Robust 3D-SLAM Algorithms in Malaysia's Palm Oil Plantations: Assessing Effectiveness under Diverse Lighting Conditions

Siti Sarah Md. Sallah[1], *Member, IEEE*, Siti Sofiah Mohd Radzi[2], *Member, IEEE*, Lee Ming Yi, Syaimaa' Solehah Mohd Radzi and Hon Hock Woon

***Abstract*— Malaysia stands as a global leader in palm oil production and export, with a vast planted area of 5.67 million hectares in 2022. In this study, we focus on the palm oil plantation context to examine the effectiveness of visual-based and LiDAR-based systems for three-dimensional (3D) simultaneous localization and mapping (SLAM); RTAB-Map and LIO-SAM, under different lighting conditions. Our research evaluates SLAM performance with a keen focus on loop closure detection and CPU/GPU resource usage, pivotal parameters in determining system efficacy. Through this investigation, we uncover crucial insights into SLAM algorithm adaptability in challenging agricultural environments, where RTAB-Map system was unable to obtain a close loop at very low and high illuminance levels. Furthermore, the environment lighting has shown a significant effect on the CPU/GPU usage for both SLAM systems.**

I. INTRODUCTION

Malaysia, the world's second-largest palm oil producer after Indonesia, has seen a significant expansion in palm oil production land, reaching 5.67 million hectares in 2022 from 5.23 million hectares in 2013 [7]. In this competitive landscape, the agricultural sector is actively adopting mechanization and automation to optimize efficiency and reduce labor costs. However, effective navigation in the ever-changing and disorganized conditions of agricultural settings remains a significant challenge. Precise mapping and localization are indispensable for enabling successful autonomous navigation, particularly in scenarios where conventional GPS signals may be compromised or unavailable. Notably, in the dense environment of palm oil plantations, the efficacy of Simultaneous Localization and Mapping (SLAM) systems hinges not only on detecting and tracking numerous features, distinguishing significant elements like palm trees from insignificant ones such as small plants and bushes, but also on addressing the unique lighting illumination issues encountered under the canopy. Mapping under the canopy introduces complexities, affecting the amount of lighting received by sensors, which can significantly impact mapping accuracy. Additionally, the high feature density further complicates the creation and updating of environment maps, potentially necessitating increased CPU/GPU utilization. Addressing these challenges becomes paramount to achieving efficient and reliable autonomous navigation within the complex landscapes of agricultural plantations. SLAM technologies play a pivotal role in various applications, ranging from autonomous vehicles and indoor navigation to robotic vision and artificial intelligence [1]. They enable the creation of precise maps and accurate localization in dynamic and changing environments. Leveraging sensor data, SLAM algorithms estimate the precise position and orientation of a robot while simultaneously constructing a comprehensive map of the surrounding environment [5] The performance of SLAM systems is notably influenced by lighting conditions, which can significantly affect sensor measurements and, in turn, impact the accuracy and reliability of mapping and loop closure processes. Understanding the interplay between SLAM algorithms and lighting conditions is of utmost importance to enhance the robustness and adaptability of autonomous navigation systems in challenging environments like palm oil plantations. By delving into the impact of different lighting conditions under the canopy on SLAM techniques, this study aims to provide invaluable insights that contribute to the advancement of agricultural robotics and mapping technologies. This paper investigates how different illuminance levels influence various SLAM techniques, using data collected from a palm oil plantation. Two states of the art SLAM algorithms were employed for the analysis, aiming to evaluate loop closures and quantify CPU/GPU resource utilization, thereby assessing the performance of SLAM methods across varying lighting conditions. Section II provides a comprehensive exposition of SLAM fundamentals and reviews prior studies on illumination impact. Section III outlines the implemented methodology, covering hardware configuration, and data collection. Section IV presents experimental findings, focusing on SLAM algorithm performance under different illuminance levels. Finally, Section V summarizes principal research findings and implications in the conclusion.

II. SIMULTANEOUS LOCALIZATION AND MAPPING (SLAM)

Previous studies have been conducted to investigate the effects of lighting conditions on SLAM. However, prior research has often concentrated on specific sensing modalities or restricted lighting conditions. The impact of illuminance level on SLAM systems is a crucial environmental factor that can significantly affect their performance. This is pri-

*Research supported by Malaysia Ministry of Science, Technology and Innovation (MOSTI) through the strategic research grant (SRF) grant number SRF P2A-SF.502000-PG2-P1-Edge-based Sensor Fusion for Reliable Environment Perception.

[1]S. S. Md. Sallah is with Advanced Intelligence Lab, MIMOS Berhad, Technology Park Malaysia, 57000 Kuala Lumpur, Malaysia. sarah.sallah@mimos.my

[2]S. S. Mohd Radzi is with Advanced Intelligence Lab, MIMOS Berhad, Technology Park Malaysia, 57000 Kuala Lumpur, Malaysia sofiah.radzi@mimos.my

marily because illuminance level has the potential to greatly influence the accuracy of mapping and the ability to detect loop closures within SLAM systems [1]. Therefore, it is imperative to possess a comprehensive comprehension of the influence of lighting conditions on the 3D SLAM process. This understanding is necessary to develop mapping and localization systems that are resilient and dependable, enabling them to effectively function in real-world environments.

A. Visual-based SLAM

Visual SLAM is a technique that leverages camera images to infer the precise position and orientation (pose) of a robot, while simultaneously constructing a detailed representation of the surrounding environment. Extensive research has been conducted on account of the widespread presence of cameras and their capacity to offer comprehensive visual data. An influential methodology is ORB-SLAM, which integrates characteristics derived from camera images with a map representation based on keyframes [5]. Another noteworthy approach is Direct Sparse Odometry (DSO), which performs direct optimization of the photometric error between successive frames, facilitating real-time monocular visual SLAM [2]. According to the source cited as [8] the RTAB-Map (Real-Time Appearance-Based Mapping) system [4, 3] demonstrates the capability to handle multiple data types including RGB-D, stereo, and LiDAR, and exhibits versatility in managing mixed modalities. The RTAB-Map system has the capability to integrate various odometry techniques, such as visual, LiDAR, or wheel-based methods. Visual odometry is a technique that employs either Frame-To-Map (F2M) or Frame-To-Frame (F2F) methods. On the other hand, LiDAR odometry utilizes Scan-to-Map (S2M) or Scan-to-Scan (S2S) approaches. The latter method involves the analysis of three-dimensional point clouds obtained from LiDAR scans. These point clouds are first down-sampled, then their normal are computed. Finally, the Iterative Closest Point (ICP) algorithm is employed to estimate the transformation between the fixed- and moving-point clouds. The RTAB-Map system integrates a loop closure detector that is based on appearance and utilizes a bag-of-words technique. This detector aids in determining whether a given image corresponds to a previously visited location or a new one [3]. For loop closure detection, the current bag-of-words approach is dependent on a camera, meaning that a camera is always required even if LiDAR is used for odometry. Several studies have investigated the impact of lighting conditions on Visual SLAM performance. For instance, [10] explored the impact of lighting variations on monocular Visual SLAM, finding that changes in illumination levels can result in pose estimation errors and affect map quality. Visual-based SLAM systems may encounter difficulties under low-light or overly bright conditions due to their reliance on camera input [1]. A study [6] use the brightness constancy assumption to evaluate real-time capable direct image alignment method for their accuracy and robustness under challenging lighting conditions. However, the brightness constancy assumption fails in cases abrupt illumination changes [6].

B. Lidar-based SLAM

The LiDAR-based SLAM) technique is predicated on the utilization of point cloud data acquired from LiDAR sensors to facilitate the processes of mapping and localization. A noteworthy method that utilizes LiDAR for SLAM is LOAM (Lidar Odometry and Mapping). LOAM employs scan-to-scan motion estimation and mapping techniques to achieve precise and real-time localization and mapping [11]. An additional commonly employed methodology is LeGO-LOAM, which integrates LiDAR odometry and graph optimization to achieve efficient SLAM in outdoor settings [9]. One of the notable benefits of LiDAR-based SLAM is its capability to generate 3D maps of the surrounding environment with exceptional accuracy and precision, even in situations where lighting conditions are suboptimal or completely absent. Additionally, this technology exhibits reduced sensitivity to visual occlusions or environments with high levels of clutter, and demonstrates increased resilience to variations in lighting conditions. Nevertheless, the utilization of LiDAR sensors can incur substantial costs and necessitate substantial computational capabilities to handle the voluminous data they produce.

III. METHODOLOGY

A. Hardware Setup

The experiment employed a custom hardware configuration as depicted in Fig. 1. The system consisted of the Xsens IMU, Zed2i stereo depth camera, and Ouster-64 lidar. This arrangement enabled the simultaneous utilization of lidar-based and visual-based SLAM techniques. The integration and management of hardware components were facilitated by the ADLINK ROSCUBE-X, RQX-580 CPU. This processing unit is an NVIDIA® Jetson AGX Xavier module-powered robotic controller with ROS 2 compatibility, encompasses an integrated NVIDIA Volta GPU, coupled with dual deep learning accelerators, and offers a diverse array of interfaces, including GMSL2 camera connectors, to facilitate advanced integration into robotic systems. The UGV utilized in the experiment maintained a constant velocity of 10-15 kilometers per hour throughout data collection period. The evaluation of the SLAM algorithm can be conducted through an analysis of the influence of lighting variations on its performance, which can be quantified by capturing and measuring the illuminance level. The determination of illuminance level can be accomplished by employing the UNI-T UT383 mini light metre, as depicted in Fig. 2. Typically, the illuminance levels in direct sunlight span from 32,000 to 100,000 lux, whereas in full daylight conditions, excluding direct sunlight, the range typically lies between 10,000 and 25,000 lux.

B. Data Collection

The data collection process involved conducting experiments at the Sungai Pelek plantation in Sepang to investigate the influence of lighting conditions on the 3D SLAM technique. The choice of the plantation was made considering its ability to accurately represent the features of a palm oil plantation. Additionally, it provided a significant land

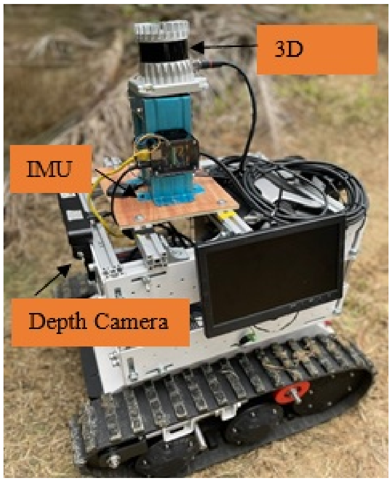

Fig. 1: Sensor setup within an unmanned ground vehicle

Fig. 2: The UNI-T UT383 mini light meter to measure illuminance levels

area of approximately 13,803 square metres (m2) to support extensive mapping efforts. According to Fig. 3, the red line represents the estimated land area, while the yellow dotted line represents the estimated trajectory of the robot during data collection in a palm oil plantation. The final destination will coincide with the initial point of departure. Fig. 4 shows the data collection was systematically carried out under different illuminance levels, specifically during two distinct time periods that represented vastly different lighting conditions: midday and evening. Midday was characterized by direct exposure to sunlight, thus representing the condition of high illuminance. On the other hand, the evening period, characterized by the presence of significant shadows, simulated a lower illuminance condition. The data collection procedure was repeated for various levels of illumination in order to maintain consistency and accommodate potential fluctuations in lighting conditions on a daily basis.

IV. RESULT AND DISCUSSION

The conducted experiments encompassed four distinct data (A, B, C and D), each depicting the identical trajectory of a robot within a palm oil plantation, while being subjected to different levels of illuminance that occur over the course of

Fig. 3: Estimated region and path for data collection

Fig. 4: Data collection in palm oil plantation with unmanned ground vehicle

a day. Table I shows the measurement of illuminance level of data A, B, C and D measured using UNI-T UT383 mini light metre.

In order to achieve a precise and uniform depiction of the surroundings, the gathered data underwent thorough scrutiny to identify any instances of loop closures in the mapping trajectory, as well as to assess the utilization of CPU/GPU resources. Fig. 5 illustrates the mapping trajectory of LIO-SAM, which is designed to detect loop closures during the mapping procedure. While, Fig. 6 illustrates the mapping trajectory of RTAB-Map. The results obtained from our experimental investigations demonstrate a persistent trend of loop closure across all data when assessed using LIO-SAM. In contrast, the outcomes illustrate a contrasting scenario when employing RTAB-Map, as only 50% of the data (Data B and C) exhibited evidence of loop closure, specifically when the illuminance level reached approximately 2000x10 lux, leading to the occurrence of loop closure. The perfor-

TABLE I: Illumination Level and Ability to Close Loop

Data	Average Illumination Level (lux)	Ability to Close Loop	
		LIO-SAM	RTAB-Map
A	19,430	Yes	No
B	22,390	Yes	Yes
C	24,560	Yes	Yes
D	61,890	Yes	No

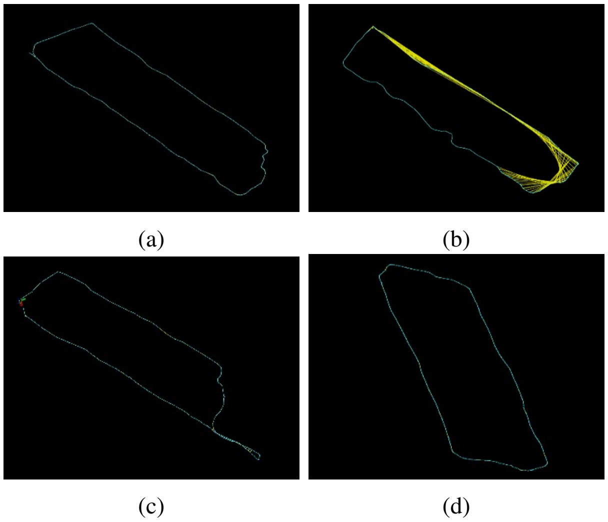

Fig. 5: Mapping trajectory generated by LIO-SAM using; (a) Data A, (b) Data B, (c) Data C, and (d) Data D

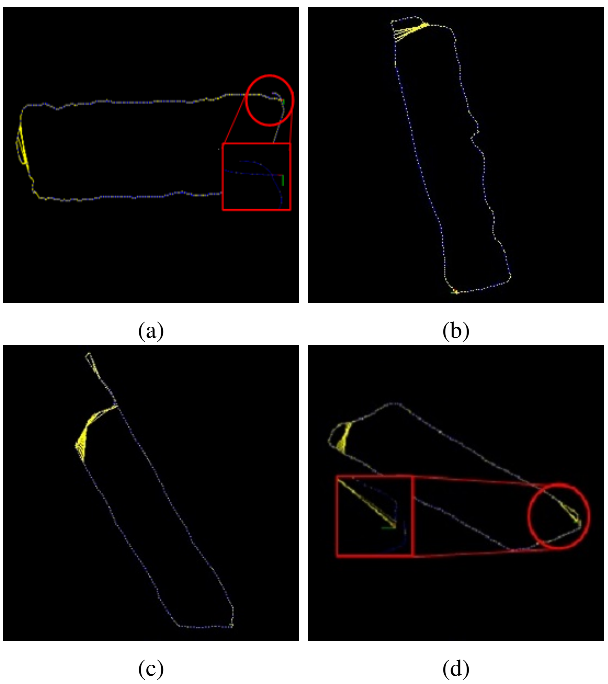

Fig. 6: Mapping trajectory generated by RTAB-Map using; (a) Data A, (b) Data B, (c) Data C, and (d) Data D

mance of RTAB-Map appears to be significantly affected by lighting conditions due to its inherent dependence on visual data. This observation implies that RTAB-Map might exhibit lower resilience towards fluctuations in illumination levels compared to LIO-SAM. This characteristic can have a significant influence, especially in dynamic outdoor settings like palm oil plantations.

The absence of connecting lines between identifier 10 and identifier 364 in Fig. 8 suggests that the system did not identify these as the same view. Alternatively, it is possible that the loop closure detection was considered unreliable for this specific pair. This particular scenario exemplifies a situation in which the system exhibits the capability to identify potential loop closures, yet lacks sufficient confidence to incorporate them into the map. Feature-based simultaneous localization and mapping (SLAM) approaches may encounter difficulties in accurately detecting and accepting loop closures in environments characterized by repetitive or low-texture areas. Other than that, the RTAB-Map algorithms commonly depend on the extraction and matching of features, such as keypoints, across multiple images. The presence of high illumination can have a significant impact on both the quality and quantity of the extracted features. This poses a challenge for the algorithm in terms of identifying consistent matches.

Fig. 7: RTAB-Map database viewer for Data A

Fig. 8: RTAB-Map database viewer for Data D

Fig. 9 presents a visual representation of the performance metrics of both LIO-SAM and RTAB-Map in relation to varying levels of illuminance. The RTAB-Map algorithm exhibits a decreased utilization of GPU resources, while the LIO-SAM algorithm showcases increased GPU usage across all levels of illuminance, when considering the identical data set.

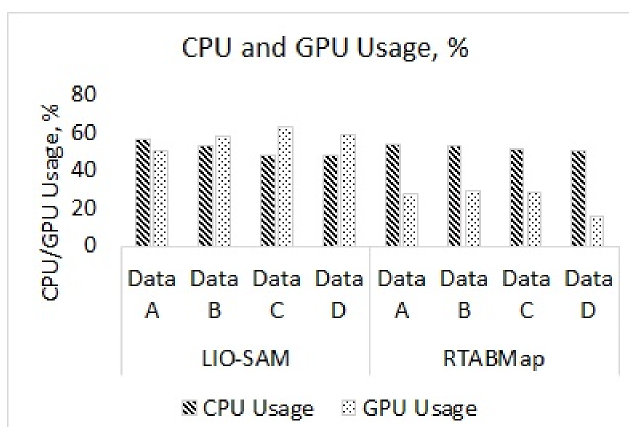

Fig. 9: Comparison of CPU/GPU usage for RTAB-Map and LIO-SAM under varying illuminance levels: Data A, Data B, Data C, and Data D

This finding indicates that, given the specific conditions, RTAB-Map demonstrates superior efficiency in terms of GPU utilization compared to LIO-SAM. Both systems modulate their central processing unit (CPU) and graphics processing unit (GPU) utilization in response to changes in illuminance levels, although employing distinct methodologies. While LIO-SAM exhibits varying behavior, RTAB-Map demonstrates a tendency to reduce both CPU and GPU utilization in response to high illuminance levels. This observation may indicate that RTAB-Map exhibits enhanced efficiency in terms of resource utilization when operating in highly illuminated environments. Nevertheless, it was noted that RTAB-Map demonstrates a significant decrease in GPU utilization in Data D, which aligns with the highest level of illuminance. The decrease in GPU utilization observed implies that RTAB-Map may be facing challenges in processing the data in these conditions or intentionally reducing processing to tackle other obstacles. The aforementioned decrease may potentially account for the inability of these data to establish a closed loop.

V. CONCLUSION

A comprehensive analysis was undertaken to investigate the efficacy of various mapping methodologies in response to different levels of illuminance. Based on the aforementioned observations, it is possible to ascertain the most suitable mapping technique for 3D SLAM applications within palm oil plantations. LIO-SAM system was able to obtain the close loop at all illuminance levels. However, RTAB-Map faced difficulties in getting a close loop for data recorded at both very low and high illuminance level. These results emphasize the significance of considering the levels of illuminance during the implementation of these technologies, thus showcasing the opportunity to tailor the choice of mapping techniques according to the particular lighting conditions of the surroundings. The present research analysis serves as a valuable resource for selecting the most appropriate SLAM method, considering specific lighting conditions and environmental contexts. By doing so, it enables the optimization of performance and reliability in real-world field applications. Considering GPU utilization, the RTAB-Map algorithm demonstrates a reduction in GPU resource usage, while the LIO-SAM algorithm displays elevated GPU utilization across various illuminance levels. The complexity of the environment has a direct impact on the computational demand of SLAM systems. The more complex the environment, the more features there are to detect, identify, and track, thereby leading to a higher volume of data to be processed.

ACKNOWLEDGMENT

We would like to extend our appreciation to MIMOS for providing the necessary facilities and to all our colleagues at the Advance Intelligence Lab. In particular, we would like to acknowledge the valuable contributions of Mohd Pazli Sulong, Norsharimie Mat Adam, and other colleagues towards this research endeavor. The funding for this research has been provided by the Malaysian Ministry of Science, Technology and Innovation (MOSTI) through a strategic research grant.

REFERENCES

[1] Cesar Cadena et al. "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age". In: *IEEE Transactions on robotics* 32.6 (2016), pp. 1309–1332.

[2] Jakob Engel, Vladlen Koltun, and Daniel Cremers. "Direct sparse odometry". In: *IEEE transactions on pattern analysis and machine intelligence* 40.3 (2017), pp. 611–625.

[3] Kesse Jonatas de Jesus et al. "Comparison of visual SLAM algorithms ORB-SLAM2, RTAB-Map and SPTAM in internal and external environments with ROS". In: *2021 Latin American Robotics Symposium (LARS), 2021 Brazilian Symposium on Robotics (SBR), and 2021 Workshop on Robotics in Education (WRE)*. IEEE. 2021, pp. 216–221.

[4] Mathieu Labbe. "Simultaneous Localization and Mapping (SLAM) with RTAB-Map". In: *Département de Génie Électrique et Génie Informatique* (2015).

[5] Raul Mur-Artal, Jose Maria Martinez Montiel, and Juan D Tardos. "ORB-SLAM: a versatile and accurate monocular SLAM system". In: *IEEE transactions on robotics* 31.5 (2015), pp. 1147–1163.

[6] Seonwook Park, Thomas Schöps, and Marc Pollefeys. "Illumination change robustness in direct visual slam". In: *2017 IEEE international conference on robotics and automation (ICRA)*. IEEE. 2017, pp. 4523–4530.

[7] Ghulam Kadir Ahmad Parveez et al. "Oil palm economic performance in Malaysia and R&D progress in 2021". In: *J Oil Palm Res* 34 (2022), pp. 185–218.

[8] Siti Sofiah Binti Mohd Radzi et al. "Visual-based and Lidar-based SLAM Study for Outdoor Environment". In: *2023 IEEE International Conference on Robotics and Automation (ICRA) Workshop on Active Methods in Autonomous Navigation* (2023).

[9] Tixiao Shan and Brendan Englot. "Lego-loam: Lightweight and ground-optimized lidar odometry and mapping on variable terrain". In: *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2018, pp. 4758–4765.

[10] Wei Tan et al. "Robust monocular SLAM in dynamic environments". In: *2013 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE. 2013, pp. 209–218.

[11] Ji Zhang and Sanjiv Singh. "LOAM: Lidar odometry and mapping in real-time." In: *Robotics: Science and systems*. Vol. 2. 9. Berkeley, CA. 2014, pp. 1–9.