Supplementary Material for "Large-scale Multi-session Point-cloud Map Merging"

1 Further Evaluation

To cover a variety of scenarios, we further test our framework on datasets of different environments. Detailed characteristics of each dataset are provided in TABLE 1.

Table 1: The overview of the datasets utilized in evaluation.

Dataset	Environment	Trajectory Length (km)	LiDAR
HeLiPR	Residential area	50	Avia & Ouster
KITTI	Urban	15	Velodyne
WildPlaces	Wild	33	Velodyne
Shenzhen	Urban	2	Hesai
Hong Kong	Urban	15	Avia

1.1 HeLiPR

HeLiPR [1] is over 50km, which is a large-scale dataset that covers diverse environments, from urban cityscapes to high-dynamic freeways, over a month. HeLiPR is the first heterogeneous LiDAR dataset, providing different LiDARs' (Spinning and Solid State) data of the same sequences for each environment.

In our experiment, we conduct our merging framework on sequences of Livox Avia and OS2-128 in two large-scale environment, Roundabout and Town, respectively. The Roundabout sequences feature three roundabouts with a prominently large roundabout paired with an external hexagon. The Town sequences showcase a juxtaposition of tight alleyways and expansive boulevards with multiple dynamic elements, including pedestrians and vehicles. We use FAST-LIO2 [2] to obtain the odometry of each sequence and perform the merging of sequences of the same LiDAR type as well as the merging of sequences of different LiDAR types.

The merging result of HeLiPR in TABLE 2, demonstrates the robustness of our method. In both the Roundabout and Town scenes, as shown in Fig 1 and Fig 2, the results include the merging of three sequences collected by Ouster LiDAR, the merging of three sequences collected by Avia LiDAR, the merging of all the six sequences. For each combination, we achieve a globally consistent large map with odometry accuracy comparable to the sequences before merging.

1.2 WildPlaces

WildPlaces [3] is over 33km, which is a challenging large-scale dataset in unstructured, natural environments, comprising eight sequences in two different locations over fourteen months. These datasets are collected using a handheld sensor by a 16-beam rotating LiDAR (Velodyne VLP16). In our experiment, we test our framework on sequences in Karawatha and Venman respectively. As WildPlaces provides both the aligned and not-aligned accurate 6DoF ground-truth pose for each sequence, we simply use the not-aligned ground-truth poses as the input for our framework. We directly compare the globally consistent 6DoF poses provided by our method with the aligned ground-truth poses. The accuracy results are shown in TABLE 2. Given the scale and time span of WildPlaces, we believe the slight increase of RMSE after merging is reasonable. The merging result for the WildPlaces dataset is shown in Fig 3.

Table 2: RMSE of the ATE(m) on HeLiPR Dataset

Environment	Sequences	FAST-LIO2	Merged	Merged Multi-LiDAR
Town	Ouster 1	2.884	2.818	4.008
	Ouster 2	2.563		
	Ouster 3	2.896		
	Avia 1	7.477	4.273	
	Avia 2	14.413		
	Avia 3	21.199		
Roundabout	Ouster 1	1.573	2.125	2.101
	Ouster 2	1.627		
	Ouster 3	2.237		
	Avia 1	9.336	2.247	
	Avia 2	10.134		
	Avia 3	8.328		
Karawatha	Velodyne0	-	2.017	-
	Velodyne1	-		
	Velodyne2	-		
	Velodyne3	-		
Venman	Velodyne0	-	1.023	-
	Velodyne1	-		
	Velodyne2	-		
	Velodyne3	-		

1.3 Shenzhen

The Shenzhen dataset, approximately $2km$ in length, was self-collected in an urban area near Shenzhen North Railway Station in Shenzhen, China. This dataset was gathered using a backpack device equipped with a Hesai 128-line LiDAR and four Hikvision cameras. After employing the R^{3}LIVE [4] algorithm for front-end odometry, the 6DoF pose data and colored point cloud were obtained as inputs for our algorithm. Consequently, our method produces a globally consistent colored point cloud map, as shown in Fig. 4. The overlapping regions are zoomed in and displayed in Fig.4(a-d). Furthermore, Fig.4(f) illustrates an example of the moving object detection and removal function of our method. The resulting map, with moving objects removed, is clear and consistent, which can benefit applications relying on the global map, such as autonomous navigation.

1.4 Hong Kong

The Hong Kong dataset, approximately $15km$ in length, was self-collected in an urban area on Hong Kong Island, Hong Kong, China. To be specific, the sequences all start at Western District Public Cargo Working Aera, and align along the Belcher's street(mainly the curved section). This dataset was gathered using a handheld device fixed behind a truck, equipped with a Avia LiDAR. After employing the FAST-LIO2 [2] algorithm for front-end odometry, the 6DoF pose data and point clouds were obtained as inputs for our algorithm. Consequently, our method produces a globally consistent colored point cloud map, as shown in Fig. 5.

References

[1] M. Jung, W. Yang, D. Lee, H. Gil, G. Kim, and A. Kim, "Helipr: Heterogeneous lidar dataset for inter-lidar place recognition under spatiotemporal variations," *The International Journal of Robotics Research*, p. 02783649241242136, 2023.

[2] W. Xu, Y. Cai, D. He, J. Lin, and F. Zhang, "Fast-lio2: Fast direct lidar-inertial odometry," *IEEE Transactions on Robotics*, vol. 38, no. 4, pp. 2053–2073, 2022.

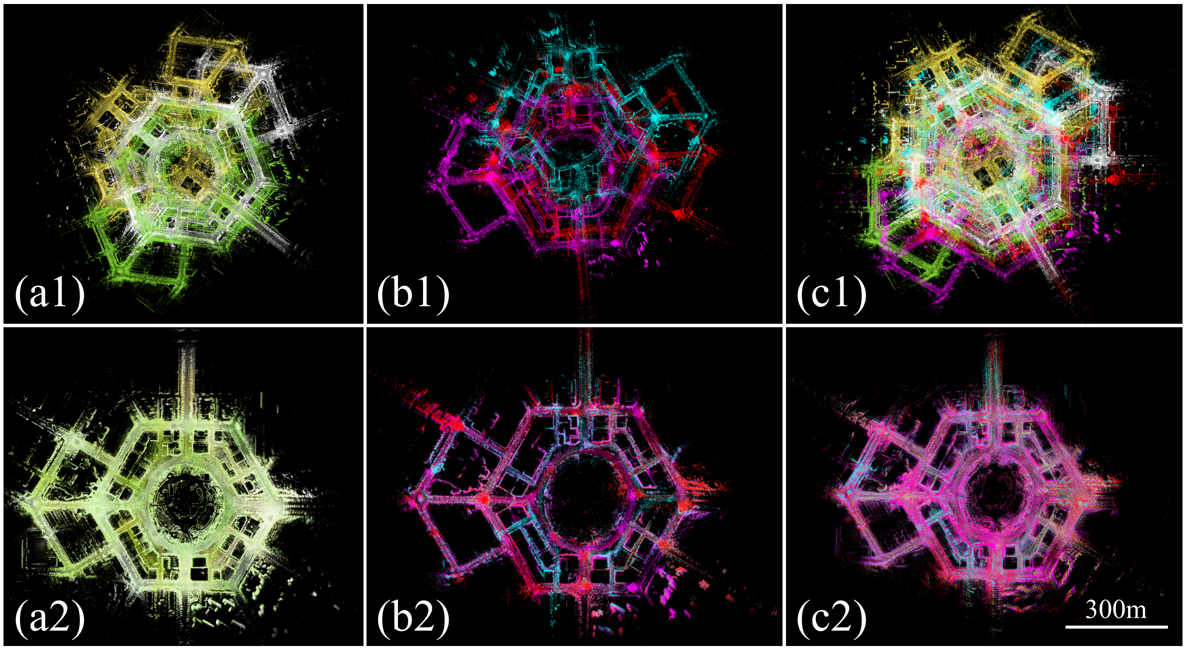

Figure 1: Merging results in Roundabout environment of HeLiPR dataset. (a1): three submaps collected by Ouster LiDAR. (a2): a merged global map of three sequences in (a1). (b1): three submaps collected by Avia LiDAR. (b2): a merged global map of three sequences in (b1). (c1): three submaps collected by different LiDARs, the white, green and yellow submaps were collected by Outser LiDAR, and the red, purple and blue submaps was collected by Avia LiDAR. (c2): a merged global map of three sequences in (c1).

[3] J. Knights, K. Vidanapathirana, M. Ramezani, S. Sridharan, C. Fookes, and P. Moghadam, "Wild-places: A large-scale dataset for lidar place recognition in unstructured natural environments," in *2023 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2023, pp. 11 322–11 328.

[4] J. Lin and F. Zhang, "R 3 live: A robust, real-time, rgb-colored, lidar-inertial-visual tightly-coupled state estimation and mapping package," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 10 672–10 678.

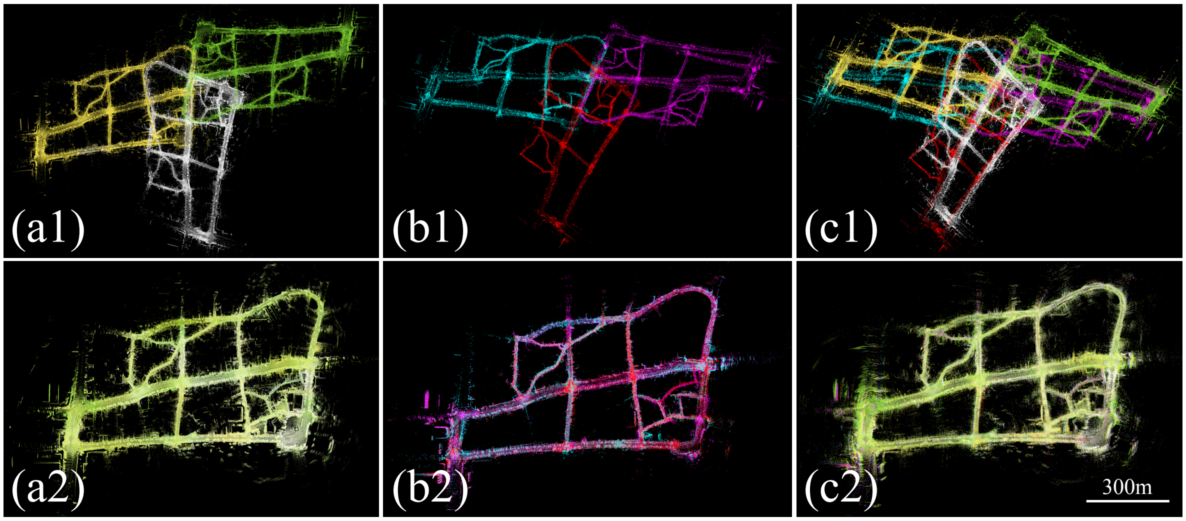

Figure 2: Merging results in Town environment of HeLiPR dataset. (a1): three submaps collected by Ouster LiDAR. (a2): a merged global map of three sequences in (a1). (b1): three submaps collected by Avia LiDAR. (b2): a merged global map of three sequences in (b1). (c1): three submaps collected by different LiDARs, the white, green and yellow submaps were collected by Outser LiDAR, and the red, purple and blue submaps was collected by Avia LiDAR. (c2): a merged global map of three sequences in (c1).

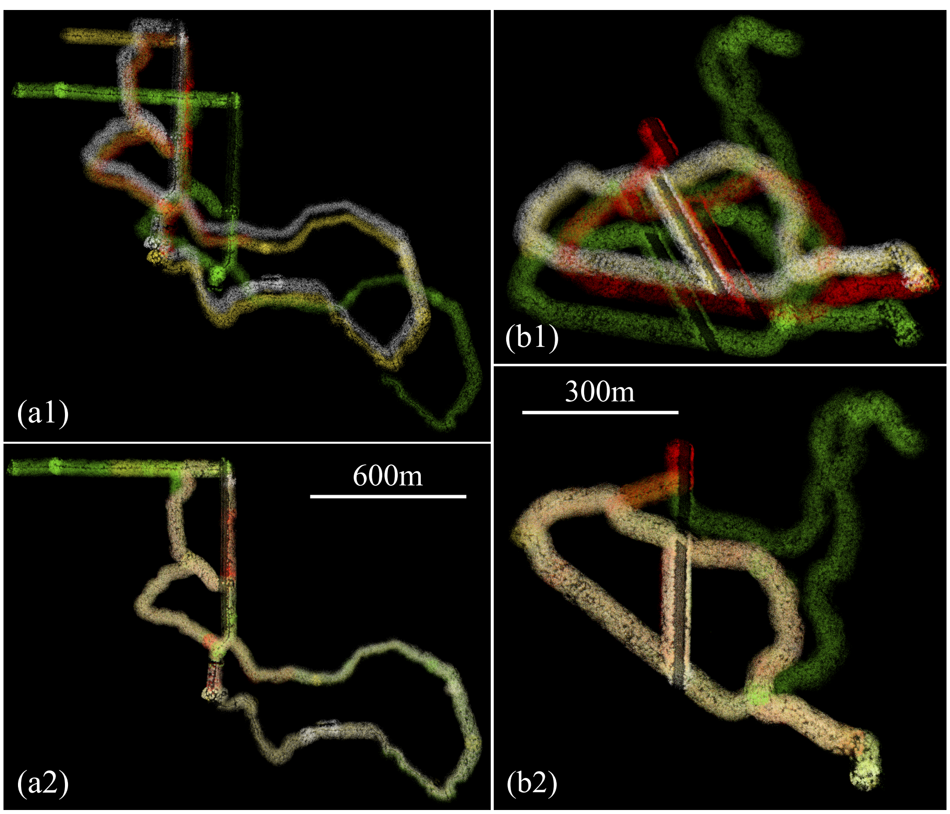

Figure 3: Test on WildPlaces dataset. (a1): original four submaps of Karawatha. (a2): a merged global map of four sequences in (a1). (b1): original four submaps of Venman. (b2): a merged global map of four sequences in (b1).

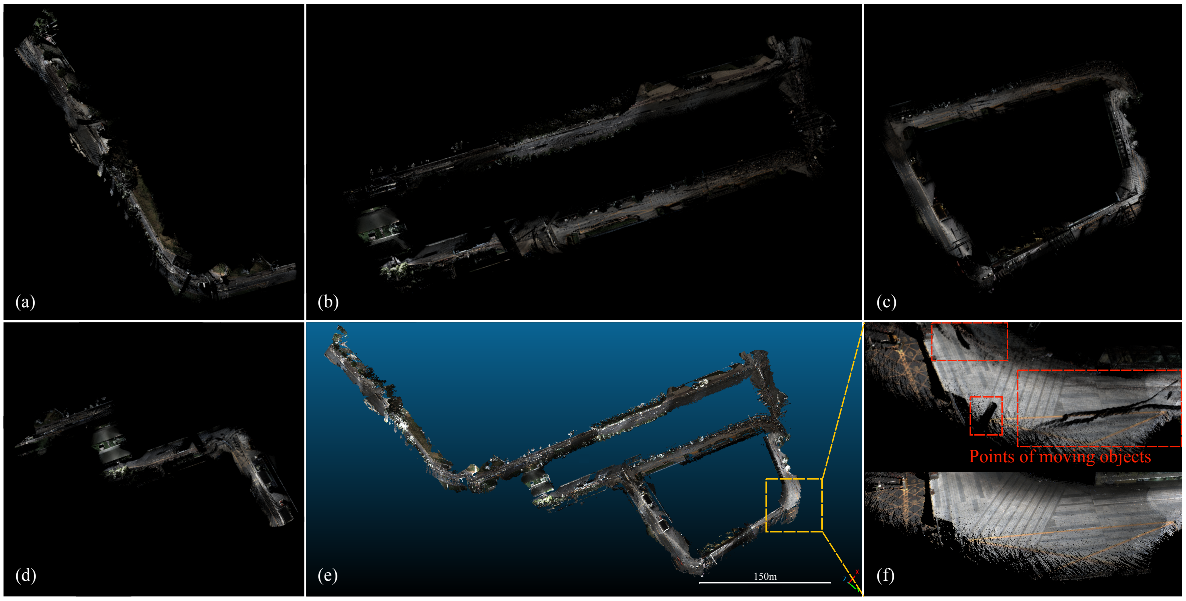

Figure 4: Test on self-collected Shenzhen dataset. (a)-(d) are four colored RGB 3D point cloud submaps, which are collected using our equipment and constructed using the r3live algorithm. (e) is the merged global map. (f) shows a magnified detail of the part outlined by the yellow dashed box in (e). The top part shows the original point cloud, the part outlined by the red dashed box represents the points of moving objects, and the bottom part shows the clean map without moving objects after processing.

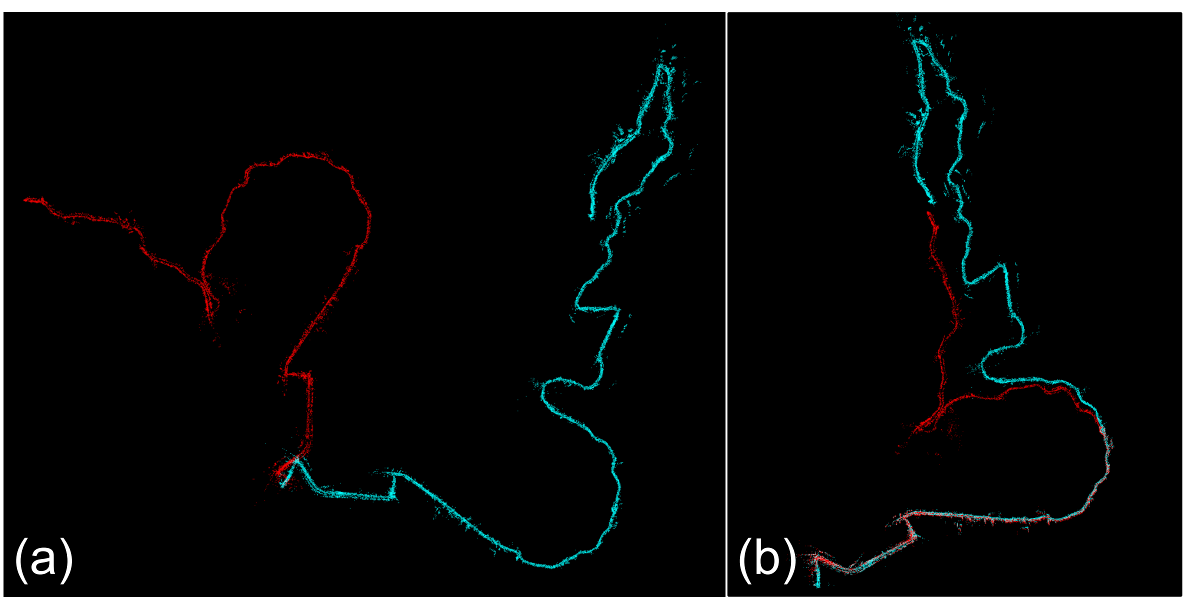

Figure 5: Test on self-collected Hong Kong dataset. (a) presents two sequences, colored in different colors, which are collected using our equipment and constructed using the FAST-LIO2 algorithm. (b) is the merged global map.