NYU TANDON SCHOOL OF ENGINEERING

DeepMapping2: Self-Supervised Large-Scale LiDAR Map Optimization

Chao Chen*, Xinhao Liu*, Yiming Li, Li Ding, Chen Feng

AI4CE Lab

New York University

Point cloud mapping in large-scale environment is challenging

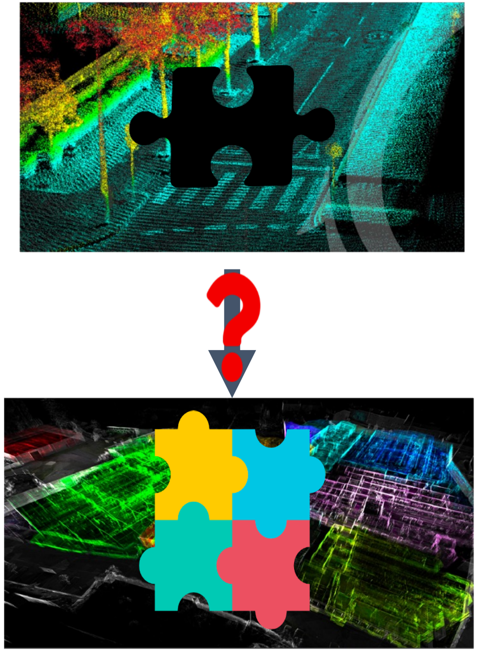
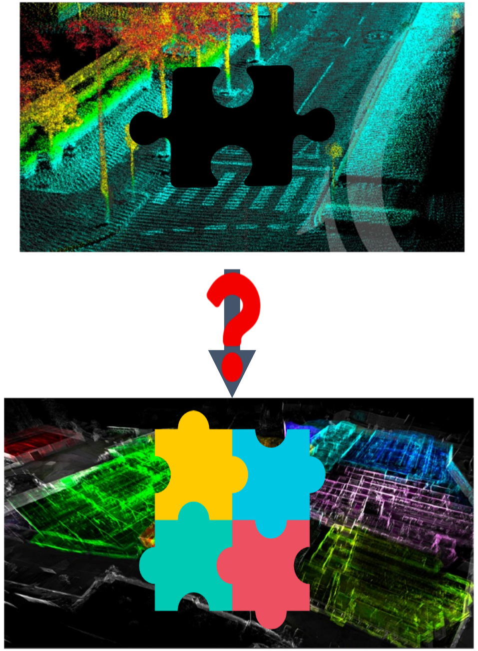


Image from: https://geo-matching.com/content/oxts-what-is-lidar
https://metrology.news/3d-point-cloud-software-for-industrial-facilities-scanning/

Point cloud mapping in large-scale environment is challenging



Large-scale LiDAR mapping result on KITTI sequences

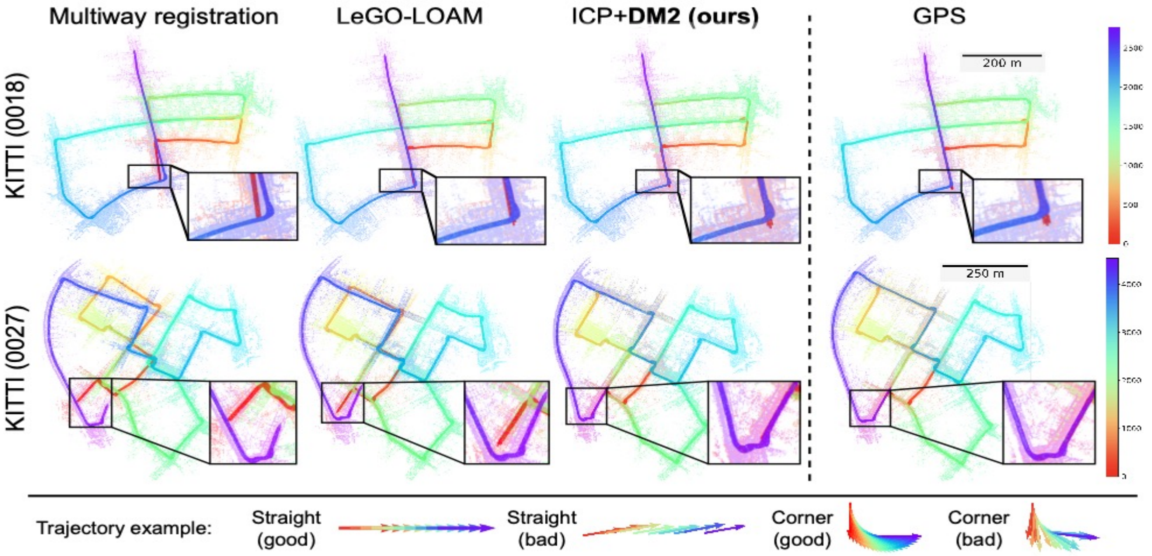


Image from: https://geo-matching.com/content/oxts-what-is-lidar
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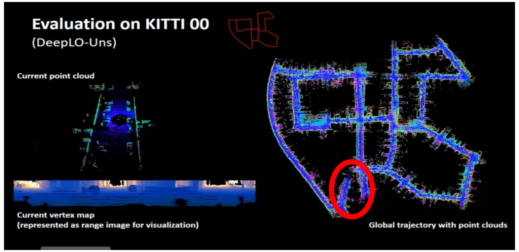
Learning-based mapping: two types of approaches

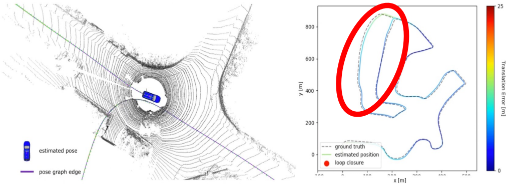
Train-then-test

- Most learning-based LiDAR SLAM methods face generalization issues

RPM



OverlapNet

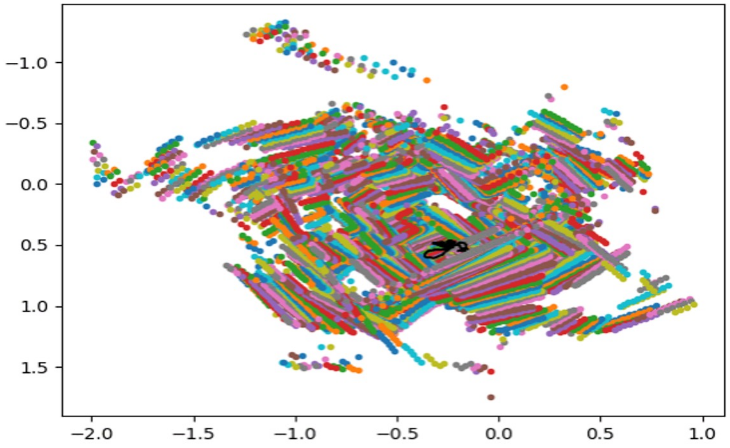


DeepLO: Geometry-Aware Deep LiDAROdometry by Cho et al. (15 September 2020)

OverlapNet - Loop Closing for LiDAR-based SLAM by Chen et al. (24 May 2021)

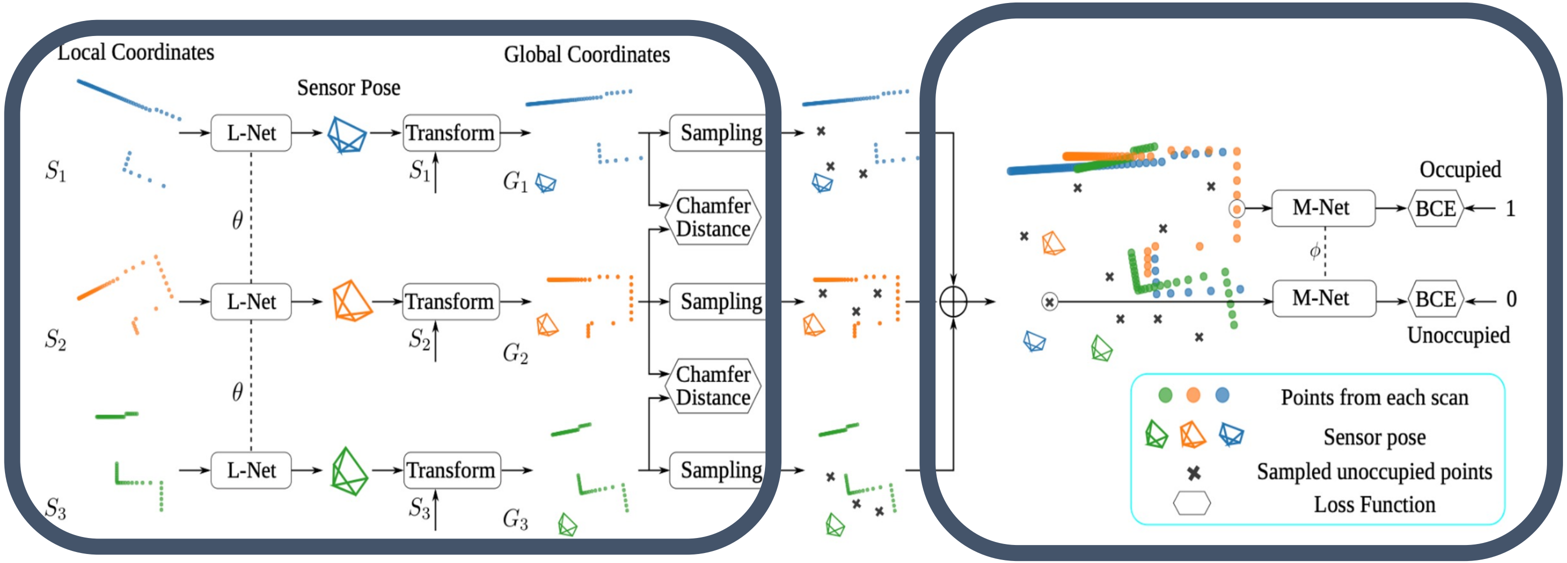
Train-as-optimization

- **DeepMapping**
  - Apply neural network as mapping optimizer
  - Regression via binary classification



DeepMapping: Unsupervised Map Estimation From Multiple Point Clouds. by Ding et al. (9 April 2019)

Original DeepMapping pipeline



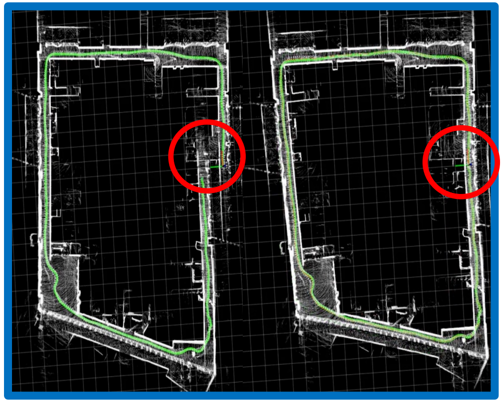
Global Pose estimation

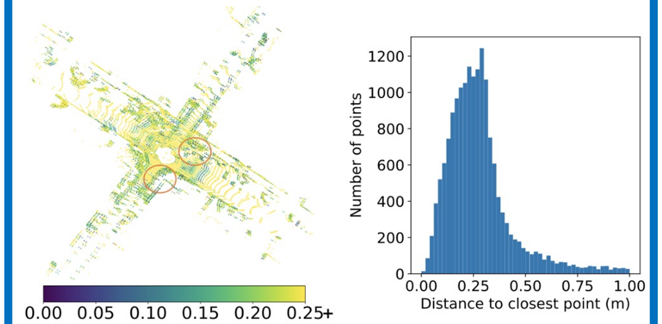
Global Refinement using global occupancy consistency

$\mathcal{L}_{ch}$: Chamfer Distance

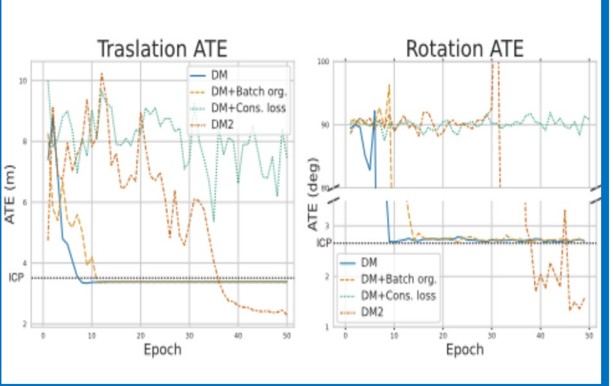
$\mathcal{L}_{cls}$: Classification loss

Issues of DeepMapping





(a) Color-coded distance (m) (b) Histogram of distance



(i1) No-explicit-loop-closure

- Lack of loop closing
- Facing drifting problem

(i2) No-local-registration

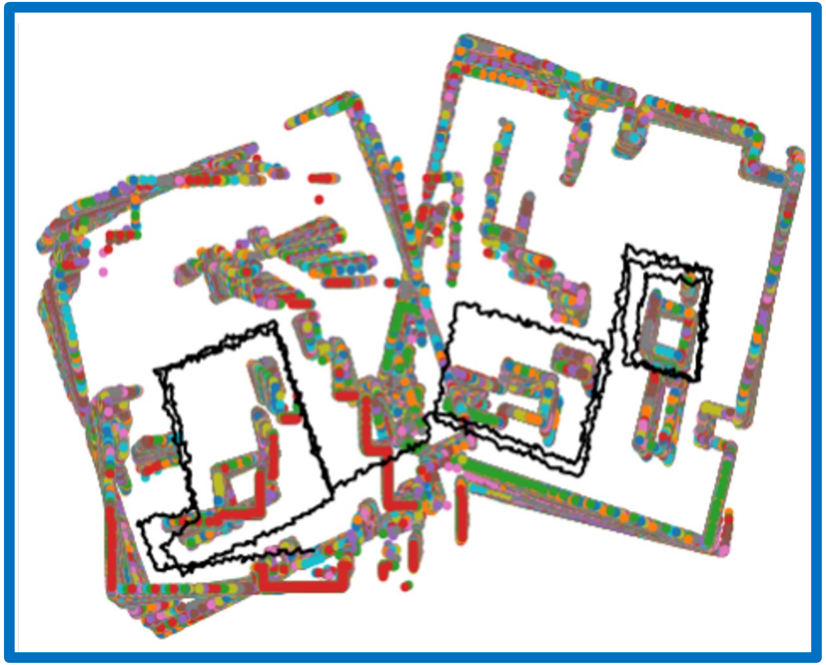
- Lack of exact point correspondence
- sparse sensor resolution/long-range sensing.

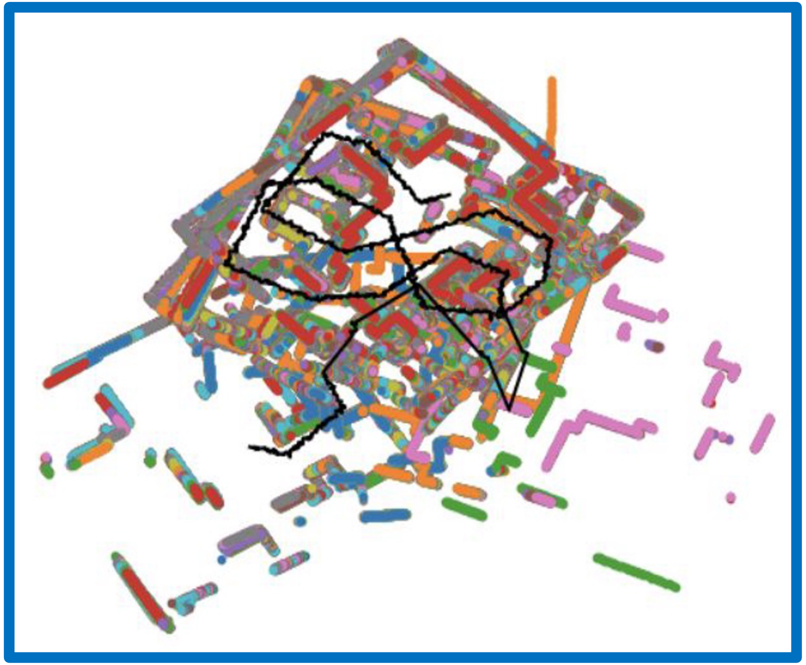
(i3) Slow-convergence-in-global-registration

- Lack enough inference cues
- Slow convergence on large datasets.

Image from: https://www.youtube.com/watch?v=MNw-GeHHSuA/

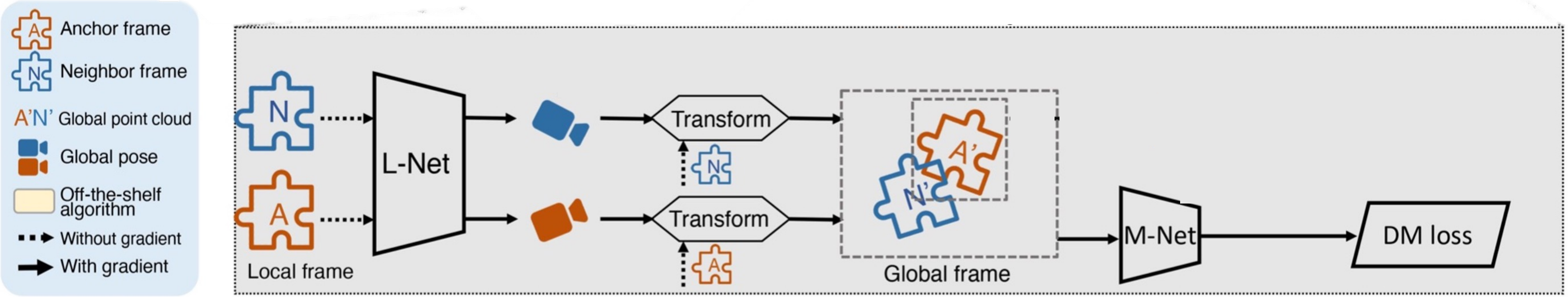
Issues of DeepMapping





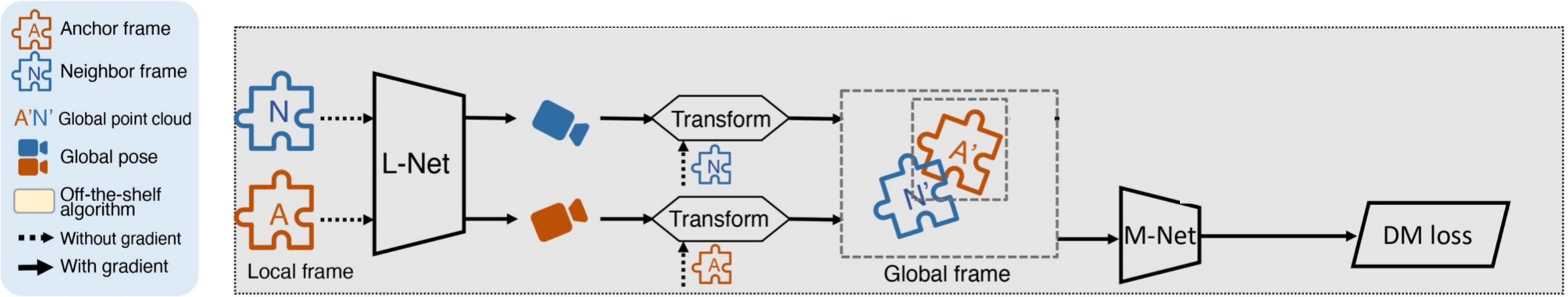
DeepMapping produces unsatisfying mapping results on large-scale environment

DeepMapping2 Pipeline

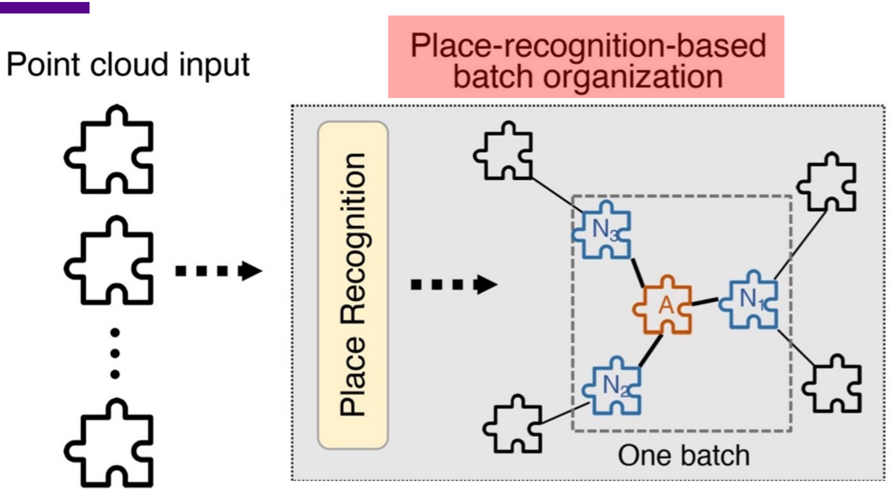


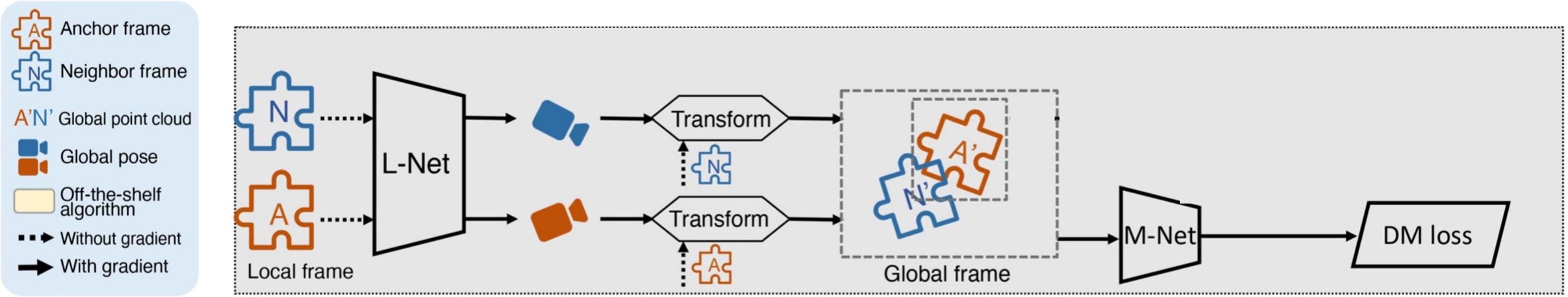
DeepMapping2 Pipeline - Preprocess

Point cloud input



DeepMapping2 Pipeline - Preprocess





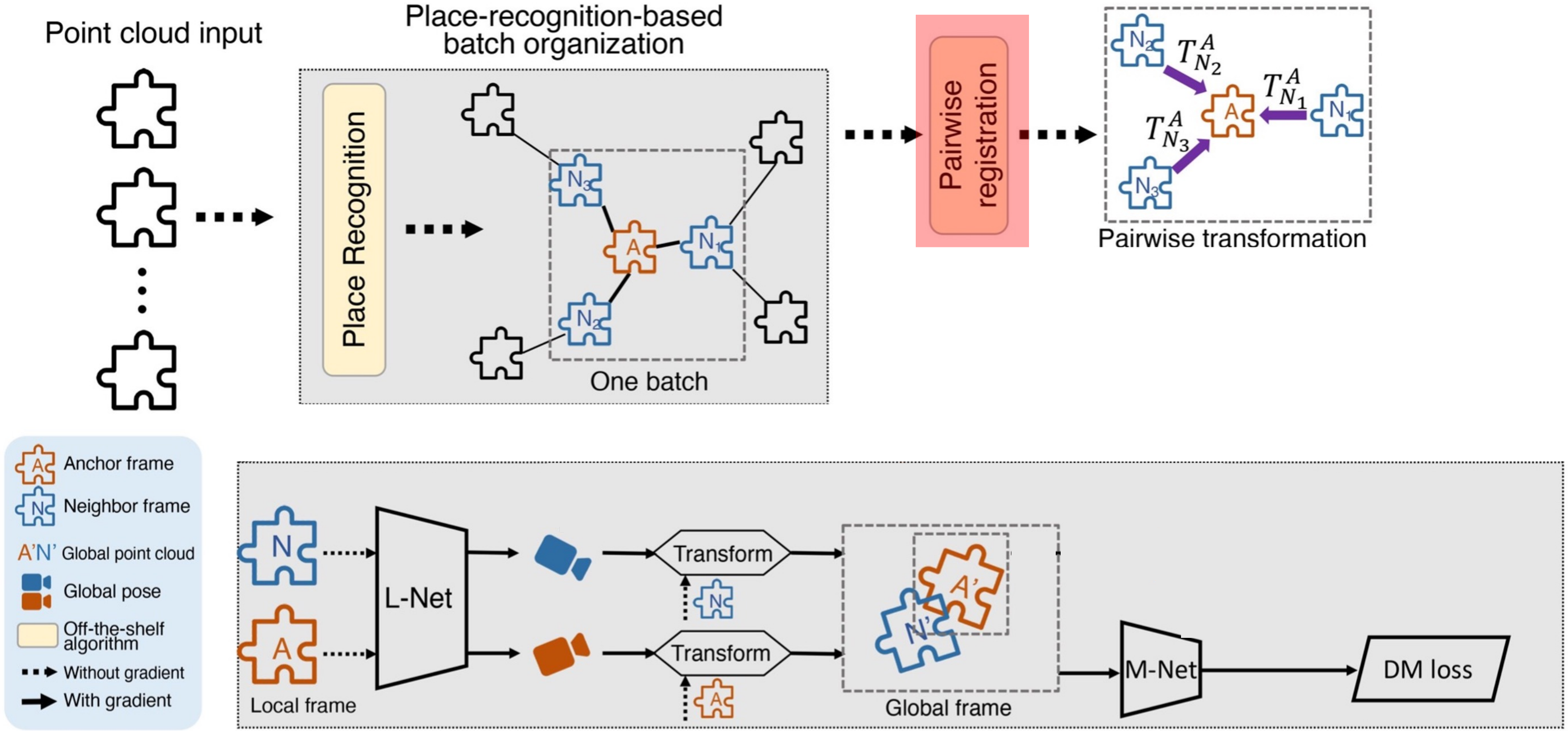
Batch Organization

(i1) No-explicit-loop-closure

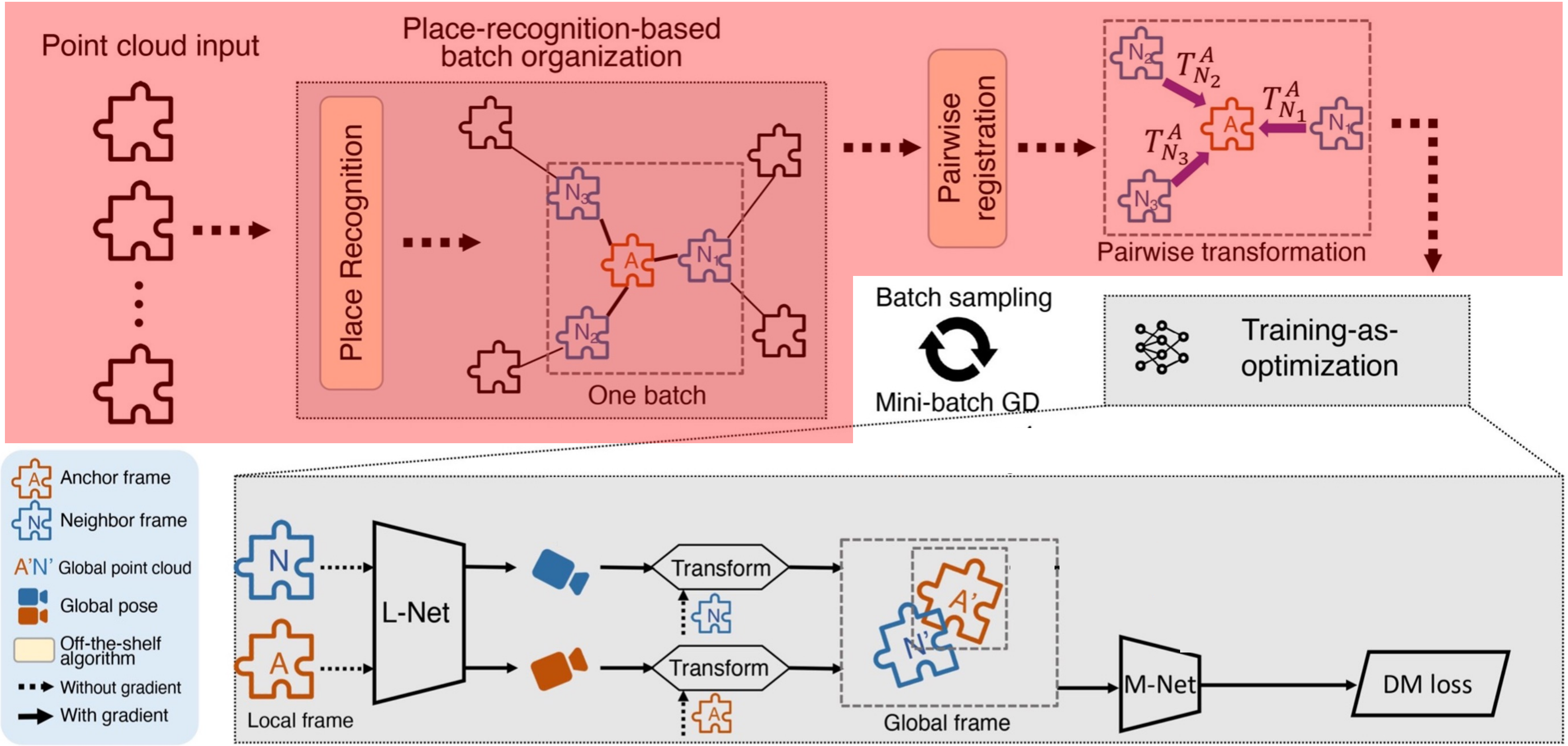
- Batch organization is based on map topology
- Batch organization by spatial topology (via place recognition) is the best

(a) Temporal batch organization (b) Random batch organization (c) Spatial topology batch organization

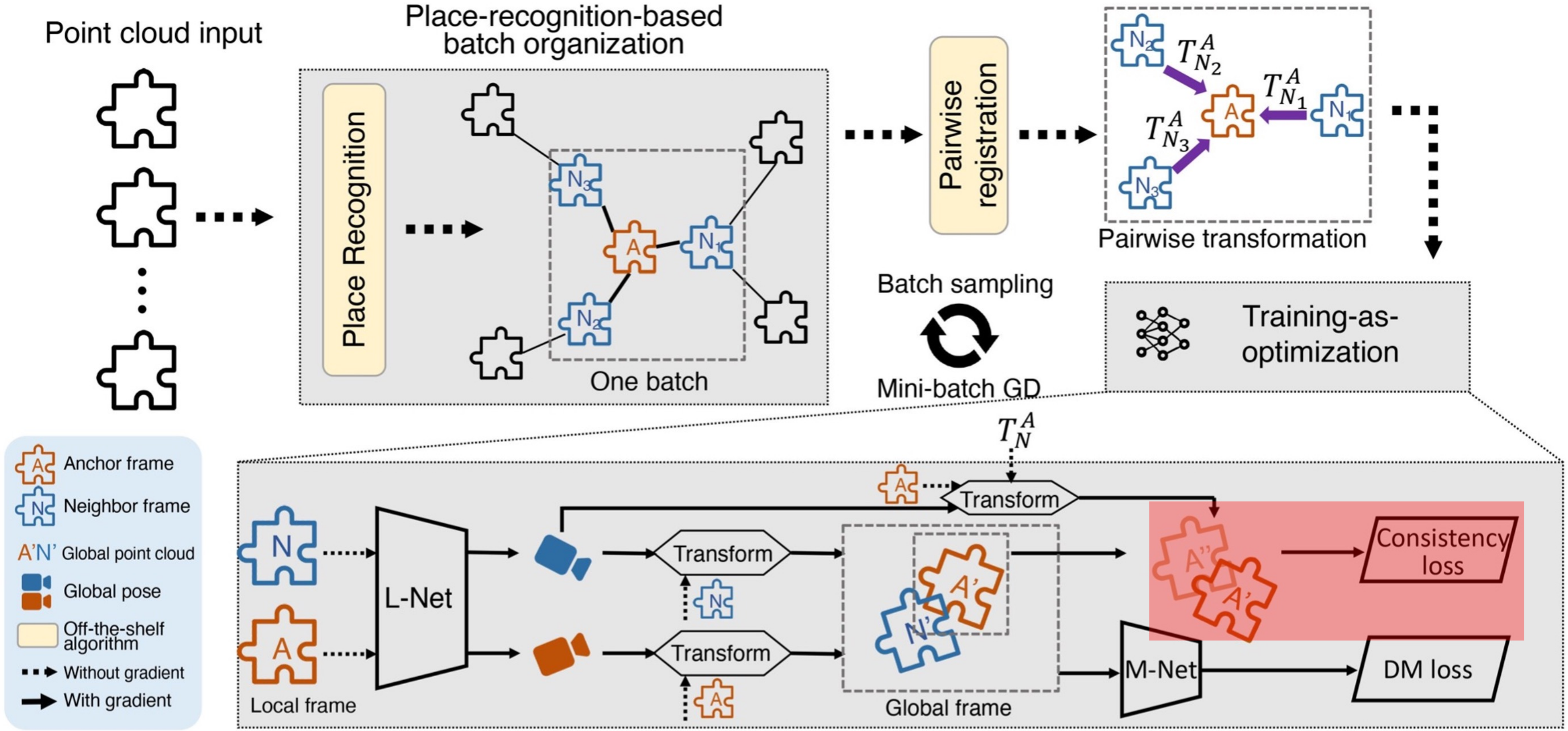
DeepMapping2 Pipeline - Preprocess



DeepMapping2 Pipeline - Preprocess



DeepMapping2 Pipeline

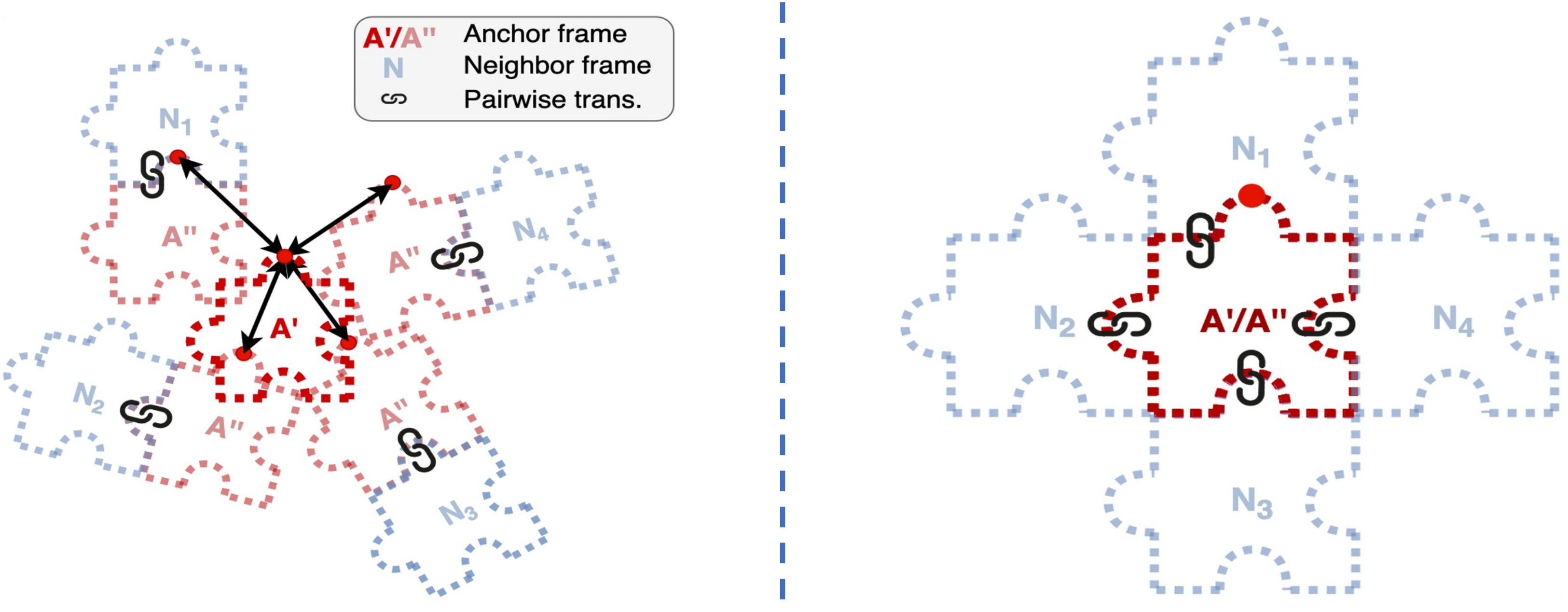


Local-to-global point consistency loss

(i2) No-local-registration

(i3) Slow-convergence-in-global-registration

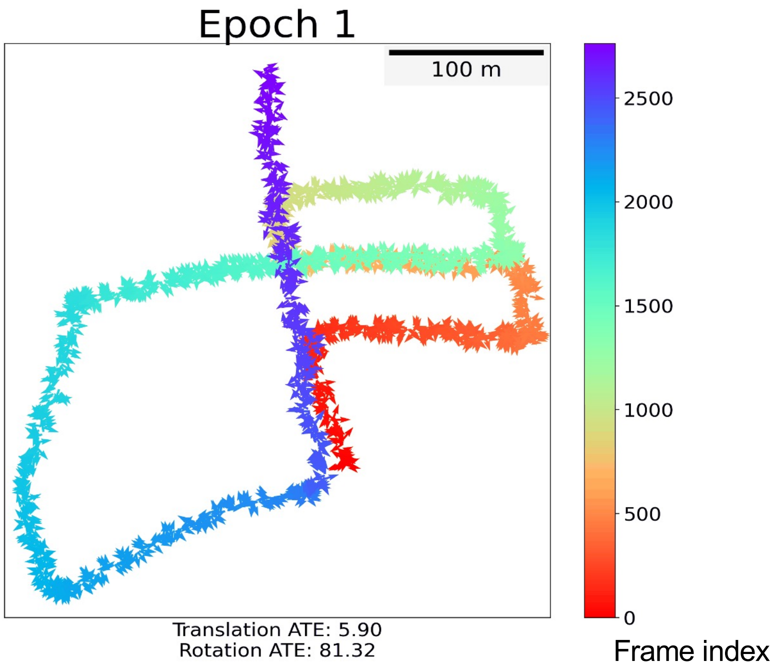
For each point in an anchor frame, we compute consistency between different versions of its global coordinate.



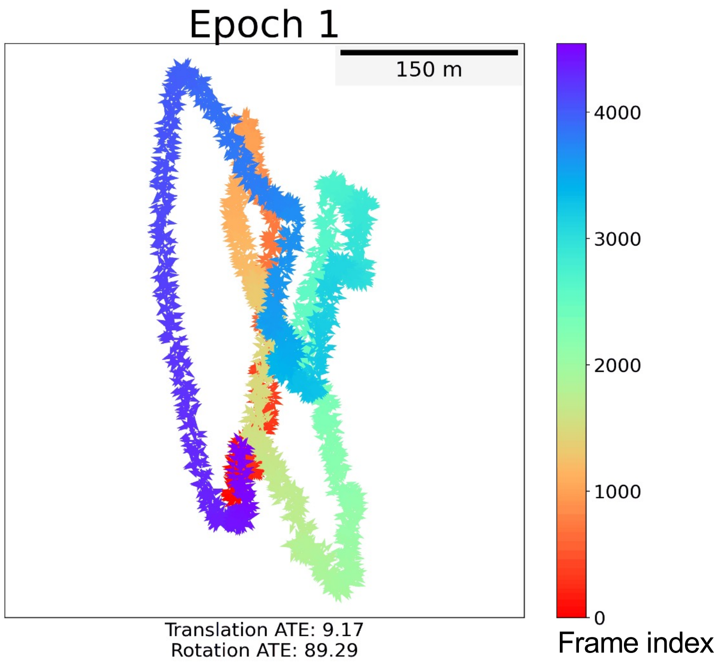
(a) Poor global registration

(b) Perfect global registration

Training animation on KITTI dataset

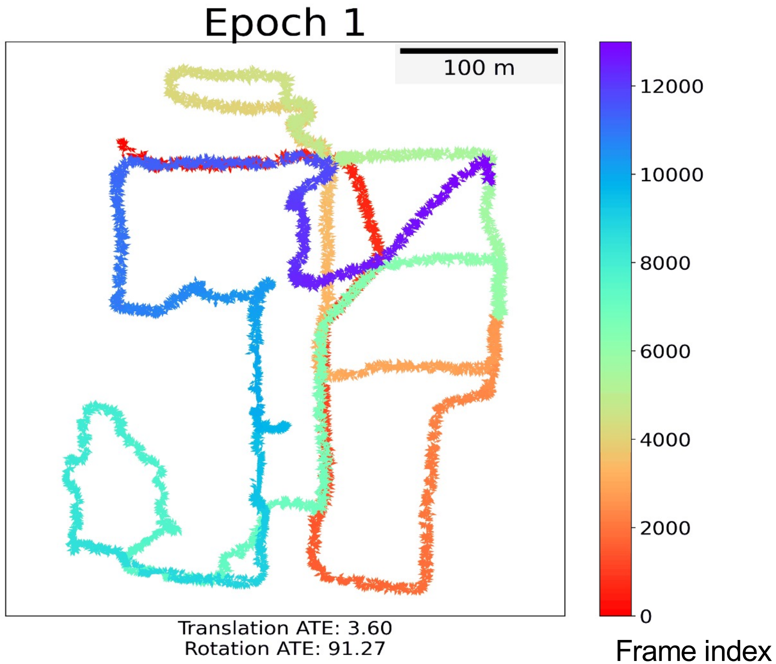


KITTI (0018)

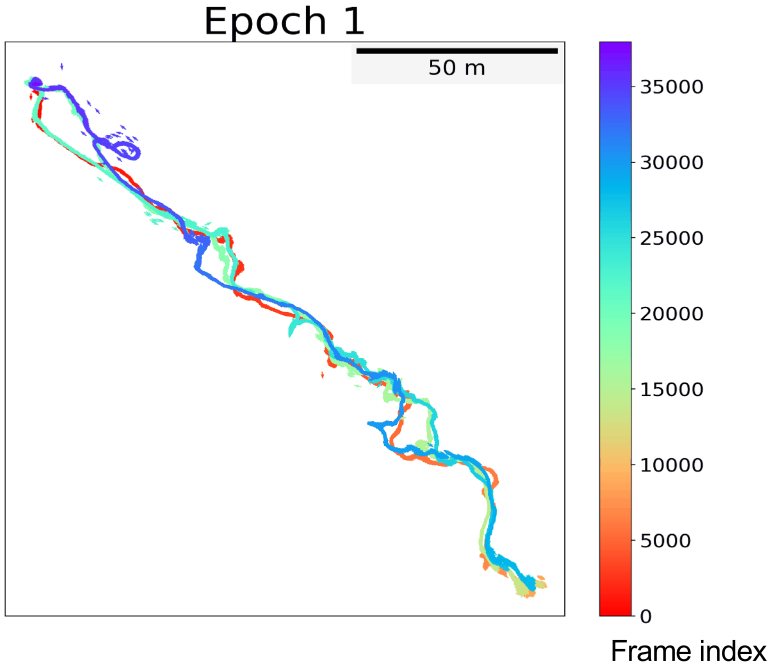


KITTI (0027)

Training animation on NCLT and Nebula dataset



NCLT



Nebula

Quantitative results

Table 1. Quantitative result on the KITTI dataset.

Method	Drive_0018		Drive_0027	
	T-ATE(m)	R-ATE(°)	T-ATE(m)	R-ATE(°)
Incremental ICP	4.38	4.61	3.53	2.67
Multiway	2.24	1.75	4.70	5.93
DGR	3.15	4.09	4.12	1.59
Lego-LOAM	1.90	1.36	2.96	2.36
HRegNet	30.61	94.90	45.49	85.36
GeoTransformer	4.03	3.02	10.15	15.34
ICP+DM	3.42	1.66	3.39	2.70
KISSICP	2.10	0.68	6.25	1.21
ICP+DM2	1.81	0.72	**2.29**	1.57
KISS-ICP+DM2	1.78	**0.68**	2.30	**1.17**
Lego-LOAM+DM2	**1.63**	1.18	2.59	2.27

Table 2. Quantitative result on the NCLT dataset.

Method	T-ATE(m)	R-ATE(°)
Incremental ICP	6.20	12.95
Multiway	6.56	12.60
DGR	8.89	42.90
Lego-LOAM	2.25	2.18
ICP+DM2	3.73	6.27
Lego-LOAM+DM2	**2.02**	**1.87**

Ablation study on the KITTI dataset

Table 3. Ablation study on the KITTI dataset.

Components			T-ATE(m)	R-ATE(º)
DM Loss	Batch Organization	Consistency Loss		
√			1.88	4.72

Ablation study on the KITTI dataset

Table 3. Ablation study on the KITTI dataset.

Components			T-ATE(m)	R-ATE(º)
DM Loss	Batch Organization	Consistency Loss		
✓			1.88	4.72
✓	✓		1.65	2.07

Ablation study on the KITTI dataset

Table 3. Ablation study on the KITTI dataset.

Components			T-ATE(m)	R-ATE(º)
DM Loss	Batch Organization	Consistency Loss		
√			1.88	4.72
√	√		1.65	2.07
√		√	1.88	4.70

Ablation study on the KITTI dataset

Table 3. Ablation study on the KITTI dataset.

Components			T-ATE(m)	R-ATE(º)
DM Loss	Batch Organization	Consistency Loss		
✓			1.88	4.72
✓	✓		1.65	2.07
✓		✓	1.88	4.70
	✓	✓	Failed	Failed

Ablation study on the KITTI dataset

Table 3. Ablation study on the KITTI dataset.

Components			T-ATE(m)	R-ATE(º)
DM Loss	Batch Organization	Consistency Loss		
√			1.88	4.72
√	√		1.65	2.07
√		√	1.88	4.70
	√	√	Failed	Failed
√	√	√	1.63	1.81

Ablation study on the KITTI dataset

Table 3. Ablation study on the KITTI dataset.

Components			T-ATE(m)	R-ATE(º)
DM Loss	Batch Organization	Consistency Loss		
√			1.88	4.72
√	√		1.65	2.07
√		√	1.88	4.70
	√	√	Failed	Failed
√	√	√	**1.63**	**1.81**

Conclusion

- DM2 achieves SOTA mapping performance in large-scale scenes
- Batch organization by spatial topology achieves loop closing implicitly
- Consistency loss speeds up the convergence
- DM2 is a general point cloud map optimization back-end

Chao Chen (陈超)
Ph.D. candidate
New York University
E-mail: cchen@nyu.edu
Webpage: https://joechencc.github.io

Xinhao Liu (刘歆昊)
Incoming Ph.D. student
New York University
E-mail: xinhao.liu@nyu.edu
Webpage: https://gaaaavin.github.io