39. SIMPOZIJ AKTUALNI ZADACI MEHANIZACIJE POLJOPRIVREDE

UDC 631.358:634.11
Stručni rad
Expert paper

MACHINE VISION RECOGNITION ALGORITHM DEVELOPMENT AS THE FIRST STAGE OF APPLE ROBOTIC HARVESTING

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ABSTRACT

Machine vision application in mechanized tree fruits harvesting operations can be implemented by image processing algorithms. In this paper, a combination of color and shape processing was used to segment the red apples images in order to detect an apple fruit in each image and to determine its location. Thirty images had been taken, randomly. Images were filtered, converted to binary images, and noise reduced. The algorithm was finally assessed. The algorithm could detect apple fruits in the 83.33% of images and determined apple locations with precision of 85.17%.

***Key words**: machine vision, image processing algorithm, fruit detection, apple harvesting.*

INTRODUCTION

Iran is the 4th apple producer in the world (Food and Agriculture Organization, 2009) which indicates the need for mechanization and implementation of appropriate technologies.

Tree fruits harvesting is a susceptible operation. Its profitability may be influenced by labor inaptitude, costs and unavailability, low quality harvesting, and operation untimeliness. So, mechanized harvesting operation may solve the problems.

Mechanized fruit harvesting may be mechanically or automatically. Mechanical fruit harvesting methods have been studied for decades (Shepardson et al, 1970; Peterson et al, 1994; Erdogan et al, 2003) and robotic harvesting has also a long history (Schertz and Brown, 1968; Jimenez et al, 2000; Bulanon and Kataoka, 2010).

Apples mechanical harvesting by mass removal techniques makes damages due to excessive apple movement during detachment, apple-to-branch, and apple-to-apple contacts (Peterson, 2005). These damages are in the form of splits, punctures and bruises (Singh and Reddy, 2006).

Problems accompanying with mechanical harvesting resulted in development of robotic methods.

Prototype machine vision based harvesters are increasingly being developed. Apple (Parrish and Goksel, 1977; Bulanon and Kataoka, 2010) and other fresh fruits and vegetables (Levi et al, 1988; Satish Mehta, 2007) have been worked on for decades.

The automated harvesting system should perform the following operations: (1) recognize and locate the fruit; (2) reach for the fruit; (3) detach the fruit without causing damage both to the fruit and the tree; and (4) move easily in the orchard (Sarig, 1990).

The first operation needs development of appropriate methods to detect and locate the fruits. Using photometric information based (Schertz and Brown, 1968) and infrared laser range finding (Jimenez et al, 2000) methods were developed. While, image processing based methods have been used to detect and located the fruits (Bulanon and Kataoka, 2010; Satish Mehta, 2007; Slaughter and Harrell, 1989).

"Both intensity/color pixel-based and shape-based analysis methods were appropriate strategies for the recognition of fruits, but some problems arose from the variability of the sensed image itself when using CCD cameras, which are very sensitive to changes in sunlight intensity as well as shadows produced by the leaves" (Jemenez et al, 2000).

Since no research has been reported on robotic apple harvesting in Iran, this paper focuses on recognition of apples, as the first stage of apple robotic harvesting.

Recognition of apple fruits using machine vision under natural daylight conditions was the objective of this study. Thirty images of Red Delicious apple canopy were selected randomly from photos taken of apple trees. The images were taken from Hamedan groves, in Iran.

MATERIALS AND METHODS

Image acquisition

Thirty digital images were obtained under the uncontrolled daylight conditions. Image frames were 3072 × 2304 pixels in the JPEG format. A digital camera (*Sony, DSC-H5, Color CCD Camera*) was used to acquire the RGB images.

Image processing algorithm

The goal was finding and locating an apple in each image obtained in uncontrolled lighting conditions. In order to segment the acquired images, a color-shape based algorithm was developed to decline luminance variety.

The algorithm was developed by MATLAB (*R2007a*) and a laptop (*Dell, Vostro 1510*) was used to process the images.

The algorithm was implemented based on the following steps:

1. The images were first enhanced. A Gaussian low-pass filter was used to reduce the noise as much as possible. Noise portends unequal color intensity distribution in the original images that formed shades and shiny regions in the images.

   The Gaussian filter was a 250 × 250 pixel matrix with standard deviations of 200 which limit image frequencies to less than 200 Mega Hertz (MHz). Filtered images were noise-reduced by removing high frequencies (more than 200 MHz). Filtering the image caused blurring.
2. Filtered images were then converted to binary form in order to be processed.
3. Binary images were processed to reduce the existing noise after converting images. In this stage, noise was defined as the areas detected as features other than apples. This stage of the project is shape-based processing of color-based processed images.
4. Binary, noise-removed images were then labeled in order to extract apple fruit feature.

RESULTS AND DISCUSSION

Since the images were acquired under uncontrolled natural daylight conditions, they included tree branches, leaves, fruits, sky, etc. Each object of the image had its own properties, making image set of features which the apple fruit was just on of them.

First stage of the algorithm was color processing. Filtering the images made them blurred (Figure 1-b). Objects of the filtered images were less than of the original images. Consequently the blurred image, obtained from Gaussian filter, included less noise.

Converting the image to binary form and shape-based analysis made the noise as low as possible (Figure 1-c, 1-d). Labeling image features resulted in showing image objects as separate images (Figure 1-e).

Errors caused by uncontrolled lighting conditions in this algorithm made it generalizable under various lighting. Color-shape based algorithm could detect the apples in 25 of 30 images. In other words, the accuracy of the algorithm was 83.33%.

The precision of the algorithm was defined as its ability to locate the apple fruits. So, the overlap between a rectangular surrounded apple in the original image and a same sized rectangular, focused on detected apple feature center in the binary image, was calculated. Pixels included in the coverage area were assumed as overlap. Figure 2-b shows the overlap area.

The algorithm could locate the apple fruits with precision of 85.17%, whereby the maximum precision measure was 99.71% and the minimum was 54.43% (Table 1).

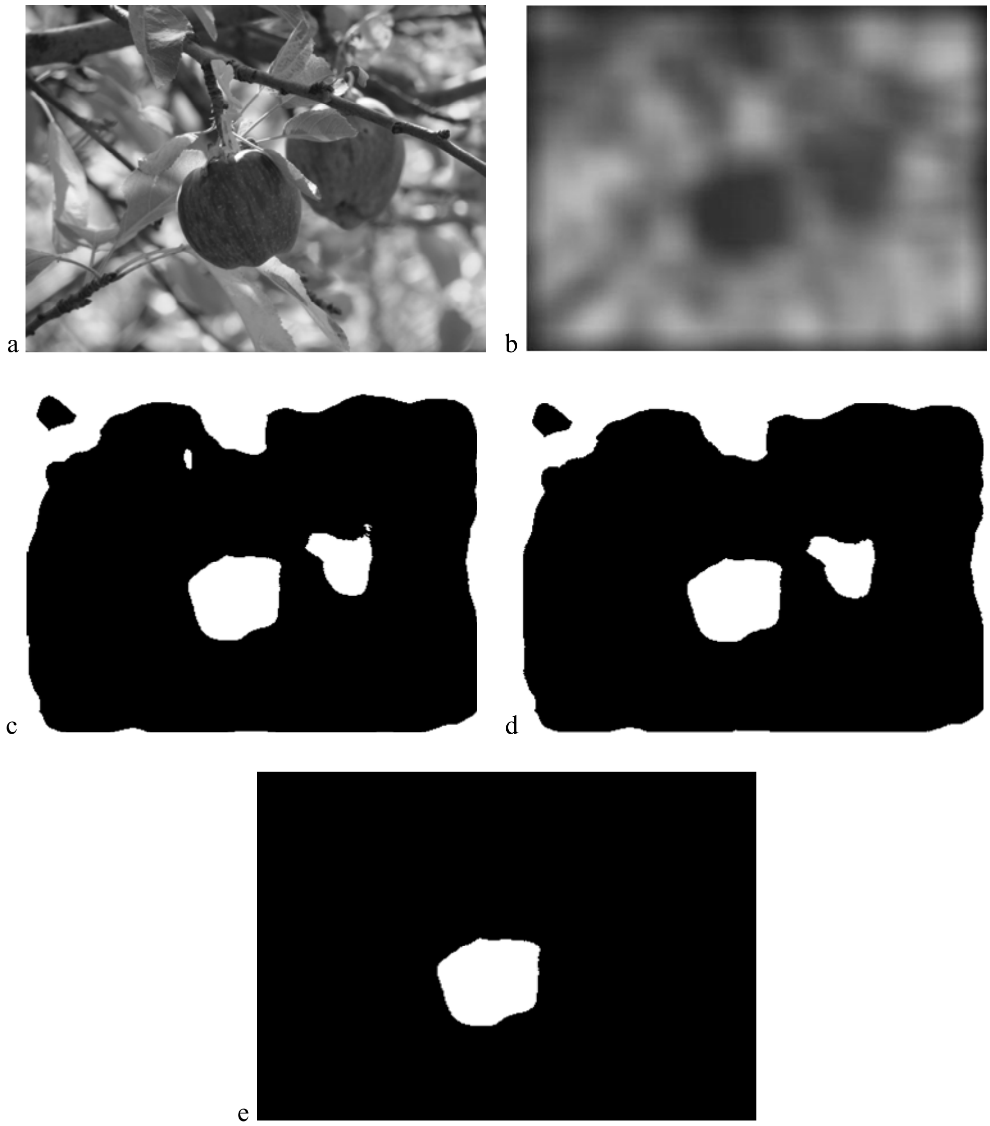

Figure 1 Color-shape based algorithm, a) Original image, b) Filtered image, c) Binary image, d) Noise-reduced binary image, e) Labeled image

Table 1 Algorithm precision descriptive statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Precision	25	0.4528	0.5443	0.9971	0.8517	0.1095	0.0120

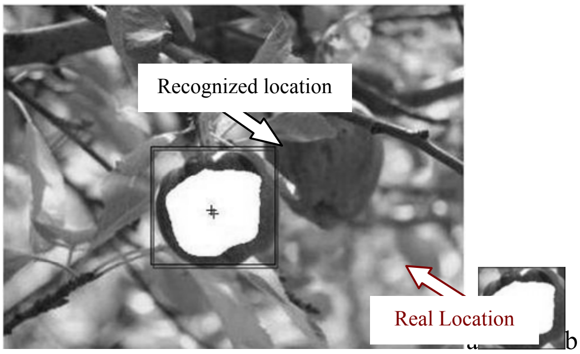

Figure 2 Overlap between recognized and real location of apple, a) Relative position of recognized and real locations, b) Overlap area

CONCLUSIONS

The main idea was to develop an algorithm be able to be generalized under various natural lighting conditions. A color-shape based algorithm was developed and assessed to detect one apple in each image. No control was applied to standardize the acquired images lighting. The algorithm was able to detect apple by accuracy of 83.33%. Its precision was 85.17% ranged from 54.43% to 99.71%.

Errors caused by uncontrolled conditions in this algorithm made it generalizeble under various lightings.

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