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Procedia Computer Science 79 (2016) 426 – 433

Procedia Computer Science

7th International Conference on Communication, Computing and Virtualization 2016

Computer Vision Based Fruit Grading System for Quality Evaluation of Tomato in Agriculture industry

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Abstract

Agriculture sector plays a key role in the economic development of India. The task of fruit grading is vital in the agricultural industry because there is a great demand for high quality fruits in the market. However, fruit grading by human is inefficient, labor intensive and prone to error. The automated grading system not only speeds up the time of processing, but also minimizes error. There is a great demand for tomatoes in both local and foreign markets. The tomato fruit is very delicate and hence careful handling of this fruit is required during grading. Thus, this paper proposes an automatic and effective tomato fruit grading system based on computer vision techniques. The proposed quality evaluation method consists of two phases: development of hardware and software. The hardware is developed to capture the image of the tomato and move the fruit to the appropriate bins without manual intervention. The software is developed using image processing techniques to analyze the fruit for defects and ripeness. Experiments were carried out on several images of the tomato fruit. It was observed that the proposed method was successful with 96.47% accuracy in evaluating the quality of the tomato.

Peer-review under responsibility of the Organizing Committee of ICCCV 2016

*Keywords:*Computer Vision;Tomato;Defect;Ripeness;Agriculture

1. Introduction

In most developing nations such as India, agriculture constitutes the major part of the country's economy [1]. It is due to this fact that a lot of money is spent each year by governments across the globe, for utilizing new

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Peer-review under responsibility of the Organizing Committee of ICCCV 2016
doi:10.1016/j.procs.2016.03.055

technologies, discovering new methodologies of farming and also new techniques for prevention of crop reduction due to pests, natural calamities and drought [2]. Generally, in India the quality inspection of fruits is performed by human experts. 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. With the advent of fast and high precision machine vision technologies, automation of the grading process is expected to reduce labor cost, improve the efficiency and accuracy of the sorting process.

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. The fruit produced in the farm is sorted according to quality, and then transported to different standard markets at different distances. Tomato is the world's largest crop and known as a protective food both because of its special nutritive value and also because of its wide spread production. Tomatoes are grown extensively in India, producing about 9.362 million tons with an area of about 535,000 ha [3]. Foreign trade policies have given high importance in boosting our agricultural exports. The surface of the tomato fruit is very soft and hence careful handling of the fruit is needed during quality evaluation. Quality of tomato fruit, in particular, depends on size, color, shape and the presence and type of skin defects. The ripeness and defect are the most important factors that determine the quality of the tomato fruit. Automated tomato grading system helps both consumers and farmers by providing good quality fruits in the market. Hence, this paper proposes to develop a system for quality inspection of the tomato in agro-industry using image processing techniques.

1.1. Related work

Over the past few decades, there has been enormous research being carried out to assist in the quality assessment of fruits and vegetables in the industry. The machine vision based systems have been used in many applications requiring visual inspection of fruits such as apple [4], dates [5], mango [6], citrus and pears [7]. Some machine vision systems are also designed specifically for factory automation tasks such as an intelligent system for packing 2-D irregular shapes [8], versatile online visual inspections [9], automated planning and optimization of lumber production using machine vision and computer tomography [10].

Several physical and chemical parameters affect the quality of tomatoes. Studies have shown that there is a positive correlation between the ripening of tomatoes and their physical properties such as color and firmness [11]. Several scales and color charts have been developed for classifying ripening stages of tomatoes, but the inaccuracy of instruments depending on tomato maturation stage [12] and lack of uniformity of the color over the tomato can reduce the reliability of the colorimeter test. Clement et al. [13] developed a tomato classifier based on color, size and weight with an accuracy of 84%. But, this method focuses mainly on size and weight. The quality of the tomato highly depends on the ripeness level and defect. Automatic systems were developed for identification of tomato defects based on color [14, 15]. The main limitation here is that the color feature alone is not effective in defect detection and hence the methods could achieve only 90% accuracy. Further, the number of samples used in the experimentation is very less. Thus, it becomes difficult for the classifier such as neural network to correctly classify the unseen sample. Several schemes [16, 17] are developed to evaluate the quality of tomato using images obtained from various imaging modalities such as MRI and spectroscopy. These modalities provide high quality images and help to improve the accuracy of the analysis. However, the use of these imaging techniques makes the image acquisition phase time consuming and costly.

It was observed from the above literature review that current tomato sorting systems are not accurate and developed machines are costly. Hence, the practical implementation of these systems is not possible for the farmer. Hence, this paper proposes to develop automatic, accurate, and a low-cost fruit grading system for quality analysis of tomato in terms of ripeness and defects. The paper is organized as follows: the details of image acquisition, different feature extraction methods, classification technique, and experimental results are discussed in the following sections. Finally the conclusions are summarized in the last section.

2. Proposed methodology

The proposed system for quality evaluation of tomato in the agriculture industry is shown in Fig.1. This system was designed to overcome the drawbacks of manual technique of fruit sorting. The system mainly consists of two parts: i) Fruit handling ii) Image processing module. The fruit handling system is used to move the tomato on the conveyer belt and for the image acquisition. The images of the tomato acquired are analyzed using image processing techniques to determine whether the tomato is defective or non-defective, and ripe or unripe.

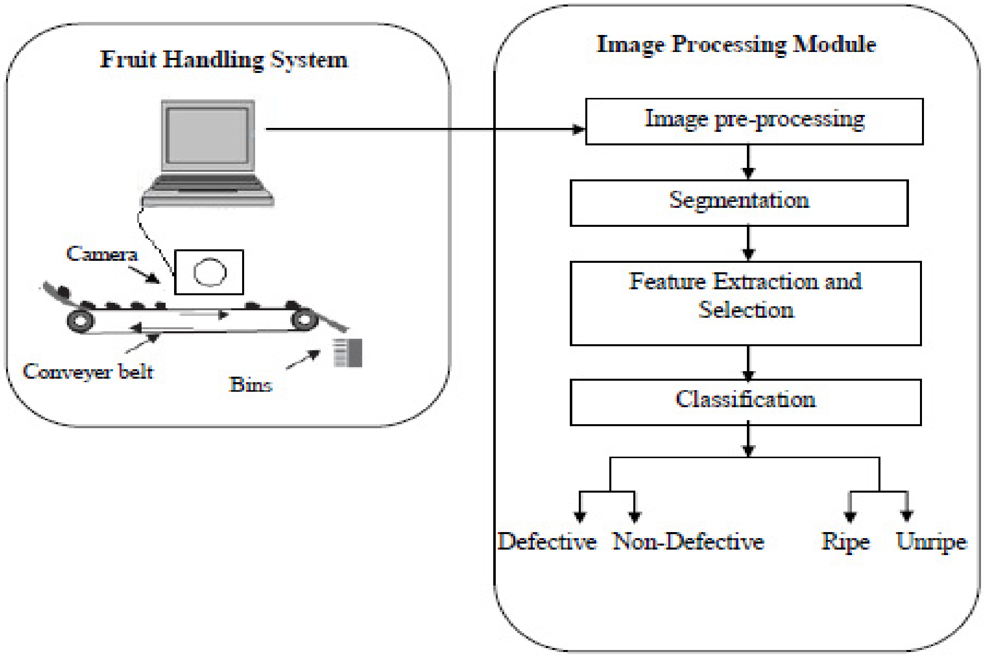

Fig. 1. Proposed tomato fruit grading system.

2.1. Fruit handling system

The fruit handling system consists of a conveyer belt, lights, 8051 controller, DC gear motor, LM293D motor driver, UART bridge, computer, and camera. The whole fruit grading system is covered with a wooden box and one florescent light is mounted within the box. The tomato is laid over the conveyor belt which moves with the help of a DC gear motor. The tomato is made to stop at the position where the camera is fixed for capturing the image of the tomato by providing delays. The image is taken with a digital camera and then sent to the processor via USB port. The image of the tomato is taken as input to the image processing module for further analysis. Once the image is classified, the control signal is given back to the hardware via RS232 serial transmission in order to move the tomato to the respective bins.

2.2. Image processing module

Image processing module analyzes the acquired image of the tomato using the following steps:

Image pre-processing: The tomato image captured by the camera consists of noise and specular reflections. These effects degrade the quality of the image and do not provide correct information for subsequent processing. Hence, median filter [18] is applied to the image to suppress the reflections and noise.

Segmentation: This phase is to extract the tomato region from the image. First, the image is converted to binary using Otsu's method [18]. This results in the image partitioned into two regions, namely, background and tomato. If the defects on the tomato have intensity similar to the background, then the tomato region consists of holes. In order to extract the complete region of the tomato, the hole is filled by pixels with value 1.

Feature Extraction and Selection: In order to detect whether the tomato is defective or non-defective, the color statistical and color texture features for individual Red (R), Green (G) and Blue (B) channels are extracted as given below:

- *Color statistical features:* The following statistical features [19] are extracted from each color channel. This results in 9 color statistical features.

$$Color\ \ mean(\mu) = \frac{1}{N}\sum_{i=1}^{N} P_i \tag{1}$$

$$Standard\ \ Deviation(\sigma) = \left(\frac{1}{N-1}\sum_{i=1}^{N}(P_i-\mu)^2\right)^{\frac{1}{2}} \tag{2}$$

$$Skewness = \frac{\sum_{i=1}^{N}(P_i-\mu)^3}{N\sigma^3} \tag{3}$$

- *Color texture features:* The four texture features are extracted from each color channel using gray level co-occurrence matrix (GLCM) of the image. The elements of the GLCM represent the values of the probability density function Pij , which counts the number of occurrences of pixel pairs having intensity values (i, j) and separated by a distance d along the direction θ [19]. The present work considers inter-pixel distance equal to 1 and four angular directions: 0°, 45°,90°, and 135°. The features extracted from the GLCM are given below:

$$Contrast = \sum_{i,j=1}^{N} |i-j|^2\ P_{ij} \tag{4}$$

$$Correlation = \sum_{i,j=1}^{N} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{5}$$

$$Energy = \sum_{i,j=1}^{N}(P_{ij})^2 \tag{6}$$

$$Homogeneity = \sum_{i,j=1}^{N}\frac{P_{ij}}{1+|i-j|} \tag{7}$$

The ripeness of the tomato is closely related to its color. Hence, the color feature is extracted from the tomato image to classify it as ripe or unripe. The R, G, B values of the image are extracted and their average is calculated according to the following equations. The threshold is selected based on the experiments and mean R is compared with the threshold. If it is greater than the threshold, then the tomato is ripe else it is considered as unripe.

$$Mean\ \ R = \frac{R}{N} \tag{8}$$

$$Mean\ \ G = \frac{G}{N} \tag{9}$$

$$Mean\ \ B = \frac{B}{N} \tag{10}$$

Where, Mean R = mean value of red layer, Mean G = mean value of green layer, Mean B = mean value of blue layer, R = Red pixel, G = Green pixel, and B = Blue pixel. Totally 21 features are extracted from the tomato image consisting of 9 color statistical features and 12 color texture features. In order to improve the classification accuracy, an optimal feature set is selected from the original feature vector by applying sequential forward selection (SFS) method. It is a greedy search algorithm that determines an “optimal” set of features for extraction by starting from an empty set and sequentially adding a single feature in the superset to the subset if it increases the value of the chosen objective function. In the present work, SFS dimensionality reduction technique resulted in 13 features.

Classification: Features extracted in the previous step are fed to the multilayer neural network as shown in Fig. 2. It consists of a set of interconnected neurons to map the input features to the output. A three layer feed forward neural network is implemented with *n* input, *h* hidden and 1 output neuron indicating the tomato as defective or non-defective. The learning of the neural network is supervised and the weights are adjusted by the back propagation procedure.

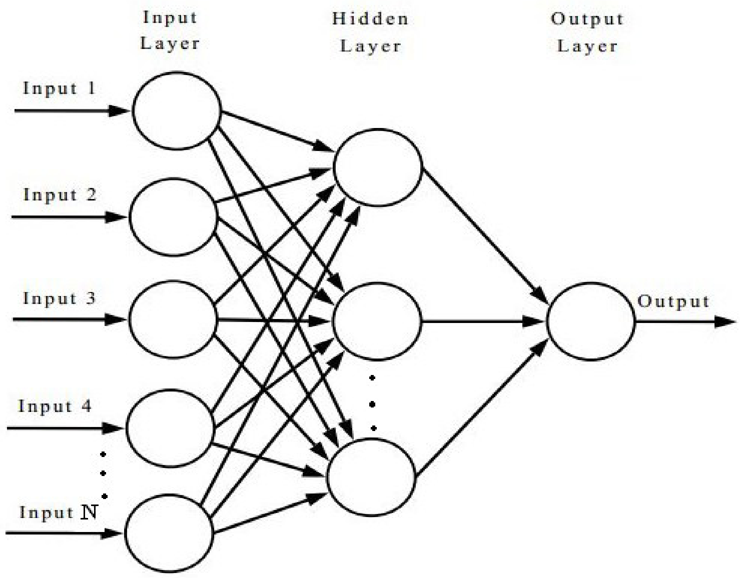

Fig. 2. Artificial neural network for classification of tomato

3. Experimental Results

The dataset considered for the experiments consists of 520 images of unsorted tomatoes collected from the different gardens and University of Agricultural Sciences, Bangalore. The dataset consists of ripe, unripe, defective and non-defective tomatoes. The ground truth required for the classification was obtained from the experts. The hardware of the fruit grading system was designed as shown in Fig.3 Each image of the tomato acquired by the camera mounted on the grading system was of size 512x512 as shown in Fig.4. The image processing module was implemented using MATLAB.

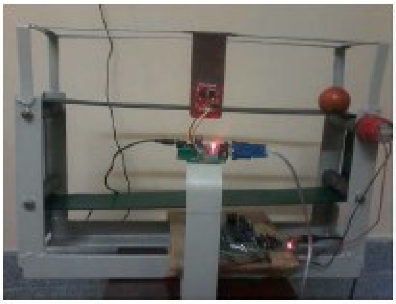

Fig.3. Tomato grading system

Fig.4. Captured image of the tomato

The signal sent by the MATLAB to the microcontroller moves the conveyer belt along with the tomato. The tomato is moved to a position where the image is to be captured. The captured image is forwarded to the image processing module which performs segmentation, feature extraction and classification. The graphical user interface developed for easy usage of the system is shown in Fig.5. The acquired image sent to the computer is loaded into the interface. The tomato is analyzed to recognize the defects upon clicking the button “check for defective”. If it is defective, then the conveyer belt moves accordingly and puts the tomato in the bin meant for defective tomatoes. Otherwise, the software proceeds to analyze the ripeness of the tomato upon clicking “check for ripeness” button. The conveyor belt moves tomato to the respective bins after classifying it as ripe or unripe. This way the system grades the tomato and puts them in different bins automatically.

Fig.5. Graphical user interface.

The leave-one-out (LOO) method was used to train and test the classifier. The LOO-based validation is performed considering all images in the dataset. Given a dataset of *n* samples, the LOO-based validation is performed with *n* iterations, such that in each iteration the classifier is trained with *n - 1* samples and tested on the remaining one sample. The average accuracy of *n* iterations is used to estimate the accuracy of the classifier. The confusion matrices of the classifier are shown in Table 1 and Table 2. The classification performance is measured using the following equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{11}$$

Where, TP (True Positive): Number of defective/ripe tomato classified as defective/ripe; FP (False Positive):

Number of non-defective/unripe tomato classified as defective/ripe; TN (True Negative): Number of non-defective/unripe tomato classified as non-defective/unripe; FN (False Negative): Number of defective/ripe tomato classified as non-defective/unripe.

Table.1 Confusion matrix for defective and non-defective classification

		Predicted class		Accuracy(%)
		Defective	**Non-defective**	
Actual class	**Defective**	180 (TP)	0 (FN)	100%
	Non-defective	0 (FP)	340 (TN)	

Table. 2. Confusion matrix for ripe and un-ripe classification

		Predicted class		Accuracy(%)
		Ripe	**Unripe**	
Actual class	**Ripe**	170 (TP)	0 (FN)	96.47%
	Unripe	12 (FP)	158 (TN)	

It can be seen in the above tables that the proposed system was able to successfully differentiate between defective and non-defective based on color statistics and textural features. Further, the system could classify the non-defective tomato as ripe or unripe using R, G, B values of the image. Most of the research work carried out in the fruit grading system focuses on color or texture of the fruit in deciding the quality of the fruit. Thus, in order to determine the effectiveness of different features in classifying the tomato as defective/non-defective their performance is compared as shown in Fig.6. It was observed that combination of color and texture improved the performance of the classifier.

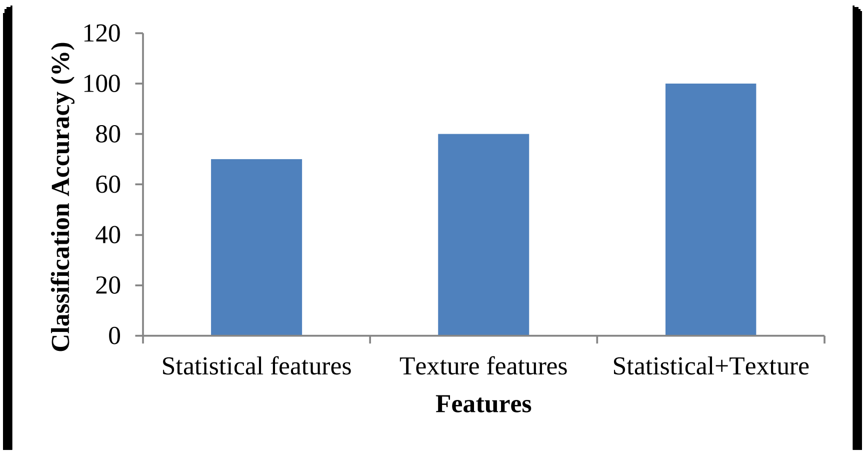

Fig.6. Comparison of the effectiveness of features

4. Conclusion

The paper presented a method for automatic grading of tomato using computer vision techniques. The hardware of the fruit grading system could move the tomato to the respective bins depending on the output of the image processing module. The software classified the tomato image as defective/non-defective and ripe/unripe with an accuracy of 100% and 96.47% respectively. Thus, the developed system will be helpful for the former and agriculture industry in effectively sorting the tomato. However, the capacity of the grading machine was 300 fruits/hr and the proposed image processing approach does not effectively work on the tomato image with high specular reflection. Thus, it needs further improvements, especially in speed and accuracy, before implementing in the field.

Acknowledgements

This work was supported by Karnataka State Council for Science and Technology, Bangalore, Karnataka. The authors would like to thank University of Agricultural Sciences, Bangalore for providing the tomato samples required for the experiments.

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