Tarım Makinaları Bilimi Dergisi (Journal of Agricultural Machinery Science)
2011, 7 (2), 145-151

An Advanced Green Citrus Detection Algorithm Using Color Images and Neural Networks

Ferhat KURTULMUŞ[1], Won Suk LEE[2], Ali VARDAR[1]
[1]Department of Biosystems Engineering, Faculty of Agriculture, Uludag University, 16059 Bursa - TURKEY
[2] Agricultural and Biological Engineering, University of Florida, Gainesville, FL 32611 – U.S.A.
ferhatk@uludag.edu.tr

Abstract: Citrus fruits have great importance in the world in terms of production among different fruits. They are grown commercially in more than 50 countries around the world. Yield mapping plays an important role for citrus growers. Computer vision methods can help detect citrus fruits for developing citrus yield mapping systems. In this study, color, texture, and shape features were investigated and a computer vision algorithm using color images was developed to distinguish green citrus fruits in natural canopies. A sub-window based image scanning method was performed to scan entire image, and features of each sub-window were calculated. Color thresholding, eigenfruit approach and circular Gabor texture features were used for extracting color, shape and texture features. Using those features, cascade feedforward neural networks were constructed and trained. For developing and testing proposed algorithm, in the natural daylight illumination conditions, images were acquired using a digital camera (Model Powershot SD880IS, Canon) with a resolution of 3648 x 2736 pixels from Orlando Tangelo citrus variety. Experiments were conducted using training and validation image sets for developing and testing the proposed algorithm.
Key words: Citrus, computer vision, eigenfruit, image processing, artificial neural networks, precision agriculture

INTRODUCTION

Citrus fruits have great importance in the world with respect to in terms of production among different fruits. World production of citrus fruits is over 88 million tons per year (Pourbafrani et al., 2010). For the entire world, citrus producers encounter unpredictable costs because of in-field spatial variability such as tree size, soil type, soil fertility and water content. Precision agriculture techniques provide benefits against in-field spatial variabilities. Yield mapping is the first precision agriculture tool or technology to be implemented since it enables growers to find causes of yield variability. Recently most yield maps can be created at the mature stage of the citrus fruits when or after they are harvested. If an earlier yield estimation can be developed, it can provide many advantages to citrus producers, such as adjusting site-specific management practices to increase yield and planning harvesting operations well in advance to reduce harvesting costs.

Detection of young fruits to create yield maps is not easy because immature citrus are green. Distinguishing them from background green canopies is a quite difficult task due to color similarity between the leaves and fruits. In addition to the color similarity, major difficulties for on-tree green citrus detection via computer vision are occlusion of fruit by leaves, branches, and other fruits in natural canopies and non-uniform illumination in outdoor conditions.

Many researchers use computer vision and image processing techniques commonly for yield mapping and robotic harvesting systems. In early research of Parrish and Goksel (1977), the feasibility of an automated apple robot harvesting system based on pattern recognition techniques using a black-and-white TV camera was investigated. Pla et al. (1993) worked on spherical objects detection using artificial illumination and tested their method for citrus fruits. Under artificial illumination conditions, their system yielded 75% and 8% of success and false detection rates, respectively. Stajnko et al. (2004) used thermal imaging technique, and developed an algorithm to estimate number and diameter of apple fruits. For mature fruit detection, Regunathan and Lee (2005) developed a color-based fruit detection algorithm. Using a multispectral imaging method, Kane and Lee (2007) developed an image processing system based on pixel classification for green citrus detection. They could successfully classify 84.5% of the fruit pixels using multi-spectral imaging. Wachs et al. (2009) also carried out a research for detecting green and red apples using color and thermal imaging techniques. To detect fruit regions, they used Haar-like features and Viola-Jones classifier (Viola and Jones, 2004) which was exposed firstly for face detection. It can be clearly understood that usage of non-traditional imaging methods such as thermal and multispectral imaging is pricy for most of the citrus producers. Developing a more affordable method for immature green citrus detection using conventional color images can provide many benefits to growers.

Many computer vision and image processing researchers concentrated on identification of objects such as human faces, pedestrians, hand gestures and license plates. Eigenface approach was exhibited by Sirovich and Kirby (1987) and used by Turk and Pentland (1991) for human face classification. This approach was an imitation of human visual system for recognizing human faces using principal component analysis (PCA). Texture is one of the most important features of human vision to sense and differentiate objects. In the field of computer vision, Gabor texture features extraction is a commonly-used method for texture analysis. Zhang et al. (2002) proposed rotation invariant circular Gabor filters for texture analysis by expanding regular Gabor filters. By inspiring those approaches, eigenfruit feature extraction and rotation invariant circular Gabor texture feature extraction were used as part of the green citrus detection algorithm for this study.

Artificial neural network (ANN), usually called "neural network" (NN) is a machine learning method and computer model that tries to imitate functionality of the human brain. The ANN has wide range of application areas such as classification, pattern recognition (face identification, object recognition, etc.), decision making, data processing and clustering. In this study, the ANN was also used for identification of green citrus using extracted features which were explained in following sections.

The goal of this study was to develop a computer vision method to detect green citrus fruits in natural outdoor tree canopies using conventional color images. This study proposed the use of color, shape and texture features together to detect immature green citrus fruits, including scanning an image using a sub-window, and identifying green citrus fruits via ANN.

MATERIALS and METHODS

Using a color digital camera (Model Powershot SD880IS, Canon) with a resolution of 3648 x 2736 pixels, a total of 96 images were taken from citrus trees under natural illumination conditions. Natural citrus canopy images were captured from an experimental citrus grove in the University of Florida, Gainesville, Florida in one week period at various times in October 2010. Citrus variety used in this study was Orlando Tangelo. When the images were acquired, the citrus fruits were at their green stage of growth. Natural citrus canopy scenes were randomly selected from sunny side and shadow side of the trees. Actual scene size of the images was approximately 33x25 cm. In this study, demonstrating the concept of green citrus detection algorithm using only color images was purposed. Therefore, natural citrus canopy images were resized to 800x600 pixels for computational convenience.

To develop and test a green citrus detection algorithm, MATLAB version 7.11.0.584 (R2010b) was used on a 64-Bit Intel® Core™ 2 Duo P8400 2.26 GHz CPU computer. To scan a citrus canopy image, a square sub-window at three different sizes was used. A sub-window was a square sub-region to take any local part of an entire image. In the training set, fruit diameters varied from about 130 pixels to 210 pixels, so 130x130, 180x180 and 210x210 pixels of sub-window sizes were selected in order to identify all fruit sizes in the canopy scenes. In the experiments, shifting step of the subwindow was 20 pixels for both horizontal and vertical directions for computational convenience. This value was also an acceptable increment not to skip any distinctive fruit regions for the used image sets.

In the proposed algorithm, three features extracted for fruit detection. Those were eigenfruit of intensity component, eigenfruit of saturation component, and circular Gabor texture. To create a training set for the ANN, 81 fruit images including non-occluded and partially occluded fruits from 32 natural citrus canopy images were randomly selected and then manually cropped and centered. A total of 146 negative training samples (background) for the ANN classifier were also cropped using randomly square scenes (excluding green fruit pixels) over the images in the training set. The negative training samples included leaves, twigs, soil and sky pixels. The features of the positive (fruit) and negative cropped sample images were extracted to create training set of the ANN.

On scanning process, three features were also extracted for each sub-window. Color information was also used for background elimination. More details were explained about background elimination and feature extraction in following sections. Using those three features, an ANN was trained and tested to detect green citrus fruits. A binary image was used to locate detection centers and to merge multiple detections for the same fruit. The identified centers of positive detections by the ANN were marked using blobs on the binary image. Solid circles representing detection centers were these blobs. Blob analysis was performed for merging multiple detections for the same fruit and counting the number of fruits. The blob analysis included finding final blobs created by touching circular blobs representing detection centers. It also determined new centers of the final blobs by its major axis. After blob analysis, connected blobs were treated as a single blob and the total number of the blobs provided the number of fruits in the image. Flow diagram of the proposed algorithm is shown in Figure 1.

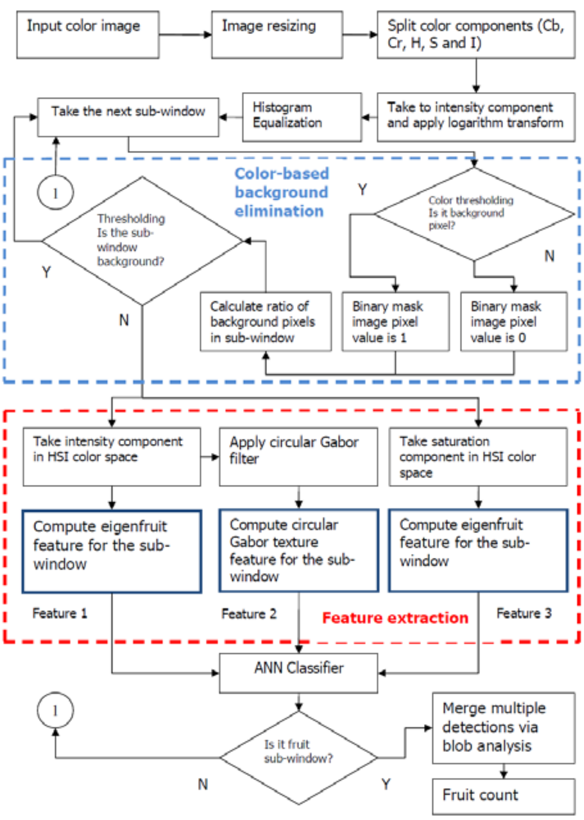

Figure 1. Flow diagram of the proposed algorithm

One of the well-known methods for illumination enhancement in image processing is logarithm transform, and many researchers used this technique for obtaining better illumination (Savvides and Kumar, 2003; Vishwakarma et al., 2009; Cheng et al., 2010). As pre-processing, this method was applied to intensity component in hue-saturation-intensity (HSI) color space of training and validation images. It expands the dark pixel values. Logarithm image was calculated as in following.

$$I' = \log(I_0) \quad (1)$$

Althogh color differences between green fruits and natural canopy are not very distinctive visually, histogram distributions of different color components were investigated for fruit and background samples in HSI, luminance-chrominance in blue-chrominance in red (YCbCr), and RGB color models. Little color differences were found in Cb, Cr and H components. Thresholds for background pixels were found using histograms, and a binary mask image ("1" for background, and "0" for fruit pixels) representing background pixels was created. Since number of the background pixels was important for elimination of the sub-window, a value "1" was used to represent background pixels. In image scanning process, a pixel ratio was used to determine whether the sub-window was fruit or background, and thereby to eliminate that sub-window. This ratio was of the number of white pixels to the number of all pixels in the sub-window. A circular region of interest (ROI) was defined as a maximum circle inside the square sub-window, and was used for excluding background pixels at the corners of the sub-window due to circular shapes of the fruits. Namely, the pixels at the corners of the sub-window were not taken into consideration when calculating the pixel ratio. Thresholding using the pixel ratio was performed to eliminate the background sub-window.

Eigenface approach is a face detection method which is proposed by Turk and Pentland (1991). By inspiring this approach, "eigenfruit" concept was proposed and used as a feature extraction method in green citrus detection algorithm.

This method is based on the PCA. A NxN image can be considered as N^2x1 vector, and let's illustrate it with Γ. If number of the images in training set is M, average image (Ψ) of the training set is described in Eq.(2).

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \tag{2}$$

Difference between the input image and the mean image can be calculated by Eq. (3).

$$\Phi_i = \Gamma_i - \Psi \tag{3}$$

The Φ_i is a vector including differences of all training images from the mean. These differences are used to compute a covariance matrix (*C*) for the training set.

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \tag{4}$$

The eigenvectors of $C=AA^T$ were calculated according to Turk and Pentland (1991). The eigenfruits are eigenvectors of covariance matrix in a training set consisted of fruit images. The PCA is used for finding best ortho-normal vectors representing the distribution of the data. Eigenvectors create a fruit space. Projection of a sample image can be made on this space. The Figure 2 shows an illustration of the fruit space and projection concept.

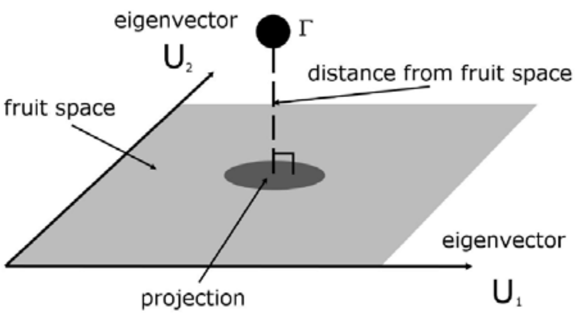

Figure 2. Projection of an image into fruit space

The feature extraction for eigenfruit approach was made by calculating distance from fruit space (dffs). The dffs is a similarity measurement between the images in the training set and the fruit candidate image. In this study, Euclidean distance was used to measure dffs as a feature of the ANN. Following is the description of the Euclidean distance.

$$e_d = \left\| \Phi - \Phi_f \right\| \tag{5}$$

In the preliminary works of this study, citrus tree images captured in natural outdoor conditions were observed by decomposing them to different color components in different color spaces such as HSI, YCbCr, and RGB. It was found that saturation component in HSI color space provided a distinctive feature for fruits partially saturated by sunlight as shown in Figure 3.

(a) **(b)**

Figure 3. A citrus tree canopy image (a) and its saturation component in HSI color space (b)

In the proposed algorithm, two types of eigenfruit feature were extracted. The first one was an eigenfruit feature using intensity component (representing gray level image) in HSI color space, and the other was an eigenfruit feature using saturation component in HSI color space. Namely, the eigenfruit feature extraction process was made two times for two different color channels separately.

In this study, rotation invariant circular Gabor texture extraction method similar to Zhang et al. (2002) was also used. The Circular Gabor filter function as described in Eq. (6).

$$G(x,y) = g(x,y)\exp(2\pi iF(\sqrt{x^2+y^2})) \tag{6}$$

$$g(x,y) = \frac{1}{2\pi\sigma^2}\exp(-(x^2+y^2)/2\sigma^2) \tag{7}$$

where $g(x, y)$ is a Gaussian function, x and y are matrix indices, σ is a scale parameter, F is frequency of the function, and i is imaginary unit. In this study, the parameter selection was made similarly to Zhang et al. (2002). By convolving the input image with the circular Gabor function, filtered image was obtained as described in Eq. (8).

$$\phi = G(x,y) \otimes I \tag{8}$$

where □ is the filtered image, $G(x, y)$ is the circular Gabor function, $\otimes$ is a convolution operator, and I is an input image. The circular Gabor texture feature σ_G was calculated by Eq. (9).

$$\sigma_G = \sqrt{\frac{1}{m \times n - 1} \sum_x \sum_y (|\phi(x,y)| - \bar{\phi})^2} \tag{9}$$

The x and y are matrix indices, and m and n are matrix sizes.

After feature extraction steps were done, input (training) data set included three aforementioned features for all negative and positive samples in the training set. In this study, normalization was applied to input data of the ANN. The feature values were normalized between -1 and 1. Following is the normalization equation used in the green citrus detection algorithm.

$$X_N = \frac{2(X' - X_{\min})}{(X_{\max} - X_{\min})} - 1 \tag{10}$$

where X_N is normalized value, X' is the value to be normalized, and X_{min} and X_{max} are minimum and maximum values of any feature, respectively.

Preliminary experiments were conducted to find suitable network architecture for classifying sub-windows. As a result of preliminary experiments, two hidden layers cascade feedforward network with 15 neurons per layer performed significantly better than any other options. The gradient descent back-propagation algorithm was used as a training algorithm. A four-layer cascade feedforward network used in this study is shown in Figure 4. Cascade-forward networks are similar to traditional feed-forward networks, but include a connection from the input and every previous layer to following layers. The neural network toolbox in Matlab was used to construct and train the network used.

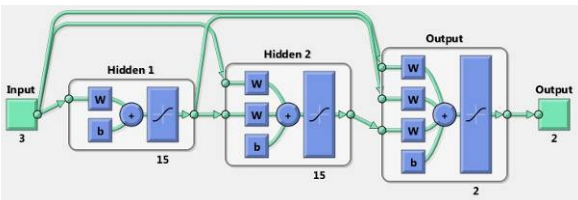

Figure 4. Cascade feedforward NN scheme

The output layer of the network had two neurons corresponding fruit and background sub-windows. Three neurons were used in input layer corresponding eigenfruit dffs using intensity component, eigenfruit dffs using saturation component and circular Gabor texture feature. The transfer function used at both hidden layers and also the output layer was hyperbolic tangent sigmoid transfer function (tansig) in Matlab. A mean square error (MSE) was used as performance function. The desired error (goal) was 0.001, and maximum epochs parameter was set to 10,000. Thus, training process of the network would continue until it reached the maximum epochs or the MSE goal. Using these parameters and the training dataset, the ANN was trained. After the training process, network file is stored.

In this study, there were 32 tree canopy images in the training set to train aforementioned feature extractors and the ANN. A total of 81 manually cropped fruit images from training set were used to create and store eigenvectors and eigenvalues for training both eigenfruit feature extraction processes. Using this training set and also a validation image set consisted of 64 images, experiments were conducted. The proposed green citrus algorithm was able to provide number of fruits which could be detected. After the experiments, correctly identified fruits, false positives (mistakes) and missing fruits were counted and recorded manually for evaluating the performance of the proposed algorithm.

RESULTS and DISCUSSION

To cope with illumination change under outdoor conditions, the logarithm transform and histogram equalization were applied as pre-processing. Figure 5 shows a result of the applied pre-processing. As seen in Figure 5, more details can be seen after the logarithm transform and histogram equalization.

(a) **(b)**

Figure 5. Effect of illumination enhancement method used in this study: (a)Original image, (b)After illumination enhancement

The Gabor texture extraction method used in this study relied on relatively homogenous texture appearance of the fruits. In Figure 6, a canopy image and its filtered illustration are shown. The filter revealed some distinctive texture regions of the fruits.

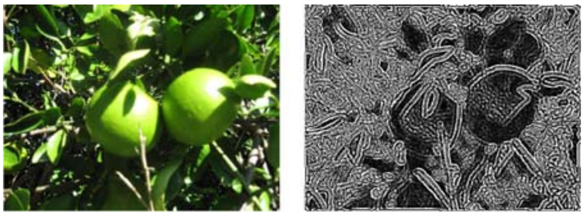

Figure 6. Original and filtered canopy images

Proposed fruit detection algorithm yielded multiple detections for the same fruit. To merge these detections and count fruits in the canopy scene, a blob-based method followed. An example process for merging multiple detections is shown in Figure 7.

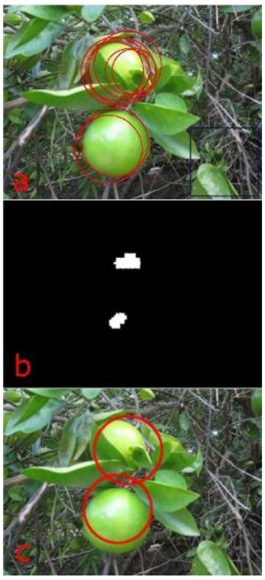

Figure 7. Steps of merging multiple detections: (a) multiple detections, (b) binary image representing detection centers, and (c) resulting image

In Figure 7, the final detection centers do not exactly overlap with fruits due to asymmetric shape of the blobs. In this study research focus was to find number of the fruits. To get more precise fruit locating, more advanced method can be developed.

In evaluation of the experiments, some objects were considered as background, if they could not be identified clearly as fruit or background due to much-occlusion or visual complexity of the tree canopy. Tables 1 and 2 show the results of the proposed algorithm for training and validation sets, respectively.

Table 1. Results of the proposed algorithm for the training set

Fruit count	Correctly identified	False positives*	Missed
81	68	3	13
(%)	84	4.2	16

Table 2. Results of the proposed algorithm for the validation set

Fruit count	Correctly identified	False positives*	Missed
146	117	30	27
(%)	80.1	20.4	19.9

*The percentage of false detections is provided with regard to the total number of correct detection plus the false positives

For the validation set, 80.1% of the actual fruits were successfully detected. The false detections were 20.4% by the algorithm. And 19.9% of the green citrus fruits were missed. Figure 8 shows the detections of a testing image.

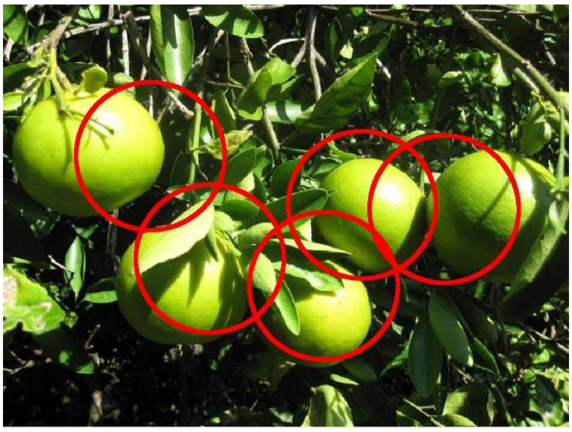

Figure 8. Correctly identified fruits by the proposed algorithm

The proposed algorithm could not detect all fruits, and there were false detections and missing fruits. Some leaves and leaf clusters having shapes similar to citrus fruits had similar features with fruits, and they were misclassified by the ANN. Sometimes a fruit was detected too many times, and it caused separate detection centers for the same fruit. Consequently, they were identified as different fruits.

Some fruit surfaces had regions highly similar to leaves' color. Due to this similarity, they were skipped during the background elimination step of the algorithm. The blob analysis also caused missing fruits. For some images including fruits so close or occluded by each other, the blobs representing more than one fruit touched each other. These touching blobs were identified as one fruit.

Due to the illumination change and visual complexity of the images captured in natural outdoor conditions, the texture features of some fruits and leaves were highly similar. This situation also caused misclassifications of the ANN.

CONCLUSIONS

An advanced green citrus detection algorithm under natural illumination conditions was developed using color information, eigenfruit and texture features. A cascade feedforward network was trained and used for classification of the sub-windows. Blob analysis was used to merge multiple detections for the same fruit and to count number of green fruits in a natural canopy image. Experiments were conducted on training and validation image sets, and results were evaluated.

Along with an advanced algorithm, traditional color image usage is promising for on-tree green citrus detection. Proposed algorithm in this study also inspires for detecting other kind of immature fruits such as apples and peaches.

ACKNOWLEDGEMENTS

This study was funded by The Council of Higher Education of the Republic of Turkey (YOK) within the scope of doctoral research abroad fellowship program. Special thanks go to Birol Kuyumcu for his continued support of this work.

REFERENCES

Cheng Y., Y. Hou, C. Zhao, Z. Li, Y. Hu, C. Wang, 2010. Robust face recognition based on illumination invariant in nonsubsampled contourlet transform domain. Neurocomputing (73): 2217–2224.

Kane K. E., W.S. Lee, 2007. Multispectral imaging for in-field green citrus identification. ASABE Paper No. 073025. St. Joseph, Mich.: ASABE.

Parrish E.A. Jr., A.K. Goksel, 1977. Pictorial pattern recognition applied to harvesting. Transactions of the ASAE (20):822–827.

Pla F., F. Juste, F. Ferri, 1993. Feature extraction of spherical objects in image analysis: an application to robotic citrus harvesting. Computers and Electronics in Agriculture 8: 57–72.

Pourbafrani M., G. Forgács, I.S. Horváth, C. Niklasson, M.J. Taherzadeh, 2010. Production of biofuels, limonene and pectin from citrus wastes. Bioresource Technology 101: 4246–4250.

Regunathan M., W.S. Lee, 2005. Citrus yieldmapping and size determination using machine vision and ultrasonic sensors. ASAE Paper No. 053017. ASAE, St. Joseph, MI, USA.

Savvides M., V. Kumar, 2003. Illumination normalization using logarithm transforms for face authentication. In Proc. IAPR AVBPA, 549–556.

Sirovich L., M. Kirby, 1987. Low-dimensional procedure for the characterization of human faces. Journal of the Optical Society of America A: Optics, Image Science, and Vision, (4): 519–524.

Stajnko D., M. Lakota, M. Hoevar, 2004. Estimation of number and diameter of apple fruits in an orchard during the growing season by thermal imaging. Comput. Electron. Agric. 42: 31–42.

Turk M., A. Pentland, 1991. Eigenfaces for recognition. Journal of Cognitive Neuroscience (3): 71–86.

Viola P., M.J. Jones, 2004. Robust real-time face detection. International Journal of Computer Vision, (57): 137–154.

Vishwakarma V.P., S. Pandey, M.N. Gupta, 2009. Adaptive Histogram Equalization and Logarithm Transform with Rescaled Low Frequency DCT Coefficients for Illumination Normalization. International Journal of Recent Trends in Engineering, Issue on Computer Science, (1): 318-322.

Wachs J., H.I. Stern, T. Burks, V. Alchanatis, 2009. Apple detection in natural tree canopies from multimodal images. In proceeding of the Joint International Agricultural Conference, JIAC, 293-302.

Zhang J., T. Tan, Li. Ma, 2002. Invariant texture segmentation via circular Gabor filters. Proceedings of the 16th International Conference on Pattern Recognition, (2): 901-904.