Photogrammetric Grading of Oil Palm Fresh Fruit Bunches

Ahmed Jaffar, Roseleena Jaafar, Nursuriati Jamil, Cheng Yee Low, and Bulan Abdullah

Abstract— Conventional grading of oil palm Fresh Fruit Bunches (FFB) is still currently manually carried out in palm oil producing industries. The most critical part of the grading process is the categorization of the oil palm fruit bunches according to their ripeness. This paper presents a computer assisted photogrammetric methodology which correlates the color of the palm oil fruits to their ripeness and eventually sorts them out physically. The methodology consists of five main phases, i.e. image acquisition, image pre-processing, image segmentation, calculation of color Digital Numbers (DN) and finally the classification of the fresh fruit bunches according to their ripeness. The software and hardware essentials for the implementation of the methodology have been developed and tested. The design of system is geared towards four main characteristics: (i) affordable in comparison to the labor cost in palm oil mills, (ii) reliable grading process equivalent to the task carried out by a skilled grader, (iii) sufficiently robust to withstand the oil palm mill environment without human intervention and (iv) synergistic integration of hardware and software systems. The system and the methodology formulated in this work have developed a complete automation grading system of oil palm FFB and thus drastically increased the grading productivity.

Index Term— photogrammetric grading, digital image processing, mechatronic design, agricultural automation

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I. INTRODUCTION

Malaysia is currently the largest producer and exporter of palm oil in the world, accounting for 41% of world production and 47% of world exports [1]. The increased industrialization in this agricultural sector has resulted in the emergence of numerous refineries in the country. As competition is stiff on the world market, research and development is critical to generate knowledge as well as to increase production and processing efficiency.

The oil palm, *Elaeis guineensis*, planted in Malaysia are mainly the *tenera* variety, a hybrid between the *dura* and the *pisifera*. In 1994, the Palm Oil Research Institute of Malaysia (PORIM) established four classes of ordinary oil palm FFB belonging to Elaeis guineensis species. The classes of FFB arranged in the ascending degree of ripeness are the unripe, the under-ripe, the ripe and the over-ripe categories. The unripe bunch has purplish black colored fruits, covering more than 90% of the bunch surface. Meanwhile, fruits belonging to under-ripe and ripe bunches appear reddish orange or purplish red and reddish orange respectively. Finally, the bunch belonging to the over-ripe class with more than 80% of the fruits in the bunch appears darkish red. Thus, the color of the oil palm fruits remains one of the important factors which determine the grade and quality of the palm oil [2, 3].

The color of each fruit on the bunch varies slightly with location as fruits on any given bunch do not ripen simultaneously. In spite of this, it has been observed that more than 85% of fruits on any bunch exhibit a similar degree of maturity, the remaining 15% which are hiddenly located in the interior regions of the bunch constitute the undeveloped and parthenocarpic fruits [4]. Hence, it can safely be inferred that once a fruit within a bunch is ripe, all other fruits on the bunch are physiologically ripe as well. Therefore, the FFB can conveniently be graded by inspecting a few fruits at designated positions on the bunch rather than inspecting all the fruits. In this work, two different locations from the middle section of the sampled fruit were identified for inspection of color and grading of ripeness.

II. PROBLEM STATEMENT

The color of oil palm FFB can be used as a yardstick to determine its maturity or defects. A number of commercial color meters are available for the measurement of fruit ripeness. However, the disadvantage of using such method on oil palm FFB is that the testing can only be done on the fruitlets of the fruit bunches and it requires the fruits to be sliced and the surface of the mesocarp exposed [5]. In order to increase the efficiency and quality of
grading FFB in palm oil mills, computer-based technologies such as machine vision [6-9] are necessary to replace the traditional grading performed by trained human inspectors. So far, the image capturing was done on stationary fruit sampling. As compared to the commonly used Matrox Intellicam software, a novel methodology assisted by customized hardware and software was developed and thus eliminating the lengthy coding process besides the increased grading consistency and reduced sorting time.

III. METHODOLOGY
A novel methodology has been developed for photogrammetric grading of oil palm fresh fruit bunches. The methodology consists of five main phases, i.e. image acquisition, image pre-processing, image segmentation, calculation of color Digital Numbers (DN) and classification of fresh fruit bunches (FFB). The image pre-processing phase comprises three steps, i.e. image binarization, morphological processing and the extraction of FFB properties. Similarly, the image segmentation phase comprises another three steps, i.e. image cropping, conversion from RGB to L*a*b color space and the segmentation of FFB image using K-means clustering. The methodology is visualized in Figure 1.

Image acquisition is crucial as only with high-quality images would the subsequent processing and analysis feasible. Both hardware and software are involved in this methodology and the selection of proper components such as light source is essential to the image acquisition process. Image pre-processing, on the other hand, is the other essential step to remove unnecessary or unwanted elements from the raw image. The object of interest, which is the FFB image, is extracted from the original image to ease the ripeness classification process during the final stage. The FFB image has to be further segmented into separate clusters based on its color by using L*a*b color model. Subsequently, the color digital numbers have to be calculated for each of the clusters in order to characterize the FFB image into either ripe or unripe category. Finally, a computerized decision-making process is executed to physically sort out the unripe FFB from the ripe ones using a mechanical sorter.

![Fig. 1. A novel methodology for photogrammetric grading of oil palm Fresh Fruit Bunches (FFB).](image1)

IV. TEST BED
A. Hardware Development
The photogrammetric grading system consists of the following modules: (i) a feeder connected to a conveyor which feeds the FFB to the subsequent station in a systematic manner, (ii) a vision inspection module which comprises of an illumination chamber, two webcams for acquiring the FFB images and a workstation for processing and storing of images, (iii) image processing algorithm, and (iv) a separator that physically separates the FFB according to its ripeness.

The illumination chamber aims to maintain a uniform lighting condition during the image acquisition phase. The inner surface of the illumination chamber was painted white and four white 8-watts fluorescent tubes were installed onto the chamber’s roof. In order to ensure cost competitiveness, the image capturing was done using two high end Microsoft Lifecam NX-600 webcams which are capable of producing 2.0 mega pixels images with a resolution of 1600 x 1190. The entrance and exit openings of the light proof chamber are approximately 480mm. The distance between the webcam and the fruit is approximately 580mm. The hardware set-up of the vision inspection chamber is shown in Figure 2.

![Fig. 2. Hardware set-up of a vision inspection module for FFB grading.](image2)

B. Software Development
The image processing algorithms as described in Section III was integrated into a Graphical User Interface (GUI) of the photogrammetric grading system. This prototype comes with a
Data Acquisition (DAQ) card that is able to trigger the webcams to take the images of the FFB. The images are then processed by the algorithm which outputs a digital actuating signal to the mechanical sorter. The GUI has been designed in such a way that the threshold slider bar is adjustable to cater for different Digital Number color values which may vary for different species of oil palm. The main interface is shown in Figure 3.

V. RESULTS AND DISCUSSIONS

A total of sixteen fruits were taken from a local oil palm plantation. The fruits weigh an average of 20 kg each and were visually graded by the local graders so that the ripeness of the fruits would be known prior to analyzing the images. Two categories of ripeness, i.e. the ripe and the unripe categories, are considered in this work. The image acquisition phase was done within a day after the fruits were delivered to the laboratory so as not to degrade the color of the fruits.

A. Image Acquisition

Two FFB images were acquired simultaneously using the left and the right Microsoft Lifecam NX-600 webcams in the illumination chamber. Image acquisition was facilitated by the Image Acquisition Toolbox and the images were formatted in JPEG. Figure 4(a) shows a sample of the acquired FFB image.

![Image Acquisition Toolbox](image1)

threshold slider bar

ripeness indexes and final result

Fig. 3. Graphical User Interface for FFB grading.

Extraction of FFB Properties

The objects identified in the binary image have to be labeled and the properties of each object have to be examined individually. The pixels labeled ‘0’ make up the background, the pixels labeled ‘1’ make up the first object, the pixels labeled ‘2’ make up the second object, and so on. As such, the number of pixels varies for every image taken. An example of an object numbered ‘15’ (which happens to be the object with the largest area property) taken with pixel information is shown in Figure 5(b). The (xy) coordinates, the index value (i.e. label number) and the RGB color information for that pixel are shown. After labeling all the objects in the binary image, object with the largest area property has to be identified. The largest object number

B. Image Pre-Processing

The objective of the image pre-processing is to eliminate the background noises from the FFB image in order to increase the accuracy of FFB grading. This was accomplished by creating a mask of the original image and performing a product of the mask with the original image. The steps required in creating the mask include image binarization, morphological processing and FFB properties extraction.

Image Binarization

The color FFB image has to be converted into binary so that further enhancement of the image can be done using morphological operations. The binarization process converts the RGB image to gray color and to binary before the inverse of the binary is obtained. These images are illustrated in Figures 4(c) and 4(d). The inverse binary image will invert the object represented in white (binary value 1) and the background indicated by black (binary value 0) for further processing. However, there are still black holes or gaps within the interior of the white area of the FFB image. These holes have to be eliminated through the morphological operations.

Morphological Processing

Morphological operators enable operations such as edge detection, contrast enhancement, noise removal, image segmentation into regions, and skeletonization. As shown in the binary gradient image in Figure 4(c), there are holes or gaps in the interior of the FFB image. After the morphological processing, the interior of the FFB image was filled as shown in Figure 5(a). No holes or gaps are seen within the object and it is completely white in color.

![Image Pre-Processing](image2)

Fig. 5. (a) Image after filling and (b) pixel information.

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indicated the FFB object itself and thus a mask can be created. The final step requires the extraction of the color FFB image from the original image by applying the image mask operation onto the original color FFB image.

These processes are illustrated in Figure 6. In Figure 6(a), the original color FFB image is shown. Figure 6(b) demonstrates the largest identified object using the area property and Figure 6(c) shows the image mask. Finally, the FFB object was extracted from the background of the original image and the result can be seen in Figure 6(d). The image shows a very clean picture of the object with the background noises removed. Thus, shadows and other small and unrelated artifacts are eliminated from the object of study.

![Fig. 6. Extraction of FFB properties: (a) original image; (b) largest object identified; (c) mask image; (d) extracted object.](image)

C. Image Segmentation

As the palm fruit images are usually fused with dirt and branches, it is quite difficult to determine the ripeness of the fruits using the average color Digital Number (DN) values in RGB color space. Although there are different color spaces, the most frequently used color space for the measurement of color in food is the L*a*b color space due to the uniform distribution of colors and its similarity to the human perception of color [10]. In the L*a*b space, the color perception is uniform which means that the Euclidean distance between two colors corresponds approximately to the color difference perceived by the human eye [11]. In this phase, the aim is to segment the FFB colors in an automated fashion using the L*a*b Color Space and K-means clustering so that the image can be broken up into several segments and the DN value can be calculated for each segment. Besides that, the comparison of the red (R), green (G) or blue (B) spectrum has to be done in order to obtain further details of the images taken.

These steps are summarized as follows: (i) crop the pre-processed image, (ii) convert the pre-processed image from the RGB color space to the L*a*b* color space, and (iii) segment the FFB image in the L*a*b* color space using the K-means clustering algorithm.

Image Cropping

After the image pre-processing phase, the extracted FFB image was cropped to the object’s bounding box size. The aim is to reduce the image size before sending for processing in order to increase the computational speed. The cropped images are illustrated in Figure 7.

![Fig. 7. Image cropping: (a) Cropped, pre-processed image; (b) cropped mask image.](image)

Conversion from RGB to L*a*b* Color Space

Even though RGB color space is the most popular model used for representing a color image, it is a device-dependent model. Images in RGB space captures the intensity of light in the red (R), green (G) or blue (B) spectrum. It, however, does not represent color according to human perception. The L*a*b* color space (also known as CIELAB or CIE L*a*b*) is derived from the CIE XYZ tristimulus values. It consists of: (i) luminosity layer ‘L*’ which comprises the lightness component, (ii) chromaticity-layer ‘a*’ indicating where color falls along the red-green axis and (iii) chromaticity-layer ‘b*’ indicating where the color falls along the blue-yellow axis. An example of the conversion from RGB image to L*a*b image is as shown in Figure 8.

![Fig. 8. Convert image from (a) RGB color space to (b) L*a*b* color space.](image)

Segmentation of FFB image Using K-Means Clustering

After the conversion of image into the L*a*b* space, it is ready for color segmentation. As the color information is within the two chromatic components in the ‘a*’ and ‘b*’ layers, the second and third layers of the cropped image have to be extracted and used for segmentation by means of K-means clustering algorithm. K-means clustering can best be described as a partitioning method [12]. That is, the function K-means partitions the observations of the images into K mutually
exclusive clusters, and returns a vector of indices indicating to which of the k clusters it has assigned for each observation.

An experiment was conducted to choose the number of clusters suitable in this research. After segmenting the FFB image into three to five clusters, cluster analysis showed that using three clusters were most appropriate. As such, the FFB image was segmented clustered into three clusters. The algorithm finds a partition in which an object (i.e. FFB image’s pixel) within each cluster is as close to each other as possible, and as far from objects in other clusters as possible. The distances between objects were measured using the Euclidean distance metric. The algorithm returned three mutually exclusive clusters and the centroids of these three clusters are as shown in Figure 9.

Fig. 9. Segmentation of the FFB image into three clusters. The centroid for each cluster is the point to which the sum of distances from all objects (i.e. pixels) in that cluster is minimized. The clustering was repeated five times to avoid local minima issue. Finally, the pixels data was labeled according to each cluster and reshaped to the same size as the cropped, preprocessed image. This is illustrated in Figure 10.

Fig. 10. Image Labeled by Cluster Index.

Using the labeled images obtained from the previous operation, three new images for each segment (cluster) have to be created. An example of the images for each segment derived from the cropped, preprocessed image is shown in Figure 11. The respective RGB values are indicated for these images.

D. Calculation of Average Digital Numbers (DN)

For comparison purposes, the average digital numbers of the unsegmented and segmented FFB images are calculated in this section. The calculation process would take the image mask and the FFB image as the input to calculate the average RGB color intensities or digital number. Each layer of RGB has to be totaled-up, and divided by the total numbers of pixels in the image mask to obtain the average DN value. Table I shows the range of RGB color intensity values obtained for 16 unsegmented FFB (1 repeated) samples. The results are plotted in Figure 12. The RGB values of samples 1 to 20 indicate the ripe FFB while the RGB values of samples 21 to 34 indicate the unripe FFB. For ripe bunches, the fruits appear more reddish which gives a higher intensity of red color as compared to the green and blue colors. The maximum intensity of red, green and blue colors is 112.12, 83.98 and 57.09 respectively. However, it is still difficult to differentiate the average RGB values for the ripe and unripe FFB. There is no clear-cut distinction of the RGB values for the ripe and unripe FFB. For the segmented FFB image, the color values for each sample from the three clusters are obtained. The differences in the color values are much noticeable and apparent after the segmentation process. The color values were then computed to get the values for R/G and R/B. To emphasize the difference between ripe and unripe classification, the maximum values of these ratio were then used to calculate the R/G* R/B. These values are summarized in Table II and the details are plotted as in Figure 13. Similarly, the color values of samples 1 to 20 indicate the ripe FFB and samples 21 to 34 indicate the unripe FFB. After the segmentation process and the comparison of colors in L*a*b* space, the classification appears to be simpler.
TABLE I
IDENTIFICATION OF THE RANGE OF AVERAGE RGB VALUES

<table>
<thead>
<tr>
<th>Ripeness</th>
<th>Average R Value</th>
<th>Average G Value</th>
<th>Average B Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ripe</td>
<td>72.8 &lt; R &lt; 111.2</td>
<td>52.3 &lt; G &lt; 71.2</td>
<td>36.11 &lt; B &lt; 48.72</td>
</tr>
<tr>
<td>Unripe</td>
<td>53.81 &lt; R &lt; 101.76</td>
<td>48.68 &lt; G &lt; 83.98</td>
<td>38.76 &lt; B &lt; 7.09</td>
</tr>
</tbody>
</table>

Fig. 12. Average RGB values for ripe and unripe oil palm FFB.

TABLE II
RANGE OF AVERAGE RGB VALUES AFTER SEGMENTATION

<table>
<thead>
<tr>
<th>Ripeness</th>
<th>Average R Value</th>
<th>Average G Value</th>
<th>Average B Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ripe</td>
<td>1.35 &lt; R &lt; 2.11</td>
<td>2.32 &lt; G &lt; 3.57</td>
<td>3.12 &lt; B &lt; 7.28</td>
</tr>
<tr>
<td>Unripe</td>
<td>1.19 &lt; R &lt; 1.39</td>
<td>1.84 &lt; G &lt; 2.37</td>
<td>2.20 &lt; B &lt; 3.15</td>
</tr>
</tbody>
</table>

Fig. 13. Values for 3 clusters after segmentation for ripe and unripe FFB.

E. Classification of Ripeness
From Figure 13, it can be concluded that the ratio values of the Digital Number of the segmented images can be used to differentiate the ripe FFB from the unripe ones. There is a distinct difference between the two categories and the threshold value for this sampling batch is approximately 3.5 as shown in Figure 14. FFB samples having greater than ripeness index number of 3.5 will be categorized as ripe and samples with less than 3.5 will be unripe.

VI. CONCLUSION
A novel methodology for photogrammetric grading of oil palm fresh fruit bunches has been formulated and integrated into the software and hardware systems. The developed methodology and systems were tested on a small sampling size of FFB taken from a local oil palm plantation but sufficient enough to prove successfully the working principle behind the photogrammetric grading methodology. The vision system was capable of capturing good quality images, extracting the RGB intensities from the images and correlating them with the ripeness of the fruit bunches accurately. Integrating all systems together has developed an agricultural grading system that is able to sort the FFB according to the different ripeness categories autonomously.

Although past research work has been done employing vision system to analyze fruit images using programming language such as C++, the use of MATLAB and its image processing toolboxes have made the acquiring of the images in this new technical computing environment much easier for analysis and visualization. This early stage of work has proven the feasibility to replace the manual grading tasks and thus increased the efficiency of quality harvesting and grading productivity in palm oil mills. This novel methodology is applicable to testing other oil palm species and ripeness categories, and can further extend to carry out on any other harvesting and agricultural products that use color images as the form of correlation to their ripeness.

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