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ORIGINAL ARTICLE

Computer vision based date fruit grading system: Design and implementation

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KEYWORDS

Fruit classification;
Pattern recognition;
Image processing;
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Abstract The Kingdom of Saudi Arabia is the world's largest producer of date fruit. It produces almost 400 date varieties in bulk. During the harvesting season the date grading and sorting pose problems for date growers. Since it is a labor intensive and time consuming process, it delays the post harvesting operations which costs them dearly.

The date grading and sorting is a repetitive process. In practice, it is carried out by humans manually through visual inspection. The manual inspection poses further problems in maintaining consistency in grading and uniformity in sorting. To speed up the process as well as maintain the consistency and uniformity we have designed and implemented a prototypical computer vision based date grading and sorting system. We have defined a set of external quality features. The system uses RGB images of the date fruits. From these images, it automatically extracts the aforementioned external date quality features. Based on the extracted features it classifies dates into three quality categories (grades 1, 2 and 3) defined by experts. We have studied the performance of a back propagation neural network classifier and tested the accuracy of the system on preselected date samples. The test results show that the system can sort 80% dates accurately.

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1. Introduction

The Kingdom of Saudi Arabia is the world's largest date producer. It produces almost 400 date varieties in bulk. After harvesting, if the dates are not processed timely (within harvesting season), it may cost dearly to the date growers. In post harvesting operations the date grading and sorting process is the prime source of delay. The reason is that it is a repetitive, labor intensive and time consuming process and it is carried out by humans manually through visual inspection. The manual processing pose added problems of maintaining the consistency and uniformity in date grading. Therefore, a computer mediated system that can mimic the human grading and sorting process may adequately expedite the process as well it may sort

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dates into uniform and consistent quality groups. For this purpose, intensive research works are being conducted to design and built intelligent, reliable, flexible and effective systems that can quickly sort a variety of fruit and other agricultural produce. The feasibility and applicability of such a system are being explored in every agriculture oriented country (Raji and Alamutu, 2005).

In this research, we investigate the requirements for designing a computer mediated date fruit quality assessment and sorting system. We have developed a technique that can effectively meet these requirements and tested its' effectiveness on real-life data. We have built a date sorter prototype. This paper elaborates on its design and performance.

The organization of the paper is as follows.

In Section 2, we describe the basic components of a computer vision system which is the core component of every computer mediated system. In Section 3, we briefly present the related work on agricultural product processing and the fruit quality factors (also referred to as factors or features) that are used for fruit grading, approaches to extract them from the fruit image. In Section 4, we describe image processing and pattern recognition techniques that we have developed and used to built the proposed date fruit grading and sorting system. We present the test results of our experiments in Section 5, and conclude the paper in Section 6 with a discussion on this research finding and on possible future work.

2. Computer-mediated fruit quality assessment and sorting systems

A computer-mediated fruit quality assessment and sorting system has two subsystems: *a computer vision system* and *a fruit handling system*. The computer vision system has two modules, namely the image processing module and the pattern recognition module. The technological advances in image technology and pattern recognition techniques are making it possible to automate inspection processes like fruit quality assessment. A typical computer vision system that can visually inspect fruit, assess its quality and sort it may consists of an electromechanical fruit handler that can place a fruit on a conveyer belt to carry the fruit through a computer vision system to the sorting bins. The computer vision system captures the image of the underlying fruit and transmits it to an image processor. The processor, after processing the image, presents it to a pattern recognizer. The recognizer performs the quality assessments and classifies the underlying fruit into pre-specified quality classes, and directs the sorter to direct the fruit to the appropriate bin. Fig. 1 shown below depicts the components of the system.

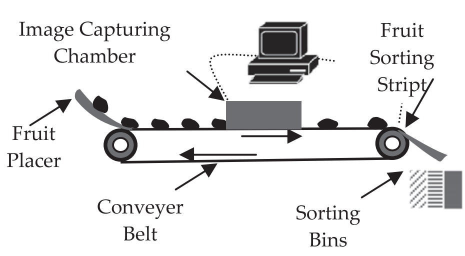

Figure 1 A layout of computer mediated fruit sorting system.

3. Related works

The design requirements for building a computer mediated fruit sorting system vary from fruit to fruit (product to product as well) for which it is designed to process. Therefore, most of the research works are focused on building dedicated systems that can sort a particular fruit or product type. Although, there are efforts to built general fruit sorting and classification systems (Kondo, 2003; Gay and Berruto, 2002) but most of the systems are dedicated systems like the system that can sort tomatoes (Laykin et al., 2002; Polder et al., 2000), apples (Unay and Gosselin, 2002, 2005a,b; Mehl et al., 2004; Li and Heinemann, 2007), citrus fruit (Aguilera et al., 2006; Regunathan and Suk Lee, 2005; Calpe et al., 1996), pepper berries (Abdesselam and Abdullah, 2000) and eggplant (Saito et al., 2003). Dedicated quality control vision based systems are also being built for other agricultural products like cereal grain (Choudhary et al., 2008), lentils (Shahin and Symons, 2001), corn products (Gunasekaran et al., 1987), tree leaves (Oskar, 2001), eggshell (Garcia et al., 2000) and fish grading (Hu et al., 1998). In addition to these applications, the systems are reported for wood processing like panel surface inspection (Aguilera et al., 2006), weed sensing (Polder et al., 2000) and trash measurement (Siddaiah et al., 2002).

The performances of grading systems depends on the quality factors that are used in their design. For fruit grading there are many factors that farmers use for measuring the fruit quality. These factors can be classified into two groups – the *external quality factors* and the *internal quality factors*. The external quality factors can be defined and extracted from the visual appearance of the fruit. Commonly used factors are*size, shape, color, gloss, surface defects* and *decay*, and *texture* (fruit surface patterns). The internal quality factors can be defined by the fruit smell like aroma, taste, flavor, sweetness and sourness, and fruit nutritive value like vitamins, minerals, nutrients and carbohydrates, and other elements like dry matter content, total soluble solids content, sugar content, and juice acidity. There are some quality factors like firmness, crispness, and toughness that can be defined by touching the fruit and may be considered external or internal factors.

Computer-mediated approaches to assess the fruit quality differ from one another on the basis of the quality factors and the classification methods that are used in their design. If they use internal quality factors and do not destroy the fruit while measuring them, such approaches are referred to as *non-destructive approaches* (Antihus et al., 2006; Nicola et al., 2006; Zude et al., 2006; Lu, 2004; Slaughter et al., 2003; Subedi et al., 2007).These techniques generally utilize spectroscopic and hyperspectral imaging. Paclık et al. (2006) have investigated the applicability of the rich spectral information provided by hyperspectral sensors that can capture detailed material composition in industrial applications. For a survey on noninvasive (nondestructive) techniques for fresh fruit and vegetable internal quality analysis readers may refer to Butz et al. (2005). Polder et al. (2000) have applied the hyperspectral imaging for measuring the ripeness of tomatoes and the results show that hyperspectral images offer more discriminating power than standard RGB-images in discriminating the ripeness. This technique has many advantages as compared to the classical methods. It is proving beneficial in determining the fruit defects (Li and Heinemann, 2007), discovering fruit quality attributes (ElMasry et al., 2007; He et al., 2005) and fruit quality evaluation (Zerbin, 2006) in general.

For marketing purposes, fruits are generally graded on the basis of their external quality features – the features that can be judged by visually inspecting and touching and occasionally smelling the fruit. The visual inspection, because of its practicability and simplicity, is the most frequent option in practice. Therefore, intensive research is being conducted to automate visual inspection process. Continued advancements in image processing and pattern recognition fields are providing effective tools and techniques to built systems capable of grading and sorting almost every agricultural produce. These systems differ from one another on the basis of image capturing processes, imaging equipment, image processing techniques and pattern recognition (mainly feature extraction and classification) methods that they are employ. However, these machines can be distinguished further from one and another on the basis of quality factors that they extract and use, and the agricultural product for which they are designed – as every product poses unique yet different requirements. In what to follows, we briefly present a review on external quality factor based systems that have been designed and tested for different fruits and agricultural products.

To automate the tomato inspection process Laykin et al., 2002 have described a system that captures images of the whole view of the underlying tomato using color cameras. The system extracts: color, color homogeneity, bruise and shape features. It can detect the stem and remove it from the image. In their experiment, they recorded different stages of the tomato color development and the quality grade of each tomato was judged by two experts. The verdict of the two judges was used as benchmark to evaluate the reliability of the system. They also studied the change in color homogeneity between the harvest date and after storage.

An intensive study on apple quality inspection is carried out by Unay (2006). The apple images were captured through color/monochrome camera in diffusely illuminated tunnel with two different light sources (fluorescent tubes and incandescent spots). To improve the image quality a noise removal operation was performed before applying the image segmentation operation to detect the defect type. The image intensity and texture based shape features were extracted from each segmented portion of the image. The performance of several classification methods (Linear Discriminant Classifier (LDC), k-Nearest Neighbors (k-NN), Fuzzy k-NN, Support Vector Machine (SVM), Decision Tree and Multi-layer Perceptrons (MLP)) were studied for defect segmentation and detection. They identify bruise, flesh damage, frost damage, hail, hail with perforation, limb rub, other, e.g., scar tissue, rot, russet and scald defects. More information on their research can be found in Unay and Gosselin (2002, 2005a,b). Kavdır and Guyer (2008) studied different techniques for apple processing. They defined features such as hue angle (for color), shape defect, circumference, firmness, weight, blush percentage (red natural spots on the surface of the apple), russet (natural net-like formation on the surface of an apple), bruise content and number of natural defects. Several classification techniques: decision rule, 1-NN, 2-NN, 3-NN, Decision Tree and MLP were studied. They found that the multi-layer perceptron (MLP) produced the highest classification results (up to 90%).

Recce et al. (1996) developed techniques for orange grading. They performed histogram analysis of the image intensity and defined defect feature operators. They used feature operators for grading oranges into three quality bands according to their surface characteristics. Blasco et al. (2007) used Sony XC-003P camera and fluorescent tube light to capture the images of the mandarin fruit. They developed and used region growing segmentation algorithm and determined the defective regions through experiments and classify fruit into defective and non-defective classes.

Abdesselam and Abdullah (2000) developed pepper berries grading system using the brightness mean of the intensity and brightness uniformity in the images taken in different lighting environment to measure the robustness. They found the average intensity defined as $I = (R + G + B)/3$ yielded good results when compared with the Blue (B) component.

Kondo (2003) describes a grading robot for peaches, pears, and apples. The robot picks a fruit from a tray and acquires its image through the mounted TV cameras and determines its quality grade from the color, size, shape bruise, disease, and insect injury features. In a similar research, Xiaobo et al. (2007) describe apple fruit grading from color by analyzing the images taken from color CCD camera. They defined and used seventeen color features and used a method called organization feature parameter for classification and found their method was more accurate than BP-ANN, but lower than SVM. Feng et al. (2008) describe a strawberry harvesting robot. It uses a global camera and a local camera for imaging. They developed a color space based image segmentation algorithm. From the binary image, the robot determines the strawberry blob and calculates the location of the fruit. The color space based fruit ripeness judgment method guided the robot to pick the fruit according to its ripeness and classify it according to its shape. Experimental results show that this method can achieve 93% accuracy of strawberry's stem detection and 90% of ripeness and shape quality judgment.

Apart from fruit grading, researchers are trying to investigate fruit characteristics that can be used for improving the fruit grading process (Morimoto et al., 2000) and for new applications like fruit volume estimation techniques as described by Forbes (2000) for fruit packaging applications. Calpe et al. (1996) have investigated degree of ripeness from the RGB components to improve the fruit grading. To improve the grading process and to address the need posed by new applications, new technologies are being invented continuously. Gay and Berruto (2002) have described innovative image acquisition techniques for fruit color grading and they report that they have achieved an average classification error less than 2%.

The effectiveness of computer vision techniques has been investigated for a large range of agricultural produce like: eggplant grading (Saito et al., 2003), crack detection in corn shell (Gunasekaran et al., 1987), weed sensing (Steward and Tian, 1998), in cotton processing (Siddaiah et al., 2002), lentils grading (Shahin and Symons, 2001), cereal grain classification (Paliwal et al., 2001), leaf classification (Oskar, 2001), fish grading (Hu et al., 1998), eggshell defect detection (García-Alegre et al., 1998) and wood panel surface grading (Aguilera et al., 2006).

In literature very little research papers are found on computer vision based automated date grading and sorting systems. However, there have been efforts to develop both: the internal (Wulfsohn et al., 1993; Lee et al., 2008; Schmilovitch et al., 1999) and the external (Fadel et al., 2006) quality factor based techniques for this purpose. In what to follows we describe our external quality factor based date grading and sorting system.

4. The proposed date fruit grading and sorting system

In this section, we describe the date fruit grading and sorting system that we have built. The system has a motor driven conveyer belt and a fruit placer. The fruit placer places one fruit at a time on the belt and the belt carries it to the imaging chamber where the fruit image is captured and transferred to the connected image processing and classification system (in this case a PC that is connected to the imaging chamber). The classification result is send to a sorting unit that directs the fruit to an appropriate bin by moving a strip which is controlled by a motor. The detailed design and techniques used for developing the components of the system are described below.

4.1. Image capturing chamber

The image capturing chamber is a wooden box that was painted black inside to reduce the light reflection. The ceiling of the chamber was quoted with reflective material to reduce the shading effect. Two Logitech (Quick cam for notebooks) cameras were mounted facing each other in the chamber. One 80 W red lamp (initially 7 W and 40 W lamps were used but they did not give good lightening effect) was mounted at the top center of the chamber. The cameras were mounted right under the light source for the best imaging. The size of the captured image was 320×240 pixels. It was kept small for fast feature extraction and processing. A sample image is shown in Fig. 2.

4.2. Preprocessing module

A binarization threshold was estimated from the image intensity histogram. The threshold was used to convert the underlying image into a binary image. Fig. 3 below shows the binarized image of the original image (shown in Fig 2). Fig. 4 shows the edges that surround the binarized regions. These edges were extracted by applying Sobel edge operator.

Figure 2 A dates image.

Figure 3 Segmented image.

4.3. Feature definition and extraction

We have defined external quality factors that we refer to as features. These features are *flabbiness*, *size*, *shape*, *intensity* and *defects*. We describe below the properties, usefulness and extraction mechanism of these features.

4.3.1. Flabbiness

The flabbiness is used by farmers to determine the date quality. The flabbiest date is considered of the best quality. We have used the color intensity distribution in the image as an estimate of flabbiness. It is observed that the image of the least flabby date is darker than the flabbier date (see Fig. 5 below). The color intensity distribution is obtained from the gray level image that is obtained form the original RGB colored image using the relationship: G(x, y) = C(x, y)·R + C(x, y)·G + C(x, y)·B, where C(x, y)·R, C(x, y)·G and C(x, y)·B are the red, green and blue components of the pixel x, y in the color image C, and G(x, y) is the transformed gray level.

4.3.2. Size

The fruit size is another quality attribute used by farmers – the bigger size fruit is considered of better quality. The size is estimated by calculating the area covered by the fruit image. To compute the area, first the fruit image is binarized to separate the fruit image from its background. The number of pixels that cover the fruit image is counted and considered as an estimate of size. We categorize fruits as big, medium and small using the average area and variance relationship: $\overline{A} \pm k\sigma^2$, where $\overline{A}$ is the average of the normalized area and σ^2 is the variance obtained from the training data set. If the normalized pixel count in a fruit image is A, and $A < \overline{A} - k\sigma^2$, where k is has been experimentally estimated to be 1.45, then the fruit is categorized as small. If $\overline{A} - k\sigma^2 < A < \overline{A} + k\sigma^2$ then it is categorized as medium; otherwise it is considered big.

Figure 4 Edges.

Figure 5 Flabbier fruit is brighter.

4.3.3. Shape

The farmers use shape irregularity as a quality measure. Fruits having irregular shapes are considered of better quality. We estimated it from the outer profile of the fruit image. The estimation steps are described below.

(1) Using an edge tracking operator to estimate the outmost edge points of the fruit image.
(2) Link the outermost edge points to form the outermost profile of the fruit image.
(3) Compute the centroid (x_g, y_g) of the profile.
(4) Starting from the topmost and leftmost point of the profile and moving clockwise calculate the sequence

$$r(t) = \sqrt{(x_t - x_g) + (y_t - y_g)^2},$$

for t = 1, 2, 3, ..., N, were x_t and y_t are the Cartesian coordinates of the profile at profile boundary time t, and N is the total number of points in the profile.
(5) Compute the Fourier coefficients of $r(t)$

$$a_n = \sum_{t=1}^{N} r(t)e^{\frac{-2j\pi nt}{N}}$$

The value of the first coefficient was used as the irregularity measure.

4.3.4. Intensity

We have observed that the better quality date yield high intensity images. The intensity is estimated in terms of the number of wrinkles. The number of edges was considered as the number of wrinkles. To determine the intensity the image is binarized and edges are extracted using Sobel operator and labeled. The intensity measure is defined as $I = \frac{a}{A}$, where a is the area covered by edges, A is the total fruit area and $0 \leqslant I \leqslant 1$.

Figure 6 Bird flicks.

Figure 7 Bruises.

4.3.5. Defects

The bruises (Fig. 7.) and bird flicks (Fig. 6) are common defects in date fruits. The bird flicks appear brighter in the image so they are determined from the color intensity. An estimate of the average brightness and variations in intensity of the bird flicked area were obtained. The average brightness was thoroughly examined and the bird flicked area size was tracked and estimated. A pixel belongs to the bird flicked area if the brightness of a pixel lies in the interval $I_b \pm k\sigma_b^2$, where I_b is the average brightness of the pixels and σ_b^2 is the variance in the bird flicked area, and k is an experimentally determined constant. The bruises are estimated from the shape as they generally deform the shape by tearing the fruit. In our observation finding an accurate estimate of bruises is an extremely difficult task.

4.4. Classification

We first visually examined the fruits that we used in this experiment and graded them manually according to their features. The fruits having good shape, large size, high intensity, high flabbiness and no defects were branded as of the best quality, i.e., grade 1. The grade 2 fruits have distorted shape, medium size, low flabbiness, low intensity and no defects and fruits having defects were considered as grade 3 fruits regardless of other features. A sample of grades 1–3 fruits are shown in Fig. 8 below.

For classification, we used back propagation neural network (BPNN) which is described below.

4.4.1. Back propagation neural network

The back propagation neural network (BPNN) contains an input layer, at least one hidden layer and one output layer. In the network, the information flows from left to right. The input feature vector $X = (x_i)$ is presented to the input layer and it is passed to output layer via hidden layer. These layers are connected by weights among neurons.

In a training cycle of the network, every training set pattern is presented as input to the network and the output o_k is computed. The output is compared with the desired response d_k. In case of error the weight of the network is modified to reduce the error. The training cycle is repeated across the training pattern to modify the weights of the network till the error attains some predefined tolerance level.

4.4.2. Implementation

To classify dates we studied two BPNN models. The first model has three layers: input layer, one hidden layer and an output layer. The input layer has five neurons representing five feature

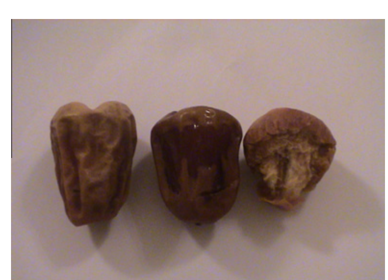

Figure 8 Grades 1, 2 and 3 fruit samples (from left to right).

elements: flabbiness, size, shape, intensity and defects. The hidden layer has 10 neurons and the output layer has three neurons: each neuron representing the fruit grade described earlier. The second model has same number of neurons in the output and hidden layers as model one but only two neurons, representing tow features only: the color (representing brightness) and diameter (representing size) features, in the input layer. The transfer function in the first layer is tan-sigmoid, and in the output layer is linear. Batch training was used to train the networks.

5. Experiments

As described earlier, we implemented two back-propagation neural network models. In Table 1, we present the results of our experiment where the two neural network models are referred to as models 1 and 2.

The system was trained on 1200 (400 Samples/Grade) training set samples. It was tested on 660 (220 Samples/Grade) test samples. The confusion tables of the test experiment are shown in Tables 2 and 3 respectively.

The Table 1 shows the percentages of correctly classified test set fruit. We investigated reasons of misclassification and observed the following (Tables 2 and 3).

(1) The grade 1 samples were misclassified as grade 3 because of the shape and size features and they were confused with grade 2 because of the color features.
(2) The grade 2 fruit were misclassified as grade 1 because of the variations in size, wrinkles and color features, and they were confused with grade 3 because of the variations in the shape, size, color and wrinkle features.

Table 1 Experimental results.

Models	Fruit Grade		
	1 (%)	2 (%)	3 (%)
1	55	76	71
2	71	80	66

Table 2 Model-1 confusion table.

Input grade	Recognized as grade		
	1	2	3
1	121	53	46
2	13	168	39
3	11	52	157

Table 3 Model-2 confusion table.

Input grade	Recognized as grade		
	1	2	3
1	156	26	38
2	17	176	27
3	24	51	145

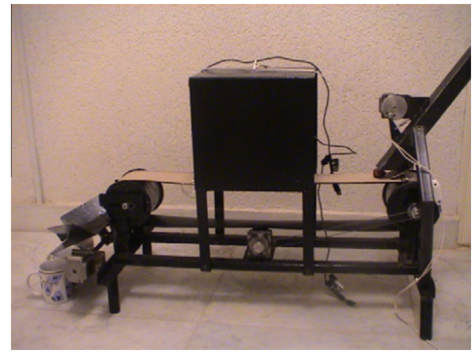

Figure 9 Date fruit grader sorter prototype.

(3) The grade 3 fruit were misclassified as grade 1 because of the variations in the defect feature. The reasons for the misclassification were mainly due to the limited visibility of the defects. The subnormal visibility affected the extraction of size and the shape features.

The results indicate that model two (with fewer input features) yielded better results (in general) and we are investigating reason for the better performance.

6. Discussions and future work

In this research we built a working model of a date fruit grading and sorting system including both: the hardware and the software. The working prototype of the system is shown in Fig. 9 below. The hardware includes the conveyer, camera control and helm control systems. The software system analyzes the fruit image and classifies them. The maximum accuracy of the system is 80% which is attained by model 2 in classifying the grade 2 fruit.

We observed problems in detecting the flabbiness from the color. An impact sensor might improve flabbiness detection. Our fruit quality grading into three grades was based on human perception. A formal feature distribution based method need to be developed to determine the fruit quality grade from the samples. We feel that this should improve the classification accuracy. To determine the feature based grades we are investigating the suitability of the unsupervised learning techniques. We are in the process of applying self organizing map to obtain the fruit grade clusters using the feature distribution in large samples.

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