GRADING OF YEMENI RAISIN (*RAZIGI CV.*) Using Non-Contact Machine Vision Techniques

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ABSTRACT

This research aimed at establishing quality standards for non-contact grading of Yemeni raisin (Vitis vinifera) of Razigi variety, by developing a digital image processing algorithm based on color and shape information. This was accomplished through developing pre-processing procedures to segment transparent interior areas in raisin color images as the regions of interest and highlight their morphology for extracting shape features. A distinct signature for each raisin grade was generated by calculating number of matches of a set of twenty selected morphological features. A minimum distance classifier was developed, trained and tested in grading raisins by sorting them into three grades, namely, A, B, and C. The classifier was successful in sorting two raisin grades, namely, A and C with 100% CCR and 0% MCR for each. Its performance was not good enough in sorting raisins of grade B as the CCR dropped to 50%. Some difficulties were encountered by the classifier in sorting half of the raisins of grade B due to their great similarity with grade A raisins. The developed algorithm confirmed its perfect performance in distinguishing between grades A and C, and successfully initiated quality standards for grading raisins using non-contact machine vision techniques with the need for some improvement to extend its precision to encompass grade B.

Keywords: *Raisin, Quality standards, Non-contact grading, Machine vision, Color information, Transparent areas, Region structural shape.*

INTRODUCTION

Yemen is famous in growing different types of grapes. Twenty cultivars are grown in different areas of Yemen. Razigi, Bayad, Black, Aasmi and Gubari are among the most grown cultivars in Yemen. They are mostly grown in Sana'a and Saadah governorates. All Yemeni cultivars are table grapes and part of their yield is dried for raisins production. Most raisins production comes from Razigi followed by Bayad and Black cultivars. Raisins are produced from fully matured grapes by different drying methods. Yemeni grapes are dried using traditional methods in rooms, under trellises or under the sun **(El-Haizamy *et al.*, 2000; and Al-Kathiri, 1993).** Drying grapes under the sun is faster than under trellises and in rooms but it produces raisins with dark brown color because of direct radiation. Dark brown raisins are not widely accepted in the local market. Raisins produced under trellises have less dark brown color. However, grapes are subjected during the long period of drying to rain that can cause rot infection, which affects both shape and color of raisins produced and consequently reduces their quality. Drying grapes inside rooms takes long time but it is considered to be the best method so far for producing yellowish and bright greenish raisins. The condition of Yemeni raisins in the local markets reflects the method of drying, handling and marketing. Raisins in the local market have different prices depending on their quality. The highest prices are given to yellow and bright green raisins, with uniform size and free of rot, dust and fruit stems. High quality Yemeni raisins can compete well in the regional and international markets and get good profits. It is necessary to have standard quality measures to ensure exporting raisins of high competitive qualities to the international market. Digital image analysis has great potentials for establishing quality measures for non-contact, automatic, reliable, fast and cheap grading of agricultural products.

Some of the raisins quality attributes such as size and existence of fruit stems can easily be determined by using one of several machine vision procedures already been developed and tested by many researchers. Raisin size can be determined by calculating the area in terms of number of pixels comprising the raisin image **(Lee and Sluaghter 2004; Ramalingam *et al.*, 2003),** while existence of raisin stems can be detected based on color or shape **(El-Faki *et al.*, 2000b; Fakagawa *et al.*, 2003).** This study focused on developing new methods for establishing standard quality measures for quantifying raisin quality attributes related to its color, effect of rot and cleanliness. All three attributes directly affect raisin color and shape **(El-Haizamy *et al.*, 2000),** hence by concentrating on these two features, it is feasible to perform raisin sorting accordingly.

REVIEW OF RELATED STUDIES

Grading Vegetables

Lu and Ariana (2008) used reflectance information for online inspection of cucumbers based on skin color with a detection accuracy of 90%. **Cho *et al.* (2007)** used an online algorithm for grading green pepper into four classes based on two geometric parameters, length and flexure. Grading accuracies ranged between 81.3 and 90.6 %. **Chong *et al.* (2005)** explored the visible/NIR spectrum to detect defects and bruises in eggplant for grading purposes. **Kondo *et al.* (2005)** developed a multi-product grading system to grade tomatoes and oranges based on external shape features fed into a back propagation neural network. The accuracy of the shape detection technique used was limited by the few points specified on the product boundary.

Grading Fruits

Fu *et al.* (2007) used Fourier Transform near-infrared (FT-NIR) spectrometry for discriminating four different pear varieties. They concluded that although the technique demonstrated great potential for nondestructive discrimination of pear varieties, yet further studies were needed before the technique can be adopted. **Guyer *et al.* (2006)** employed Opto-electronic techniques to detect infested whole cherries using complete spectra information from a spectroradiometer with an accuracy range 80-85%. **Jackson and Haff (2006)** developed an algorithm using a Bayesian classifier to detect olive fruit fly infestations in x-ray images of olives. The algorithm differentiated slightly damaged, severely damaged and non-infested olives with accuracies of 50, 86 and 90%, respectively. **Pearson *et al.* (2001)** used an image sorter developed in a previous research **(Pearson, 1996)** to improve sorting of pistachio nuts by detecting shell and kernel defects. They achieved correct classification rates ranging from 89.7 to 98.7%.

Grading Cereals and Other Agricultural Products

Dowell *et al.* (2007) developed automated visible and NIR spectroscopy procedures to sort wheat kernels to enhance the development of wheat breeding lines. **Pasikatan and Dowell (2003)** evaluated a commercial color sorter with dual-peak visible-NIR filters in removing red wheat from ten wheat blends containing 95% white and 5% red wheat by mass. **Shahin and Symons (2002)** used a neural network to grade grains based on color and morphological techniques. **Cheng *et al*. (2006)** developed three image processing algorithms to sort five varieties of rice. The average accuracies achieved were in the range of 91.9 - 99.4%.

OBJECTIVE

This research aimed at establishing quality standards for non-contact grading of Yemeni raisins, of Razigi variety, employing image processing based on color and shape information extracted from raisin color digital images. The specific objectives were to:

1. Develop pre-processing procedures to:
   - Segment transparent interior regions in raisin color images based on color as objects of interest,
   - Highlight region morphology in preparation for extracting shape features.
2. Establish distinct signature for each raisin grade by calculating number of matches of a set of twenty selected morphological features.
3. Develop, train, and test a minimum distance (MD) classifier for grading raisins by classifying them into three grades, namely, A, B, and C.

MATERIALS AND METHODS

Image Acquisition

Leaf images of raisins of three grades were captured using a 3-CCD Sony XC-003 RGB color camera fitted with a VCL-25WM lens. Raisins of different sizes were placed on an area fiber optic backlight (4.25″x3.37″). Illumination for training and testing image sets were fixed at 860 FC. Correct classification rates (CCR) and misclassification rates (MCR) were calculated for each grade to assess the accuracy of the classifier. The training set consisted of nine images, three from each grade. All images of training set were captured at 0° orientation angle. Testing set consisted of 30 raisin images, ten from each grade.

ALGORITHM DEVELOPMENT

It was noticed when imaging raisins while being placed on the fiber optic backlight, that a main difference between different raisin grades appeared in the form of availability of transparent areas within the raisins color images. These transparent areas get noticeably larger with higher grades. Therefore, this phenomenon was utilized to serve as the basis for discrimination among the three grades of Razigi raisins. Accordingly, the transparent areas were segmented as regions of interest based on internal region characteristic of color. Subsequently, external region characteristic of the structural shape was identified through skeletonization. Grading was accomplished using the concept of Signature Algorithm (SA) developed by **El-Faki (2007).** The algorithm for raisin grading consisted of two main parts, namely, pre-processing and classification as explained in the following sections.

Preprocessing

Step I: Region Segmentation

Each of the RGB color images of raisin were subjected to the following processes successively:

1. image was posterized (the number of gray levels were reduced to two levels {0, 255}),
2. the blue component of the color image was removed,
3. image was thresholded using a constant threshold value of 128 to obtain a binary image,
4. image was inverted,
5. image mode was changed from RGB to gray,
6. image was saved in a raw format for later processing.

The six above processes were performed using Adobe Photoshop version 7.0 ME. All subsequent steps were performed using algorithms and programs developed, compiled and run employing Borland C++ version 5.02. Some equations regarding decision functions computation were formulated using MS. Excel.

Step II: Skeleton Computation (region structural shape)

A thinning algorithm based on mathematical morphology developed by **El-Faki (2000a),** was used for deriving the medial axis transform of object regions in the binary image resulted from step I. The output was a unity-thick skeleton of the region of interest and its boarders. The trials carried out by the researcher confirmed that through this operation it is more likely that the underlying unique characteristics of the transparent areas associated with a raisin grade will have a better chance to be disclosed. Figure 1 demonstrates an example of the results obtained after implementing steps I and II of the preprocessing part of the grading algorithm. Images shown in this example were selected to illustrate the three raisin grades A, B and C.

Classification

All skeleton images of raisins were subjected to four operations to get their signatures as follows:

(i) *Features Selection* for analyzing raisin skeletons by template matching using mathematical morphology to extract image components that were useful in the representation and description of region shape,
(ii) *Prototyping* for generating the best representative signature in terms of a feature vector for each of the three grades,
(iii) *Decision Functions Computation* for computing three decision functions based on the three grade prototype signatures resulted from operation ii to form a new Minimum Distance (MD) Classifier particularly optimized for raisin,
(iv) *Grading* for feeding all feature vectors of the testing set to the MD classifier to designate each raisin to its grade.

RESULTS AND DISCUSSION

Three 20-feature vectors were formed using the training set to represent the three signature prototypes for grades A, B and C as illustrated in Figure 2. It clearly shows the capability of each feature to sense each grade differently, which is expressed in terms of different columns' heights. Consequently, the classifier performed perfectly in sorting two raisin grades, namely, A and C with 100% CCR and 0% MCR for each. However, its performance concerning grade B was not good enough as its grading accuracy dropped to a CCR of 50%. Table 1 presents the classifier's CCRs and MCRs for the three raisin grades, and it can be noticed that only five raisins out of the whole testing set were misclassified. All five misclassified raisins were originally from grade B, four were mistakenly designated to grade A and only one was mistakenly designated to grade C. The similarity between some raisins of grade B and grade A caused the classifier difficulties in separating them. Actually, the similarity between grades A and B makes discrimination between them a hard task even for humans and it needs an expert in raisin production and/or selling to do it correctly. This explains why more raisins of grade B were mistakenly designated to grade A than to grade C. It was evident from the classification results that the classifier was successful in sensing the feature difference between grades A and C. Moreover, the classifier was able to separate between all raisins of grades A and C, which were recognized as being distinctively different from each other and different from grade B as well.

The algorithm gained its discrimination power from the concept of the degree of prevalence of transparent areas within the raisin image as the decisive factor for discrimination. This concept facilitated materializing the variability among the three raisin grades in terms of black regions in raisin images, which are visible in Figure 1 (a1, b1, and c1). Therefore, the concept proved its validity in aiding raisin grading. What about Fig. 1 (a_2, b_2 and c_2)

CONCLUSIONS

Color and shape information extracted from digital color images of raisins was used as the basis for sorting raisins into three grades A, B and C. Preprocessing and skeletonization operations formed the foundation on which the classifier mechanism of discrimination among grades was built. The classifier was successful in sorting two raisin grades, namely, A and C with 100% CCR and 0% MCR for each. Its performance was not good enough in sorting raisins of grade B as the CCR dropped to 50%. The algorithm developed for grading raisins confirmed its effectiveness in discriminating between two grades A and C. Quality standards for grading raisins employing non-contact machine vision techniques had been successfully initiated with the need for some improvement to extend the perfect performance to include grade B. Finally, the extent of success accomplished by this technique in raisin grading and before this in plant identification makes its scope of relevance well extendable to other agricultural and non-agricultural applications.

Table 1. Distribution of raisins among grades A, B and C and correct classification misclassification rates of each grade.

Number of raisins sorted by grade			
From	**To**		
	A	**B**	**C**
A	10	0	0
B	4	5	1
C	0	0	10
Total	10	10	10
CCR (%)	100.0	50.0	100.0
MCR (%)	0.0	50.0	0.0

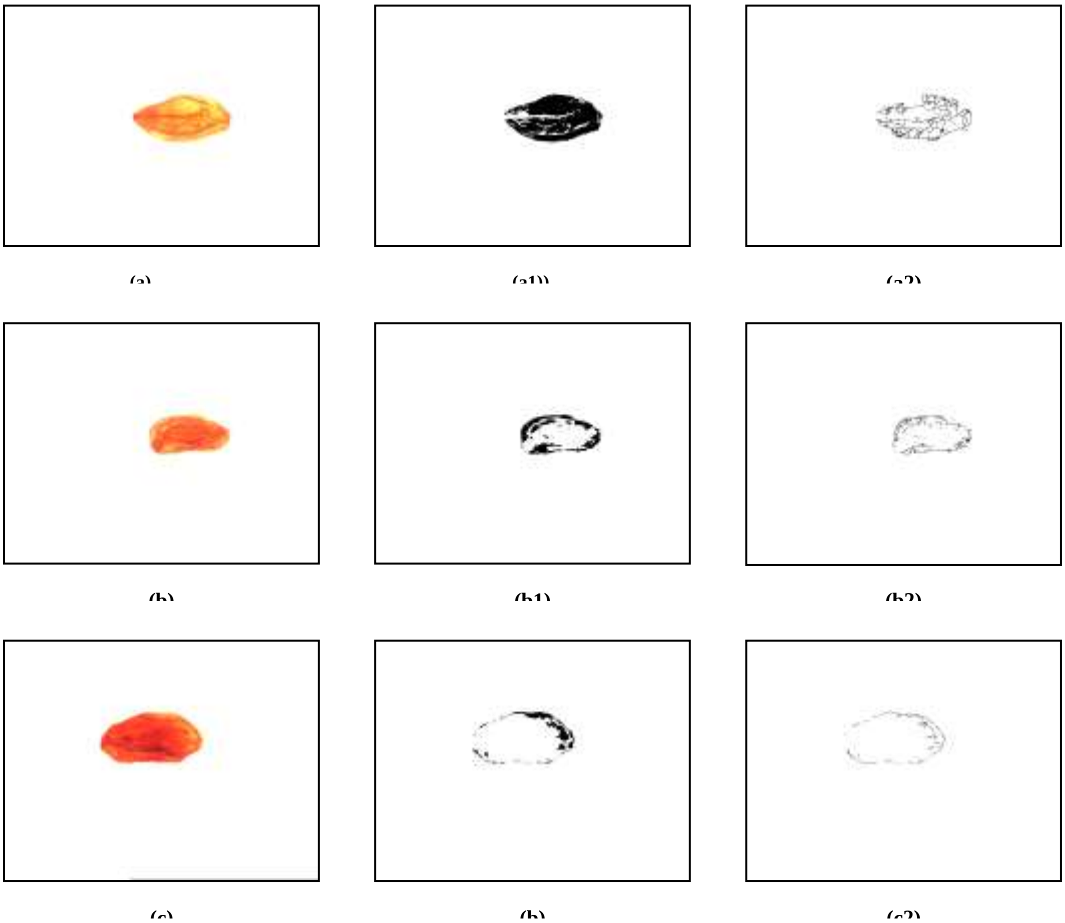

Figure 1. Outputs of preprocessing color images for grading raisins, showing: (a, b, c) original RGB color images of grades A, B and C, respectively, (a1, b1, c1) region segmentation (transparent areas), (a2, b2 and c2) Skeletonization.

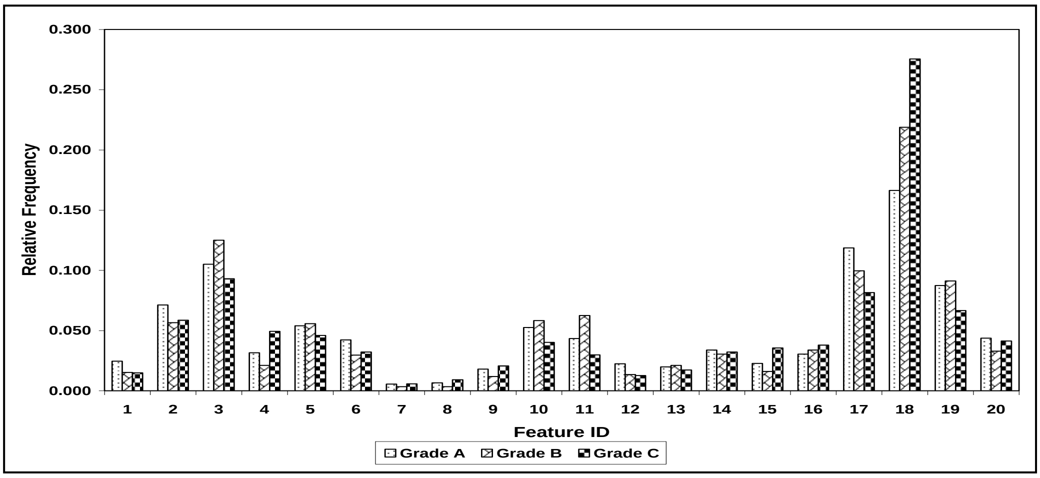

Figure 2. The twenty features comprising the signature prototypes of grades A, B and C.

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تدريج الزبيب اليمني (*صنف رازقي*) باستخدام تقنيات الرؤية الآلية دون ملامسة

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يهدف هذا البحث الى استحداث معايير للجودة لتصنيف الزبيب اليمني (صنف رازقي) دون ملامسة وذلك عن طريق تصميم نظام رياضي لمعالجة صور رقمية تعتمد على المعلومات المستخلصة من اللون و الشكل. وقد أنجز ذلك بإنشاء طرق معالجة مبدئية لفصل المساحات الشفافة داخل صور الزبيب الملونة باعتبارها المناطق موضع الاهتمام، وإبراز تفاصيل بنيتها لاستخلاص معالم ومميزات شكلها. ثم تلي ذلك إنتاج توقيع متميز لكل فئة من فئات الزبيب باحتساب عدد مرات التطابق لمجموعة مكونة من عشرين معلم مورفولوجي بعد تمريرها على صور الزبيب الرقمية. ولاستكمال عملية التصنيف فقد صمم مصنف من نوع البعد الأدنى وتم تدريبه واختبار مقدرته التصنيفية في فرز الزبيب الى ثلاث فئات من حيث الجودة و هي أ، ب و ج. وقد نجح المصنف في فرز فئتين وهما أ، و ج بدقة تصنيف صحيح قدره ١٠٠% وبدون أي خطأ. أما بالنسبة لفرز الفئة ب فإن أداء المصنف لم يكن بنفس مستوى الدقة حيث هبطت الدقة الى ٥٠%. واجه المصنف بعض المصاعب فيما يخص فرز نصف عينة الفئة ب بسبب التشابه الكبير بينها و الفئة أ. أثبتت الخوارزمية المصممة مثالية في الأداء بتمييزها بين الفئتين أ و ج بدقة تامة، وهكذا تم تأسيس معايير للجودة لتصنيف الزبيب دون ملامسة باستخدام تقنيات الرؤية الآلية مع حاجة الخوارزمية لبعض التحسين لتوسيع إحكامها ليشمل الفئة ب.

الكلمات الدالة: الزبيب، معايير الجودة، التصنيف دون ملامسة، الرؤية الآلية، معلومات اللون، المساحات الشفافة، شكل بنية المناطق.