

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Results and Discussion

Reliable localization is a critical capability for autonomous robotic systems, as it directly affects navigation accuracy, mapping quality, and overall system safety. Although many SLAM techniques have shown strong performance in controlled environments, real-world operation introduces additional challenges such as sensor noise, environmental variability, and temporary sensor unavailability. As a result, evaluating a SLAM system solely under ideal conditions is insufficient to fully characterize its performance.

This study conducts a systematic experimental evaluation of multiple SLAM-based localization approaches using a known reference trajectory as ground truth. The evaluation focuses not only on trajectory accuracy during normal operation, but also on system behavior when sensor input is partially lost. By doing so, the experiments aim to reflect more realistic operational scenarios encountered in practical robotic applications.

Experiment 1 Trajectory Estimation under Normal Conditions. The first experiment evaluates localization performance during standard operation, where all sensors function normally. Five independent test runs were performed using different trajectory layouts to assess consistency across varying motion patterns.

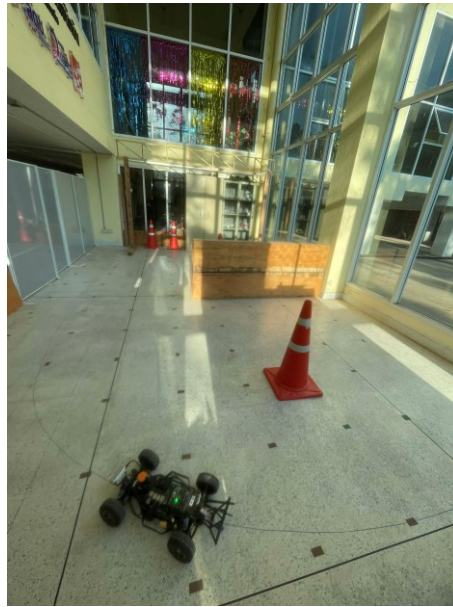


Figure 4.1 Comparing LiDAR SLAM and RTAB-Map Against a Ground-Truth Path test

Experiment 2 Loop Closure Activation Test. The second experiment investigates the loop closure capability of the SLAM systems. In this setup, the robot follows a closed-loop trajectory and returns to a previously visited location



Figure 4.2 Experimental Environment Setup for Robustness Evaluation Experiment 2

Experiment 3: Robustness Evaluation under Sensor Degradation The third experiment examines system robustness by simulating sensor failure conditions. During robot operation, the camera input is intentionally disabled while the robot continues to move.

An important distinction in this evaluation is the architectural difference between the tested systems. One approach relies heavily on camera-based perception

for both localization and mapping, while the proposed system separates these responsibilities by using LiDAR data for localization and depth data primarily for mapping. This experimental design allows the study to highlight how sensor dependency and system architecture influence accuracy, robustness, and fault tolerance.

The following sections present detailed results and discussions for each experiment, beginning with trajectory comparison under normal conditions and followed by robustness analysis during camera interruption.

4.1.1 Comparing LiDAR SLAM and RTAB-Map SLAM Against a Ground-Truth Path

Experiment 1 evaluates localization performance of two SLAM pipelines. LiDAR-based SLAM (`odom_slam`) and RTAB-Map SLAM (RTABMAP). Both systems estimate the robot trajectory in a 2D plane and are compared against a true path reference. The goal is to assess how closely each SLAM output follows the ground-truth trajectory during normal operation, and to identify where and why deviations occur.

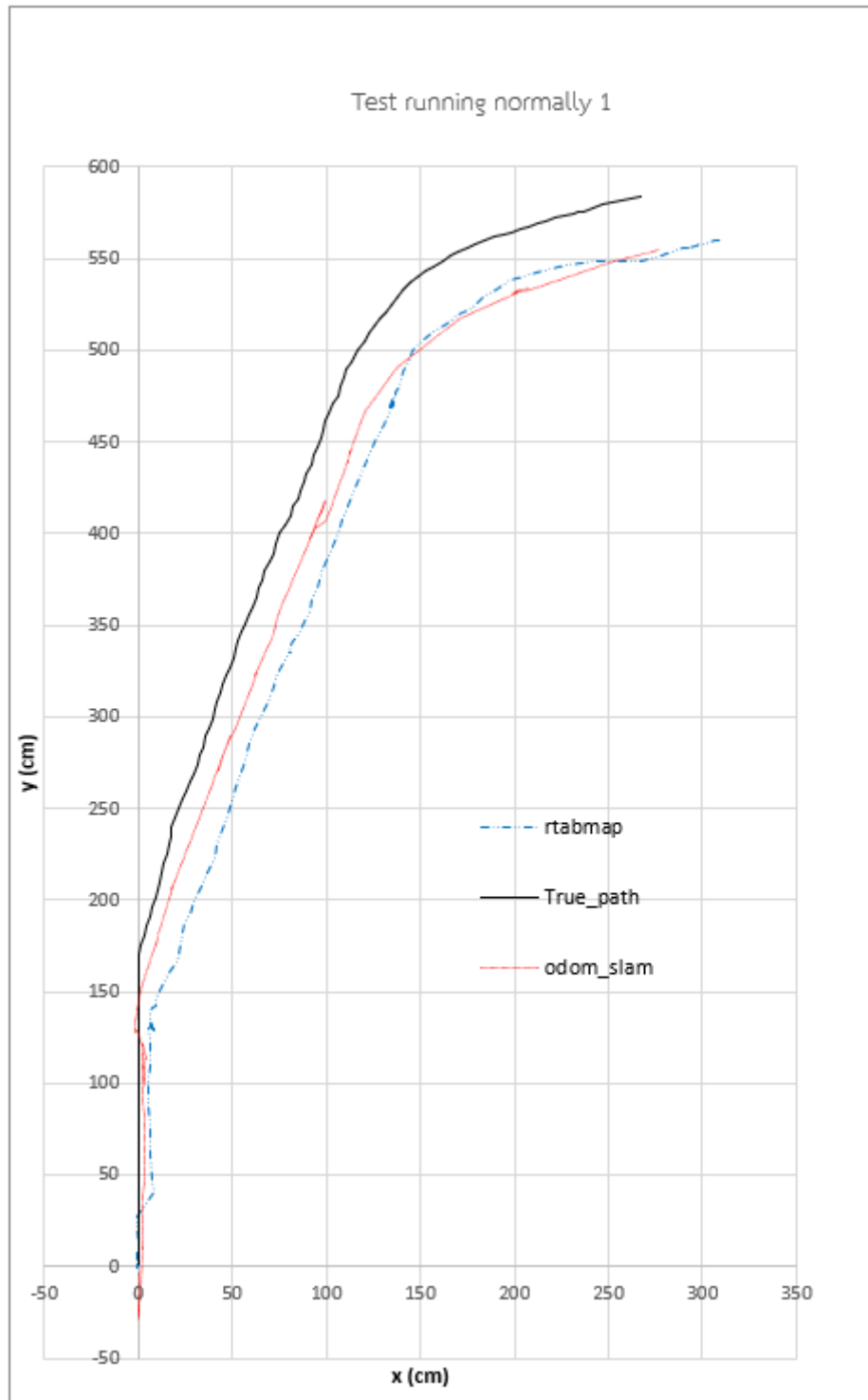


Figure 4.3 Comparing LiDAR SLAM and RTAB-Map Against a Ground-Truth Path test 1

Table 4.1 Experimental Localization Data and Absolute Error Measurements test 1

true path		rtab_odom		odom_slam		Error	Error
X	Y	x	y	x	y	rtab	odom_slam
0.0	0.0	0.0	0.0	0.0	-3.3	0.0	3.3
0.0	10.0	0.3	10.6	2.2	10.1	0.7	2.2
0.0	40.0	7.9	40.6	2.7	38.8	8.0	3.0
0.0	90.0	5.8	88.3	2.3	90.7	6.0	2.4
0.0	170.0	11.1	150.5	-2.0	133.2	22.4	36.8
11.0	210.0	29.2	199.5	18.5	208.0	21.0	7.8
40.0	299.0	59.1	285.8	50.9	292.0	23.2	13.0
61.0	360.0	82.7	340.9	71.7	345.9	28.9	17.7
88.0	428.0	108.4	407.6	99.8	418.2	28.9	15.3
106.0	475.0	126.2	452.7	118.4	461.7	30.1	18.2
129.0	517.0	146.0	500.1	137.0	489.9	24.0	28.2
175.0	556.0	183.9	529.6	207.1	533.8	27.8	39.1
208.0	567.5	227.3	546.9	247.4	546.1	28.2	44.8
247.0	579.5	275.7	550.5	253.1	548.1	40.8	32.0
267.0	584.0	310.2	560.6	277.7	554.9	49.2	31.0

Table 4.2 Localization Error Summary Table test 1

Metric	rtab_odom	odom_slam
Max Error	49.18	44.83
Mean Error	22.61	19.65
RMSE	26.31	24.23

In the first test, the robot motion involved two turns. The first turn had a relatively straight trajectory. From the graph, it can be observed that both paths show accumulated error over distance. The red and blue lines represent odom_slam and rtab_odom respectively. At 90 cm on the y-axis, from the table, rtab has an error of 6

cm, while odom_slam has only 2.4 cm error. This indicates that rtab_odom begins to deviate earlier compared to odom_slam when compared with the true path.

In the next part of the test, which is a straight path followed by a second turn, error accumulation gradually increases until it becomes more significant. From Table 4.2, it can be seen that the Mean Error and RMSE of odom_slam are lower than those of rtab_odom.

The primary source of localization error originates from cumulative drift due to odometry integration, exacerbated during rotational motion where orientation uncertainty propagates into significant positional deviation. The RTAB-Map (depth-only) configuration exhibits earlier divergence from ground truth due to weaker geometric constraints and delayed loop closure correction, while the odom_slam approach maintains lower overall error due to more stable pose estimation and reduced reliance on post-hoc corrections.

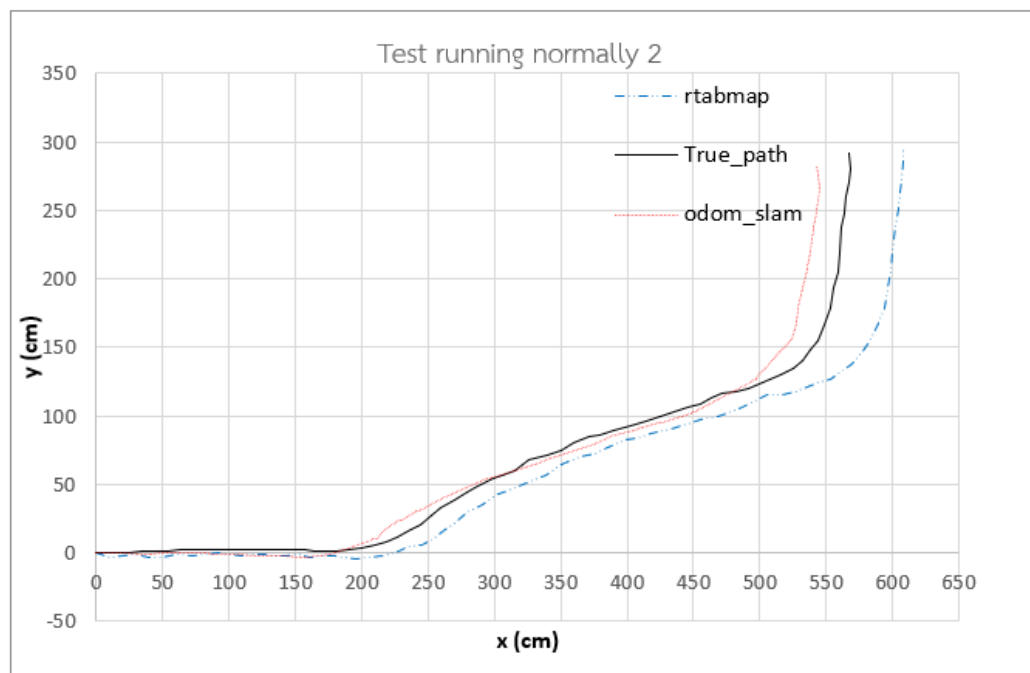


Figure 4.4 Comparing LiDAR SLAM and RTAB-Map Against a Ground-Truth Path test 2

Table 4.3 Experimental Localization Data and Absolute Error Measurements test 2

true path		rtab_odom		odom_slam		Error	Error
X	Y	x	y	x	y	rtab	odom_slam
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
124.0	2.0	127.1	-0.9	121.0	1.8	4.2	3.1
172.0	1.0	195.1	-3.8	176.5	-0.6	23.6	4.8
227.0	11.0	235.0	4.7	217.2	16.7	10.2	11.3
270.0	39.0	279.8	29.6	262.4	40.7	13.6	7.8
287.0	49.0	290.4	34.9	295.0	54.3	14.5	9.6
371.0	85.0	376.4	72.1	374.9	79.3	13.9	7.0
415.0	96.0	408.0	83.5	407.5	90.3	14.3	9.5
455.0	109.0	486.9	106.3	453.4	104.3	32.0	4.9
525.0	135.0	577.1	146.2	523.4	154.5	53.3	19.6
556.0	193.0	599.2	206.0	535.6	207.5	45.1	25.0
562.0	237.0	604.7	251.6	540.9	240.1	45.1	21.3
567.0	292.0	608.2	296.3	542.7	283.2	41.5	25.8

Table 4.4 Localization Error Summary Table test 2

Metric	rtab_odom	odom_slam
Max Error	53.26	25.84
Mean Error	20.75	9.98
RMSE	27.23	13.18

In Test 2, localization accuracy remains stable during the initial straight trajectory, where both methods exhibit low error due to minimal orientation change and consistent sensor observations. However, significant divergence occurs during the final turning segment, where orientation errors propagate into large positional deviations. The RTAB-Map approach shows substantial drift due to its reliance on weak geometric constraints and lack of immediate correction mechanisms, resulting in rapid

error accumulation. In contrast, the `odom_slam` method maintains significantly lower error across all metrics, indicating more robust pose estimation and better handling of rotational motion. The results highlight that turning maneuvers are the dominant source of localization error, especially for loosely coupled and depth-dependent SLAM systems.

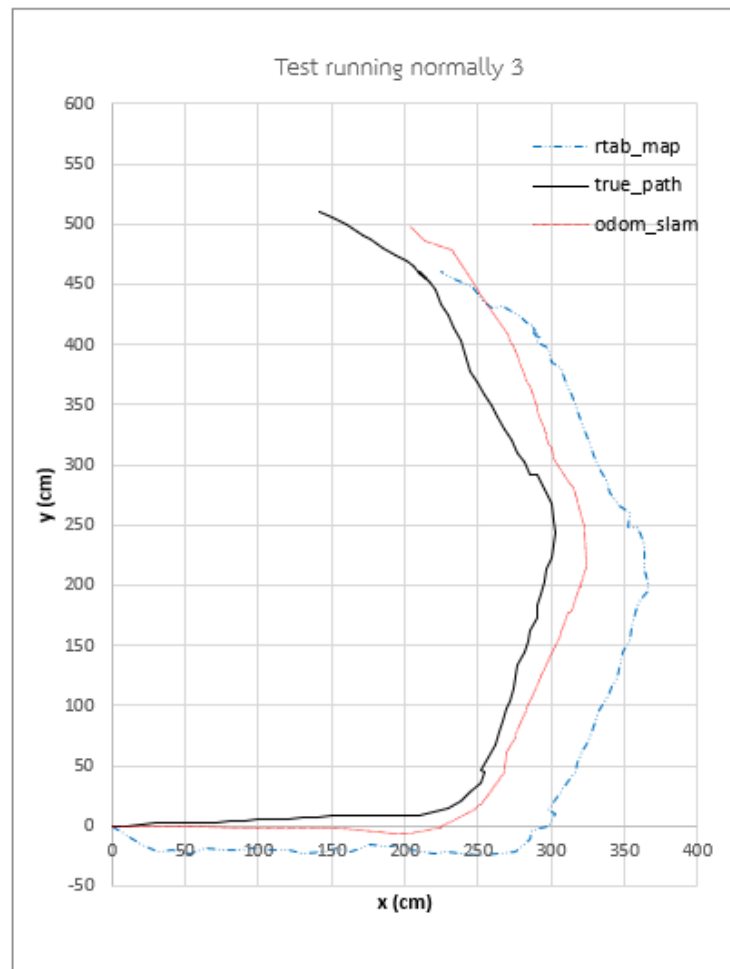


Figure 4.5 Comparing LiDAR SLAM and RTAB-Map Against a Ground-Truth Path test 3

In Test 3, the trajectory consists of a continuous curved path, which introduces sustained orientation changes and eliminates stable motion segments. This results in significant error accumulation for both methods, particularly due to orientation error propagation. The RTAB-Map (depth-only) approach exhibits severe drift, with error increasing exponentially over time due to weak geometric constraints and lack of effective correction mechanisms such as loop closure. In contrast, the

odom_slam method demonstrates comparatively stable performance, maintaining lower error despite degradation. The results highlight that continuous curvature represents a worst-case scenario for loosely coupled and depth-dependent SLAM systems, where small orientation errors compound rapidly into large positional deviations.

Table 4.5 Experimental Localization Data and Absolute Error Measurements test 3

true path		rtab_odom		odom_slam		Error	Error
x	y	x	y	x	y	rtab	odom_slam
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
40.0	2.0	41.6	-19.2	52.1	-0.3	21.2	12.3
120.0	6.0	130.1	-23.1	130.2	-1.8	30.9	12.8
190.0	8.5	219.7	-22.5	192.6	-6.0	43.0	14.8
238.0	21.0	285.0	-10.8	248.0	14.3	56.7	12.0
254.0	45.0	311.5	37.7	268.8	48.1	57.9	15.1
272.0	104.0	332.2	96.0	283.4	97.2	60.7	13.3
273.0	193.0	354.7	166.0	316.8	188.0	86.1	44.1
303.0	244.0	358.7	248.2	322.5	244.9	55.9	19.5
263.0	340.0	321.5	331.8	296.2	326.7	59.1	35.8
239.0	404.0	314.5	357.5	274.3	398.5	88.7	35.7
225.0	433.0	288.5	409.2	252.5	440.3	67.8	28.4
142.0	510.0	255.2	460.6	203.3	497.8	123.5	62.5

Table 4.6 Localization Error Summary Table test 3

Metric	rtab_odom	odom_slam
Max Error	123.48	62.55
Mean Error	50.09	20.42
RMSE	60.68	26.68

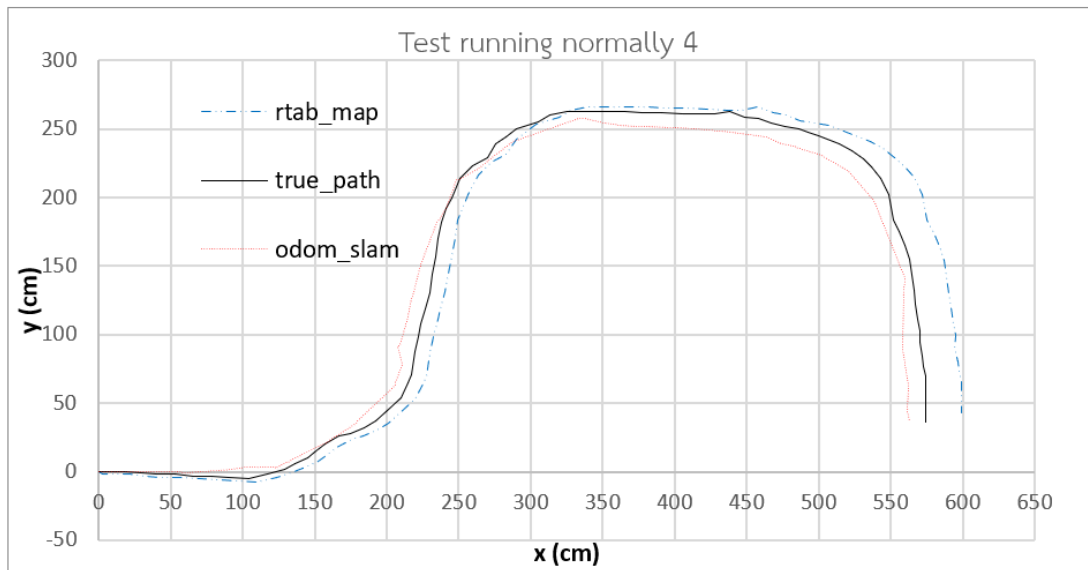


Figure 4.6 Comparing LiDAR SLAM and RTAB-Map Against a Ground-Truth Path test 4

Table 4.7 Experimental Localization Data and Absolute Error Measurements test 4

true path		rtab_odom		odom_slam		Error	Error
X	Y	x	y	x	y	rtab	odom_slam
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
30.0	-1.0	33.2	-3.0	31.2	0.0	3.8	1.5
91.0	-4.0	84.2	-5.1	93.3	2.1	6.9	6.6
129.0	2.0	123.2	-4.3	129.5	6.5	8.6	4.5
145.0	10.0	143.5	3.5	134.6	9.3	6.7	10.4
175.0	10.0	145.6	23.9	176.1	33.4	32.5	23.4
200.0	45.0	201.0	35.8	203.9	60.7	9.2	16.2
234.0	157.0	243.0	144.9	224.4	153.3	15.1	10.3
245.0	200.0	252.9	194.1	248.7	213.0	9.8	13.5
336.0	263.0	339.9	263.3	333.5	257.6	3.9	6.0
486.0	250.0	487.4	256.3	483.3	237.2	6.4	13.1
543.0	214.0	566.2	214.8	522.4	217.7	23.2	21.0
552.0	184.0	575.5	183.6	539.9	193.8	23.5	15.6
574.0	36.0	599.4	42.8	562.9	37.4	26.3	11.2

Table 4.8 Localization Error Summary Table test 4

Metric	rtab_odom	odom_slam
Max Error	32.54	23.41
Mean Error	11.73	10.21
RMSE	15.24	12.35

Test 4, both localization methods demonstrate improved performance due to the smoother trajectory and reduced motion complexity compared to previous tests. Error remains relatively low during the initial straight segment and increases gradually along the curved path. The RTAB-Map (depth-only) approach exhibits a consistent outward drift, indicating systematic bias in pose estimation likely due to accumulated orientation error and weaker geometric constraints. The odom_slam method maintains slightly better accuracy, with lower mean error and RMSE, suggesting more stable handling of gradual curvature. The results indicate that while both methods perform adequately under moderate motion conditions, turning segments still contribute to error accumulation, though to a lesser extent than in more complex trajectories.

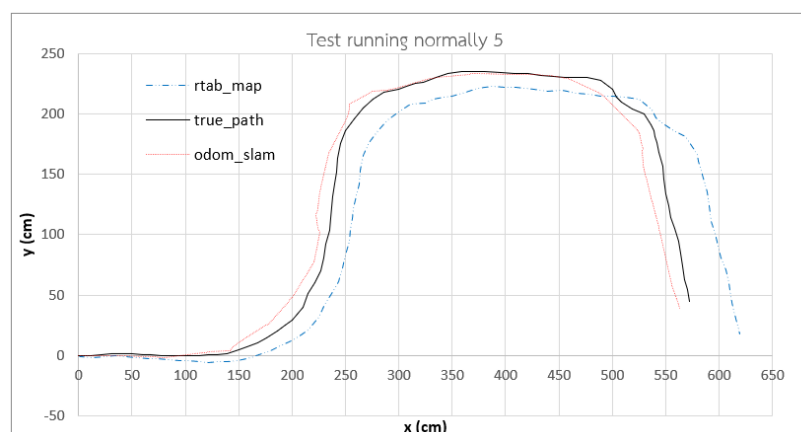


Figure 4.7 Comparing LiDAR SLAM and RTAB-Map Against a Ground-Truth Path test 5

Table 4.9 Experimental Localization Data and Absolute Error Measurements test 5

true path		rtab_odom		odom_slam		Error	Error
X	Y	x	y	x	y	rtab	odom_slam
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
60.0	1.0	65.0	-2.3	65.7	-1.1	6.0	6.1
113.0	0.0	112.0	-4.7	117.0	2.2	4.8	4.6
176.0	15.0	189.1	7.8	175.6	25.2	14.9	10.2
215.0	51.0	231.0	42.5	199.7	48.5	18.1	15.5
227.0	70.0	247.5	72.2	221.5	79.9	20.6	11.4
237.0	122.0	256.3	113.0	224.0	121.8	21.3	13.0
242.0	152.0	264.1	153.4	233.9	166.9	22.1	17.0
267.0	205.0	280.8	186.3	253.5	207.7	23.2	13.8
300.0	220.0	310.6	207.7	290.1	219.2	16.2	9.9
335.0	230.0	349.8	214.3	334.8	229.9	21.6	0.3
408.0	233.0	439.4	219.0	406.8	232.5	34.4	1.3
433.0	232.0	465.9	217.4	438.6	231.8	36.0	5.6
476.0	230.0	500.5	214.4	458.1	229.3	29.1	17.9
530.0	200.0	569.0	181.4	522.5	188.0	43.2	14.2
547.0	157.0	588.7	135.6	529.0	157.4	46.9	18.0
562.0	95.0	602.1	80.8	544.7	101.6	42.6	18.5
572.0	45.0	619.1	17.8	562.9	38.9	54.4	11.0

Table 4.10 Localization Error Summary Table test 5

Metric	rtab_odom	odom_slam
Max Error	43.20	17.89
Mean Error	20.77	9.38
RMSE	29.25	12.06

In Test 5, both localization methods perform well during the initial straight and moderately curved segments, maintaining low error due to stable motion

and consistent sensor observations. However, significant divergence occurs during the final trajectory segment, where a change in direction introduces increased orientation uncertainty. The RTAB-Map (depth-only) approach exhibits substantial drift, driven by accumulated error and limited correction capability, particularly during motion transitions. In contrast, the odom_slam method maintains lower error across all metrics, demonstrating more robust handling of orientation changes and improved trajectory consistency. These results reinforce that directional transitions and accumulated drift are key contributors to localization error, especially in loosely coupled and depth-dependent systems.

Table 4.11 Comparative Error Analysis of RTAB-Map and Odom_SLAM over Five test Runs

	cm									
	test 1		test 2		test 3		test 4		test 5	
	rtab	odom_slam	rtab	odom_slam	rtab	odom_slam	rtab	odom_slam	rtab	odom_slam
Max Error	49.18	44.83	53.26	25.84	123.48	62.55	32.54	23.41	43.20	17.89
Mean Error	22.61	19.65	20.75	9.98	50.09	20.42	11.73	10.21	20.77	9.38
RMSE	26.31	24.23	83.51	24.23	83.51	24.23	15.24	12.35	29.25	12.06

The figure test running normally shows three path true_path (black solid line): will be the reference trajectory along with odom_slam (red dotted line) LiDAR SLAM estimate and finally rtabmap (orange dashed dotted line) RTAB-Map estimate in the unit of centimeter.

Overall, both SLAM trajectories follow the same global shape as the true path, meaning both systems successfully track the robot's general motion trend. However, both estimated paths sit consistently below the true path for a large portion of the run, indicating a systematic offset rather than random noise. Odometry data can be noisy, particularly in dynamic or unstructured environments. This noise impacts the accuracy of the SLAM system, making it difficult for the robot to maintain a reliable and consistent map of its surroundings (Davison, 2003)

Table 4.11 presents the quantitative comparison of localization performance between RTAB-Map and Odom_SLAM over five experimental trials, evaluated using maximum error, mean error, and RMSE in centimeters. Across most test scenarios, Odom_SLAM demonstrates lower mean error and RMSE values

compared to RTAB-Map, indicating more consistent trajectory estimation. In particular Test 4 and Test 5 show noticeably smaller RMSE values for Odom_SLAM (12.35 cm and 12.06 cm, respectively) compared to RTAB-Map (15.24 cm and 29.25 cm). Mean error values follow a similar trend, suggesting that Odom_SLAM maintains closer alignment with the ground truth trajectory in these trials. This suggests that in moderately structured environments or under relatively stable motion conditions, the LiDAR-based SLAM approach provides robust incremental pose estimation.

However, the results also reveal variability in performance. In Test 3, RTAB-Map exhibits a significantly higher maximum error (123.48 cm) and RMSE (83.51 cm), indicating a substantial deviation from the reference trajectory during that run. These deviations imply that RTAB-Map may be more sensitive to environmental characteristics such as feature sparsity, motion irregularities, or sensor noise.

4.1.2 Loop Closure Experimental Results

In the upper image (before loop matching), slight misalignment can be observed in the highlighted region. As the robot moves along the path, small pose estimation errors accumulate due to incremental scan matching and odometry integration. These errors result in a minor positional offset between newly acquired LiDAR scans and the previously constructed map. Once the robot revisits the same physical area, the SLAM system identifies similarity between the current scan and earlier observations. This triggers loop closure detection, where an additional constraint is introduced into the pose graph. After this constraint is incorporated, global optimization is performed to reduce accumulated drift.

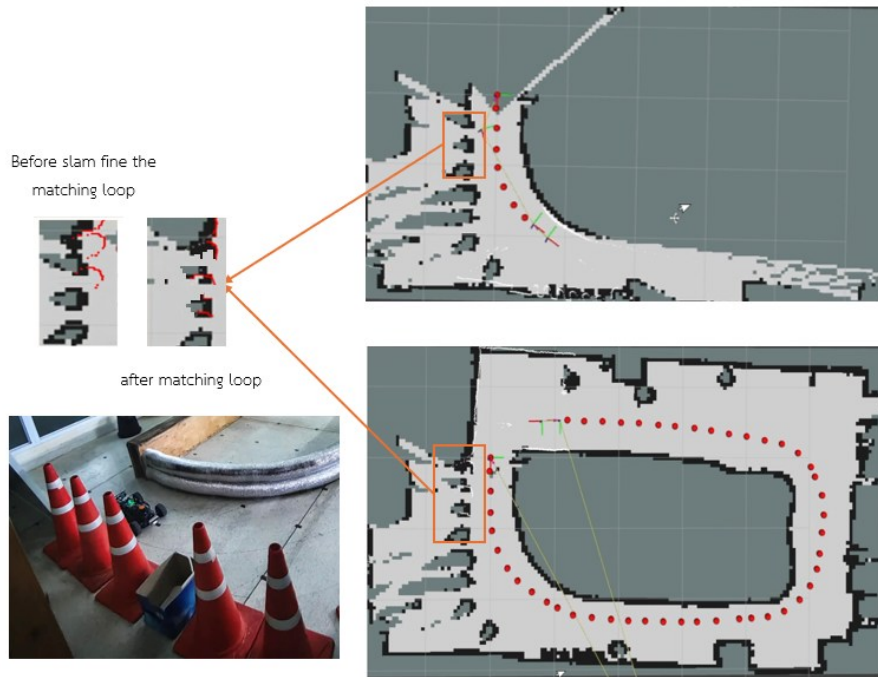


Figure 4.8 presents the loop closure performance of the SLAM system during a closed loop.

The lower image (after loop matching) demonstrates improved alignment within the highlighted region. Structural features, such as wall boundaries and corners, show better registration compared to the pre-closure state. Rather than correcting only the final pose, the optimization process redistributes accumulated error across the entire trajectory, resulting in a more globally consistent map.

These results confirm that the SLAM framework successfully detects revisited locations and applies pose graph optimization to mitigate long-term drift. Although minor residual discrepancies may remain, the overall structural consistency of the map is significantly improved following loop closure.

4.1.3 Robustness Under Camera Failure During Operation

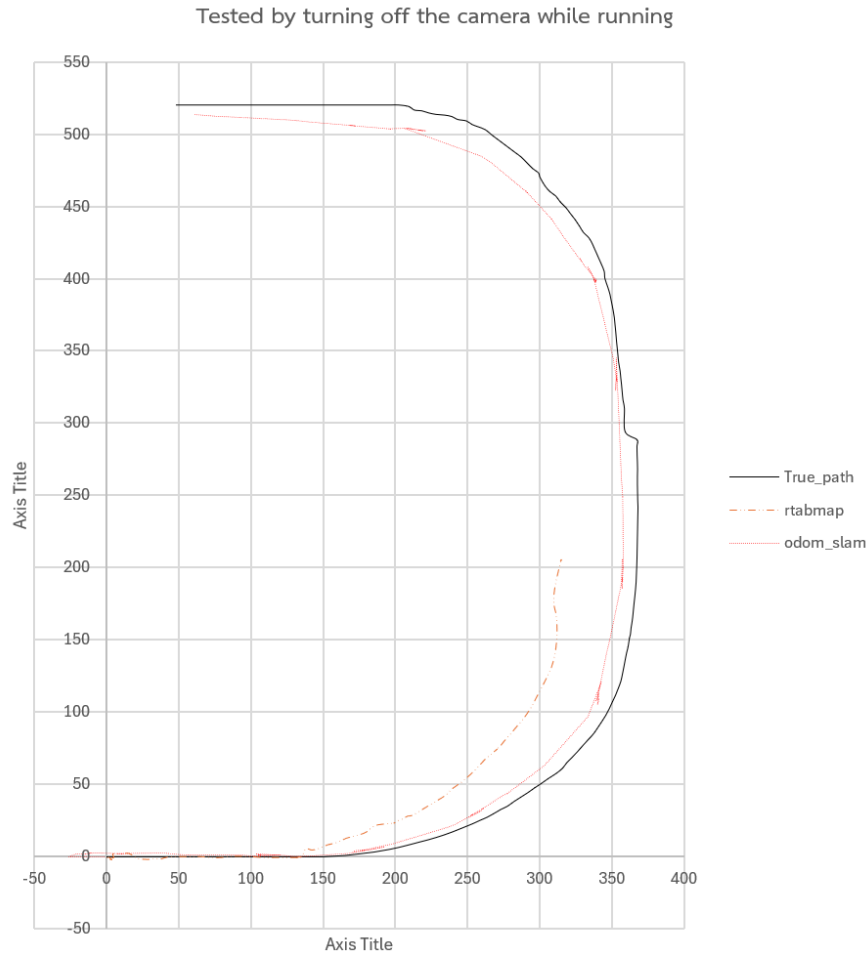


Figure 4.9 Robustness Under Camera Failure During Operation

The second experiment investigates system robustness when a critical sensor becomes unavailable during active operation. In practical robotic deployments, vision-based sensors are prone to failure due to lighting changes, occlusions, hardware instability, or communication interruptions. Therefore, this experiment intentionally disables the camera while the robot is in motion to evaluate how different SLAM approaches respond to sensor loss and whether they can maintain localization and recover mapping functionality once the camera input is restored. This experiment compares the behavior of RTAB-Map SLAM, which relies heavily on visual or depth data for perception and pose estimation and the proposed system, which separates responsibilities by using LiDAR-based SLAM for localization and a depth camera primarily for mapping.

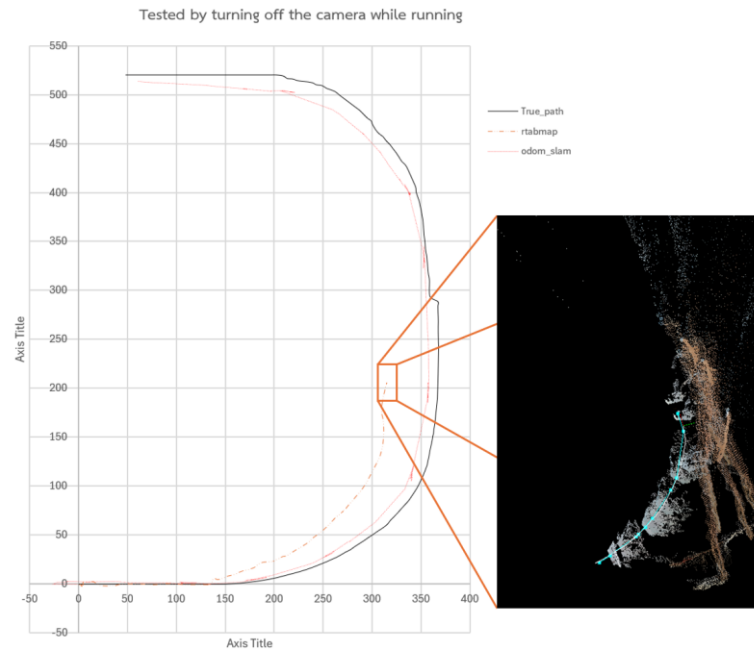


Figure 4.10 Robustness Under Camera Failure During Operation During the Moment of camera failure

When the camera is turned off during operation, the plotted trajectories show a clear difference between the two approaches. The true path continues smoothly, representing the actual motion of the robot. The LiDAR-based localization component in the proposed system continues to estimate the trajectory, whereas the RTAB-Map trajectory stops updating or diverges significantly from the true path. After the camera is turned back on, the proposed system resumes generating point cloud data while maintaining a continuous and stable trajectory. This indicates that localization remains uninterrupted throughout the sensor failure, and mapping functionality is restored once depth data becomes available again.

RTAB-Map relies on visual and depth observations to generate odometry constraints and to expand its pose graph. When the camera input is removed, the system loses its primary source of environmental information. As a result, RTAB-Map is unable to compute new motion estimates or register new observations, which leads to a stagnation of the estimated trajectory. This behavior is reflected in the results, where the RTAB-Map path no longer follows the true trajectory once the camera is disabled.

This outcome highlights a fundamental limitation of vision-dependent SLAM systems: without sufficient perceptual input, the system cannot maintain observability of motion. In such cases, pose estimation either halts or becomes unreliable, particularly if no alternative odometry source is available to compensate for the missing sensor data.

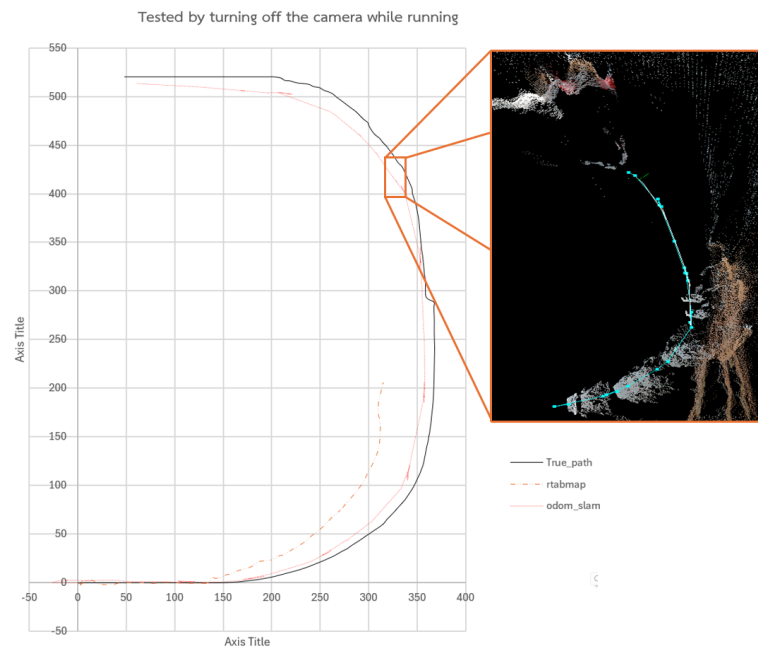


Figure 4.11 The system back on, the propose system resumes generating point cloud data.

In contrast, the proposed system maintains localization throughout the experiment because pose estimation is handled independently by LiDAR SLAM. LiDAR-based localization relies on geometric features extracted from laser scans, such as walls and structural edges, which remain observable even when the camera is inactive. As long as the surrounding environment provides sufficient geometric structure, the LiDAR SLAM module can continue matching scans and estimating motion.

This separation between localization and mapping allows the system to remain operational despite the loss of visual perception. While depth-based mapping temporarily pauses due to the absence of camera input, the robot's pose estimation remains consistent and continuous.

Once the camera is re-enabled, the proposed system immediately resumes generating point cloud data from the depth sensor. Because the localization pipeline never stopped, newly acquired depth measurements can be correctly associated with the current robot pose. This results in a coherent continuation of the map without introducing large discontinuities or misalignments.

The absence of abrupt pose jumps or distorted point clouds suggests that the coordinate frame relationships remain stable throughout the experiment. This indicates effective synchronization between LiDAR-based localization and camera-based mapping once sensor input is restored.

The results of this experiment demonstrate that tightly coupled vision-based SLAM systems are more vulnerable to sensor dropout during motion. When visual data is unavailable, pose estimation may fail entirely, preventing continued navigation. In contrast, the proposed architecture improves fault tolerance by decoupling localization from visual perception. By relying on LiDAR for pose estimation and using the depth camera as a supplementary mapping sensor, the system can tolerate temporary camera failures without losing localization.

Such robustness is particularly important for real-world robotic applications, where uninterrupted sensor availability cannot always be guaranteed. Experiment 2 confirms that disabling the camera during operation causes RTAB-Map SLAM to lose its ability to update the robot trajectory, resulting in a stalled or inaccurate pose estimate. The proposed system, however, continues to operate due to its reliance on LiDAR-based localization. When camera input is restored, mapping resumes seamlessly without disrupting localization. These results demonstrate that separating localization and mapping across different sensor modalities enhances system reliability under sensor failure conditions.