Applied Mechanics and Materials Vol 771 (2015) pp 242-247
© (2015) Trans Tech Publications, Switzerland
doi:10.4028/www.scientific.net/AMM.771.242
Submitted: 2014-08-26
Accepted: 2015-01-23

Natural Produce Classification Using Computer Vision Based on Statistical Color Features and Derivative of Radius Function

Anton Satria Prabuwono[1,2,a*], Joko Siswantoro[1,3,b], Azizi Abdullah[1,c]

[1]Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor D. E., Malaysia

[2]Faculty of Computing and Information Technology, King Abdulaziz University, Rabigh 21911, Saudi Arabia

[3]Faculty of Engineering, Universitas Surabaya, Jl. Kali Rungkut, Surabaya, 60293, Indonesia

[a]antonsatria@eu4m.eu, [b]joko_siswantoro@ubaya.ac.id, [c]azizi@ftsm.ukm.my

Keywords: Natural produce classification, Computer vision, Statistical color features, Derivative of radius function, *k*-nearest neighbors, Artificial neural network.

Abstract. In agriculture industry, natural produce classification is used in sorting, grading, measuring, and pricing. Currently, a lot of methods have been developed using computer vision to replace human expert in natural produce classification. However, some of the method used long features descriptor and complex classifier to obtain high classification rate. This paper proposes natural produce classification method using computer vision based on simple statistical color features and derivative of radius function. The *k*-nearest neighbors (*k*-NN) and artificial neural network (ANN) were used to classify the produce based on the extracted features. Preliminary experiment results show that the proposed method achieved best result with average classification accuracy of 99.875% using ANN classifier with nine nodes in hidden layer.

Introduction

Natural produce classification aims to classify the produce into one of classes. In agriculture industry, natural produce classification is used in sorting [1], grading [2], measuring [3], and pricing [4]. Usually, natural produce classification is performed manually by human expert. However, manual classification is inaccurate and difficult to standardize [2]. Currently, a lot of methods have been developed using computer vision to replace human expert in natural produce classification [1, 2, 4-9]. Generally, an image of produce is acquired and then processed to extract its features such as color, shape, and texture. The produce is then classified using a classifier based on the extracted features.

VeggieVision [4] is the first produce recognition system. The system was developed to recognize a produce in supermarket and grocery stores during weighing in order to identify the price of produce. *VeggiVision* used color, texture, size, and density features; and nearest neighbors classifier. The best accuracy of 95% was reported, however this result was achieved in the top four choices. Kılıç, et al. [2] proposed a classification system for quality evaluation of beans using computer vision. They used statistical color features as input for artificial neural network (ANN) classifier. The correct classification rate of 90.6% was achieved. Roomi, et al. [1] proposed mangoes classification method object contour modeling and region base descriptor. Bayes classifier was used and obtained classification accuracy of 90.91%. Woo Chaw and Mirisaee [9] proposed a method for fruit recognition based on color and shape features. The proposed method used *k*-nearest neighbors (*k*-NN) classifier and was accurate up to 90%.

Recently, some researcher used a combination of very long features descriptor for produce recognition, such as Unser's descriptors, color coherence vectors, border/interior, global color histogram, appearance descriptors, color autocorrelogram, local activity spectrum, quantized compound change histogram, and edge orientation autocorrelogram [5, 6, 8]. Furthermore, they also used a complex classification method to obtain classification accuracy more than 97%, namely fusion of support vector machine (SVM) with radial basis function (RBF) kernel [5], bagging ensemble of linear discriminant analysis [6], and fusion of binary classifier [8]. Zhang and Wu [7] proposed fruit classification method base on color histogram, Unser's features, and shape features. They employed principle component analysis (PCA) to reduce dimension of features from 74 features to 14 features. However, the best classification accuracy was only 88.2% using max-win voting SVM (MWV-SVM) with Gaussian radial basis (GRB) kernel.

Previous researches show that to obtain high classification accuracy some researchers employed a very long features descriptor and complex classifier. However, more time is required to extract the long features from an image and to train a complex classifier using the long features. This paper proposes natural produce classification method using computer vision based on simple statistical color features and derivative of radius function. Two simple classifiers, *k*-nearest neighbors (*k*-NN) and artificial neural network (ANN) were used to classify the produce based on the extracted features.

Material and Methods

Computer Vision System. The proposed method used a computer vision system consisted of camera, light source, personal computer, and software, as shown in Fig. 1. A Logitech web camera HD Pro Webcam C910 was used for image acquisition. The camera was connected to personel computer with USB cable. The system used a tube lamp light located on the ceiling of room as light source. A 3.00 GHz Pentium (R) Dual-Core portable computer with 2.00 GB RAM and 32-bit Windows 7 operating system was used to control camera, process acquired image, extract features and classify the produced. The proposed method was implemented in a program coded in Matlab R2010a. The main processing steps for the proposed method consisted of image acquisition, segmentation, features extraction, and classification. The detail of main processing step will be explained in the next subsections.

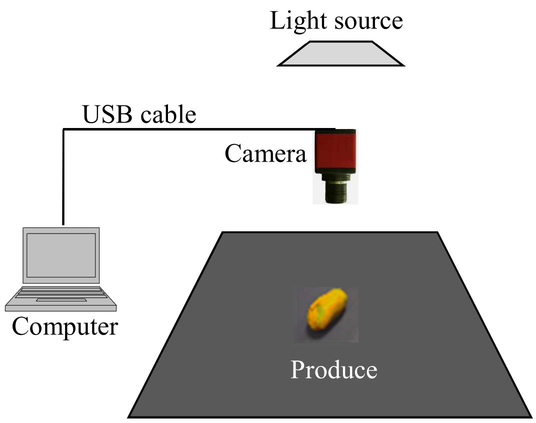

Fig 1. The experimental setup for the computer vision system

Image Acquisition. Image acquisition was performed from top view of produce. The produce was placed on a table about 40 cm below the camera. To increase contrast between produce and background, an image of produce was acquired with a black background. The image was saved in RGB color space with a dimension 640 × 480 pixels and a resolution 96 dpi. Figure 2 shows the sample of acquired image.

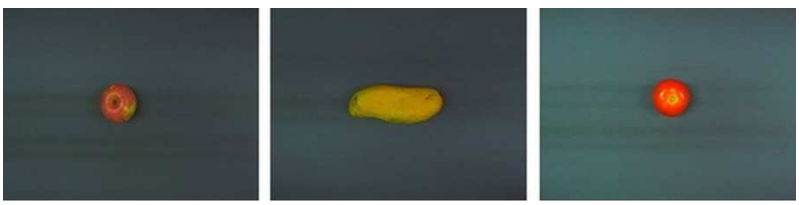

Fig 2. The sample of acquired image

Segmentation. Segmentation aims to separate the produce from its background. Only information contained in the produce will be used in classification. Therefore, it is required to perform image segmentation before classify the produce. To segment the produce from its background, the image of produce was firstly converted to HSV color space. Only image in S channel was used in segmentation because in this image the produce can be easily separated from its background. A 15 × 15 Gaussian filter was applied to remove noise in S image. Automatic thresholding as described by Gonzalez and Woods [10] was used to construct a binary image. The binary image consisted of white pixels and black pixels that represent the produce and its background respectively. To remove white spots in black area and black spots in white area, morphological openings with a 5 x 5 rectangle structural element and closings with a 3 × 3 rectangle structural element were performed respectively. Figure 3 shows all images used in segmentation and its result.

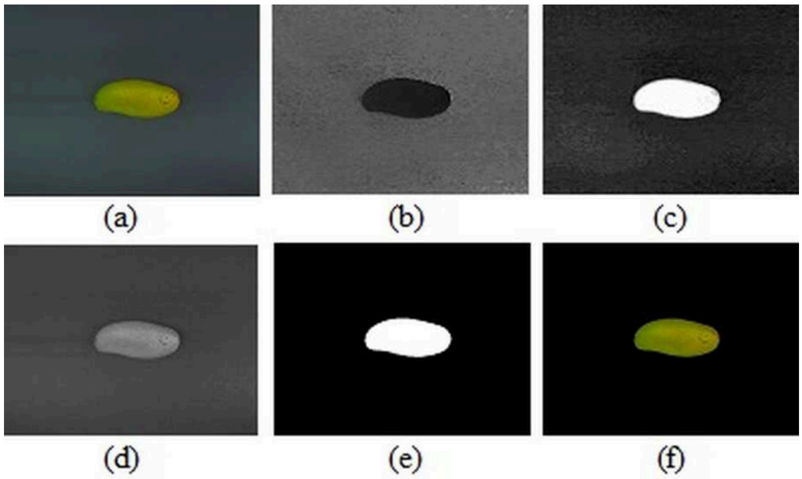

Fig 3. (a) Original image, (b) Image in H channel, (c) Image in S channel, (d) Image in V channel, (e) Binary image, (f) Segmented image

Feature Extraction. The proposed method used statistical color features and derivative of radius function as input for classifier. Statistical color features were extracted from pixel color values of the produce in HSV color space. The features consisted of mean, standard deviation, skewness, and kurtosis for pixel values in H, S, and V channel. These features describe color distribution of the object of interest. Mean, standard deviation, skewness, and kurtosis were calculated using equation (1), (2), (3), and (4) respectively,

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$s = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\right)} \tag{2}$$

$$skew = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^3}{s^3} \tag{3}$$

$$kurt = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^4}{s^4} \tag{4}$$

where n is the number of pixels in the object of interest and x_i is the pixel i value of H, S, and V channel in the produce. Therefore, there were twelve statistical color features extracted from the image. Radius function $r(\theta)$ is defined as distance from the center of produce to its boundary in direction θ, as shown in Fig. 4 [11]. The 36 values of radius function is measured for $0 \le \theta \le 2\pi$ with interval $\Delta\theta = 2\pi/36$. Two objects with the same shape may have different radius function, but they have similar derivative of radius function with respect to θ. This can be explained using a fact that two objects with the same shape have radius function with almost constant difference. Derivative of radius function was approximated using forward difference, as shown in equation (5). After all 36 derivatives of radius function were calculated then summarized by calculating their mean, standard deviation, skewness, and kurtosis. Therefore, there were four derivatives of radius function features extracted from the image.

$$\frac{dr}{d\theta} = \frac{1}{\Delta\theta}\left(r\left(\theta + \Delta\theta\right) - r\left(\theta\right)\right) \tag{5}$$

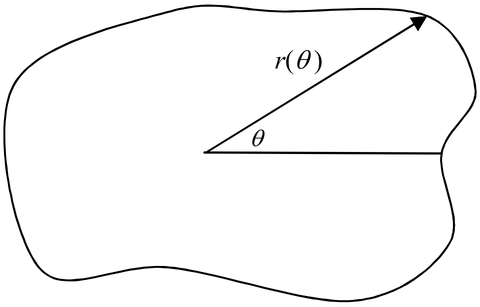

Fig 4. The illustration of radius function

Classification. Classification was performed using k-NN and ANN. k-NN is a simple non-parametric statistical classification technique performed by classifying an unknown object to the class most frequently represented among k nearest training samples [12]. ANN is a computational network inspired by biological nervous system that combines statistical technique with the objective of machine learning. ANN has self-learning capability and can be used to solve classification and prediction problems. The structure of ANN consists of input layer, hidden layers, and output layers. Every layer has a number of nodes that connected to all nodes in other layers. There are no fixed rule to determine the number of hidden layers and the number of nodes in hidden layers [12].

Validation. Currently, experiments are carried out in the laboratory to validate the proposed method. For preliminary experiment, 160 images of natural produces were acquired from 53 apples, 52 mangoes, and 55 tomatoes. 50% (80) samples were randomly chosen as training and the rest (80 samples) for testing. Training and testing processes were repeated 10 times and its classification accuracy was calculated for each process using the following equation.

$$Accuracy = \frac{the\,number\,of\,\,samples\,correctly\,classified}{total\,number\,of\,\,samples} \times 100\% \tag{6}$$

Result and Discussion

The 16 features consisted of 12 statistical color features and 4 derivatives of radius function were extracted from each image both in training and testing sample. Average time used to process a raw sample image and extract its features was less than 0.22 second. Extracted features from training samples were then used as input of k-NN and ANN classifiers. k-NN took less than 0.01 second for classifying a testing image while ANN took less than 1 second for training and also less than 0.01 second for classifying a testing image. Therefore, the total time used to classify a new produce image is less than 0.23 second.

k-NN classifier assigned each testing sample to the class for the closest training sample. Euclidean distance was used to measure the closeness between testing sample and training sample. The number of nearest neighbors k was heuristically determined for $1 \leq k \leq 10$, such that the best classification accuracy is achieved. Figure 5 depicts the results of k-NN classifier depend on the number of k. The best average classification accuracies for k-NN classifier were 94.25 % and 74.5% for training and testing samples respectively, achieved using $k = 1$ and $k = 2$. For $k = 1$ and $k = 2$, the results of k-NN classifier show that all mangoes are classified correctly, some of apples are misclassified as tomatoes, and a few of tomatoes class are misclassified as apples and mangoes. These results indicate that *k*-NN classifier requires more features to correctly classify the produce.

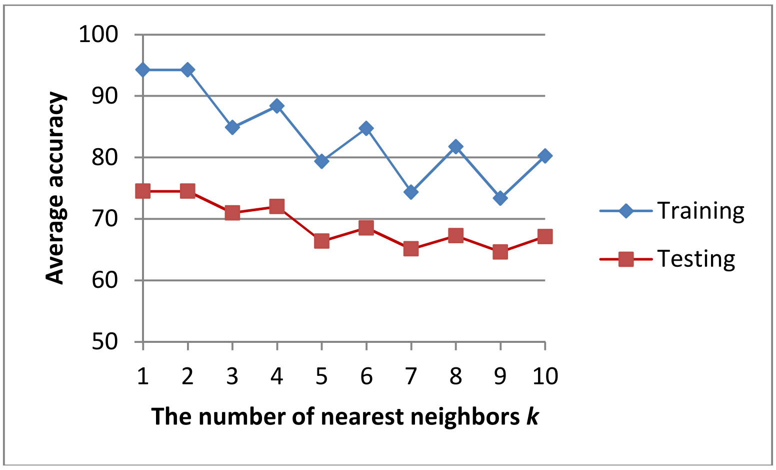

Fig 5. Classification result using *k*-NN classifier

The structure of ANN classifier used in the experiment consisted of input layer with 16 nodes, one hidden layer, and output layers with three nodes. The number of nodes in hidden layer was also heuristically determined from two nodes to 12 nodes, such that the best classification accuracy is achieved. The *tansig* function was used as transfer function both for input layer to hidden layer and hidden layer to output layer. The ANN was trained using Levenberg-Marquardt backpropagation algorithm. Figure 6 depicts the results of ANN classifier depend on the number of nodes in hidden layer. The best average classification accuracies for ANN classifier were 100 % and 99.875% for training and testing samples respectively, achieved using nine nodes in hidden layer. From 10 classification repetitions using ANN classifier, almost all classifications produced an accuracy of 100% except one classification produced an accuracy of 98.75% for testing sample. This means that only one sample in testing sample was not correctly classified.

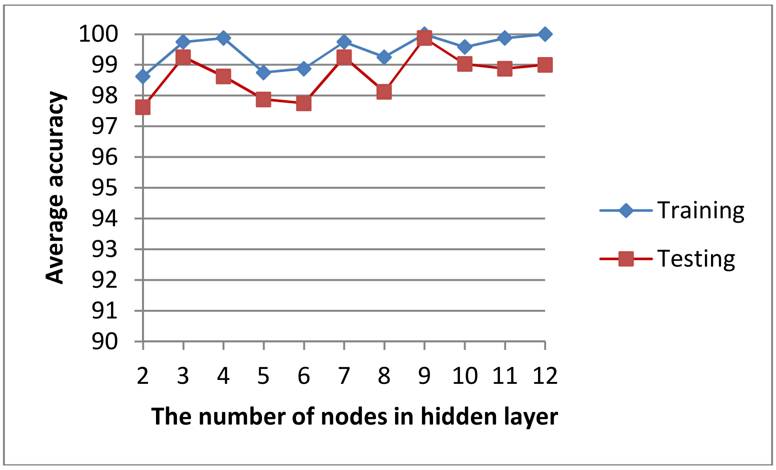

Fig 6. Classification result using ANN classifier

Conclusion

This paper proposes natural produce classification method using computer vision based on simple statistical color and derivative of radius function features. The proposed method used a camera to acquire image of produce from top view. The image was processed to extract its features. The features consisted of 12 statistical color features and 4 derivatives of radius function. *k*-NN and ANN were used to classify the produce based on the extracted features. The number of nearest neighbors and the number of nodes in hidden layer for *k*-NN and ANN classifier respectively were determined heuristically. The preliminary experiment was performed using 160 samples consisted of 53 apples, 52 mangoes, and 55 tomatoes. The 50% samples were randomly chosen as training and the rest for testing. The total time needed to classify a produce image was less than 0.23 second both for *k*-NN and ANN. The best classification accuracies were 74.5% and 99.875% for *k*-NN and ANN classifier respectively. Future research will focus on investigating the application of proposed method for classifying produce with the larger number of classes.

Acknowledgments
The authors would like to thanks Ministry of Higher Education Malaysia and Universiti Kebangsaan Malaysia for providing facilities and financial support under Grants No. ERGS/1/2013/ICT07/UKM/02/2.

References

[1] S.M.M. Roomi, R.J. Priya, S. Bhumesh, P. Monisha, Classification of mangoes by object features and contour modeling, in 2012 International Conference on Machine Vision and Image Processing (MVIP) (2012) 165-168.
[2] K. Kılıç, İ.H. Boyacı, H. Köksel, İ. Küsmenoğlu, A classification system for beans using computer vision system and artificial neural networks, Journal of Food Engineering 78 (2007) 897-904.
[3] J. Siswantoro, A.S. Prabuwono, A. Abdullah, B. Idrus, Monte Carlo method with heuristic adjustment for irregularly shaped food product volume measurement, The Scientific World Journal 2014 (2014)
[4] R.M. Bolle, J. H. Connell, N. Haas, R. Mohan, G. Taubin, VeggieVision: a produce recognition system, in Proceedings 3rd IEEE Workshop on Applications of Computer Vision 1996 (WACV '96) (1996) 244-251.
[5] F.A. Faria, J.A. dos Santos, A. Rocha, R.S. Torres, Automatic classifier fusion for produce recognition, in 25th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI) (2012) 252-259.
[6] A. Rocha, D.C. Hauagge, J. Wainer, S. Goldenstein, Automatic produce classification from images using color, texture and appearance cues, in XXI Brazilian Symposium on Computer Graphics and Image Processing 2008 (SIBGRAPI '08) (2008) 3-10.
[7] Y. Zhang, L. Wu, Classification of fruits using computer vision and a multiclass support vector machine, Sensors 12 (2012) 12489-12505.
[8] A. Rocha, D.C. Hauagge, J. Wainer, S. Goldenstein, Automatic fruit and vegetable classification from images, Computers and Electronics in Agriculture 70 (2010) 96-104.
[9] S. Woo Chaw and S.H. Mirisaee, A new method for fruits recognition system, in International Conference on Electrical Engineering and Informatics 2009 (ICEEI '09), 2009, pp. 130-134.
[10] R.C. Gonzalez and R.E. Woods, Digital Image Processing, 2nd edition, Prentice Hall, 2002.
[11] C. Zheng and D.-W. Sun, 3 - Object Measurement Methods, in Computer Vision Technology for Food Quality Evaluation, S. Da-Wen (Ed.), ed Amsterdam: Academic Press, 2008, pp. 57-80.
[12] C.-J. Du and D.-W. Sun, 4 - Object Classification Methods, in Computer Vision Technology for Food Quality Evaluation, S. Da-Wen (Ed.), ed Amsterdam: Academic Press, 2008, pp. 81-107.