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Discriminating defected and sound fruits of olive according to external damage area using image processing techniques

Amir-Hossein Afkari-Sayyah[1], Hossein Azarmdel[2], Mansour Rasekh[3] and Tarahom Mesri-Gundoshmian[4]

1-Associated professor, Dept. of Mechanics of Agricultural Machinery, Faculty of Agricultural Technology and Natural Resources, University of Mohaghegh Ardabili, Ardabil, Iran
2- Graduated student, Dept. of Mechanics of Agricultural Machinery, Faculty of Agricultural Technology and Natural Resources, University of Mohaghegh Ardabili, Ardabil, Iran
3- Associated professor, Dept. of Mechanics of Agricultural Machinery, Faculty of Agricultural Technology and Natural Resources, University of Mohaghegh Ardabili, Ardabil, Iran
4- Assistance professor, Dept. of Mechanics of Agricultural Machinery, Faculty of Agricultural Technology and Natural Resources, University of Mohaghegh Ardabili, Ardabil, Iran

Corresponding author: Amir-Hossein Afkari-Sayyah

ABSTRACT: Olive is one of the fruits which are freshly consumed and its oil is used for cooking foods, producing drugs as well as industrial purposes. Nowadays, by increasing olive production, it is necessary to design and fabricate mechanized implements with high precision in sorting and grading processes in order to increase production output. To discriminate the defected and sound olives by image processing techniques, defect area was considered as a decisive factor in classification. A computer program, written in MATLAB 2011a, was used to process and analyze the images. By extracting the defected areas, two groups of olives (sound and defected) were classified in both LED and florescent illuminated samples. This task was done by classification analysis in toolbox of SPSS software. By conducting this analysis, the classification values obtained about 82.5 and 92.5% in florescent and LED illumination respectively.

Keywords**:** olive, MATLAB software, discriminant analysis

INTRODUCTION

Today quality is one of the most important factors in marketing of agricultural products. The presence of skin damages in olives is the most decisive factor in determining their external quality (Riquelme, 2008). Olive is organically and mechanically defected in growth stages and conveying process respectively. So in the bulk of olive fruit there are different kinds of defects which reduce the quality of fruit and its oil. Traditionally olive fruit is sorted by human. This kind of sorting characterized by low speed and accuracy, this is related to human tiredness and different discrimination. Therefore high speed sorting and grading are inseparable parts of agricultural production and exportation. One of the practical techniques for sorting and grading is image processing. Therefore applying this technique in automatic sorting lines needs appropriate conditions like illumination in order to increase sorting efficiency.

A machine vision system (MVS) provides an alternative to the manual inspection of biological products. Machine vision is the technological integration of a camera and a computer. Digital image processing, as a computer based technique, has been extremely used by scientists to solve problems in agriculture. An image-capturing system was designed to provide an enclosed and uniform light illumination in order to obtain appropriate images from the samples. The images were sent via a USB capture device to a computer provided with image acquisition and processing toolboxes of MATLAB software (Version R2011a, The Math Works Inc., MA, and USA) to visualize, acquire and process the images directly from the computer. Defected areas of samples were extracted and coded in order to be analyzed in the images. This information was used as inputs to classify the samples into sound and defected categories.

The image processing method is widely used for sorting and classifying of different kinds of fruits. Ghazanfari, (1998) used a machine vision system to classify unshelled pistachio nuts based on USDA standard grades. The obtained grey-level histogram data from the grey-scale images of the nuts were analyzed to select a set of suitable recognition features. Based on the analyses, the mean of the grey-level histogram over 50-60 grey-level range and the area of each nut (the integral of its grey-level histogram) were selected as recognition features. Leon, (2006) measured Color in L*a*b* units extracted from RGB digital images. Their investigation presented five models for the RGB to L*a*b* conversion and they were: linear, quadratic, gamma, direct, and neural network. Additionally, a method was suggested to estimate the parameters of the models based on a minimization of the mean absolute error between the color measurements obtained by the models, and by a commercial colorimeter for uniform and homogenous surfaces. Riquelme, (2008) classified olive according to external damage using image analysis. The original images were processed using segmentation, color parameters and morphological features of the defects and the whole fruits. They focused on discriminating a large number of external defects in olives based on the commercial categories established by product experts. Lopez-Garcia, (2010) automatically detected skin defects in citrus fruits using a multivariate image analysis approach. They studied usage of a general approach that was originally developed for the detection of defects in random color textures. It was based on a Multivariate Image Analysis strategy and used Principal Component Analysis to extract a reference eigenspace from a matrix built by unfolding color and spatial data from samples of defect-free peel. Test images were also unfolded and projected onto the reference eigenspace and the result was a score matrix which was used to compute defective maps. In addition, a multiresolution scheme was introduced in the original method to speed up the process. Unlike the techniques commonly used for the detection of defects in fruits, this was an unsupervised method that only needs a few samples to be trained. It was also a simple approach that was suitable for real-time compliance. Linker, (2012) determined the number of green apples in RGB images recorded in orchards. They developed an algorithm to estimate the number of apples in color images acquired in orchards under natural illumination condition. The algorithm was intended to enable estimation of the orchard yield and be part of a management decision support system. Garrido-Novell, (2012) used discriminant analysis for grading and color evolution of apples using RGB and hyperspectral imaging vision cameras. The potential of RGB digital imaging and hyperspectral imaging (900–1700 nm) was evaluated for discriminating maturity level in apples under different storage conditions along the shelf-life. They used discriminant analysis (DA) for dimensionality reduction and RGB data analysis. This analysis technique was used because it requires a low number of variables to create the functions, a low computational power and it has yielded good results in previous studies (Valero, 2004; Hernandez-Sanchez, 2006). This paper aims to introduce a system which uses machine vision algorithms and discriminant analysis (DA) to detect sound and defected olives according to their external damage area in order to separate them in sorting lines and studying the effect of illumination methods.

MATERIALS AND METHODS

1. Fruit samples

Olive cultivar "oily" obtained from an orchard (Loshan town, Gilan Province, Iran). The samples were transported to laboratory located in Mohaggeg Ardebili University and stored in water in order to prevent color changes during experimental process. In collected fruits there were samples which displayed color variations that may have resulted from different environmental growth conditions causing variations in pigmentation. A total of 80 olives containing 40 for each lighting type including 20 sound olives without any defects and 20 physically and organically defected olives were randomly selected for this study (Fig. 1).

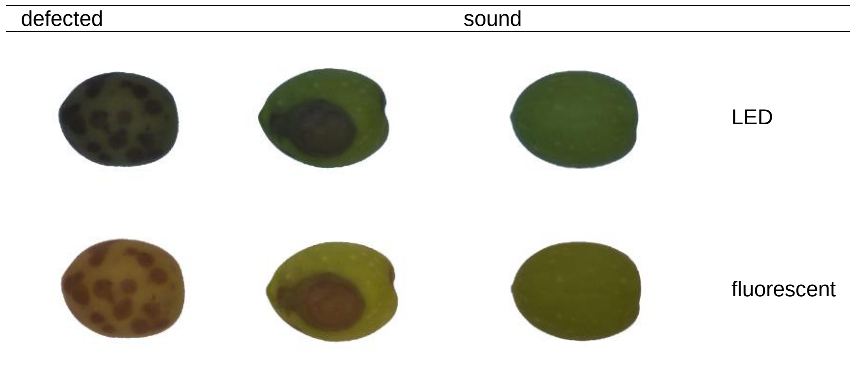


Figure 1. Sound and defected olives captured in LED and flourscent illumination

2. Image Processing

The steps involved in image processing were : image acquisition, pre-processing, feature extraction and data analysis. A computer program, written in MATLAB 2011a, was used to process and analyze the images.

2.1. Image acquisition

The image acquisition system consisted of a CCD color camera (Sony DSLR- α200) with a resolution of 10.2 mega pixel and a laptop computer (HP 4530S) to save and process the images. The camera was placed vertically on the top of the lighting chamber. The images were captured in an appropriate situation without any vibration. The distance between camera lens and the sample was constant in capturing process. The lighting system was composed of a hemispheric chamber, two sets of lighting lamps including four rings with a chain of 50 LED lamps for each ring and four fluorescent lamps (18W, 220V, 80mA) to investigate and compare effects of lighting type on detection accuracy. The chamber was like the one that (Riquelme et al, 2008) used in their research. In order to get rid of shadows around the samples and light spots on their surface, light was filtered by a white paper which was placed between the lamps and the sample. The scheme of the lightening chamber is shown in (Fig.1).

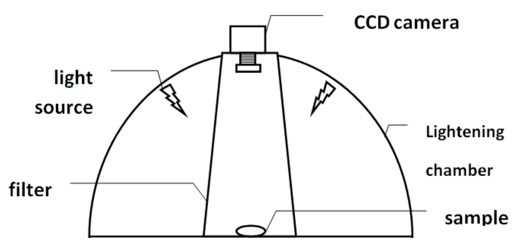


Figure 1. Lightening chamber

2.2. Pre-processing

For pre-processing the images, the fruit area was separated from the background with the algorithm of Otsu (1979), which is based on statistical and space information of histograms (Gaussians distributions). This step also named segmentation. Using the function 'graythresh' in toolbox of MATLAB software, the optimal threshold of an image is applied for objects of the images. The procedure is very simple: when the threshold (T) is applied, the image is converted automatically into binary values (black and white), where '1' means background and '0' foreground (object) (Riquelme, 2007):

$$g(x,y) = \begin{Bmatrix} 1 \leftrightarrow f(x,y) < T \\ 0 \leftrightarrow f(x,y) > T \end{Bmatrix}$$

This procedure is shown in fig (2) for fluorescent illumination as representative method for both illumination types.

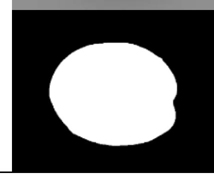
pre-processing procedure	image
RGB image	
RGB image to gray	
Gray image to binary	

Figure 2. image pre-processing procedure

2.3. Feature extraction

As in any typical image-analysis application, only the initial data (in this case the raw image) and the desired result (the percentage of defect in olive image) are specified and the choice of the specific steps which should be performed in order to produce the desired final result are left to the researcher (Linker et al, 2012). After segmentation, the next step was extracting defect areas that are used in determining sound and defected samples. Segmentation determines which regions of the image correspond to the background and which represent the sample itself.

Extraction of the defect area of defected samples is also shown in Fig (3):

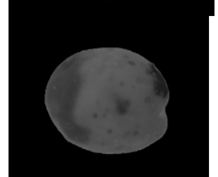
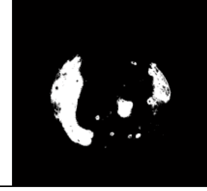
feature extraction procedure	image
replacing sample in binary image	
RGB image to gray	
extracting defect area	

Figure 3. Feature extraction procedure

The percentage of the defect area was quantified as following:

$$\text{Defect percentage} = \frac{\text{number of black oixels}}{\text{number of black pixels+number of white pixels}} \times 100$$

3. Data analysis

To determine significant differences between sound and defected olives using corresponding values, it was necessary to code these values. The samples with defected area greater than 2 percent were coded as '2' and the rest were coded as '1' for fluorescent and LED illuminated samples. Then theses codes were introduced into discriminant analysis (DA). This analysis was performed to segregate between two groups of samples. It was done by classification analysis in toolbox of SPSS software and the total classification value was computed.

RESULTS AND DISCUSSION

After extracting the defected area percentage of each sample the related coded values were used in classification process. These values are illustrated in diagram (1).

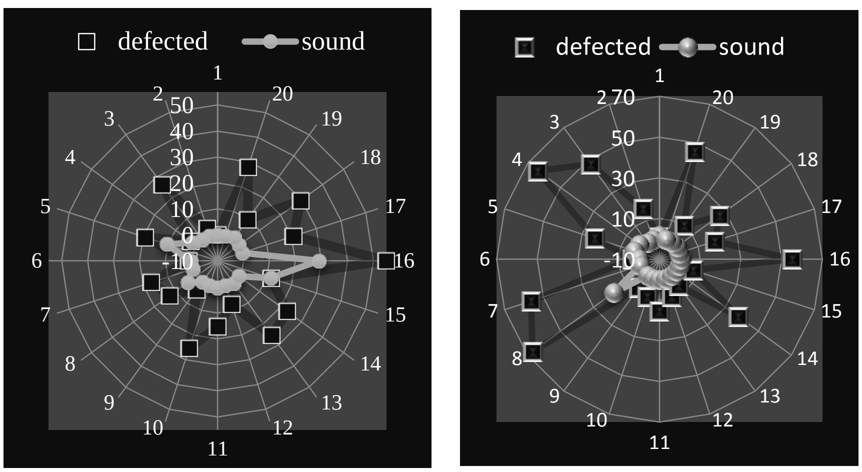


Diagram1. Detected values of sound and defected samples. florescent (left) and LED illumination (right)

Defect values for defected and sound samples are shown by black squares and white circles respectively. The values related to sound olives are concentrated in the center of the diagram (1) and those of defected samples are scattered with different values. Because the color images are transformed to gray scale, some of pixels have close intensity level to those of sound ones. As it is shown in diagram (1) in florescent illumination (left) there are four sound samples which were detected as defected and 2 defected samples were detected as sound olives. For LED illumination (right) only 1 sample was detected as defected and 2 defected samples were detected as sound olives. This misclassification in both illumination types is because of pigmentation on skin of this variety which was resulted from different growth conditions. To classify the sound and defected olives the defected areas were coded in order to introduce to a (DA) analysis. The results of discriminant analysis are shown in table (2).

Table 1. Discrimination analysis results

	Test of function	Wilk's lambda	Chi- square	Canonical correlation	Degree of freedom	α-level
fluorescent	(1)	0.568	21.226	0.657	1	0.000
LED	(1)	0.286	48.318	0.851	1	0.000

The table contains significant test for two groups of samples ($\alpha < 0.01$). More parameters were also computed in this analysis as Wilk's lambda (contribution to overall performance which describes the proportion of variance values that cannot be described according to group differences). This was 0.568 and 0.286 for florescent and LED illumination respectively. Thus the defects extracted from LED illumination can properly describe group differences (sound and defected olives) in greater proportion. The canonical correlation in LED illumination (0.851) was more than that of florescent illumination. Predicted group membership and total classification are shown in table (2).

Table 2. Predicted group membership and total classification in two illumination methods

		Predicted group membership (%)		Total (%)
		Sound	defected	
Florescent	sound	75	25	82.5
	defected	10	90	
LED	sound	90	10	92.5
	defected	5	95	

As it is shown in table (2) for samples which were illuminated in florescent light, 25% of sound olives were detected as defected samples. On the other hand 10% of defected olives were classified as sound samples. This was 10% and 5% for sound and defected olives respectively in LED illumination method. Finally the total classification values extracted by conducting discriminant analysis in both florescent and LED illumination were 82.5% and 92.5% respectively. This difference could be related to monotonous light emission of numerous LED lamps around samples in comparison with regional light emission of florescent lamps. Since, on the other hand, LED lamps work with DC current the images were without any resonance and it yielded a same condition to capture the images.

Conclusion

The results extracted by processing the parameters of acquired images of defected and sound olives showed that extracting defected areas by image processing technique could be an appropriate method to detect sound and defected olives. Since the color of olive fruits are light green in comparison with darker defects, then a gray scale can be used for sorting of olive fruits. This can lead us to use a simple program in order to reduce the total processing time which is one of the most important factors in sorting lines. By extracting the defected areas the values were coded in order to classify sound and defected olives. The total classification values for detecting defected and sound olives in both florescent and LED illumination were 82.5% and 92.5% respectively.

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