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An Image Processing Technique for Lane Path Detection in Palm Oil Plantation

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Abstract

Image processing for lane detection is commonly utilized by researchers for autonomous navigation purposes. In this paper, lane path detection in palm oil plantations had been demonstrated by acquiring raw videos using a vision sensor. The videos were recorded on two different paths in a palm oil plantation labelled Path 1 and Path 2. Various image processing techniques had been utilized inclusive of RGB to HSV conversion colour space, Gaussian Blur, Canny Edge Detection, Region of Interest and Hough Transform. Then, a histogram graph was used to assess the performance of the lane path detection by varying the brightness level of the images. With the histogram graph value entrenched, it shows that the level brightness of 0 and 50 shows the ideal performance of lane detection for both Path 1 and Path 2 in contrast to other brightness levels. The outcome justifies a suitable brightness value must be set to achieve a good detection result. Nonetheless, further advancement to the program of lane detection is required to intensify its functionality when it encounters effects from the environment particularly, illumination from the sunlight, shadows as well as the ground surface, such as drains and water puddles.

1. Introduction

Implementing autonomous navigation in agriculture has given a lot of benefits where it helps to reduce numbers of labour required to execute tasks, increase yields and efficiency, and improve the safety of the process. In Malaysia, recent developments in agricultural engineering especially in palm oil plantations, have focused on analysing the ripeness of palm oil fruit using machine vision techniques [1], [2] and a harvesting robot for palm oil fruit [3],[4]. Nevertheless, the development of fully autonomous navigation systems for palm oil plantations is far behind schedule, even though these systems are necessary for attaining complete automation of the processes [5]. In a palm oil plantation, autonomous navigation is useful for the harvesting process, surveillance purposes as well as conducting tree maintenance of the plantation. Therefore, an image processing technique which is a favoured method by most researchers is employed for navigation and path planning motives [6]. Commonly, a vision sensor or a camera is used to acquire data and subsequently link to a controller [7].

Research conducted by H. Gan et al develops a navigation system for a mobile robot to move in a citrus grove farm by using a machine vision algorithm. The procedure comprises applying a colour threshold technique, transforming the filtered image into Canny Edge and probabilistic Hough line around the upper edge of the farm canopies [8]. Furthermore, Asif et al propose a vision system by using a series of image processing steps to detect inter-row space between weed crops for a robot to navigate. The steps consist of implementing a K-mean clustering algorithm to differentiate the soil and crop based on a different colour in Red, Green, and Blue (RGB) colour space, Region of Interest (ROI), edge detection as well as Hough Transform [9]. Khan et al propose a robust and real-time for off-road lane detection by implementing an image processing technique. A Backfly 2.3MP Mono GigE PoE camera is used as the vision sensor to obtain the RGB image. ROI as well as Random Sample Consensus (RANSAC) is implemented as it shows good accuracy of crop row detection in stretching scenarios [10].

Then, lane detection by using a binocular vision system that is convenient for a hilly field road region was proposed by Li et al. [11]. The system comprises the Otsu threshold method, conversion of RGB to Hue, Saturation and Value (HSV) colour space and a series of logic operations. Moreover, HSV segmentation is also involved to identify shadows formed on the road. The outcome shows that the system can perform road and non-road identification. Meanwhile, Du et al. present a lane navigation system purposedly for canola and flaxseed plantations to identify and remove weeds. They implemented a pre-counter gradient which is a combination of a colour-based contour algorithm and special pre-processing. Moreover, HSV colour space conversion, Gaussian Blur and Canny Edge Detection is also applied. The result demonstrates that a robot can navigate in a straight and irregular path line [12].

In a palm oil plantation, the lane path or road is an off-road type where a line marking feature like a white line that commonly appears in a common road is not present. Hence, it is difficult to extract the navigation path for a vehicle or mobile robot to follow. Therefore, based on research papers that have been studied, a computer vision system by applying an image processing technique appears as a solution [13], [14]. The technique does help to create a line boundary between the road, that is the desired navigation path and the non-road which is either the grass or bushes. This paper would like to contribute to such a technique to detect a straight-line path in the palm oil plantation. So, a few steps of image processing technique were applied such as converting the captured images from RGB to HSV colour space, Gaussian Blur, Canny Edge Detection, ROI, and Hough Transform. Two different paths were arranged in a controlled environment which does not have the presence of humans and animals used to test the developed technique. Several experiments were arranged by varying levels of brightness to test its functionality to perform lane detection. The performance of lane detection in the experiments was determined by using a histogram chart.

2. Research Method

2.1 Hardware Setup

Fig. 1 shows the block diagram of the hardware setup implemented for lane path detection in palm oil plantations. A vision sensor camera, namely an Intel Real Sense Depth Camera D435i was used to record the raw video of the lane. It has an output resolution of up to 1920 x 1080 with a frame rate of 30 frames per second (fps). This camera is selected since it is suitable for outdoor environments with various illumination conditions from the sunlight [15], [16]. Additionally, it can tolerate bumps and shocks with less significant performance deterioration [17]. The camera was then linked to a controller via a Universal Serial Bus (USB) port. The controller used in this research is a Raspberry Pi 400.

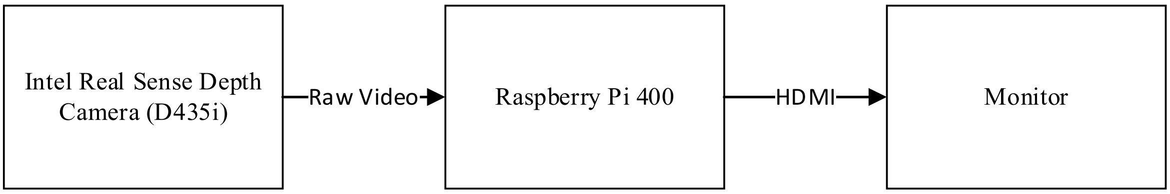

Fig.1 *Block diagram of the hardware setup*

It runs using a 64-bit processor quad-core with 4 gigabytes (GB) of Random Access Memory (RAM) [18]. With Linux as the Operating System (OS), the controller is powerful enough to store images and video files along with running the image processing technique. Meanwhile, the Raspberry Pi 400 does include micro-High-Definition Multimedia Interface (HDMI) ports. Hence, a monitor up to 4Kp60 resolutions was linked to it to display the images and videos processed by the technique for lane detection. To power all the components a USB cable Type-C was used and connected to a 5V USB power adapter. All the components were installed and set up in/on the car as shown in Fig. 2.

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Fig. 2 *System setup*

Based on Fig. 2, the camera was attached to a car windshield using a suction cup camera holder. Such arrangements were carried out since this position provided a better view compared to placing the camera inside the car. This can avoid reflection of the car windshield that distorts the images captured by the camera [19]. As for the controller and monitor, they were placed on the car dashboard.

2.2 Software Setup

As for the software used to perform lane detection, a Python Integrated Development Environment (IDE), Version 3.7.3 was employed. Via this IDE the program code for lane detection is simply developed. Integrated with OpenCV and NumPy libraries, the code can process the array structure of the images for analysis and recognize the target object where in this situation, to detect the lane on the road. The flowchart for this proposed lane path detection in palm oil plantation is shown on Fig. 3.

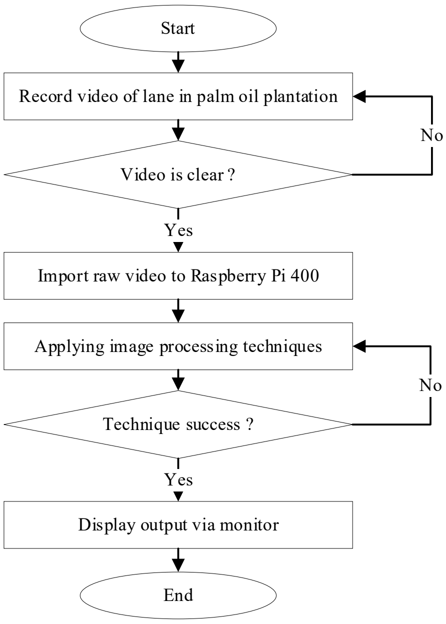


Fig. 3 *Flowchart of the lane path detection system*

2.3 Palm Oil Path Characteristics

The video footage of the palm oil road was recorded from two different paths, denoted as Path 1 and Path 2. Both paths display certain similarities and distinctive characteristics, which could potentially impact the effectiveness of lane detection. Figure 4 illustrates an image captured from Path 1, offering a visual representation of one of the selected paths. This study aims to analyze and evaluate the influence of these path variations on lane detection performance, providing insights into the challenges and considerations related to implementing such technologies in palm oil plantation areas.

Fig. 4 *Sample image frame for Path 1*

According to the observations from Figure 4, the lane path width is approximately 5.48 meters, and the distance between the palm oil trees and the road is estimated to be 1 meter. This proximity of the trees to the road resulted in the appearance of shadows from the fronds of the palm oil trees on the road surface. Notably, the trees were planted at the same level as the road. The video recording took place on the 15th September 2022, during hot weather conditions. The prevailing weather conditions might have contributed to additional challenges for the lane detection system, considering factors like potential heat distortion or glare on the road surface. To further investigate the impact of these variables, Figure 5 showcases an image captured from Path 2, providing an additional perspective of the road characteristics and the surrounding environment.

Fig. 5 *Sample image frame for Path 2*

Based on the analysis of Figure 5, it can be observed that the path width is like that of Path 1, measuring approximately 5.48 meters. However, a notable difference exists in the distance between the palm oil trees and the road, which is measured at 2.5 meters. This distance is greater than that observed in Path 1, primarily due to the presence of a drain between the trees and the road. Consequently, the shadows from the fronds of the palm oil trees were absent on the road surface. The level at which the trees were planted is considerably higher than the road, as indicated by the presence of a cliff in the landform. This elevation difference between the trees and the road could introduce additional challenges for the lane detection system, requiring it to account for varying road surfaces. The video recording was conducted on the 16th of September 2022, following a period of rainfall. Consequently, water puddles formed on the road, further contributing to the complexity of the road environment. These conditions, in combination with the unique landscape features, present additional considerations for the lane detection system's performance on Path 2.

2.4 Image Processing Technique

Image processing technique is the main part of this study. Figure 6 shows the steps of the image processing executed for lane path detection in palm oil plantations.

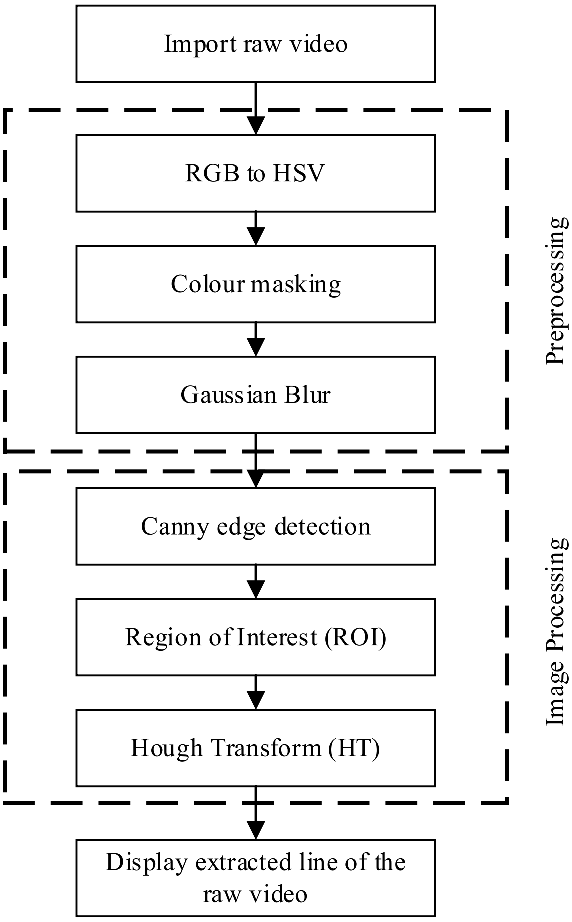


Fig. 6 *Steps of image processing for the lane path detection*

Based on Figure 6, the first procedure of any vision-based technique is importing the selected raw video into the Raspberry Pi 400 controller. The duration of the video imported was about 30 seconds at 30 fps. Once the video is imported, it is subjected to pre-processing technique. The procedure starts with converting the RGB image into an HSV image, as shown in Figure 7.

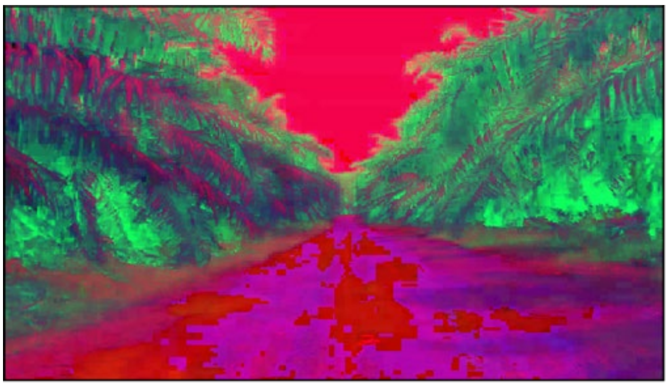


Fig. 7 *HSV converted image*

Real-world images often exhibit variations in color values due to diverse lighting conditions, presence of shadows, and camera-generated noise during recording [20], [21]. To address these challenges, the RGB color space is converted into the HSV color space, enabling efficient color masking. Specifically, the HSV range for the upper and lower values of green color is defined to mask out the green color present in the grass and trees. Subsequently, a Gaussian Blur, illustrated in Figure 8, is applied to the image. This step serves to eliminate noise and achieve image smoothing, enhancing the clarity and quality of the subsequent image processing tasks.

Fig. 8 *Gaussian-blurred image*

Indeed, Gaussian blur is a crucial preprocessing step in the lane detection process. The input frames or images often contain unwanted noise, which can lead to false detections. By applying Gaussian blur, the image is effectively smoothed, reducing the impact of noise while preserving the visibility of the lanes for detection [22]. Following the Gaussian blur, Canny Edge Detection, as depicted in Figure 9, is employed to identify the edges within the image. This technique helps to highlight the edges of the lanes, allowing for more accurate lane detection and further processing in the lane detection algorithm.

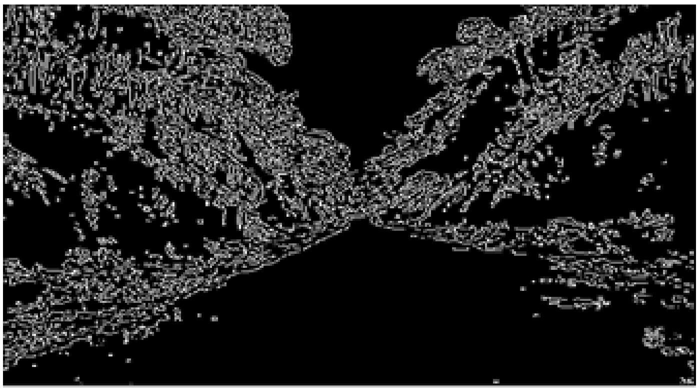


Fig. 9 *Canny Edge detection*

The utilization of the Canny Edge technique enables the extraction of essential information from various visual objects while simultaneously reducing the volume of processed data [23]. This technique plays a pivotal role in highlighting the edges relevant to lane detection. Subsequently, the implementation of the ROI becomes crucial. The ROI process involves masking out unwanted portions of the image to focus solely on the necessary area for lane detection. As illustrated in Figure 10, the ROI helps in isolating the specific region containing the lanes, streamlining the lane detection algorithm, and optimizing its performance.

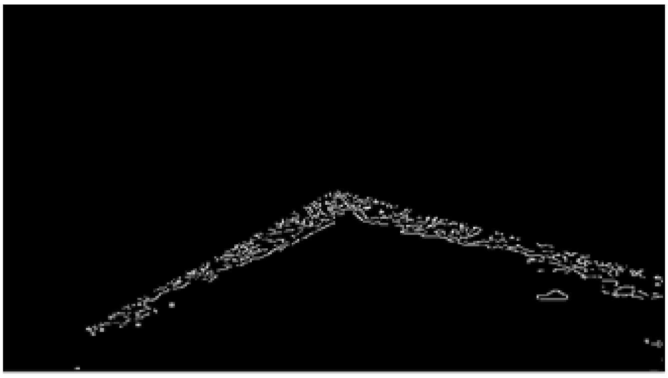


Fig. 10 *ROI selection*

Figure 10 illustrates the application of a triangular mask on the image, effectively focusing on the targeted lane for lane detection. This ROI technique isolates the specific area of interest, facilitating more accurate and efficient lane detection [24]. The key component of the image processing technique in this project is the Hough Transform (HT). HT is utilized to extract road features and recognize the lane on the palm oil path, which has been masked using the ROI technique. Properly setting the maximum gap between lines, the threshold for intersecting points, and the minimum line length are essential parameters for successful implementation of this method. In this project, the extracted lines are applied to the boundaries between the grass and the road, as depicted in Figure 11. The detected lane is represented by a red-colored line, demonstrating the successful identification of the lane through the application of the HT.

Fig. 11 *Extracted line using HT technique*

As a summary, the image processing technique for lane detection in palm oil plantations involves converting RGB to HSV color space, applying color masking for green areas, using Gaussian blur to reduce noise, performing Canny Edge Detection, implementing ROI to focus on the lane, and applying HT for lane extraction. The detected lane is represented by a red line on the boundary between grass and road. This approach enables accurate lane detection despite real-world image challenges like lighting variations, shadows, and noise.

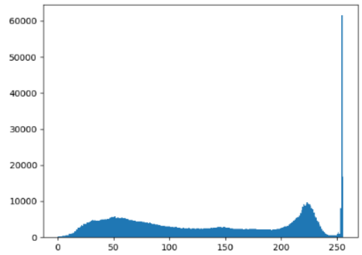
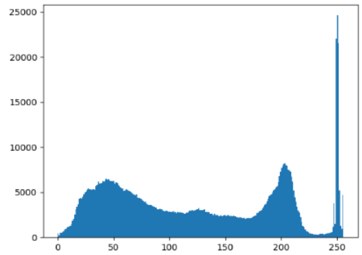
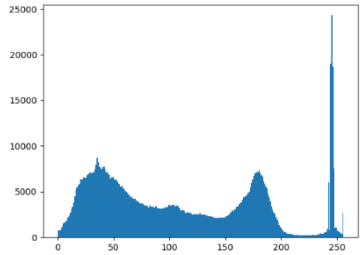
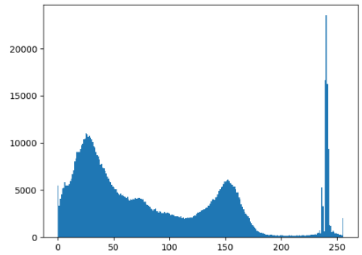
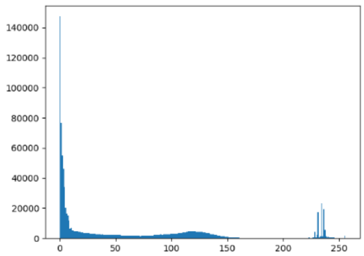
3. Research Method

In the evaluation of lane detection performance in palm oil plantations, Histogram charts play a crucial role. Histograms are essential components of image processing, graphically representing the distribution of pixel intensities in an image [25]. The x-axis of the chart represents the pixel or luminance value, ranging from 0 (pure black or dark) to 255 (pure white), while the y-axis indicates the frequency of occurrence of each luminance value in the image. For this project, the lane detection performance is assessed by applying various brightness values to both lanes. The Histograms allow visualizing how changes in brightness affect the intensity distribution, providing valuable insights into the lane detection algorithm's robustness under different lighting conditions. By analyzing the Histograms, the project aims to optimize lane detection accuracy and adaptability to varying environmental factors encountered in palm oil plantations.

3.1 Software Setup

Table 1 shows the result of the extracted lane and histogram chart for palm oil Path 1. The brightness level was set at levels 100, 50, 0 (original value of the image), -50, and -100.

Table 1 *Extracted lane and histogram output for palm oil Path 1*

Extracted lane output	Image Dimension (Pixel)	Histogram output
 Brightness: 100	491 x 364	
 Brightness: 50	485 x 362	
 Brightness: 0	487 x 361	
 Brightness: -50	490 x 367	
 Brightness: -100	487 x 361	

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Based on the histogram results presented in Table 1, the images with brightness levels at 0 and 50 exhibit similar luminance value distributions, with the highest peak on the right side of the histogram (approximately 25,000). This peak indicates the influence of sunlight exposure and the set brightness level. The left side of the histogram shows a distribution attributed to the presence of trees and their shadows. At these brightness levels, the lane detection performs well, and the red line representing the lane remains prominent. However, at -50 brightness, the pixel values on the left side of the histogram are significantly higher compared to levels 0 and 50, indicating less brightness exposure. Therefore, the red line representing the lane becomes narrower, resulting in a decline in lane detection performance. The histogram outputs at brightness levels of 100 and -100 demonstrate remarkable differences compared to the other histogram charts. At brightness 100, the right chart exhibits a very high number of luminance values (approximately 60,000) due to excessive brightness exposure. Conversely, at -100, the leftmost part of the histogram has the highest peak, with approximately 140,000 dark luminance values. Both charts display limited pixel distribution in the middle, suggesting the loss of many details and causing inaccurate lane detection performance.

As a summary, the lane detection performance for Path 1 is influenced by the brightness level and environmental factors such as tree shadows, sunlight exposure, and the lane's landform. Setting the image brightness too high or too low leads to deteriorating lane detection performance. Thus, an appropriate level of brightness is necessary to achieve a good result, where the pixel values are distributed in the middle of the histogram chart. This balance ensures optimal lane detection performance in varying lighting and environmental conditions.

3.2 Lane Path Detection for Path 2

Table 2 displays the results of extracted lanes and histogram charts for lane detection on palm oil Path 2. Similar to Path 1, the brightness levels of Path 2 images were adjusted to 100, 50, 0 (original image brightness), -50, and -100 for evaluation. Based on the histogram analysis, brightness levels of 0 and 50 exhibit high luminance distribution at the middle of the graph. The peak on the right side is primarily attributed to image brightness exposure and environmental factors, such as sunlight illumination. The left side pixel distribution corresponds to the color of trees and the road. At these brightness levels, lane detection performs effectively. However, at brightness level 100, the pixel distribution at the middle is reduced compared to levels 0 and 50. Increasing brightness to the maximum causes' loss of image detail, leading to a decline in lane detection accuracy.

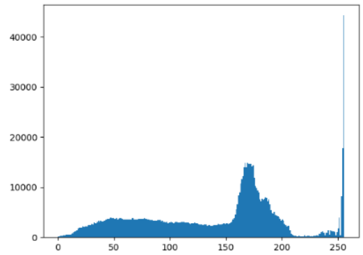
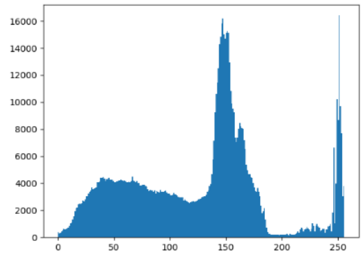
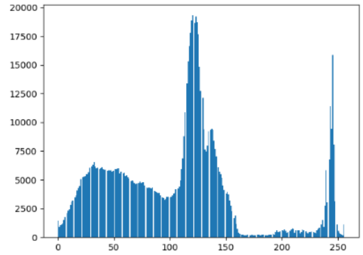
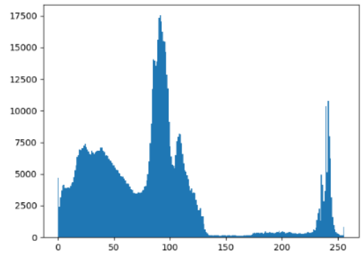
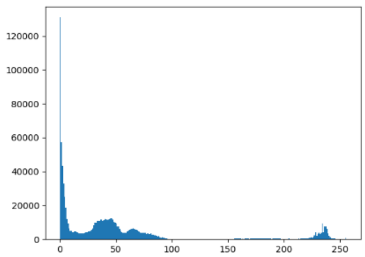
For brightness levels of -50 and -100, lane detection results differ from other brightness levels. At -50, the red lane line does not align with the grass-road boundaries, as indicated by the histogram's high number of dark pixels (17,500). This inaccuracy results from the image being too dark. At -100, the histogram shows a significant peak of dark pixels on the left side (approximately 120,000), with a small peak on the right due to the sky color. This image loses many details, leading to the missing left lane line in the detection. Path 2 is influenced by image brightness levels, with accuracy dropping significantly at extremely low brightness settings. Path 2's different landform, including the presence of drains and water puddles along the boundaries, adds complexity to lane detection. Additionally, the weather during Path 2 recording, being cloudy, contributed to the darker image compared to Path 1's recording on a hot day.

As a summary, the accuracy of lane detection in Path 2 is affected by image brightness levels, weather conditions, and specific landform characteristics. Properly setting brightness levels is crucial for achieving accurate lane detection, particularly in challenging road environments like palm oil plantations.

3.3 Discussion

The comparison between Path 1 and Path 2 reveals notable differences in their road characteristics, lighting conditions, tree shadows, lane detection accuracy, histogram analysis, and landform. Path 1 showcases a smoother road surface with well-defined lane markings, whereas Path 2 presents a more challenging road surface with potential water puddles and a drain running alongside the lane. The recording conditions also differ, with Path 1 captured on a hot day and Path 2 under cloudy weather. These varying lighting conditions impact image brightness and quality, which can influence lane detection performance. Additionally, the shadow effect from the surrounding trees differs between the two paths, with Path 1 displaying shadows from palm oil tree fronds on the road.

Table 2 *Extracted lane and histogram output for palm oil Path 2*

Extracted lane output	Image Dimension (Pixel)	Histogram output
 Brightness: 100	492 x 364	
 Brightness: 50	490 x 367	
 Brightness: 0	485 x 363	
 Brightness: -50	492 x 367	
 Brightness: -100	491 x 365	

The lane detection accuracy on Path 1 appears to be more consistent, particularly at brightness levels of 0 and 50, while Path 2's accuracy significantly drops at brightness levels -50 and -100. The histogram charts further illustrate differences in pixel distributions, with Path 1 exhibiting pixel distributions around the middle of the histogram, while Path 2's histogram at brightness -100 shows a significant peak of dark pixels, indicating loss of image details. Furthermore, the unique landform of Path 2, featuring drains and water puddles, introduces additional challenges for lane detection compared to the relatively smoother surface of Path 1. These findings underscore the impact of various environmental factors on lane detection performance in palm oil plantations and highlight the importance of optimizing lane detection algorithms for safe navigation in such challenging road environments.

4. Conclusion

This paper's findings demonstrate that the lane detection program performs optimally when the brightness level is appropriately set. Specifically, for both Path 1 and Path 2, the brightness levels of 0 and 50 yield the best results. At these levels, the images receive sufficient sunlight exposure and brightness, leading to a well-distributed pixel distribution in the middle section of the histogram chart. On the contrary, setting the brightness at extreme levels, such as 100 and -100, results in deteriorated lane detection performance. The extracted lane output becomes inaccurate due to the loss of essential pixel details in the image. Moreover, the environmental conditions, including shadows from trees, sunlight illumination, weather, and landform, also significantly impact the lane detection performance. For future improvements, this project can enhance the lane detection program's programming, particularly in handling challenging scenarios such as shadows, drains, and water puddles. By addressing these issues, the overall lane detection performance can be further optimized, ensuring safe and reliable navigation in palm oil plantations.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Noorfadzli Abdul Razak, Juliana Johari;* ***data collection:*** *Aina Madihah Kamarudzaman;* ***analysis and interpretation of results:*** *Noorfadzli Abdul Razak, Aina Madihah Kamarudzaman, Fazlina Ahmat Ruslan;* ***draft manuscript preparation:*** *Mahanijah Md Kamal, Mohd Azri Abdul Aziz. All authors reviewed the results and approved the final version of the manuscript.*

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