American-Eurasian J. Agric. & Environ. Sci., 12 (10): 1288-1294, 2012
ISSN 1818-6769

DOI: 10.5829/idosi.aejaes.2012.12.10.2435

Recognition of Pomegranate on Tree and Stereoscopic Locating of the Fruit

Adel Bakhshipour, Abdolabbas Jafari and Seyed Mehdi Hosseini

Department of Agricultural Engineering, Shiraz University, Shiraz, Iran

Abstract: Mechanized harvesting of pomegranate is still a challenge due to tangled shape of the tree. Robotic harvesting seems to be the final solution in this case. The first step for this aim is to recognize the pomegranate fruit and locate its spatial position on the tree which has been the objectives of this approach. Color features of three different color spaces, RGB, HSV and YC_rC_b were studied to discriminate the fruit from the surrounding objects in the images. Two-dimensional locations of the fruits were determined using their corresponding centroid in the images. Stereoscopic images captured from two identical cameras were used to determine the depth of the ROIs in the images. This would yield the 3D location of the fruits which is needed for the harvesting robot to pick the fruit. Results showed that C_r component of the YC_rC_b color space has been the best criterion for segmentation of fruit from the other objects in the images with 100% correct recognition rate. Maximum distance estimation error (DEE) of 2.4 cm was determined for the stereoscopic vision system which shows its consistency to be used as a recognition and locating tool for pomegranate harvesting robot.

Key words: Stereovision · Image processing · Harvesting · Pomegranate

INTRODUCTION

Pomegranate (*Punica granatum* L.) belongs to the based on possible relationships between fruit properties, Punicacea family [1]. The fruit is consumed directly as well as fresh juice which can also be used in beverages, jellies and as a flavoring and coloring agent [2]. It is extensively cultivated in Iran, Spain, Egypt, Russia, France, Argentina, China, Japan, USA and in India [3]. The harvesting approach for this fruit has not changed significantly and still is done traditionally by hand. Manual harvesting of the fruits is a hard work which has many negative physical and physiological effects on farmer's health, also it has the disadvantage of low capacity and high labor costs. Mechanization of harvesting is a way to keep up with the competition as labor costs rise and the supply of workers reduces every year. So, it seems to be so important to develop an automated machine to harvest fruits.

Visual navigation of agricultural machinery is a research hotspot of intelligent agricultural machinery recently [4, 5]. Computer vision is a novel technology for acquiring and analyzing an image of a real scene by computers and other devices in order to obtain information or, to control machines or processes [6]. Color is an effective descriptor to enhance an object in an image to simplify object identification and extraction from an image [7]. The algorithm must take into account the appearance of highlights and shadows and must remove the effect of lights and shadows to successfully recognize the fruit.

Many researchers have been interested in investigating computer vision and image processing applications in various agricultural fields and applications [8-12]. Ghazali *et al*. developed an intelligent system to identify and discriminate the weed types using image processing techniques. Classification result of weed showed the successful rate more than 80% [13].

Arivazhagan *et al*. [14] used computer vision strategies to recognize a fruit type using intensity, color, shape and texture features. Slaughter and Harrell [15] used chrominance and intensity factors to recognize oranges on a tree.

Bulanon *et al*. [7] developed an algorithm for the automatic recognition of Fuji apples on the tree; they enhanced the difference between fruit from other objects in the image, based on red color difference. After segmentation they determined the center of the resulting objects as the location of apples. However these researches did not propose any approach to determine the distance between apples and camera.

Corresponding Author: Adel Bakhshipour, Department of Agricultural Engineering, Shiraz University, Shiraz, Iran.
Tel: +98 711 613 8370, Fax: +98 711 228 6104.

The first problem in a fruit-harvesting robot is finding the three-dimensional location of the fruit on the tree. Stereovision techniques are used in machine vision systems to determine the spatial coordinate of a specific object in a scene. Stereoscopic vision is a reliable tool in order to obtain image and depth data for scene at the same time [16].

To obtain more complete field information, a stereovision system can provide a three-dimensional (3D) field image by combining two monocular field images taken from a binocular camera simultaneously [17].

There have been considerable advances in the field of stereovision during recent years [18]. In recent years, stereovision has been used in the various fields for the delivery of 3D information. The recent advances in machine vision techniques and robotics enhances the role of stereo system in different automation fields.

Huang and Lee [19] developed a vision-guided grasping system for Phalaenopsis tissue culture plantlets. They implemented an image processing algorithm to determine the suitable grasping point on the plant root in the 2D images.

Sun *et al*. [20] investigated the use of stereovision techniques for measuring the thickness and detecting the presence or absence of a ridge of a sample of wheat grains placed on a tray with dimples.

Kise *et al*. [17] developed a stereovision based crop-row detecting method. Field validation tests indicated that the stereovision-based guidance system could localize crop rows accurately and reliably in a weedy field with missing sections of soybeans.

Monocular machine vision has been in use on agricultural vehicles for more than twenty years. It provides a (2D) representation of the target scenes, but it cannot reliably determine the distances which objects are located within the field of view of the camera [21].

Laser based 3D locating seems to be a fast and convenient method for depth or distance measurement and there are several applications of laser distance finders [22-24] but in the case of fruit harvestingthis method is not practical for fruit positioning among the boughs and leaves of the tree. When a beam of laser light is intersected by an object, this object is considered as the target while the light might be intersected by a leave or a small bough before reaching to the target fruit. It means that laser based locating cannot differentiate between the object of interest and the noise. Therefore the method should have some sources of intelligence to distinguish the main object and then locate it. Such preference was the reason that stereo vision approach was tried for this problem.

The most effective method of discrimination between the pomegranate fruit and other surrounding objects on the tree has been studied in this research. Although, by the aid of shakers it is possible to harvest a wide range of different fruits, but in case of pomegranate with slim stems, shakers are useless. Robotic harvesting is anticipated to be the only possible way.

So the aim of this study was to develop an intelligent stereoscopic vision-based algorithm for a pomegranate fruit harvester robot. The main contribution of this paper is finding the best possible discriminator for detecting the pomegranate and also exploiting the stereo vision method as an applicable method for locating the fruit on the tree.

MATERIALS AND METHODS

Sample and image Preparation: The trees used to capture images in this project were randomly selected from the Botanical garden of Shiraz University. In total (2×55) RGB color images were taken (2 images from each fruit) under several natural daylight conditions (sunlight, shaded and cloudy) during a week in the harvesting season, on the first week of October 2010. 40% of the images were used to develop algorithms and 60% to test the algorithm.

Two CCD cameras with similar specifications (Canon IXUS 960IS; 12 megapixel camera with 3.7x optical zoom lens) were used to take images from each pomegranate simultaneously. Cameras were mounted on a common chasis side by side with a distance of 15 cm between their lenses. The axel was at the identified distance from fruits. Images were then transferred to computer and were analyzed using image processing toolbox version 7.0 for MATLAB [25].

Image Analysis: In this study, at first a suitable algorithm was developed to separate the pomegranate fruit from leaves, tree branches and other possibly unacceptable materials. The image processing-analysis is the heart of the machine vision system. An important quality attribute used in image processing is color which is resulting from the interaction between light, the object and the observer [26]. Primitive investigations showed that there was good difference between color components of pomegranate fruit and other objects in the images. So Color features were used to separate pomegranate from other objects in the images. YC_rC_b color space was used for the quantification of colors in the image. Y, C_r and C_b are respectively luminance, red color difference and blue color difference. The following equation converts a RGB color space to YC_rC_b:

$$Y = 0.3R + 0.6G + 0.1B \quad (1)$$

where, R, G and B are the red, green and blue color intensity values ranging from 0 to 255. Red and blue color components are extracted from luminance image as below:

$$C_r = R - Y \quad (2)$$
$$C_b = B - Y \quad (3)$$

As primitive tests showed that the red color difference leads to the most useful results in this case. Note that each color component in RGB color space varies in different lighting conditions. These components increase as the ambient luminance increases and decrease with the decrease of ambient luminance or lighting. The appropriate algorithm must be able to solve this problem. Red, green and blue color differences have the capability to remove the negative effect of lighting changes. Since the sum of the coefficients of R, G and B values in C_r equation (Eq. 4) is zero, adding or subtracting a constant value to the R, G and B color components doesn't change the C_r component. So red chrominance value (C_r) would be insensitive to the luminance variations. It means that the situation of the fruits in light or shadow does not affect the segmentation results:

$$C_r = R - Y = 0.7R - 0.6G - 0.1B = 0.7(R + M) - 0.6(G + M) - 0.1(B + M) \quad (4)$$

Flowchart of the recognition algorithm is shown in Figure 1. At first, the red color difference intensity histogram (Figure 2) was developed to obtain optimal threshold value. Histogram shows the frequency of a specific color component value distribution in an image, including object and background. Although the threshold value extracted from the histogram did not lead to successful recognition of the fruit, it was a good estimation to find the best value. Applying this value the fruit in the image has been recognized and separated from other unwanted objects. Subsequent dilation and erosion operations were performed to omit the small objects misclassified as fruit and to modify the problem of fruits overlapping. After removing all undesired objects from the background and filling unwanted noisy holes within the fruits, pomegranate fruit and the background were completely separated.

Another issue is that there are more than one fruit in one image; algorithm should be designed so that one fruit is chosen as target fruit. To solve this problem, the algorithm removed all objects in the image except the fruit

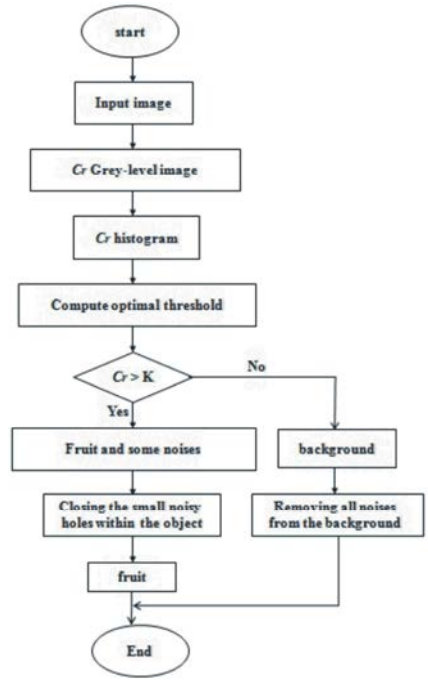

Fig. 1: Flowchart of the recognition algorithm; C_r: red color difference, k: optimal threshold

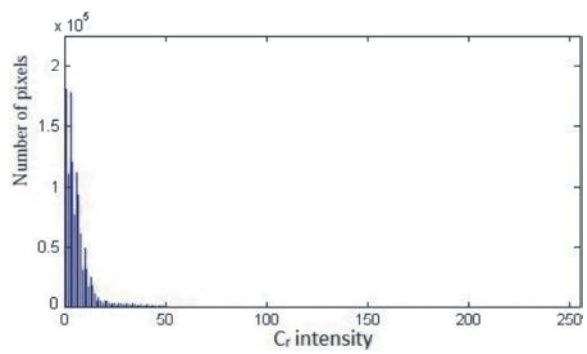

Fig. 2: C_r intensity histogram of a single picture

which had maximum area. The robot should continue capturing images from a scene until the number of objects whose size is greater than a specified value vanishes. Considering that, generally, the closer fruits are to the camera the larger they appear, the two possibilities are:

- The fruit is in the access range of the harvesting robot but the fruit size is smaller than required. Then the harvester should not pick these small fruits.
- The fruit size is as required but it is far from the picking arm and robot operation range. In this case, because the harvester is considered to turn around the tree, finally that fruit will be detected and selected in other images.

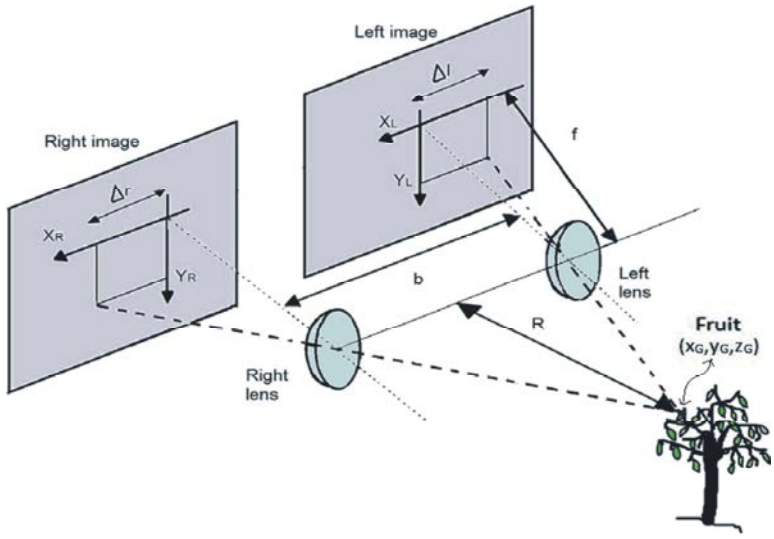

Fig. 3: Schematic of stereo-image processing geometry

The center of the area for the selected object was determined to allocate fruit on the tree in 2-D images.

Determining the Distance of Fruit from Viewer: Distance of fruit from viewer was calculated in the second step of this study using simple stereovision approaches and geometric formulas. To determine the third dimension of fruit location, two cameras with the same resolution and focal length of the lens (*f*) were used to take images from each scene. These cameras were in the same elevation and same distance from the fruit and there was a defined distance (b=15 cm) between the centers of the two cameras (the centers of two lenses). Figure 3 shows a schematic of the stereoscopic system.

In Fig. 3, if the position of fruit in left image, right image and the global 3D location of the fruit on the tree are defined as (x_L, y_L), (x_R, y_R) and (x_G, y_G, z_G) then, assuming the fruit location coordinate in the left image as the basis for robot operation;

$$x_G = x_L \text{ and } y_G = y_L = y_R \tag{5}$$

But as both of images are on the same plane and they have the same central horizontal axes then:

$$x_L - x_R = d \tag{6}$$

where difference (*d*) is defined as the disparity of the target in a stereo image pair and is used to calculate the depth of the target [27]. The 3D location of a point in the left camera coordinates can be obtained as follows:

$$\frac{b}{(d-b)} = \frac{z_G}{f} \rightarrow z_G = \frac{bf}{(d-b)} \tag{7}$$

RESULTS AND DISCUSSION

To select the best color component that provide the optimum segmentation, the pixel values of branches, leaf and fruit were compared for each color component.

Figures 4 - 6 show the scatter plots for several color components in RGB, HSV and YC_rC_b color spaces. R, G and B components were plotted vs. grey values. In the same way the red, green and blue color differences were plotted vs. image luminance and the H, S and V values vs. the mean of them. Among all color values, except the case of C_r component, the fruits and other objects were highly overlapped in the images. So it was almost impossible to find an appropriate threshold to distinguish pomegranate fruits in the images using aforementioned color values (Figures 4-6). On the other hand, there was evident distinction between red color difference components of the fruit and the leaves and boughs. Therefore C_r component was selected to recognize the pomegranate fruits in the image.

Figure 7 indicates a gallery of the steps passed for fruit recognition. Selection carried out based on the maximum size and distance from the camera has selected one pomegranate fruit as the first target for picking. Other objects have been removed from the image at this stage. The target fruit has been recognized and separated from other objects in the image completely.

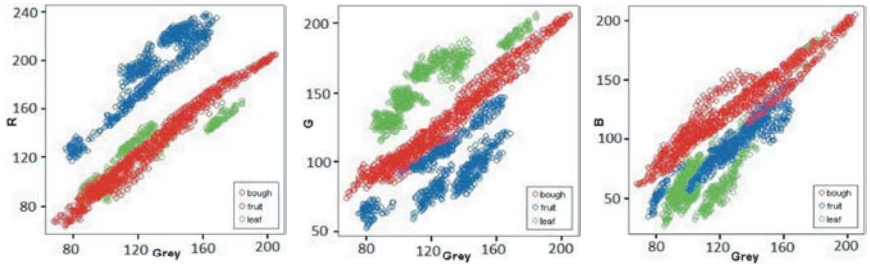

Fig. 4: Scatter plots of color components in the images (RGB color space)

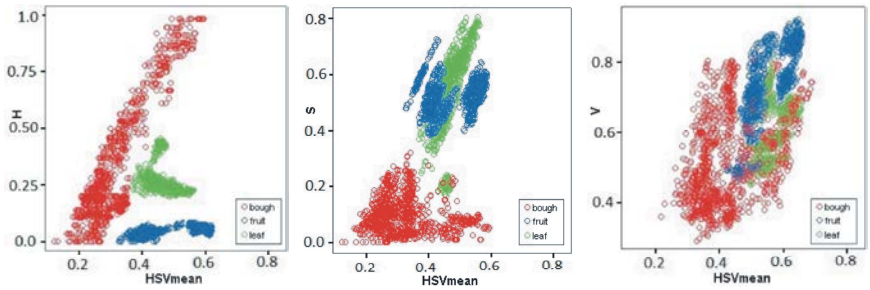

Fig. 5: Scatter plots of color components in the images (HSV color space)

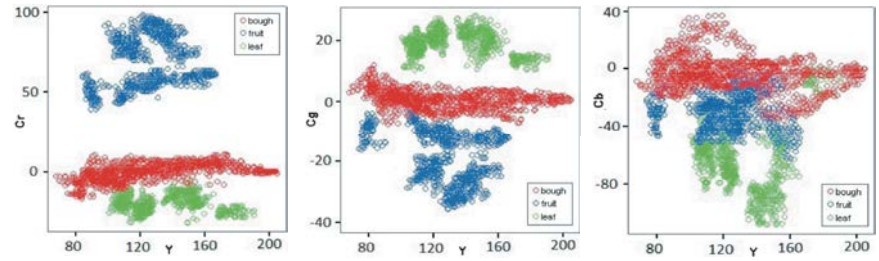

Fig. 6: Scatter plots of color components in the images (YC_rC_b color space)

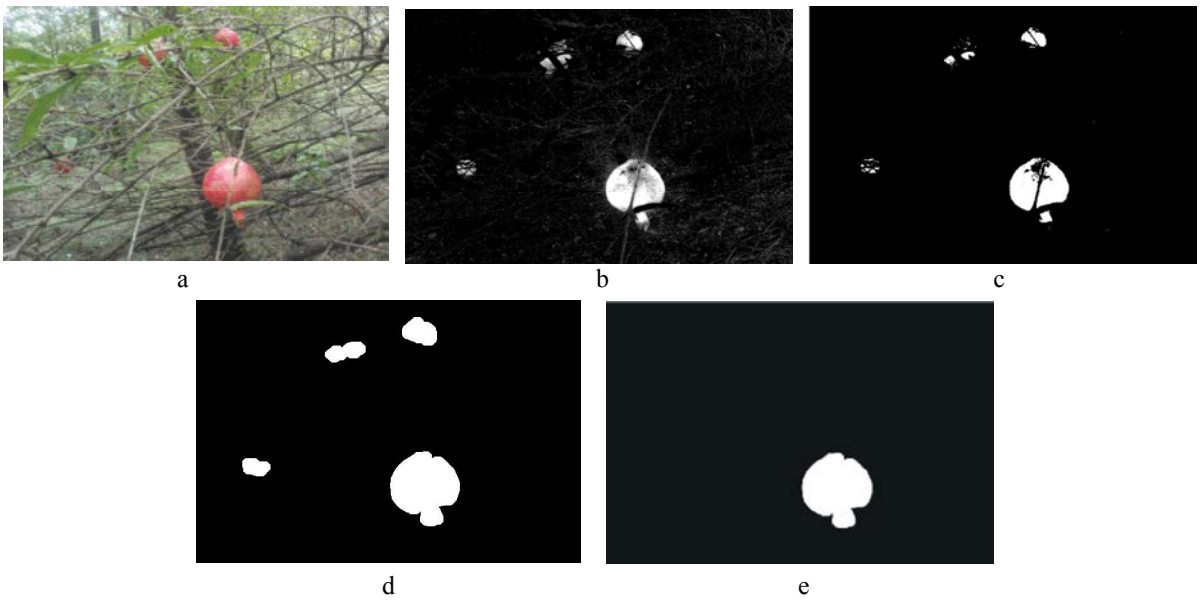

Fig. 7: Result of fruit recognition algorithm; a) main image, b) C_r component c)binary image after threshold on C_r component d)filling the objects e) selecting the biggest object in the image in the range of the robot arm

Discrimination error of algorithms is normally considered as the differences between the number of pixels correctly distinguished as the target and actual number of target pixels. Presence of some leaves and boughs in front of the fruits obstruct the use of such definition especially while further modifications are designed in the algorithm to enhance the detection result. Therefore, overall performance of the algorithm was determined based on the fruit detection error which was defined as the number of objects incorrectly detected as fruit.

Among the 33 images excluded for assessment of the algorithm no one of the objects was seen to be detected incorrectly as the pomegranate fruit. Although there were some remote fruits mostly covered by leaves and branches caused to be removed from the images. 3.7% of the fruits (5 from 134 fruits in 33 images) were omitted from the images due to the aforementioned situation.

After recognition of the target fruit, locating was carried out by considering the centroid of the fruit in the binary image as the target point, was found.

Distance estimation error (DEE) was also defined as the difference between the estimated and actual distance of the fruit to the camera. 15 samples of the fruits were used for this evaluation which yielded a maximum error of 2.4 cm when the distance to camera was 2 m. DEE decreased to almost zero when the distance diminished from 2 m to 25 cm.

CONCLUSIONS

A typical fruit harvesting robot utilizes machine vision systems to recognize and locate the fruits on the tree. Pomegranate recognition algorithm developed in this study used color differences components (YC_rC_b color space) as criteria for discrimination the pomegranate fruits from the leaves and boughs. None of the other objects in the images were considered by the algorithm as pomegranate while 3.7% of the fruit samples were removed from the images. However this is not a problem for the harvester because the robot is assumed to turn around the tree and look for the fruits. So the omitted fruits in one image will be detected in other closer views at different positions.

Locating the fruits was carried out by means of stereovision system. In as much as there was not a large distance between the two cameras to affect the distortion of the image and pomegranate is almost spherical, the centroid of the fruit was accurate enough to be considered as the target point for a picking arm. Distance estimation error of the algorithm was less than 2.4 cm which is reasonable for the picking arm of a robot.

REFERENCES

1. Akbarpour, V., K. Hemmati and M. Sharifani, 2009. Physical and Chemical Properties of Pomegranate (*Punica granatum* L.) Fruit in Maturation Stage. American-Eurasian Journal of Agriculture and Environmental Sciences, 6(4): 411-416.
2. Raisi, A., A. Aroujaliana and T. Kaghazchia, 2008. Multicomponent pervaporation process for volatile aroma compounds recovery from pomegranate juice. Journal of Membrane Science, 322: 339-348.
3. Patil, A.V. and A.R. Karade, 1996. In: T.K. Bose and S.K. Mitra, (eds.) Fruits: Tropical and Subtropical. Naya Prokash, Calcutta, India, pp: 252-279.
4. Slaughter, D.C., D.K. Giles and D. Downey, 2008. Autonomous robotic weed control systems:A review. Computers and Electronics in Agriculture, 61: 63-78.
5. Torii, T., T. Teshima, T. Okamoto and K. Imou, 2003. Vision based navigation of a boom sprayer. Journal of the JSAM, 65: 70-75.
6. Sun, D.W., 2003. Computer Vision: An Objective, Rapid and Non-Contact Quality Evaluation Tool for the Food Industry. Journal of Food Engineering, 61: 1-2.
7. Bulanon, D.M., T. Kataoka, Y. Ota and T. Hiroma, 2002. A Segmentation Algorithm for the Automatic Recognition of Fuji Apples at Harvest. Biosystems Engineering, 83 (4): 405-412.
8. Onyango, C.M., 2003. Segmentation of row crop plants from weeds using colour and morphology. Computers and Electronics in Agriculture, 39: 141-155.
9. Rashidi, M. and M. Gholami, 2008. Classification of fruit shape in kiwifruit using the analysis of geometrical attributes. American-Eurasian Journal of Agricultural and Environmental Sciences, 3: 258-263.
10. Bakhshipour, A., A. Jafari and A. Zomorodian, 2012. Vision Based Features in Moisture Content Measurement During Raisin Production. World Applied Sciences Journal, 17(7): 860-869.
11. Rashidi, M., M. Malekiyan and M. Gholami, 2007. Egg Volume Determination by spheroid approximation and image processing. World Applied Science Journal, 4(3): 590-596.

12. Abedini, M., M.A.M. Said and F. Ahmad, 2012. Clustering Approach on Land Use Land Cover Classification of Landsat TM Over Ulu Kinta Catchment. World Applied Sciences Journal, 17(7): 809-817.
13. Ghazali, K.H., M.M. Mustafa and A. Hussain, 2008. Machine Vision System for Automatic Weeding Strategy using Image Processing Technique. American-Eurasian Journal of Agriculture and Environmental Sciences, 3(3): 451-458.
14. Arivazhagan, S., R.N. Shebiah, S.S. Nidhyanandhan and L. Ganesan, 2010. Fruit Recognition using Color and Texture Features. Journal of Emerging Trends in Computing and Information Sciences, 1(2): 90-94.
15. Slaughter, D. and R. Harrell, 1989. Discriminating fruit for robotic harvest using colour in natural outdoor scenes. Transactions of the ASAE, 32(2): 757-763.
16. Ogale, A.S. and Y. Aloimonos, 2007. A roadmap to the integration of early visual modules, International Journal of Computer Vision, 72(1): 9-25.
17. Kise, M., Q. Zhang and F. Rovira-Más, 2005. A Stereovision-based Crop Row Detection Method for Tractor-automated Guidance. Biosystems Engineering, 90(4): 357-367.
18. Nalpantidis, L. and A. Gasteratos, 2010. Stereovision for robotic applications in the presence of non-ideal lighting conditions. Image and Vision Computing, 28: 940-951.
19. Huanga, Y.J. and F.F. Lee, 2010. An automatic machine vision-guided grasping system for Phalaenopsis tissue culture plantlets. Computers and Electronics in Agriculture, 70: 42-51.
20. Sun, C., M. Berman, D. Coward and B. Osborne, 2007. Thickness measurement and crease detection of wheat grains using stereovision. Pattern Recognition Letters, 28: 1501-1508.
21. Rovira-Más, F., Q. Wangb and Q. Zhang, 2010. Design parameters for adjusting the visual field of binocular stereo cameras. Biosystems Engineering, 105: 59-70.
22. Naesset, E., 1997. Determination of mean tree height of forest stands using airborne laser scanner data. ISPRS Journal of Photogrammetry and Remote Sensing, 52: 49-56.
23. Hsu, C.C., M.C. Lu, W.Y. Wang and Y.Y. Lu, 2008. Three-dimensional measurement of distant objects based on laser-projected CCD images. IET Science, Measurement and Technology, 3(3): 197-207.
24. Lee, K.H. and R. Ehsani, 2009. A laser scanner based measurement system for quantification of citrus tree geometric characteristics. Applied Engineering in Agriculture, 25(5): 777-788.
25. MATLB version7.10.0.499, 2010, computer software, The Math Works Inc., Natick, Massachusetts.
26. Fernández, L., C. Castillero and J.M. Aguilera, 2005. An application of image analysis to dehydration of apple discs. J. Food Engineering, 67: 185-193.
27. Lin, T.T., Y.K. Hsiung, G.L. Hong, H.K. Chang and F.M. Lu, 2008. Development of a virtual reality GIS using stereovision. Computers and Electronics in Agriculture, 63: 38-48.