University of Missouri

City-Scale Point Cloud Stitching Using 2D/3D Registration for Large Geographical Coverage

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First Workshop on Analysis of Aerial Motion Imagery (WAAMI)

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- Related Works
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- Experiments & Evaluations
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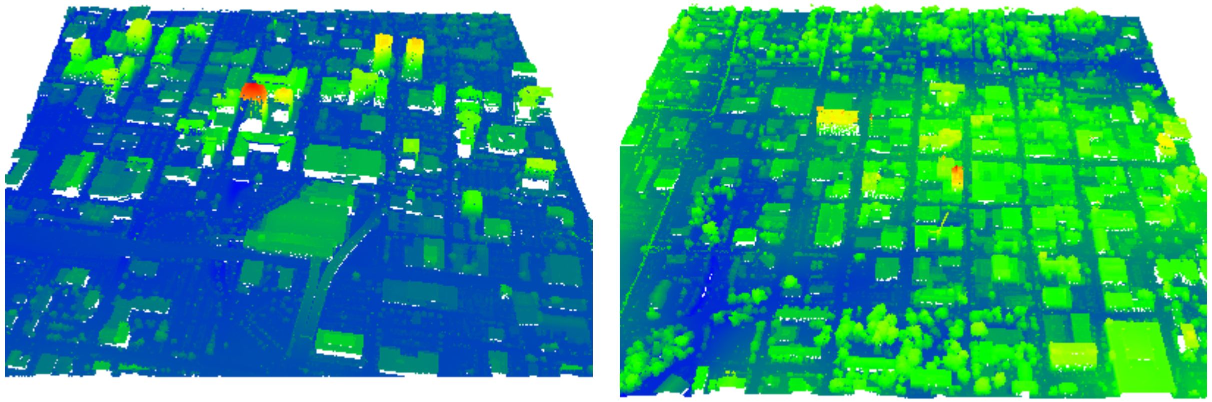
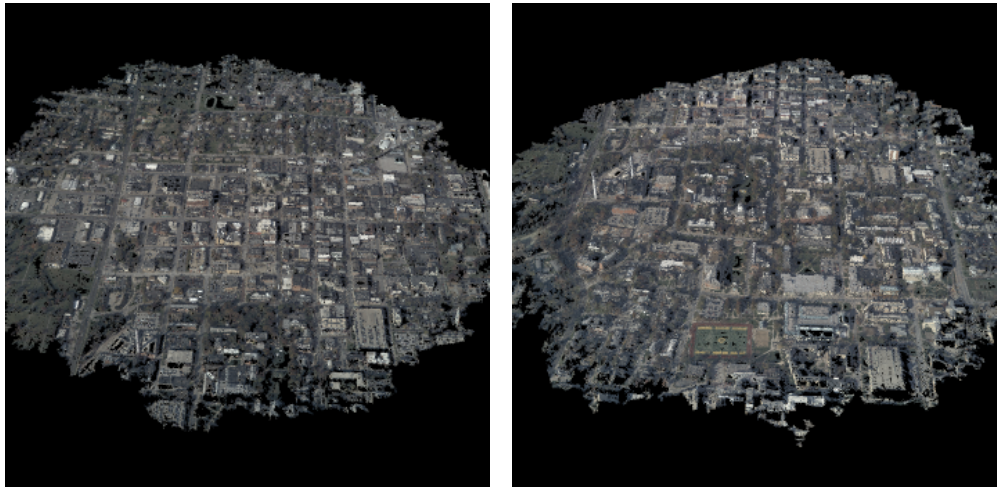
Introduction

- What is a point cloud?
- Point clouds are datasets that represent objects or space. These points represent the X, Y, and Z geometric coordinates of a single point on an underlying sampled surface. Some point clouds also have color information.

- How to generate a point cloud, especially a city-scale point cloud?
- City-scale point clouds are commonly either generated using airborne LiDAR (light detection and ranging) techniques or reconstructed using MVS algorithms from a set of 2D imagery.



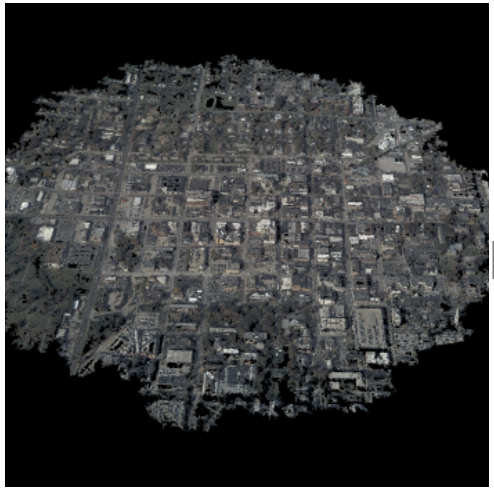
City-scale point clouds collected using airborne LiDAR techniques



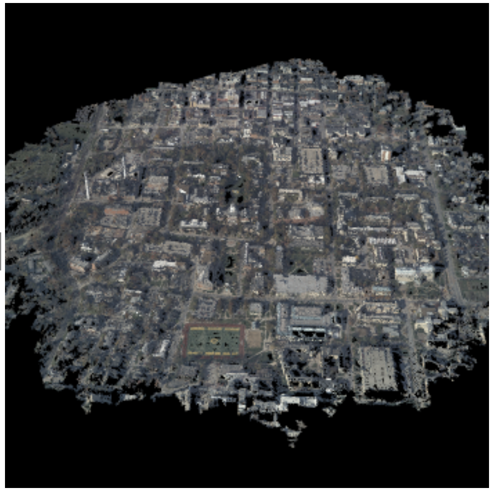
City-scale point clouds reconstructed using a MVS algorithm

Problem Statement

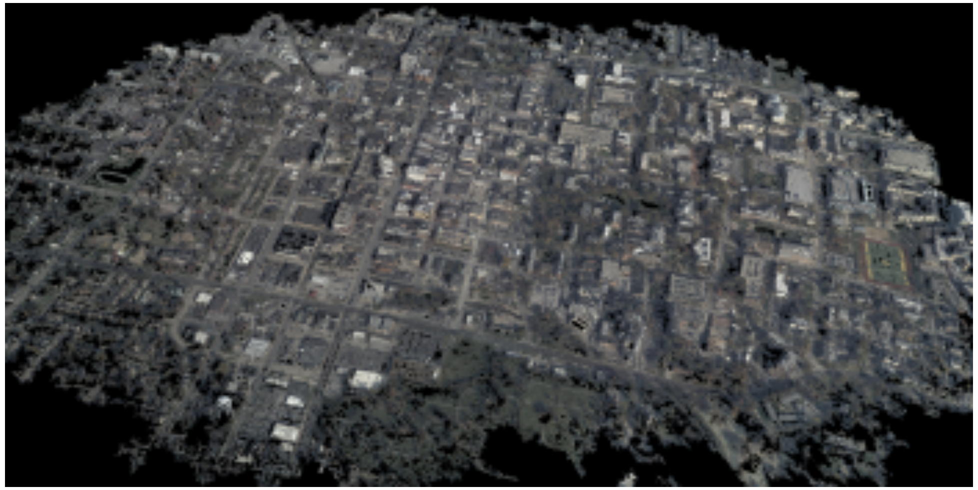
Combining multiple city-scale point cloud data (LiDAR scan or reconstructed results from algorithms) with limited overlapping fields to produce a larger geographical coverage or one point cloud data with higher density



City-scale reconstruction using VisualSFM[1,2]



City-scale reconstruction using VisualSFM[1,2]



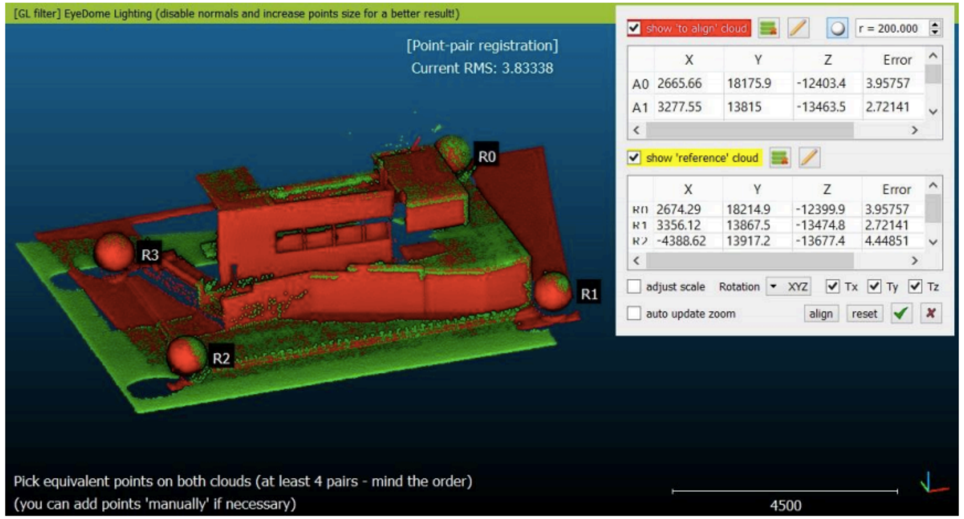
Stitched Point Cloud for a larger geographical coverage

[1] Changchang Wu, "Towards Linear-time Incremental Structure From Motion", 3DV 2013
[2] Changchang Wu, Sameer Agarwal, Brian Curless, and Steven M. Seitz, "Multicore Bundle Adjustment", CVPR 2011

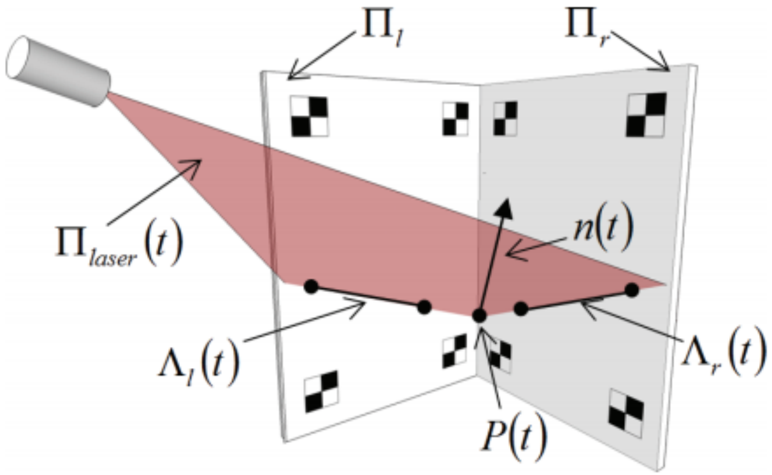
Related Works

- Manual labeling by picking at least 4 corresponding 3D points
  1. Not automatic
  2. Time-consuming
  3. Limited accuracy

- Manual adding markers to objects for automatic matching
  1. Suitable for only small in-lab objects
  2. Semi-automatic



Manual labeling using CloudCompare[1]



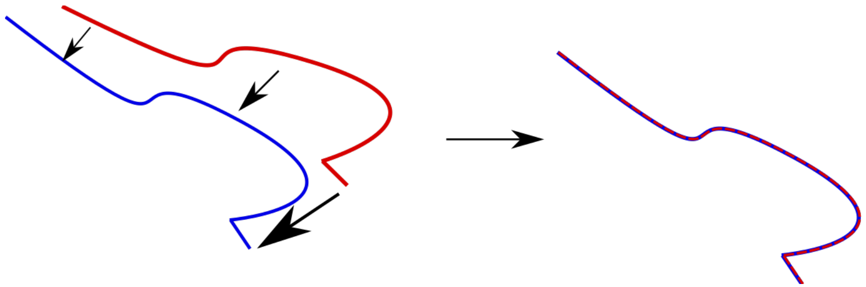
Manual added markers for matching[2]

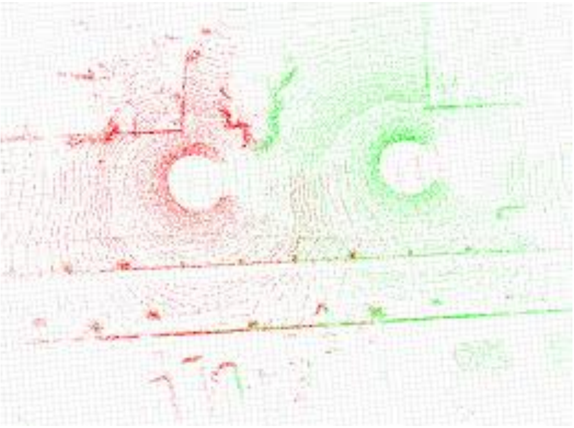
[1] https://www.danielgm.net/cc/
[2] Matiukas V, Miniotas D. Point cloud merging for complete 3D surface reconstruction. Elektronika ir Elektrotechnika. 2011 Jan 1;113(7):73-6

Related Works

Automatic algorithms have also been developed for point cloud stitching:

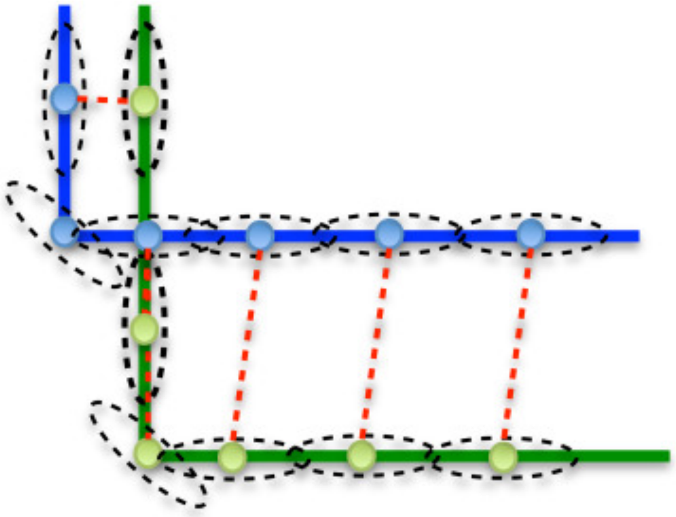
Iterative closest point (ICP) [1,2]

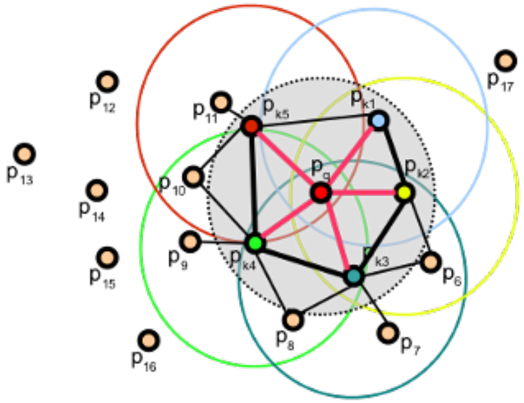




Generalized Iterative closest point (GICP) [3]

Color-supported generalized Iterative closest point (CGICP) [4]





Fast Point Feature Histograms (FPFH) [5]

[1] ... An ICP variant using a point-to-line metric.
[2] Yang J, Li H, Jia Y. Go-icp: Solving 3d registration efficiently and globally optimally. InProceedings of the IEEE International Conference on Computer Vision 2013 (pp. 1457-1464).
[3] Segal, Aleksandr, Dirk Haehnel, and Sebastian Thrun. "Generalized-icp." In *Robotics: science and systems*, vol. 2, no. 4, p. 435. 2009.
[4] Korn, Michael, Martin Holzkothen, and Josef Pauli. "Color supported generalized-ICP." In *2014 International Conference on Computer Vision Theory and Applications (VISAPP)*, vol. 3, pp. 592-599. IEEE, 2014.
[5] Rusu, Radu Bogdan, Nico Blodow, and Michael Beetz. "Fast point feature histograms (FPFH) for 3D registration." In *2009 IEEE international conference on robotics and automation*, pp. 3212-3217. IEEE, 2009.

Related Works

- Limitations of the existing automatic registration algorithms:
  1. Require a large amount of overlapping or even full overlapping region
  2. Lack of accuracy when applied on city-scale data due to repetitive texture and similar structures

Manually Aligned Ground Truth

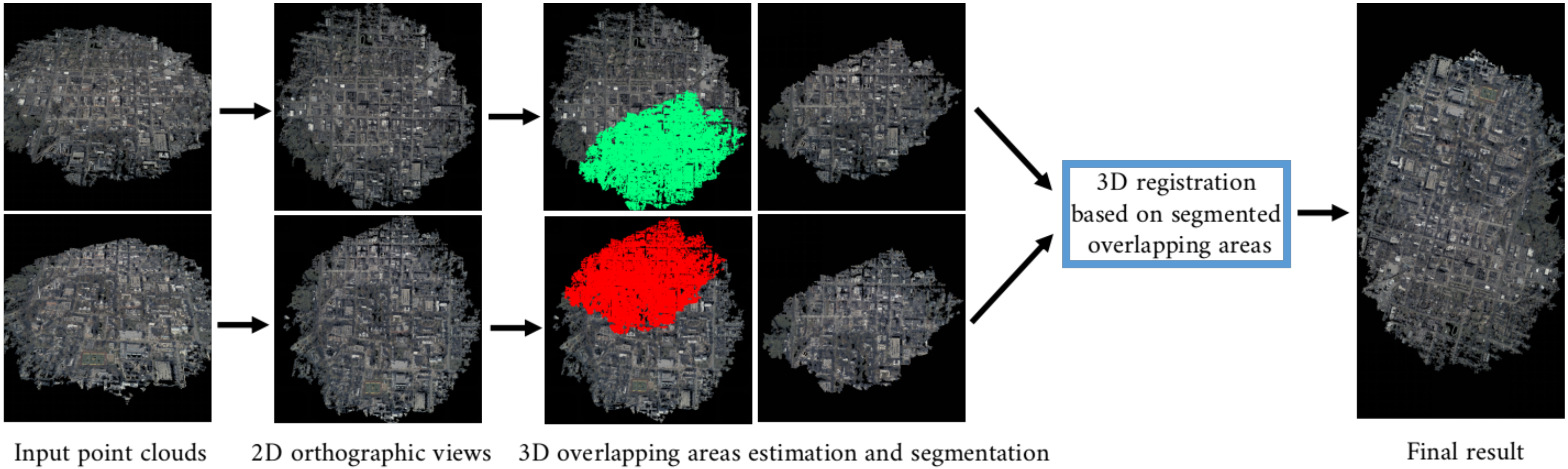
Iterative Closest Point (ICP)

Generalized-ICP (GICP)

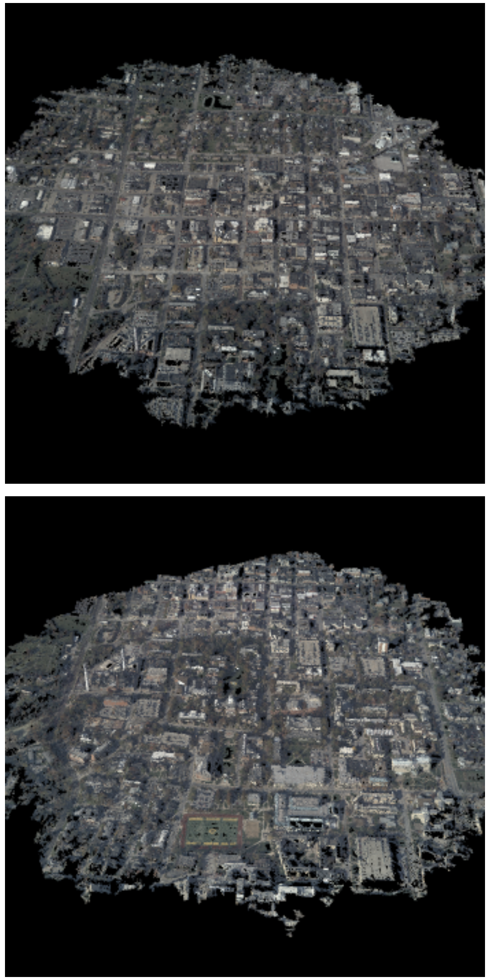
Color Supported Generalized-ICP (CGICP)

Fast Point Feature Histograms (FPFH)

Proposed Approach: Overall Flow

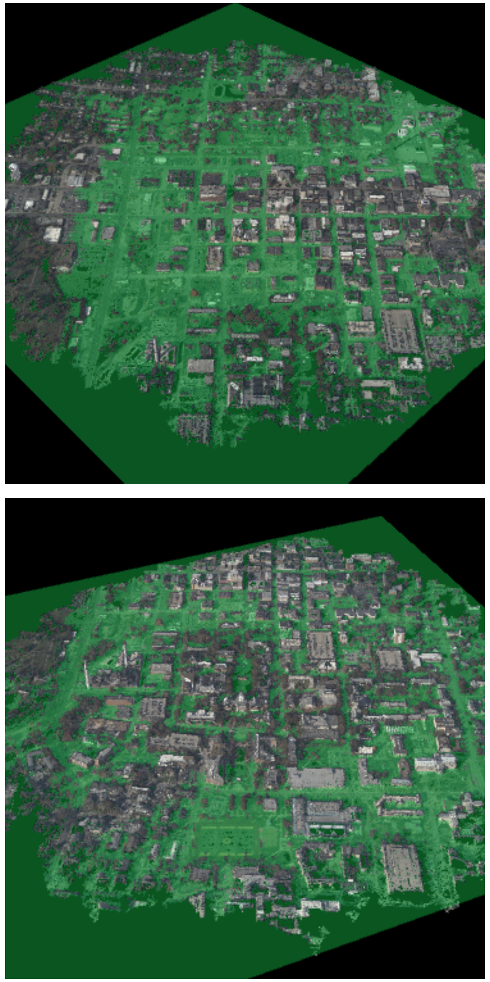


Proposed Approach: 2D Orthographic View Generating



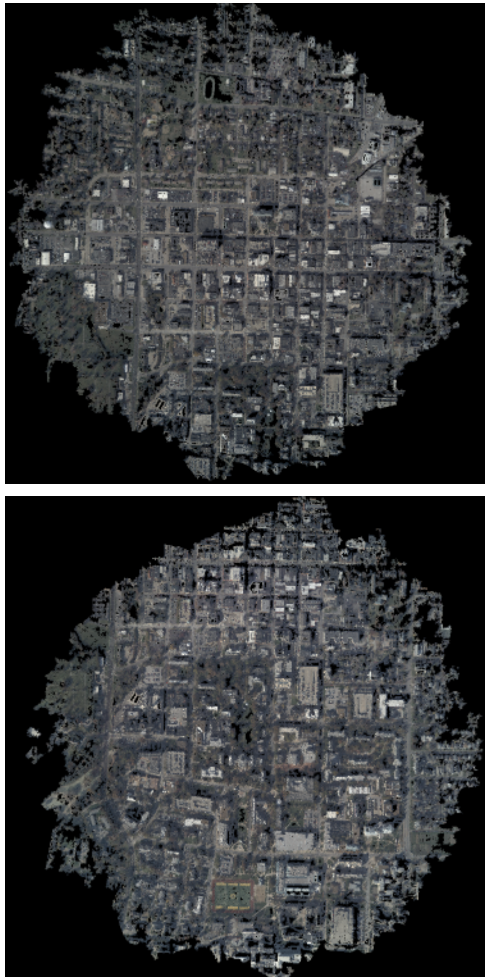
Point cloud A (top) and B (bottom) generated using VisualSFM

Apply the singular value decomposition (SVD) to fit the best plane as the ground plane



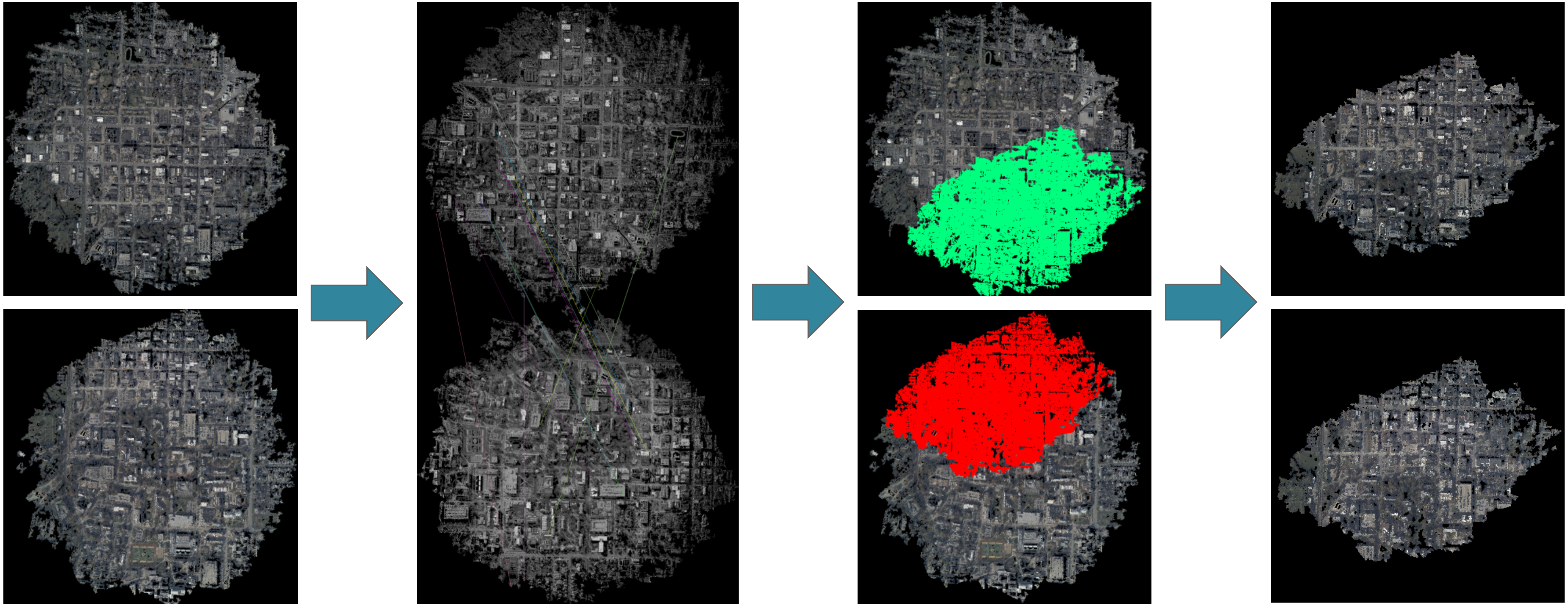
Ground plane generated by SVD (shown in green)

Project voxels down to ground plane to generate orthographic views



Orthographic views of the two point clouds

Proposed Approach: 2D Image Registration and 3D Overlapping Area Segmentation



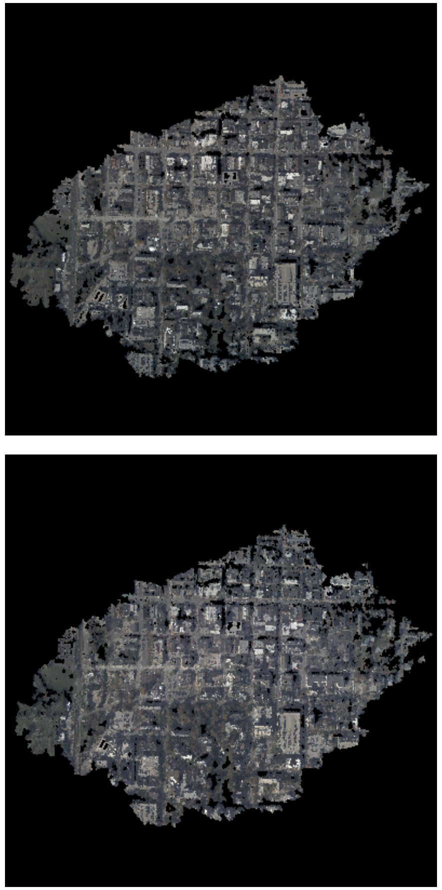
Orthographic views of the two point clouds

2D image feature point matching using SURF

Overlapping area estimated using 2D image registration

Segmented out 3D overlapping areas

Proposed Approach: 3D Registration Based On Segmented Overlapping Areas



Segmented out 3D overlapping areas

- ICP[1]
- GICP[2]
- CGICP[3]
- FPFH[4]

→

- Transformation matrix 1
- Transformation matrix 2
- Transformation matrix 3
- Transformation matrix 4

→

Final transformation matrix with the least RMSE

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}\left(P_{target} - P_{source}\right)^2}{n}}$$

[1] ... An ICP variant using a point-to-line metric.
[2] Yang J, Li H, Jia Y. Go-icp: Solving 3d registration efficiently and globally optimally. InProceedings of the IEEE International Conference on Computer Vision 2013 (pp. 1457-1464).
[3] Segal, Aleksandr, Dirk Haehnel, and Sebastian Thrun. "Generalized-icp." In *Robotics: science and systems*, vol. 2, no. 4, p. 435. 2009.
[4] Korn, Michael, Martin Holzkothen, and Josef Pauli. "Color supported generalized-ICP." In *2014 International Conference on Computer Vision Theory and Applications (VISAPP)*, vol. 3, pp. 592-599. IEEE, 2014.
[5] Rusu, Radu Bogdan, Nico Blodow, and Michael Beetz. "Fast point feature histograms (FPFH) for 3D registration." In *2009 IEEE international conference on robotics and automation*, pp. 3212-3217. IEEE, 2009.

Experiments & Evaluations: Reconstructed Point Clouds

Manually Aligned Ground Truth

Our Result

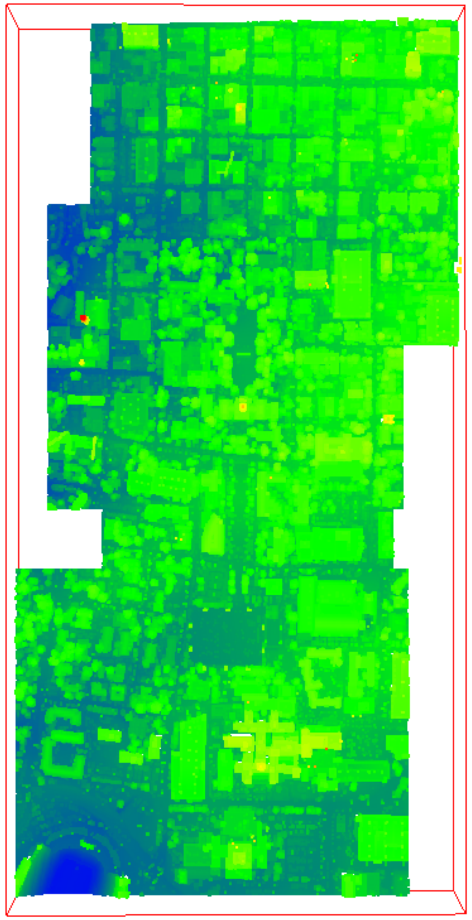
Iterative Closest Point (ICP)

Generalized-ICP (GICP)

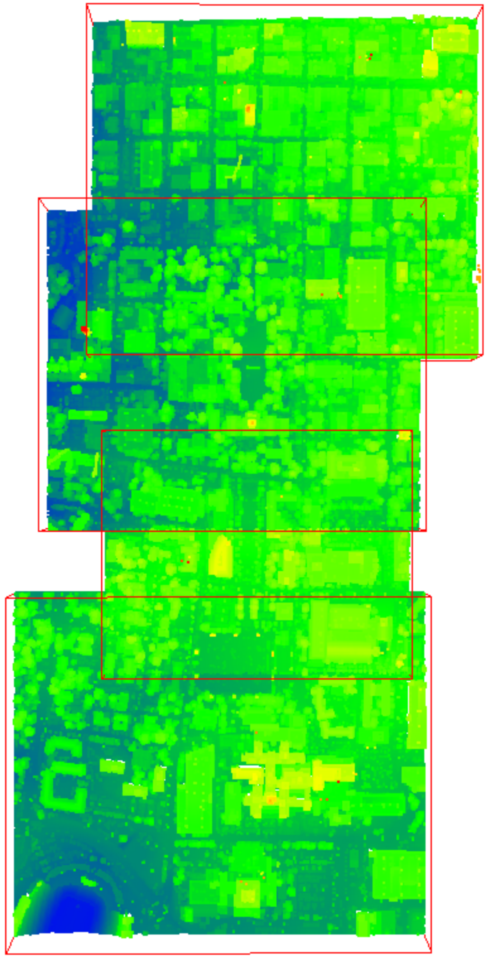
Color Supported Generalized-ICP (CGICP)

Fast Point Feature Histograms (FPFH)

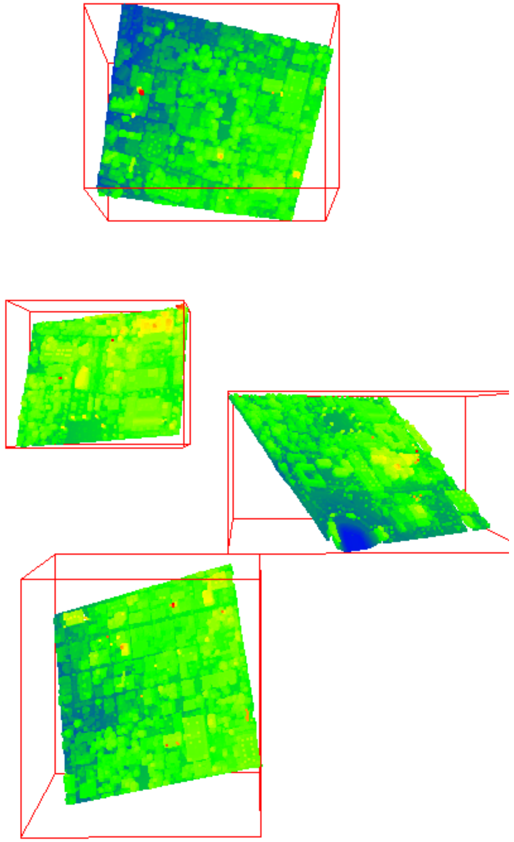
Experiments & Evaluations: Airborne LiDAR Data



LiDAR Ground Truth

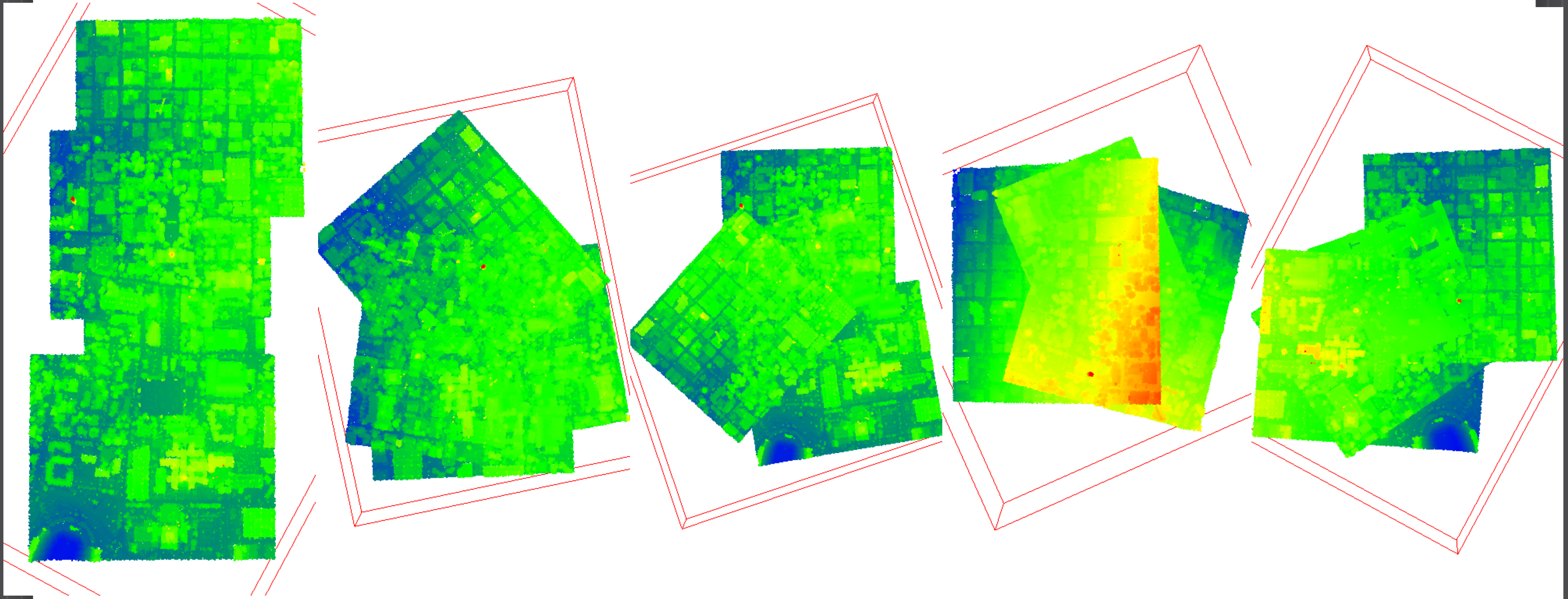


LiDAR Ground Truth Split into 4 sub-volumes



4 sub-volumes after different random transformation

Experiments & Evaluations: Airborne LiDAR Data



Ours *ICP Result* *Generalized-ICP Result* *Color Supported Generalized-ICP Result* *Fast Point Feature Histograms Result*

Experiments & Evaluations: Airborne LiDAR Data

- We quantitatively evaluate our proposed method versus other algorithms using the evaluation methodology proposed in *Tanks and Temples* MVS benchmark[1]

- The precision score (*P(d)*), recall score (*R(d)*), and F-score (*F(d)*) are calculated using Equation 1 (*d* is set to 0.7 meter, which is the same as the *Ground Sample Distance* in this LiDAR dataset).

$$P(d) = \frac{100}{|R|} \sum_{r \epsilon R} [e_{r \to G} < d]$$

$$R(d) = \frac{100}{|G|} \sum_{g \epsilon G} [e_{g \to R} < d]$$

$$F(d) = \frac{2P(d)R(d)}{P(d) + R(d)}$$

Equation 1

	Precision	Recall	F-score
Method	$P(d)$	$R(d)$	$F(d)$
Ours	**94.12**	**97.95**	**96.00**
B. Eckart *et al.* [18]	29.10	24.16	26.40
A.V. Segal *et al.* [19]	26.04	22.89	24.36
M. Korn *et al.* [20]	19.86	14.63	16.85
R.B. Rusu *et al.* [21]	24.19	24.42	24.30

[1] https://www.tanksandtemples.org/tutorial/

Conclusions

- In this paper, we proposed a novel point cloud stitching pipeline for city-scale point clouds of urban scenes.
- The proposed pipeline consists of three main components, which fully utilizes 2D image mosaicking techniques together with 3D registration techniques.
- This pipeline uses 2D image mosaicking techniques to locate the overlapping 3D areas among multiple point clouds first, which is our key contribution and demonstrated to be very critical based on the experiments, then applies 3D registration techniques for better transformation matrix estimation.
- The quantitative evaluations show that our method outperforms competing methods by a huge margin and achieved 94.12 as precision score, 97.95 as recall score, and 96.00 as F-score.
- This proposed technique can be used for a variety of applications, such as city-scale data collection, construction design, environment change detection due to constructions or natural disasters.