# Papaya Size Grading using Centroidal Profile Analysis of Digital Image

SLAMET RIYADI, HAFIZAH HUSAIN, AINI HUSSAIN, MOHD. MARZUKI MUSTAFA
Vision and Robotics Research Group (VIROB)
Department of Electrical, Electronics & System Engineering
Faculty of Engineering, Universiti Kebangsaan Malaysia
Bangi 43600 Selangor
MALAYSIA

*Abstract:* - For export purpose, papayas are classified into four size grades and packaged accordingly. Currently, the classification process requires the papayas to be weighed individually and such practice is time consuming and labor-intensive. The objective of this paper is to develop an automatic papaya size grading system using centroidal profile analysis of its digital image. The methodology involves data acquisition task to obtain the digital image of papaya and its actual weight. In the pre-processing task, the RGB image is converted to grayscale and the exact image of a papaya is distinguished from background using the automatic thresholding technique based on Otsu method. Then, the centroidal profile consists of mean of diameter, sum of diameter and maximum of diameter was extracted from the papaya object. The features fusion was perform to extract further their uniqueness, i.e. the mean-sum of diameter, mean-max of diameter and sum-max of diameter. These features sets are then fed separately to the neural network for the size grade classification. The proposed technique has shown satisfactory result with classification accuracy of more than 95%.

*Key-Words:* - Papaya fruit size grading, centroidal profile, digital image analysis, neural network

## 1 Introduction

Exotica, a Malaysian papaya cultivar, is one of the major fruit export commodity of Malaysia. To maintain quality, their main task is to ensure that only high graded papayas are considered for export. When the papayas are packaged, it is important that all of the items within a package are approximately uniform in size. Nowadays, inspection and classification task are made manually, which is subjective and varies among different expert or along the day. This manual procedure is time consuming, labor-intensive and inefficient due to huge production volume. Furthermore, it can cause surface damage to the papaya yield and in addition, inefficiency in handling will result in low productivity.

Machine vision system has been used extensively in the food and agricultural industry due to quality inspection and grading [13]. Heinemann et al in [10] has developed an automated machine vision for grading of potatoes that are capable of classifying moving and stationary potatoes with 88% and 97% accuracy respectively. Another similar work was reported on apple classification with accuracy of 89.2% [1]. Centroidal profile extracted from digital image such as diameter of object has been used for produce inspection. In [2], the author estimated the size of irregular fruit by comparing the measurements of length, width and perimeter, and in [5], the diameter is used to evaluate the fruit size.

This paper will discuss at length the development of an algorithm based on centroidal profile analysis of papaya image for size grade classification. The papaya size is classified based on the grading system set by Federal Agricultural Marketing Authority of Malaysia. Table 1 enlists the grading regulation for the exotica papaya for export [3].

Table 1. Size grading of exotica papaya

| Size Grade | Weight (grams) |
|---|---|
| XL | > 850 |
| L | 650 – 850 |
| M | 450 – 640 |
| S | 250 – 450 |

## 2 Methodology

The methodology of this research involves several tasks such as data acquisition task, image pre-processing, centroidal profile extraction and classification task using neural network as summarized in Fig. 1 and explained in detail in this section.

DATA ACQUISITION:
- Capturing papaya images
- Measuring papaya weight using digital weighing

↓

PRE-PROCESSING:
- Image resizing
- Converting RGB to grayscale image
- Segmentation using automatic tresholding (Otsu)
- Removing noise using morphological techniques

↓

IMAGE PROCESSING:
Extracting the centroidal profile: mean, sum & maximum of diameter

↓

CLASSIFICATON into 4 grades : S, M, L or XL
Using MLP Neural Network

Fig. 1. Methodology of the research

## 2.1 Data Acquisition

Papaya samples in varying size were collected from an orchard in Selangor, Malaysia. These fruits would be carried out as soon as possible after harvest and inspected to determine their weight digitally. The images of papaya were captured at random orientation from perpendicular views using the Olympus Camedia C-5050 digital camera. Images were taken with camera flash in standard room lighting. The camera was setup in a fixed position to get an appropriate silhouette of object as shown in Fig. 2. A bright yellow paper was used as background surface to facilitate and simplify the segmentation task.

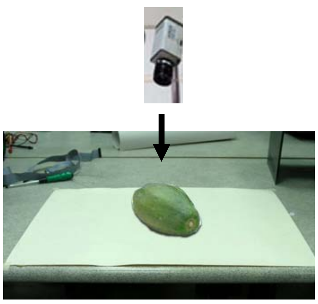



Fig. 2. Configuration of capturing images of papaya

## 2.2 Pre-processing

The pre-processing task involves some procedures to prepare the image to be ready for image processing. Firstly, images were normalized to produce uniformity in term of image size and to reduce the processing time. The original image with 640x480 dimensions as shown in Fig. 3 (a) was resized to be one third of its normal size.

An appropriate silhouette should be determined to get an accurate processing result. For this task, RGB image was converted to grayscale level using this formula,

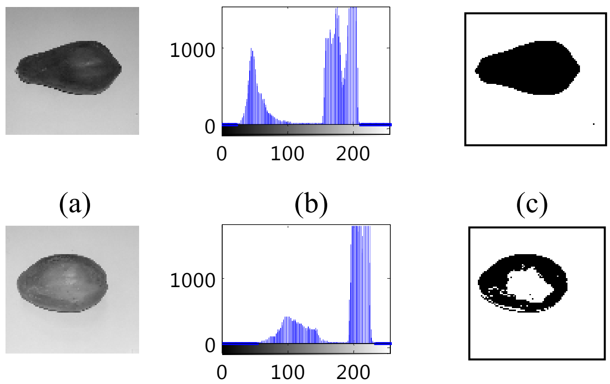
$$\text{Gray level} = 0.3\ R + 0.59\ G + 0.11\ B \qquad (1)$$

where R, G and B are the primary values of its red, green and blue respectively.

(a) (b)

Fig. 3. (a). Original RGB image; (b). Grayscale level

The result of grayscale transformation as shown in Fig. 3 (b) is then attempted to be segmented from the background. Image thresholding classifies grayscale pixels into two categories resulting in binary image. Since the intensity values are different in each image, global threshold value (*T*) throughout the image could not perform an accurate segmentation (Fig. 4).




(a) (b) (c)

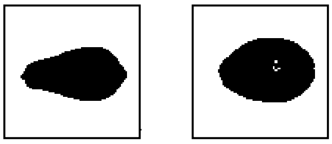
(d) (e) (f)

Fig. 4. (a) and (d) Grayscale image; (b) and (e) alues; (c) and (f) Segmentation result using global thresholding (*T*=120)

Otsu method for automatic threshold selection from a histogram of image was successfully applied at various segmentation cases. This method is based on selecting the lowest point between two classes of the histogram using consideration of between-class variance which is defined in [4] as,

$$\sigma_b^2(i) = \omega_0(i)\omega_1(i)[\mu_1(i) - \mu_0(i)]^2 \qquad (2)$$

where $\omega_0$, $\omega_1$, $\mu_0$ and $\mu_1$ are the frequencies and mean values of two classes respectively. All possible thresholds $T=i$ are evaluated and the one that maximizes $\sigma_b^2(i)$ is chosen as the optimal threshold level $T_{\text{opt}}$ (Fig. 5).



(a) (b)

Fig. 5. Segmentation result of image in Fig. 4(a) and (d) using automatic thresholding; (a) *T*opt=119; (b). *T*opt=160

The room lighting or camera flash acts as noise and can affect the image quality as shown in Fig. 6(a). Using region filling technique that involves morphological operations such as dilation, complement and intersections were implemented to remove the noise. As shown in Fig. 6(b), the black dot ('0') inside the white object represents the noise. Beginning with a point *p* of the noise, the objective is to fill the entire region of noise with '1' using the following procedure as described in [10],

$$X_k = (X_{k-1} \oplus B) \cap A^C \qquad k=1, 2, 3, \ldots \qquad (3)$$

where $X_0 = p$ and

$B$ : represents the symmetric structuring element

$A$ : represents the original binary image.

The algorithm is terminated if $X_k = X_{k-1}$.

(a) (b) (c)

Fig. 6. Noise removal using region filling technique (a). Original image; (b). Binarized image with noise (c). Noise-free image

## 2.3 Centroidal Profile Extraction

The centroidal profile was extracted from the binarized image. Firstly, the center of mass was determined. The easiest way to estimate the centroid is as the average of each point of the object [6]. Supposed that $I$ is a binary image containing only the object of interest, where $I(x,y)=1$ for object pixels and $I(x,y)=0$ for background, then the centroid $C(x_C,y_C)$ can be calculated using

$$C(x_C, y_C) = \frac{1}{N}\sum_{i=1}^{N} I(x_i, y_i) \qquad (4)$$

where $N$ is the total number of object pixels and $I(x_i,y_i)$ represents the $i$-th pixel of object.

Next, the Euclidean distance can be calculated by measuring the distance between centroid and the boundary object at the selected boundary points $B(x_j,y_j)$ using formula in [8],

$$E = \sqrt{(x_j - x_C)^2 + (y_j - y_C)^2} \qquad (5)$$

$j = 1, 2, 3, \ldots, n$

where $n$ is the total of boundary points which can be determined by choosing the suitable degree interval α (Fig. 7). Then the diameter of object can be computed as the sum of two corresponding distances crossing the centroid.

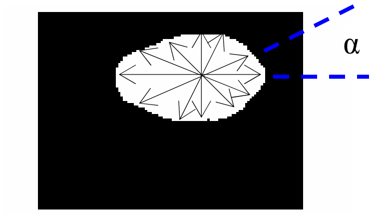


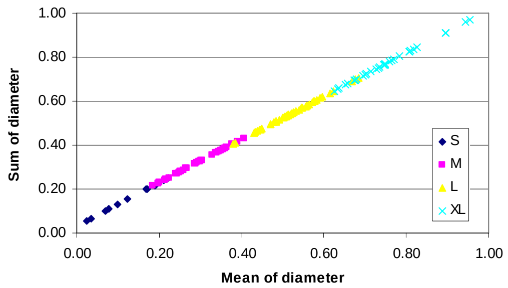

Fig. 7. Centroidal profile of a papaya image

A set of centroidal profile of an image consists of mean, sum and maximum of diameter are then extracted. In this research, we choose several values of α (that is π/9, π/45 and π/90) to obtain several sets of the centroidal profile of an image. By using smaller α, more papaya diameters can be obtained from a single image. Next, we perform feature fusion to further enhance the uniqueness of the extracted features. As a result, three pairs of fused feature vector sets have been produced. The fused pairs are the mean-sum of diameter, mean-max of diameter and sum-max of diameter. Fig. 8 (a), (b) and (c) depict the scatter plots of the fused feature pairs of mean-sum of diameter, mean-max of diameter and sum-max of diameter, respectively.

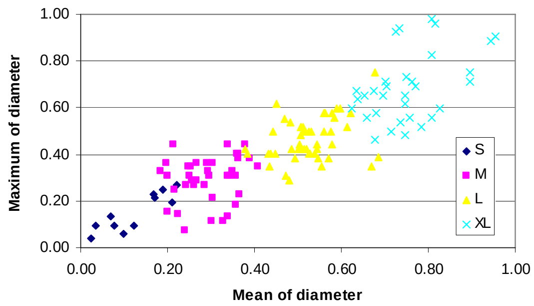
## 2.4 Neural Network Classifier

In the neural network classifier, its capability to learn and perform classification task largely depends on the information provided by the input data. Data gathered from the extraction process sometimes may be meaningless or irrelevant for the task [9]. In order to get the relevant information for learning task, the appropriate features should be selected.

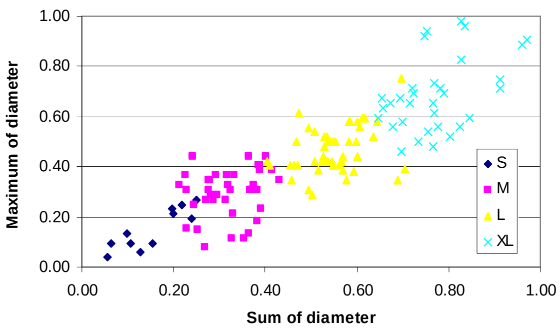
As shown in Fig 8, the fused pair of mean-sum of diameter exhibits linear behavior since each class is clustered separately while the other two pairs assume nonlinear characteristics. For this reason, the three selected fused feature sets extracted from the centroidal profile are then trained separately using the single-layer perceptron (SLP) and the multi-layer perceptron (MLP) artificial neural network model to classify the papaya accordingly. We use both SLP and MLP to study the efficiency of each model. For detail explanation of the neural model, readers are referred to [7][12]. A total of 40 images were used for training and another 130 images were used for testing. The target values were set up as '0', '0.33', '0.67' and '1' to represent the grade 'S', 'M', 'L' and 'XL' of papayas, respectively.




(a)




(b)




(c)

Fig. 8. Fused features pairs selected for the neural learning system

## 3 Result and Discussion

The results of papaya grading based on size using the SLP and MLP model with the selected fused feature sets are tabulated in Table 2 (a) and (b) respectively. The classification test on the fused features set of sum-mean of diameter using SLP and MLP model produce similar results. Therefore, using this fused pair as neural input, SLP model is preferred than MLP due to the simplicity of SLP. For fused pairs of the mean-max of diameter and the sum-max of diameter, the results show that the classification procedure using MLP model is better than SLP. This fact is reasonable since these fused pairs are non linear as shown in Fig 8 (b) and (c). Additionally, since the fused feature sets of mean-max and the sum-max are more unique and formed better clusters, they resulted in yielding better classification ability.

The effect of using different values of α is also studied and tabulated. The classification procedure using α = π/90 obtained the best result compared to α = π/9 and π/45. This could be due to more information being used resulting in better representation of the object.

Table 2 (a). SLP papaya size classification result

| Pair fused features | % classification accuracy with different values of α | | |
|---|---|---|---|
| | α = π/9 | α = π/45 | α = π/90 |
| Mean-Sum | 92.3 | 92.3 | 93.1 |
| Mean-Max | 91.5 | 93.1 | 93.1 |
| Sum-Max | 93.1 | 93.1 | 93.8 |

Table 2 (b). MLP papaya size classification result

| Pair fused features | % classification accuracy with different values of α | | |
|---|---|---|---|
| | α = π/9 | α = π/45 | α = π/90 |
| Mean-Sum | 90.0 | 92.3 | 93.1 |
| Mean-Max | 94.6 | 95.4 | 95.4 |
| Sum-Max | 94.6 | 94.6 | 94.6 |

The misclassifications are mainly caused by papayas having estimated size that falls in between the grade category (Fig. 8). Additionally, there are some papayas that do not comply with the assumption that the fruit densities are relatively constant. If the fruit densities were different, the weight will differ significantly although the silhouettes of the papayas have the same centroidal features.

## 4 Conclusion

This paper describes a papaya size grading technique using fused features from the centroidal profile analysis. The fused feature pairs are the mean-sum of diameter, mean-max of diameter and sum-max of diameter. Using the mean-sum fused pair as input, the SLP model is preferred due to its simplicity. MLP, on the hand, produces better classification if the fused feature pair of either the mean-max or sum-max of diameter was used. In short, the findings suggest that the derived fused feature sets can be used effectively to represent the image of papayas and be used as input for the size classification of papayas for the purpose of fruit grading. Further testing with larger database is required to validate the proposed method and the use of higher order feature fusion can be considered in the future to improve the performance.

## 5 Acknowledgment

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