



Omek Consortium



Technion - IIT

Point Cloud Registration Using A Viewpoint Dictionary

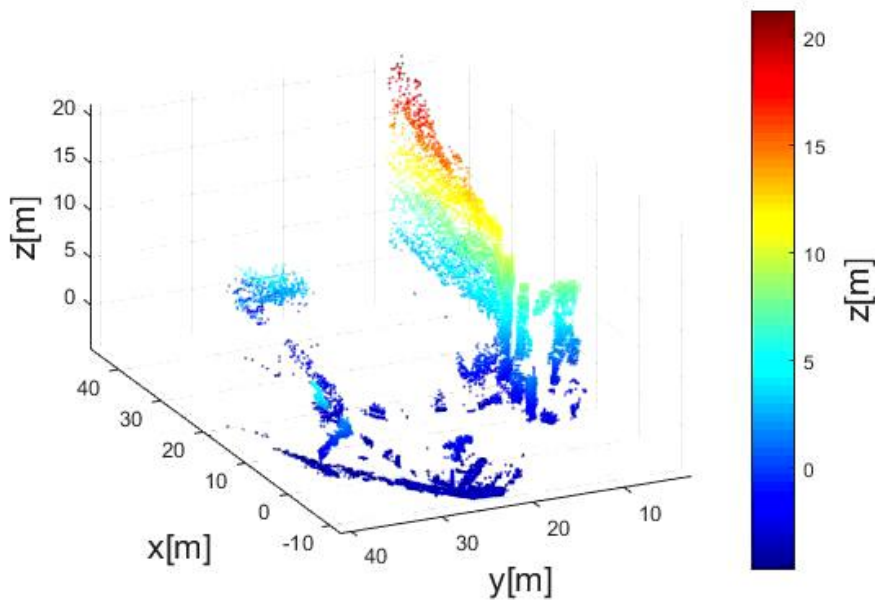
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Andrew and Erna Viterbi Faculty of Electrical
Engineering

Technion, Haifa, Israel

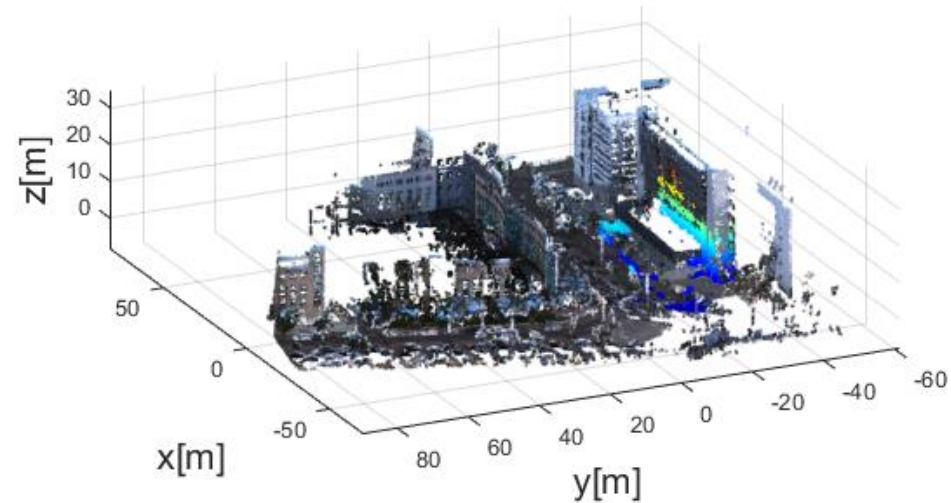
Goal

- Registration between a **global large-scale** point cloud and a **local** point cloud



Local cloud

(stereo reconstruction)
sporadic coverage, limited
field-of-view

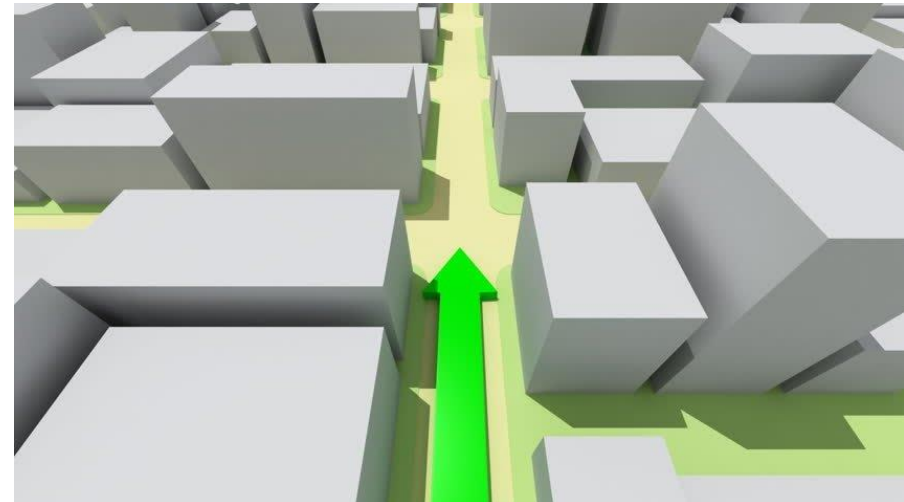


(terrestrial LiDAR)

dense coverage, multiple
viewpoints

Motivation

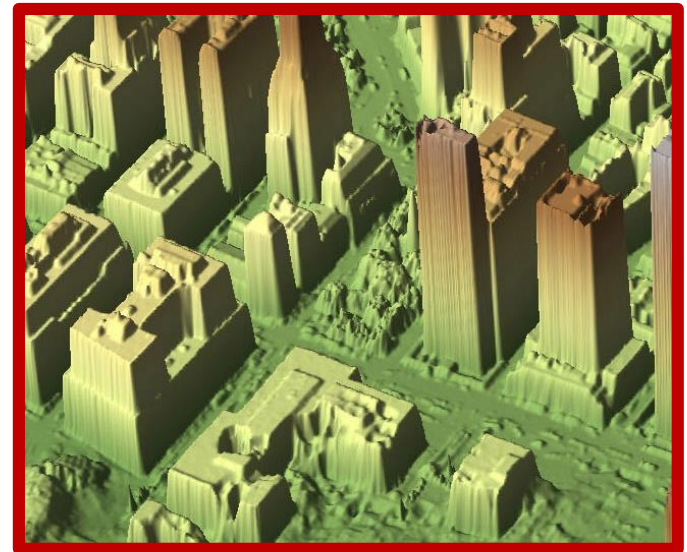
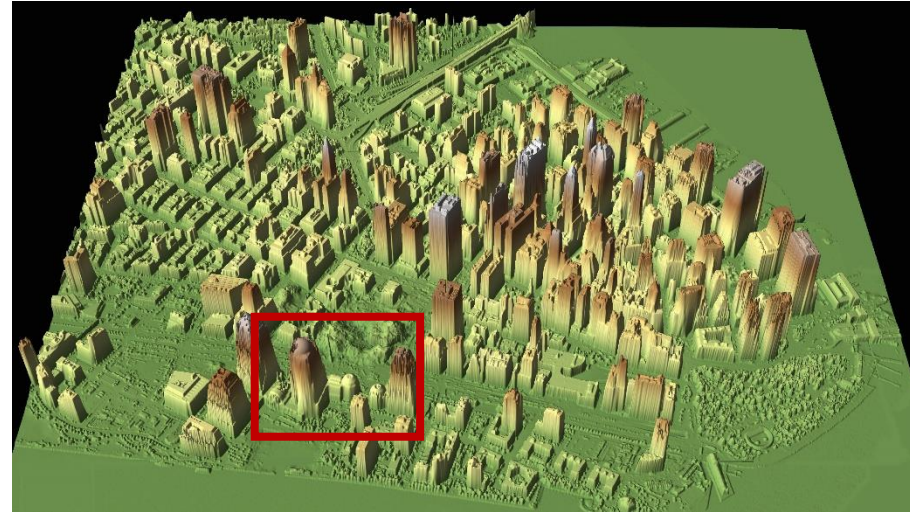
- Applications:
 - Accurate localization in large-scale environments (with better reliability than consumer-grade GPS)



Motivation

- Applications:
 - Accurate localization in large-scale environments (with better reliability than consumer-grade GPS)
 - Multi-platform 3D environment modeling - registration between:
 - airborne and terrestrial LiDAR clouds
 - Structure from Motion (SfM) and LiDAR clouds
 - etc.

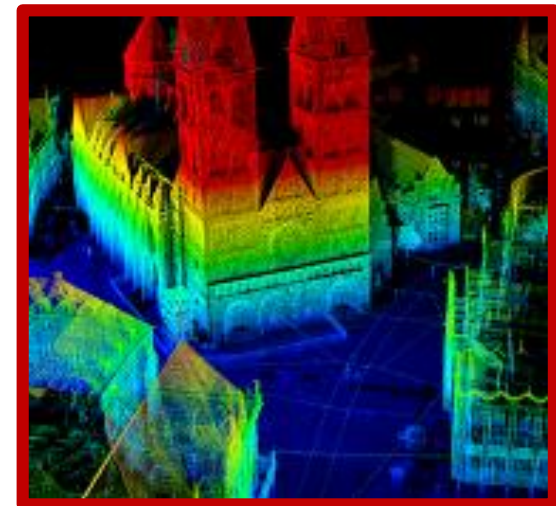
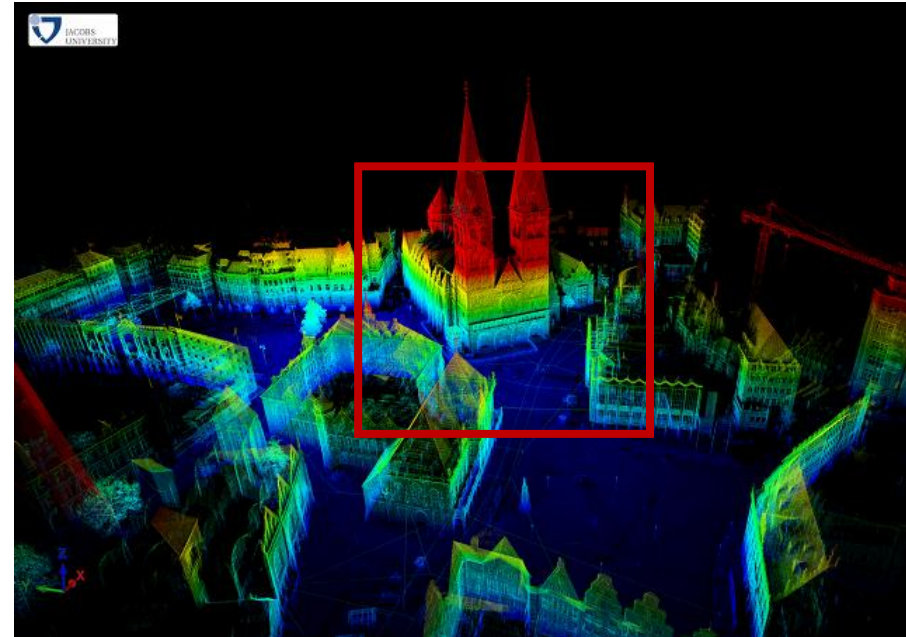
Airborne LiDAR



Motivation

- Applications:
 - Accurate localization in large-scale environments (with better reliability than consumer-grade GPS)
 - Multi-platform 3D environment modeling - registration between:
 - airborne and terrestrial LiDAR clouds
 - Structure from Motion (SfM) and LiDAR clouds
 - etc.

Terrestrial LiDAR

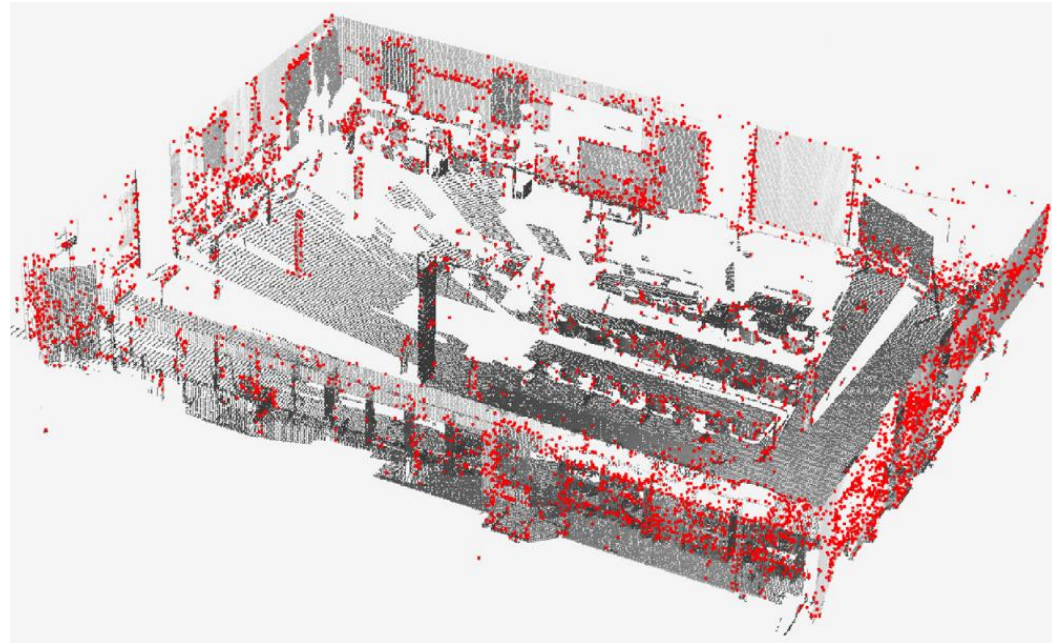


Outline

- Introduction
- Keypoint-based point cloud registration
- Point cloud registration using a **viewpoint dictionary**
- Conclusion

Keypoint-based point cloud registration

- Main steps:
 1. Keypoint detection
 - Surface variation (Pauly et al., 2002)
 - 3D SIFT (Rusu et al., 2011)



3D SIFT keypoint detection
(PCL, Rusu et al., 2011)

Keypoint-based point cloud registration

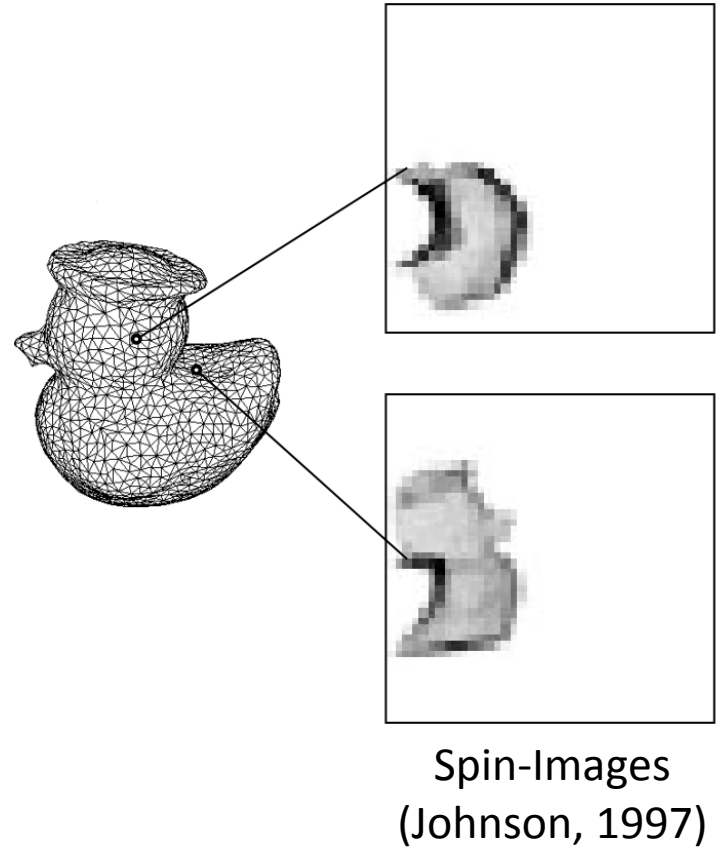
- Main steps:

1. Keypoint detection

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- 3D SIFT (Rusu et al., 2011)

2. 3D Descriptor computation

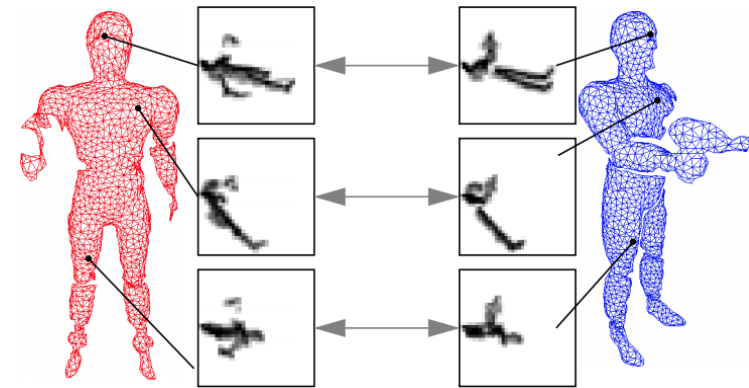
- Spin-Images (Johnson, 1997)
- Fast Point Feature Histogram - FPFH (Rusu et al., 2009)



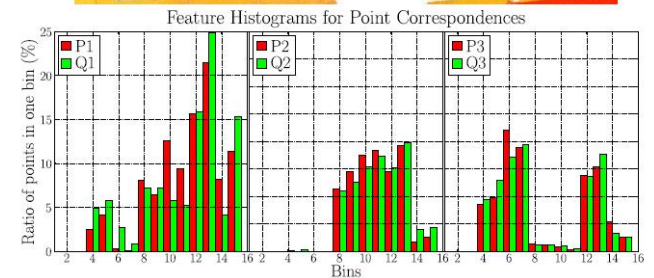
Keypoint-based point cloud registration

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3. Finding keypoint correspondences



Johnson, 1997

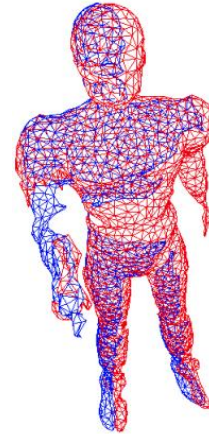


Rusu et al., 2009

Keypoint-based point cloud registration

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4. Coarse registration (e.g., using some variation of RANdom SAmple Consensus - RANSAC)



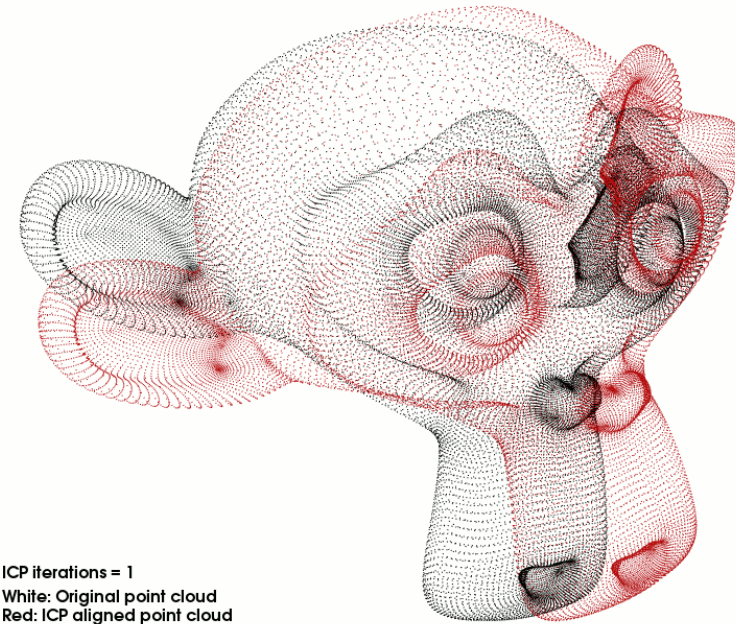
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Keypoint-based point cloud registration

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 5. Registration refinement - some variation of ICP - Iterative Closest Point (Besl and McKay, 1992)

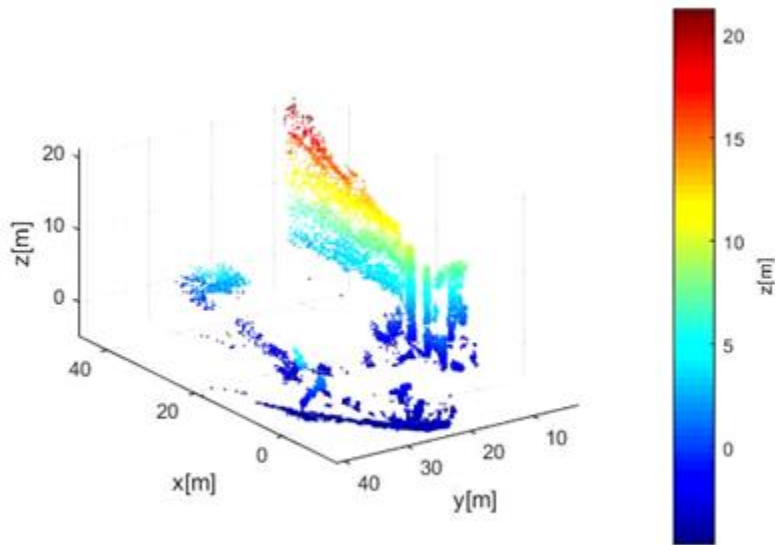


Source: pointclouds.org

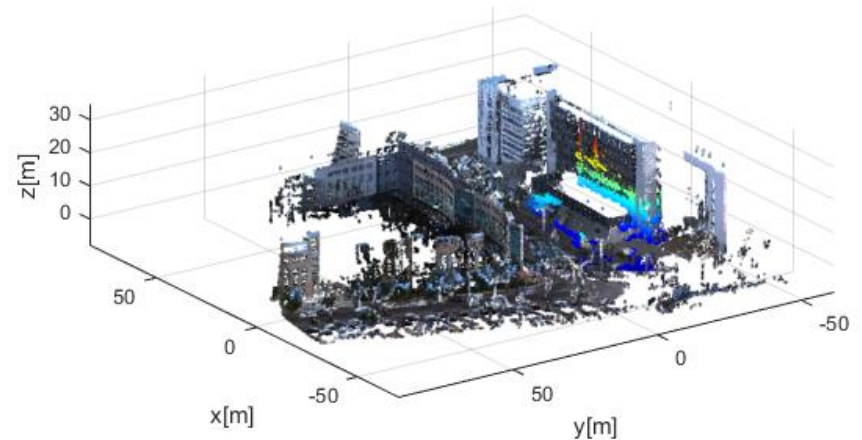
Limitations of using keypoints

- Keypoint-based methods **do not perform well** when point clouds are **significantly different**

	Stereo (data)	LiDAR/SfM (model)
Scene coverage	sporadic	full
Noise level	high	low
Density	low	high



Stereo (local cloud)

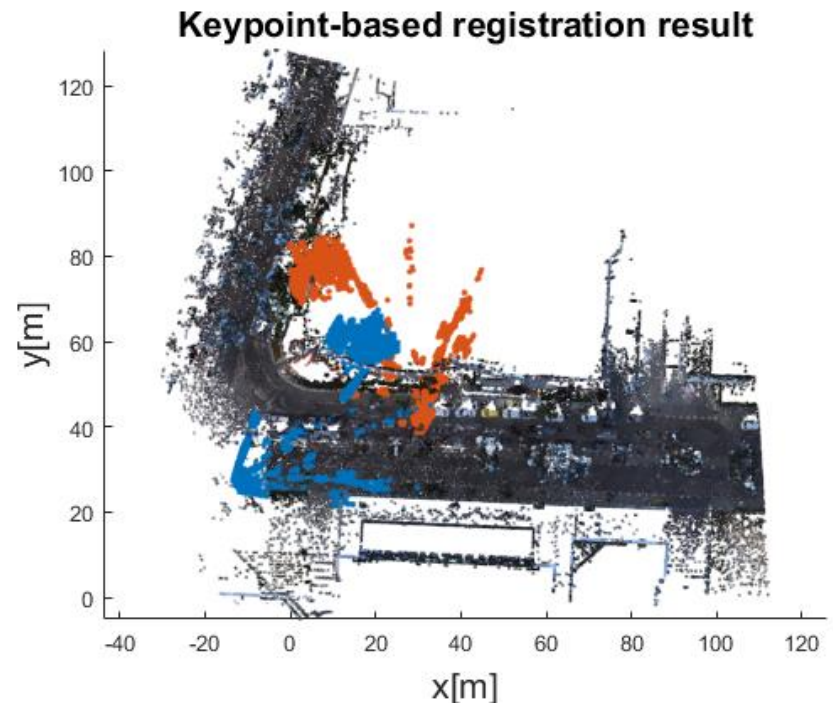


LiDAR (global cloud)

Limitations of using keypoints

- Keypoint-based methods **do not perform well** when point clouds are **significantly different**
- Main difficulties:
 - Less repeatable keypoint detection
 - Fewer reliable correspondences
 - Unstable performance
 - Ground truth
 - Keypoint-based registration result

	Stereo (data)	LiDAR/SfM (model)
Scene coverage	sporadic	full
Noise level	high	low
Density	low	high



Outline

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- Point cloud registration using a **viewpoint dictionary**
- Conclusion



Proposed method: Point cloud registration using a viewpoint dictionary

- Main concepts:

- Large-scale global cloud →

Dictionary of viewpoint-based smaller clouds

- Local to global cloud registration →

Dictionary search

- Advantages:

- Robust to point cloud noise

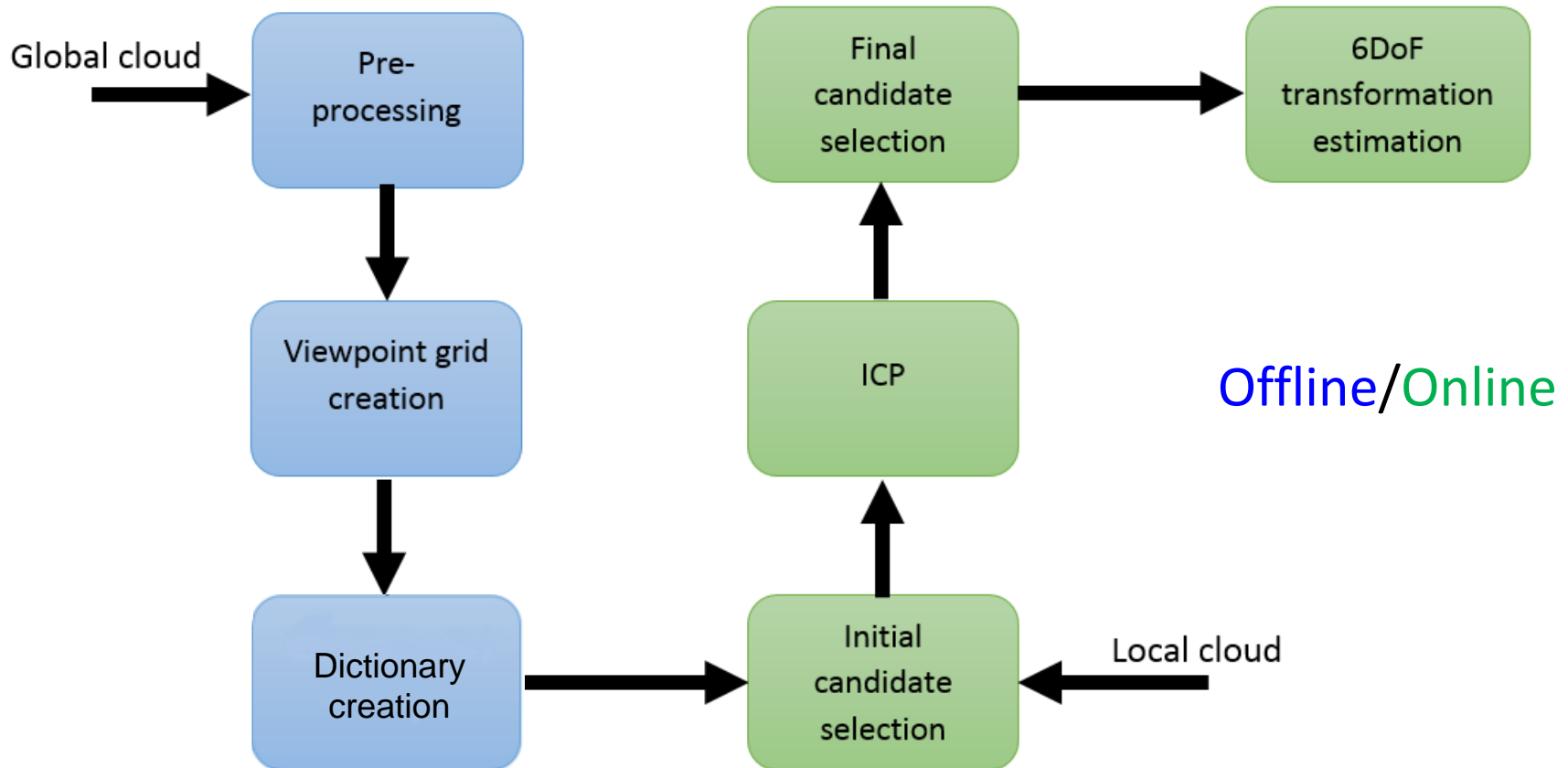
- Can handle sporadic local clouds (e.g., stereo)

- Challenges:

- Keep the dictionary compact

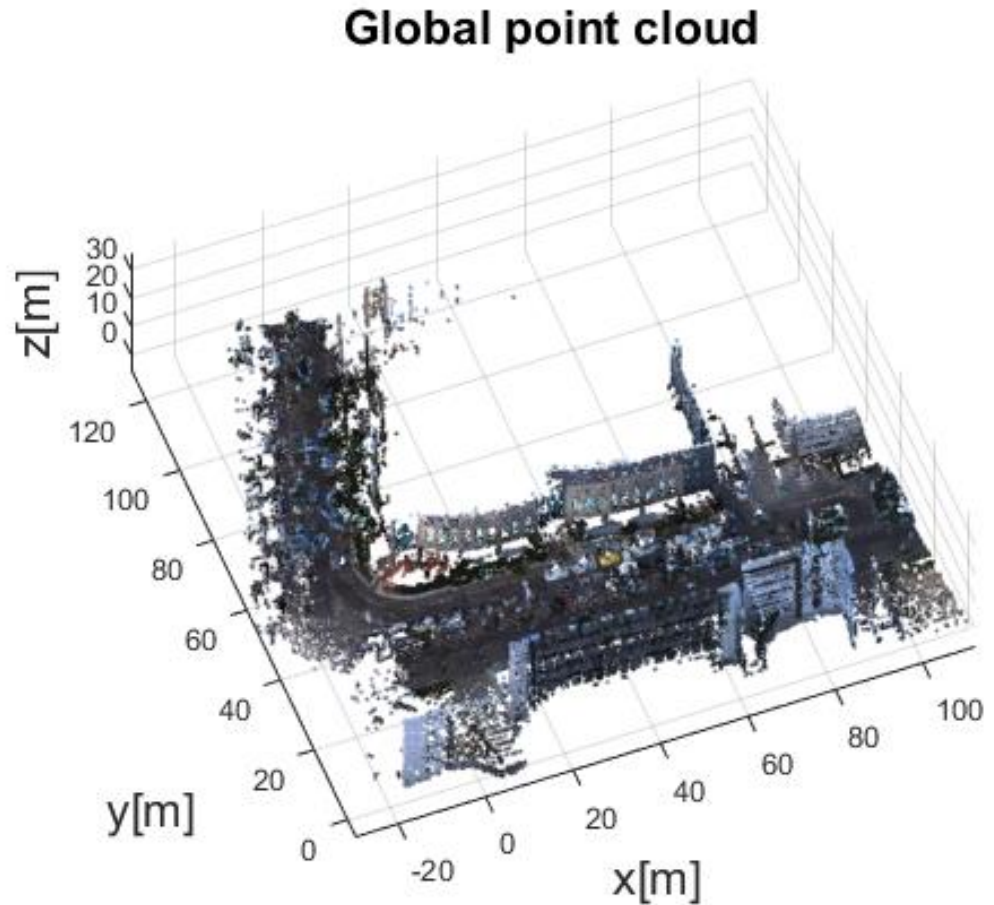
- Perform dictionary search efficiently

Point cloud registration using a viewpoint dictionary - overview



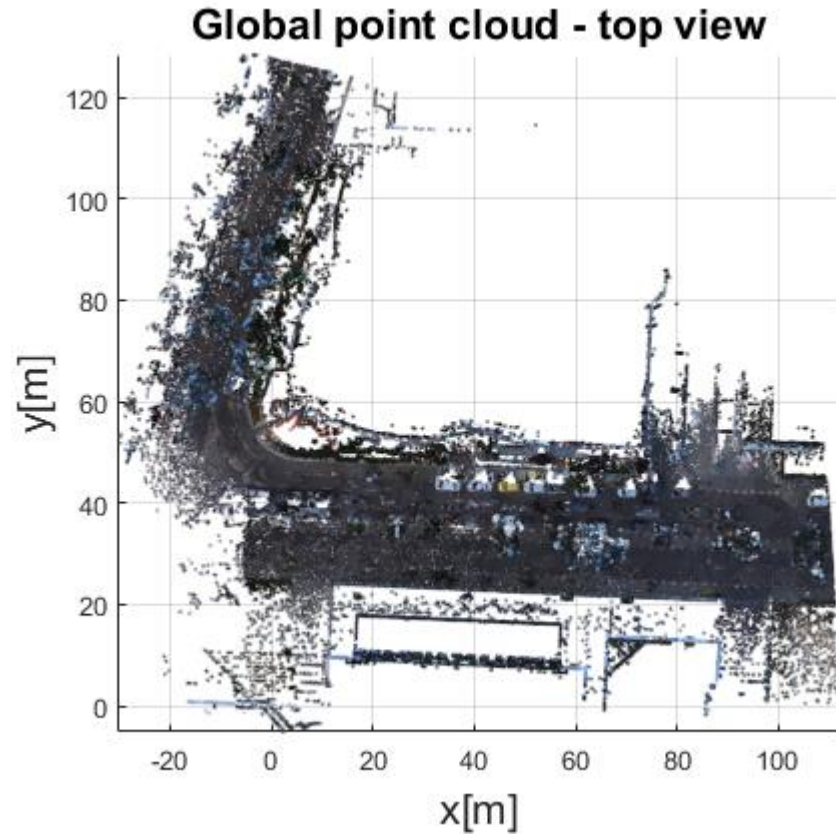
Main steps:

1. Create a grid of synthetic viewpoints



Main steps:

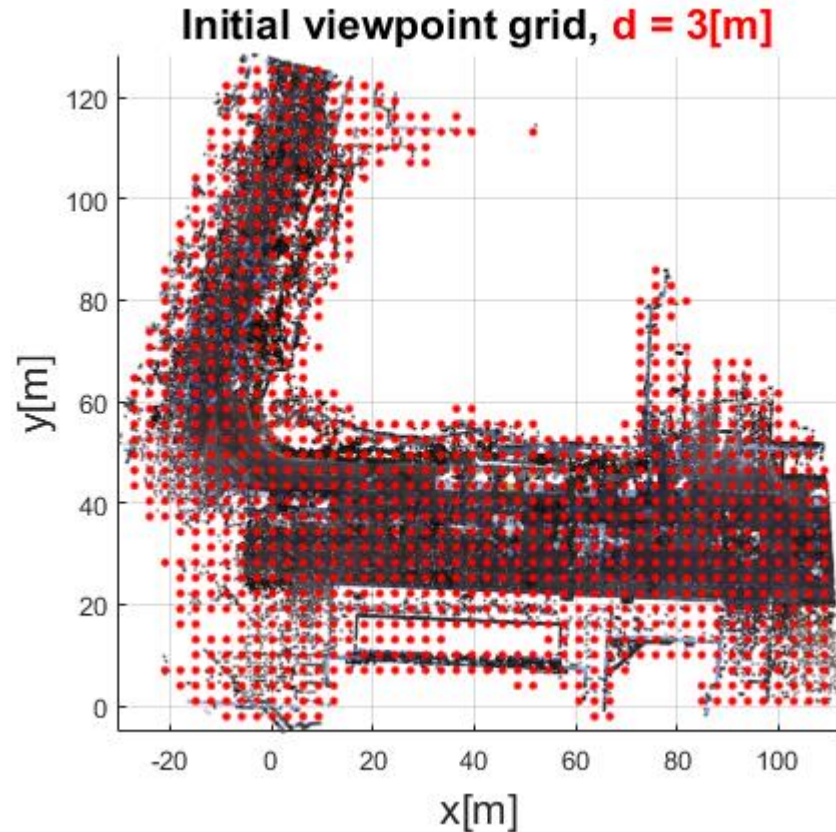
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Main steps:

1. Create a grid of synthetic viewpoints

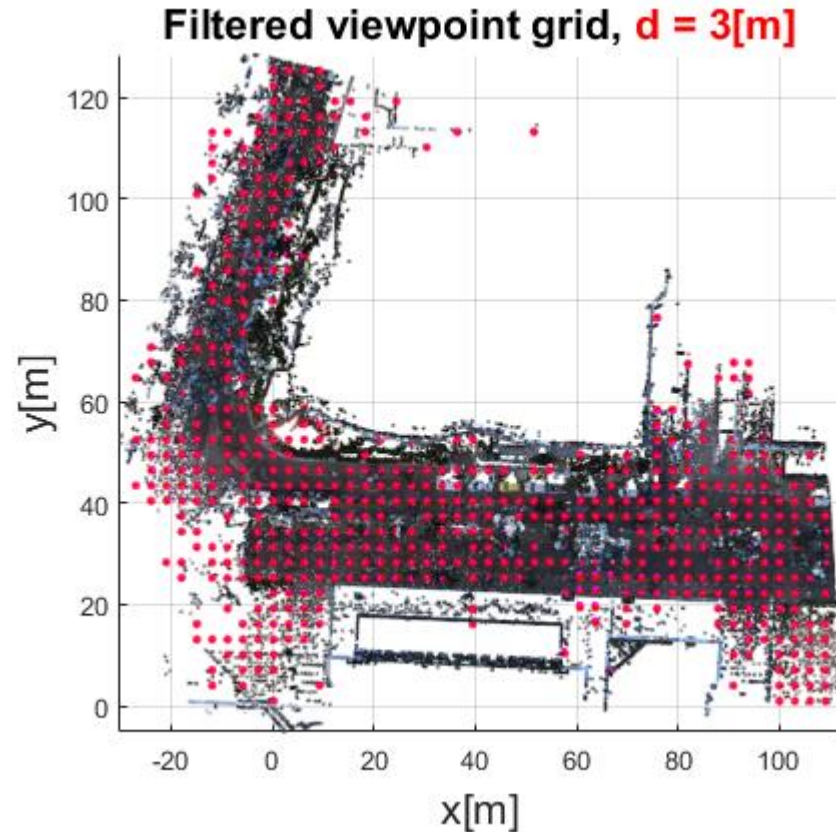
- Initial grid is regular in the x, y plane
- Viewpoints are set at a constant height above ground



Main steps:

1. Create a grid of synthetic viewpoints

- Initial grid is regular in the x, y plane
- Viewpoints are set at a constant height above ground
- Possible viewpoint restrictions:
 - Avoid viewpoints on rooftops
 - Filter out viewpoints in vegetation

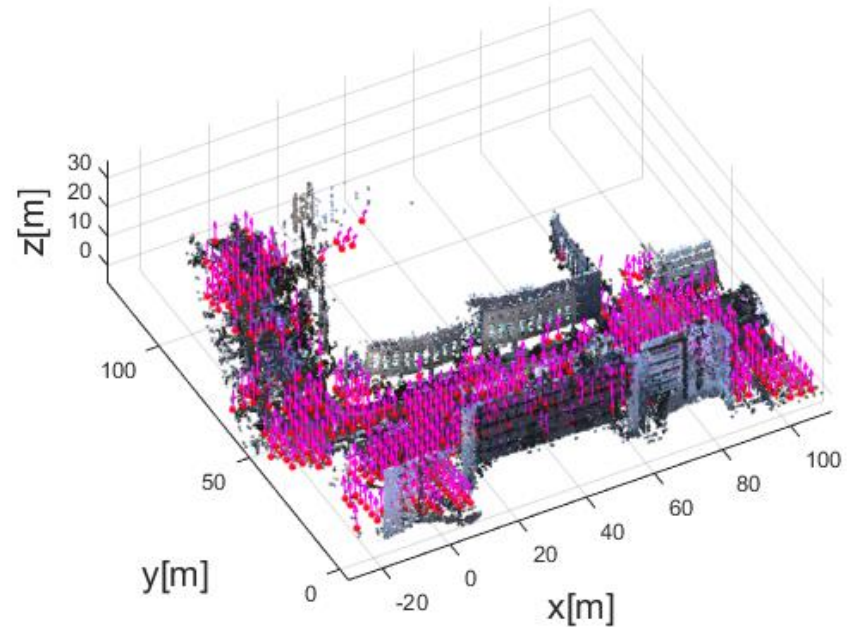


Main steps:

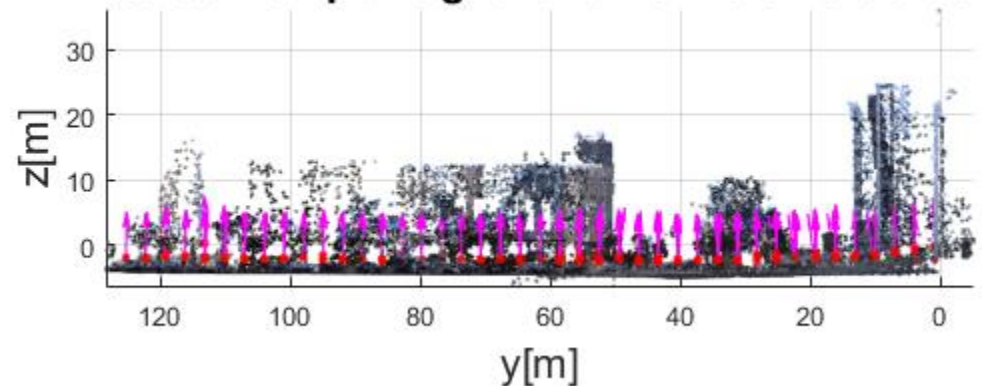
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Filtered viewpoint grid and normals



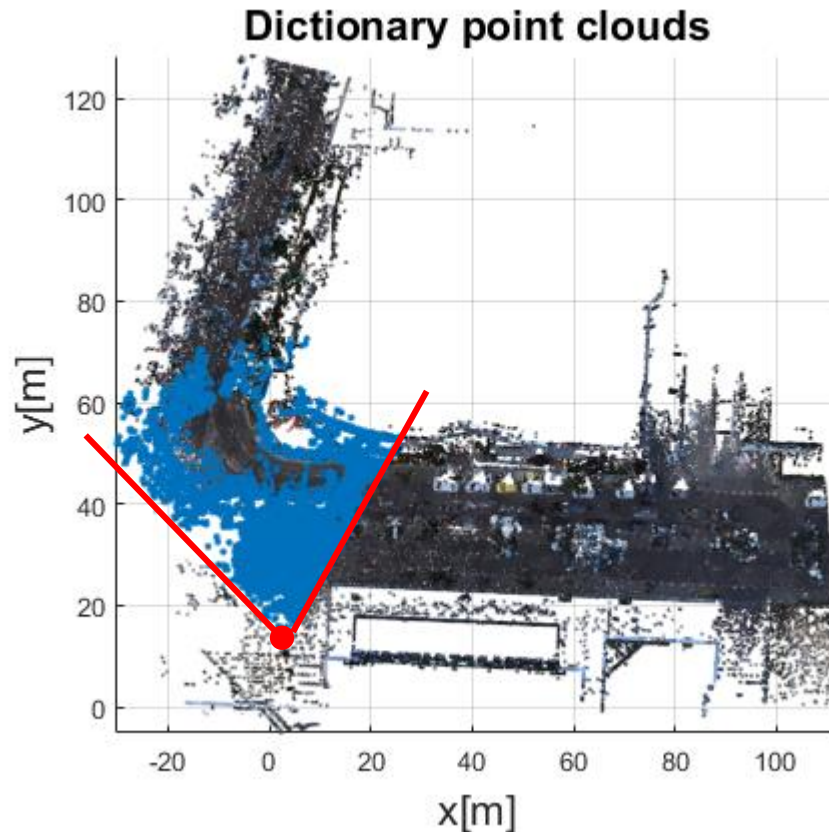
Filtered viewpoint grid and normals - side view



Main steps:

2. Create dictionary clouds for each viewpoint

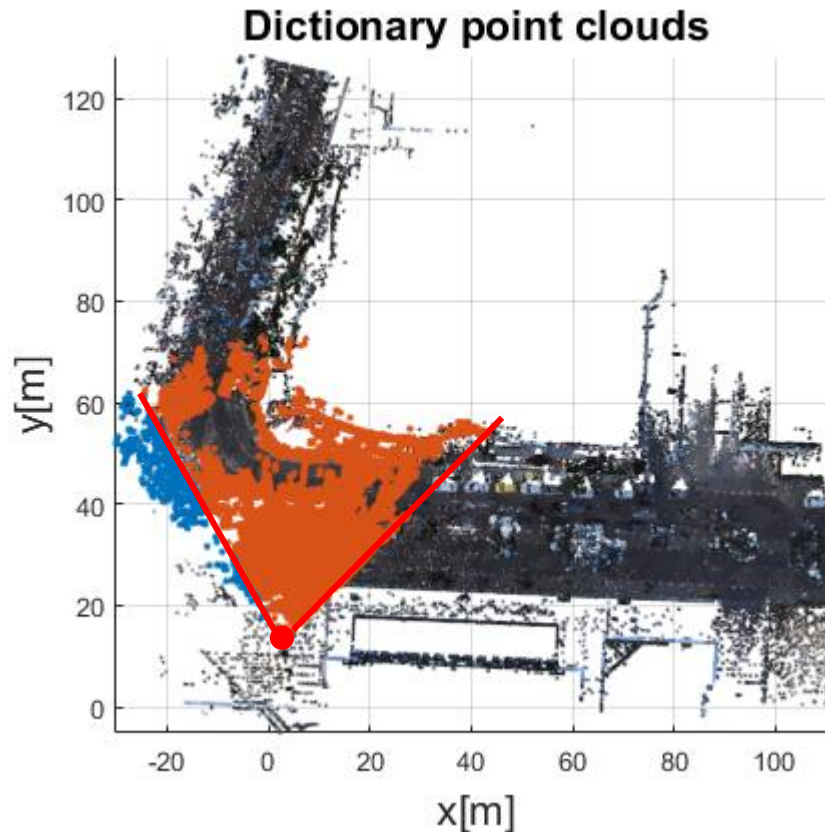
- Divide area around each viewpoint into overlapping “slices”



Main steps:

2. Create dictionary clouds for each viewpoint

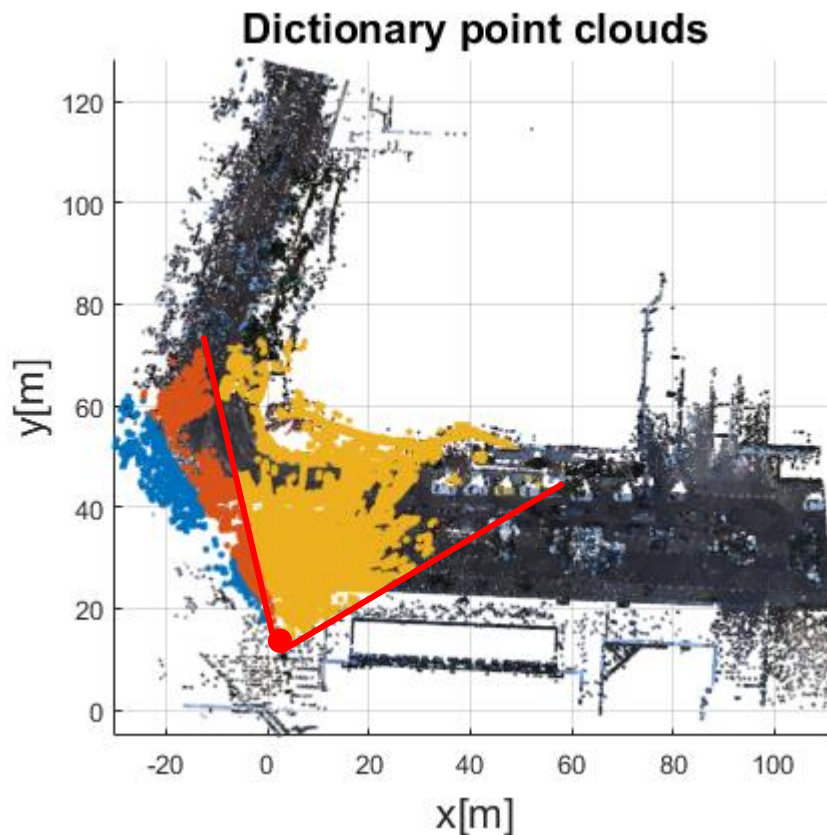
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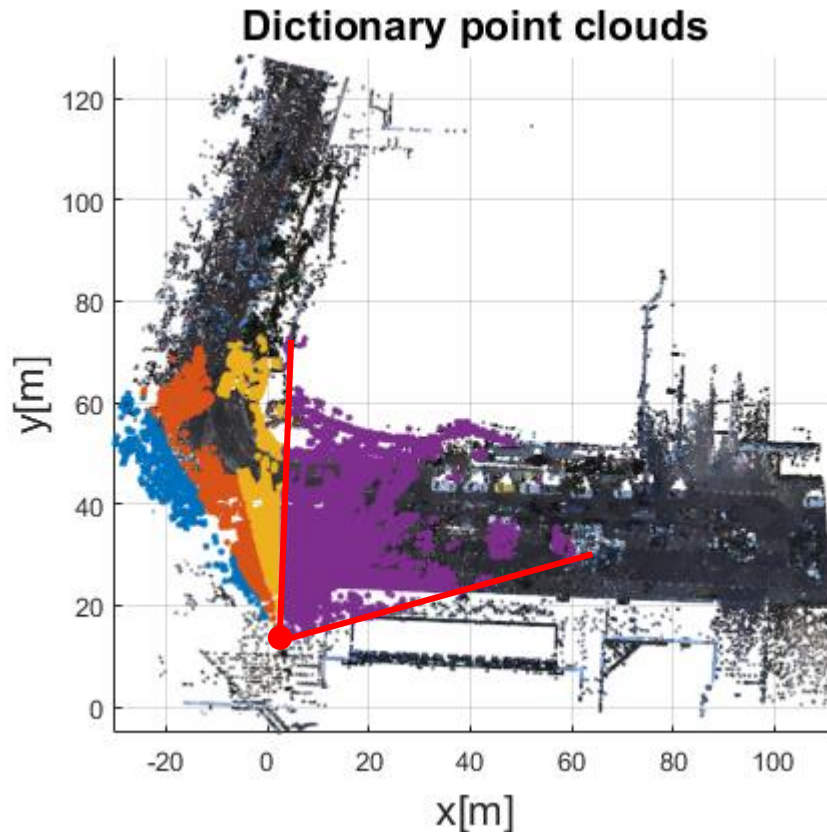
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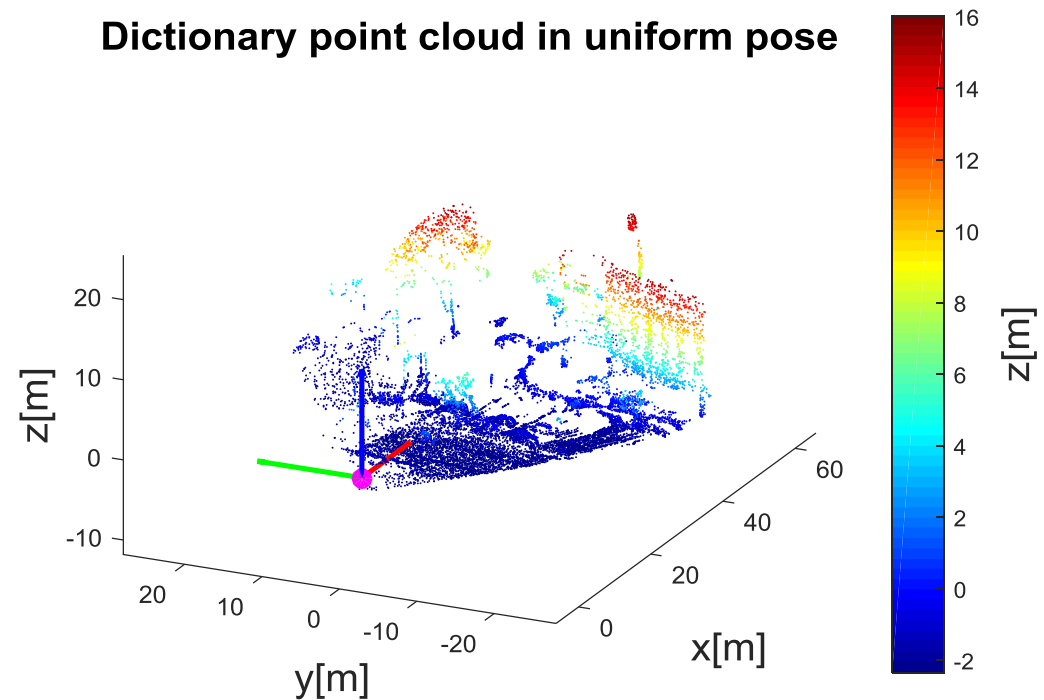
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Main steps:

2. Create dictionary clouds for each viewpoint

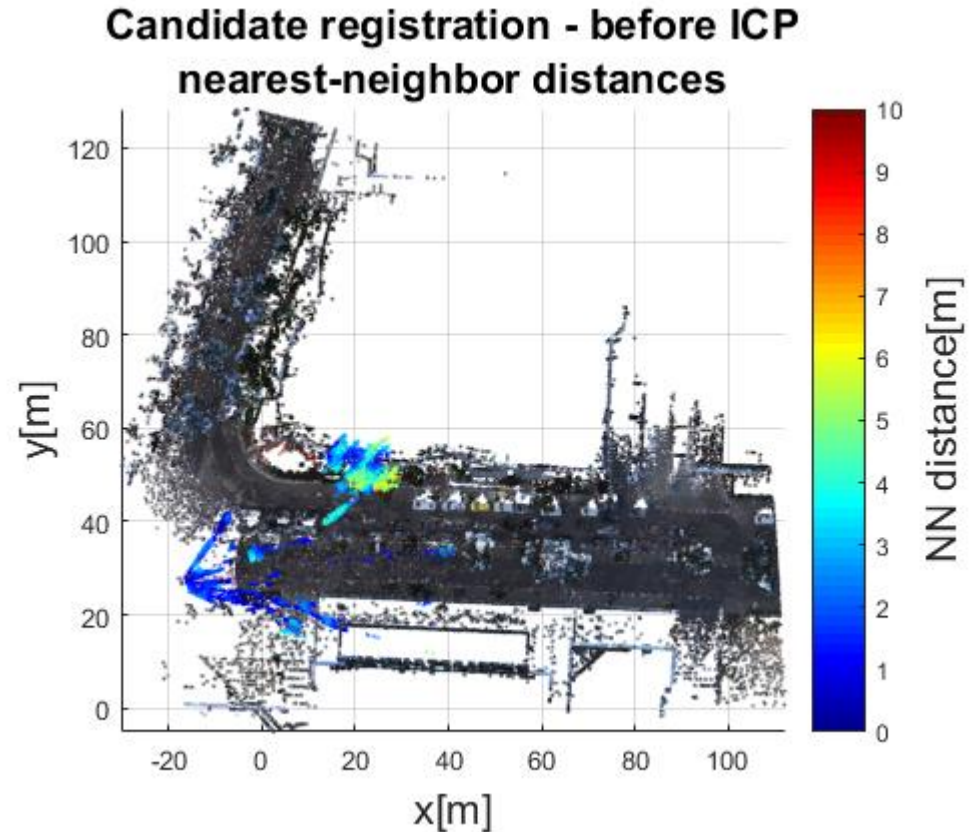
- Divide area around each viewpoint into overlapping “slices”
- Each “slice” (dictionary cloud) is aligned to a **uniform pose** such that:
 - Viewpoint at origin
 - Viewpoint normal $\parallel \vec{z}$
 - Viewing direction $\parallel \vec{x}$



Main steps:

3. Given a local cloud, select candidate dictionary clouds

- Local cloud is transformed to the **uniform pose**
- Candidate selection criterion:
 - Minimal Root-Mean-Square Error (RMSE) between local and dictionary clouds

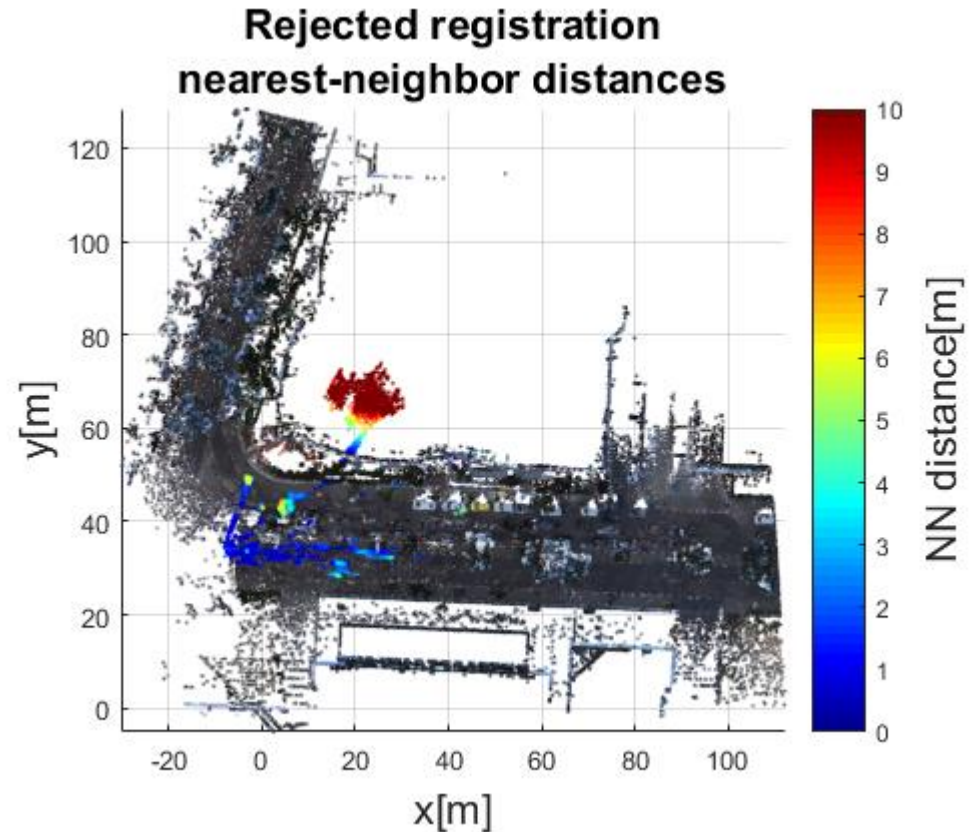


$$RMSE = 1.97[m]$$

Main steps:

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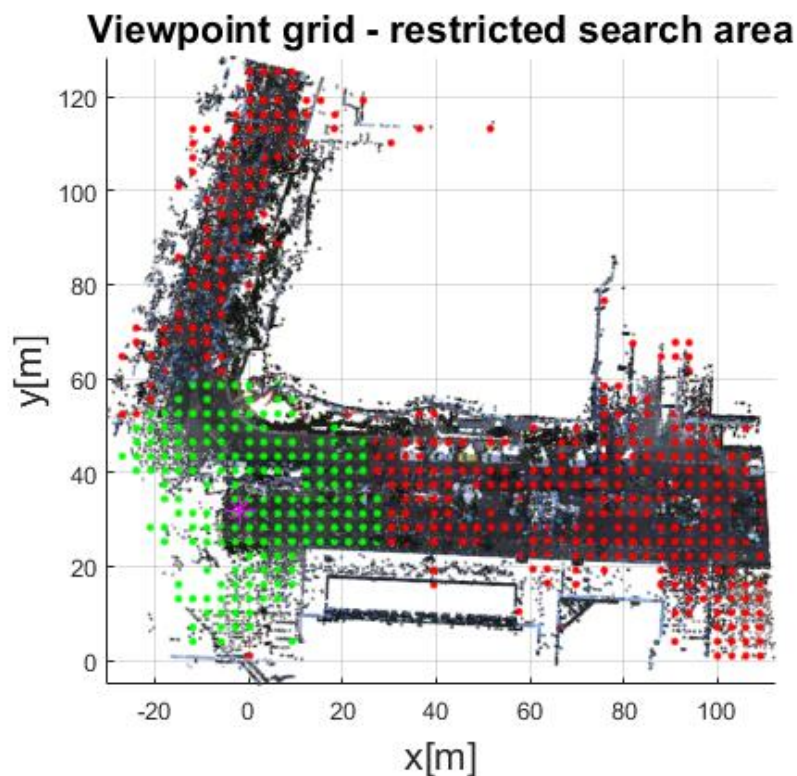
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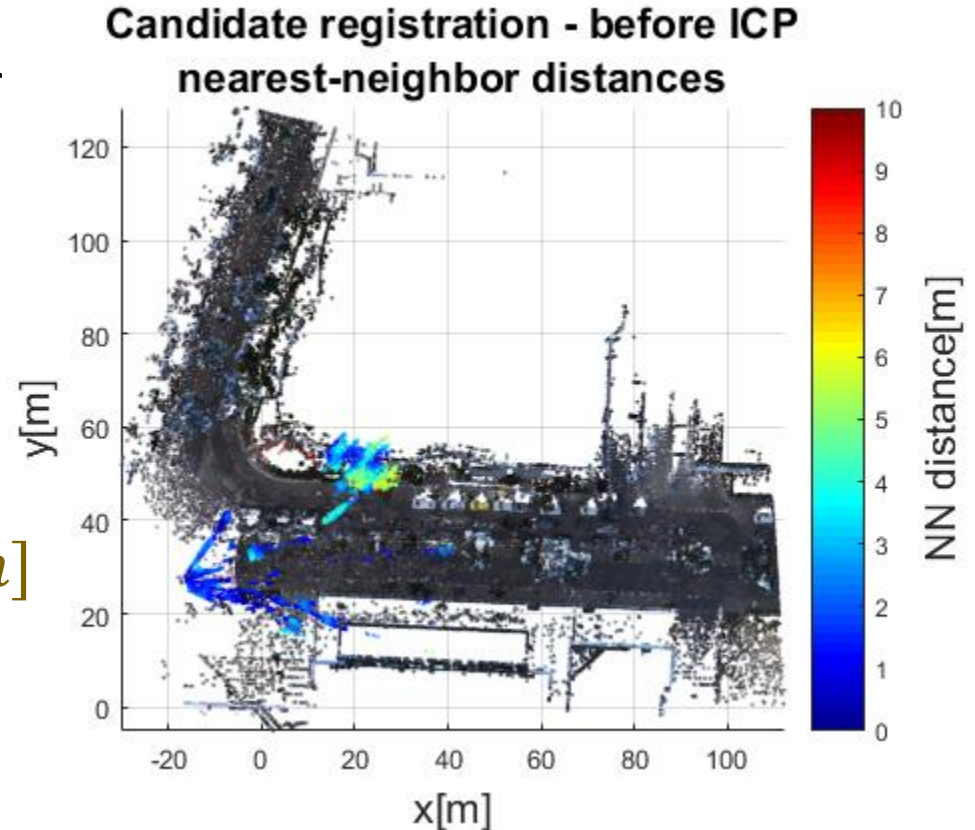
- Local cloud is transformed to the **uniform pose**
- Candidate selection criterion:
 - Minimal Root-Mean-Square Error (RMSE) between local and dictionary clouds
- A **GPS reading**, if available, can be used to restrict **search area**



Main steps:

4. Use ICP on candidates to refine registration

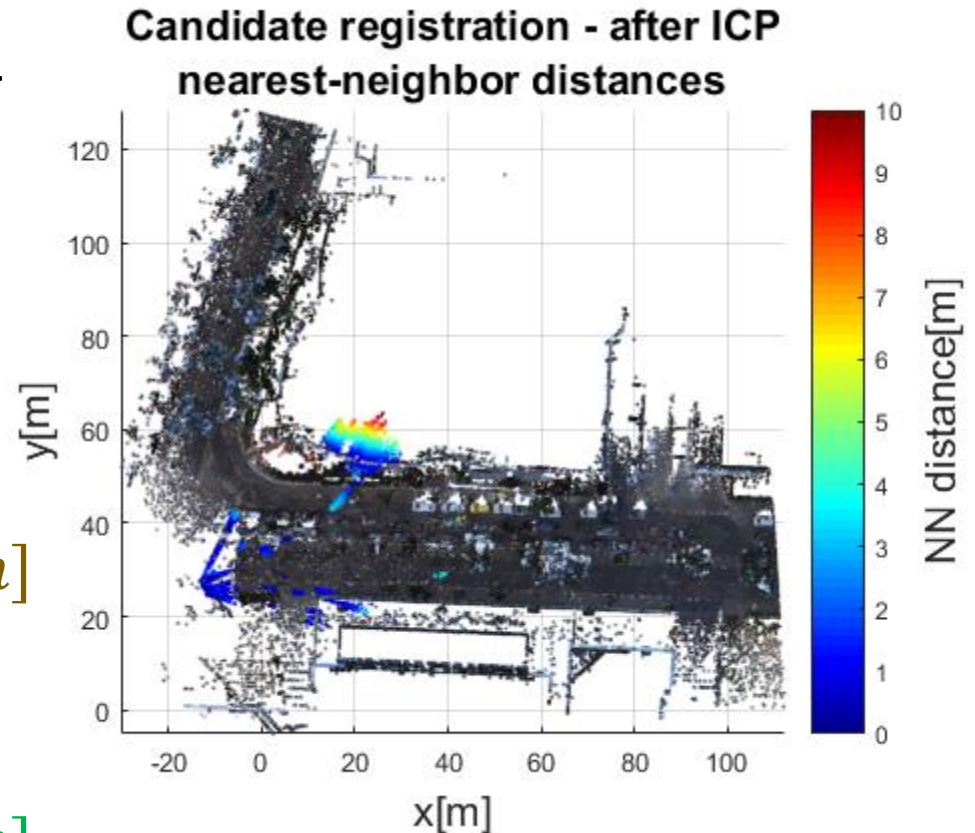
- Use of ICP allows sub-viewpoint-grid localization accuracy
- Before ICP:
 - $RMSE = 1.97[m]$
 - $Loc. error = 3.91[m]$



Main steps:

4. Use ICP on candidates to refine registration

- Use of ICP allows sub-viewpoint-grid localization accuracy
- Before ICP:
 - $RMSE = 1.97[m]$
 - $Loc.error = 3.91[m]$
- After ICP:
 - $RMSE = 1.22[m]$
 - $Loc.error = 1.71[m]$



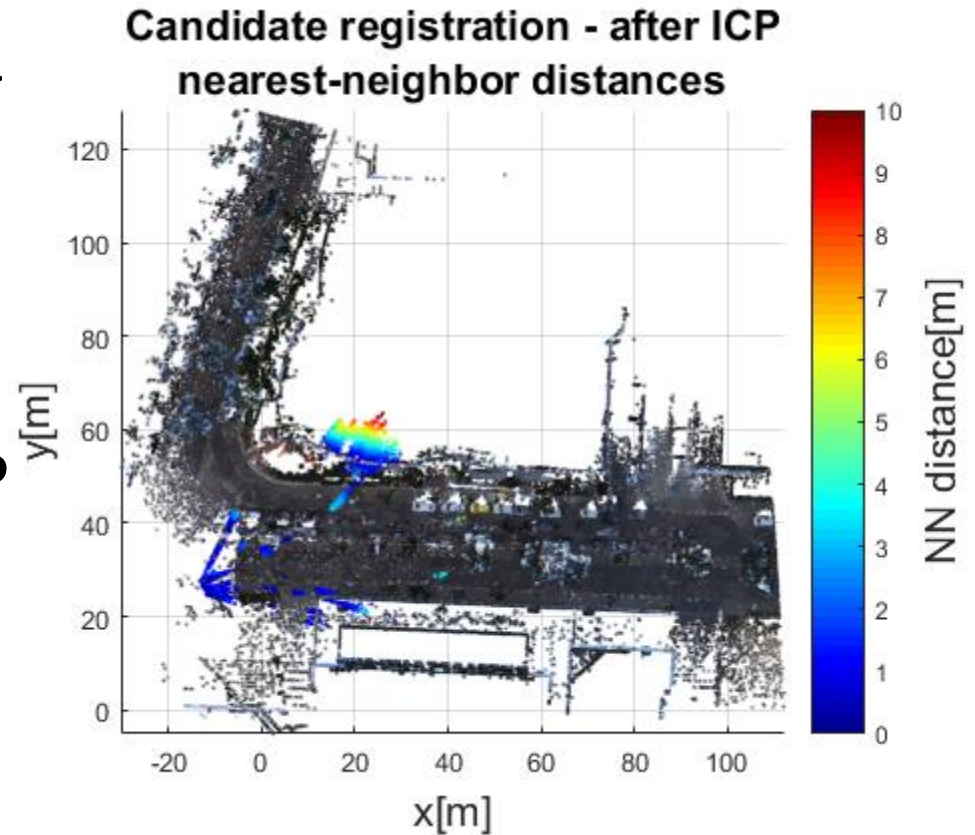
Main steps:

4. Use ICP on candidates to refine registration

- Use of ICP allows sub-viewpoint-grid localization accuracy
- Candidate with lowest RMSE after ICP



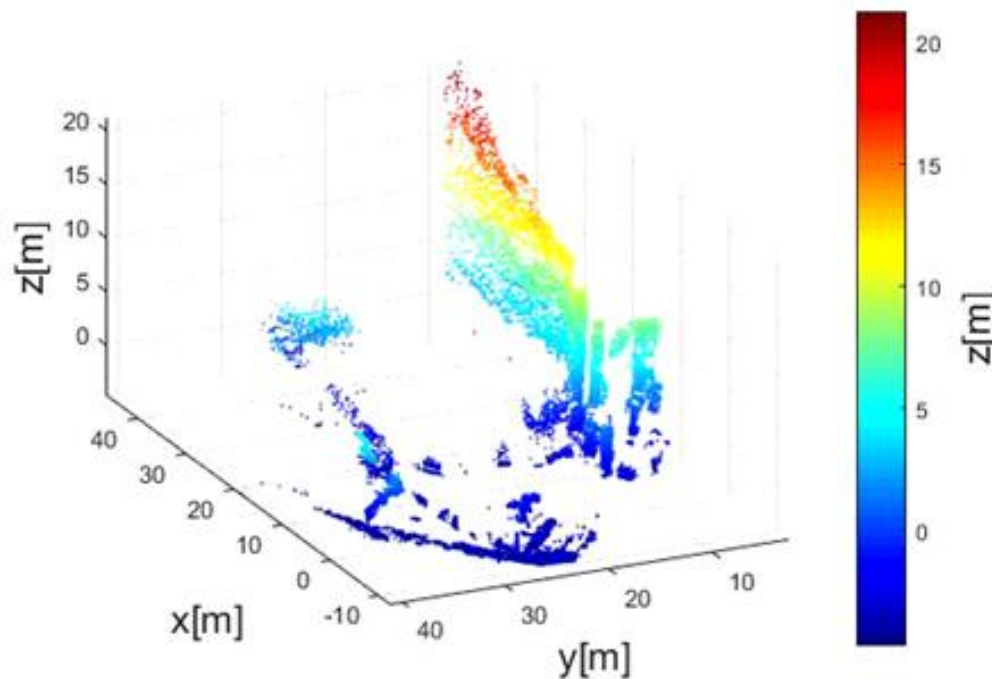
Final transformation
(local to global)



Results – stereo local clouds

Keypoints Vs. viewpoint dictionary

- 7 stereo local clouds:
 - Noisy
 - Sparse
 - Sporadic scene coverage



Results – stereo local clouds

Keypoint-based registration

- Keypoint-based registration pipeline:
 - Keypoint detection: Surface variation (Pauly et al., 2002)
 - 3D descriptors: Spin-Images (Johnson, 1997)
 - Coarse registration: RANSAC
 - Registration refinement: ICP
- # local clouds where *localization error* $< 3m$: **0/7**
 - **Lowest loc. error was 25m**
 - Difficulty to establish correct correspondences

Results – stereo local clouds

Viewpoint dictionary based registration

Local cloud #	Localization error [m]	Yaw Error [deg]	Pitch Error [deg]	Roll Error [deg]
1	2.96	-6.35	-3.40	-6.00
2	74.94	135.83	-3.93	-2.75
3	2.41	4.18	-2.87	-2.85
4	0.48	0.94	1.90	-1.31
5	0.51	2.23	1.59	-3.29
6	1.16	3.13	0.45	-2.02
7	12.10	51.65	-0.19	3.87

- # local clouds where *localization error* < 3m: **5/7**
- Using keypoints: **0/7** (lowest loc. error was 25m)

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Conclusion

- Proposed novel point cloud registration framework:

- Large-scale global cloud →

Dictionary of viewpoint-based smaller clouds

- Local to global cloud registration →

Dictionary search

- Demonstrated advantages over using keypoints

- Can handle substantially different characteristics of the global and local clouds (LiDAR vs. stereo)

- Future work:

- Dedicated viewpoint descriptors
 - **Compact dictionary storage**
 - **Efficient dictionary search**



Acknowledgments

- Collaboration:
 - CEVA
 - Elbit Systems Land and C4I
- Point cloud data:
 - Elbit Systems Land and C4I



Omek Consortium



Thank You!