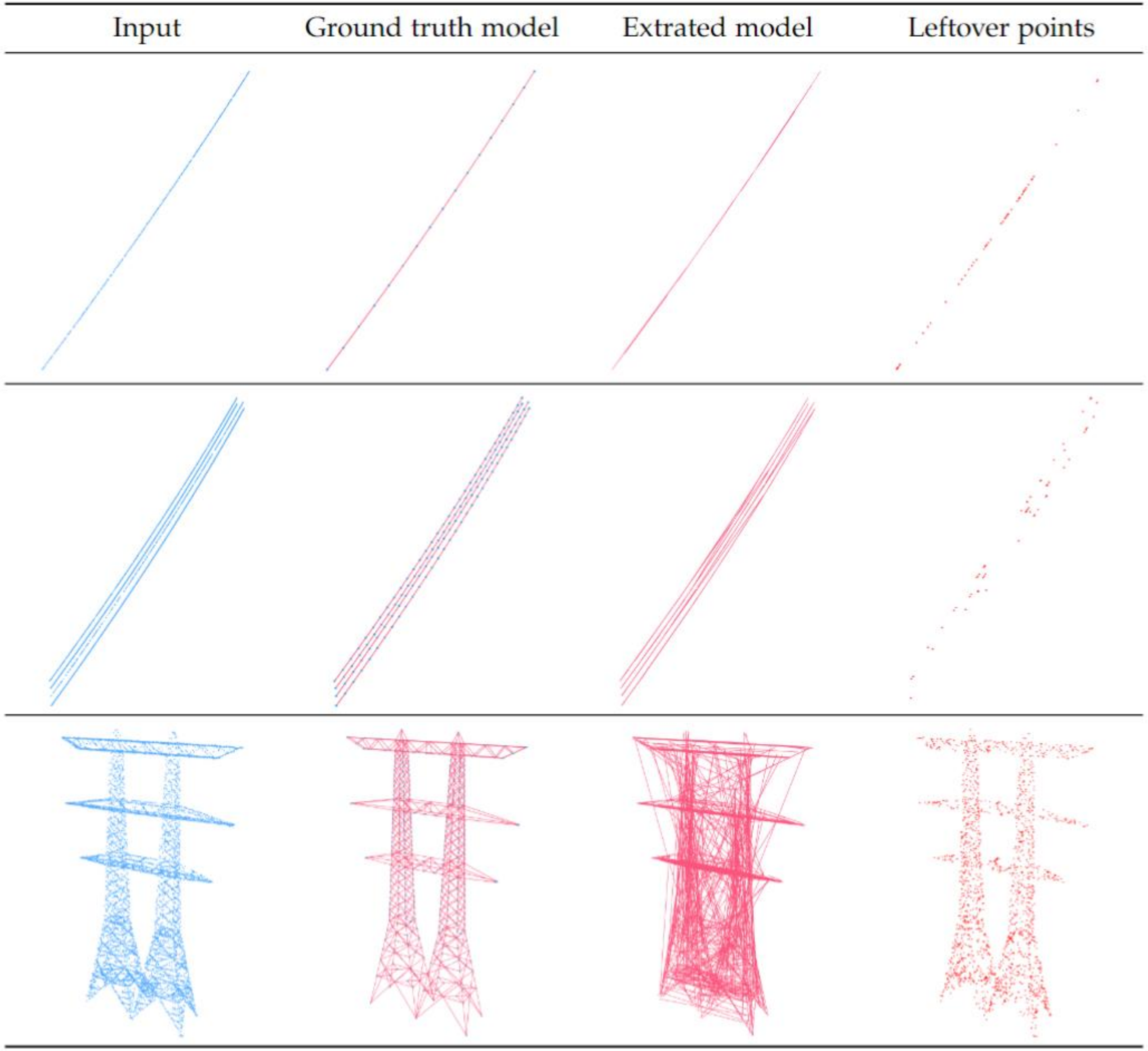
Preserved rate

Point cloud	M_{total}	$M_{unmatched}$	Unmatched rate (%)
1 powerline	52	4	7.7
4 powerlines	68	27	39.7
pylon 1	649	64	9.9

Unmatched rate

Point cloud	Min	Max	Mean	Median	Std dev.	RMSE
1 powerline	0.454	5.586	1.218	0.587	1.655	2.055
4 powerlines	0.156	1.005	1.005	0.953	0.462	1.106
pylon 1	0.634	56.236	56.236	58.041	24.203	61.223

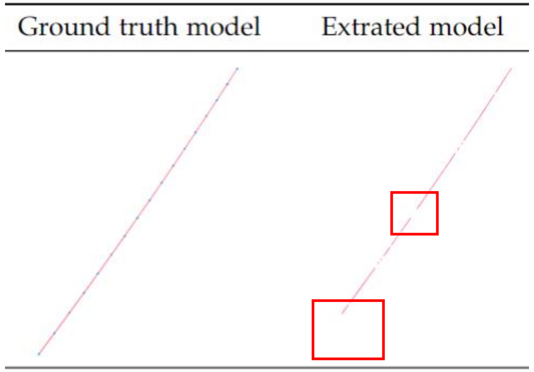
Angle deviation analysis



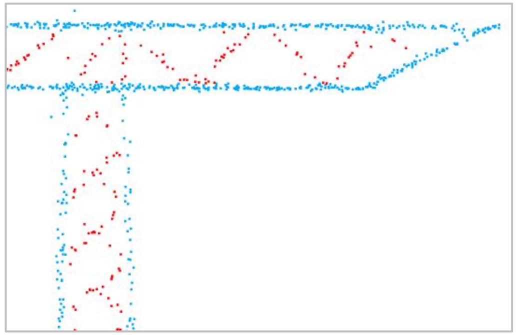
Experiments

Main problems for primitive detection algorithms

Overlooking problem



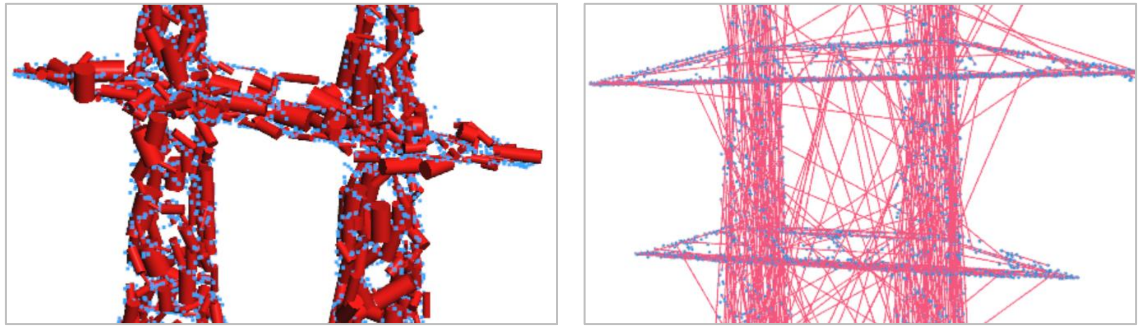
Simple case result of 3D-2D RANSAC



Internal structure (red) and external structure (blue) of a pylon

- More severe on model fitting-based methods
  - 3D RANSAC, 3D-2D RANSAC, Hough transform.
- Due to the scoring mechanism of the model fitting process
  - Score dominated by the number of inlier points.

Wrong fitting problem



Wrong fitting primitives of Region growing (left) and Hough transform (right)

- More severe on difficult test case
  - Normal estimation (3D RANSAC, Region growing)
    - it is hard to estimate accurate normals for complex objects.
  - Validation mechanism of model fitting process (3D-2D RANSAC, Hough transform)
    - Validation is also dominated by the number of inlier points.

Experiments

MRF results

Point cloud	Input edges	Preserved edges	Preserved rate (%)
1 powerline	2842	2757	97.0
4 powerlines	38474	35497	92.3
pylon 1	69172	51355	74.3

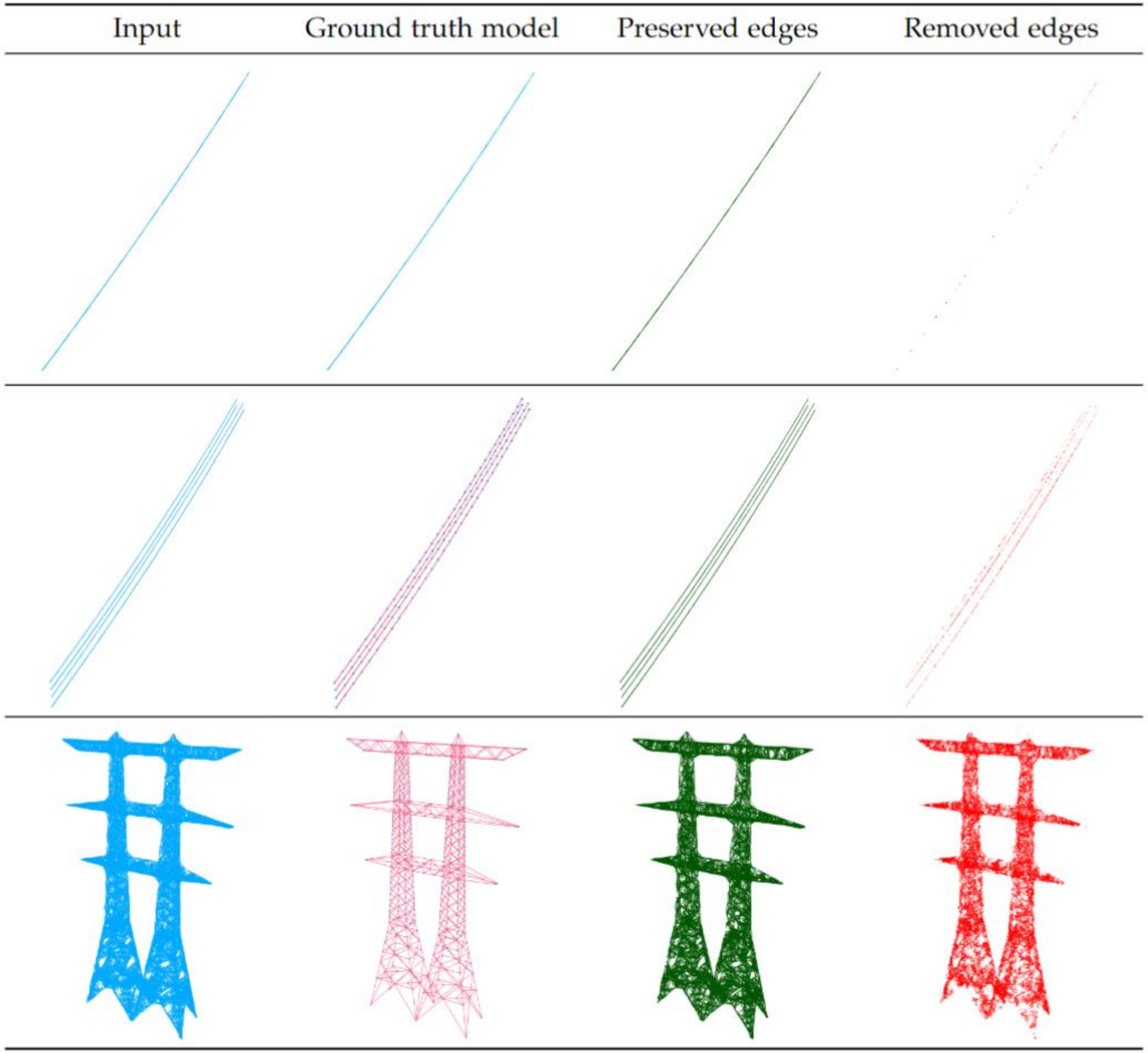
Preserved rate

Point cloud	M_{total}	$M_{unmatched}$	Unmatched rate (%)
1 powerline	2757	390	14.1
4 powerlines	35497	17921	50.5
pylon 1	51355	21560	42.0

Unmatched rate

Point cloud	Min	Max	Mean	Median	Std dev.	RMSE
1 powerline	7.252	11.405	9.214	9.347	1.044	9.273
4 powerlines	3.226	29.511	17.207	17.040	6.320	18.331
pylon 1	25.025	81.435	49.413	48.836	9.472	50.313

Angle deviation analysis



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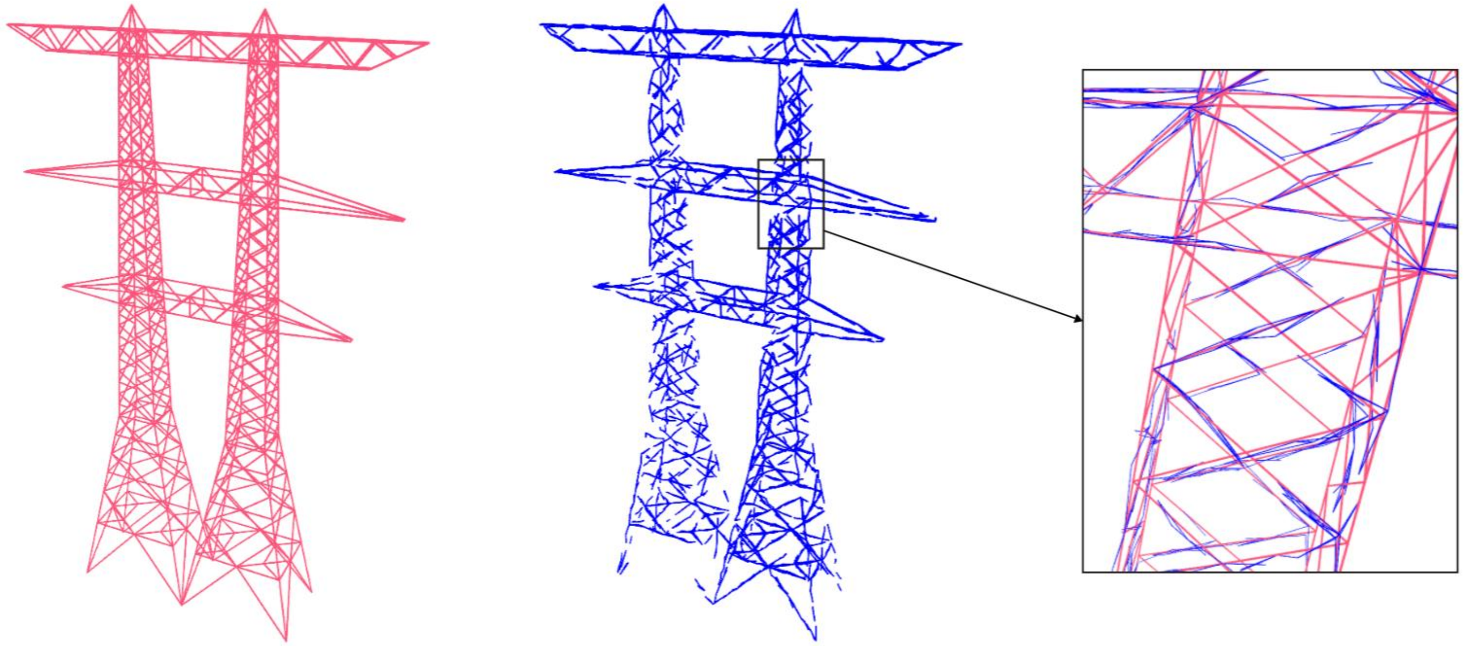
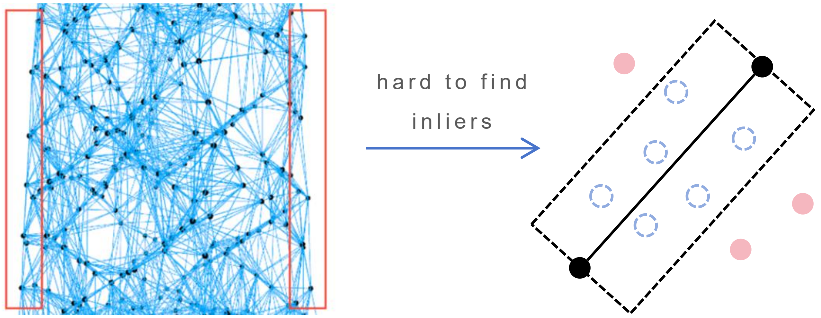


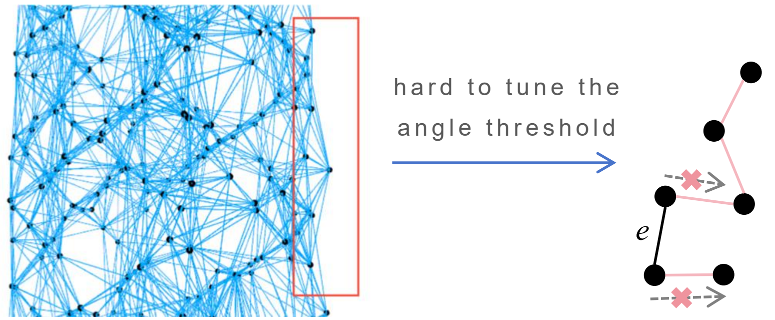
Experiments

Problem of the MRF algorithm

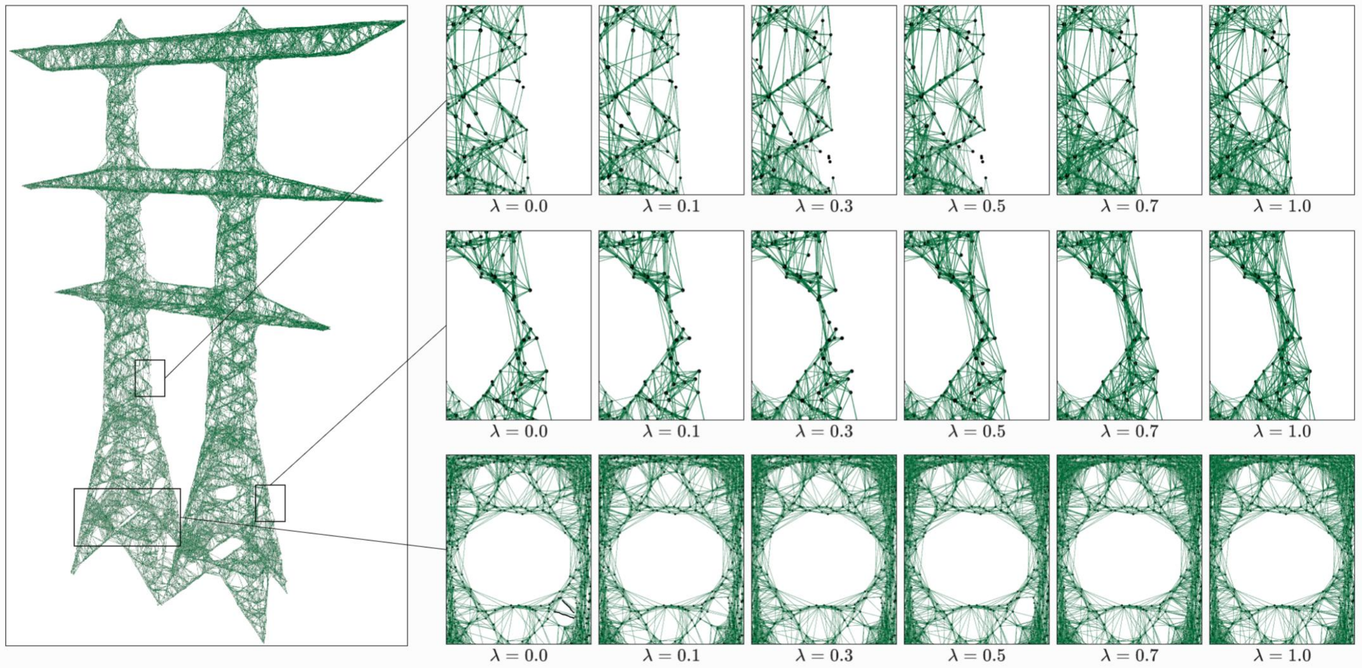
Inlier probability term



Edge length term



Weight tuning for pairwire term



Conclusions

Conclusions

The answer of the research questions

Is it possible to extract wireframe models from point clouds of man-made urban linear objects with an algorithm that has generalization ability?

- **Partially yes.**

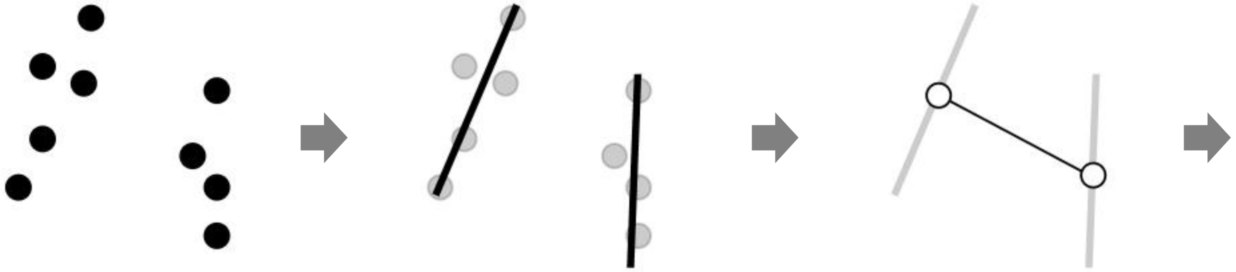
Is there any algorithm that gives or has the potential to give promising extraction results of the wireframe models of man-made urban linear objects?

- **No promising results yet, but the potential exists.**

Conclusions

Future work

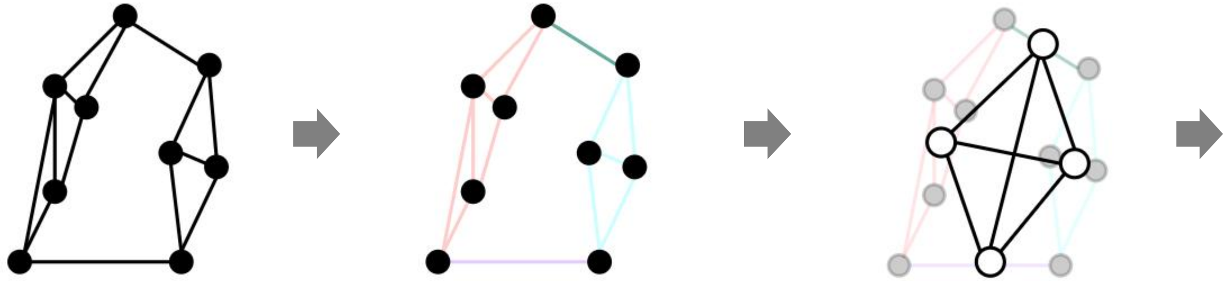
Integration of Primitive detection method with Energy minimization



$$E(x) = D(x) + \lambda V(x)$$

Point cloud — Primitive detection — Graph — Energy minimization

Graph-based Region growing with Energy minimization



$$E(x) = D(x) + \lambda V(x)$$

Graph — Region growing — New graph — Energy minimization

Thank you

References

1. Biljecki, F., Stoter, J., Ledoux, H., Zlatanova, S., & Çöltekin, A. (2015). Applications of 3D City Models: State of the Art Review. ISPRS International Journal of Geo-Information, 4(4), Article 4. https://doi.org/10.3390/ijgi4042842

2. Jin, Y.-H. and Lee, W.-H. (2019). Fast Cylinder Shape Matching Using Random Sample Consensus in Large Scale Point Cloud. Applied Sciences, 9(5):974.

3. Guo, B., Li, Q., Huang, X., and Wang, C. (2016). An Improved Method for Power-Line Reconstruction from Point Cloud Data. Remote Sensing, 8(1):36.