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INFORMATION PROCESSING IN AGRICULTURE 4 (2017) 150–160

journal homepage: www.elsevier.com/locate/inpa

Geometry-based mass grading of mango fruits using image processing

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ARTICLE INFO

Article history:
Received 6 May 2016
Accepted 22 March 2017
Available online 1 April 2017

Keywords:
Horticultural crops
Quality
Sorting

ABSTRACT

Mango (*Mangifera indica*) is an important, and popular fruit in Bangladesh. However, the post-harvest processing of it is still mostly performed manually, a situation far from satisfactory, in terms of accuracy and throughput. To automate the grading of mangos (geometry and shape), we developed an image acquisition and processing system to extract projected area, perimeter, and roundness features. In this system, images were acquired using a XGA format color camera of 8-bit gray levels using fluorescent lighting. An image processing algorithm based on region based global thresholding color binarization, combined with median filter and morphological analysis was developed to classify mangos into one of three mass grades such as large, medium, and small. This system achieved an accuracy of 97% for projected area and Feret diameter, 79% for perimeter, and 36% for roundness. To achieve a finer grading, two different grading features could be used in sequence. The image grading system is simple and efficient and can be considered a suitable first stage to mechanizing the commercial grading of mangos in Bangladesh. Moreover, the method has the potential to be applied to other crops with suitable adjustments.

1. Introduction

Production and consumption of agricultural products, especially fruit and vegetables, in Bangladesh has shown a marked upward trend over the past few years. The associated fruit and vegetable processing industry is, however, at various stages of development and not yet able to implement comprehensive best agricultural practices [1]. Mango (*Mangifera indica*) is an important and popular fruit in Bangladesh, occupying the largest area (32,011 ha) of any fruit crop and with a total annual production of 104,7849 metric tons), only being behind banana and jackfruit [2].

Postharvest processing of mango fruits comprises a series of unit operations, including cleaning, waxing, sorting, grading, packing, transport, and storage; while grading being considered the most important post-harvest step. Grading based on geometry and shape are the two major parameters that consumers identify with the quality of mango fruit. Moreover, mango fruits with abnormalities in shape do not meet quality requirements for export. Even though Bangladesh produces a substantial mango crop, and overseas demand is steadily increasing, current post-harvest processing, which is still

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Peer review under responsibility of China Agricultural University.
http://dx.doi.org/10.1016/j.inpa.2017.03.003
2214-3173

predominantly performed manually, cannot meet international quality requirements. Farmers continue to examine and sort/grade harvested mangos by visual appearance (Fig. 1). Hence, this practice is highly subjective assessments lead to variability in grading opeartions. Since manually grading mangos based on geometrical or shape features is laborious, stressful and costly [3,4], a simple, reliable and objective, automated grading and sorting system would be of great benefit to the mango industry in Bangladesh.

Awareness of food safety has also risen among the consumers, such that a lack thereof is now a great concern. Consumers have become more discerning about the quality of the food they consume, and they are also more demanding for fresh quality produce that utilizes "just in time" delivery. This has put pressure on agricultural vendors to consistently deliver quality products and venture beyond simply rejecting damaged fruits in grading. Proper grading is also needed to ensure as high-valued products are sold at premium prices.

Traditional visual inspection is labor intensive, expensive, and prone to human error, leading to variability in the final product. Thus, there is a critical need to be able to quickly, accurately, and efficiently evaluate agricultural products without the use of human labor. Therefore, automated grading and sorting systems that use image processing techniques to determine geometrical and shape parameters, such as size, shape, color, ripeness, mass, bruising, disease, and rot, are being developed in many countries [5–8]. In addition, an automated grading system would free up labor, which is already in short supply and expensive, to more important farming or horticultural operations – thereby made available for crop production.

For Bangladesh to expand its agricultural sector further, from the current state of agricultural production and processing, it needs to tap into the export and processing markets by upgrading postharvest management practices to ensure that value-added, high-quality agricultural produce is supplied by the agro-processing sector. A concerted effort in the area of machine vision will enable the production of high-quality mango fruit, and empower Bangladesh to compete in global export of fresh produce. Modern technologies have enabled wide application of machine vision techniques for quality analysis elsewhere, but a simpler technique would be a good start for regions that have not seen any mechanization. Algorithms for detecting fruit size [4,9], color, shape or ripeness [10–12], defects [3,13–17], sugar content [18], and mass [19], were successfully applied in those machine vision based grading systems.

As a way of introducing mechanized postharvest processing and fruit quality control in Bangladesh, the goal of this work was to develop a machine vision system capable of grading fruit based on extracted geometrical and shape features. The first objective was to develop a machine vision system that can efficiently acquire images suitable for further processing. The second objective was to develop an algorithm for grading mango based on selected features using image analysis.

2. Materials and methods

Three varieties of mango of varying mass were collected from a local farmers' market in the Mymensingh district, Bangladesh during the harvest season of mid-June, 2014. The fruits were stored at 25 °C for one day, allowing them to reach an equilibrium temperature. The test samples were immersed in water and cleaned manually before acquiring imagery. After discussion with local mango growers, vendors and horticulturists, three standard mass grades were set: namely large (over 300 g), medium (150–300 g) and small (below 150 g). A total of 120 fruits (3 size groups) were selected and three mangos from each group were used for the image acquisition with a total of 40 images being acquired.

2.1. *Image acquisition system*

Several types of imaging cameras for machine vision systems, ranging from monochrome cameras for detecting geometrical

Fig. 1 – Manual sorting of mangos in a local rural industry (Pran Agro. Ltd.). Photo courtesy: The Daily Star Weekly, Magazine, July 15, 2011.

and shape parameters to multispectral cameras for surface defect and disease detection on meat, grain, fruit, and vegetable have been reported [8]. Varying formats of color camera (e.g., VGA, XGA, SXGA, UXGA) with 8 or 10 bit gray levels are starting to be used and these cameras have the potential to acquire high resolution color imagery. In this work the images were acquired using a XGA format 1/2″ Sony CCD ICX205AK color camera (The Imaging Source: DFK 41AU02; Germany) of 8 bit gray levels and fitted with a C-mount lens. The image acquisition device comprised a XGA format CCD camera fitted with a C-mount lens of 6 mm focal length with a polarized light (PL) filter, a desktop computer (Intel®Core™ i3-2120 CPU@3.30 GHz) and twelve fluorescent lamps (each 18 W, 54 V, color temperature: 6500 K; Philips Lifemax) for illumination of the samples. The fluorescent lamps cause halation (purple color pixels) on the fruit skin due to the presence of a cuticle layer on the surface [20]. To eliminate halation, a PL filter was fitted to the camera lens. The diagram of the image acquisition system shows the arrangement of camera, lighting, sample layout, and image transferred to the personal computer (Fig. 2).

Image acquisition occurred in a controlled environment, where dust and stray light were avoided. The downward looking camera was placed 220 mm above the samples, which provided a field of view of 150 mm × 150 mm. The distance between the center of a fruit object and the lighting panel was maintained at about 200 mm. Camera parameters such as shutter speed of 1/30 s, iris of 1.4, gain of 1000 dB, and gamma correction of 120 were found to be suitable for the fluorescent lamps lighting panel. White balance setting was adjusted and then images were captured using IC capture image acquisition software Ver. 2.3.382.1796 (The Imaging Source, Germany) with a resolution of about 0.17 mm pixel^{-1} and size of 980 × 880 pixels and were saved in bitmap (BMP) format.

2.2. *Image processing and analysis*

Post-processing of the resulting images was conducted using Visual C++ and OpenCV (Open Source Computer Vision) library functions under Windows 7. In addition, WinROOF (version 5.6, Mitani corporation, Japan) was used to verify image processing data. For the statistical analysis of image data STATA (Stata Corp. LLC, Version 14, TX, USA) was used.

The image segmentation algorithms are categorized into three techniques namely: thresholding, pattern recognition and deformable models. The aim of thresholding segmentation is to search for adjacent pixels which have similar properties and within the ranges of defined threshold values. Thresholding algorithms can be further classified into the following approaches: edge-based, region-based and hybrid. The ideas of region-based algorithms come from the observation of the similar properties of the neighboring or connected pixels in the same region such as specific ranges of color or gray level intensities [21,22]. A comprehensive report on various image segmentation approaches using color, texture, and shape that have been studied for various fruits has been described [23]. In this study, a region-based global thresholding color segmentation method was used to get more information at the pixel level as compared to greyscale images and searching for pixels with similar feature values of connected pixels.

To develop the image processing algorithm different color spaces, such as RGB (Red, Green and Blue) and HSI (Hue, Saturation and Intensity), were evaluated for thresholding. The HSI color model is superior over RGB or CMYK due to various principal facts; firstly, the intensity component is decoupled from the color information represented as hue and saturation; secondly, the hue and saturation components are intimately related to the way in which humans perceive color [24], and thirdly, the hue value is invariant to changes in light

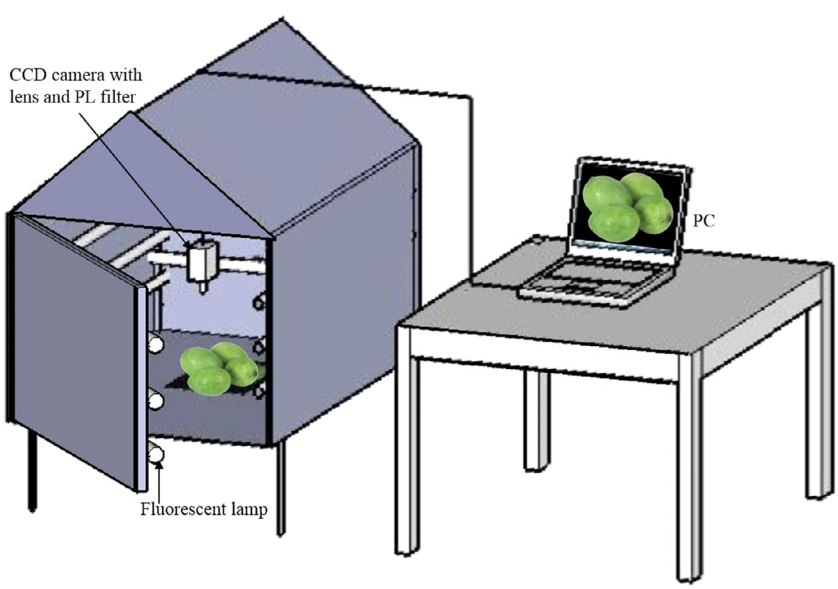

Fig. 2 – Schematic diagram of the machine vision system for image acquisition.

intensity [25]. These features make the HSI model an ideal tool for developing digital image processing algorithms. It is the most widely used color representation in machine vision [26] and consequently used in this study.

The RGB values of the fruit surface and image background were measured and the values of RGB were converted to HSI using the color space conversion relationships described in [24]. For RGB to HSI conversion the following steps were used in sequence: (i) read the RGB image which is in the range of [0, 255], (ii) represent the image in the [0, 1] range by dividing each RGB component by 255, (iii) calculate HSI components and (iv) represent the saturation and intensity in the ranges of [0,100] and [0,255] for convenience.

Plotting HSI color values of the mango surface and background created a histogram based on color information. From the histogram, the suitable color channel was selected as threshold limit (T) for segmenting the source image of the object from the background. The global threshold segmentation algorithm used for converting source image to binary image is given (Eq. (1)) as:

$$g(x,y) = \begin{cases} 1, & \text{for } f(x,y) > T \\ 0, & \text{for } f(x,y) \leqslant T \end{cases} \tag{1}$$

where $g(x,y)$ is defined as threshold image, $f(x,y)$ is the source image and T is threshold value. All the pixels of source image with color information equal or lower than T are turned to zero and considered as background (black) and those pixels greater than T to one and considered as object pixels (white).

After thresholding the image, features such as projected area, perimeter, Feret diameter and roundness of the objects were extracted to evaluate the geometrical and shape properties. A brief description of obtaining these features is described herein and the procedure is shown in Fig. 3.

The projected area of the image defines the area of individual mangos. The projected area was determined by counting the number of pixels within the object boundary of the threshold image. A *FloodFill* algorithm was applied to identify all pixels in each mango region. The *FloodFill* argument has a property called "area", which provides the number of pixels in the filled region connected to a given node in a multidimensional array [27]. In OpenCV, a predefined library function called *cvFloodFill* that fills a connected component or a region in an image with new color starting from a seed pixel was used for filling the area. In this process, a seed pixel was selected from the image and all similar neighboring points (four or eight connected nodes) were colored with a uniform color [28,29]. Connectivity in four way directions was used in this study. Flood filling also creates a mask image and a pixel $(x+1,\ y+1)$ in the mask image corresponds to image pixel (x,y) in the source image. The mask image can also be used for other purposes, such as determining the perimeter of the filled image [30]. The perimeter was determined by connecting the boundary pixels of the object profile in the mask image. Pixel information of each mango was converted to the respective units of area into mm^2 and perimeter into mm, by multiplying by the image resolution value. The Feret diameter and roundness of each mango were calculated using the following relationships [31] involving area and perimeter.

$$\textit{Feret diameter} = \sqrt{(4 \times \textit{Area}/\pi)} \tag{2}$$

$$\textit{Roundness} = (4\pi \times \textit{Area})/\textit{Perimeter}^2 \tag{3}$$

The statistical significance of the mean differences of estimated features across different sizes of the mangoes was evaluated using paired *t*-test. For the statistical analysis of image data STATA (Stata Corp. LLC, Version 14, TX, USA) was used. Finally, the testing was performed by comparing the mango grades obtained through the algorithm with the measured individual mass of the mangos of the three selected grades.

3. Results and discussion

Captured color images of mangos under fluorescent lamp illumination (Fig. 4) revealed that the objects are easily distin-

Fig. 4 – Acquired original color image of three grades of mango (A: 330 g; B: 220 g; C: 145 g).

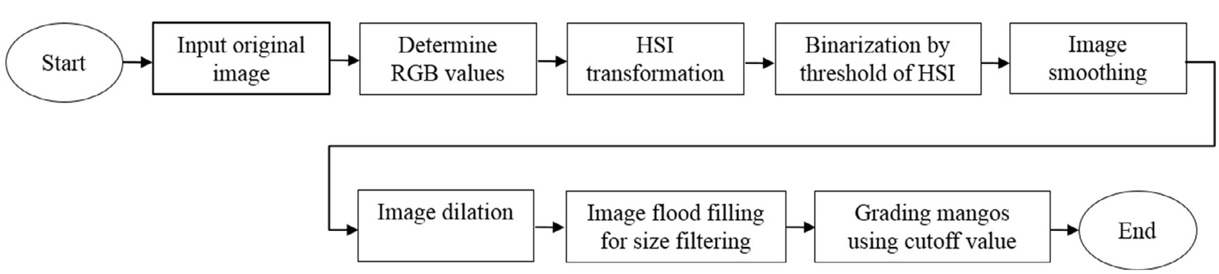

Fig. 3 – Flowchart of the developed image processing grading algorithm.

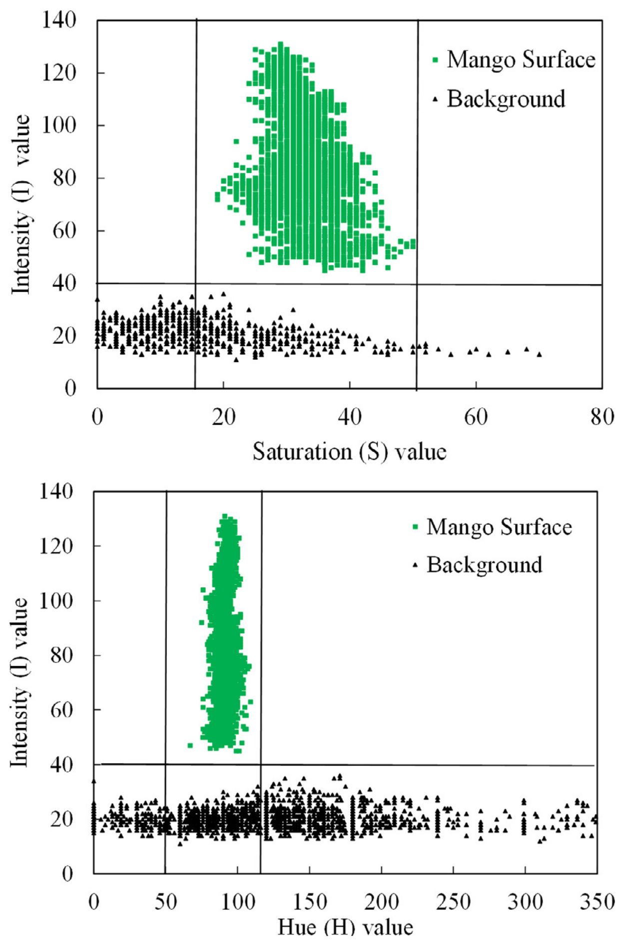

Fig. 5 – The relationship of HSI color spaces of mango surface and image background.

guishable from the background using color segmentation. The segmentation result is influenced by the initial seed choice, but there is no standard approach for selection the seed pixel [32]. Ma et al. [22] reported that the rule of unseeded region growing algorithms is near-identical to seeded region growing except when the within-class variance is too large. The relationship of HSI color values (Fig. 5) revealed similar properties of the neighboring/connected pixels in the same region, such as specific ranges of color information for mangos and image background. Thus, the object region can be distinguished from the image background based on HSI color information. Hence, an arbitrary set of pixels (color range) was used as seeds, and the threshold value (*T*) was chosen from the minimum and maximum HSI values that were found among several regions in the mango surface. For example, the minimum to maximum H, S and I threshold limits were 40–115, 15–50, and 30–140, respectively and were found suitable for segmentation (Fig. 5).

In the resulting binary image (Fig. 6(b)) using the HSI thresholds, small regions of noise were found in the image background. These isolated noise pixels were eliminated using a median blur type smoothing operation (Fig. 6(c)) as they were too small and too low compared to their neighbors [24]. Subsequently, to handle smooth concavities, for bridging gaps and to enlarge the boundaries of regions of foreground pixels [24] a single dilation morphological operation was performed (Fig. 6(d)). The smoothing and dilation operations were done using OpenCV [29].

Fig. 6 shows some stages of the image processing results as outlined in the flowchart of the grading algorithm (Fig. 3). In the source image, segmented based on HSI color values (Fig. 5), the target objects (mangos) appear in white, while the rest of the image (background) was converted to black forming the binary image (Fig. 6(b)). After applying the grading algorithm using the binary image, flood filling (using any desired color) can be applied as a method to easily identify the mango grades, and overlaid on the original image to help with the detection and visualization.

3.1. *Performance of grading algorithms*

A simple filtering operation, finding object area from the segmented image below and over a selected value, was used to grade the mangos based on mass. In the original image

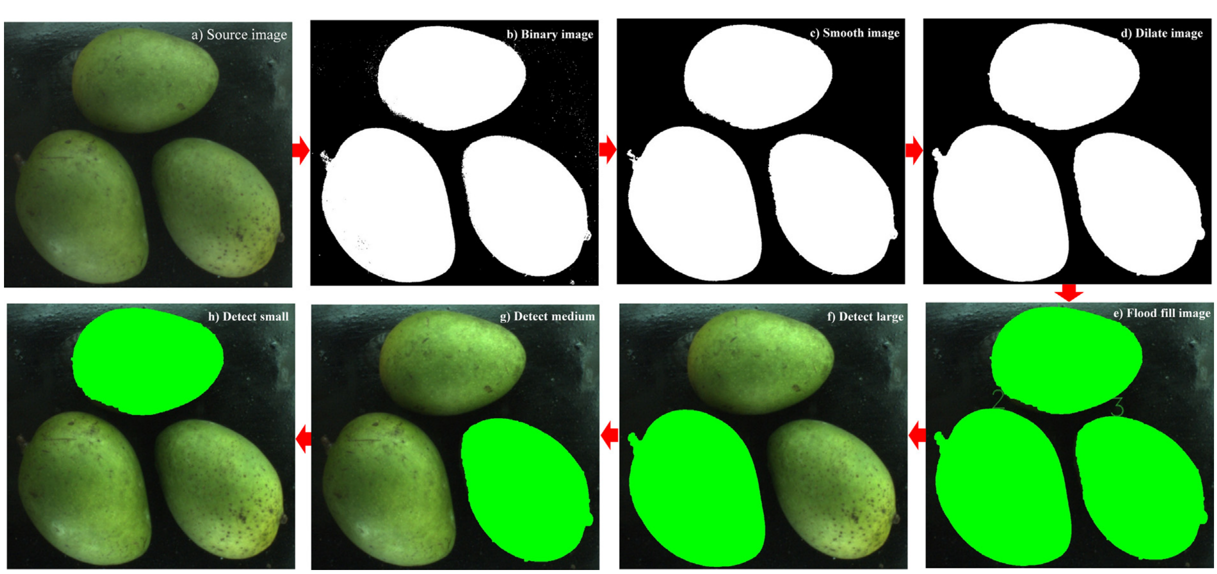

Fig. 6 – Image processing operations performed for developing the mango grading algorithm.

Table 1 – Extracted size and shape features from the preprocessed mango images.

Features	Area						Perimeter						Feret diameter, mm			Roundness		
Mango class	Small		Medium		Large		Small		Medium		Large		Small	Medium	Large	Small	Medium	Large
	pixel	mm^2	pixel	mm^2	pixel	mm^2	pixel	mm	pixel	mm	pixel	mm						
Minimum	124,778	3606	146,049	4221	169,010	4884	1398	238	1445	246	1524	259	424	448	488	0.6648	0.6087	0.6452
Maximum	140,848	4071	157,882	4563	186,827	5399	1610	274	1777	302	1889	321	399	431	464	0.8017	0.9080	0.9743
Average	136,209	3936	152,688	4413	180,659	5221	1518	258	1618	275	1734	295	416.52	441.01	479.70	0.7439	0.7376	0.7604
Standard deviation	3458.32	99.95	3253.05	94.01	4281.57	123.74	39.92	6.79	76.00	12.92	85.10	14.47	5.33	4.71	5.71	0.0382	0.0685	0.0767
Cutoff value	<140,000		140,000–160,000		>160,000		<1550		1550–1650		>1650		<422	422–451	>451	<0.78	0.78–0.8	>0.8
Accuracy (%)	90		100		100		80		70		87		90	100	100	80	20	10

(Fig. 4) for the large, medium and small mango mass grades with an average mass of 330, 220, and 145 g, respectively, the projected area, the perimeter, and the Feret diameter showed an overall linear trend, but roundness did not. The projected areas of different grades of mangos in terms of pixel counts and physical units along with other features (perimeter, Feret diameter, and roundness) are presented in Table 1. It is clear that in the case of projected area and Feret diameter, there is clear separation of minimum, maximum, average and standard deviation values for all three class of mangos and no overlaps were found among them (Fig. 7A and C). However, for the other two features clear separation was not observed and overlaps were found among each mango class (Table 1). Table 2 shows that the features area, perimeter, and Feret diameter differ significantly across three mango mass and the mean differences are significant at 99% confidence level. This implies that the image processor has been able to accurately differentiate among the small, medium and large mass of mangos in terms of area, perimeter, and Feret diameter. In case of roundness feature, did not find any statistical difference across different mass of the mangos. However, from Fig. 7B and D it is apparent that when using perimeter and roundness the grading of different mango classes (based on mass) cannot be obtained as accurately as with projected area. Therefore, projected area can serve as a good indicator of the mass of mangos. This indicator gave an excellent grading accuracy of 97 ± 3% (Table 1). Furthermore, the fruits laid out in their natural resting position, with the major dimensions such as length and width parallel to the horizontal, the images tend to be replicable.

From Eq. (2) it can be seen that the Feret diameter is mainly dependent upon the projected area parameter and directly proportional with it. Thus, grading mango using Feret diameter as an indicator provides similar information leading to similar results as obtained from the projected area. Therefore the projected area was used to select the cutoff value for grading. For each cutoff value the closest rounded number of Min and Max values was considered as shown in Table 1. Because of the data overlap, the cutoff values for perimeter and roundness parameters were chosen empirically in such a way that the grading accuracy was maximized. It should be noted that with perimeter the maximum accuracy was obtained using the average value, and as described earlier the next rounded digit was chosen as the cutoff value. With perimeter, the average grading accuracy was 79 ± 8% (Table 1). This accuracy of grading has resulted because the perimeter is also a good indicator of mass, as these quantities are generally positively correlated.

However, in the case of roundness, a suitable cutoff value that is wide apart for grading mangos according to mass was difficult to obtain. A highest average accuracy of only 36.7 ± 43% was obtained with the best cutoff value. The grading inaccuracy can be explained as roundness is a shape factor that is independent of the mass of an object. For example, round (roundness → 1.0) and elongated (roundness → 0.0) shaped mangos occur in all mass categories. Based on the results and observation obtained using image processing techniques, the grading of mango with projected area as the indicator is recommended for best accuracy (Table 1).

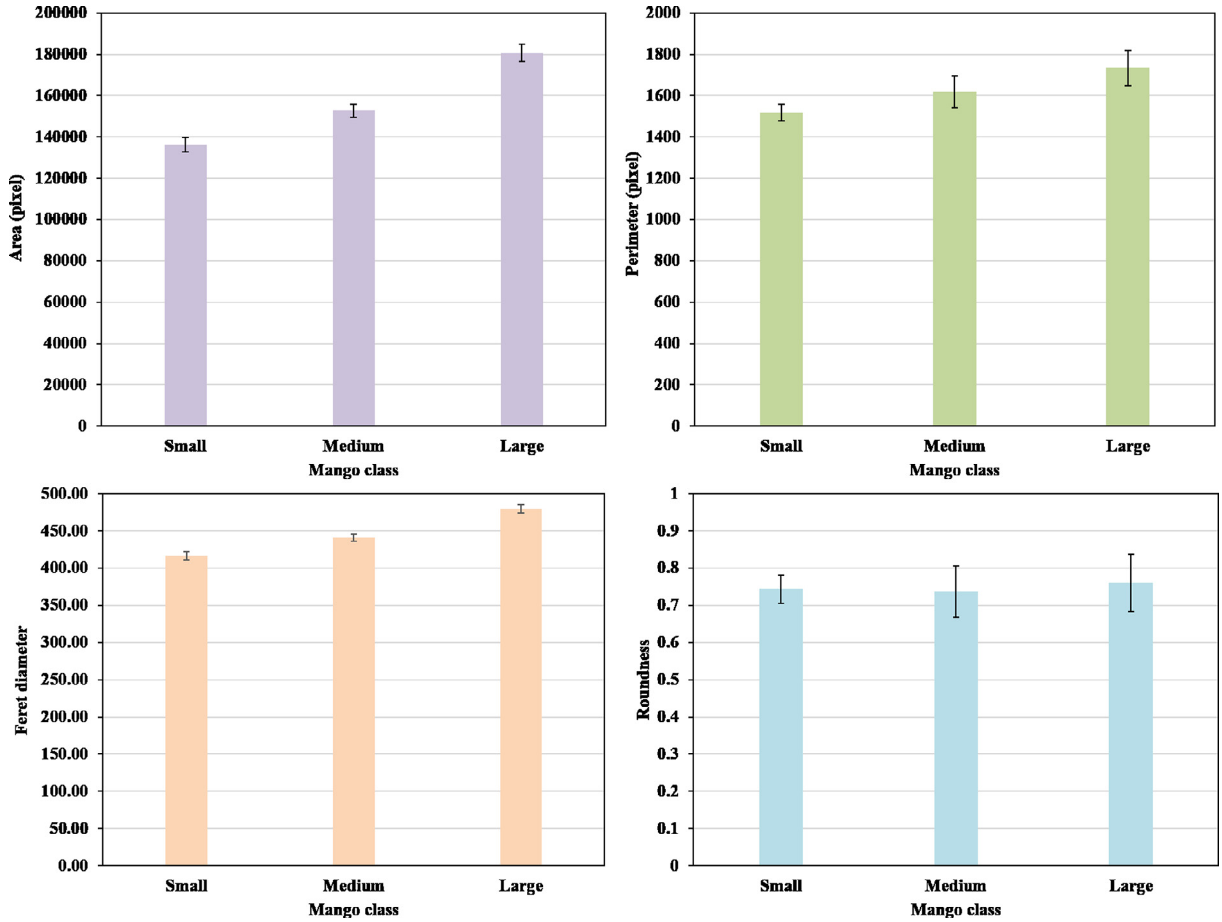

Fig. 7 – Relationship between projected area, perimeter, Feret diameter and roundness features of each mango mass grade class.

3.2. Algorithm validation and effect of grading parameters on mango grades

The developed algorithm is versatile in grading the products based on the desired grading parameters/features already considered (e.g., area, perimeter and roundness). Visualizing the graded mangos in the form of images based on these grading parameters is similar to manual inspection. All samples in the testing set were processed through the algorithm into three grades based on individual grading parameter and 15 samples shown in Figs. 8–10.

It can be readily seen that projected area (Fig. 8) and perimeter (Fig. 9) serve as better grading parameters that produce visually similar products under each graded category, but not the roundness parameter (Fig. 10) that shows dissimilar sized and shaped objects. Even though all these parameters efficiently graded the mangos based on the selected criteria, the projected area was taken as the benchmark, which is the reason why roundness groups produce visually dissimilar sized (projected area) mangos. In other words, the mango mass is well correlated with projected area (97%) and Feret diameter (97%), followed by perimeter (79%), and poorly correlated with roundness (37%). Careful observation especially with roundness graded samples revealed that mangos with the lowest roundness (Fig. 10A) were more elongated than mangos with highest roundness, irrespective of their overall projected area. The presence of stem with calyx and external rough/irregular surface affected the roundness feature more than perimeter and projected area.

As an extension of this mango grading algorithm, it is possible to obtain refined grades of mango by applying the grading indicators in sequence. For example, uniform shaped mangos of uniform mass can be obtained by subjecting the projected area graded mangos to the roundness grading procedure successively. It should be noted that this multiple grading criteria works on the same input image and the order of these criteria application is immaterial. Alternatively, when uniform mass objects are presented (thus eliminating the roundness to projected area mismatch), the roundness algorithm grades the objects based on shape and refined grades will result. Such grading operations with multiple criteria are clearly becomes tedious in manual sorting.

To calculate the defect percentage on the mango surface using pixel ratio of defective and total area pixels, an image processing algorithm was developed by Tomas [4]. The images were obtained under natural light and the chrominance (C_b) color value was used for segmentation. Spreer and Muller [7] measured three geometric dimensions (length, maximum width, and maximum thickness) of mango fruits using optical measurement techniques and proposed a relationship to

Table 2 – Mean difference of the extracted features across different class of the mangos (paired t-test).

Features	Large vs small				Large vs medium				Small vs medium			
	Difference	St. Error	T-value	P-value	Difference	St. Error	T-value	P-value	Difference	St. Error	T-value	P-value
Area	44450.2	1004.85	−44.24	0.0000	27971	981.74	−28.49	0.0000	−16479.2	866.84	−19.01	0.0000
Perimeter	−215.66	17.16	−12.57	0.0000	115.96	20.83	−5.57	0.0000	−99.70	15.67	−6.36	0.0000
Feret diameter	63.18	1.43	−44.28	0.0000	38.678	1.35	−28.63	0.0000	−24.49	1.30	−18.86	0.0000
Roundness	0.0165	0.0156	−1.05	0.2965	−0.0228	0.0188	−1.21	0.2294	0.0063	0.0143	0.4417	0.6698

measure the mangos mass based on these properties. A linear statistical model between mango image pixels and mango weights using image processing was described in Teoh and Syaifudin [19]. For all these studies, the pictures of the mangos were acquired by color digital camera. In our study, we used a color CCD camera with a 6 mm lens and a PL filter to obtain high quality, low noise imagery. The HSI color model was used for image thresholding and simple morphological and filtering techniques were applied to develop the grading algorithm. The contributions of this study lay in the introduction of a simple image processing technique for mango grading to rural industries of Bangladesh, and the promise of refined mango grading by applying a combination of grading procedures.

3.3. *Possible applications of the grading algorithm*

Even though developed as a modest and initial attempt to mechanize mango grading in developing countries that have seen no mechanization in the rural industries, some of the possible practical applications of the mango grading algorithm include: (i) refined or fancy grade generation by successive application of grading criteria; (ii) determine the correlation between the combination of geometrical parameters (e.g., area, perimeter, Feret diameter) and mass of the fruit; (iii) based on these grading parameters, study the effect of different cultivars/varieties in a breeding program; (iv) algorithm forms the part of software component in an automated grading system; (v) general scale up techniques, such as high-capacity, high-speed of operations, and adding parallel units will increase the throughput of systems employing this basic algorithm; and (vi) with simple modifications the algorithm can be made to handle grading of other horticultural crops.

3.4. *Limitations and future work*

In this study, a rudimentary machine vision was employed to improve mango fruit grading in the developing country of Bangladesh. The technique is simple compared to state-of-art technologies available elsewhere, and has limitations in the analysis and practical application as well. For example, the images were manually rectified to avoid shadows and possible objects touching one another, and the effect of fruit orientation was not considered. Observations of issues were made with regard to unsmooth periphery due to erroneous segmentation in some binary images (Figs. 8–10). In addition, the grading algorithm classified mangos into three standard mass grades and the approach was based on human perception of overall size during manual grading. A more robust approach is needed to implement a formal feature distribution based classifier techniques such as artificial neural networks (ANNs) or support vector machines (SVMs) to improve the grading accuracy. Most of these issues can be addressed by improvement of the layout mechanism and advanced image processing techniques.

The current work developed the software that includes image acquisition, processing and analysis techniques to grade mango in a static setting. However to implement the algorithm into an automated inspection system there is a

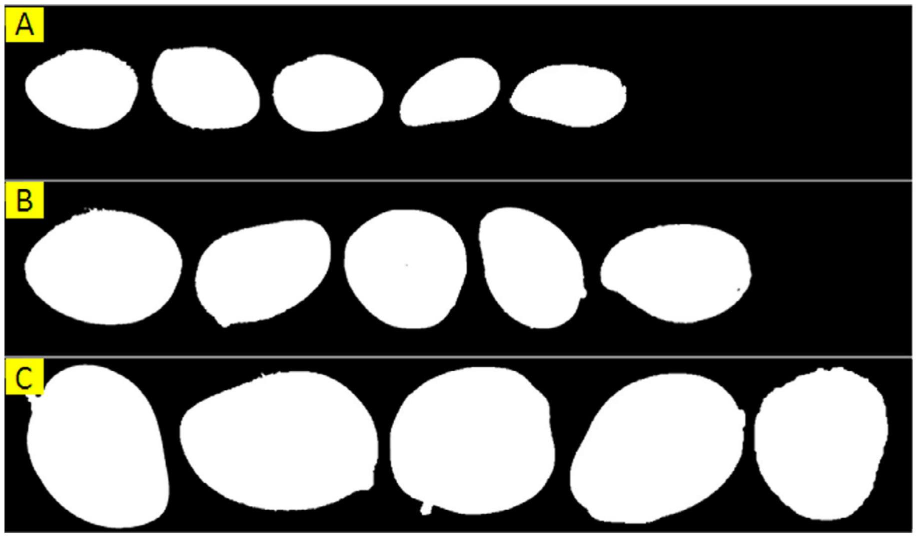

Fig. 8 – Example of projected area-based grading of mangos into three size or mass grades (A: pixel <140,000, B: pixel 140,000–160,000, C: pixel >160,000).

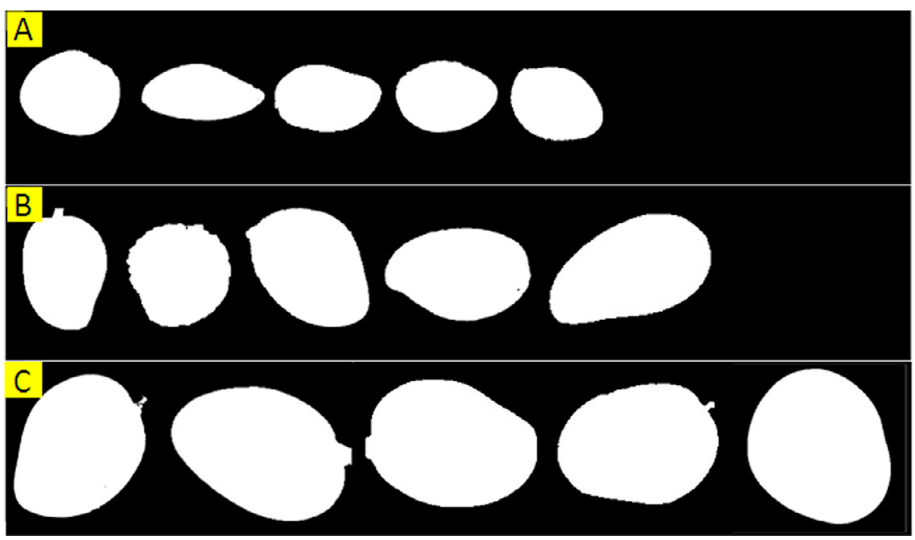

Fig. 9 – Example of perimeter-based grading of mangos into three size or mass grades (A: pixel <1550, B: pixel 1550–1650, C: pixel >1650).

need to implement a conveyor system for acquiring images while fruits are in motion. It is also essential to integrate the grading software with the hardware that actually performs the mechanical action of grading the objects. Furthermore, the presence of pedicles (fruit stalk) on the mango affects the calculations, especially the roundness, and this can be addressed by advanced programming techniques which can identify these slender protrusions and eliminating them. Future work will address the limitations discussed, and a real-time machine vision system employing the developed algorithm for automated mass grading of mangos will be implemented.

4. Conclusions

Fluorescent lighting was efficient in providing the necessary illumination to produce good quality images for machine vision system to grade mangos. The mass of mangos had a direct relationship with their projected areas, Feret diameter, and perimeter, but not with roundness. The developed geometry-based algorithm is simple, yet it successfully graded mangos into three mass grades based on projected area as well as Feret diameter as the indicator with excellent accuracy (97%). Other parameters, such as perimeter, or roundness can also be used as indicators to grade mangos, but their accuracy were limited (36–79%). Application of grading with two indicators in sequence (e.g., projected area followed by roundness) can produce refined or fancy grading of mangos. The developed complete machine vision system will serve as the front-end decision support for a grading process, which will guide the actual hardware performing the physical separation needed to be integrated with this system. This simple, accurate, and efficient process can be seen as the first stage of mechanizing the mango grading operations in

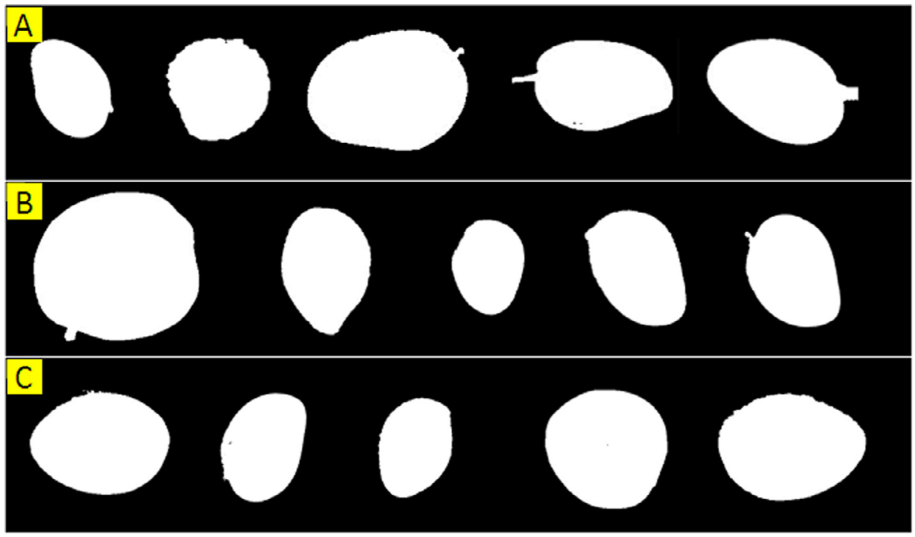

Fig. 10 – Example of roundness-based grading of mangos into three size or mass grades (A: <0.78, B: 0.78–0.8, C: >0.8).

developing countries such as Bangladesh. The method being general in nature can be applied to other crops as well with proper adjustment in the image acquisition and in the grading algorithm threshold values.

Acknowledgement

This work has been partially supported by the TWAS (Ref.: 13-311 RG/ITC/AS_C); and MoICT, Bangladesh (code: 3-0001-2801-5965).

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