

Chapter 2

Machine Vision Based Techniques for Automatic Mango Fruit Sorting and Grading Based on Maturity Level and Size

C. S. Nandi, B. Tudu and C. Koley

Abstract In recent years automatic vision based technology has become more potential and more important to many areas including agricultural fields and food industry. An automatic electronic vision based system for sorting and grading of fruit like Mango (*Mangifera indica* L.) based on their maturity level and size is discussed here. The application of automatic vision based system, aimed to replace manual based technique for sorting and grading of fruit as the manual inspection poses problems in maintaining consistency in grading and uniformity in sorting. To speed up the process as well as maintain the consistency, uniformity and accuracy, a prototype electronic vision based automatic mango sorting and grading system using fuzzy logic is discussed. The automated system collects video image from the CCD camera placed on the top of a conveyer belt carrying mangoes, then it process the images in order to collect several relevant features which are sensitive to the maturity level and size of the mango. Gaussian Mixture Model (GMM) is used to estimate the parameters of the individual classes for prediction of maturity. Size of the mango is calculated from the binary image of the fruit. Finally the fuzzy logic techniques is used for automatic sorting and grading of mango fruit.

Keywords Electronic vision · Fruit sorting and grading · Video image · Maturity prediction · Gaussian mixture model (GMM) · Fuzzy logic

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1 Introduction

Machine vision and image processing techniques have been found increasingly useful in the fruit industry, especially for applications in quality inspection and defect sorting applications. Thus fruit produced in the garden are sorted according to quality and maturity level and then transported to different standard markets at different distances based on the quality and maturity level. Sorting of fruits according to maturity level is most important in deciding the market it can be sent on the basis of transportation delay.

In present common scenario, sorting and grading of fruit according to maturity level are performed manually before transportation. This manual sorting by visual inspection is labor intensive, time consuming and suffers from the problem of inconsistency and inaccuracy in judgment by different human. Which creates a demand for low cost exponential reduction in the price of camera and computational facility adds an opportunity to apply machine vision based system to assess this problem.

The manual sorting of fruits replaced by machine vision with the advantages of high accuracy, uniformity and processing speed and more over non-contact detection is an inevitable trend of the development of automatic sorting and grading systems [1]. The exploration and development of some fundamental theories and methods of machine vision for pear quality detection and sorting operations has been accelerate the application of new techniques to the estimation of agricultural products' quality [2].

Many color vision systems have been developed for agricultural grading applications which include direct color mapping system to evaluate the quality of tomatoes and dates [3], automated inspection of golden delicious apples using color computer vision [4]. Color image processing techniques, presented in [5] was proposed to judge maturity levels or growing of the agricultural products.

In recent years, machine vision based systems has been used in many applications requiring visual inspection. As examples, a color vision system for peach grading [6], computer vision based date fruit grading system [7], machine vision for color inspection of potatoes and apples [8], and sorting of bell peppers using machine vision [9]. Some machine vision systems are also designed specifically for factory automation tasks such as intelligent system for packing 2-D irregular shapes [10], versatile online visual inspections [11, 12], automated planning and optimization of lumber production using machine vision and computer tomography [13], camera image contrast enhancement for surveillance and inspection tasks [14], patterned texture material inspection [15], and vision based closed-loop online process control in manufacturing applications [16].

Here the proposed technique applies machine vision based system to predict the maturity level and size of mango from its RGB image frame, collected with the help of a CCD camera. In additions, the method can be extended and applied to analyze and extract the visual properties of other agricultural products as well. The materials and methods, details preprocessing of image, different feature extraction methods and the basic theory of GMM are discussed in the following sections. Finally the results, discussions and conclusions are summarized at the last section.

2 Materials and Methods

2.1 Sample Collection

For the experimental works total 750 number of unsorted mangoes of five varieties locally termed as “Kumrapali” (KU), “Amrapali” (AM), “Sori” (SO), “Langra” (LA) and “Himsagar” (HI) were collected from three gardens, located at different places of West Bengal, India. Collection of mangoes were performed in three batches with an interval of one week in between batches and in each batch 250 numbers of mango were collected, having 50 numbers of each variety i.e. KU, AM, SO, LA and HI. Steps were taken to ensure randomness in mango collection process from the gardens in each batch. After collection of mangoes each mango were tagged with some unique number generated on the basis of variety, name of the origin garden, batch number and serial number etc. Three independent human experts work in the relevant field were selected for manual identification of maturity.

Each mango was used to pass through a conveyer belt every day until it rotten and was presented to the experts (after removing tags) for recording of human expert predicted maturity level. Then the mangoes were stored in a manner as used during transportation.

2.2 Experimental Procedure

A schematic diagram of electronic vision based system for automatic mango fruit sorting and grading is shown in Fig. 1. The camera used in the study was a 10 megapixel CCD (charge-coupled device) camera for capturing the video image. Then the still frame are extracted using MATLAB software from the video images with frame rate of 30 frames/sec. The camera was interfaced with a computer through USB port. The proposed algorithm was implemented in Lab VIEW[®] Real Time Environment for automatic sorting and grading. Light intensity inside the closed image capturing chamber was kept at 120 lux, measured with the help of lux meter (Instek-GLS-301) and was controlled automatically by the light sensor along with light intensity controller and light source supplier.

The automated fruit sorting and grading system consists of a motor driven conveyer belt to carry the fruits serially. The fruit placer places one fruit at a time on the conveyer belt and the belt carries it to the imaging chamber where the video image of fruit is captured by the computer through CCD camera. The proposed algorithm runs into the computer automatically to classify the fruit on the basis of four different maturity level like raw (M1), semi-matured (M2), matured (M3) and over matured (M4) and then give a direction to the sorting unit to place the mango in appropriate bin. The sorting unit consists of four solenoid valves driven by respective drive units, which are controlled by the computer. The time delay in between image capturing

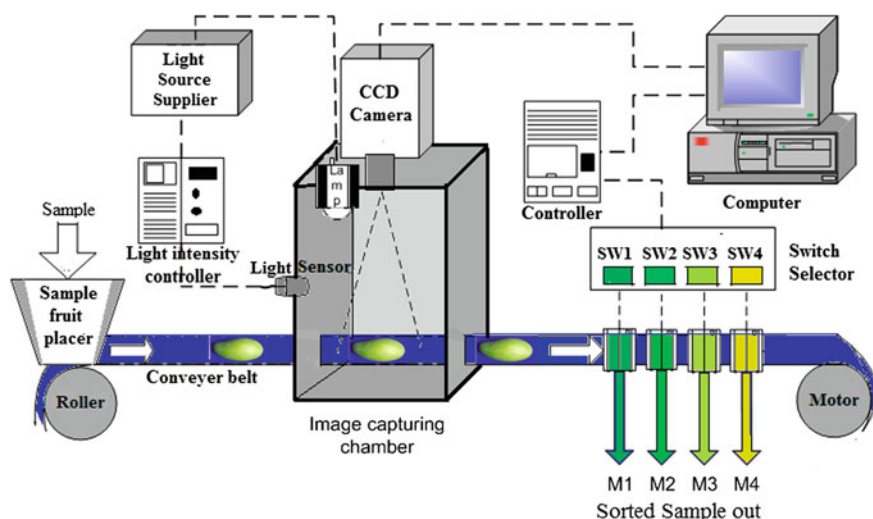


Fig. 1 Proposed model of machine vision based automated mango fruit sorting and grading system

of a fruit and the triggering the solenoid valve is estimated by the computer on the basis of conveyer belt speed.

The color of the conveyer belt was chosen blue for two reasons. First, blue does not occur naturally in mangoes. Second, blue is one of the three channels in the RGB color space, making it easier to separate the background from the image of mango.

The image capturing chamber is a wooden box and the ceiling of the chamber is quoted with reflective material to reduce the shading effect. A CCD camera is mounted in the top center of the image capturing chamber. One fluorescent lamp is mounted at the top of the chamber. The camera is mounted right side the light source for the best imaging. The distance between the CCD camera and the fruit on the conveyer belt is kept 20 cm.

The light intensity inside the imaging chamber is measured and consequently controlled by a separate light intensity controller, which keep the light intensity constant irrespective of power supply voltage and any variation of the filament characteristics and changes in ambient environment. However, even with the lamp current being constant, the light output of the lamp still varies resulting from the lamp ageing, filament or electrode erosion, gas adsorption or desorption, and ambient temperature. These effect cause changes in the RGB values of the images. The light intensity controller corrects for the lamp output changes, maintaining a constant short and long-term output from the lamp. The light output regulating unit is made up of a light sensing head and a controller. The (silicon based) light sensor is also mounted near to the sample fruit inside the chamber monitors part of the light source output; the controller constantly compares the recorded signal to the pre-set level and

changes the power supply output to keep the measured signal at the set level i.e. 120 lux.

In this system the motor speed and distance between the two consecutive mangoes are taken as input. If the motor speed and distance between two consecutive mangoes are known then we can find a frame that will be the best still image of full mango within the imaging chamber. In our system the speed of the conveyer belt was 2 ft/sec, length of the imaging chamber was 1ft and the distance between two consecutive mangoes on the conveyer belt was 1ft. So 7,200 samples/hour can be sorted by our system. This rate can be increased by increasing the speed of the conveyer belt and reducing the distance between two consecutive samples in the conveyer belt. But if we increase the speed of the conveyer belt the motion blur effect will occur. So this can't be increased very much. We have to trade off between this two. The size of the still frame in this system was 480×640 pixels.

2.3 Color Calibration of CCD Camera

The value of RGB is device dependent. So camera calibration [17] is essential for color inspection systems based upon machine vision to get the intrinsic and extrinsic parameters for providing accurate and consistent color measurements. When a camera creates an image, that image does not represent a single instant of time. Because of technological constraints or artistic requirements, the image may represent a scene over a period of time. Most often this exposure time is brief enough that the image captured by the camera appears to capture an instantaneous moment, but this is not always so, and a fast moving object or a longer exposure time may result in blurring artifact which makes this apparent. As object in a scene movie, an image of that scene must represent an integration of all positions of those objects, as well as the camera viewpoints, over the period of exposure determine by the shutter speed. Motion blur error during extraction of still frame from video image can be reduced by increasing the shutter speed of the camera and can be eliminated by using camera having global shutter technology. Many software products (e.g. Adobe Photoshop or GIMP) offer simple motion blur filters. However, for advanced motion blur filtering including curves or non-uniform speed adjustment, specialized software products are necessary.

2.4 Images of Different Category and Different Maturity Level of Mango

An image matrix for five varieties ("KU", "SO", "LA", "HI" and "AM") of mango having four different maturity levels (M1, M2, M3 and M4) are shown in Fig. 2.



Fig. 2 Images of five varieties mango having different maturity level. 1st row: "KU", 2nd row: "SO", 3rd row : "LA" and 4th row: "HI" and 5th row: "AM". Images are taken with an interval of 2 days, shown in (a) 1st column: raw (M1) (b) 2nd column: semimatured (M2) (c) 3rd column: matured (M3) (d) 4th column: over-matured (M4)

3 Pre-processing of Images

The performance of the sorting and grading system depends on the quality of the images captured by the video camera, since various measures/features calculated from the images of the mangoes will be used for sorting and grading. Video signal collected from camera found to be contaminated with motion blur artifact and noise, thus proper extraction of images from video frames and then filtering is essential. On the other hand mangoes moving through the conveyer belt, can be at any position along with the background thus in order to reduce computation, removal of background by detecting the edges of the image and alignment of the mango images in axial position is necessary. The present section discuss about all these preprocessing issues, in brief.

3.1 Still Frame Extraction from Video Image

At first the video streams acquired by the CCD camera are separated into sequence of images and then to remove motion deblurring wiener filtering method [18] was used. Motion compensated four frames are shown in Fig. 3.

3.2 Filtering of Mango Image

Though the images were taken in controlled environment under fixed illumination of light of 120 lux with the help of tungsten filament lamp, but there were some noises in the picture. To remove these noises a simple median filter found to provide reasonable good performance but it is computationally intensive. For that pseudo-median filter [19] was used in the work, as it is computationally simpler and possesses many of the properties of the median filter. This filtering process often helped to obtain smooth continuous boundary of the mango.

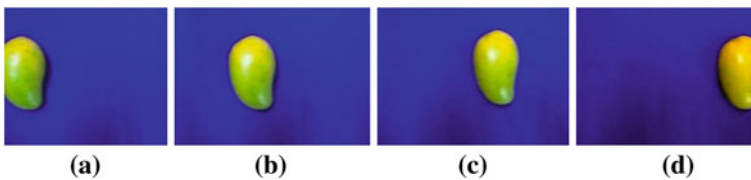


Fig. 3 Extracted still frames from the video image with an interval of 5 frames, (a) frame no.10, sample entering into the imaging chamber (b) frame no.15, sample near the middle of the imaging chamber (c) frame no. 20, sample crossing the middle position of imaging chamber (d) frame no. 25, sample going out from imaging chamber

3.3 Edge Detection and Boundary Tracing

Experimentally it was observed that for all the set of the RGB mango images the G value is always greater than the B value for that reason the color of the background was kept blue with R, G and B value of close to 0, 0 and 255 respectively, as much as possible. So with the help of simple comparison the back ground was eliminated, and the image was converted to binary image (BW). Small patches containing number of pixel less than 800 were removed. This cutoff number was determined experimentally, by studying all the images of the mango.

In order to find the boundary or the contour of the mango, a graph contour tracking method based on chain-code was adopted. This algorithm found to work reasonable fast, as the boundary of the mango is not so complex. The details of algorithm can be found in [20]. Here a brief description is given. The algorithm first detects every run at each row and records every single run's serial number and the corresponding start-pixel coordinates and end-pixel coordinates are stored in a table named as "ABS". Through this method, the run-length code of the image is obtained. Then, a 3×3 pixel box is adopted to detect the relationship between the objective pixel and its eight-connected surrounding pixels. All the runs are categorized into 5 classes, and then each run's serial number along with the corresponding class label was recorded in another table named as "COD". Then, the algorithm searches the ABS-table and COD-table sequentially. Based on the coordinates and class of each run recorded on the table, the starting pixel of the contour is recognized and the contour is successfully followed. And the chain code is generated while following the contour. An image of mango along with the traced boundary is shown in Fig. 4.

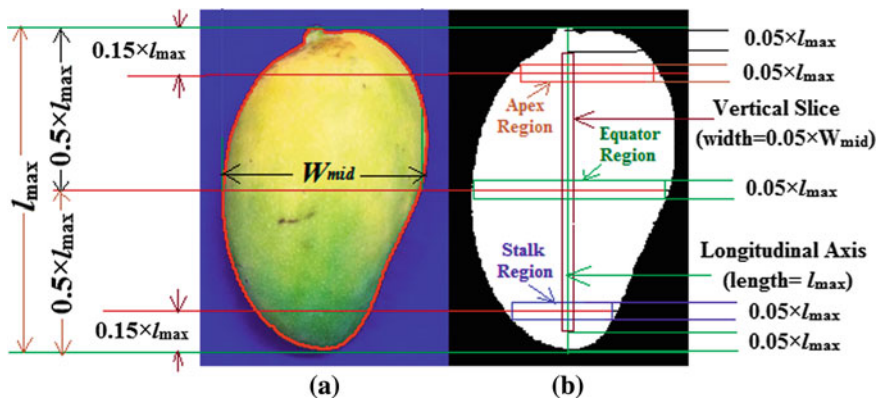


Fig. 4 Filtered images of Mango, **a** raw mango image along with the obtained contour, **b** binary image of the same mango after removing the small patches, also shows the different positions and their name as used in the work

3.4 Alignment of the Mango Image

After getting the contour of the mango, search to find the longitudinal axis of the mango is obtained. Let $C(x_i, y_i)$, $i = 1, 2, \dots, N$ (N is the total number of points in the contour) represent the obtained contour of a mango, then two end points (x_1^l, y_1^l) and (x_2^l, y_2^l) are the points for which $l = \sqrt{(x_i^l - x_j^l)^2 + (y_i^l - y_j^l)^2}$ is maximum, where $i, j = 1, 2, \dots, N$. After getting the coordinates of the two boundary points along the longitudinal axis the image was rotated by an angle determined by $\theta = \tan^{-1}[(y_2^l - y_1^l)/(x_2^l - x_1^l)]$, this rotation will align the mango vertically but may not be able to place the “apex” region at the top, it may be at the bottom position. To fix the problem another rotation of 180° was made if the “apex” region is in bottom position. The detection of the “apex” or the “stalk” was made on the basis of geometrical properties of the varieties of the mango under test. For all the varieties of the mango the width of the apex is always higher than the stalk, this properties was utilized to place the apex region at the top of the image. The center point of the apex/stalk region is the point lies on the longitudinal axis at a distance of $0.15 \times l_{\max}$ from the two end points of the longitudinal axis. This relation was determined experimentally, and found true for all the varieties of the mango under test.

4 Extraction of Features

In order to predict the maturity level with the help of computer, some suitable measures collected from the images of the mangoes need to be investigated, which are most correlated with the maturity level. This section discuss about the various features, selection of the features are mainly based on the experienced gain by the authors, while discussing this issue with the experts involves in manual sorting and grading process. Total 27(F1, F2, F3,F27) numbers of features are extracted, out of these 15(F1, F2, F3F15) numbers are main features and rest 12(F16, F17F27) numbers are derived features. Different main features and the derived features are discussed in the following sections.

4.1 Main Features

4.1.1 Average R, G and B Value of the Entire Mango

This represent the average R, G and B value of the entire mango and was calculated from the following equation:

$$A_{k=R,G,B} = \frac{1}{rc} \sum_{i=1}^r \sum_{j=1}^c (I_k \times BW) \quad (1)$$

where, BW is the binary image acting as a mask set the region outside the contour of the mango to 0, and I_k is the captured RGB image, r and c represent the total number of rows and columns of the image.

4.1.2 Gradient of R, G and B Value Along the Longitudinal Axis

Due to the fact that the mango start ripe from the apex region, so the slope of the R, G and B varies from apex region to stalk region (shown in Fig. 5), and this variation found to be different under different maturity level of the mango. The slope of the R, G and B were determined by the following equation. First by taking a slice image along the longitudinal axis, the width of the sliced image is the 5% of the width of the mango at the middle position of the longitudinal axis and length in between 5% below and above of the two end points of the longitudinal axis.

$$S_{k=R,G,B} = slope \left(\sum_{i=-1}^p s_k(i, j) \right) \quad (2)$$

where p , is the width of the slice. The slope was determined by searching the best fit straight line by least mean square sense.

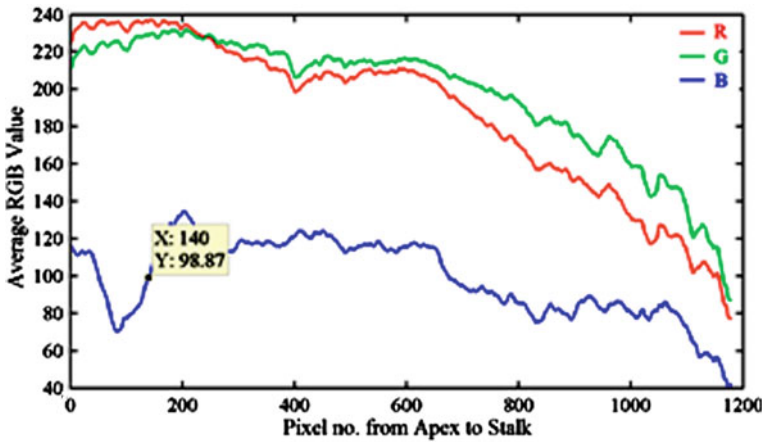


Fig. 5 Variation of R, G and B value along the longitudinal axis

4.1.3 Average R, G and B value of the Apex, Equator and Stalk region

For collecting the average R, G and B value for these three regions, slice images along the horizontal axis were extracted from the RGB image of the mango, the width of the each slice (along the longitudinal axis) is $0.05 \times l_{\max}$ and length is in between the end points of boundary along the horizontal axis cutting the center point of each region as shown in Fig. 4b. The average values were calculated according to:

$$As_k = \frac{1}{rc} \sum_{i=1}^r \sum_{j=1}^c Is_k \quad (3)$$

where Is_k , is the sliced RGB image, $k = R, G \text{ and } B$ and $s = Apex, Equator \text{ and } Stalk$.

4.2 Derived Features

From the above discuss main features some other derived features were calculated, these are as follows:

4.2.1 Difference of Average R, G and B Value of the Entire Mango

Differences of average R, G and B value of the entire mango i.e.

$$(A_R - A_G), (A_G - A_B) \text{ and } (A_R - A_B) \quad (4)$$

4.2.2 Differences of Average R, G and B Value for the Corresponding Apex, Equator and Stalk Region

Differences of corresponding average R, G and B value for the apex, equator and stalk region, i.e.

$$(A_{apex_R} - A_{equator_R}), (A_{equator_R} - A_{stalk_R}) \text{ and } (A_{apex_R} - A_{stalk_R}) \quad (5)$$

similarly for G and B also.

In the present work parameters of the individual classes are estimated from the above features using Gaussian Mixture Model. There are several techniques available for estimating the parameters of a GMM [21]. A brief theory of GMM is presented in next section, the details and the methods adopted in the present work for estimation of individual classes can be found in [22].

5 Gaussian Mixture Model

A Gaussian mixture density is a weighted sum of mixture component densities. The Gaussian mixture density can be described as:

$$p(\vec{x}|\theta) = \sum_{k=1}^M \omega_k p_k(\vec{x}) \quad (6)$$

where, M is the number of mixture components and ω_k , $k = 1, \dots, M$, are the mixture weights, subject to $\omega_k > 0$ and $\sum_{k=1}^M \omega_k = 1$, $p_k(\vec{x})$ are the component densities and $\vec{x}$ be a d -dimensional feature vector, $\vec{x} \in \mathbb{R}^d$. With $d \times 1$ mean vector μ_k and $d \times d$ covariance matrix S_k , each component density is a d -variate Gaussian density function given by:

$$p_k(\vec{x}) \approx N(\mu_k, S_k) \\ = \frac{1}{(2\pi)^{\frac{d}{2}} |S_k|^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} (\vec{x} - \mu_k)^T S_k^{-1} (\vec{x} - \mu_k) \right\} \quad (7)$$

For the classification of different category of mango, one needs to find the proper values of ω_k , μ_k and S_k , so that the GMM provide the best representation for distribution of the training feature vectors.

6 Maturity Prediction Using Gaussian Mixture Model

The variation of the three measures i.e. average R of entire mango, average R of apex region and difference between average R to G value for the three mangoes (two from KU variety and one from HI variety) with respect to different maturity level(day) are shown in Fig. 6a, b and c. From the Fig. 6a, b and c, it can be observed that these features are correlated with the maturity level, on the other hand the nature of variation of these measures for different variety of mangoes are different. Prediction of maturity level of mango using Support Vector Machine based Regression analysis can be found in [23]. The variation of average R with respect to average G for the four different maturity levels (i.e. M1, M2, M3 and M4 of KU) is shown in Fig. 6d. From this figure it can be observed that these two measures are not sufficient to classify the mangoes into four different classes accurately, due to overlapping of the features, which is due to variation of color texture of different samples.

The Probability Density Function (PDF) estimated using only two features i.e. average values of total G and B values is shown in Fig. 7a. When the same GMM was used to find the PDF of raw mangoes came from different gardens over three batches, it was observed that there are strong correlations of the mangoes in a batch originated from a specific garden, but PDF distribution of different batches and different gardens

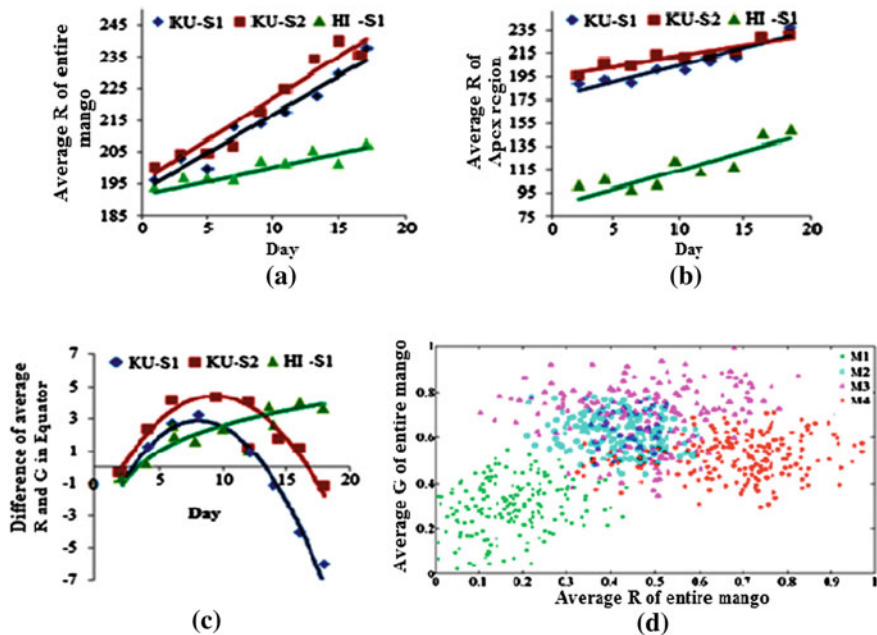


Fig. 6 **a** Variation of average R of entire mango with maturity level(day), **b** variation of average R in apex region with maturity level(day), **c** variation of difference of average R and G in equator with maturity level(day), **d** variation of average R to average G with four different maturity level(i.e. M1, M2, M3 and M4 of KU)

are often found to be different. This fact can be observed from the Fig. 7b, where it is seen that the several GMM components has been formed for the mangoes originated from different gardens and in different batches.

The summary statistics for some of the most correlated features is represented by box-whiskers plots, shown in Fig. 7c. The box corresponds to the inter-quartile range where top and bottom bound indicate 25 and 75th percentiles of the samples respectively, the line inside the box represents median, and the whiskers extend to the minimum and maximum values. The details of the box-whiskers plot can be found in [24]. After estimation, the evaluation of the classification performance was performed on a test data set, in which the objective was to find the class model which has the maximum a posteriori probability for a given observation sequence. The classification accuracy obtained using GMM. Misclassification may occur when different maturity level mangoes having similar color pattern, but it was observed that extraction of multiple features particularly gradient based features helped to correctly identify those mangoes, as some raw mangoes having color pattern of matured mango particularly in the apex region, but those mangoes shows high gradient value of 'R' along the longitudinal axis.

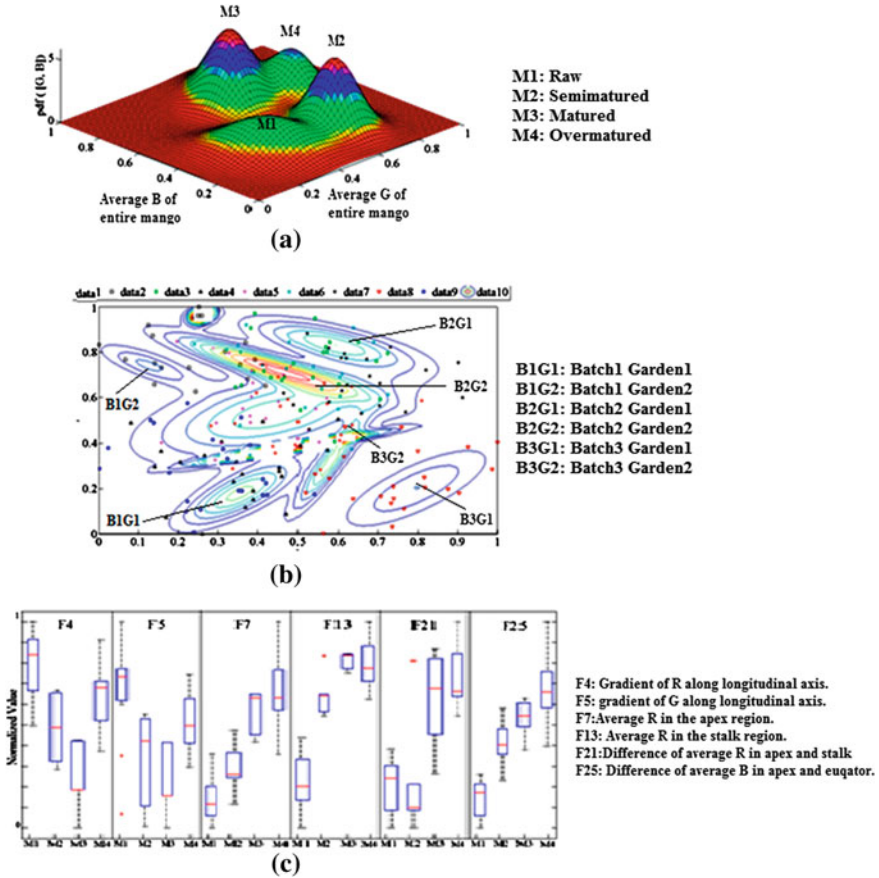


Fig. 7 **a** PDF distribution with average value of B and G of entire mango, **b** PDF distribution with the data set of mango collected from different batches and different gardens, and **c** box-whiskers plots for most correlated features

7 Size Calculation

The fruit size is another quality attribute used by farmers, the bigger size fruit is considered of better quality. The size is estimated by calculating the area covered by the fruit image. First the fruit image is binaries shown in Fig. 4b to separate the fruit image from its background. The number of pixels that cover the fruit image is counted and estimated the size. The fruits are categorized as small, medium, big and very big depending on the number of pixel of the binary image of the mango. According to the variety the range is converted in normalized domain and the corresponding membership function is shown in Fig. 11.

Table 1 Fuzzy if-then rules for classification

M/ s	M1	M2	M3	M4
SS	Q1	Q2	Q2	Q2
MS	Q1	Q2	Q3	Q3
BS	Q2	Q3	Q4	Q3
VB	Q2	Q4	Q4	Q3

M1: Raw

M2: Semi-mature

M3: Mature

M4: Over mature

SS: Small size

MS: Medium size

BS: Big size

VB: Very big size

Q1: Poor quality

Q2: Medium quality

Q3: Good quality

Q4: Verygood quality

8 Sorting and Grading Methodology Using Fuzzy Logic Technique

The sorting system depends on the prediction of maturity level and calculation of size. The flowchart of sorting and grading process is shown in Fig. 8.

Figure 9 shows the complete process of developing a fuzzy inference system (FIS) for sorting and grading process using MATLAB [25]. The process consist of three main steps: defining the input and output in Membership Function Editor, set the fuzzy rule in Rule Editor, and obtaining the output for each rule in Rule and Surface Viewer.

Fuzzy rule based algorithm is used to sort the mango fruit into four quality grades like poor (Q1), medium (Q2), good (Q3) and very good (Q4) based on their maturity level and size. The grading system has two inputs (maturity level and size) and one output (quality). Total 16 fuzzy if-then rules are created in order to sort the mango fruits into four different quality levels (Q1, Q2, Q3, and Q4). The fuzzy rule base is shown in Table 1. Examples of some rules are illustrated as in Table 2. The fuzzy inference system is shown in Fig. 10.

The rule viewer shown in Fig. 13 consists of the system's inputs and output column. The first and second column is the inputs which are maturity level and size while third column is the quality level output (defuzzification output). Based on the defuzzification results from the rule viewer in Fig. 13 where the maturity (= 0.66) is in matured set with membership grade 1 and size (= 0.5) is in big and medium set both with 0.5 membership grade. The defuzzification value of quality is calculated by using centroid method. Then the classification of fruit is determined based on crisp logic given in Table 3.

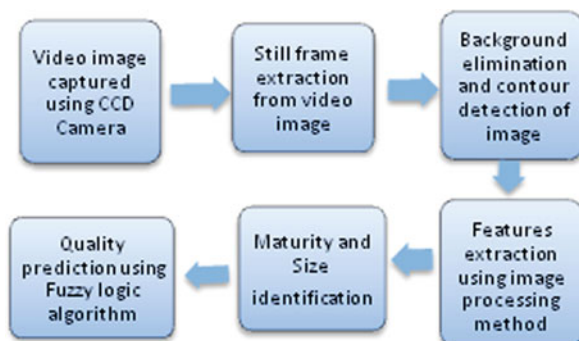


Fig. 8 Flowchart of sorting and grading process

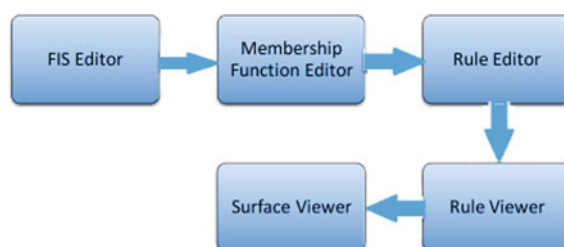


Fig. 9 Flowchart of Fuzzy Inference System

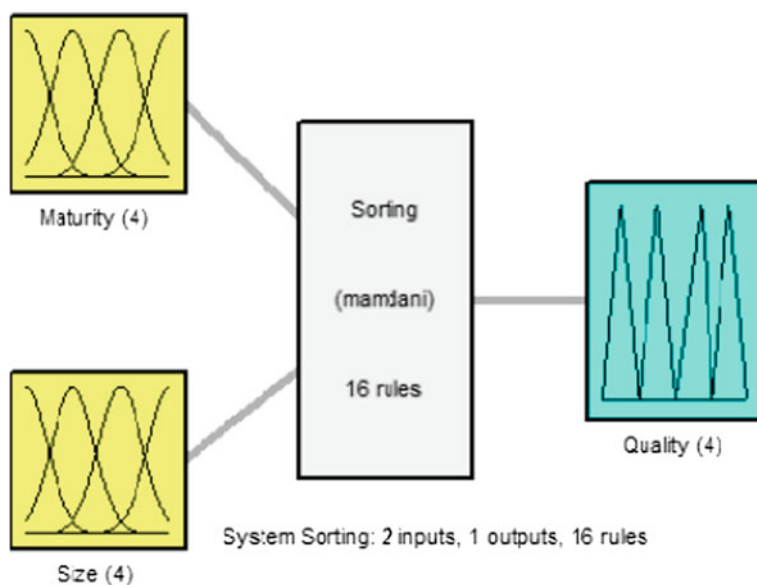


Fig. 10 Fuzzy inference systems

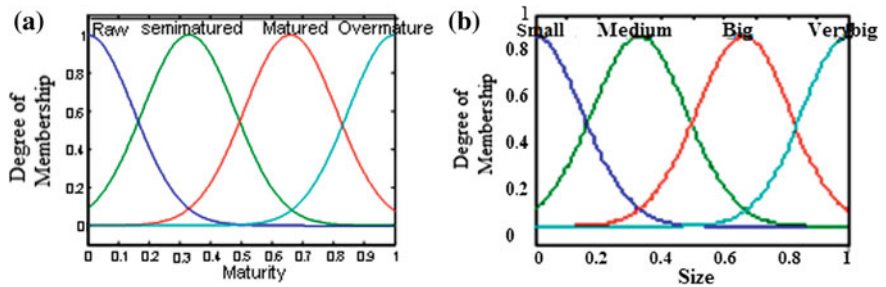


Fig. 11 Input membership functions representing maturity level (a) and size (b)

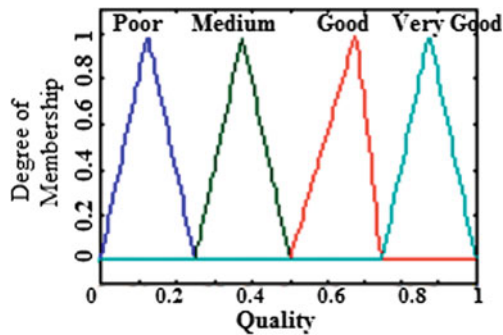


Fig. 12 Membership function representing quality output

Table 2 Fuzzy if-then rules

Rule 1	Rule 6
If maturity level is raw and size is small then quality is poor	If maturity level is semimature and size is medium then quality is medium
Rule 11	Rule 16
If maturity level is mature and size is big then quality is very good	If maturity level is overmature and size is very big then quality is good

The quality value is 0.626. Therefore, the mango used in experiment is graded as good quality.

9 Results and Discussion

The classification accuracy obtained using fuzzy logic algorithm based system and the average classification accuracy by the three experts for the five varieties of mango is presented in Table 4.

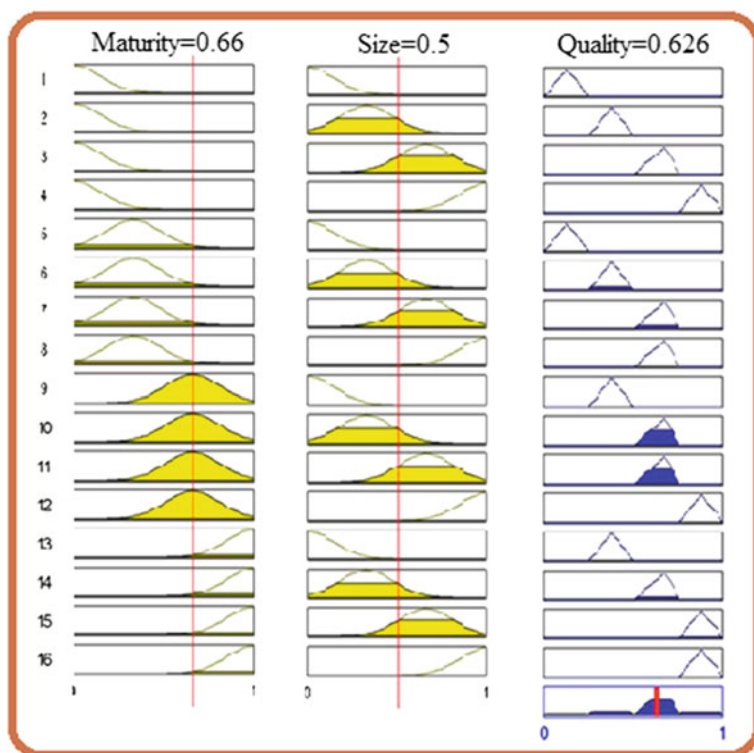


Fig. 13 Defuzzification results from rule viewer

Table 3 Fuzzification algorithm

Defuzzification output	Quality grade
(Quality value < 0.25)	Poor (Q1)
(Quality value ≥ 0.25) && (Quality value < 0.5)	Medium (Q2)
(Quality value ≥ 0.5) && (Quality value < 0.75)	Good (Q3)
(Quality value ≥ 0.75)	Very good (Q4)

10 Conclusions

In this chapter an application of machine vision based technique for automatic sorting and grading of mango according to the maturity level and size using fuzzy logic is discussed. Different image processing techniques were evaluated, to extract different features from the images of mango. Gaussian mixture model is used to estimate the parameters of individual classes to predict the maturity level. This technique found to be low cost effective and moreover intelligent. The speed of sorting system is limited by the conveyor belt speed and the gap maintained in between two mangoes

Table 4 Performance analysis

Variety (Local name)	Q1		Q2		Q3		Q4	
	Experts	System	Experts	System	Experts	System	Experts	System
KU	91.2	90.4	89.4	88.7	90.3	89.4	90.2	89.4
AM	90.7	90.1	90.0	89.1	88.9	88.2	90.1	89.4
SO	90.2	89.7	90.7	89.1	90.0	88.3	89.8	89.5
LA	91.1	90.5	90.9	88.6	89.2	88.8	91.0	89.7
HI	90.1	89.4	90.6	90.0	90.4	89.1	91.3	90.0

rather than response time of the computerized vision based system, which is on the order of ~ 50 ms.

Test has been conducted for the five varieties of mango fruit only, but can be extended for other fruits where there are reasonable changes in skin color texture occur with maturity. The variations of classification performances with the variation of other factors like changes in ambient light, camera resolution, and distance of the camera were not studied. The study shows that, machine vision based system performance, is closer to the manual experts, where experts judge the mangoes maturity level not only by the skin color but also with firmness and smell.

References

1. B. Jarimopas, N. Jaisin, An experimental machine vision system for sorting sweet tamarind. *J. Food Eng.* **89**(3), 291–297 (2008)
2. Y. Zhao, D. Wang, D. Qian, Machine vision based image analysis for the estimation of Pear external quality, in *Second International Conference on Intelligent Computation Technology and Automation*, 2009, pp 629–632
3. D.J. Lee, J.K. Archibald, G. Xiong, Rapid color grading for fruit quality evaluation using direct color mapping, *IEEE Trans. Autom. Sci. Eng.* **8**(2), 292–302 (2011)
4. Z. Varghese, C.T. Morrow, P.H. Heinemann, H.J. Sommer, Y. Tao, R.W. Crassweller, Automated inspection of golden delicious apples using color computer vision, *Am. Soc. Agric. Eng.* **16**, 1682–1689 (1991)
5. Y. Gejima, H. Zhang, M. Nagata, Judgement on level of maturity for tomato quality using L^*a^*b color image processing, in *Proceedings 2003 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM 2003)*, 2003
6. B.K. Miller, M.J. Delwiche, A color vision system for peach grading. *Trans. ASAE* **32**(4), 1484–1490 (1989)
7. A. Janobi, Color line scan system for grading date fruits, in *ASAE Annual International Meeting*, Orlando, Florida, USA, 12–16 July, 1998
8. Y. Tao, P.H. Heinemann, Z. Varghese, C.T. Morrow, H.J. Sommer, Machine vision for color inspection of potatoes and apples. *Trans. ASAE* **38**(5), 1555–1561 (1995)
9. S.A. Shearer, F.A. Payne, Color and defect sorting of bell peppers using machine vision. *Trans. ASAE* **33**(6), 2045–2050 (1990)
10. A. Bouganis, M. Shanahan, A vision-based intelligent system for packing 2-D irregular shapes. *IEEE Trans. Autom. Sci. Eng.* **4**(3), 382–394 (2007)
11. H.C. Garcia, J.R. Villalobos, Automated refinement of automated visual inspection algorithms. *IEEE Trans. Autom. Sci. Eng.* **6**(3), 514–524 (2009)

12. H.C. Garcia, J.R. Villalobos, G.C. Runger, An automated feature selection method for visual inspection systems. *IEEE Trans. Autom. Sci. Eng.* **3**(4), 394–406 (2006)
13. S.M. Bhandarkar, X. Luo, R.F. Daniels, E.W. Tollner, Automated planning and optimization of lumber production using machine vision and computed tomography. *IEEE Trans. Autom. Sci. Eng.* **5**(4), 677–695 (2008)
14. N.M. Kwok, Q.P. Ha, D. Liu, G. Fang, Contrast enhancement and intensity preservation for gray-level images using multiobjective particle swarm optimization. *IEEE Trans. Autom. Sci. Eng.* **6**(1), 145–155 (2009)
15. H.Y.T. Ngan, G.K.H. Pang, Regularity analysis for patterned texture inspection. *IEEE Trans. Autom. Sci. Eng.* **6**(1), 131–144 (2009)
16. Y. Cheng, M.A. Jafari, Vision-based online process control in manufacturing applications. *IEEE Trans. Autom. Sci. Eng.* **5**(1), 140–153 (2008)
17. W. Qi, F. Li, L. Zhenzhong, Review on camera calibration IEEE, in *Chinese Control and Decesion Conference*, 2010, pp 3354–3358
18. X. Jiang, C. Cheng, S. Wachenfeld, K. Rothaus, in *Motion Deblurring Seminar: Image Processing and Pattern Recognition*, Winter Semester 2004 / 2005
19. A. Rosenfeld, A.C. Kak, *Digital Image Processing*, (Academic Press, New York, 1982), cap 11
20. S.D. Kim, J.H. Lee, J.K. Kim, A new chain-coding algorithm for binary images using run-length codes. *CVGIP* **41**, 114–128 (1988)
21. S. Biswas, C. Koley, B. Chatterjee, S. Chakravorty, A methodology for identification and localization of partial discharge sources using optical sensors, *IEEE Trans. Dielectr. Electr. Insulation* **19**(1), 18–28 (2012)
22. E. S. Gopi, *Algorithm Collections for Digital Signal Processing Applications using Matla* (Springer, New York, 2007)
23. C. S. Nandi, B. Tudu, C. Koley, Support vector Machine based maturity prediction, in *WASET, International Conference ICCESSE-2012*, 2012, pp. 1811–1815
24. K. Fukunaga, *Introduction to Statistical Pattern Recognition* (Academic Press, Boston, 1990)
25. The Mathworks, *Fuzzy Logic Toolbox User's Guide*, (Release 2009b)

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