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

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***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. 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. In this study, we focus on the palm oil plantation context to examine the effectiveness of under canopy localization and mapping based on two state of art SLAM algorithms; RTAB-Map and LIO-SAM, with different lighting conditions. Our research evaluates SLAM performance with a keen focus on loop closure detection as a part of SLAM algorithm's performance parameter. Additionally,we also explored the impact of this algorithms on GPU/CPU performance.Through this investigation, we uncover insights into SLAM algorithm adaptability in challenging agricultural environments and to contribute valuable knowledge to our development in downstream application.**

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 [1]. 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. Mapping under the canopy introduces complexities, affecting the amount of lighting received by sensors, which can significantly impact mapping accuracy. 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 [2]. 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 [3]. Several studies have investigated the impact of lighting conditions on Visual SLAM performance. For instance, [4] 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 [2]. A study [5] 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 [5].

In this study, we have compared two SLAM (Simultaneous Localization and Mapping) algorithms: RTABMAP which is using a combination of 3D Lidar, stereo camera, and IMU (Inertial Measurement Unit) as inputs, whereas LIO-SAM specifically utilizes Lidar and IMU data. For this research, we aimed to investigate and compare the qualitative differences especially in loop closure ability between these two algorithms, with both of them incorporating Lidar as one of the input sensors and how it is affected by lighting condition under the canopy.

II. SIMULTANEOUS LOCALIZATION AND MAPPING (SLAM)

SLAM system consists of mainly front end and back end components. The loop closure is typically considered as part of the back end of a SLAM system which has local and global loop close. Front-end odometry is responsible for the continuous and real-time estimation of the robot's pose, providing immediate updates during motion. It operates seamlessly as the robot moves, ensuring a short-term and immediate understanding of its position and orientation. In contrast, local loop closure is triggered when the robot revisits a nearby or recently visited location, addressing short-term errors within the immediate vicinity. This mechanism enhances the accuracy of the SLAM system by correcting errors associated with specific locales. On a broader scale, global loop closure comes into play when the robot revisits a location that may be distant from its current position, focusing on correcting long-term errors across the entire trajectory. This ensures a globally consistent map representation by aligning different parts of the map and enhancing the system's performance over extended exploration periods. Together, these components contribute to a comprehensive SLAM solution, providing both short-term accuracy and long-term consistency in robotic localization and mapping.

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A. RTAB-MAP

According to the source cited as [6] the RTAB-Map (Real-Time Appearance-Based Mapping) system [7, 8] demonstrates the capability to handle multiple data types including RGB-D, stereo, and LiDAR for its front-end components. 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 incorporates a loop closure detector that utilizes a bag-of-words (BoW) technique based on appearance[8]. This detector helps determine whether an image corresponds to a location visited before or a new one. Keypoint detectors and descriptors extract distinctive features from image frames, particularly visual data from cameras. These features are local descriptors capturing information about specific points and grouped into a visual vocabulary using the k-means algorithm, where each cluster represents a visual word. Images are then represented as histograms of visual words, providing a concise descriptor of image content. RTAB-Map continuously compares these representations, and loop closures are identified when the current image shares many visual words with a past keyframe. Detected loop closures contribute to a graph representing the robot's trajectory and keyframe connections. The graph is optimized to enhance SLAM consistency, with loop closure constraints refining the entire trajectory to align with corrected loop closures.

B. LIO- 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 [9]. An additional commonly employed methodology is LeGO-LOAM, which integrates LiDAR odometry and graph optimization to achieve efficient SLAM in outdoor settings [10]. In the context of LiDAR-based SLAM, LIO-SAM, is another significant advancement [11]. LIO-SAM formulates lidar-inertial odometry atop a factor graph, allowing for the incorporation of various measurements, including loop closures, from different sources as factors into the system. It utilizes inertial measurement unit (IMU) pre-integration to enhance point cloud de-skewing and initial lidar odometry optimization. To ensure real-time performance, LIO-SAM adopts strategies such as local-scale scan-matching for its local loop close, selective keyframe introduction, and an efficient sliding window approach. For global loop close, LIO-SAM often employs radius search approach to compare the current scan with scans from the past base , identifying overlaps or similarities indicative of revisited locations.

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. 2a. 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. Fig. 2b shows the unmanned ground vehicle being used in the plantation.

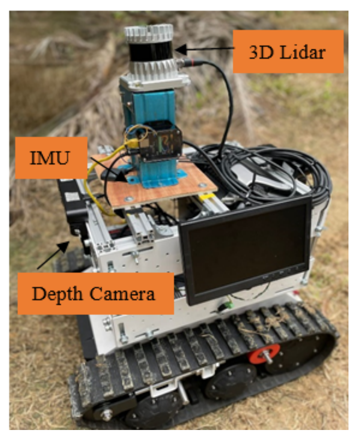


Fig. 1: Sensor setup within an unmanned ground vehicle

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 area of approximately 13,803 square metres (m^2) to

(a) (b)

Fig. 2: (a) The UNI-T UT383 mini light meter to measure illuminance levels, and (b) Data collection in palm oil plantation with unmanned ground vehicle.

support extensive mapping efforts. 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.

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.

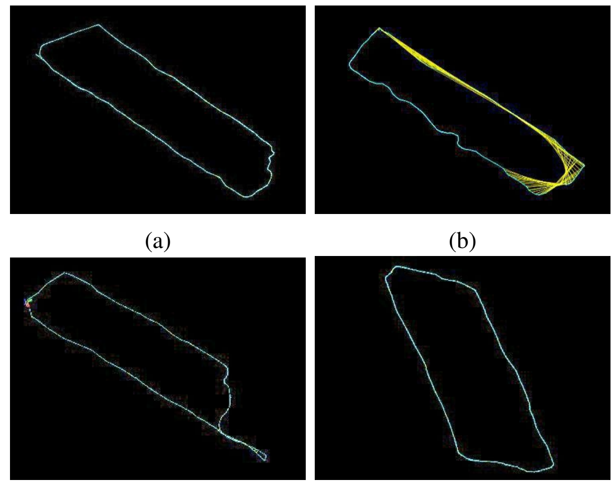
Fig. 3: Estimated region and path for data collection

IV. RESULT AND DISCUSSION

The conducted experiments encompassed four distinct collected data (A, B, C and D), each depicting the identical trajectory of a robot within a same area in the palm oil plantation, while being subjected to different levels of illuminance that occur over the course of a day with different times. Table I shows the measurement of illuminance level of data A, B, C and D measured using UNI-T UT383 mini light metre.

TABLE I: Illumination Level and Ability to Close Loop

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

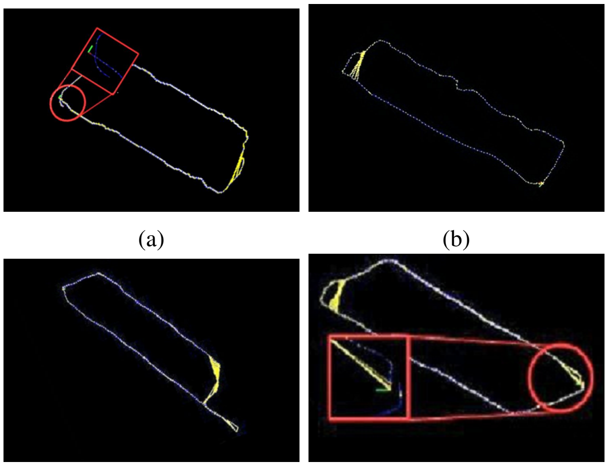


(a) (b) (c) (d)

Fig. 4: Mapping trajectory generated by LIO-SAM using; (a) Data A, (b) Data B, (c) Data C, and (d) Data D. Yellow line indicates the closed loop.

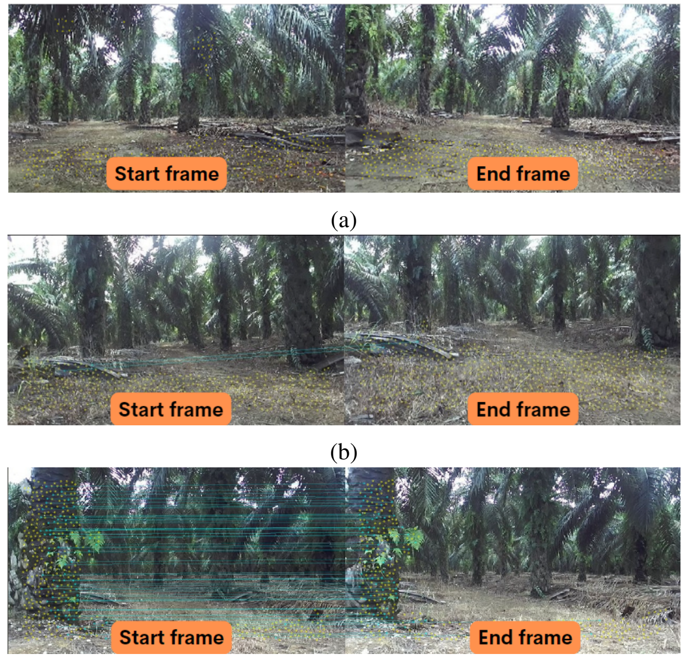
In order to achieve a precise and uniform depiction of the surroundings, the gathered data underwent thorough scrutiny to identify any instances of loop closures in the mapping trajectory, as well as to assess the utilization of CPU/GPU resources. Fig. 4 illustrates the mapping trajectory of LIO-SAM, which is designed to detect loop closures during the mapping procedure. While, Fig. 5 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 20,000 lux, leading to the occurrence of loop closure. The performance 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 two frames as in Fig. 6a suggests that the system did not identify these



(a) (b) (c) (d)

Fig. 5: Mapping trajectory generated by RTAB-Map using; (a) Data A, (b) Data B, (c) Data C, and (d) Data D. Yellow line indicates local loop closure.



(a) (b) (c)

Fig. 6: RTAB-Map database viewer for; (a) Data A, where the close loop is not detected due to no matched features detected, (b) data D, where the close loop is not detected due to insufficient features, and (c) data B, where the close loop is detected. Green line indicates matched features.

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. Fig. 6b shows the closed loop is not detected due to insufficient features. In Fig. 6c, there are many green lines formed to show the matched features between two frames. Therefore, the close loop is detected. 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 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.

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. The present research analysis serves as a valuable resource for selecting the most appropriate SLAM method, considering specific lighting conditions and environmental contexts. Considering GPU utilization, the RTAB-Map algorithm demonstrates a reduction in GPU resource usage but requires an improved or more robust image feature descriptor version to adapt variation in lighting condition.

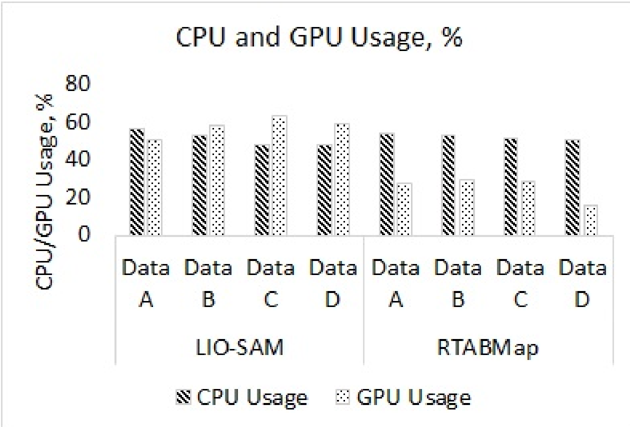


Fig. 7: Comparison of CPU/GPU usage for RTAB-Map and LIO-SAM under varying illuminance levels: Data A, Data B, Data C, and Data D

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