Inspection of Mango with Machine Vision Technique

Nursabillilah Mohd. Ali[1], Nur Rafiqah Abdul Razif[1], Mohd Safirin Karis[1], Oh Kok Ken[1], Wira Hidayat Mohd Saad[2], Amar Faiz Zainal Abidin[3]
[1]*Fakulti Kejuruteraan Elektrik, Universiti Teknikal Malaysia Melaka, Malaysia.*
[2]*Fakulti Kejuruteraan Elektronik & Kejuruteraan Komputer, Universiti Teknikal Malaysia Melaka, Malaysia.*
[3]*Fakulti Kejuruteraan Elektrik, Universiti Teknologi Mara, Pasir Gudang, Johor, Malaysia.*
nursabillilah@utem.edu.my

***Abstract*—The entire project deals with development of colour detection and shape identification algorithm to detect and count the total number of mango on its tree with a camera and related MATLAB toolboxes. The conventional method in harvesting mango has its limitation which leads to the degradation of mango's quality. Besides, the rate of production and the structure of the tree will be affected too. Nonetheless, the usage of algorithm of image processing could be employed for a better and precise mango's farming. It differentiates the number of ripe and unripe mango based on the images captured and thus forecast the growth rate of the mango tree. Improving the rate of production as well as quality of the harvested mango are the main advantages. In short, it provides a quick review for the mango grower, agricultural developer and investor.**

***Index Terms*—Colour Detection; Growth Rate; Mango's Quality; Shape Detection.**

I. INTRODUCTION

According to Department of Agriculture [1], in year 2013, 5,270.4 hectares of land is mango farm with a harvested area of 3259.8 hectares. The total value of production costs around RM 61,958,000. Sustainable agricultural concept requires an adequate and optimum level of modern technology to yield a good quality crop. There were numerous obstacles encounter by mango's grower to nurture a standardized product. One of the issues troubling agriculture's entrepreneur is heavy loss due to damaged and spoilt mangoes [2]. The common reasons were inadequate knowledge in technical and management wise. For instance, manual plucking and vibrator's assistance method to harvest goods is a leading factor. Both ways of harvesting without proper judgment made on the crops would surely dampen the production rate and generated revenue. Shortage in skilled labour will result in unripe fruit to be pluck off or over-ripened mango becomes useless. In addition, challenging or unpredictable environmental changes would also affect the yields. Mango tree is not sustainable to windy condition. For example, mango will be blown and sway in the wind. Most mangoes will turn bad after falling into bare ground without any protective wrapper.

Machine vision technique based on shape analysis will be applied to tackle the issues arises [3]. Nevertheless, a compatible color detection algorithm will be complement for the former method to further improve the system's efficiency. Both of the methods used will quantify the related parameters in the project. A better perspective of monitoring system using aerial vehicle is expected to further enhance the result. Relevant experiments will be conducted throughout the project to offer a judgment that applied machine vision technique is capable to replace human workforce. The allocated device will scan the ripeness of the mango and provide logical justification.

The development and application of image analysis and computer vision in quality evaluation of products in the agricultural and food processing field suggested by [4]. Grading of fruit via computer vision also is an automated, non-destructive and cost-effective method. The difference features in terms of flabbiness, colour and size would mark the significant role in visual perception. In comparison, quality assessment is quite subjective for human inspectors especially on smell, texture and flavour. Besides, it would be time-consuming and labour-extensive.

The experiment started with reading an input image, which is the image of a mango. Next, the techniques partition pixels with respect to the predefined threshold value. The adaptive threshold calculates the difference in threshold for each pixel within a neighbourhood. Meanwhile, in region based, it segments the images by identifying coherent, homogenous regions of the similar criterion. These could be divided into two groups which are merging and splitting. Merging is a bottom-up method which continually combines sub-section to form a larger one. Nonetheless, splitting is the top-down version that divides image into smaller region. Next, segmentation of images is performed by interpreting grey level discontinuities using edge detection operator. These edges would be combined into contours and used as region borders. Finally, classification of shape, intensity, size and flabbiness is conducted on feature extracted from previous process. All the sampled mangoes is characterized and separated into three categories.

In [5], sorting of mangoes into different groups is necessary for transporting them into different locations iterated by [5]. In contrast to [6], the experimental setup is done on a conveyor belt in automated system. The main purpose of splitting mangoes into batches according to its maturity and ripeness is to prevent wastage of production. Hence, the system aims to sort the mangoes according to the days left before it is rotten. The experiment started with pre-processing of image which is image acquisition and enhancement. Since there were possibilities of motion blur artifact and noises from input image, denoising is conducted by pseudo median filter. The reason of having pseudomedian filter is due to its computationally simpler and possesses properties of median filter. Next, images were converted into binary images and its boundary could be traced by using graph contour. It allows the maximum axial length to be calculated which is correlated in [5]. The change in colour in the apex region is more vivid than other regions such as equator and stalk during the ripening process. The fact is that it provides a clear indication where the Red and Green values found to be decreasing from apex region to stalk region. Moreover, the obvious slope was also resembled the function of maturity. Several features of were initially chosen based on observation. These features have shown correlation with the maturity of the mangoes. Finally, a GUI is developed to label the tag number and the expiry date on the respective mangoes. All of the software and algorithm development is directly linked to Lab VIEW and its Image Processing Toolbox with a Charge Coupled Device (CCD). As the number of features evaluated increases, the average sensitivity also increases. In order to conclude research paper [5], the experimental result was found to provide average classification accuracy up to 96 %.

Similar to [5], an experiment conducted by [6] which would feasibly determine the physical properties of mango using machine vision. Image processing techniques which involved detection, segmentation and analysis over a mango's physical properties discussed in [6]. For example, physical properties related to size, shape, surface area and colour from images. Machine vision technology has become a vital source in agricultural industry as the harvester's manual sorting ability declines drastically. However, the method also had been applied in various applications such as traffic sign [7-10].

Firstly, the experiment started with image acquisition part. It utilizes a digital camera to capture the top view image of the mango. With the image resolution of three million pixels, the captured image is stored in RGB format. High resolution is required to measure the size in an accurate way. Calibration is need for colour and size parameters by having black and white chessboard grid (5mm x 5mm) as background image. The mango's surface hue model is constructed using hue values from those pixels. With a chromaticity similarity, the original input image is used to segment the mango region. Nonetheless, erroneous is still predominant within the segmented image because of effect and blurry input images. A spline curvature fitting is done to overcome the problem. After obtaining a better and clearer segmented image, physical properties analysis is performed over mango's projected area, length, width, colour and surface area. The discussion will mainly focus on the length and width calculation and the determination of colour. Length if the distance between the pole and tip of the mango as major axis. Meanwhile, width is the maximum distance from a boundary pixel to another one as minor axis which lies perpendicularly with major axis. Both the axes could be determined by computing the angle of mango boundary pixels. The tip of the mango is estimated by finding a boundary pixel which has global minimum angle. In contrast, the pole is estimated by finding a boundary pixel which has local minimum angle and it is supposed to locate about half of the mango's perimeter from the tip. Major axis and length is determined. The image is then rotated in order to determine the width. As mentioned earlier, the minor axis lies perpendicularly to major axis; it has the maximum distance between two boundary pixels. Thus, the width could be determined. As a result, sixty top-view mangoes has been sampled, each region in colour analysis is recorded corresponding to their average RGB values. It is found that the colour spatial distribution is not directly related to its size. In short, a multiple view mango images should be done to estimate the 3-Dimensional volumetric of the mango by using voxel crafting techniques suggested in [6].

II. METHODOLOGY

There were two major experiments done at different places within the project namely indoor and outdoor. Shape analysis is made over the pre-processed images for further classification.

A. Indoor Experimentation

Samples of mango are plucked and cleaned before assembling onto a cardboard. The sensor, Logitech Webcam model C310 is used to inspect the quality of the sampled mangoes. After pre-processed by Image Processing Toolbox in MATLAB, the extracted features from the blob image were then tabulated into tables. Thus, the correlation coefficient could be calculated from these data in order to determine the closeness between the measured value and the actual value.

Figure 1: Sampled Mango

Based on the extracted features too, important parameters such as perimeter and area of each blob could be analyzed. Form factor and eccentricity would be the determining criterion for the next sampling analysis with the threshold values of those parameters.

III. RESULTS AND DISCUSSION

A. Correlation Coefficient Analysis

It is noticed that the actual minor axis length differ much from the measured minor axis length. The same condition happened to major axis length as well. The difference is defined by camera's perception and human's measuring perception. For instance, what does the camera captured and labeled is express in number of pixels. In contrast, human uses a definitive terminology unit length corresponded with meter (S.I. unit).

In order to analyze the obtained data, we utilize the concept of correlation in statistical theory and analysis. The analysis of correlation could determine the strength of relationship between two variables. In this case, these two variables were actual minor axis length and measured minor axis length. The nearer the correlation coefficient to one indicates the stronger the relationship between these variables.

In mathematical form, the calculation for correlation coefficient of minor axis length could be done as follow:

$$SS_{xy} = \sum xy - \frac{(\sum x)(\sum y)}{n} \quad (1)$$

$$SS_{xx} = \sum x^2 - \frac{(\sum x)^2}{n} \quad (2)$$

$$SS_{yy} = \sum y^2 - \frac{(\sum y)^2}{n} \quad (3)$$

$$r = \frac{SS_{xy}}{\sqrt{SS_{xx}SS_{yy}}} \quad (4)$$

Where:

SS_{xx} is the variance for data set x
SS_{xy} is the variance for data set y
SS_{xy} is the variance for data set xy
x is the actual minor axis length
y is the measured minor axis length
n is the number of samples
r is the correlation coefficient of the variables x and y

Based on the calculation made by comparison between actual and measured samples, it indicates that the minor axis length of tested sample has close relationship of 87.35 %. Meanwhile, major axis length has the similarity of 95.56 %. The proper method must be chosen wisely to produce and accurate reliable and acceptable result [11]. The experiment deducts the similarity of actual object and the image captured is relatively high. Thus, data and information retrieved could be used for further analysis function.

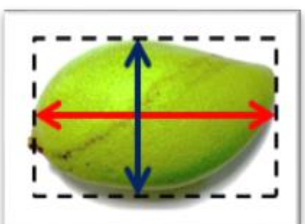

Figure 2: Major and minor axes of mango

In Figure 2, the red line marks the length of major axis and blue line indicates the length of minor axis.

B. Eccentricity

The main purpose of conducting this test is to distinguish the mango's tree leaf and the mango itself. Both of the objects have close similarities in terms of colour and size. However, these objects also exhibit differences in eccentricity.

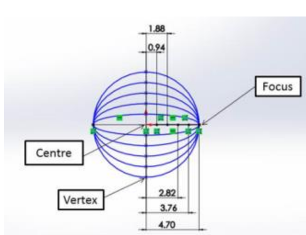

Figure 3: Illustration shows the position of centre, focus and vertex in ellipse and circle.

$$Eccentricity, e = \frac{\text{Distance from centre of a focus}}{\text{Distance from focus to a vertex}} \quad (5)$$

With the usage of ten samples of mangoes and ten samples of mango tree's leaves, the images captured would be analyzed by its corresponding eccentricities. In the scattered graph, it is clearly seen that the mango's eccentricity varies from 0.18 to 0.64. In contrast to mango tree's leaf, the eccentricity varies from 0.6190 to 0.9640. The average values of each parameter are 0.4746 and 0.8945.

$$Form\ factor = \frac{4 \times \pi \times Area}{(Perimeter)^2} \quad (6)$$

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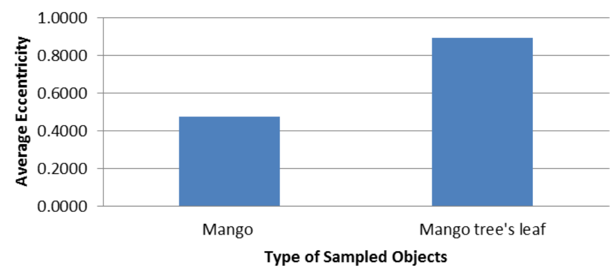

Figure 4: Average Eccentricity against Type of Sampled Objects

In graph, it is clearly seen that average eccentricity of mango tree's leaf is higher than average eccentricity of mango.

C. Form Factor

In general, form factor in morphological definition is given by the following formula:

$$Form\ factor = \frac{4 \times \pi \times Area}{(Perimeter)^2} \quad (7)$$

The graph plotted from the tabulated result clearly indicates that most of the mangoes have almost constant value of form factor, which is near to one. In contrast, most of the mango tree's leaves have the value of form factor less than one. The average value of mango is 1.1159 and mango tree's leaf is 0.7973.

Based on the Figure 5, the average form factor of mango is generally higher than mango tree's leaf.

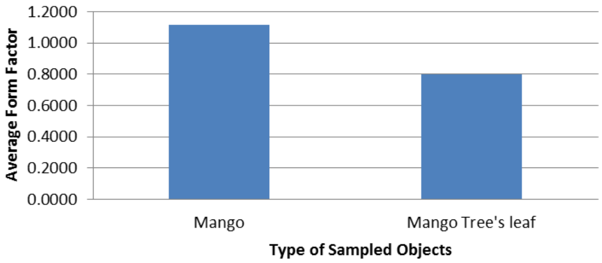

Figure 5: Average Form Factor against Sampled Objects

D. Training Classifier

Generally, the system would classify the mango and mango tree's leaf based on its eccentricity and form factor. Confusion Table 1 shows the result of 825 samples undergone experimentation.

Table 1
Confusion Table

Condition	Positive	Negative
TRUE	291	459
FALSE	29	46

Based on the confusion table, number of true positive object is the exact number of mango is classified correctly by the system. Meanwhile, number true negative object is the exact number of object other than mango that has been classified correctly by the system. False positive is the number of case error arises where the system detects any object other than mango as a mango. False negative is the number of object where system failed to classify an exact mango as mango.

In indoor test, the light intensity does not vary much and hence the obtained result is rather consistent. The captured image of mango tree's leaf has approximately 87.35 % similarity with the actual one. In addition, image of mango recorded a 95.56 % similarity with the actual one. As a result, the experiment has put forward to conduct the shape analysis of the image.

The parameters involved were solely form factor and eccentricity. With the average threshold values, next batch of images is underwent the second test. Samples of mangoes and mango tree's leaves were chosen and placed randomly within the targeted background. After confusion table is tabulated, it was found that there were 291 true positive categories and 459 true negative categories within 826 input samples. Nonetheless, the false positive and false negative contributed less than 10 % of the samples which are 29 and 46. The accuracy of the system is approximately 90.92 % in mango's identification with an erroneous rate of 9.0 %.

IV. CONCLUSION

The merging of machine vision technology into agricultural sector has resulted in improvement of harvested crop's quality. One of the most obvious advantages of conducting technical research over the sampled object is capable to understand its feature properly before making comparison with upcoming experiment. With the usage of MATLAB, the Image Processing Toolbox assists in the feature extraction and classification wise. The result indicates the potential usage of this monitoring tool in object (mango) detection from a given static image. Quality of result is much dependent on the surrounding tree leaves and intensity of light. Once the optimum condition is traced, the experimentation must be done continuously. Hence, user would eliminate the some manual observation work and the rate of production can be forecast based on the ripeness of each mango. In this case ripeness of mango would be determined by its size and colour. The main advantage is to ensure the fruit could be harvest at the right time. Quality of the fruit is expected to maintain with high level as over-ripen or unripe fruit would not be harvest. Furthermore, formation of shadow is not uncommon if the light source is not pointed directly over the tested sample. The outdoor experiment is prone to inconsistent light source which is sunlight. Operational hours of the outdoor experiment must be determined appropriately corresponding to the source sunlight. The greater the number of samples used in first stage of feature extraction and segmentation would lead to higher performance of the system. For instance, the number of false positive value would be lessened and true positive value would increase. Thus, accuracy of the system is expected to rise after there is an increment of input samples. The greater the sample inputs for Training Classifier in Computer Vision System Toolbox, the higher the accuracy of the system too.

Table 2
Measuring Factors

Measuring Factors	Percentage (%)
Accuracy	90.91
Precision	90.94
Misclassification Rate	9.09
True Positive Rate	86.09
False Positive Rate	5.94
True Negative Rate	90.71
False Negative Rate	14.69
Prevalence	40.97

Figure 6: Graph of Confusion Matrix

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