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# Shape Characteristics Analysis for Papaya Size Classification

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***Abstract*—Prior to export, papaya are subjected to inspection for the purpose of quality control and grading. For size grading, the fruit is weighed manually hence the practice is tedious, time consuming and labor intensive. Therefore, this paper will discuss the development of a computer vision system for papaya size grading using shape characteristic analysis. The methodology involves data acquisition to collect the images and their weights. The RGB images were converted to binary images using automatic thresholding based on the Otsu method. Some morphological procedures were involved for image enhancement to distinguish the papaya object from the background. Then the shape characteristics consisting of area, mean diameter and perimeter were extracted from the papaya images. We classified according to combinations of the three features to study the uniqueness of the extracted features. Each combination was fed separately to a neural network for training and testing. The proposed technique showed the ability to perform papaya size classification with more than 94% accuracy in this research.**

***Index Terms*—Image processing, neural network, papaya fruit size grading, shape characteristic.**

## I. Introduction

THE Papaya fruit is one of the major export commodities of Malaysia. Prior to export, the fruit is subjected to inspection for the purpose of quality control and size grading. Size grading is important to obtain uniform size of all items within a package. Currently, the inspection and classification tasks are made manually, which is subjective and varies among different experts or throughout the day. This manual procedure is time consuming and labor-intensive. The advent of computer and machine vision technology offers great potential to automate the process.

Computer and machine vision has been used widely in the food and agricultural industry for quality inspection and grading [1]. Size is the first parameter identified with quality which can be estimated in different ways using image analysis. Aleixos et al has developed an automated machine vision system for size grading of citrus fruits using shape features such as maximum and minimum diameter [2]. Ying et al used the Fourier transform in combination with an artificial neural network to describe and identify Huanghua pear shape with 90% accuracy [3]. Blasco et al have successfully developed a machine vision system using the chain-code-based algorithm to calculate the area and the size measured as the length of the principal axis of inertia [4]. A set of geometrical parameters such as area, perimeter and diameter are used by Leemans et al to perform grading of apples [5]. However, up to now no such work relating to papaya grading has been reported. Therefore, this paper intends to discuss and present details relating to the development of a classification algorithm to grade papaya size based on shape characteristic analysis. The following grading scheme set by the Federal Agricultural Marketing Authority FAMA (2004) of Malaysia has been used and is shown in Table 1.

TABLE I
SIZE GRADING OF EXOTICA PAPAYA

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

## II. Methodology

The methodology for papaya grading involves several tasks such as weight and image data acquisition and collection, pre-processing for image enhancement and segmentation, image analysis for shape feature extraction and papaya classification according to size. Fig. 1 summarizes the procedures involved.

### *A. Data Acquisition*

Papaya samples of various sizes were collected for data acquisition. These fruits were collected as soon as possible after harvest and inspected to determine their weight digitally. The images of papaya were captured at random orientations 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.

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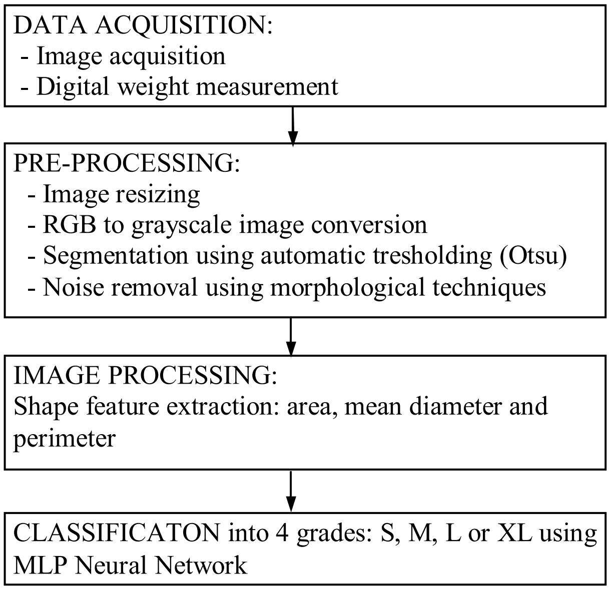



Fig. 1. Image acquisition, processing and analysis procedures

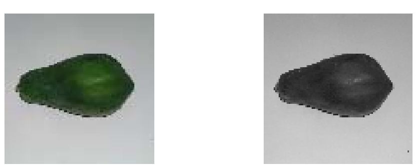
## B. Image Pre-processing

The pre-processing task involves some procedures to prepare the images to be ready for image processing. The images were initially normalized to produce uniformity in terms of image size and to reduce the processing time. The original image with dimensions of 640×480 pixels as shown in Fig. 3 (a) was resized to one third of its normal size.

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

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

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



(a) (b)

Fig. 2. (a). Original RGB image; (b). Grayscale image

The result of the grayscale transformation as shown in Fig. 2 (b) is then attempted to be segmented to identify the background. Image thresholding classifies grayscale pixels into two categories resulting in a binary image. Since the intensity values are different in each image, a global threshold value ($T$) throughout the images could not perform accurate segmentation (Fig. 3).

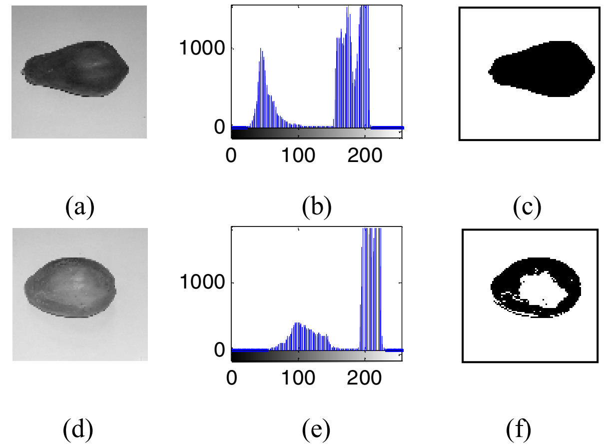
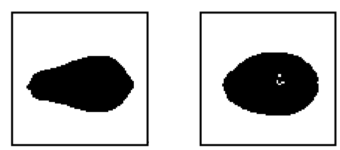



Fig. 3. (a) and (d) Grayscale image; (b) and (e) Histogram are shown different intensity values; (c) and (f) Segmentation result using global thresholding ($T$=120)

The Otsu method for automatic threshold selection from a histogram of image was successfully applied in various segmentation cases. This method is based on selecting the lowest point between two classes of the histogram by considering the between-class variance which is defined as [6],

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

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. 4).



(a) (b)

Fig. 4. Segmentation result of the images in Fig. 3 (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. 5 (a). A morphological algorithm based on dilation, complementation and intersection was implemented to remove the noise using region filling technique. As shown in Fig. 5 (b), the black dot ('0') inside the white object represents the noise. Beginning with a point $p$ in the noise, the objective is to fill the entire region of noise with '1's using the following procedure [7],

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

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. 5. Step-by-step results of the region filling technique to remove noise inside the object; (a) Original; (b) Binary image with noise (c) Noise free binary image

### C. Shape Characterization

General descriptors of shape such as area, mean diameter and perimeter, are important characteristics of shape in size classification [7]. Area is the most basic measure of object size in image. A simple approach in measuring the area is to count the number of pixels representing the object. Suppose that $I$ is noise free binary image as shown in Fig. 5 (c) where $I(x,y)=1$ for object pixels and $I(x,y)=0$ for background pixels, then the estimation of area is provided by the equation,

$$Area = \sum_{x,y} I(x,y) \tag{4}$$

This algorithm assumes that there is only one object in the binary images. It is quite simple to estimate the area using this technique. The important issue for accuracy is the precision of segmentation task which is discussed in the image pre-processing section.

The diameter of an object is a common feature for fruit grading based on size. First, the center of mass was determined. The easiest way to estimate the centroid is as the average of each point of the object [7] as described below

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

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

Next, the Euclidean distance $E$ can be calculated by measuring the distance between the centroid and the boundary of the object at the selected boundary points $B(x_j,y_j)$ using the following

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

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

where $n$ is total number of boundary points which can be determined by choosing the suitable degree interval α (Fig. 6). Then the diameter of object can be computed as the sum of two corresponding Euclidean distances crossing the centroid. In this research, $\alpha = \pi/9$ was chosen and the mean of nine Euclidean distances was chosen as the diameter.

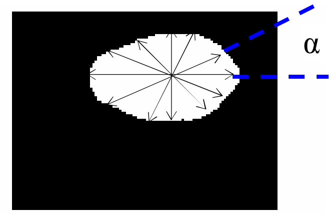



Fig. 6. Diameter of a papaya image

The perimeter is defined as the arc length of a spatially sampled curve. Using to the free noise binary image as shown in Fig. 5(c), the edge of the object is initially detected. In this research, edge detection was performed using the 4-connected neighborhood technique. This means that a pair of adjoining pixels is part of the same object only if they are both on and are connected along the horizontal or vertical direction as shown in Fig. 7 (a). Below is the procedure to detect the edge of an object using the 4-connected neighborhood technique to estimate the perimeter,

--------------------------------------------------------------------

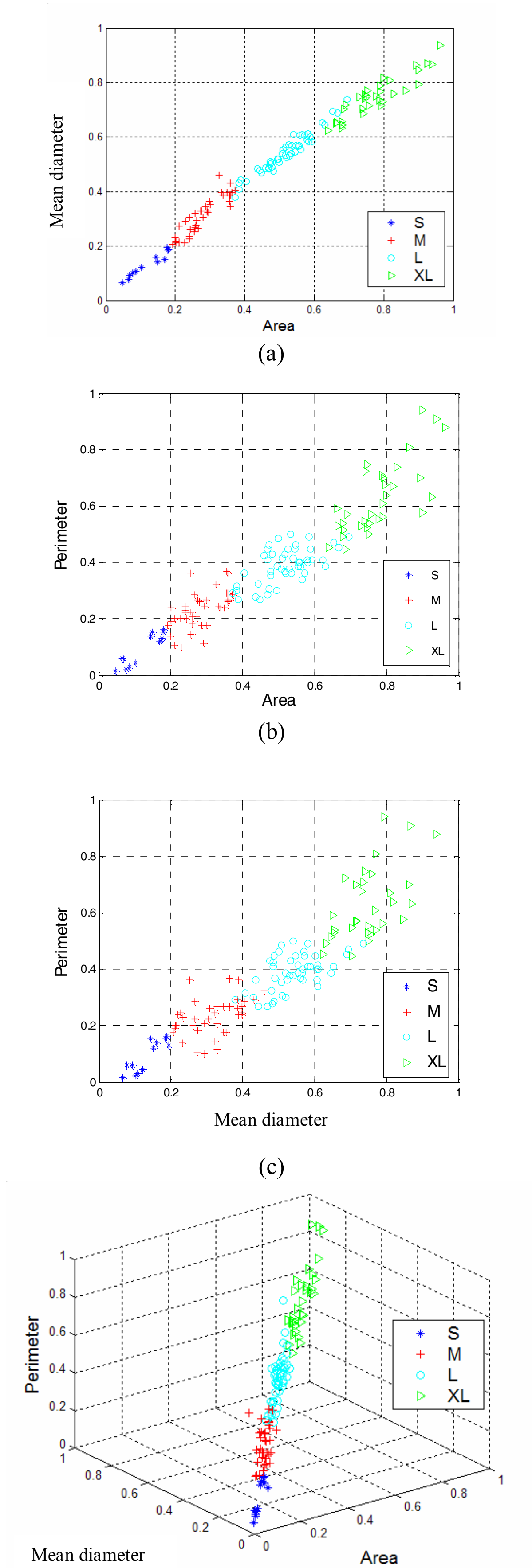
- *Read image*
- *Check each object pixel I(x,y)=1 whether it has 4-connected neighborhood*
  *If YES then I(x,y)=0 else I(x,y)=1*
- *Perimeter is the sum of edge pixels of object detected in image*

--------------------------------------------------------------------

(a) (b) (c)

Fig. 7. (a) 4-connected neighborhood pixels to detect the edge of object; (b). Original binary image; (c). Detected edge of object

Using the three shape characteristics, we then performed analysis based on their combinations to study the uniqueness of the extracted features. The combination of features are area-mean diameter, area-perimeter, mean diameter-perimeter and area-mean diameter-perimeter as depicted in Fig. 8 (a), (b), (c) and (d), respectively. According to the scatter plots in Fig. 8, each size of papaya was clustered in its class based on the extracted features. In other words, the size of papayas can be potentially classified using shape characterization.




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

Fig. 8. Analysis using combinations of extracted shape characteristics

### D. *Neural Network Classifier*

Neural networks have been successfully employed in numerous applications. In this research, we use the back-propagation algorithm of the multilayer perceptron (MLP) artificial neural network model as depicted in Fig. 9 . The four combinations of features are fed to the network for classification training and testing. Detailed explanation of the neural model is available in [9] and [10]. A total of 40 images were used for training and 130 images were used for testing. Outputs "0", "0.33", "0.67" and "1" represents grade "S","M", "L" and "XL" papayas, respectively.

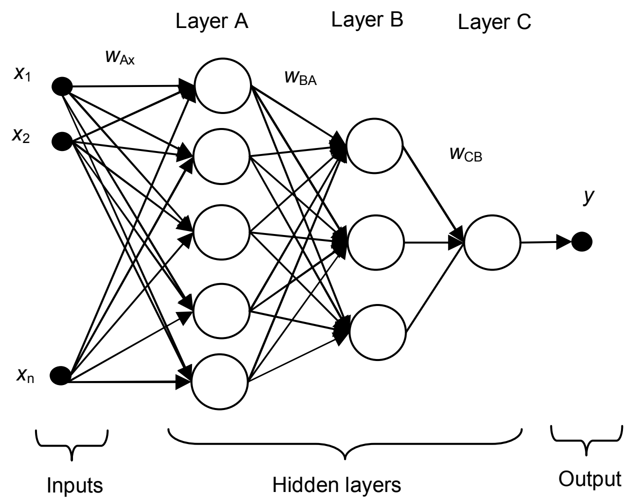



Fig. 9. The multi layer perceptron model of neural network

## III. Result and Discussion

Four pairs of features combination were trained separately using an MLP model. When it was completed, the net is tested for its ability to classify the grades of papaya according to their size. Table II tabulated the result of papaya classification using four combinations of shape characteristic features. Results show that the best performance in classification was obtained using the combination of the area and mean diameter features.

TABLE II
Result of Papaya Size grading

| Feature combination | % classification accuracy | | | | |
|---|---|---|---|---|---|
| | Grade | | | | |
| | S | M | L | XL | All |
| Area-mean diameter | 66.7 | 97.4 | 95.8 | 100 | 94.6 |
| Area-perimeter | 83.3 | 97.4 | 93.8 | 93.8 | 93.8 |
| Mean diameter-perimeter | 91.7 | 97.4 | 89.6 | 87.5 | 91.5 |
| Area-mean diameter-perimeter | 91.7 | 97.4 | 87.5 | 100 | 93.8 |

This fact can be seen in the scatter plot in Fig. 8 which shows that the grades of papaya size was separately clustered using the feature combination of area and mean diameter compared to others combinations. Misclassification occurs mainly due to papaya size falling in between grade categories.

## IV. Conclusion

This paper considered the development of papaya size grading using shape characterization. Four combinations of area, mean diameter and perimeter were tested for the classification task. The combination of the area and mean diameter features provided a unique shape characteristic for papaya size grading as with it we successfully classified papayas with more than 94% accuracy. This technique can be improved upon using other shape features and combinations. In addition, further testing with a larger database is required to validate the proposed technique.

## V. Acknowledgment

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## VI. References

*Periodicals:*

[1] T. Brosnan and D.W. Sun, "Inspection and grading of agricultural and food products by computer vision system – a review", *Computer and Electronics in agriculture*, 36, pp. 193 – 213, 2002.

[2] N. Aleixos, J. Blasco, F. Navarron, and E. Molto, "Multispectral inspection of citrus in real-time using machine vision and digital signal processing", *Computer and Electronics in Agriculture* , 33, pp. 121 – 137, 2002.

[3] Ying, Y.B., Jing, H.S., Ma, J., Zhao, Y. & Jiang, Y.Y. 1999. Shape identification of Huanghua pear using machine vision. Transaction of the Chinese Society of Agricultural Engineering 15(1): 192 – 196

[4] J. Blasco, N. Aleixos, and E. Molto, "Machine vision system for automatic quality grading of fruit", Journal of Biosystems Engineering 85(4), pp. 415-423, 2003.

[5] Leemans, V., magein, H. & Destain, M.F. 2002. On-line fruit grading according to their external quality using machine vision. Biosystem Engineering 83(4): 397 – 404.

*Papers from Conference Proceedings (Published):*

[6] H. Tian, S.K. Lam and T. Srikanthan. Implementing Otsu's thresholding process using area-time efficient logarithmic approximation unit. *Proceeding of ISCAS'03,* IV-21- IV-24, 2003.

*Books:*

[7] R. Gonzalez, R.E. Woods: *Digital Image Processing*. 2nd Ed. New Jersey: Prentice Hall. 2001.

[8] Costa, L.F. & Cesar, R.M. 2000. Shape analysis and classification: Theory and practice. Florida: CRC Press pg 421 – 441.

[9] N.K. Bose and P. Liang. Neural network fundamentals with graphs, algorithms and application. New Delhi: McGraw-Hill. 1998

[10] R.O. Duda, P.E. Hart and D.G. Stork. Pattern Classification. CA: John Willey & Sons. 2001

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