Ananas comosus crown image thresholding and crop counting using a colour space transformation scheme

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ABSTRACT

The implementation of unmanned aerial vehicle (UAV) technology having image processing capabilities provides an alternative way to observe pineapple crowns captured from aerial images. In the majority of pineapple plantations, an agricultural officer will physically count the crop yield prior to harvesting the Ananas Comosus, also known as pineapple. This process is particularly evident in large plantation areas to accurately identify pineapple numbers. To alleviate this issue, given it is both time-consuming and arduous, automating the process using image processing is suggested. In this study, the possibilities and comparisons between two techniques associated with an image thresholding scheme known as HSV and L*A*B* colour space schemes were implemented. This was followed by determining the threshold by applying an automatic counting (AC) method to count the crop yield. The results of the study found that by applying colour thresholding for segmentation, it improved the low contrast image due to different heights and illumination levels on the acquired colour image. The images that were acquired using a UAV revealed that the best distance for capturing the images was at the height of three (3) metres above ground level. The results also confirm that the HSV colour space provides a more efficient approach with an average error increment of 47.6% when compared to the L*A*B*colour space.

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1. INTRODUCTION

Remote sensing technologies, along with image processing methods, have allowed precision engineering to be integrated and applied in the agricultural sector [1]. Among the most widely adopted technologies in this sector are satellite imagery [2] and unmanned aerial vehicles or drones (UAV) [3]. Even though the technology is capable of capturing large crop areas, satellite imagery is expensive, and the images are useless under cloudy or low light conditions. In comparison, UAV provides a cost-effective approach for acquiring an unobstructed view of a plantation area with acceptable image quality. Accordingly, this form of technology could have a positive impact on estimating crop yield before the harvesting season. In Malaysia, one agriculture commodity that would potentially benefit from this technology would be pineapples. In local and international markets, high-quality pineapples are in high demand and canned pineapple products are exported overseas generating significant income, contributing to the Malaysian economy.

Conventional techniques applied for counting pineapple crop yield takes a considerable amount of time and are labour-intensive which require an agriculture officer to physically count the number of crops that can be harvested from a selected plot of land. Although in this case, the actual yield counted is normally inaccurate since it is based on predefined assumptions regarding the selected block in the designated area [4]. The implementation of a UAV for alleviating this issue is anticipated to reduce the amount of time needed for counting and provide a more accurate count of the fruit before the harvesting season. The application of this method is ideal for pineapple plantations as the crown of the fruit is normally unobstructed and highly exposed from above. While numerous studies have investigated the use of ground-level images to detect the maturity of fruit [5-7], these approaches are impractical for crop yield estimation given it obstructs the line of sight from one fruit to the next [8]. Consequently, this is one of the main reasons for adopting a UAV to estimate the crop yield of pineapples.

In obtaining an effective crop yield count from aerial images, the pre-processing stage must be robust, given the varying light conditions and heights in capturing these images. The application of the colour component in the image segmentation process is also important, especially for detection [9], recognition [10], identification [11, 12] and classification [13] of the objects. Previously, several colour spaces have been proposed which include RGB [14], YCbCr [15], HSV [16] and L*A*B* [17]. From among these colour spaces, HSV and L*A*B* have been highly effective for thresholding and to reduce noise [18, 19], and have been applied to detect apples, oranges and bananas given their smooth background. HSV has also been implemented to estimate the crop yield of oranges, and for successfully detecting partially obstructed fruits [20, 21]. In other studies, the HSV colour space has been used along with texture and shape features to discriminate between apples, oranges, bananas and cherries [22, 23]. Jednipat and Supawadee demonstrated the estimation technique using colour thresholding of L*A*B* and the HSV colour space where the findings revealed that the experiment yielded excellent results [24].

Despite the successful reporting of colour space implementation for fruit detection, image processing experiments have been undertaken against well-contrasted and smooth backdrops [25]. However, the estimation of pineapple yields from aerial images presents a new perspective in the pre-processing method as the fruit is of similar colour tone to the surrounding background. Additionally, the presence of the leafy structure surrounding the fruit adds to the texture-like element when viewed from above. Aside from this, the challenge also arises from weather elements that influence the illumination level on the field or crop area [26, 27]. Accordingly, a robust image processing algorithm is needed for the estimation of pineapple yield from aerial images. This paper contributes in this field of study by proposing a novel approach towards automatic counting (AC) of pineapple yield by employing high-quality image processing. To the best of the author's knowledge, this technique is the first of its kind to estimate crop yield by detecting pineapple crowns since most researchers focus on pineapple bodies to detect maturity. The objective of this paper presents a comparative study which focuses on HSV and L*A*B* in colour thresholding schemes to improve image quality. The performance of the proposed algorithms is also assessed as errors in detecting the crop count from image samples.

2. RESEARCH METHODS

The approach adopted in this study included data acquisition, extraction of the image samples from the video, comparing the performance of colour thresholding using L*A*B and HSV colour spaces, and lastly, measuring the performance using relative error and average error. A general overview of the research method is illustrated in Figure 1.

2.1. Data acquisition and image extraction

Aerial views of the pineapples were acquired from coordinate 1º48'55.9" N,103º15'33.5" E at the Simpang Renggam plantation in the state of Johor, Malaysia. Data were collected in March 2019. The plantation covers a large area comprising of 14,826 acres which is further divided into approximately 644.16 blocks. Each block comprising of 23 acres is then partitioned into 16 divisions: each measuring roughly 1.44 acres with each division consisting of around 110 lines of pineapples. The segregation of the area into blocks, divisions and lines are illustrated in Figure 2. Cultivation of the pineapples for each block is not undertaken simultaneously but is undertaken in phases which are then reflected in varying stages of maturity during the harvesting season. For this study, the primary cultivar for the designated plantation was N36 (Kaling Pineapple). The MD2 (Milie Dillard 2 Pineapple) is cultivated in a smaller area of the plantation.

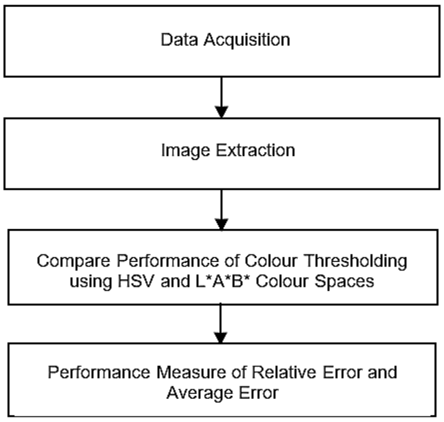


Figure 1. Overview of the research method

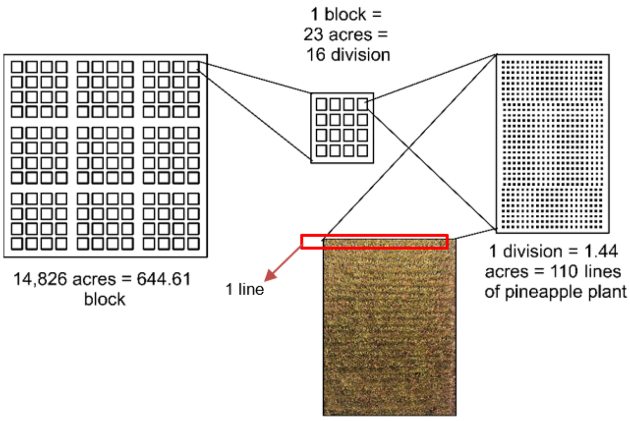


Figure 2. Segregation of the plantation area into blocks, divisions and lines

Figure 3 illustrates the experimental setup used in this study. Data were acquired using a DJI Phantom 3 Advanced quadcopter with a 4K resolution RGB camera and videos were recorded at the height of 3 metres, line by line from the ground level. This research limited the area for the initial investigation. The image of the pineapples was initially concentrated and evaluated on 110 lines but restricted to the case of the proposed method. Here only 1 line of pineapple fruit was used to extract the video into an image, as shown in Figure 2. The images were then extracted frame by frame using MATLAB software, resulting in a total of 1,503 samples. The size of each image was 2,704 x 1,520 pixels. The focus of the pre-processing algorithm was directed towards isolating the crown section of the pineapple and detecting the crop count. These tasks were also performed using MATLAB.

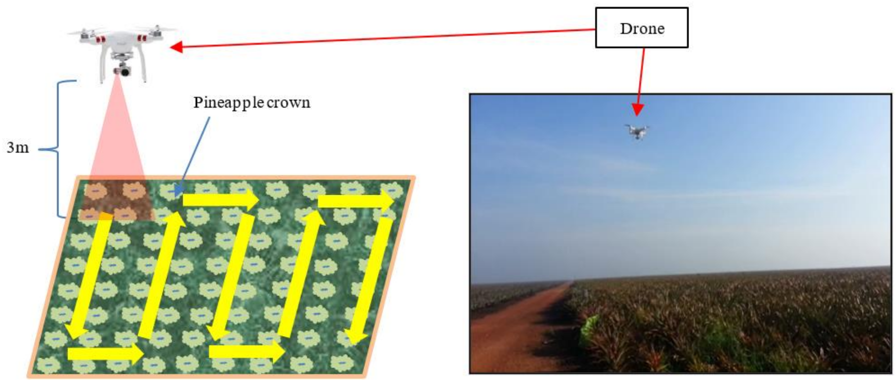


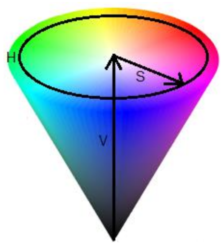
Figure 3. An illustration in real-time of the experimental setup at the pineapple plantation

2.2. Colour thresholding

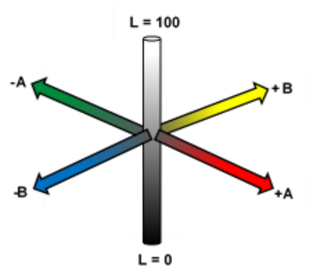
Figure 4 (a), shows that the HSV colour space is represented as a conical coordinate of points in a colour model [28, 29]. The original RGB model has 'H' as the hue, represented by the angle, 'S' as the saturation corresponding to the radius, and 'V' as the brightness characterised by the height of the cone. The hue is of a dominant colour as perceived by an observer. The value range of the hue varies from T1 = 0.195 to T2 = 0.401, containing a green colour from the combination of yellow-green to green-cyan, which signify the colour of the centre pineapple crown. For the saturation component, it is among the white light that is mixed with a hue, resulting in varying levels of saturation. The minimum value is 0.245 while the maximum value is 0.902 for the pineapple crown except for the backgrounds such as the ground, leaf and grass. Brightness is a chromatic notion of intensity which varies from true colour to black. The brightness component is used to remove the background area and the pineapple crown tip.

Figure 4 (b) illustrates the L*A*B* colour space consisting of a 3-axis colour system [30], and is device-independent and of an efficient format for transferring between devices. Here, L* represents lightness which can range from 0 (black) to 50 (mid-grey) to 100 (white). In this research, the value ranged from 36.759 (dark) to 58.381 (mid-bright) and was set as the brightness for the pineapple crown. For positive A* values (from 1 to 100) it designates the amount of the red component, while negative A* values (from –1 to –100) indicate the amount of green component. For the A* channel value ranging from -26.988 to -14.071 it indicates the green component which is set as the colour of the pineapple crown centre.

Meanwhile, positive B* values (from 1 to 100) signify the amount of the yellow component, while negative B* values (from –1 to –100) indicate the blue component. The B* channel values range from 8.170 to 46.861 at the yellow axis, upon which yellow is the combination colour with green for the crown centre. Other than the selected value, it will remove the background and the crown tip. This specific limit was set up for both colour spaces as the best threshold value for detecting the central pineapple crown under the influence of different height and levels of lighting on the image projections.



(a)



(b)

Figure 4. (a) HSV colour space and (b) L*A*B* colour space

Colour thresholding in the HSV and L*A*B* spaces was performed by creating the most efficient mask for background removal. The threshold level is expressed by (1), where x and y signify the threshold coordinate value points, while $p(x,y)$ and $f(x,y)$ are the grey level image pixels [31].

$$T = T[x, y, p(x,y), f(x,y)] \quad (1)$$

Subsequently, image $g(x,y)$ acquired through the thresholding operation can be defined using (2):

$$G(x,y) = \begin{cases} 1 & , \text{ if } f(x,y) > 1 \\ 0 & , \text{ if } f(x,y) \leq 0 \end{cases} \quad (2)$$

Following the thresholding process, the crown was rendered white while the surrounding background was reduced to black. The background in the image included the ground, leaf and grass which were depicted in a binary image. A morphological operation was then applied to remove any additional noise in the image. Dilation expands the white region while allowing merging with smaller spots within the proximity of the crown. Subsequently, the image was filled to erode further any speckles that remained. A disc-shaped structuring element was then created to maintain the circular form of the object followed by implementing the bounding box method to detect the crown of the pineapples.

In this study, the best colour space was determined based on the lower value of absolute (AE) and relative error (RE) that detected the pineapple crown with less noise from the background image which was calculated after the bounding box was identified. The cumulative bounding box was calculated automatically by the system in which AE is defined as the absolute magnitude of the difference between the actual and computed value, which indicates a number of false detections. The actual value is manually counted, Mc from the number of bounding boxes while the measured value is the real crop count, Ac which is observable from the unprocessed sample images. Thus, a smaller value of AE indicates a smaller error. The expression for AE as given by (3) [32]:

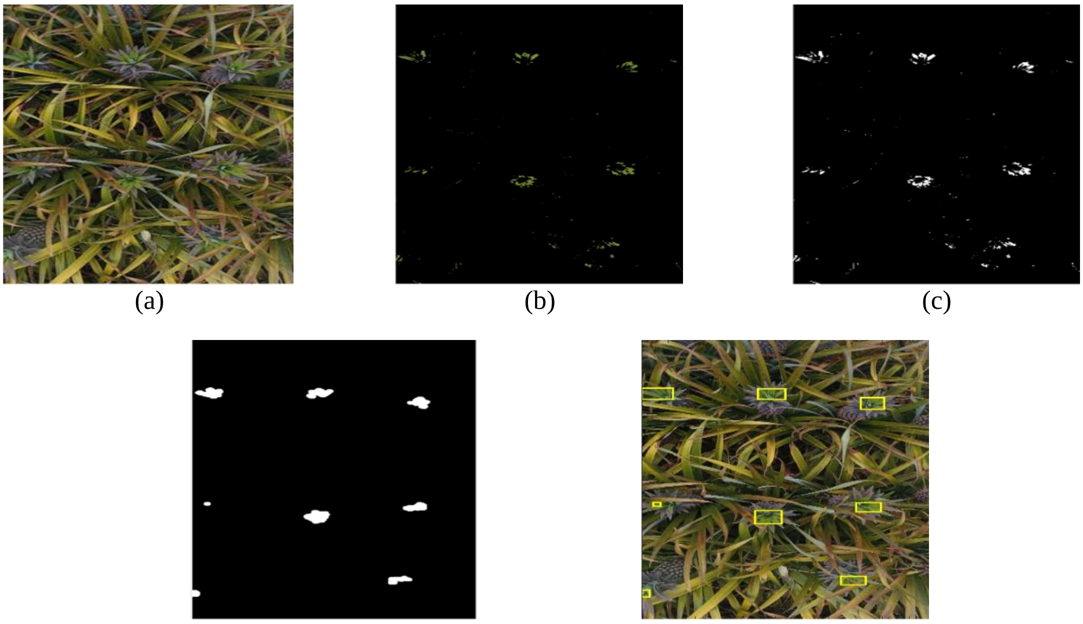
$$AE = |Mc - Ac| \tag{3}$$

As shown in (4), RE is the ratio between AE and Mc. Similarly, a smaller RE would be the desirable attribute.

$$RE = \frac{|Mc - Ac|}{Mc} \times 100\% \tag{4}$$

3. RESULTS AND DISCUSSION

Ten sample images were randomly selected from the video for demonstration purposes. The images were used to evaluate the thresholding schemes based on both colour spaces. Figure 5 illustrates the processes performed on one of the samples using the HSV space. Initially, the extracted image undergoes background removal through a masking process that considers the hue, saturation and brightness components. A binary image is then created after the thresholding procedure, which is then followed by the morphological operation and the bounding box procedure. The final image in the sequence displays the position of crown that is detected by the algorithm.



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

Figure 5. (a) Extracted image; (b) background removal using HSV colour space; (c) binary image; (d) morphological operation; (e) bounding box crown detection

Figure 6 shows the processes carried out on one of the samples applying the L*A*B* colour space. Similarly, the extracted image undergoes background removal through a masking process that considers the lightness, red, green, yellow and blue components and the thresholding produces the desired binary image. Subsequently, this is followed by the morphological operation and the bounding box procedure. The final image shows the position of the crown that is successfully detected by the algorithm. Here, the performance of the suggested automated counting technique is compared by applying HSV and L*A*B* colour thresholding for manual counting, which was performed by the observer. Other researchers have applied automated detection and a counting system to other fruits such as apples, oranges, etc., resulting in different performances being measured.

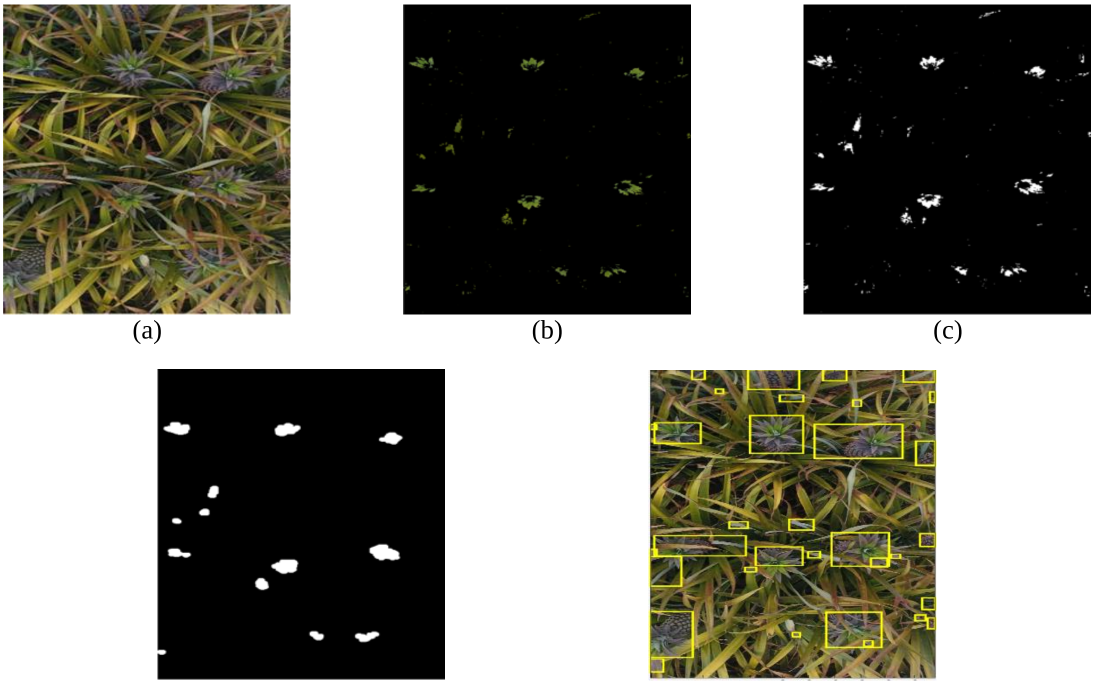


Figure 6. (a) Extracted image; (b) background removal using L*A*B* colour space; (c) binary image; (d) morphological operation; (e) bounding box crown detection

Table 1 shows the resultant AE and RE for pineapple yield estimation based on the HSV colour space. Generally, RE ranges between 0 and 28.6% with an average error of 12.0%. Table 2 summarises the AE and RE for crop yield estimation established based upon the L*A*B* colour space. The later scheme of processing attained a higher RE, ranging between 12.0% and 114.3%, with an average error of 59.6%. Based on the results, the HSV colour scheme demonstrated superior capability for crown detection. Compared to both colour thresholding, the L*A*B* colour thresholding detected more false detections from the background such as the leaves, grass and ground while using HSV detects the crown more accurately with less error.

Figure 7 illustrates the automated counting process via image processing; Ac manual counting by the observer, Mc plot for the ten samples using both colour spaces. The bar graph represents Mc for each image sample. Meanwhile, the red line denotes Ac for the HSV colour space, and the green light denotes Ac for the L*A*B* colour space. As can be seen from the graph, it remains evident that Ac for the L*A*B* colour space deviates furthest from Mc.

The findings are also supported by the plot shown in Figure 8. Generally, RE of the crop count using the L*A*B* colour space remains high. The error is contributed by the inability of the L*A*B* colour space to provide contrasting elements between the crown and the surrounding leafy structures and is not sufficiently robust enough to deal with the varying illumination levels on the images. From these experiments, it is evident that HSV is more effective for the estimation of pineapple yield in comparison to the L*A*B* colour space.

Table 1. AE and RE for pineapple yield estimation using HSV colour space

Sample	Manual Counting by observer, Mc	Automated counting via image processing, Ac	No. of false detection, AE	Relative error, RE (%)	Average Error (%)
1	6	6	0	0	12.0
2	6	7	1	16.7	
3	8	9	1	12.5	
4	8	9	1	12.5	
5	8	9	1	12.5	
6	8	8	0	0	
7	7	8	1	14.3	
8	8	7	1	12.5	
9	7	9	2	28.6	
10	9	10	1	11.1	

Table 2. AE and RE for Pineapple yield estimation using L*A*B* colour space

Sample	Manual Counting by observer, Mc	Automated counting via image processing, Ac	No. of false detection, AE	Relative error, RE (%)	Average Error (%)
1	6	8	2	33.3	59.6
2	6	10	4	66.7	
3	8	9	1	12.5	
4	8	10	2	25.0	
5	8	11	3	37.5	
6	8	13	5	62.5	
7	7	11	4	57.1	
8	8	15	7	87.5	
9	7	15	8	114.3	
10	9	18	9	100.0	

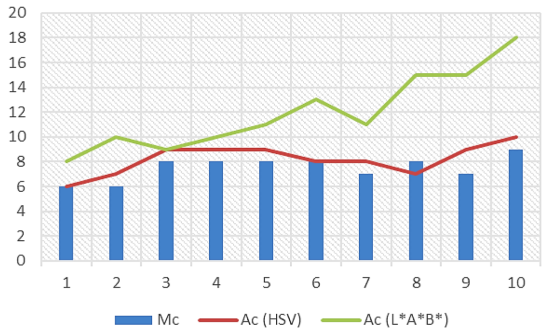


Figure 7. Ac and Mc plot for each sample using both colour spaces

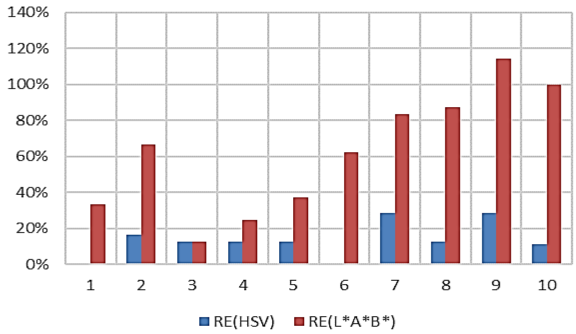


Figure 8. RE for each sample using HSV and L*A*B* colour space

4. CONCLUSION

This paper focuses on the prospective application of HSV and L*A*B* spaces for estimating pineapple yield captured from aerial images. Each sample underwent a similar image processing protocol such as image extraction, colour thresholding, background removal, conversion to a binary image, and crown detection using the bounding box method. For better performance, the average error for all samples should be less. The HSV colour space, on the other hand, demonstrated a more efficient approach having an average error of 12.0% compared to the L*A*B* space having an average error of 59.6%. However, it is important to note that the images were captured at a height of 3 metres from the ground under varying light conditions. Therefore, further work is required to improve detection accuracy at higher altitudes with enhanced robustness to compensate for different weather conditions.

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