TECHNION Israel Institute of Technology

SIPL Signal and Image Processing Lab

In collaboration with: GeoSim

Omek Consortium

Local-to-Global Point Cloud Registration using a Dictionary of Viewpoint Descriptors

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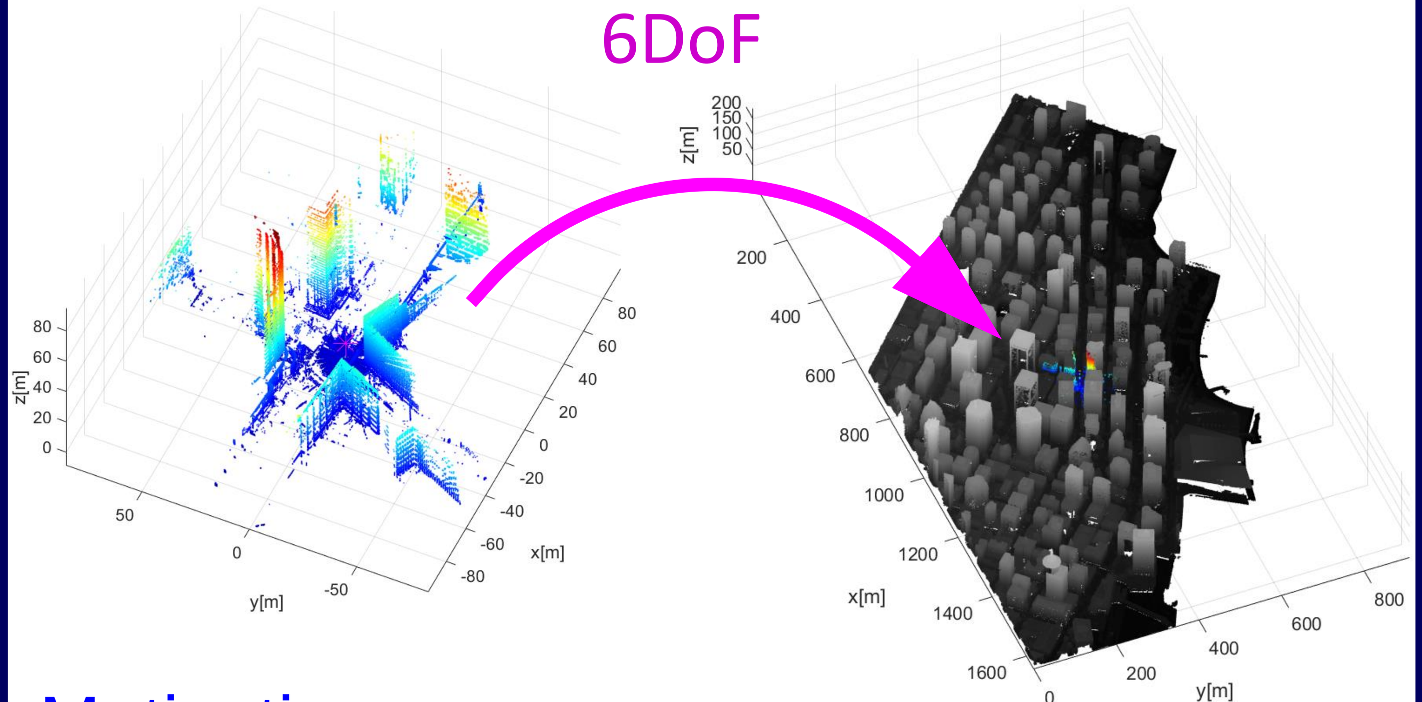
Goal

- Registration (alignment) between a **global**, large-scale **point cloud**, and a single **local scan**.

Local cloud (Terrestrial LiDAR) **Global cloud (Airborne LiDAR)**



Motivation

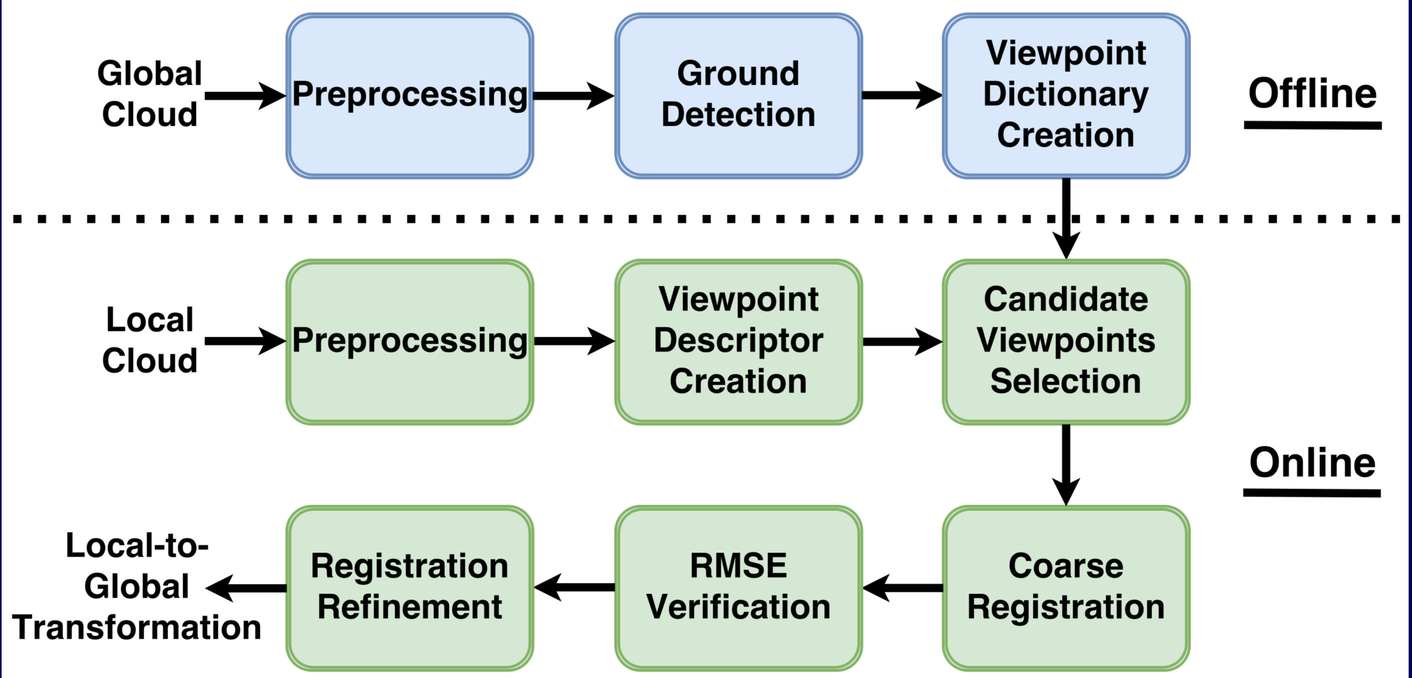
- Combining **airborne** and **terrestrial** LiDAR scans for large-scale **urban modeling**.
- **Localization** in an urban environment even **without GPS**.

Challenges

- **Airborne** vs. **terrestrial** data characteristics:
  - **Very** different point density distributions (**airborne** → more points on **horizontal** surfaces, **terrestrial** → more points on **vertical** surfaces).
  - Missing data, different types of occlusion.
- Urban environments contain many **flat surfaces** and **repetitive features**.
- We found existing 3D **feature-based methods** (e.g., Spin-Images, Fast Point Feature Histograms - FPFH) to be **unreliable under these conditions**.

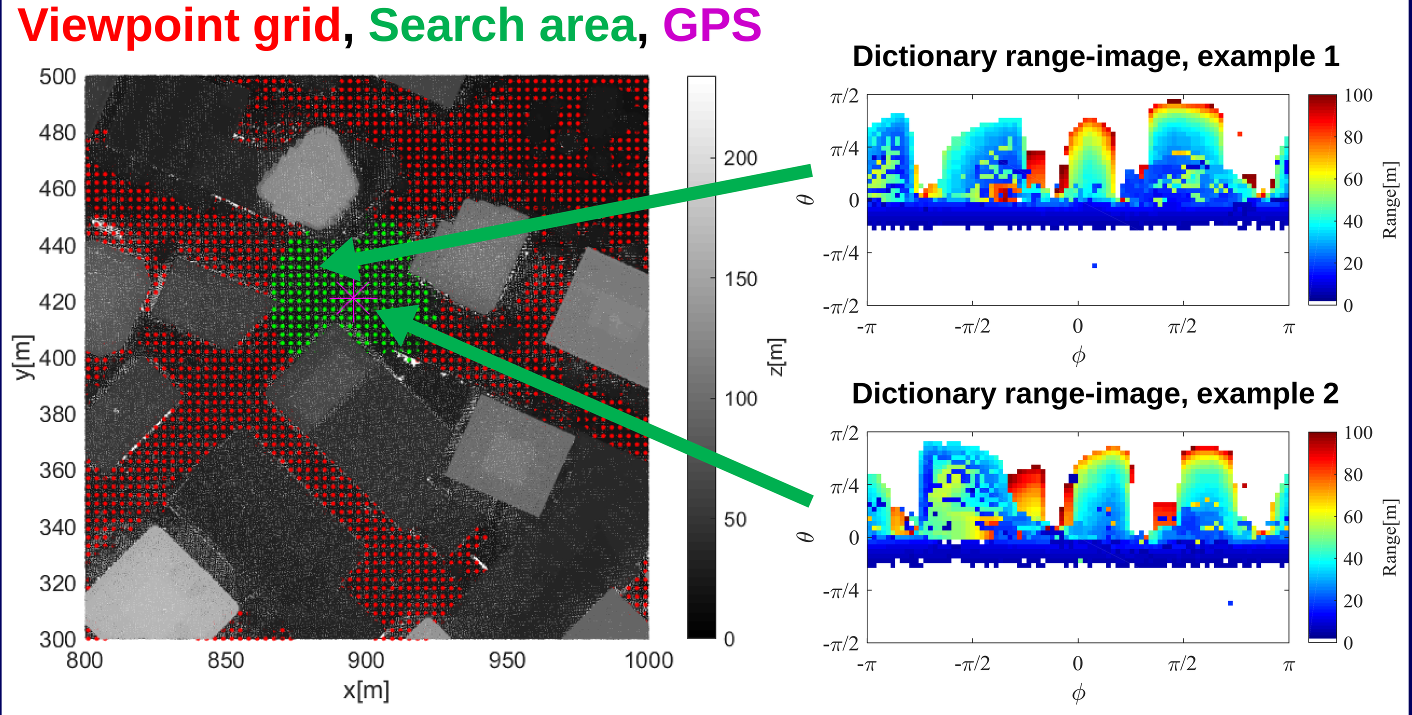
Registration algorithm – Overview

- Main concepts:
  - Convert global cloud to a **dictionary of viewpoint descriptors**.
  - Find registration via **dictionary search**.



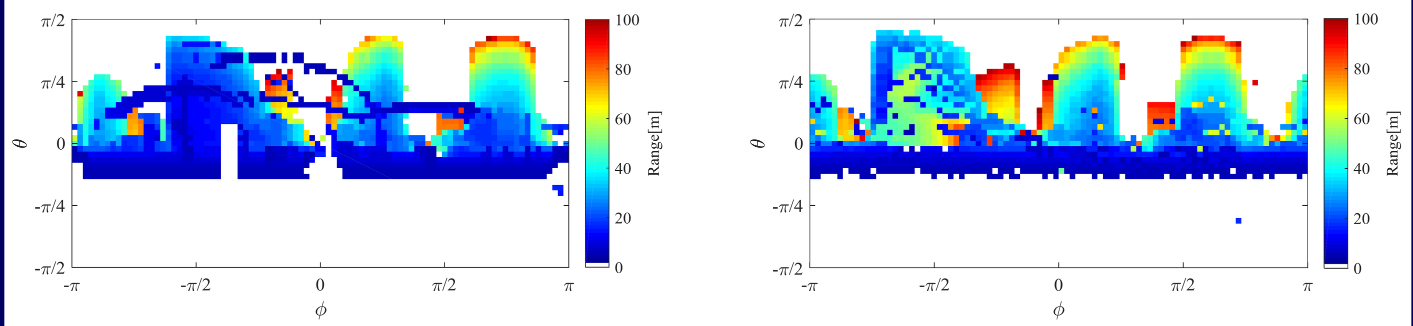
Viewpoint dictionary creation

- **Detect ground** (e.g., by region growing).
- Define a **viewpoint grid** over the global cloud (e.g., grid distance = 3m).
- Compute a **panoramic range-image** for each viewpoint.



Panoramic range-images as viewpoint descriptors

- Use the **view of the global scene** from each viewpoint as a **descriptor** and match with **local range-image**.



Candidate viewpoint selection via phase-correlation

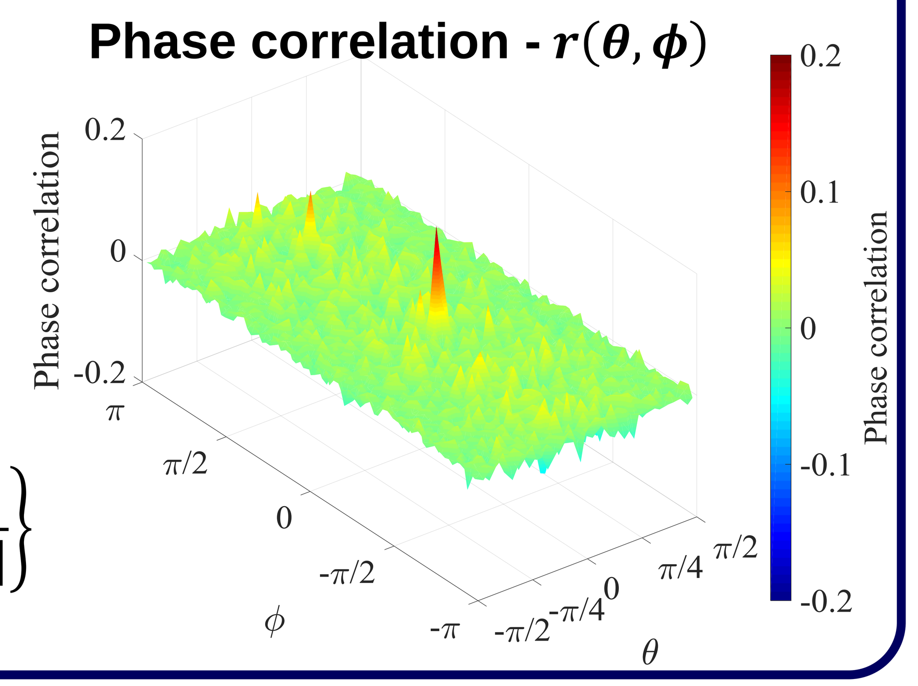
- Select a **subset of grid viewpoints** (e.g., 10) with largest **phase-correlation** peaks.
- Peak location → coarse orientation estimate.

2D Discrete Fourier Transform

$$G_L = \mathcal{F}\{g_L(\theta,\phi)\}$$

$$G_D = \mathcal{F}\{g_D(\theta,\phi)\}$$

$$r(\theta,\phi) = \mathcal{F}^{-1}\left\{\frac{G_L^* G_D}{|G_L^* G_D|}\right\}$$

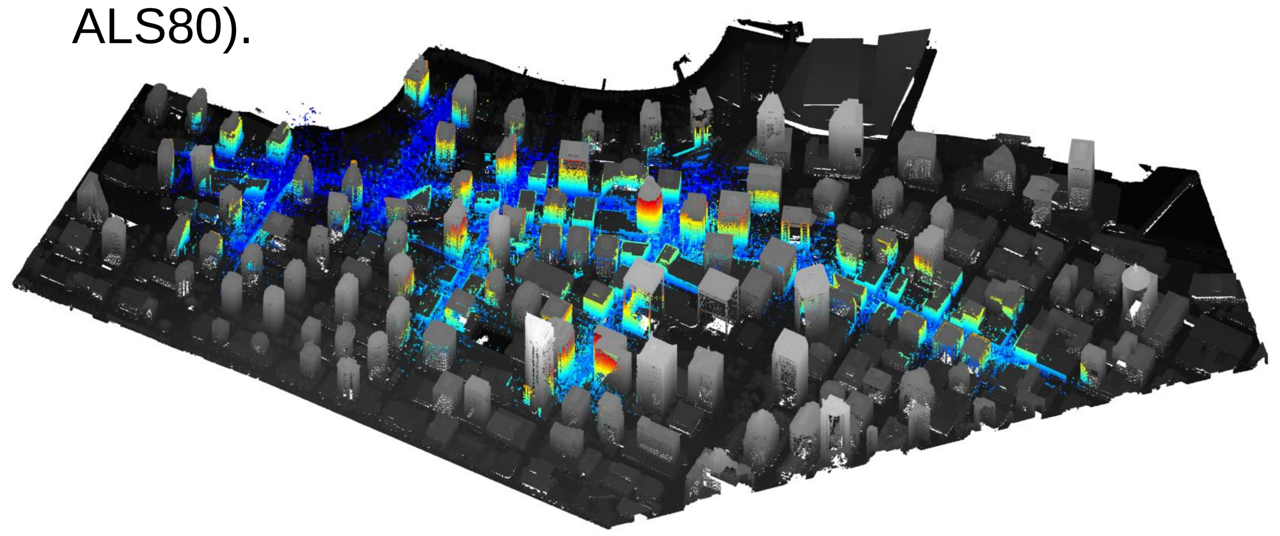


Verification and registration refinement

- Select N_{final} (e.g., 3) **coarse registrations** with **lowest RMSE** (Root-Mean-Square Error between the local and global clouds).
- **Refine** selected registrations using **ICP** (Iterative Closest Point).
- Select final registration with lowest RMSE.

Results

- The registration algorithm was tested on a large-scale and challenging dataset:
  - **108** terrestrial LiDAR scans (Z+F Imager 5010).
  - Airborne LiDAR scan (global cloud) area: $\sim 1km^2$ (Leica ALS80).



	Localization error [m]		Relative Rotation Error [deg]		Registration runtime per cloud [sec]*	
	Mean	STD	Mean	STD	Mean	STD
Using GPS (30m search radius)	**0.43**	0.27	**0.76**	0.37	**2.0**	0.4
No GPS (search entire grid)	0.44	0.27	0.78	0.39	15.4	0.7

* Run on PC (i7-5820K CPU @ 3.30 GHz), MATLAB implementation

- **Comparison to FPFH** - tested on a **subset of 24 local clouds**:
  - **Using FPFH, only 6 out of 24** clouds had **localization error lower** than **3m** (the other 18 registrations failed).
  - Using the **proposed method**, the **maximal localization error** was **0.79m** (the max. error over all 108 clouds was 1.85m).

Conclusion

- 3D **feature-based** methods were found to be **unreliable** for **local-to-global terrestrial-to-airborne** registration.
- **Registration performance** of the proposed **viewpoint-dictionary-based** method is **significantly better**.