Talanta 116 (2013) 894–898

Contents lists available at ScienceDirect

Talanta

journal homepage: www.elsevier.com/locate/talanta

Infrared machine vision system for the automatic detection of olive fruit quality

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ARTICLE INFO

Article history:
Received 30 April 2013
Received in revised form
24 July 2013
Accepted 30 July 2013
Available online 7 August 2013

Keywords:
Near infrared
Algorithm
Quality
Olive fruit
Image analysis

ABSTRACT

External quality is an important factor in the extraction of olive oil and the marketing of olive fruits. The appearance and presence of external damage are factors that influence the quality of the oil extracted and the perception of consumers, determining the level of acceptance prior to purchase in the case of table olives. The aim of this paper is to report on artificial vision techniques developed for the online estimation of olive quality and to assess the effectiveness of these techniques in evaluating quality based on detecting external defects. This method of classifying olives according to the presence of defects is based on an infrared (IR) vision system. Images of defects were acquired using a digital monochrome camera with band-pass filters on near-infrared (NIR). The original images were processed using segmentation algorithms, edge detection and pixel value intensity to classify the whole fruit. The detection of the defect involved a pixel classification procedure based on nonparametric models of the healthy and defective areas of olives. Classification tests were performed on olives to assess the effectiveness of the proposed method.

This research showed that the IR vision system is a useful technology for the automatic assessment of olives that has the potential for use in offline inspection and for online sorting for defects and the presence of surface damage, easily distinguishing those that do not meet minimum quality requirements.

1. Introduction

The presence of damage on the skin of the olives is the most decisive factor in determining the fruit's external quality. The classification of olives is important in order to determine whether they meet the requirements for marketing as table olives or for oil extraction. The control of olives is based on human supervision, and it is important to detect whether they have any disease or damage to the skin.

A new approach to the infrared (IR) system, which improves its effectiveness and can be optimized by using a set of IR monochrome images, makes it possible to discover and assess features that are difficult to see using traditional systems. The use of these techniques has increased in recent years because they provide important information on the natural attributes of the products studied.

Another important feature of these systems is that they enable these products to be studied in electromagnetic spectrum regions where the human eye cannot operate, such as the ultraviolet (UV), IR and near-infrared (NIR) regions. The high risk of human error in sorting processes is well known and is one of the most important obstacles that machine vision can help overcome [1].

For all these reasons, the application of machine vision to food analysis has increased considerably in recent years. Some research institutes and manufacturers of are seeking to develop automatic classification techniques. Moltó et al. [2] studied image analysis techniques in order to measure some parameters that define the quality of various fruits and vegetables. Later, Moltó et al. [3] attempted to determine citrus size, color, shape and defects. Heinemann et al. [4] developed an algorithm to evaluate apple size, shape, color and surface defects using machine vision. These parameters have also been assessed by other authors using artificial vision systems [5–9].

There are some articles on the detection of damage and quality control in fruits. One of the first approaches to detecting bruising on apples was based on using interferential filters [10]. The techniques used to detect defects have varied from the use of wavelets [11] to the recognition of edges [12]. The methods for obtaining multiple images are based on using photographs [13], X-rays [14], and three-dimensional images [15].

The most recent techniques for defect detection combine IR and visible (RGB) data [16] or the use of hyperspectral imaging

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0039-9140/$ - see front matter
http://dx.doi.org/10.1016/j.talanta.2013.07.081

[17]. A multispectral vision system that was developed included four wavelength bands in the visible/NIR range for sorting apples [18]. The 750- and 850-nm bands, however, offered a good contrast between defective and healthy tissue and were well suited to detecting internal tissue damage. Bennedsen and Peterson [19] developed a multispectral machine vision system for detecting surface defects on apples, and other researchers [20] developed a multispectral inspection system for detecting and sorting citrus fruits according to 11 types of external defects by combining the information obtained from four image acquisition systems that are sensitive to NIR, visible, UV and fluorescent images. A further step was taken in the development of a prototype for the real-time inspection of citrus canker based on two wavelengths centered at 730 and 830 nm [21]. In order to discriminate between the stem end and the actual defects, they combined a further two bands. All these studies have found that the use of monochromatic images corresponding to wavelengths in the NIR contain a large amount of information on fruit surface defects and external damage that visible images do not provide.

In previous works, we have used spectroscopy as a rapid non-destructive method to determine the quality of olives in the process [22]. Diaz et al. [23] used a vision system to link the quality parameters of table olives with their physicochemical characteristics. The system was based the development of a fast and efficient algorithm that would be incorporated into an automatic sorting process. Other studies on the use of artificial vision for olive fruits include work on classifying external damage contour edges by using visible images [24], predicting the ripening index [25] and determining the parameters of oil quality based on artificial vision and ANN [26].

In view of these studies have shown that the infrared region which provides better contrast in the detection of tissue damage is near infrared area of 700–900 nm.

This paper discusses recent advances in the use of this technology for assessing fruit quality and proposes a method for classifying olive fruits according to their quality by determining the percentage of external damage using an IR vision system with band ranging from 760 nm to 1000 nm. The lower cost of these systems allows them to now be used in laboratories for food quality, and they are an emerging and promising tool for food quality and safety control.

2. Materials and methods

2.1. Image system

The images were acquired with a digital 2CCD (charge-coupled device) Progressive Scan Multi-Spectral Camera JAI AD-080CL, which combined a visible color channel (Bayer mosaic CCD) and an NIR channel (monochrome CCD) which provided IR information. The major advantage of this camera is that it captures both channels simultaneously through the same optical path. This camera is based on a dichroic prism, allowing precise separation of the visible (color) and Near-Infrared parts of the spectrum into two separate channels. The Visible (color) channel is referred to as Channel 1 and the Near-Infrared channel is referred to as Channel 2. Channel 1 and 2 can be configured to operate separately or synchronously. The dichroic prism incorporated in the AD-080CL separates the visible (color) part of the spectrum into a wavelength band from 400 nm to 650 nm (Channel 1) and the Near-IR part into a band ranging from 760 nm to 1000 nm (Channel 2). It can be used for inspection tasks, where images from the visible (color) and NIR spectra are required in combination. This system can generate images with 8- or 10-bit depth and 24-bits in RGB images, using a standard Camera Link interface with a resolution of 1024×768 active pixels per channel. The camera was installed in an enclosed cabin under controlled lighting in order to achieve a consistent image in all acquisitions. The lighting was provided by a halogen lamp with some filters, which created a diffused light simulating the illuminant D65 (6500 K). This is the standard set by the International Commission on Illumination and simulates normal light conditions until noon, thus avoiding glow effects on the fruit. The images were taken from a distance of about 45 cm, with the olives on a neutral white background. For the online application of this method, the devices were installed in the processing line on a belt that transported olives into the mill, where the lighting conditions were the same as those described above. Being a high-speed camera, it can take high-quality pictures of the fruit, reaching a motion capture of up to 30 frames per second with full resolution.

2.2. Methodology

Freshly collected samples from the 2011–2012 olive crop at the Venta del Llano Instituto de Investigación y Formación Agraria y Pesquera (IFAPA) in Mengíbar in Jaén, Spain were used. Real samples were collected from a factory in Jaén province.

The algorithms used were developed with the image analysis software Image Pro-Plus version 6.0 (Media Cybernetics, Inc). Forty-five IR images of healthy olives and of olives with defects were acquired. The defects included damage with or without skin perforation, scar tissue, frost damage, visible flesh damage and recent bruises.

Using this technique it was possible to distinguish apparently damaged olives which looked healthy to the human eye. The difference between healthy and damaged skin could be seen clearly in the NIR bands, which provided a good contrast between the damaged and healthy skin and were well suited to detecting internal skin damage [27]. Fig. 1 shows an RGB image of healthy and defective olives where the external damage is not clear and the corresponding IR image can where the damage can clearly be seen.

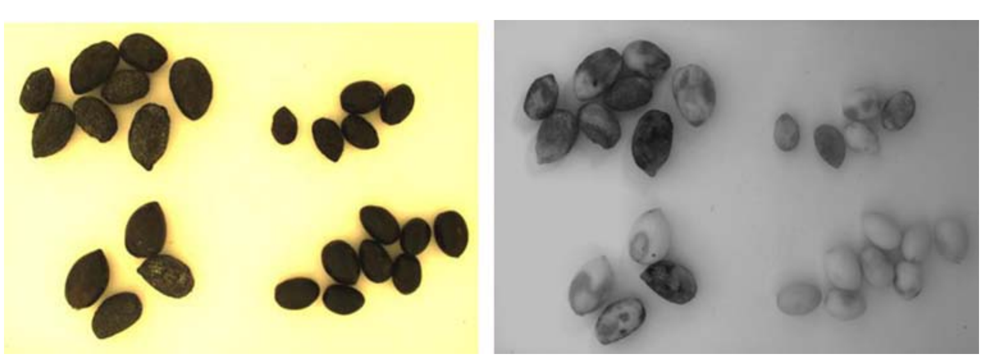

Fig. 1. Visible (RGB) and infrared (IR) images of a batch of olives.

In the wavelength bands of IR images, defect pixels covered a wide range of intensities, and each pixel of the fruit was grouped as either non-defective or defective. After selecting the images, areas of interest or objects in the image were selected using edge detection algorithms and labeling [28,29]. Edge detection was performed to identify objects in the IR image, so that separate the different objects in the image to build a mask. This mask is applied to the original image to finally segmentation of external defects inside each object. A routine was developed to calculate the position and size of each defect based on this segmentation.

2.2.1. Identification and separation of objects in the NIR image

The procedure to separate objects involved using an NIR monochrome image in order to segregate each olive fruit. In order to identify objects in the NIR monochrome image, a contrast equalization procedure was performed, followed by spatial filter enhancement ('Flatten'), which reduces the intensity variation in the background pixels. Spatial filtering was applied to the images in order to enhance or attenuate spatial detail, which would in turn enhance visual performance or facilitate further processing. Spatial filtering can be considered as a 'local' procedure in image processing in that it changes the value of each pixel according to the values of the surrounding pixels [30]. From a practical point of view, this step consists mainly of classifying the original gray levels in the original NIR image according to the value of the neighboring pixels. This task was carried out using two algorithms: (a) Border- Neighbor, which determines the edges of the olive (taking into account the pixel intensity values in the histogram) and considers the darker pixels as edges of objects [31]; and (b) the connected components algorithm, which is used to give each olive a value [32]. The edge-based algorithm enumerates each set of pixels that make up an olive [33].

2.2.2. Creating a mask and segmentation of gray levels

Based on these objects, a skeleton image was constructed. It was intended to represent the shape of an object with a relatively small number of pixels. Thus, all pixels of the skeleton were structurally necessary. The position, orientation and length of the skeleton lines corresponded to those equivalents in the original image. The task of extracting the features of an image was simplified in order to obtain the skeleton. A filter mask 'pruning' was applied, which reduced the image to a skeleton and eliminated protrusions. The skeleton was added to the original IR image and marked the position of the defects in the original image. To that end, a gradient-based segmentation of gray levels, areas with the highest values of gray representing the area of pixel defects and areas with the lowest value of gray representing the healthy areas of the fruit. After an evaluation of the defect areas, the results were translated into percentages based on the sum of all pixels in the defective areas of the olives and the sum of all pixels in the healthy areas of the olives.

This made it possible to measure some geometric properties of the defects and, in particular, the defect area of each olive.

Each pixel of the fruit is classified into the different groups: sound olives or defective olives, according to the values of its spectral components. For each olive, results were obtained as the total percentage of defects and the total percentage of sound skin.

In order to classify olives according to their degree of defect, five different categories have been agreed. Table 1 defines those categories as follows: sound olives, olives with minor defects, olives with moderate defects, olives with several defects and defective olives.

In Fig. 2 is showed an image analysed with its corresponding results of classification.

Table 1
Olive classification based on percentage of healthy and defective skin.

Category		
0	**Healthy olive**	100% Healthy area
1	**Minor defects**	$>75\%$ Healthy area
2	**Moderate defects**	$>50\%$ Defective area
3	**Several defects**	$>75\%$ Defective area
4	**Defective olive**	100% Defective area

3. Results

In order to test this method, 45 sample images were taken of both healthy olives and defective olives. The number of olives in the images varied, in order to obtain all possible combinations of healthy and defective olives.

Fig. 2 shows the original RGB image, the IR image and the image results obtained after applying the algorithms to determine the defects in a set of olives (in percentage). As can be seen in the RGB image, visually apparent damage on the fruit cannot be detected, whereas in the IR image these defects are clearly distinguished.

Fig. 3 shows an analyzed image, with the classification results. Table 2 shows the results of the classification of some samples of olives, using the proposed automatic method.

The results of classification for some of the images analyzed are shown in Table 2. The results are given as the healthy and defective percentages for each olive as well as their classification into different classes defined.

These results indicated that spectral components of IR images are a useful tool for detecting surface damage in olive fruits. Spectral imaging provides a valuable tool to detect external defects that are not clearly visible to the human eye. The near infrared bands provide a good contrast between defective and healthy tissue and are well suited for detecting damage to internal tissues, such as skin and shock damage. The method, based on selecting on a rank of spectral and applying the appropriate filter in order to acquire spectral images, appears to be suitable for the automatic detection of defects in olive fruits. These results show that is possible extract information from the visual characteristics and infrared vision system and visible to develop applications for the automatic prediction of the health status of olive samples at the start of the process of producing olive oil. The proposed methodology, based on the edge-detection and connected components algorithms, is able to estimate the percentage of defects in the olives.

4. Conclusions

After further optimization and more accurate calibration, the new vision system could be incorporated into a sorting machine for screening of the health status of olives and thus provide the basis for a defect detection system for olives. The development of an offline machine vision system could be used as a model for defect detection in olives at the factory level.

The development of classification systems for non-destructive methods is applied to each fruit and ensures that their characteristics meet the standards. Concretely, optical techniques offer possibilities in the assessment of surface characteristics and inner qualities or composition. This system can be potentially used on-line in the classification of olives, which means that it would help to improve the quality control of olive oil in factories. Additionally, the systems used to measure optical properties provide significant information about the characteristics of each fruit, which is useful for the assessment of products.

Fig. 2. Image analysed with its corresponding results of classification.

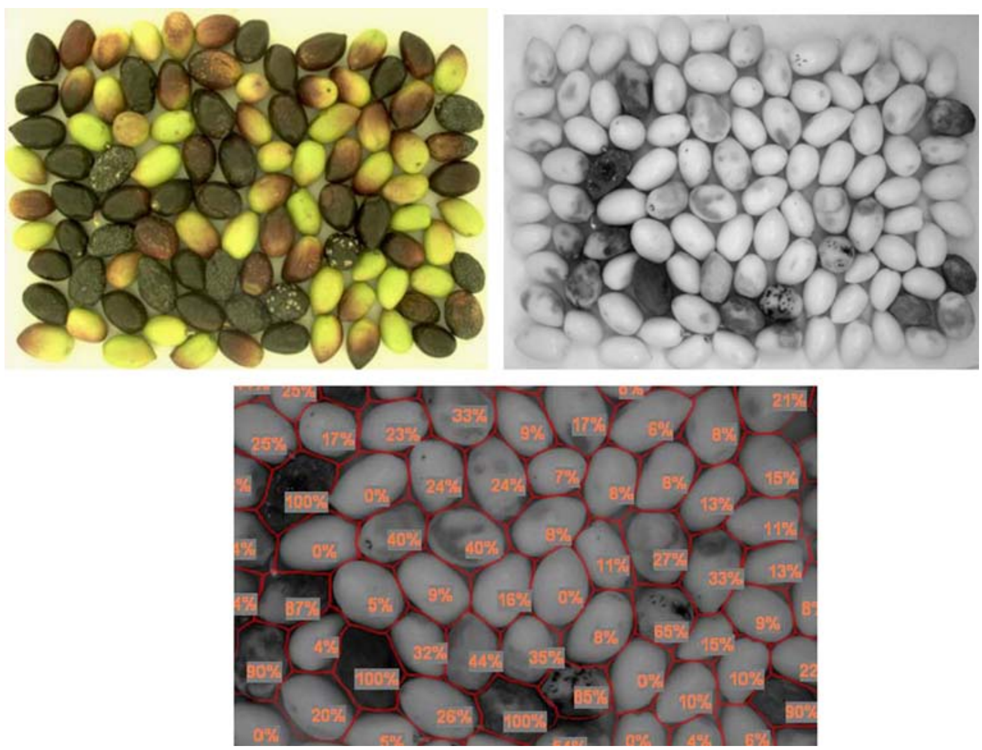

Fig. 3. Original image in RGB, IR image and results in zoom images obtained. Results of classification for an analyzed image.

Table 2
Results of the classification of some samples of olives, using the proposed automatic method.

Images	% Defective	% Healthy	Total no. of olives	Class 0	Class 1	Class 2	Class 3	Class 4
Img 1	14.06	85.94	116	75	40	1	0	0
Img 2	34.95	65.05	80	7	35	29	0	9
Img 3	22.34	77.66	111	6	64	41	0	0
Img 4	15.88	84.12	110	14	78	18	0	0
Img 5	47.35	52.65	139	0	40	71	15	13
Img 6	68.56	31.44	107	0	3	51	30	23
Img 7	70.32	29.68	105	0	2	50	27	26
Img 8	68.42	31.58	122	0	0	80	22	20
Img 9	89.62	10.38	123	0	0	19	62	42
Img 10	70.98	29.02	115	0	0	62	34	19

The future of spectral systems applied to food inspection is promising, with industry and consumers becoming increasingly aware of the need to ensure quality and food safety. This technology is an important tool for the inspection and control of these parameters automatically, so our future work will be directed to continue developing these methodologies, developing more robust calibration models using a larger amount of fruits and varieties and the use validation of models and developing these processes on-line for implementation in the factories as would suppose a great help during the process of olive oil production at very low cost. The future of spectral systems applied to food inspection is promising, as both industry and consumers are increasingly aware of the need to ensure quality and food safety. Consequently, this technology is an essential tool for automatic inspection and control of these parameters. The future of spectral systems applied to food inspection is promising, with both industry and consumers becoming more aware of the need to ensure quality and food safety.

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