An Automatic Foreign Materials Detection of Barberries Using Red-Free Image Processing

Alireza Pourreza, Hamidreza Pourreza, Mohammad Hossein-Aghkhani

Abstract — In this study, a new approach is introduced for automatically detecting of visual foreign materials like peduncles, leaves and blight products in mass of Barberries. The segmentation algorithm has been developed for red-free images of barberries. Cr plane of YCbCr color space is used to detect the target area of images. Because of shining of barberry's glossy cortex during imaging, there are many pixels with the same color of the target areas in Cr plane. A simple equation using statistic parameters of binary images is used to find a compatible threshold for detecting the target areas in each image. With this algorithm, the foreign materials are acceptably detected compared to manually segmented images. This method is very useful when there are many unwanted partially big regions in the image with the same color of target areas.

I. INTRODUCTION

BARBERRY is a resistant shrub which is able to grow up in low-water or salty fields and mostly is produced in Iran. Red fruit of this shrub is very familiar and widely used in Iranian foods because of its color and delicious taste. Green barberries gently get dark red color by losing water. Also in inappropriate storing situation, brown and dark brown color spreads in barberries. Conversion in its pigments is the reason of this color transformation [1].

Separating foreign materials like peduncles, leaves and blight products is very important in packing process of barberries. The quality of packed barberries is measured by percentage of foreign materials [1]. Most of these undesirable materials could be detected visually because they are different in shape and color. Fig. 1 shows barberries with different kinds of foreign materials. Fig. 1(a) shows some barberries without any undesired materials which are regarded as the high quality product. Blight barberries have darker color with the symptoms of infection as illustrated in Fig. 1(b). Leaves and peduncles as the two other kinds of foreign materials are shown in Fig 1(c) and Fig 1(d). All these undesired materials have visual denotation so image processing would offer a good approach to automatic detection of them.

Automatic detection via image segmentation has been considered effective by lots of researchers nowadays. In agriculture and food processing, especially, image processing and machine vision has a considerable influence on accuracy and reliability of detection. Camargo and Smith have successfully identified the visual symptoms of plant disease using a color image processing algorithm [2]. Kang and Sabarez have also introduced a food region segmentation algorithm for multiple products are captured in an image [3]. Many other researches have focused on segmentation of food images as an important factor in food quality measurement ([4], [5], [6], [7], [8], [9]).

Fig. 1 Barberries with different kinds of foreign materials. (a) Barberries without any undesired materials which are regarded as the high quality product; (b) Barberries with some blight ones which have darker color; (c) Barberries with some pieces of dried leaves of its plant which have green color; (d) Barberries with parts of stem or peduncles which have yellow color.

Separating undesired materials which is done manually today, is a very difficult and expensive process in this industry. Using image processing method to find these foreign materials will have great advantages in automatic packing process by the increase in accuracy of foreign material detection and also in labor cost. Thus, it will help to produce more qualified and high grade products with lower cost.

Manuscript received March 29, 2010.
Alireza Pourreza and Mohammad-Hossein Aghkhani are with the Agricultural Machinery Department of Agricultural Engineering Faculty, Ferdowsi University of Mashhad, Iran.
Hamid-Reza Pourreza is with the Computer Engineering Department of Engineering Faculty, Ferdowsi University of Mashhad, Iran. (corresponding author phone: +98-935-800-6214; fax: +98-511-601-8053; e-mail: alireza.pourreza@gmail.com).
II. MATERIALS AND METHODS

The approach which is described in this study is based on red-free image analysis. In this method, first, the RGB color space is changed to YCbCr. Then Cr plane is chosen for the analysis because Cr plane is regarded as the redness of the images and the disparity between gray level of the target areas and healthy barberries is maximum in this plane. Finally, segmentation is done by binarizing the Cr plane, noise reduction, reconstruction, and post processing. The result is compared with the manually segmented images to test the accuracy of the algorithm. The flowchart in Fig. 2 illustrates different steps which are proceeded in the algorithm.

A. Image Acquisition

In order to evaluate the algorithm, 120 red-free images were captured and cropped to 800×800 pixels. The barberries were exposed to indirect green light in a dark room. Indirect lighting condition was applied to diffuse the received light of barberries and reduce the reflection of barberry's glossy cortex and thereupon having lower noisy pixels. These images contain a mass of barberries beside the real foreign materials like peduncles, leaves and blight barberries which were supplied from a packing factory.

B. Methods

1) Color space transformation

The RGB data were transformed to YCbCr color space and the algorithm is applied on Cr plane because it has the maximum disparity between pixel levels of barberries regions and undesired materials regions. The YCbCr color space is widely used in digital photography and video systems. Component (Y) of this color space displays the information of luminance (brightness or intensity). Two other components which include the information of color (chrominance) are Cb; red component minus a reference value, and Cr; blue component minus a reference value. Eq. (1) represents how the transformation from RGB to YCbCr is done [10]:

\[
\begin{bmatrix}
Y \\
Cb \\
Cr
\end{bmatrix} = \begin{bmatrix}
16 & 65.481 & 128.553 & 24.966 \\
128 & -37.797 & -74.203 & 112.000 \\
128 & 112.000 & -93.786 & -18.214
\end{bmatrix} \begin{bmatrix}
R \\
G \\
B
\end{bmatrix}
\]

2) Image segmentation

Image segmentation starts by using two thresholds to convert the Cr plane to binary (Black & white) image. First threshold is used to create a binary image containing all the target areas and it will be used as the marker for the next step. Second threshold creates another binary image. At this step, noise reduction is applied on the second binary image by eliminating all the regions which their total number of pixels is lesser than N pixels. N is the summation of two statistics values; the mean and the standard deviation of the areas in the second binary image. The result image is used as the mask for the next step. At the next step, the mask is reconstructed by dilation by marker. Finally, the regions segmented in reconstructed binary image, is filled and the areas of foreign materials can be extracted from this binary image.

![Flowchart](image)

Fig. 2  The segmentation flowchart to automated detection of undesired materials

3) Main Steps of the algorithm

The main steps of the algorithm are as follows:

Step 1: Convert the input red-free RGB image to YCbCr color space

Step 2: Use first threshold to create first binary image named Marker

Step 3: Use second threshold to create second binary image

Step 4: Compute N=M+STD when M is the mean of areas and STD is the standard deviation of areas of the second binary image

Step 5: Eliminate the regions containing less than N pixels, the result is the Mask

Step 6: Reconstruct the Mask by the Marker

Step 7: Fill all the regions in reconstructed image

4) Evaluation of the algorithm

In order to evaluate the algorithm, manually segmented images are compared to the same images segmented automatically. Manually segmented images were created by delineating the foreign materials on a layer overlaid the
Both manually and automatically segmented are binary images in which undesired materials regions have the pixel value 1 (white) and other regions have the pixel value 0 (black).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Pixel value in manually segmented image</th>
<th>Pixel value in automated segmented image</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>FP</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>FN</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

There are four possible outcomes from matching test between manually and automatically segmented binary images [11]. Table 1 illustrates four different conditions in which we can compute True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). The total number of pixels which confirm the conditions of each row makes the value of the factor shown in the first column of the same row in table 1.

To simplify the notation the manually segmented image was labeled (m) and the automatically produced image (a). Both manually and automatically segmented images are matrices of size \([x \times y]\) in which \(x\) is the number of rows and \(y\) is the number of columns. Thus, \(a(x,y)\) (for instance) represents a pixel position with the value of 0 or 1, then:

\[
TP = \sum_{i=1}^{x} \sum_{j=1}^{y} (m(i,j) \times a(i,j))
\]  
\[
TN = \sum_{i=1}^{x} \sum_{j=1}^{y} ((1 - m(i,j)) \times (1 - a(i,j)))
\]  
\[
FP = \sum_{i=1}^{x} \sum_{j=1}^{y} ((1 - m(i,j)) \times a(i,j))
\]  
\[
FN = \sum_{i=1}^{x} \sum_{j=1}^{y} (m(i,j) \times (1 - a(i,j)))
\]

Sensitivity or True Positive Rate (TPR) determines a diagnostic test performance on pixels recognized correctly in target areas by the algorithm. FPR, on the other hand, defines how many incorrect pixels are recognized among all the pixels which were not in the target areas [11]:

\[
TPR = \frac{TP}{P} \quad \text{While} \quad P = TP + FN
\]

\[
FPR = \frac{FP}{N} \quad \text{While} \quad N = FP + TN
\]

ROC Curve (Receiver Operating Characteristics) illustrates an evaluation of a segmentation performance. TPR and FPR are as \(y\) and \(x\) axes respectively in ROC curve. The area under Roc is considered as an evaluation of the segmentation algorithm efficiency (Marchant et al., 2001). As well as Roc curve, the accuracy of the algorithm is computed by Eq. (4) [12]:

\[
ACC = \frac{TP + TN}{P + N}
\]

Fig. 3 Manually segmented of a sample image. (a) Original red-free image; (b) foreign materials manually segmented

III. RESULTS

To test the algorithm, 120 images containing barberries and foreign materials have been employed. As mentioned in section II.B.4, manually segmented images were created by delineating the foreign materials on a layer overlaid the images in which the pixels pertaining to foreign materials are white (1) and other pixels pertaining to barberries are black (0). Fig. 3(a) shows one sample red-free image and Fig. 3(b) displays the foreign materials manually segmented.
A. Thresholding method

Two thresholds are used in this study. First one is obtained manually by investigating the histogram of gray-level. Using first threshold, as mentioned in section II.B.2, is to produce a binary image containing all the target areas. However, this binary image illustrates many unwanted regions as well as target areas. Fig. (4) shows the procedure applied on a sample image to produce the first binary image (Marker). Fig. 4(b) illustrates the Cr plane of the image in YCbCr color space which is used for segmentation. By inspection in the graph of Fig. 4(c), it is realized that a threshold value around 123 will make the binary image containing all the target areas as it is expected (Fig. 4(d)).

In order to find out which of these regions are the target areas, second binary image is employed. A variety of threshold values between 100 and 126 are used and steps 4 to 7 mentioned in section II.B.3 are applied on all 12 images. The results for one image with different threshold values are shown in appendix.

B. Estimating the accuracy of segmentation

TPR and FPR are computed for the result of each threshold. Then the mean of TPR and FPR in each threshold are calculated between the results of all 12 images. Table 2 shows these mean values. To recognize the optimal threshold, ROC curve was plotted using the mean values of TPR and FPR in each threshold level when TPR values are in vertical axis and FPR values located in horizontal axis. As illustrated in Fig. 5, the curve is very tendentious to the upper left corner and this shows that the algorithm is very successful to denote the foreign materials in the image. Table 2 also shows the accuracy of the proposed method using the equation 4.

IV. CONCLUSIONS

The method of segmentation introduced in this study, efficiently denoted the regions regarding to the foreign materials in a red-free image of a mass of barberries. The considerable ability of this algorithm is to find the target areas with different shapes and colors. The results and acceptable accuracy measured in this study can prove this statement. This method could be applied on the images of other products which have no background and there are many areas with the same color of the target areas in the image. Specifying the kind of foreign materials and the percentage of each in the image is the future attempt to develop this system.

<table>
<thead>
<tr>
<th>Factor</th>
<th>126</th>
<th>124</th>
<th>122</th>
<th>120</th>
<th>115</th>
<th>110</th>
<th>105</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPR</td>
<td>0.909968</td>
<td>0.909828</td>
<td>0.893388</td>
<td>0.891322</td>
<td>0.852599</td>
<td>0.686151</td>
<td>0.509868</td>
<td>0.415946</td>
</tr>
<tr>
<td>FPR</td>
<td>0.066283</td>
<td>0.052266</td>
<td>0.033491</td>
<td>0.024756</td>
<td>0.00893</td>
<td>0.006938</td>
<td>0.00512</td>
<td>0.004422</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.922709</td>
<td>0.938691</td>
<td>0.958684</td>
<td>0.963656</td>
<td>0.979196</td>
<td>0.980993</td>
<td>0.980045</td>
<td>0.973844</td>
</tr>
</tbody>
</table>

Fig. 4 A sample image is transformed to a binary image using first threshold. (a) Original red-free image; (b) Cr plane of the image in YCbCr color space; (c) Histogram of gray-level; (d) The binary image produced by threshold value of 123

Fig. 5 The ROC curve; X axis shows the FPR values and Y axis shows the TPR values
Appendix

(1) Red-Free image of Barberries
(2) Manually segmented image
(3) Automatic segmented image using the threshold 100
(4) Automatic segmented image using the threshold 105
(5) Automatic segmented image using the threshold 110
(6) Automatic segmented image using the threshold 115
(7) Automatic segmented image using the threshold 120
(8) Automatic segmented image using the threshold 122
(9) Automatic segmented image using the threshold 124
(10) Automatic segmented image using the threshold 126

REFERENCES