An Image Processing Technique for Grading of Harvested Mangoes .

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Abstract - *The proper grading of fruits is very important to increase the profitability in agricultural and food industry . In this paper, a scheme for automated grading of mango according to maturity has been proposed. The proposed scheme grades the mangoes in four different categories, which are determined on the basis of market distance and market value. The image of mango is given to the system thereafter several pre-processing algorithms like Gray-Scaling, Blurring, Thresholding are applied followed by RGB to HSV conversion algorithm and K-means algorithm are applied to get the final result.*

Key Words: Maturity, Quality, Grading, Days-to-rot, Grey scaling , Blurring.

1.INTRODUCTION

Because of flavor and taste Mangoes is popular fruit. Mango cultivation is carried out in different favorable regions. During summer mangoes are harvested from gardens and then transported to various markets by distributors. According to distance and demand of market quality, the distributors demand batches of homogeneous quality and maturity. The variations become much wider due to variation in variety, location and weather condition at the time of harvesting.

The grading of mangoes is thus an essential step, however it is a tedious job and it is difficult for the graders to maintain constant vigilance. If this task could be performed automatically, the result would be more objective; it would also save labor and enhance output. In past, much research work has been carried for automated grading of fruits through analyzing aroma using electronic nose, in order to predict the ripeness of fruit [1]. In another work, a spectroscopy based fiber-optic and microoptic device is presented for testing the quality and safety of foods [2]. Recently peach maturity prediction has been performed by estimating the fruit flesh firmness using multivariate retrieval techniques applied to the reflectance spectra acquired with the spectrometer [3] . The application of machine vision in agriculture has increased considerably in recent years. There are many fields in which computer vision is involved, including terrestrial and aerial mapping of natural resources, crop monitoring [4], quality control in food and agriculture [5]–[7], No such system still proposed for prediction of actual-days-to-rot, which is essential during transportation from one place to another and it also helps to select the market distance and market demand for sending fresh fruits (before start rotten).

In most of the work, practical purpose of grading and the automated system for the purpose have not been taken into account. In the proposed work authors developed an automated system for grading of harvested mangoes based on actual-days-to-rot and quality level. The necessity, the key innovation of this proposed work and also the main concern of this paper is clearly summarized in the following:

• The proposed system not only predicts maturity level and quality level, but also predicts the actual-days-to-rot of mangoes. So the vendors can increase their profitability by reducing losses due to rotting of mangoes during transportation.

The main contribution of the present work is, development of a real time automated for grading of harvested mangoes according to maturity level in terms of actual-days-to-rot and the quality attributes like color of the fruit. The prediction of actual-days-to-rot is more important than the maturity level, in decision making on the account of transportation delay. The proposed method is discussed in Section 2. Pre-processing, 3. RGB to HSV ,4. K-means algorithm. We summarize our work and conclude this paper in Section 5.

2. Overview

The system aims in the automatic grading of mangoes based on the color of the mangoes. The color of the fruit gives us idea about the ripeness of the fruit. There are different maturity levels of the fruit based on its color.

The system takes the images of mangoes as input and then performs several pre processing techniques like gray scaling, blurring and thresholding after which the actual processing of the system begins.

The whole image of the mango is divided into blocks of size 16 x 16 pixels and each block is examined for black surface . The system is first trained with the training data set to which input will be compared. The training data set's each block's RGB values are converted into HSV values and stored into an array. The centroids of each HSV values of the training data set is calculated using K-means algorithm.

After the centroids of each array of hue ,saturation and value is calculated the input image's HSV values will be compared to the trained values that are stored in the database. The database contains the values for good as well as bad blocks of mangoes. The difference of centroid of a block of input image is calculated with the training data set. The block is graded based on the difference of centroid. The blocks are graded into the category from which the centroid distance is minimum. The data set will have values for the following categories: Excellent,Good,Average and Bad. Each block will be graded into these categories. The whole mango will be graded into a single category based on the grade that the majority of blocks have eg : If the majority of blocks are graded into good then whole mango will be graded under 'good' category.

2. Pre-processing

2. 1 Grey Scaling

In order to convert a particular color into grey-scale we need to work out what the intensity or brightness of that color is. A quick way of calculating the intensity is to obtain the mean value of the red, green and blue components. The formula for this is:

Although it can produce reasonable results, this method is not perfect. The reason for this is that the human eye does not perceive reds, greens and blues at the same intensity level. The color green, for example, at maximum intensity looks brighter than blue at maximum intensity.

Another method of grey-scale conversion which takes into account the human perception of color uses different weights for the red, green and blue components. This means that when we are calculating the value for the intensity each of the color components are multiplied by a weight value. There are a number of different values used for these weights but one of the most popular is the following:

To illustrate the above points let's have a look at an image of some colored bars:

After converting this image to gray-scale using the mean method:

The intensity levels are not right here as there should be a gradual change in intensity going from the black to the white.

Converting the image to grey-scale using the weighted method will give us the following:

As you can see the weighted conversion is a much more accurate representation of the original colored image than the mean conversion.

2. 2 Blurring

1. Gaussian Blur theory

The blur can be understood as taking a pixel as the average value of its surrounding pixels.

On the above graph, 2 is the center point, the surrounding points are 1.

The center point will take the average value of its surrounding points, it will be 1. From value perspective, it's a smoothing. On graphic, it's a blur effect. The center point will lose its detail.

Obviously if the value range is very large, the blur effect is very strong. The above are graphs of original, 3 pixels blur radius and 10 pixels blur radius. The bigger the blur radius, the more blur the picture is.

2. Weight of normal distribution

Normal distribution is an acceptable weight distribution model.

On graphic, normal distribution is a Bell-shaped curve, the closer to the center, the bigger the value.

3. Gaussian function

The normal distribution above is one dimensional, the graph is two dimensional. We need two dimensional normal distribution. The density function of normal distribution is called Gaussian function. The one dimension format is :

Here μ is the average of x, Because center point is the origin point when calculating average value, so μ equals to 0.

Based on the one dimension function , we can derive the two dimensional Gaussian function.

With this function, we can calculate the weight of each point.

4. Weight matrix

Assume the coordinate of the center point is (0,0), then the coordinates of 8 points which are nearest to it are:

To calculate the weight matrix, we need to set the value of σ, σ=1.5, then the weight matrix of blur radius 1 is

The sum of the weights of these 9 points is 0.4787147. If only calculate the Weighted average of these 9 points, then the sum should be 1, hence the above 9 values should divide 0.4787147.

5. Calculate Gaussian Blur

With weight matrix, we can calculate the value of Gaussian Blur. Assume we have 0 pixels now, the gray value(0-255):

Each point multiplies its weight value:

Now we have:

Add these 9 values up, we will get the Gaussian Blur value of the center point.

2.3 Thresholding

Thresholding is a process of converting a grayscale input image to a bi-level image by using an optimal threshold. The purpose of thresholding is to extract those pixels from some image which represent an object (either text or other line image data such as graphs, maps). Though the information is binary the pixels represent a range of intensities. Thus the objective of binarization is to mark pixels that belong to true foreground regions with a single intensity and background regions with different intensities.

Thresholding algorithms

For a thresholding algorithm to be really effective, it should preserve logical and semantic content. There are two types of thresholding algorithms:

- Global thresholding algorithms.
- Local or adaptive thresholding algorithms.

In global thresholding, a single threshold for all the image pixels is used. When the pixel values of the components and that of background are fairly consistent in their respective values over the entire image, global thresholding could be used.

In adaptive thresholding, different threshold values for different local areas are used.

3. RGB to HSV

The HSV colour model describes colours according to their **H**ue, **S**aturation, and **V**alue. In some computer graphics programs, it is used as an alternative to the RGB system to quantify colours. In HSV, hue is a number in the interval [0, 360). A colour's hue is its general position on a colour wheel, where red is at 0°, green is at 120°, and blue is at 240°. For example the RGB code of a yellow/orange colour has high red and green components and a low blue component, with the red level slightly higher than the green. On the colour wheel, the angle of this hue is a little less than 60°. The hue of any neutral colour white, Gray, or black is set at 0°. Value, in HSV, is the highest value among the three R, G, and B numbers. This number is divided by 255 to scale it between 0 and 1. In terms of perception, HSV Value represents how light, bright, or intense a colour is. Value does not distinguish white and pure colours, all of which have V = 1. HSV Saturation measures how close a color is to the gray-scale. S ranges from 0 to 1. White, gray, and black all have a saturation level of 0. Brighter, purer colors have a saturation near 1. In other colour models that include a saturation component, the precise mathematical definition of S may vary.

4. K-means algorithm

k-means is one of the simplest unsupervised learning algorithms that solven clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriori. The main idea is to define k centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as bary center of the clusters resulting from the previous step. After we have these k new centroids , a new binding has to be done between the same data set points and the nearest new center. A loop has been generated.

As a result of this loop we may notice that the k centers change their location step by step until no more changes are done or in other words centers do not move any more. Finally, this algorithm aims at minimizing an objective function know as squared error function given by

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2$$

where,

'$\|x_i - v_j\|$' is the Euclidean distance between x_i and v_j.

'c_i' is the number of data points in i^{th} cluster.

'c' is the number of cluster centers.

5. CONCLUSIONS

In this research we built a proposed model of a mango fruit grading system. The software system analyzes the input image, preprocessing of image, features extraction and finally gradation. Proposed grading system grades the mango into four grades (though actual gradation can be extended up to sixteen) based on experts perception. Results show that the mango grading algorithm is designed viable and accurate. The actual days-to-rot prediction accuracy is 84% and the accuracy for measurement of surface defect is over 90%. The average time to grade one mango is approximately 0.4 second.

The limitation of this proposed system is that in the proposed system we have considered one side of mango image, the images of the mangoes form different sides can be considered.

REFERENCES

[1] J. Brezmes et al., "Evaluation of an electronic nose to assess fruit ripeness," IEEE Sensors J., vol. 5, no. 1, pp. 97–108, Feb. 2005.

[2] A. G. Mignani et al., "EAT-by-LIGHT: Fiber-optic and micro-optic devices for food quality and safety assessment," IEEE Sensors J., vol. 8,

no. 7, pp. 1342–1354, Jul. 2008.

[3] M. Stefania, D. Marco, M. Rossano, C. Giovanni, and R. Damiano, "A spectroscopy-based approach for automated nondestructive maturity grading of peach fruits," IEEE Sensors J., vol. 15, no. 10,

pp. 5455–5464, Oct. 2015.

[4] G. Q. Jiang, C. J. Zhao, and Y. S. Si, "A machine vision based crop rows detection for agricultural robots," in Proc. IEEE Int. Conf. Wavelet Anal. Pattern Recognit., Qingdao, 2010, pp. 114–118.

[5] K. K. Patel, A. Kar, S. N. Jha, and M. A. Khan, "Machine vision sysrem:A tool for quality inspection of food and agricultural products," J. Food Sci. Technol., Apr. 2012, vol. 49, no. 2, pp. 123–141.

[6] C. McCarthy, "Practical application of machine vision in australian agricultural research at NCEA," IEEE RAS TC Agricult. Robot. Autom.

Webinar, Mar. 27–28, 2014.

[7] L. Wang, X. Tian, A. Li, and H. Li, "Machine vision applications in agricultural food logistics," in Proc. IEEE 6th Int. Conf. Business Intell. Financial Eng., Nov. 2013, pp. 125–129.