Development of a low cost machine vision system for sorting of tomatoes

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Abstract: Sorting of tomatoes has been an issue faced by producers as well as sellers due to the sheer volumes handled and the delicate nature of the fruit. This paper describes the development of a low cost machine vision system using webcams and image processing algorithms for defect detection and sorting of tomatoes. In the case of agricultural products, good efforts and appropriate techniques are necessary to distinguish between defected and good ones when using machine vision for sorting. Tomatoes having two major defects namely Blossom End Rot (BER) and Cracks could be separated from good tomatoes with calyx. The sorting decision was based on three features extracted by the image processing algorithms. The color features were used for detecting the BER from good tomatoes and shape factor combined with the number of green objects was used for differentiating the calyxes from crack defects. Two methods, rule based and neural network approaches, were developed for decision based sorting. A control system was developed with a belt conveyor to transport the tomatoes and a cylinder pushrod coupled to a solenoid was used to push the defective tomatoes after determining their defect by the algorithms. The color image threshold method with shape factor were found efficient for differentiating good and defective tomatoes. The overall accuracy of defect detection attained by the rule based approach and the neural network method were 84 and 87.5% respectively. The inspection speed of 180 tomatoes min^{-1} was achieved by the algorithms and the prototype developed. Comparison of the results obtained by the rule based and neural network approaches are also presented in this paper.

Keywords: Machine vision, defect detection, rule based approach, neural network, tomato sorting

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1 Introduction

Sorting and grading, though traditionally done by manual means, are two major labor intensive operations in the fruit processing industry (Ashraf et al., 2011). Labor shortages and lack of overall consistency in the process outcome have resulted in many research for automated solutions. Visual quality grading remains one of the most difficult processes to automate in fruit and vegetable processing as well as in other areas of the food processing industry (Iraji et al., 2011). Color is a key parameter in the implementation of many quality decisions, and thus a low-cost integrated color vision system, which includes the image acquisition and processing, is necessary for tackling many of the existing problems in the food processing industry (http://foodtech.gatech.edu/citrus.htm).

Computer vision is one of the most important sensing mechanisms used for measurement of external features viz. color, color homogeneity, bruises, size, shape, and other feature identification in many agricultural products (Delwiche et al., 1994; Katsumata and Matsuyama, 2005; Hanan et al. 2009; Wang et al. 2011). Choi (1995) utilized the color image analysis procedure to classify fresh tomatoes into six maturity grades based on hue information. Edan et al. (1997) developed a weighted color parameter based on human perception that provided a stable model that was invariant to changes in lighting

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conditions with excellent classification into 12 maturity classes of tomato. Gerhard et al. (2001) proposed various fuzzy consumer aspects to grade the tomatoes into several overall quality classes. The objective in that study was to achieve an automatic rating of fruit quality, to model factors involved in consumer preference and producer's needs. However, Iraji et al. (2011) commented that such a mapping of fuzzy image analysis attributes to an overall visual quality reductions spoiling tests. It must be possible to rearrange the reasoning and optimize the decision according to varying consumer expectations. Wen and Tao (1999) developed a near-infrared machine-vision system for automating apple defect inspection by using a rule-based approach. The results showed that the rule-based system was effective for apple defect detection. Compared with the neural network method, the rule-based approach had more flexibility for changing or adding parameters, features, and rules to meet various sorting requirements.

Laykin et al. (1999) developed an automatic quality-sorting machine using vision and impact sensors. Tomato was selected as the prototype product during the development stage and the system was designed and built accordingly. Chamberlain (1976) developed a color sorting criterion for tomatoes based on light reflectance. Kang et al. (2000) used a 670 nm, 3 mW solid state laser diode module as the light source to monitor quality changes of tomatoes stored at room temperature for eight days. The scattering images were captured and the total number of pixels in the image was taken as an indicator of fruit ripeness. Polder et al. (2003) used Independent Component Analysis (ICA) to estimate the most important compounds that played a major role in ripening of tomatoes. Concentration images of the compounds obtained were fed to an unsupervised real time sorting machine, using the total compound concentrations and the spatial distribution of the concentrations as the criteria for estimation. Bato et al. (1999) in their experiment implemented image processing algorithms for orientation and shape determination of strawberries.

2 Rationale and objectives

Usually, machine vision systems for fruit inspection require high cost cameras and sophisticated image processing software (Arefi et al., 2011). For image acquisition, these cameras need to be connected to a computer through a frame grabber, which receives the composite video data, separates the video and synchronization information, digitizes it and transfers to the computer for further processing and storage. The software are generally developed using C or C++ / Visual C++ languages which require image processing libraries. These libraries are developed by other developers, and sometimes the desired functionality of the image processing tasks are not available with any such single library, and it may need many libraries to fulfill the task. The development of such software also consumes a significant amount of time and requires special knowledge of the languages and strong image analysis expertise. From the operational point of view, this system could be controlled by algorithms written in high level language and the control efficiency will depend on the features of the operating system. It will not be an easy task to develop an algorithm integrating all the above mentioned features into one system to function fast enough for the need of industry with less cost.

In this study as the main objective it was intended to develop a low cost machine vision system with appropriate algorithms to sort tomatoes with specific defects, blossom end rot and cracks. The system was to be used for automated sorting, and it integrated image acquisition, image processing, decision making, and controlling by using one high level language like Matlab. The system used low-cost webcams that required no frame grabber hardware, thus making the overall system cheaper and flexible from the design point of view. As specific objectives, development of algorithms, development of prototype system, conduct of performance evaluation tests, and comparison of rule-based and neural network method on defected and good tomatoes were planned.

3 Methodology

3.1 Common defects in tomatoes

When concerned with the tomato quality, the marketable quality is the standard commonly used, and there are defined quality indicators for tomatoes. In addition, there are defined categories and standardization of tomato defects for quality evaluation.

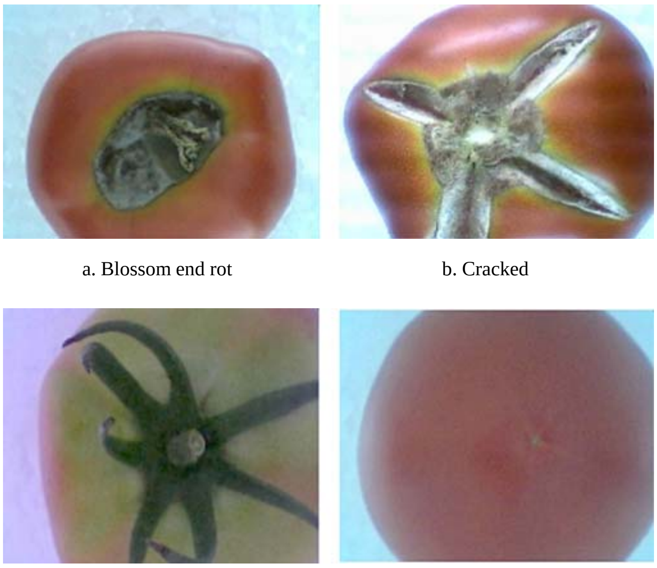
The defects due to mould, blossom end rot (BER) or breakdown, damages done by pests and insects, defects caused by diseases and fungal growth are considered to be “major quality defects”. Sizes outside of the stated grade, colour not meeting the specific ripeness requirements, surface scarring or russetting, minor cracks to the surface, minor signs of age such as wrinkling and softening fruit are considered to be “minor quality defects”(Food Surveys; Online).

3.2 Sorting of defected tomatoes

The objective of the developed system was to detect the two kinds of defects i.e., BER and crack in the tomato images, and also to identify the good tomatoes with calyx from those having BER and crack defects. In order to create the library, 160 images of the tomato of Kingkong II type were taken and used for the experiment. These 160 images contained four categories of images. Forty images from each category of BER defects, crack defects, calyx images, and rest of good tomatoes. In the image processing algorithm, color images were processed by extracting Red (R), Green (G) levels, Hue (H) matrix and applying a threshold level, which was one of the most common and convenient techniques for segmentation and a widely used tool in many machine vision systems. It lent itself to simple implementation in hardware, which therefore resulted in high throughput rates, as generally required by industrial applications (Awcock and Thomas, 1996). The algorithm uses blob-extraction label function to label the segmented images based on connected components, whose general procedure is outlined by Haralick et al. (1992). Figure 1 shows the four classes of tomatoes considered for the decision of acceptance or rejection by the algorithms.

3.3 Image processing system

The image processing system comprised of many sequential and parallel activities: reading, resizing, filtering, sharpening of images captured, separation of green and red matrices from RGB images, activation at thresholds, binarizing, blob extraction, shape factor estimation and finally the decision making by rule-based approach as is shown in Figure 2.



a. Blossom end rot b. Cracked

c. Good tomato showing Calyx d. Free from any defect

Figure 1 Sample images of different classes

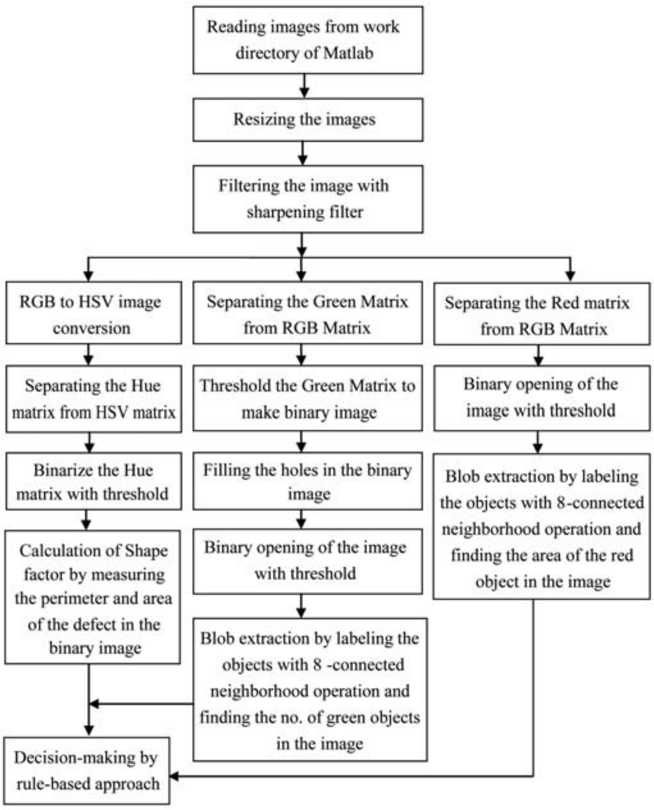


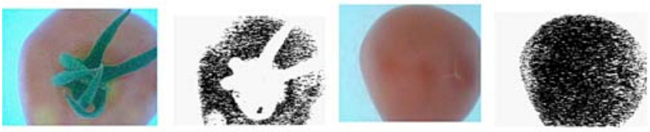
Figure 2 Image processing Algorithm

3.4 Defect detection system

It was observed that the histograms of the tomatoes with defects are different from those of the good tomatoes and of calyxes (Figures 3 and 4). The defects could be detected by using a threshold value to the images after processing them. The following logical criteria was considered for defect detection:

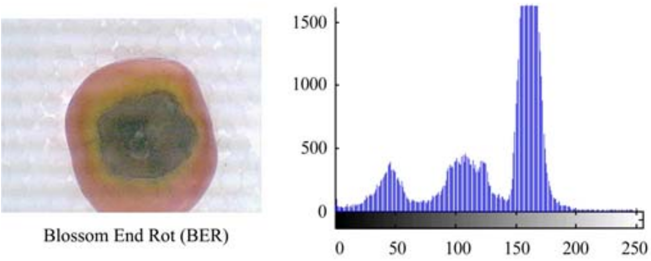
a. Segmentation by threshold on Green Matrix (Calyx and Cracks)

b. Segmentation by threshold on Red Matrix (Rot and Cracks)

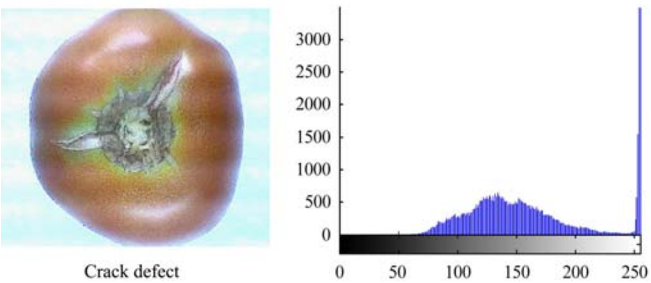


c. Segmentation by threshold on Hue Matrix (Calyx and No defect)

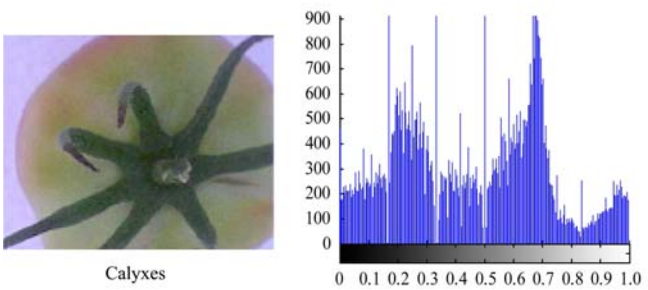
Figure 3 Segmentation by threshold on R, G and H matrices



a. Histogram (Frequency vs Gray level) of the Red Matrix for Blossom End Rot



b. Histogram (Frequency vs Gray level) of the Green Matrix for crack defect



c. Histogram (Frequency vs. Hue level) of the Hue Matrix for Calyxes

Figure 4 Histogram analysis for Red, Green and Hue Matrix

1) Blossom End Rot (BER) defects are usually circular in nature and spread over the red matrix of the tomato. Therefore, area of the red matrix was considered as a criterion for detection of tomatoes with BER defect from good ones.

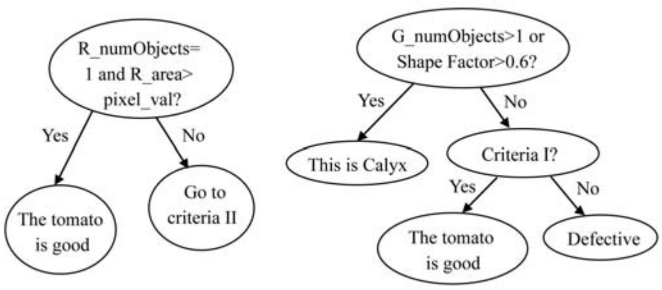
2) Cracks are elongated in nature from center of the red matrix, not connected with each other, and the percentage of green color is more than that of BER defect, but less than that of Calyxes. Therefore, the number of green objects is one of the criteria of its detection.

3) Calyxes are similar to the crack defect in shape but the percentage of green objects is more than crack defect. The shape of the perimeter is different from what is obtained for those with crack defect. Therefore, the shape factor combined with the number of of green objects was considered for distinguishing it from cracked, BER and good tomatoes.

4) The good tomatoes had a red matrix, regular in nature and free from uneven coloring. Therefore, it could be easily separated from the other three defective classes based on the color based decisions.

3.5 Decision sorting algorithms

The decision sorting was developed by decision logic using selected criteria and threshold values which were applied on images after processing. This approach was rule based using two-criteria decision logic steps as is shown in Figure 5, and experiments revealed that it can clearly detect the BER defect from good and calyxes but is less efficient in crack-calyx identification. Therefore, the neural network approach (Figure 6) was also integrated to solve this problem.



a. Criteria I b. Criteria II

Figure 5 Decision logic for sorting by rule based approach

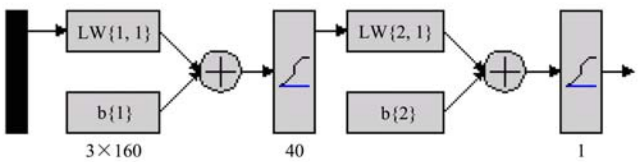


Figure 6 Back propagation network with 40 hidden neurons

3.5.1 Rule based approach

3.5.2 Neural network approach

To improve the performance of the crack-calyx recognition the neural network approach has been applied to the defect detection system. In this process, 160 images of four categories were trained by back propagation method as in Hagan et al. (1996). Three features were selected for each image, i.e., R-area, G-num Objects and the Shape Factor.

3.6 Control algorithm

The control algorithm was written by using data acquisition toolbox of Matlab (2009). The algorithm consisted of steps required to configure the parallel port, and to select its status pin 13 to sense the input, and pins 8 and 9 to control the actuators (Figure 7).

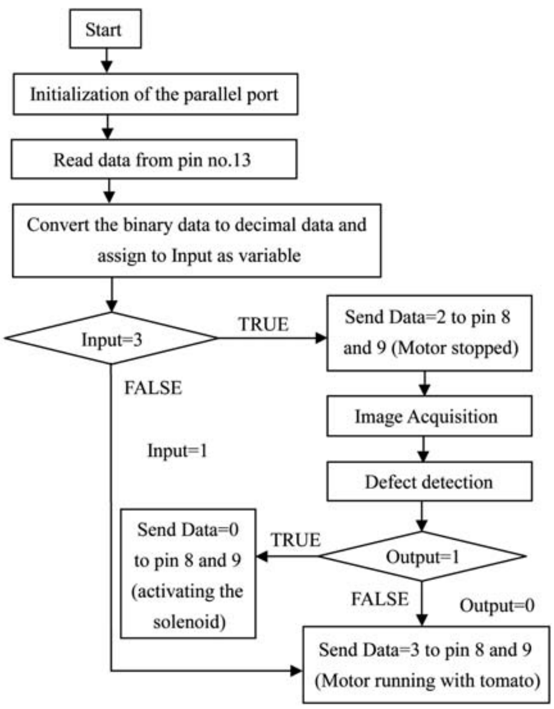


Figure 7 Flow chart for defect sorter control algorithm

3.7 Experimental setup

In the developed prototype, two low cost web-cams placed at the top and bottom to cover the whole image of the tomato were used to acquire the images. The tomatoes were carried by a specially designed belt conveyor, which had a circular opening to hold each fruit while exposing both sides of it to the cameras (Figures 8 and 9). The presence of the tomato at the location for capturing its images was detected by a proximity switch which sent pulses to the PC through the interfacing circuit. The image-processing algorithm was developed using Matlab source codes, for extracting the features described above. Based on the outcome of the decision making algorithm on sorting, a pulse was issued to the solenoid for rejecting the defective tomatoes. The control and image acquisition algorithms were also developed using Matlab.

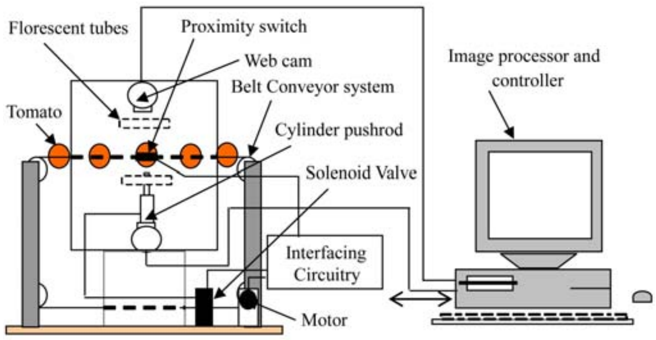


Figure 8 Schematic of the defect detection and sorting system prototype

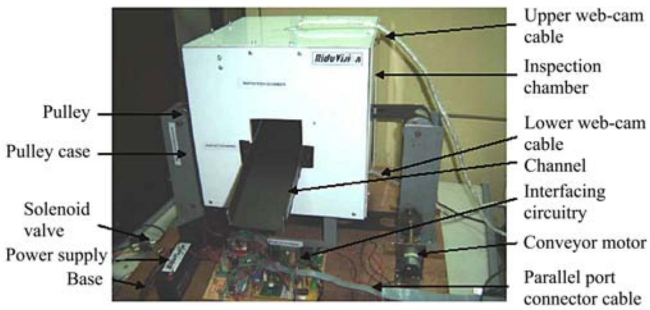


Figure 9 Prototype developed for the performance evaluation

4 Results and discussion

4.1 Defect detection based on area of the red objects and number of green objects

The tomatoes with BER defects and good tomatoes could be clearly differentiated by considering the area threshold alone. An area threshold of 76,000 was sufficient to classify between BER and good ones, and this feature alone was insufficient for crack-calyx recognition. As is shown in Figure 10, the crack recognition accuracy was found to improve with the increase of threshold area to 76,777. This is because the green objects are more in the calyx with the increase of the area. With further increase of area threshold (>76,800), the crack defect recognition accuracy improved to its highest. However, a significant decrease in the good tomato recognition was observed because it exceeded the range of the area of the good tomatoes and the other objects were miscounted causing it to be classified as a defective one.

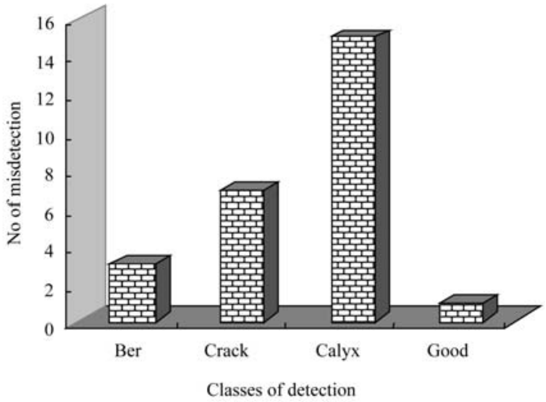


Figure 10 Defect detection of various classes at area threshold of 76,777

4.2 Defect detection based on area, number of green objects and shape factor

Higher mis-detection of cracks was observed at area thresholds >76,000. However, counting the shape factor with area and when the number of green objects >1, the crack-calyx detection accuracy was improved. At a particular threshold of area > 76,700 and number of green objects >1, the overall accuracy of defect detection improved significantly (Figure 11) and the crack calyx detection accuracy showed closer values.

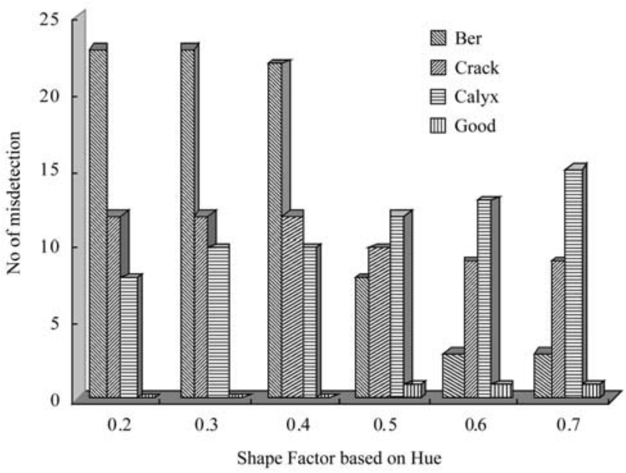


Figure 11 Comparison of detection with Shape Factor variation (At Area> 76,777 and No. of Green Objects >1)

4.3 Overall accuracy of detection at different shape factor threshold levels

Since hue contains the color information which is more distinguishable than RGB, the shape factors were estimated to find the differences in the crack-calyx recognition. In Figure 12 the overall accuracy increased with increase in the shape factor (at some levels) is shown.

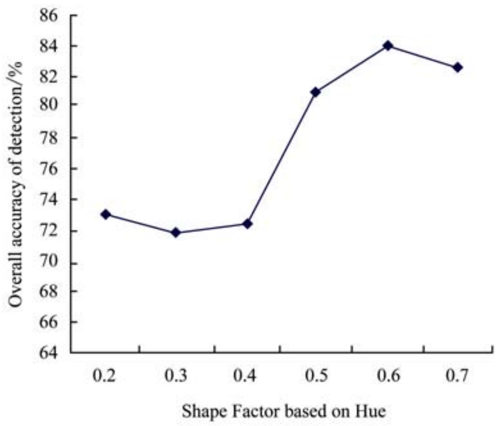


Figure 12 Overall accuracy at different Shape factors based on hue matrix

4.4 Test accuracy with different neurons in the hidden layer

Figure 13 shows the recognition accuracy found dependent on the number of neurons in the hidden layer and also with the number of simulated images. Therefore, the increase of neurons was found less efficient with less neurons because of similar matching of the images that caused misclassification.

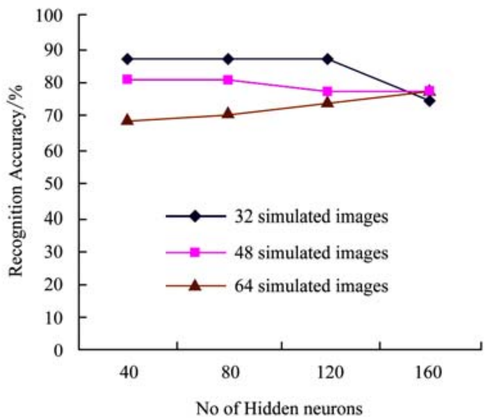


Figure 13 Recognition accuracy with different No. of neurons in the hidden layer

4.5 Comparison of rule based and neural network approaches for Cracks-Calyxes detection accuracy

Figure 14 shows that the accuracy of the detection of calyx and cracks using rule-based and neural network methods. It was found that the neural network method detected cracks significantly better than rule-based method, while rule-based method detected calyxes significantly better than the neural network method. The calyx detection was less in neural network method than the rule based approach because the images of training set could not be differentiable and cracks could have been mixed with calyxes.

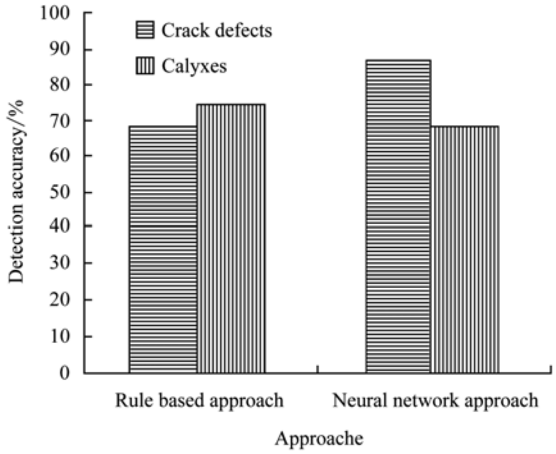


Figure 14 Comparative accuracy of rule based and neural network approaches

5 Conclusions and recommendations

Based on the experimental results following conclusions were drawn:

1) The color image threshold method was found efficient for the tomato sorting application because the defects can be detected based on color.

2) Differentiation between BER defected and good tomatoes could be done by area threshold alone.

3) The thresholds, area and the number of green objects were found insufficient for detection of calyxes different from crack defects because of the similarity in the color distribution. Therefore, the shape factor was used for its differentiation.

4) The overall accuracy of defect detection attained by the rule based approach and the neural network method were 84 and 87.5% respectively.

5) The sorting speed by the control program was 1 tomato s^{-1}, because of the parallel port programming and simplicity in the algorithm.

6) The inspection speed attained by the algorithm was 180 tomatoes min^{-1}.

Following recommendations were made considering the scope of the method:

1) The algorithms of rule-based approach may be developed by considering a relative threshold so that any size of the tomatoes can be inspected by the algorithm to make it robust.

2) The relative threshold should be calculated as the ratio of the red matrix of the defective segment to the total area of the tomato.

3) A Graphical user interface can be developed for the operator with the GUIDE tools in the Matlab or by using Visual Basic development platform so that it could be more interactive.

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