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Size Properties of Mangoes using Image Analysis

Tomas U. Ganiron Jr.

International Association of Engineers (IAENG)
South Kowloon, Hong Kong

tomas@qec.edu.sa

Abstract

This experimental study aimed to develop an efficient algorithm for detecting and sorting mango. Using the acquired image, the features of the mango were extracted and used to identify the class of the mango. The extracted features of the mango are perimeter, area, roundness, and percent defect. The roundness and percent defect were used to identify whether the mango's quality was export, local or reject. The area was used to determine the size of the mango. An optimal threshold was used in segmentation and boundary tracing was used to determine the perimeter. This study becomes significant and may contribute to the perspective of new knowledge on image clustering model.

Keywords: *Algorithm, image processing, sorting mangoes, defective pixels, chemical compound*

1. Introduction

Mango is one of the world's favorite tropical fruits with an increasing production trend every year.

In general, the color of the fruit indicates its maturity and the presence of defects. Its physical appearance affects its value in the market so it is important to observe proper handling of fruits after harvesting. Sorters must know the requirements that should be followed so that the fruits can be accepted for export.

Sorting objects is usually done using its physical features. Automatic sorting has been studied and developed for different products. An automatic color sorting system for hardwood edge glued panel parts classified wood according to its color and grain using the K – nearest neighbor approach with L1 distance norm. [1]. A vision system can also be applied to food products like fish and fruits [2]. Vision system using the nearest neighbor techniques has been applied to a recognition system for vegetables using L1 distance between histogram vectors [3, 4].

The process of classifying mangoes generally relies on its physical characteristics. This process is presently done using manual labor and is greatly dependent on the human visual system. Uniformity in the classification process is important so that its output is guaranteed to satisfy the requirements for exporting mangoes [5, 12].

Fruit categorizations in agriculture have changed from traditional grading by humans to automatic grading over the past 20 years. Many companies are moving to automated grading in many crops such as grading on peaches and oranges [2]. One of the researchers has made an apple grading system based on image analysis. The idea behind their study was to train the system with many examples so it will become expert by distinguishing differences on the fruit to create data as a reference for their system [3, 11]. In order to classify mangoes we need to

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be aware of the mango grading standard. Color and the size are the most significant criteria that are used to sort fruits.

However, for sorting of mangoes there is another major factor which is the skin texture of mangoes that can improve the accuracy of the classification system.

The purpose of the study was to implement an image-processing algorithm that can help in automating the process of mango classification.

The specific objectives were to implement an image analysis algorithm that can measure the size and shape of a mango and at the same time determine its defective areas and classify the mango using the extracted features.

2. Literature Review

Mango is one of the potential fruits for both local and international markets. Its industry plays an important role in the country's export economy. It is grown in all regions but area of concentration is in the Central and Northeast [6, 8-9]. At present, mango production has greatly been developed through improved varieties to meet the consumer taste and preference. Overseas demand for mango has steadily in-creased both in the forms of fresh and canned fruit [7, 10].

In grading mangoes for export, the farmers must examine all the harvested mature mangoes by eyes and hands. This is quite subjective. So, farmers need alternatives for sorting and grading mangoes since hand labor is costly and inaccurate. An automated mango sorting system could be more feasible.

In recent years, machine vision technology has become more potential and more important to many areas including agricultural industry [10, 13, 18]. The uses of machine vision technology for quality inspection, classification, sorting, and grading agricultural products become more interest [11]. Later, there is a developed a real-time plant recognition algorithm, which is able to distinguish between broadleaf and grassy plant species [12].

It was then applied to build a sprayer control system. Moreover, this was improved the methods and evaluated three image processing methods for their ability to identify species of plants [12, 14]. The study concluded texture analysis yields best result. Chemist proposed a multi resolution-based method for recognizing weeds in corn fields [15]. They used a color camera, which provides four-band images, to capture agronomic scene [15, 16]. These multi-band images were processed to obtain color and geometrical features of the vegetation and soil.

A Bayesian network was then used to recognize and classify the vegetal species [17]. Recently, they showed another use of image processing approach in crop modeling They developed a system that analyzes and models leaf images [17]. Some other reports on fruit analysis include works of [19]. The first developed an automated fruit grading system using color image processing and some special censors. The latter used color image processing techniques in judging the maturity level of tomatoes [16]. Both RGB and L*a*b* color metrics were used. The research concluded that the* value of the tomato's external surface color can be used as a maturity index.

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In order to classify mangoes we need to be aware of the mango grading standard. Color and the size are the most significant criteria that are used to sort fruits.

However, for sorting of mangoes there is another major factor which is the skin texture of mangoes that can improve the accuracy of the classification system.

Mostly, the fruit that go through the grading process has their own characteristic to be considered depending on the type of fruits. The attributes chosen for the oranges, peaches and apples [21] are size, color, stem location and detection of external blemishes. Size has been identified using machine vision by measuring area or diameter of fruits. The averaged surface color is a good indicator for these types of fruits. To determine the stem location, they take the images of the random fruit from oranges, apples and peaches. Then, the images analysis algorithms were applied and shown centroid of the stem in the computer. The external blemishes were detected using the combination of infrared and visible in-formation. Sometimes, to grade the apple, researchers use other characteristic such as color, calyx and stem recognition, and defects characterization [22]. The calyx and stem ends will appear on an image as defects, and then were detected using a correlation pattern recognition technique. The image of calyx end and stem end were built by average five images. The parameter has been set up by 0 if there is no relation and if they are match perfectly. The defects characterizations are divide into typical defect, well contrasted defect, diffuse defect and bruise. In grading process of tomato and straw-berry the feature are size, color, shape has been considered [23, 24]. The size was taken by using weight measured and the area of a fruit by image analysis. The color can be either a normalized red/green index or better the dominating wavelength as maturity index. The shape considered as misshapen or perfectly shaped. The spots and scars can be classified by detecting greenback fruit or fruit with bot-tom-end rot.

Computer vision systems can be used for automated fruits inspection and grading [25]. These systems have been widely used in the food and agricultural industry for inspection and evaluation as they provide suitable rapid, economic, consistent and objective assessment. The automated inspection of produce using machine vision not only results in labor savings, but also improves inspection objectivity [23, 25]. Over the past decade, advances in hardware and software for digital image processing and analysis have motivated several studies on the development of the system to evaluate quality of diverse and processed foods.

There are several methods have been used in the fruit grading process such as computer vision. Nowadays, most of the commercial fruit have been graded by the ma-chine-vision technology such as strawberries [25], orange, peaches and apples and tomato [25]. The machine-vision technology is the technology that consist a color CCD camera equipped with an image grab device, a bi-cone roller device controlled by a stepping motor, and a lighting source to grade fruit based on the characteristic such as color, size, shape and defection.

The knowledge-based system has been developed to simulate human cognitive and problem solving process. The real example for the knowledge based is an expert system. The accuracy of fuzzy expert system is better than expert system than Boolean values. The efficiency of an expert system can be improved by implementing the fuzzy expert system [22, 23].

A Professor from West Germany introduced the fuzzy set theory in 1965 [21]. In practice, grading of fruit usually uses subjective criteria. In doing so, one has to depend on one's wisdom, experience, professional knowledge and information, which are difficult to define and/or describe accurately. When making an analysis using incomplete data, a lot of uncertainties will arise and this will confuse decision-makers and will complicate decision making in fruit classification under uncertain situations. Although many classification methods for selecting or ranking have been suggested in the literature, there is so far no method which can give a satisfactory solution to every situation [12, 25].

3. Methodology

All digital images were taken at Venvi Enterprise and were processed later. A total of 140 green mango images were acquired with a resolution of 640 ´ 480 pixels using Canon Digital IXUS 400. The images were acquired between 9AM to 2PM using natural light. Using the Universal Serial Bus (USB) connector the images were downloaded to the computer's hard disk before the analysis. A white background was used so that segmentation can be done easily. The setup is shown in figure 1 and a sample image is shown in Figure 2.

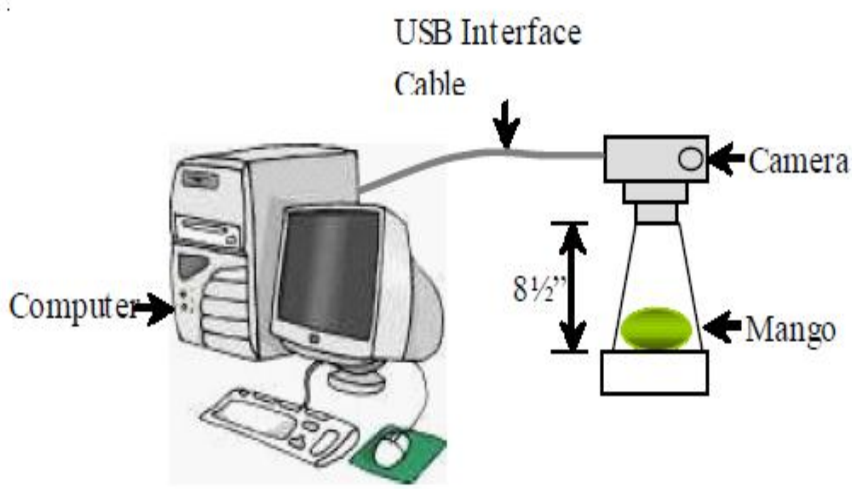


Figure 1. The image acquisition setup

Figure 2. A sample mango image

3.1. Image analysis

The flowchart of the image analysis algorithm is shown in Figure 3.

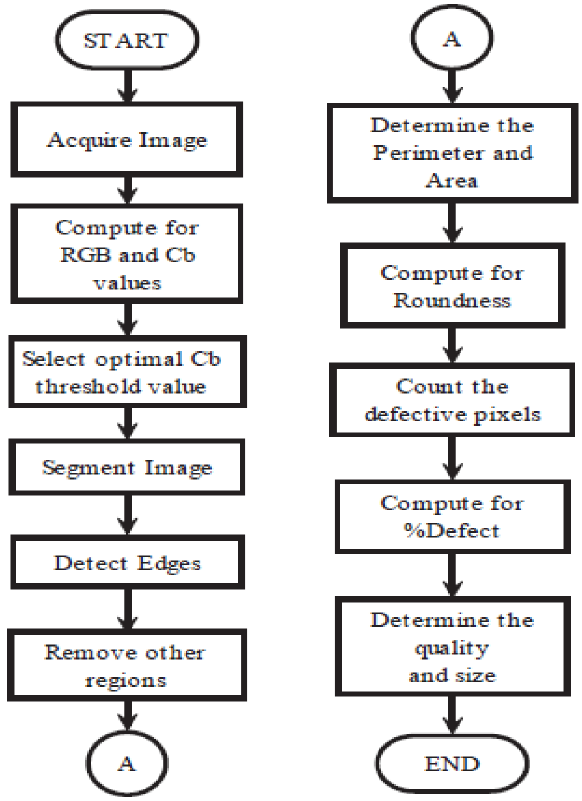


Figure 3. Flowchart of the algorithm

After acquiring the image, RGB and Cb values were calculated. Since segmentation uses a threshold value, an optimal Cb value was used. The selection of the optimal value is called isodata algorithm and can be outlined as follows:

1. Assuming no knowledge about the exact location of objects, consider as a first approximation that the four concerns of the image contain background pixels only and the remainder contains object pixels.

2. At step t, compute $m^t{}_B$ and $m^t{}_O$ as the mean background and object grey-level respectively, where segmentation into background and objects at step t is defined by the threshold value T^t determined in the previous step:

M'B = Σ(i.j)background f(i,j)/number background pixels (1)

μ'O = Σ(i.j)objects f(i,j)/number object pixels (2)

Set T(t + 1) = μ'B + μ'O /2 (3)

T(t + 1) provides an updated background distinction

If T (t+1) = T (t), halt; otherwise return to step 2.

When the Cb value of a pixel is greater than the threshold then it is marked as 0 (background) otherwise it is 1 (object). After segmentation edges were detected and marked as 2. Since a large image requires a lot of memory and longer processing time a bounding box was used to limit the area. Boundary tracing was used to determine the boundary of each region that was formed after segmentation. Region identification was done simultaneously with boundary tracing and the label started with 3. The region with the highest boundary length was considered as the mango. Other regions were removed so that the final segmented image will result to an image with one region only.

The features of the mango were extracted using the final segmented image. The perimeter is equal to the boundary length while the area is the total object pixels excluding the edge pixels. Roundness can then be computed by using equation (4)

$$\text{Roundness} = (4p \times \text{Area})/\text{Perimeter}^2 \qquad (4)$$

Using a Cb threshold of 118 the object pixels were classified as healthy or defective. After counting the defective pixels the percent defect is calculated by using equation (5).

$$\%\text{Defect} = (\text{Defective pixels} / \text{Area}) \times 100\% \qquad (5)$$

3.2. Object classification

The class of a mango was determined using nearest neighbour technique. This algorithm classified an input pattern by looking for the closest match in the training set. The training phase was called lazy learning since the training instances were simply memorized. The complete training set was stored and further calculations were delayed until a request for classifying was received. During the testing phase the input pattern was classified by looking for a training instance that was closest to it. Brute force nearest neighbour compared all the training instances to the unknown using a distance function. Continuous attributes usually use the Minkowski metrics like Euclidean or Manhattan distance while discrete attributes look for exact matches. The quality of the mango was determined by using brute force and Euclidean distance.

3.3. Mango image segmentation

After acquiring all mango images, a set of images is randomly picked and used as a training set for building a mango's surface chromaticity model. Mango pixel regions are segmented by hand from the training images. A mango's surface hue model is then constructed using hue values computed from those pixels. This model is then used to segment mango region from the original input images using a simple chromaticity similarity. Figure 4 shows hue histogram of an input image. Some spatial morphology such as closing and opening operations [10] is then applied to suppress the segmentation errors. The segmentation result is shown in Figure 5.

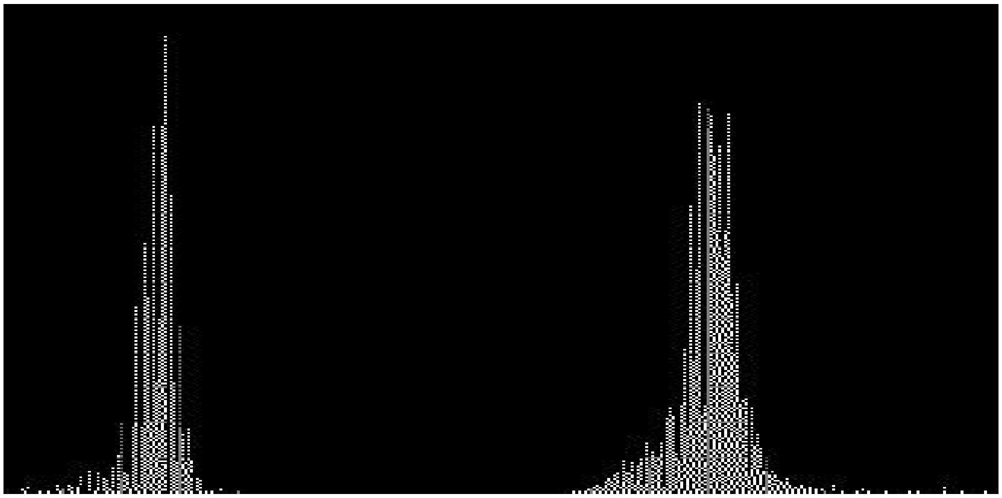


Figure 4. Hue histogram of an input image

Figure 5. Segmented mango image

Although the spatial filtering can eliminate most segmentation false, however, there is still some erroneous segmentation found along the edges of the mango shown in Figure 6. This could be due to the sampling effect and blurry image.

Figure 6. Erroneous segmentation along the edges

To smooth the mango region, spline curvature fitting using MATLAB function is then applied. The initial control points for spline fitting are extracted from preliminary boundary pixels. To do this, first apply boundary detection algorithm on the early segmented image. Then every nth boundary pixels are selected and used as initial control points. A cropped region of spline-fit mango image is shown in Figure 7.

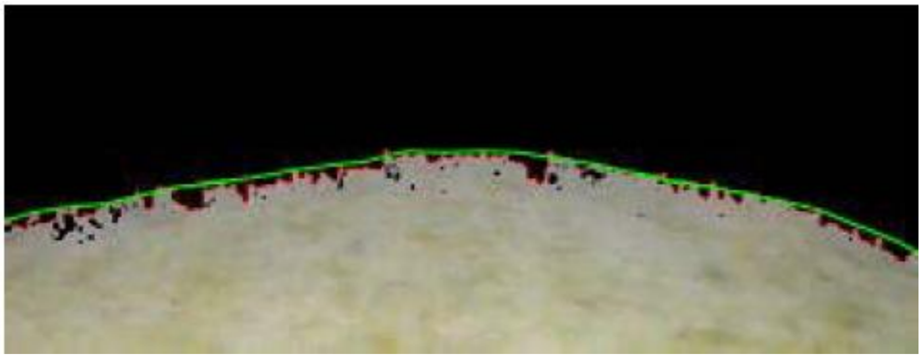


Figure 7. Result after spline fit

3.4. Physical properties analysis

After obtaining clean segmented mango region, analyze the image to obtain some physical properties of the mangoes such as size, shape, area, and color. In this research, we define a set of parameters that are used to refer to mangoes' physical properties as follows:

3.4.1. Projected area (A): is defined as the area of the 2D projection image of the top view mango. This can be easily estimated by counting number of pixels inside the boundary.

3.4.2. Length (L): is defined as the distance between the pole and the tip of the mango. The line between the pole and the tip called mango's major axis.

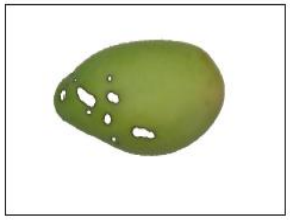
3.4.3. Width (W): is defined as the maximum distance from a boundary pixel to another boundary pixel that is on the other side of the major axis, and the line between them, which is called mango's minor axis, is perpendicular to the major axis.

3.4.4. Color: can also be spatially analyzed and indexed in the database for future classification. The color features are measured separately in five regions; northeast, southeast, southwest, and northwest of the major and minor axes, and at the center where major and minor axes intersected. The color model in RGB as it is original color space when acquiring image and it is easily to transform to other color metrics when needed.

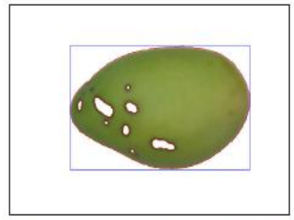
3.4.5. Surface area (S): is defined as the area of the surface of mango in 3D. To measure surface area of the mango, all the mangoes were peeled using hand peelers. The peels images are then captured and digitized using a scanner at 300dpi. The image is then binarized, where white pixels correspond to mango peel and black pixels correspond to background. However, the image obtaining from scanner is not clean. A salt-and-pepper noise reduction technique must be applied.

4. Results and Discussion

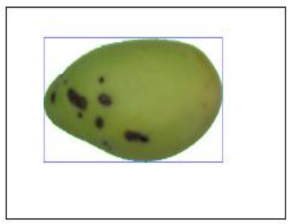
The human visual system perceives a color stimulus in terms of luminance and chrominance so that YCbCr color space is used in the study. The Cb color value is used in segmenting the mango from the background. The isodata algorithm was used in determining the threshold con-verged for all the images that were used in the study. Figure 8 shows the step by step processes that lead to the final segmented image.



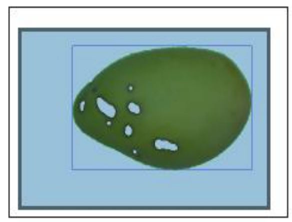
a. Segmented image.



b. Marked edges with bounding box.



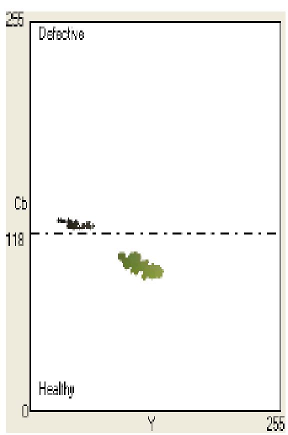
c. Image after boundary tracing and region identification.



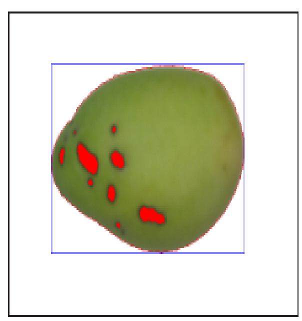
d. Final segmented image.

Figure 8. Processed leading to the final segmented image

Using the final segmented image the object's pixels are classified as healthy or defective. Figure 8 shows the result of pixel classification of the object in the sample image. After pixel classification the extracted features and the mango's class are displayed as shown in Figure 9.



a. Defective and healthy pixels of the sample image.



b. The segmented image with defective pixels.

Figure 9. Pixel classification of the object in the image

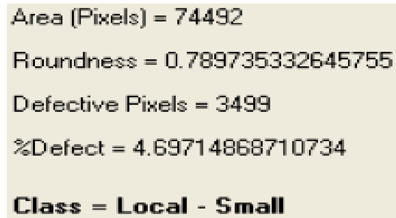


Figure 10. Extracted features and class of the mango

5. Conclusion

An image analysis algorithm has been implemented to measure the size, roundness, and percent defect of a mango. Nearest neighbour technique with Euclidean distance was used to determine the quality of the mango since the data points cannot be easily separated. The size was determined using thresholds since the data points with the same size lie nearer to each other.

The processes that lead to the final segmented image were very important since its result will be used for feature extraction. The threshold used in classifying the object's pixels properly identified the defective areas of the mango.

The algorithm correctly segmented the mango even if its position was changed. However, it cannot correctly identify the stem since it can be brown or green. The green stem pixels were classified as healthy while the brown stem pixels were classified as defective.

References

[1] K. V. Ravishankar, "Assessment of Genetic Relatedness among Mango Cultivars of India using RAPD Markers", Journal of Horticultural Science and Biotechnology, vol. 75, no. 2, **(2000)**, pp. 198-201.
[2] J. M. Lattin, "Analyzing Multivariate Data", Pacific Grove, CA: Thomson Brooks/Cole, (**2003**).
[3] S. B. Sivapalasingam, "A Multistate Outbreak of Salmonella Enterica Serotype Newport Infection Linked to Mango Consumption: Impact of Water-Dip Disinfestation Technology", Clinical Infectious Diseases, vol. 37, no. 12, (**2003**), pp.1585-1590.
[4] C. C. Teoh, "Use of Image Analysis for Grading Size of Mango", In International Symposium on Greenhouses, Environmental Controls and In-house Mechanization for Crop Production in the Tropics, vol. 710 , (**2005**), pp. 485-490.
[5] M. Khan, "Analysis of the Effect of Process Variables on the Osmotic Dehydration of Mango and Process Optimizations using a Genetic Algorithm Approach", In III International Symposium on Applications of Modeling as an Innovative Technology in the Agri-Food Chain, vol. 674, (**2005**), pp. 181-188.
[6] M. Cavalcanti, "An Adaptive Threshold Level for Segmentation of Grayscale Images Using Image Processing to Sort Mangoes by Weight Estimation", In XXVIII International Horticultural Congress on Science and Horticulture for People : International Symposium, vol. 934, (**2010**), pp. 943-948.
[7] D. Ruhm, "Applications of the Ruhm-Mango-Kreps Conditional Risk Charge Algorithm", AST/N Bulktin (**2010**).
[8] A. Deshpande, "X-Ray Imaging for Non-Destructive Detection of Spongy Tissue in Alphonso Mango", Computer Vision and Information Technology: Advances And Applications, vol. 252, (**2010**).
[9] M. Chhabra", "Automated Detection of Fully and Partially Riped Mango by Machine Vision", In Proceedings of the International Conference on Soft Computing for Problem Solving, Berlin, (**2012**), December 20-22.
[10] D. Bulanon, "A Low-cost Machine Vision System for Mango Sorting", Journal of Hokkaido Branch of the Japanese Society of Agricultural Machinery, vol. 46, (**2012**), pp. 99-103.
[11] C. Teoh, "Image Processing and Analysis Techniques for Estimating Weight of Chokanan Mangoes", Journal of Tropical Agriculture and Food Science, vol. 35, no.1, (**2010**), pp. 183.
[12] D. Majumder, "Genetic Diversity of Mango (Mangifera indica L., Anacardiaceae)", International Journal of Agriculture Environment & Biotechnology, vol. 4, no.1, (**2011**), pp. 45-51.
[13] T. Chalidabhongse, "2D/3D Vision-based Mango's Feature Extraction and Sorting", In Control, Automation, Robotics and Vision, (**2006**), pp. 1-6.

[14] B. Jarimopas, “Firmness Properties of Mangoes”, International Journal of Food Properties, vol. 10, no. 4, (**2010**), pp. 899-909.
[15] I. Pott, “Quality Improvement of Non-Sulphited Mango Slices by Drying at High Temperatures”, Innovative Food Science & Emerging Technologies, vol. 6, no.4, (**2010**), pp. 412-419.
[16] A. González, “Use of UV-C Irradiation to Prevent Decay and Maintain Postharvest Quality of Ripe”, International Journal of Food Science and Technology, vol. 36, no. 7, (**2008**), pp. 767-773.
[17] F. Hahn, “Mango Firmness Sorter”, Biosystems Engineering, vol. 89, no. 3, (**2008**), pp. 309-319.
[18] P. Yimyam, “Physical Properties Analysis of Mango using Computer Vision”, In Proceeding of ICCAS, (**2005**).
[19] S. Neidhart, “The Control of Postharvest Ripening Processes and its Implications for the Productivity of Mango Processing”, Sustainable Land Use in Mountainous Regions of Southeast Asia, (**2007**), pp. 134-146.
[20] E. Rivera, I. Belencio, M. L. Paredes, A. Yap and R. Flores, “Trends and Developments in Evaluating a Concrete Rectangular Beam through Short Messaging Systems”, BS Thesis, Civil Engineering Department, FEATI University, Manila, (**2003**).
[21] M. Reyes, “Non-Destructive Inspection of Mango Fruit (Mangifera indica L.) with Soft X-ray Imaging”, In VI International Symposium on Mango, vol. 509, (**2009**), pp. 787-792.
[22] K. Walsh, “Sorting of Fruit using Near Infrared Spectroscopy: Application to a Range of Fruit and Vegetables for Soluble Solids and Dry Matter Content”, Journal of Near Infrared Spectroscopy, vol. 12, (**2008**), pp. 141-148.
[23] M. Valente, “Multivariate Calibration of Mango Firmness using VIS/NIR Spectroscopy and Acoustic Impulse Method”, Journal of Food Engineering, vol. 94, no.1, (**2009**), pp. 7-13.
[24] N. Mustafa, “Agricultural Produce Sorting and Grading using Support Vector Machines and Fuzzy Logic”, In Signal and Image Processing Applications, (**2009**), pp. 391-396.
[25] W. Spreer, “Estimating the Mass of Mango Fruit (Mangifera indica, cv. Chok Anan) from its Geometric Dimensions by Optical Measurement”, Computers and Electronics in Agriculture, (**2009**).
[26] E. Bayogan, “Carabao Mango Harvest Quality and production Practices and Problems of Growers in Davao Oriental, Philippines”, ACTA Horticulturae, vol. 699, (**2009**), p.103.
[27] P. Sirisomboon, “Instrumental Textural Properties of Mango at Commercial Harvesting Time”, International Journal of Food Properties, vol. 14, no. 2, (**2011**), pp.441-449.
[28] C. Tautho, “Production, Postharvest Handling and Marketing Practices of Mango Growers in Bukidnon”, Philippine Journal of Crop Science, vol. 27, (**2007**).

Author

Tomas U. Ganiron Jr

He obtained his Doctor of Philosophy in Construction Management at Adamson University (Philippines) in 2006, and subsequently earned his Master of Civil Engineering major in Highway and Transportation Engineering at Dela Salle University-Manila (Philippines) in 1997 and received Bachelor of Science in Civil Engineering major in Structural Engineering at University of the East (Philippines) in 1990. He is a registered Civil Engineer in the Philippines and Professional Engineer in New Zealand. His main areas of research interest are construction engineering, construction management, project management and recycled waste materials.

