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Color Quantization and Image Analysis for Automated Fruit Quality Evaluation

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***Abstract*—Machine vision has become an important non-destructive visual inspection technology for automation in the past two decades. Using machine vision for production automation can reduce operating costs and increase product value and quality. For agricultural products, color is often a good indicator of product quality and maturity. This paper presents a novel image-dependent color quantization technique designed specifically for real-time color evaluation in production automation applications. In contrast with more complex color space conversion techniques, the proposed method makes it easy for a human operator to specify and adjust color-preference settings for different color groups representing distinct quality or maturity levels. The performance of this robust color quantization and image analysis technique in evaluating fruit maturity and detecting skin delamination defects is demonstrated using Medjool date samples collected from field testing.**

I. Introduction

COLOR is often the best indicator of fruit quality and maturity. For example, for red delicious apples, dark red color generally indicates higher quality than light red. Tomatoes are green before they ripen, turning pink, light red, and finally dark red as they mature. A machine vision system capable of automated color analysis can be used to evaluate fruit quality and maturity, potentially replacing manual inspections, reducing labor costs, and providing more consistent results.

Many color vision systems have been developed for agricultural grading applications. These applications include the color grading of fresh market peaches [1]-[4], apples [5]-[6], potatoes [7], peppers [8], cucumbers [9], tomatoes [10], and dates [11]. To improve consistency, most of these color-grading systems convert color images captured in red, green, and blue (RGB) color components to a hue-saturation-intensity (HSI) representation. Unfortunately, neither RGB nor HSI color spaces are particularly well suited to color grading. Of greatest concern is that selected reference colors seldom represent a convenient or intuitive partitioning of the multi-dimensional color space. This makes it difficult to define and adjust the boundaries between adjacent color grades and to analyze observed distributions of colors.

Researchers have developed a variety of nondestructive techniques for detecting internal and external defects in agricultural and food products. These techniques include nuclear magnetic resonance [12]-[13], X-ray for evaluating frost damage in citrus and hollow-heart in potatoes [14] and density and moisture content in apples [15]. Despite the potential of these methods, associated high costs, substantial processing overheads, and safety concerns make them ill suited for use on a packing line.

This paper uses Medjool dates as an example to demonstrate the performance of a novel color quantization and color analysis technique for fruit maturity evaluation and surface defect detection. Date growers harvest all fruit in a very short window of 3 to 4 weeks, yielding dates with varying levels of maturity. After harvesting, the fruits currently undergo manual inspection to determine if they are ripe and ready for packaging or if further processing is required. Unripe dates are sent to gain moisture in a hydrating building (most mature), to ripen in the sun (medium), or to dry in a heated building (least mature). Insufficient drying can cause dates to rot and turn sour, while excessive drying can cause the fruit skin to peel, lowering the fruit quality and decreasing its value. After the drying process, most dates ripen and become ready for packaging, although some end up in lower quality grades because of skin delamination that occurs as they dry. It is therefore critical that the maturity of each harvested date is evaluated accurately before drying, and that skin delamination defects are detected reliably before packing.

The relatively few papers on date quality evaluation that have appeared in the literature can be categorized based on the properties they evaluate, including moisture [16]-[18], water and soluble solids [19], firmness [20], and dryness [21]. Most related work is based on the testing and evaluation of limited samples, or operation at a very slow processing speed (e.g., 1 to 2 pieces of fruit per second). In contrast, this paper focuses on a color quantization and color analysis algorithm that is capable of processing 20 pieces per second for commercial production.

The proposed color quantization method does not require complicated machine learning or artificial intelligence algorithms. It allows the user to obtain results in a manner

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similar to human color perception by making simple adjustments to color boundary thresholds. For example, the method allows the threshold for a particular grade to be adjusted so that it includes fruit that is "slightly darker red" or "brighter yellow." In combination with the proposed image analysis technique capable of detecting surface defects such as skin delamination, this robust color quantization method has been applied in commercial production to evaluate date maturity levels and to detect surface defects with very high accuracy.

In Section II, we discuss the specific challenges of color grading. The details of our new method are presented in Section III, including color quantization, calibration, segmentation, and defect detection. We demonstrate the robustness of this novel algorithm with experimental results of date-maturity evaluation and skin delamination detection in Section IV. We summarize our work and conclude the paper in Section V.

II. Challenges and Existing Methods

A. Challenges

Depending on maturity level, date colors range from yellow to dark red with many shades in between. The strong correlation between maturity level and color allows experienced sorters to determine maturity levels by visually examining the color of the fruit, a process used by the Bard Valley Medjool Date Grower Association in California, USA. This important but labor-intensive sorting process constitutes a major expense for packers and growers. A robust color grading technique could automate sorting and reduce costs.

Fig. 1 shows three distinct maturity levels. The two images on the left of the top row are dark red, indicating mature fruit ready for packing. The remaining images in the top row have varying levels of orange, indicating fruit that is not fully mature and in need of further drying. Images on the bottom row have varying levels of yellow; the higher the percentage of yellow, the less mature the fruit.

The first challenge of the proposed evaluation algorithm is therefore to separate dates into three different maturity levels – red, orange, and yellow –with a high degree of accuracy. Fruit in the first category can be packed immediately for sale. Fruit in the second category must be further classified based on the shade of orange, as darker orange colors are more mature. Fruit in the third category must also undergo further classification based on the percentage of yellow.

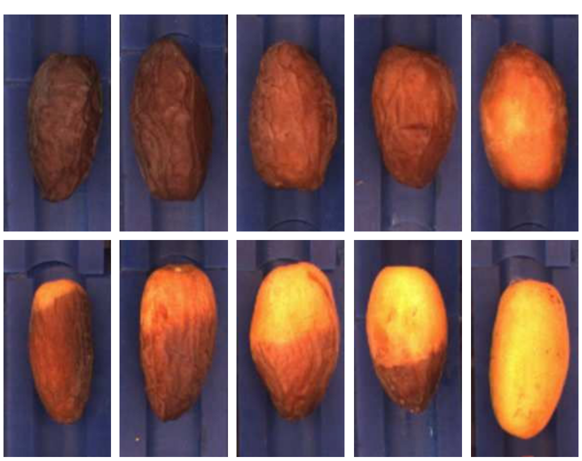


Fig. 1. Three distinct maturity levels: red, orange, and yellow.

The second challenge to address is the detection of surface defects (most notably skin delamination) caused by improper drying. Fig. 2 shows five samples with varying defect severities. Skin delamination is evaluated as the percentage of the fruit that has delaminated skin.

Fig. 2. Fruit with skin delamination caused by improper drying.

B. Drawbacks of Existing Methods

RGB and HSI are the most commonly used color spaces for color grading. RGB is the most studied color space because electronic images are often acquired in terms of RGB components. Color grading in the RGB color space is complicated by the 3D representation of colors, making the selection and adjustment of color preferences difficult. Because thresholding is needed in all three color channels, adjacent grades may correspond to regions that are not contiguous, making it difficult for an operator to make even slight adjustments to classification thresholds during production. Moreover, the 3D nature of the RGB space makes it difficult to perform the analysis associated with the detection of skin defects.

Most color grading systems use HSI rather than RGB values to specify color preferences because it is based on human-distinguishable hues and a more intuitive representation than RGB. However, HSI has its disadvantages. First, the set of expected colors for a given application will not necessarily correspond to contiguous hue values. Hue is generally normalized to lie between 0° and 360°, with red represented as 0°, green as 120°, and blue as 240°. Nearly all formulations of HSI require segment-specific computations for each 60-degree segment of the hue circle, but this introduces visible discontinuities into the color space that make it difficult for a user to set or adjust color grade boundaries using hue values alone. Another disadvantage of using hue for color grading is that it does not contain brightness information – a dark red with low intensity can have the same hue value as a much brighter red. This can be overcome by including the intensity component from the HSI color space in the computations, but setting and adjusting color grade boundaries in the resulting 2D space (hue, intensity) encounters the same problem that arises in the 3D

RGB space: adjacent color grades are likely to correspond to noncontiguous regions and adjustments to grading thresholds (region boundaries) are not intuitive. Moreover, the analysis required by defect detection in 2D would add unwanted complexity to the system.

III. Algorithms

A. Image-dependent Color Quantization

Most color cameras used for machine vision and automation output RGB signals. Individual RGB channels are usually digitized into 8-bit values (0 to 255), so 24 bits are required to represent the color value of each pixel. Although 24 bits allow the specification of more than 16 million unique colors, the range of distinguishable colors for any grading application is much smaller. If the range of *colors of interest* is well defined for a given application, color grading can be significantly simplified.

Given a set of specific colors of interest for the product to be evaluated, it is possible to map the color range to 1D color indices such that the increasing index values reflect increasing product preference. The proposed new color quantization method quantizes colors of interest in 3D RGB color space into 8-bit values. Thus, only a small subset of the 16M possible colors can be represented, but 256 distinct levels are sufficient to represent the colors of interest for many applications. If higher color resolution is required, 16-bit integers (65536 levels) can be used.

The formula of this color quantization is:

$$\begin{aligned} \text{Color Index} &= c_1 RGB + c_2 R^2 + c_3 G^2 + c_4 B^2 \\ &+ c_5 RG + c_6 RB + c_7 GB + c_8 R + c_9 G + c_{10} B + c_{11} \end{aligned} \tag{1}$$

where R, G, and B are the 8-bit color values of a given pixel in the original image, and each c_i ($1 \le i \le 11$) is an application-specific weight that can be derived through calibration. As can be seen, a third-order term (R×G×B) and the full rank of second-order polynomials are employed to convert the original 3D information to a 1D color index for each pixel. The 11 coefficients in the formula are obtained through calibration using RGB values of a selected set of colors of interest and a preferred linear color index for each. Given at least 11 sample colors with distinct RGB values from the application's color range, the 11 coefficients can be solved for using singular value decomposition (SVD) [22].

For date maturity level evaluation and defect detection, as shown in Fig. 3(a), colors range from yellow to dark red, with orange and light red in between. Many colors such as green and blue will not occur and can be excluded. Using the proposed color quantization technique, the resulting color indices are shown in Fig. 3(b). The preferred color (dark red) is assigned the highest color index value.


(a)
(b)
Fig. 3. (a) Colors of interest and (b) quantized color indices.

B. Calibration

Thirteen sample colors ranging from yellow to red as shown in Fig. 3 were used to calibrate the system for date maturity evaluation. Using SVD, the optimal values of the 11 coefficients were calculated. This set of 13 RGB values was selected to cover the full range of colors at all maturity levels. The values were used to create a 13×11 matrix, with one row per sample color. The colors (rows) were arranged in the order of color preference, from least mature to most mature fruit. For each color sample, a human expert specified a desired color index in the range from 0 to 235. (Index values for fruit colors were limited to 235 to distinguish from shadow pixels on the blue carrier that are darker than fruit and assigned index value 255.) The desired index values were arranged into a 1×13 matrix with values [18 36 54 72 90 108 126 144 162 180 196 220 235]. The 13 equations were then solved using SVD, resulting in the 11 coefficient values: [0.000955, 0.000541, 0.018773, 0.25405, -0.025364, -0.055644, -0.391265, 0.510995, 10.321283, 2.867669, 0.080986]. These coefficients were used to convert RGB color values to color indices for further processing.

C. Fruit Segmentation

Fruit must be separated or *segmented* from the background of the image before its color can be analyzed. Blue plastic material was chosen to build the fruit carrier for imaging for two reasons. First, blue does not occur naturally in dates. Second, blue is one of the three channels in the RGB color space, making it easier to filter than colors that require multiple channels to represent. The fruit is segmented from the blue background by creating masks corresponding to the fruit area using the blue and red channels. The proposed color quantization method is then used to remove areas of shadow and increase the accuracy of the mask. Fig. 4 summarizes the segmentation steps, and Fig. 5 shows results on sample images.

Fig. 5(a) shows the original RGB image. The blue and red channels (Figs. 5(b) and 5(c), respectively) are first *binarized* to generate blue and red masks. For each pixel in the image, the corresponding value in the blue mask (Fig. 5(d)) is set to 0 if the value of the blue channel is high (blue background), otherwise it is set to 255 (fruit). Values in the red mask (not shown) are set to 255 if the red channel is high (fruit), otherwise they are set to 0. The two masks are then combined using a logical binary OR operation to create an intermediate mask (Fig. 5(e)) without the holes and missing areas commonly seen in individual blue and red masks (see Fig. 5(d)). By using the logical binary AND operator on corresponding pixel and mask values, the intermediate mask is used to select the fruit area from the original RGB image (Fig. 5(f)).

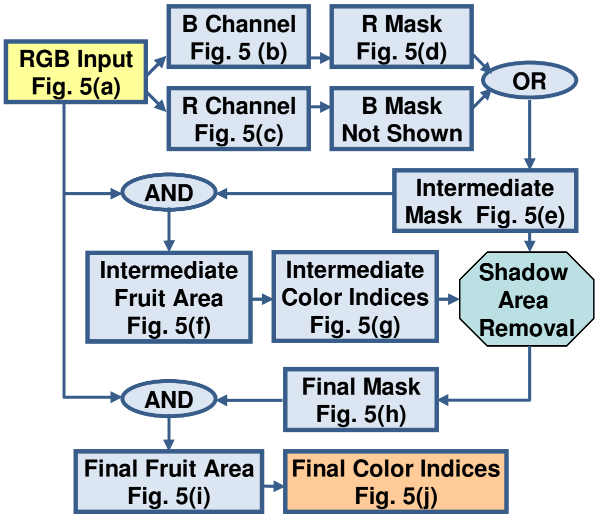


Fig. 4. Flowchart of fruit segmentation process.

At this point, pixels in the fruit area can be converted to color index values using the proposed color space conversion method (Fig. 5(g)), but it can be seen (e.g., upper left portion of date) that the fruit area includes pixels from shadows cast by the fruit on the carrier that are close in color to dark red fruit. It is desirable to remove these shadow pixels before color analysis as they would adversely affect grading accuracy. Using the technique described in Section III.A, the system is calibrated in such a way that these shadow colors are converted to a color index of 255. As the flowchart in Fig. 4 shows, a final mask (Fig. 5(h)) is generated by removing areas of shadow from the intermediate mask. This is accomplished by setting mask pixels to 0 if the corresponding pixels in Fig. 5(g) have a color index of 255 (shadow). Occasionally, some dark red pixels inside the fruit area are removed mistakenly because they are indistinguishable from shadow pixels, but these voids are filled in by a later step that includes connected component analysis. Using the final mask with shadow areas removed, the fruit area can be accurately segmented (Fig. 5(i)) and the proposed color space conversion method can be used to obtain final color indices, as shown in Fig. 5(j).

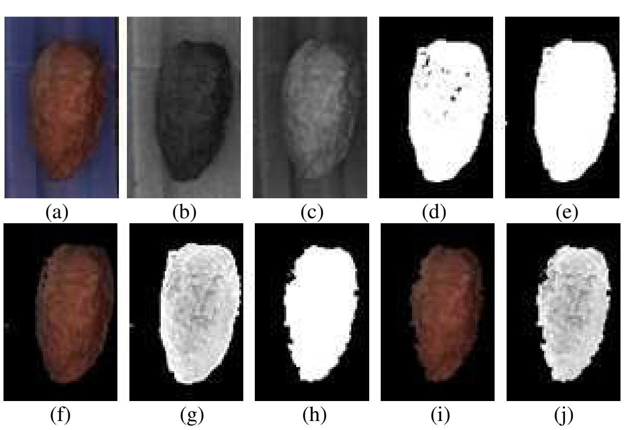


Fig. 5. (a) original image, (b) blue channel, (c) red channel, (d) binary image of blue channel, (e) binary image of blue ORed with binary image of red, (f) segmented fruit image using (e) as a mask, (g) color indices of (f), (h) binary image after filtering out dark blue background, (i) segmented fruit image using (h) as a mask, and (j) color indices of (i).

D. Maturity Evaluation and Defect Detection

As described in Section II.A, the color of each date determines its classification within the red, orange, or yellow maturity levels. In a similar fashion, surface defects are evaluated based on the percentage of the fruit surface with delaminated skin. Fig. 6 shows the flowchart of the proposed algorithm for both tasks.

The algorithm starts with the segmented fruit image as shown in Fig. 5(i). Since yellow fruit has a strong red color component, a binarization based on the R channel can reliably detect the yellow regions of the fruit. Here the percentage of the fruit surface that is yellow is used to detect yellow fruit. (Recall that this percentage is an indication of the maturity level of the fruit.)

The *calyx* area of fruit (the end opposite the stem) often has a bright red color component. This area is generally very small (3 to 10 pixels) and appears at the very top or bottom of the fruit in the image. Based on these characteristics, the calyx can be detected based on the size and location of the binarized red component. After yellow and the calyx are detected, the average of fruit color indices (shown in Fig. 5(j) is calculated to determine if the fruit is red (average index value above a selected Red threshold) or orange (average value above a selected Orange threshold).

Fruit pieces that are not classified as either red or orange are then processed further to detect surface defects. Ripe fruit with high percentages of delaminated skin may appear similar in color to unripe (orange) fruit with no surface defects. The two are distinguished from each other by an additional processing step called *skin crease detection*. A skin crease or fold can be detected based on the contrast of the fruit color indices of nearby pixels as shown in Fig. 5(j). The Canny edge operator is applied to the fruit color index image. If the resulting number of edge points exceeds a user-selected threshold (indicating the presence of many creases and hence delaminated skin), then the fruit is categorized as having surface defects. Otherwise (few edge points), the fruit is considered orange fruit. Fruit with surface defects are further sorted according to the percentage of skin delamination.

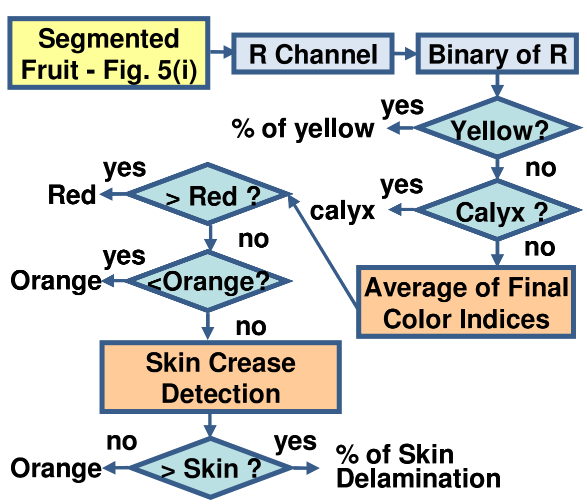


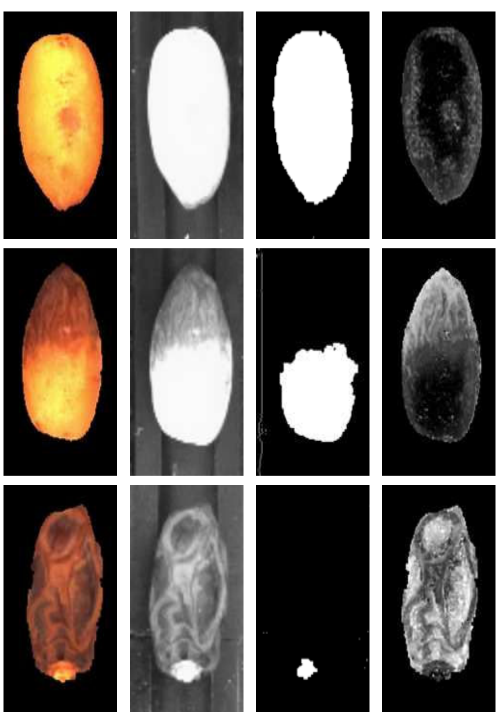
Fig. 6. Flowchart of maturity evaluation and defect detection algorithm.

IV. Experimental Results

A. Sample Processing Result

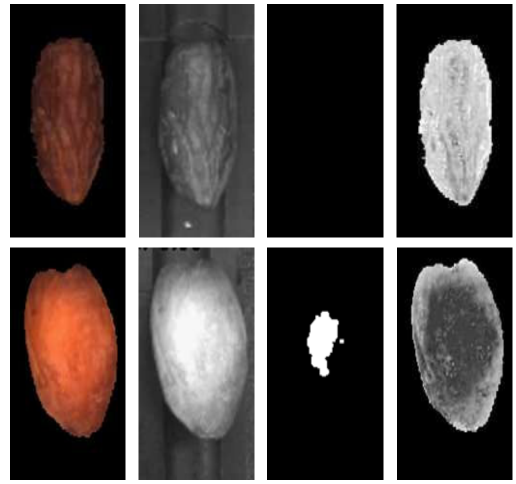
Fig. 7 shows the processing result of yellow fruit and fruit with calyx. Column (a) in Fig. 7 shows the segmented fruit image obtained using the fruit segmentation algorithm described in Section III.C. Column (b) shows the R channel of each image. Notice the high intensity in the yellow and calyx regions. A user-selected threshold (240 in our experiments) on red intensity values is able to separate the yellow regions from non-yellow regions (shown in Column (c)). Column (d) shows the color indices obtained using the proposed color quantization method. Fruit with yellow area more than a user selected threshold (13% in our experiments) are considered yellow fruit, and their maturity level was evaluated based on the percentage of yellow area of the whole fruit. Fruit pieces with a very small yellow area (less than 2%) near the top or bottom end of the fruit were categorized as "calyx". The calyx area is considered a defect and has to be separated from the rest of the fruit. As shown in Fig. 6, fruit that are not considered "yellow" or "calyx" will undergo further processing.

Fruit with the yellow area smaller than 13% and not on the end of the fruit are considered either red, orange, or having a skin delamination surface defect. Fig. 8 shows the processing result of a red and orange fruit. As shown in Fig. 8, red (ready for packing) fruit has 0% yellow, while orange fruit has a small yellow area generally near the center of the fruit (clearly not a calyx at the end). However, fruit with surface defects could also have a yellow area smaller than 13% (including 0%). Column (d) of Fig. 8 shows the color indices of the two samples. It can be seen that color indices of the red fruit are very high (bright) and color indices of the orange fruit are much lower (darker). Fruit that are obviously red or orange can be separated from each other by examining the average of the fruit color indices. A high threshold of 200 was selected in our experiments to detect red fruit. A low threshold of 140 was selected to separate orange fruit. All other fruit that are not separated at this stage require further processing.



(a) (b) (c) (d)

Fig. 7. Yellow fruit and fruit with calyx.



(a) (b) (c) (d)

Fig. 8. Red and orange fruit.

Fruit that have average color indices between the high (200) and low (140) thresholds could be red, orange, or with skin delamination. Fruit in these categories are distinguished from each other by quantifying the amount of skin crease. Fig. 9 shows one sample of orange fruit (top row) and two samples of fruit with skin delamination defects. The orange fruit has an average color index between the two selected thresholds and hence was not detected in the previous step. Column (c) of Fig. 9 shows the color index images of the fruit samples. As can be seen, skin delamination appears as a "crease" that is apparent in the color index image. The Canny edge operator was used to detect the crease and the result is shown in column (d). The orange fruit in Fig. 9 (top row) has far fewer creases in the color index image. The other fruit samples in Fig. 9 have more creases that reflect the amount of skin delamination. However, each crease represents just the boundary edge of a delaminated region. To determine the actual amount of skin delamination, the color index images (two bottom rows in column (c) of Fig. 9) are thresholded. Column (e) shows the binarized color index images superimposed on the original images. The severity of the skin delamination defect is evaluated as the percentage of skin that is delaminated.

B. Performance Evaluation

A total of 664 yellow or partial yellow, 320 orange, 322 red, and 812 defective Medjool dates at differing maturity levels were randomly selected for testing. All yellow fruit pieces were correctly categorized and the percentage of yellow was calculated with fairly high accuracy (relative to a conventional visual inspection). 92.5% of the red fruit, 82.8% of orange fruit, and 88.7% of the fruit with defects were accurately classified. The percentage of skin delamination was

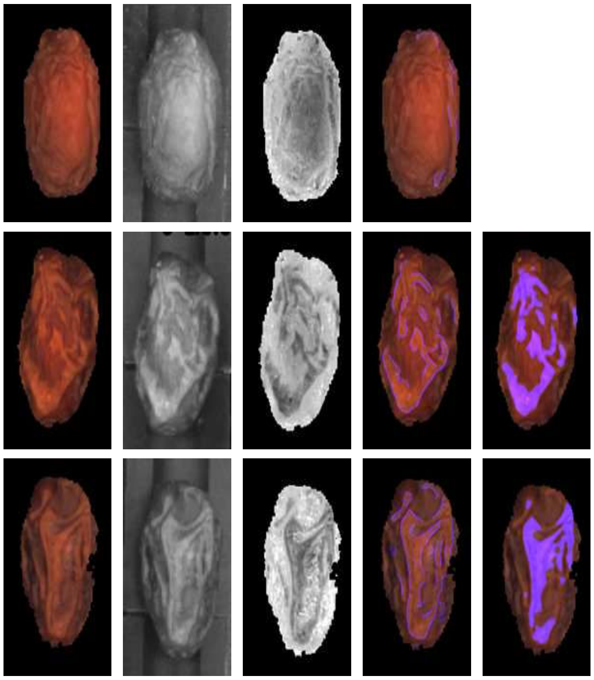


Fig. 9. Fruit with and without skin delamination surface defect.

calculated with very good accuracy relative to a visual inspection by an expert.

The proposed color quantization and image analysis algorithms were implemented with the OpenCV library in Microsoft Visual Studio. A prototype system has been built and tested in a packing facility in Arizona, USA. The system meets the maturity evaluation standard set by the Bard Valley Medjool Date Grower Association, and it meets the industry requirement of grading at least 20 pieces of fruit per second using a single commercial personal computer with two color cameras for four processing lanes.

V. Conclusion

A new color quantization and image analysis method for automated fruit quality evaluation has been presented. Date maturity evaluation and surface defect detection were used as an example to demonstrate the performance of this novel algorithm. The proposed approach uses a third-order polynomial to convert 3D RGB values into a simple 1D color index. The approach also allows a more complicated image analysis to be performed on the converted color indices for the detection of surface defects. Furthermore, by converting 3D colors to linear color indices, date maturity evaluation is much more straightforward and intuitive. The implementation of this new color space conversion method and the results presented demonstrate the simplicity and accuracy of the proposed technique. This new technique can be applied to other color grading applications that require the setting and adjustment of color preferences.

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