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IMAGE ANALYSIS FOR APPLE DEFECT DETECTION

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Summary. The objective of this research was to develop and test an image processing system which could identify defects on apple surfaces. A system for identifying surface defects on apples was designed, based on analyzing images acquired while apples were rotating in front of the camera. When multiple images were combined and adjustments made for rotation, dark areas caused by defects would appear with almost the same shape and at the same place in three or more frames. While minimizing false positives, the classification accuracy was very high. The proposed algorithm was effective in detecting various defects such as bruises, frost damage, and scab. The average classification accuracy was 96% for the samples in the experiments.

Key words: apple, damage, vision system, algorithm.

INTRODUCTION

Post harvest sorting of apples is a difficult, labor intensive process in the commercial fresh apples industry. The use of computer vision has attracted much interest and reflects the progress of computer vision technology for fruit inspection. [Yang, 1994] used a flooding algorithm to segment patch-like defects on monochrome images. This method could be difficult to apply on bi-color fruits where the defects are darker then the ground color, but lighter than the blush color. This method of feature identification is applicable to other types of produce with uniform skin colour. This technique was improved by [Yang and Marchant, 1995], who applied a 'snake' algorithm to closely surround the defects. [Molto et al. 2002] used linear discriminant analysis to segment pixels into three and four classes. A discriminant function sorted the apple as accepted or rejected. The accuracy was good for apples. [Leemans et al. 1998] used a Gaussian model of the color to segment defects on Golden Delicious apples with two enhancement steps. The detection was effective, but revealed some difficulties. To segment the defects, each pixel of an apple image was compared with a global model of healthy fruits by making use of the Mahalanobis distances. The proposed algorithm was effective in detecting various defects such as bruises, russet, scab, fungi or wounds. Experimentation by [Paulus et al. 1997] used Fourier analysis of apple peripheries as a quality inspection technique. This methodology showed the way in which external product features affect the human perception of quality. If the classification involved more product properties and became more complex, the error of human classification increased. [Leemans et al. 1998] investigated the defect segmentation of 'Golden Delicious' apples using machine vision. The study showed apple images segmented by the three algorithms applied sequentially. In similar studies [Yang,1996] assessed the feasibility of using computer vision for the identification of apple stems and calyxes. Neural networks were used to classify each patch as stem/calyx or patch-like blemish. An overall accuracy of 95% was reported for Golden Delicious and Granny Smith. [Chen et al. 2002] presented hyperspectral imaging technology for inspection and grading of agricultural products for inspection. The sensor module included a back illuminated CCD and a control unit. Hyper-spectral imaging systems can be used to fined optimal bands and develop algorithms for many food commodities. [Ariana et al. 2006] investigated multispectral imaging to detect various defects on apples. Artificial neural network classification models were developed for two classification schemes; a two class and a multiple-class. The technique is promising for accurate recognition of different types of apple disorders.

The objective of this research was to develop and test an image processing system which could identify defects on apple surfaces. It was proposed to analyze multiple images acquired while the apples were rotating in front of the camera.

MATERIALS AND METHODS

Gala, Jonagold, Ligol, Melrose, Fiesta and Golden Delicious apples were picked at the Albigowa Fruit Research Station, near Rzeszow, in September 2003. Apples were selected with different surface defects. Between picking and testing, apples were stored at 0°C. The day before testing the apples through the sorting system, bruises were intentionally inflicted on some of the apples by dropping apples 150–200 mm onto a hemispheric surface of wood. This created a bruise of approximately 12–15mm diameter. All images were taken the day after harvest. After image acquisition, apples were returned to cold storage so that they could be used for the evaluation of the image processing. Apples were regular in shape and were typical size for each variety. A set of 200 apples, including fruits of different qualities and damage was used to test the developed algorithm. The defects encountered were fungi attack, frost damage, bruising, punches, insect holes, and scab.

Images were acquired using one CCD camera (Model SSC-DC58AP, RGB Sony) equipped with 25 mm lens, computer with MultiScan program image analysis, and diffuse light from two halogen lamps (Fig. 1). Apples were oriented vertically in the stem- calyx direction and then they were rotated. The camera was mounted 400 mm to the side of the sample. Eight images of each apple were taken. Images were digitized using a frame grabber, and displayed on the monitor.

The image capturing system consisted of a camera with spatial resolution (1024×1024 pixels, 256 grey levels) and high sensitivity. The system consisted of an optical splitter and filters, which were similar to that developed by [Throop and Aneshansley,1997]. They found that 740 nm performed best for dark marks caused by fungal or bacterial diseases, insects, hail damage, and 950 nm was the optimal wavelength for detecting bruises, punctures, and scald. The splitter was mounted in front of the camera and contained optics that divided the incoming image.

Different threshold segmentation methods were used in this study. A filtered image was produced by subtracting the original image and setting all negative grey levels. This is a simple threshold segmentation based on flat-field corrected images. In this case, an image of a white sphere, the size of the apples, was inverted and added to the original apple image. Another segmentation was used in which the images were segmented several times at different threshold levels. This segmentation aimed at identifying the darkest areas in the original image. The resulting, binary image was referred to as a marker image. Having established the position of the defects, segmentation was used to determine the area of these defects. Another method was used in which a correction image was created through filtering and averaging of the eight frames. These images were then threshold segmented to identify the defects. All image processing was done using Multiscan with the image and signal processing toolbox.

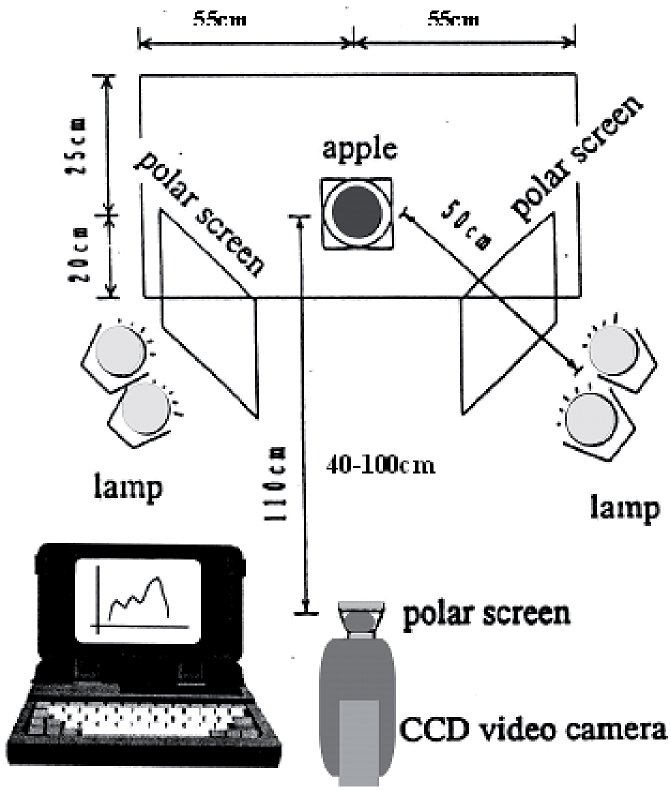

Fig. 1. Machine vision system

RESULTS AND DISCUSSION

As the apple was rotated 45° between the acquisitions of each frame, a given part of the surface appeared at different positions in as many as eight frames. As the apples in this work were rotated through 360°, some defects could be visible in more than one frame. It was decided to consider defects appearing in three or more frames to evaluate the performance of the system. The images, which were observed, contained dark areas of which some were actual defects. The image processing routines were segmented to identify potential defects, followed by combing the frames in order to separate defects from false positives. After segmentation, the individual frames were combined. In the combined image, defects appeared with almost the same shape and at the same place in three or more frames. After the frames were resized, they were flat-field corrected using an average of eight images. This average was inverted by subtracting the pixels values from 255, and then it was resized to the proportions of the apple to be flat-field corrected. After resizing, the frames were combined to form an image of the entire apple surface. Apples rotated through 360°, and by acquiring 8 frames, each part of the apple surface was overlapped as many times. From this a matrix was created from segmented versions of the frames, in which the apple and the background were identified by pixel values of 1 and 0, respectively. Then the resulting image was created by this matrix. The segmented frames were combined as described for the grey scale images. In each segmented frame, dark areas represented potential defects Areas classified as non-defective was assigned a value of 0. When the segmented images were overlapped, the same dark area was identified in more than one frame. The potential defect had been identified in at least three frames at the same location on the apple. These cases were classified as defects.

A set of 300 apples, including fruits of different qualities and damage, was used to test the developed algorithm (Fig. 2).

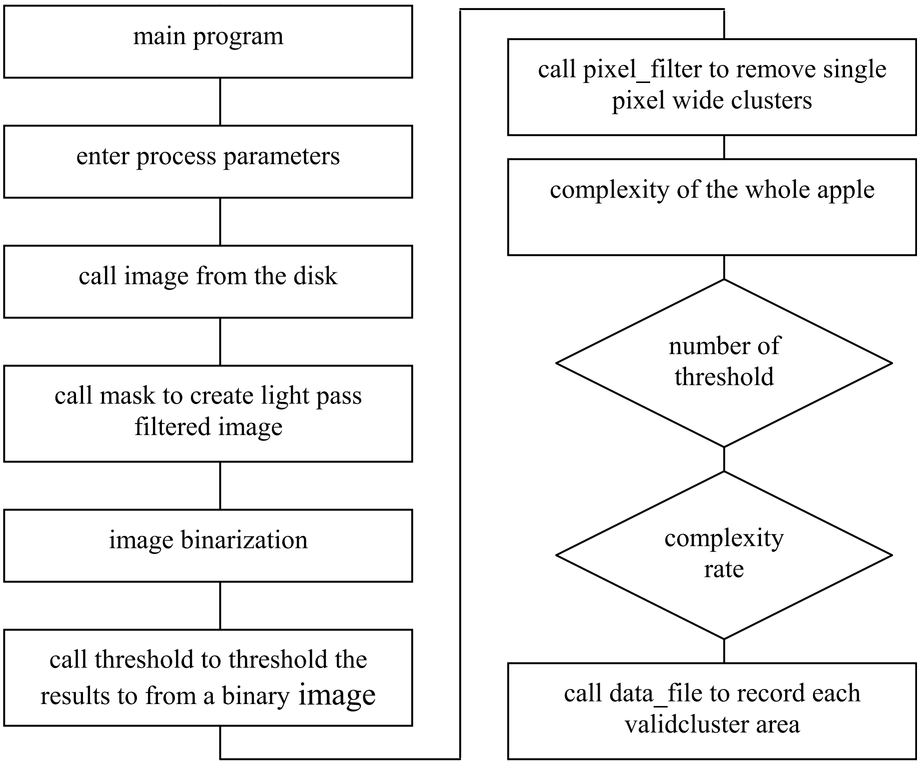

Fig. 2. The algorithm of process on apple image

Some results are shown in Fig. 3 where defect segmentation appears in the right part of the figures. Five particular fruits were chosen to show the difficulties because of the high variability among apples. The apple ground colors in images were yellow, red and green. The first apple had an old insect bite which had produced growth damage. On the defect segmentation the contrast between healthy and defective areas was clear, it appears equally size and shape of scar tissue. The second defect (lower part of the Fig. 3) resulted from a bruise. The healthy tissue was impaired, providing poor contrast, and the defect border was strongly blurred. The third defect (right part of Fig. 3) showed fungi attack. Here, the contrast was low compared to the ground skin color of apple. The fourth damage resulted from an early scab attack. The contrast was very clear, but the middle of the defect was made of scar tissue, and the defect presented a wide range of color. The last defect (lowest part of Fig. 3) was frost damage. The contrast between sound and defective area was very clear. Generally, the segmentation algorithm was able to detect the defects as indicated by Fig. 3. However, the ability to segment them was of concern. The border of the fruits was slightly segmented as defect. It was less explored then the central part of scar tissue. The segmentation of the defect border was correct for all damages, except for the bruising and fungi attack, which were detected, but less accurately. The main weakness of this algorithm was detecting defects with color close to the ground color of apple. It might be improved by using different filtering methods applied to an apple image before or after segmentation. This way the border of the defect smoothed by filtration, would be advantageous for defect shape determination.

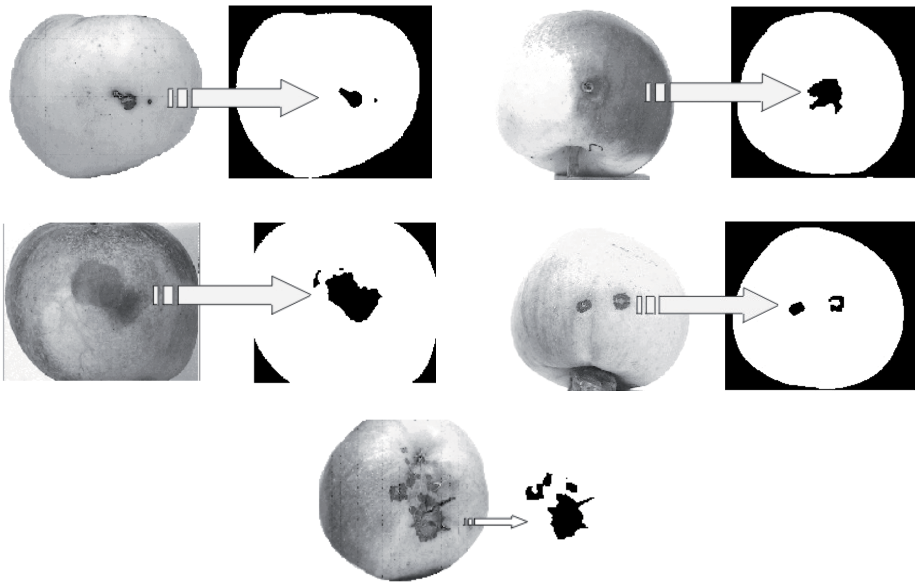

Fig. 3. Examples of processed image on apples

Measured area of defects by a vision system versus manual measured area (human visual inspection) for tested apple varieties are presented in Fig. 4 and Fig. 5. The defects of fungi attack, frost damage, bruising, punches, insect holes, scab have been processed by the algorithm. Linear relationships were developed between those parameters with determination coefficients in the range of 0.96-0.99. Diagrams for Melrose, Jonagold, Alwa and Golden Delicious had the least amount of scatter about the regression line.

Distribution of the healthy fruits surface segmented as defect for all tested varieties is shown in Fig. 6 for Melrose, Jonagold, and Alwa, 65% of the healthy fruits have less than 5% of their surface segmented as defect, however for Fiesta, Gloster and Golden Delicious it was only 35%. While 83% of fruits of Jonagold and Alwa have less than 10% of their surface segmented as defect, the remaining apples had only 63% defects.

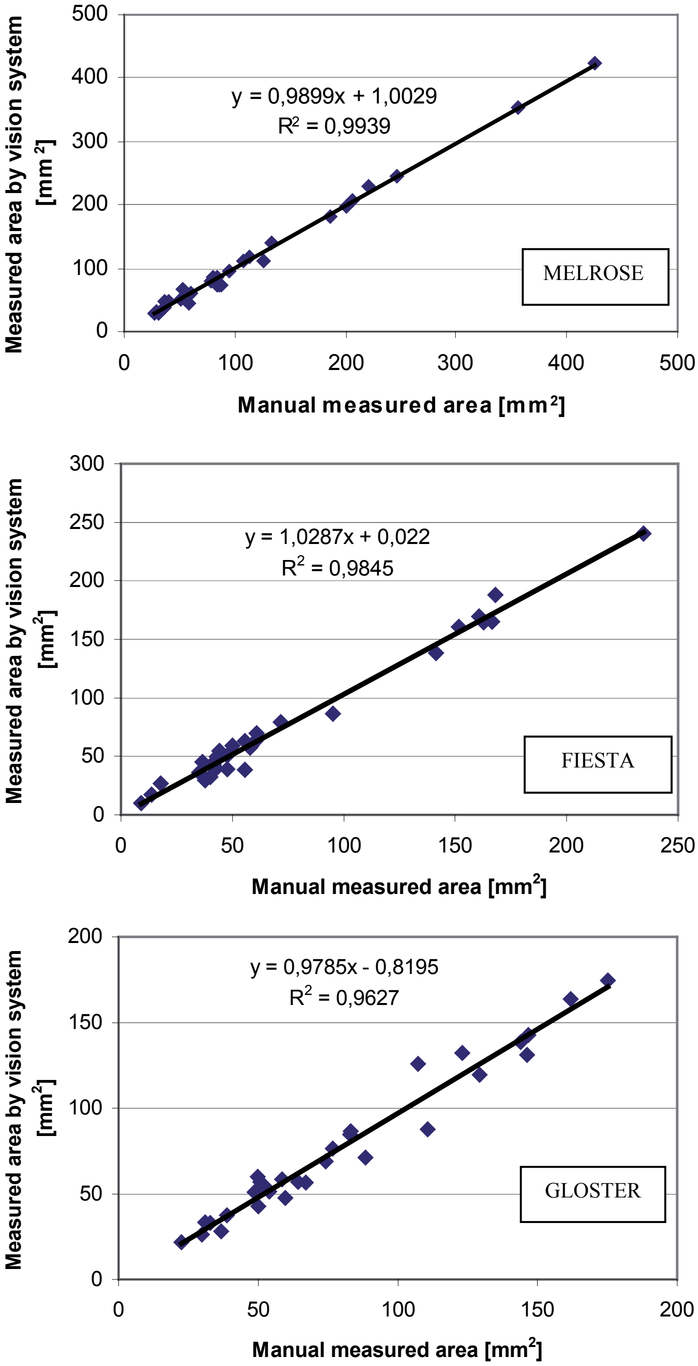

Fig. 4. Measured area by vision system versus manual measured area for tested varieties

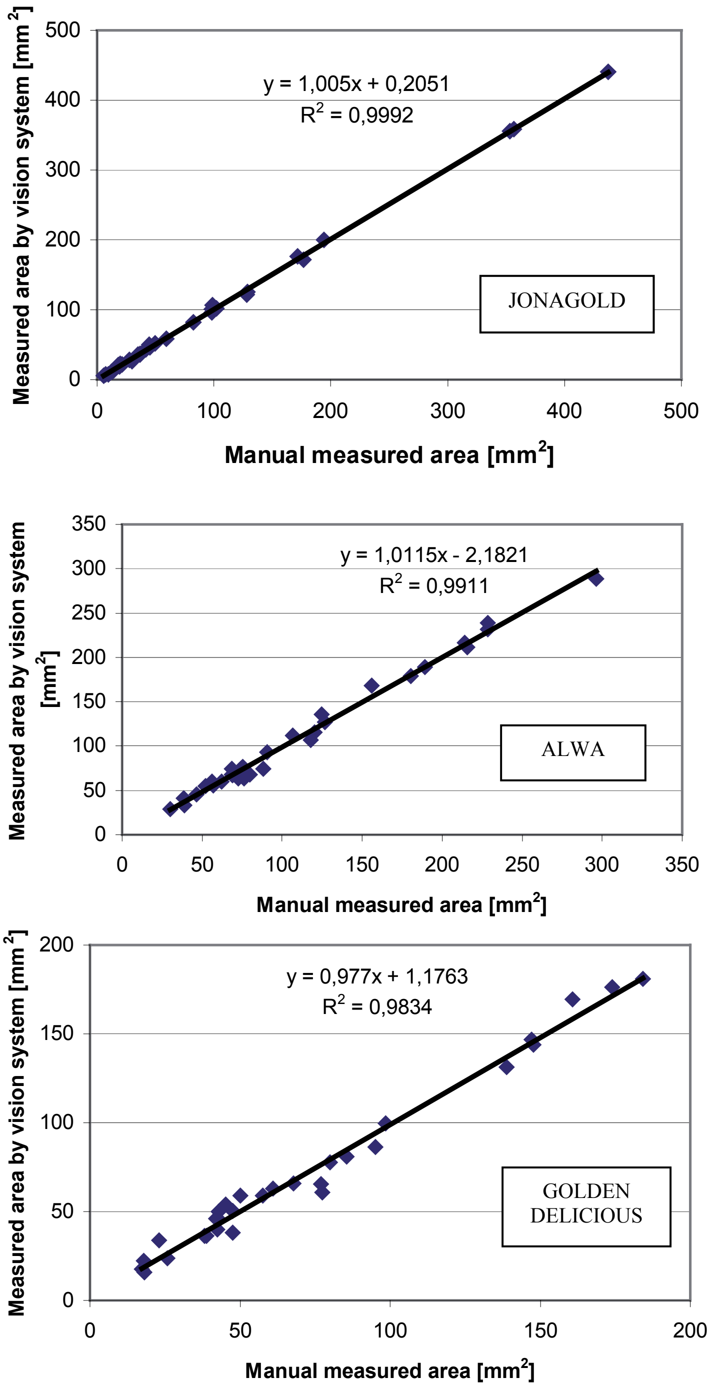

Fig. 5. Measured area by vision system versus manual measured area for tested varieties

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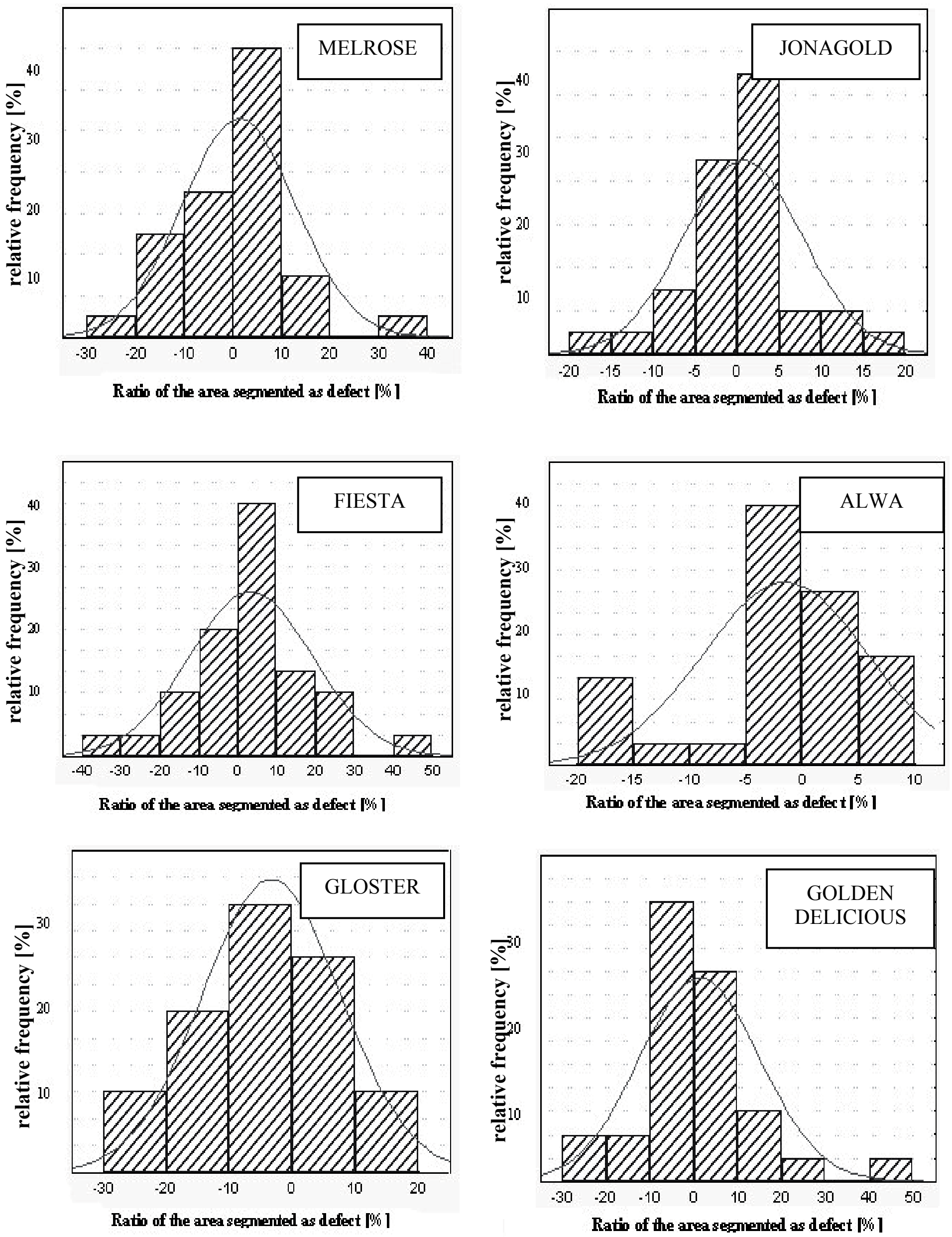

Fig. 6. Distribution of the healthy fruits surface segmented as defect for all tested varieties

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CONCLUSION

A system for identifying surface defects on apples was designed, based on analyzing images acquired while apples were rotating in front of the camera. When multiple images were combined and adjustments made for rotation, dark areas caused by defects would appear with almost the same shape and at the same place in three or more frames. The proposed algorithm was able to detect defects such as bruises, frost damage, and scab. The method had a classification accuracy of 96% for the samples in these experiments.

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