Computer vision developments for the automatic inspection of fresh and processed fruits

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Abstract: *The quality of a fresh or processed fruit or vegetable is defined by a series of characteristics which make it more or less attractive to the consumer, such as ripeness, size, weight, shape, colour, presence of blemishes and diseases, presence or absence of fruit stems, seeds, etc. In summary, these characteristics may cover all of the factors that exert an influence on the product's appearance, on its nutritional and organoleptic qualities or on its suitability for preservation. Most of these factors have traditionally been assessed by visual inspection performed by trained operators. However, the application of machine vision in agriculture has increased considerably in recent years since it provides substantial information about the nature and attributes of the produces, reduces costs, guarantees the maintenance of quality standards and provides useful information in real time. Moreover, machine vision opens the possibility of exploring agricultural products in invisible regions of the electromagnetic spectrum, as in the ultraviolet or infrared regions.*

Instituto Valenciano de Investigaciones Agrarias (IVIA) has developed during the past 15 years computer vision systems for the automatic, on-line inspection of fresh and processed fruits and vegetables. This paper shows the most important outcomes in this matter achieved by the department called Centro de Agroingeniería. One of such systems is a machine for the automatic inspection of pomegranate arils for fresh consumption. This machine individualizes, inspects, classifies and separates the arils in four categories, removing those that do not fulfil the minimal specifications. Multivariate analysis models are used to classify the arils with an average success about 90%.

Another application is a machine to classify mandarin segments for canning. The system distinguishes among sound, broken or double segments, and is able to detect the presence of seeds in the segments. The system analyses the shape of the each individual segment to estimate morphological features that are used to classify it into different commercial categories. The machine classifies correctly more than 75% of the analyzed segments. Both systems are currently patent pending.

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In the field of computer vision systems for the inspection of fresh, whole fruit, most research has been focused on citrus fruits. While most commercial systems only detect the blemishes on the skin of fruit, a multispectral system has been developed to identify them. The system is capable of identifying the 11 most common defects of citrus skin using near infrared, colour and ultraviolet. It also uses induced ultraviolet fluorescence. The success rate achieved with such system reached 87% when identifying about 800 defects in five species of oranges and mandarins.

The use of hyperspectral sensors makes it possible to conduct a more sophisticated analysis of the scene by acquiring sets of images corresponding to particular wavelengths. Using this technology, we have conducted different works aimed at detecting damages in citrus fruits, including fungal infestation. The acquired multi-dimensional spectral signature characterising a pixel has been used to analyse scenes and to detect different types of defects such as decay, more easily than using standard colour imaging systems.

1 Introduction

The quality of a particular fresh or processed fruit or vegetable is defined by a series of characteristics which make it more or less attractive to the consumer. Such features include ripeness, size, weight, shape, colour, the presence of blemishes or diseases, the presence or absence of fruit stems, seeds, and so forth. In summary, these characteristics may cover all the factors that exert an influence on the product's appearance, on its nutritional and organoleptic qualities or on its suitability for preservation. Most of these factors have traditionally been assessed by visual inspection performed by trained operators. However, the application of machine vision in agriculture has increased considerably in recent years, since it provides substantial information about the nature and attributes of the produce, reduces costs, guarantees the maintenance of quality standards and provides useful information in real time. Moreover, machine vision opens up the possibility of exploring agricultural products in invisible regions of the electromagnetic spectrum, such as the ultraviolet or infrared regions.

The Instituto Valenciano de Investigaciones Agrarias (IVIA) has been developing computer vision systems for the automatic, on-line inspection of fresh and processed fruits and vegetables for the last 15 years. This paper shows the most important outcomes achieved in this field by the Institute's Agricultural Engineering Centre (Centro de Agroingeniería).

2 Inspection of pomegranate arils

Spain produces about 20 000 tons of pomegranate (*Punica granatum* L.) fruits per year and production is concentrated in the period between October and January. Many studies have demonstrated the enormous nutritional and nutraceutical properties of this fruit. However, it is difficult to peel and to extract the edible parts (arils) and this reduces its acceptance by the consumer in favour of other fruits that are easier to prepare. Marketing of pomegranate arils in a way that makes them easy to eat is a way to promote consumption of the fruit.

During the production of the ready-to-eat arils, fragments of internal membranes or skin and other unwanted material are released during the extraction process. Moreover, some defective arils (broken, abnormally shaped or with different physiological disorders) may appear, together with arils of different colours ranging from white to red. Defective arils may shorten the shelf life of the product, and arils with different colours in the same package may degrade the appearance of the product and hence reduce its price.

The objective of this work was to develop an engineering solution for the automatic sorting of pomegranate arils. This included designing mechanisms for separating and transporting the arils, developing real-time computer vision algorithms for inspecting and classifying the arils, developing algorithms and practical devices for synchronising the inspection unit with the sorting system, building a system for classifying the arils into categories, and developing communication and control procedures to supervise the whole machine (BLASCO *et al.* 2008a and 2009a).

The proposed solution was implemented in the construction of a prototype capable of sorting all the objects that left the extracting machine into a maximum of four categories (**Figure 1**). Computer vision algorithms had to assess the colour of each object individually, and had to be capable of discriminating between arils and undesired material. The control algorithms had to synchronise image acquisition from two different cameras, analyse the images and the displacement of the objects on the conveyor belts, and activate the sorting unit. Real-time image processing was essential in order to achieve the required throughput. Intuitive and fast classification techniques were compared and implemented in the prototype, and the solution that was finally adopted was the one that was easiest to operate by a non-experienced user, without compromising quality standards.

Figure 1: Prototype developed for the sorting of pomegranate arils

The algorithms were developed to work with two RGB (red, green, blue) progressive-scan cameras at the same time, since the acquisition of the images is a very time-consuming process (40 ms per image). The image analysis was designed to process one image obtained with one camera in parallel with the acquisition of another image with the other camera. The result is that the processing of one image and the acquisition of the next overlap in time, thus saving time and optimising the operation.

The acquisition of the images is triggered by pulses received from an optical encoder attached to the shaft of the carrier roller and connected to the serial port of the computer. Cameras are triggered as the belts move forward 350 mm. This design makes the acquisition of the image independent of the speed of the belts, and thus ensures that there are never any overlaps or gaps between consecutive images.

The background is removed by a threshold in the red channel, since the red of the arils contrasts sharply against the blue conveyor belts. Once the background had been removed, each connected region was labelled as a possible object of interest (under normal circumstances, it should be an aril or some other material). In the same operation, the program estimated the size and centroid of each of these objects and the average RGB coordinates of their pixels. Extremely small or large objects were classified as unwanted material.

Finally, the average colour coordinates were used to classify the object into one of four pre-defined categories. The procedure to determine the class is described below. After processing each image, the machine vision computer sent the category and position of the object to a second computer (called the *control computer*), which tracked the object until it was sorted. This communication was implemented via TCP/IP.

2.1 Performance

Pomegranates (*Punica granatum*, cv. Mollar de Elche*)* were used throughout the tests. The colour of their arils ranged from white-pink to red-brown. During normal use of this kind of sorting machines in industry, changes caused by the evolution of the colour of the arils throughout the season require frequent retraining of the machine vision system. But these machines are usually handled by workers without any knowledge of computer vision or experience in statistics and they need a fast way to adapt the inspection software to the evolution of the colour of the product. Colour thresholds are intuitive and easy to implement by means of virtual switches in the graphical user interface. A threshold on the ratio between average red and green (R/G) colours of each object was one of the methods chosen for implementation in the prototype and its performance in classifying the arils was compared with a standard linear discriminant analysis (LDA).

Sets of objects for training and validation were built from samples obtained from the extracting machine. Depending on the colour, these objects were sorted into five categories by experienced workers: white aril, pink aril, red aril, brown (decaying) aril and unwanted material. This last category contained mainly the internal membranes, which were mostly white and bigger than the arils. The training set was made up of 100 arils from each colour category and 50 membranes (a total of 550 objects). The validation set consisted of independent samples of 400 arils from each category and 100 membranes (1700 objects). Images of all these objects were acquired using the prototype. The two classification methods were assessed by implementing all the classification functions in the image analysis software and automatically classifying all the objects in the validation set accordingly. These results were then compared with the classification carried out by human experts, in order to build the confusion matrix for each method.

The development and successful commissioning of the automatic inspection machine constituted an important engineering achievement in itself. The classification results were similar for each of the two methods used, the R/G ratio and LDA. **Table 1** shows the confusion matrix for the validation set using the R/G ratio. Raw material was the class in which the best correct classification was obtained (98%). The most sensitive classes from the commercial point of view were red and brown arils, where successful classification reached a rate of 90%.

Table 1: Confusion matrix of the classification performed at the beginning of the season using thresholds on the R/G ratio

Actual \ Classified	White	Pink	Red	Brown	Raw mat.
White aril	92.0%	4.0%	0.0%	2.7%	1.3%
Pink aril	1.5%	91.4%	1.5%	5.6%	0.0%
Red aril	0.0%	2.3%	89.2%	8.5%	0.0%
Brown aril	0.8%	4.7%	5.5%	89.0%	0.0%
Raw mat.	1.7%	0.0%	0.0%	0.0%	98.3%

3 Inspection of satsuma segments

In the industry of mandarin segments, when the fruits come onto the production line they are peeled, the segments are then separated, peeled, inspected and canned. Most the operations are performed automatically, the inspection of the quality being the only part of the process that has not already been automated. Operators carry out visual inspections for broken segments or those that contain seeds as they go past on a conveyor belt. When a defective segment is detected, it is removed from the conveyor belt manually. Problems related to subjectivity, fatigue or the disparity of criteria among operators as to how to decide which are broken and which are not lower the quality of the inspection and, consequently, the final product.

This second study was aimed at sorting mandarin segments in a similar way to the method used in the previous machine. Image processing was used for on-line detection of seeds in the segments and for the detection of broken segments, estimating the degree of breaking. These objects were classified in commercial categories. Pieces of skin or double segments (which are those that were not properly split in previous processes) have to be detected and removed (BLASCO *et al.* 2007a and 2009b). **Figure 2** shows segments pertaining to different categories.

Satsuma segments entered the inspection machine from a vibrating plate that spread them across the width of the machine. The high speed of six narrow conveyor belts then facilitated their separation. Since the average weight of the segments was about 5 g, to achieve 1 ton per hour, the machine inspected about 55 segments per second travelling at 1 m/s.

The computer vision system also consisted of two progressive-scan RGB cameras that acquired 0.65 mm/pixel images. Segments were transported on six semi-transparent conveyor belts, which allowed them to be backlit, thus facilitating the detection of seeds and the segmentation of the shape of the segments.

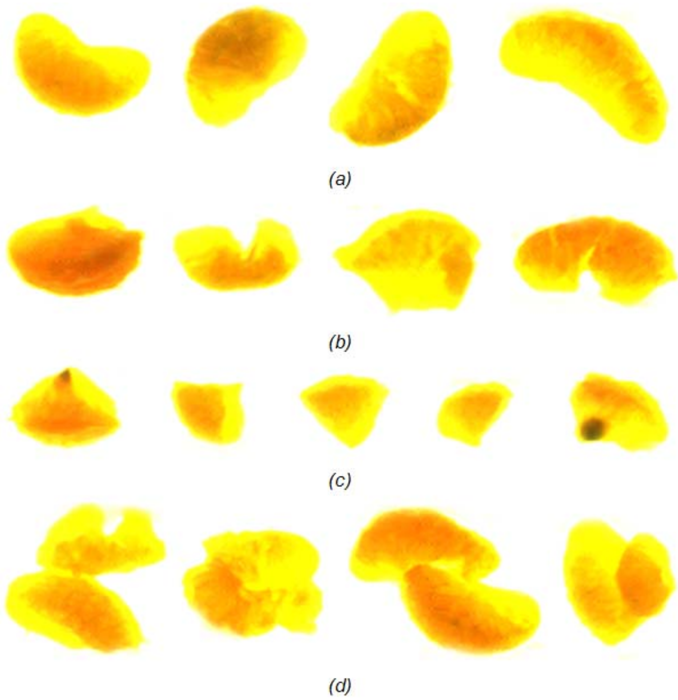

Figure 2: Different classes of segments: a) sound and entire segments, b) broken segments, c) pieces of segments and segments with seeds, d) double segments

When backlit, the objects contrasted sharply with respect to the translucent conveyor belts, thus facilitating the detection and elimination of pieces of raw material and segments with seeds, and also enhancing the silhouette of the objects. The shape of the remaining objects was analysed to estimate morphological features that made it possible to determine whether they were intact segments, broken segments or pieces of them. The sequence of the shape analysis started with the detection of the boundary of the objects. Then, the centroid was calculated as well as the number of pixels in the object. The principal axis of inertia was used to estimate the length and the orientation of the object. Parameters like elongation, roundness, symmetry and compactness were also used to describe the shape of the object. The fast Fourier transform (FFT) of the perimetral signature was also calculated (TAO *et al.* 1995, MIAO *et al.* 2006).

In all, 620 segments (including both good and broken segments) were chosen at random, labelled as good or broken, and then imaged. The morphological parameters described above were calculated for each segment and stored. LDA, with the above-mentioned shape parameters as independent variables and the label as the grouping variable, was used to generate a model to classify *whole* and *broken* segments. The model was then applied to an independent set of 15 000 images of segments in order to assess its performance. These results were compared with the visual classification of the experts.

3.1 Performance

The results of the classification given by the image processing algorithm were compared with the visual inspection of the producer company's experts to obtain success ratios for each category (**Table 2**). The system was capable of detecting 96% of the segments that contained seeds and 96% of pieces of skin that were travelling on the conveyor belt. The rate of success of the algorithms in separating out sound segments was 93%, while the rate of successful detection of broken ones was only 83%, mainly due to the fact that most breakages in many segments correspond to small fragments at one end, and these are difficult for the current system to detect. The average rate of success in the detection of double segments reaches 82%. Specific algorithms have to be developed to detect these small breakages. The average processing time of the images was 48 ms.

Table 2: Confusion matrix of the classification obtained by the automatic system

Classified / Actual	Complete	Broken	Half segments	Seeds	Skins	Doubles
Complete	93.2%	5.8%	0.3%	0.7%	0.0%	0.0%
Broken	9.9%	83.4%	6.7%	0.0%	0.0%	0.0%
Half segments	1.1%	4.7%	94.2%	0.0%	0.0%	0.0%
Seeds	2.5%	0.9%	0.3%	96.3%	0.0%	0.0%
Skins	1.1%	1.5%	1.2%	0.0%	96.2%	0.0%
Doubles	10.0%	3.3%	0.1%	0.0%	4.2%	82.4%

4 Inspection of fresh citrus

Commercial machine vision systems are commonly capable of detecting blemishes on the surface of fruits. They cannot, however, identify them or distinguish between groups of blemishes or determine their severity, which is valuable information for packing houses.

This work illustrates an approach that uses multispectral imaging for identifying the type of defect once it has been detected and separated from the sound skin of citrus (BLASCO *et al.* 2009c).

Images of the same fruit were acquired using three different systems: visible (VIS) and near infrared (NIR) reflectance, and ultraviolet induced fluorescence (UVFL). Two VIS- and NIR-sensitive cameras were used to acquire all the images. A progressive-scan colour camera was used to acquire fluorescence and visible images, which consisted of three monochromatic images of RGB wavelengths (BLASCO *et al.* 2007b). Basically, the colour image acquisition system consisted of a colour camera, a lighting system composed of fluorescent tubes and polarised filters in order to avoid bright spots in the scene. The acquisition of the NIR images was performed using a Hamamatsu Beam-Finder III C5332-01 camera, sensitive from 400 nm to 1800 nm. The lighting system was made up of incandescent lamps. To prevent interference of visible information, a 700 nm cut-band filter was coupled to the camera lens. The fluorescence images were acquired using the same colour camera that was employed to acquire the colour images. In this case, fruits were illuminated using black light fluorescent tubes that emit radiation with a wavelength between 350 nm and 400 nm, and a peak at 370 nm.

Once the images have been segmented (BLASCO *et al.* 2007c), a collection of regions of interest (supposedly sound peel and defects) were identified. Shape analysis using different techniques was also used.

The probability of a region of interest in the segmented image being identified as a particular defect was estimated using a non-linear Bayesian approach. Colour coordinates and morphological features extracted for each region were used as independent variables. Visible and non-visible information was combined in this algorithm to detect dangerous blemishes that can spread a fungal infestation and thus prevent the fruits from being commercialised.

A total of 2132 oranges and mandarins containing different blemishes were collected at random from a packing line and imaged using the acquisition systems described above, thus giving a total of 10 660 images. Another set consisting of 10 images for each type of defect detected with each spectral system (10 x 5 x 11 = 550 images) was also acquired and used to train the algorithms. The defects found on the fruits were described as those that only affect the appearance of the fruit, such as oleocellosis, chilling injury, sooty mould, phytotoxicity, scales, scarring, thrips, and other defects with greater economic importance, such as anthracnose, stem-end injury, green mould (decay caused by *Penicillium digitatum*) and medfly (*Ceratitis capitata*) (Wiedemann) egg deposition. Their size varies from large defects, such as anthracnose or chilling injury, to small ones like scales or medfly. The colour also differs from one to another and may range from the white of stem-end injury, the silver or grey of thrips, the orange or green of *P. digitatum* or the brown of oleocellosis to the black of anthracnose. **Figure 3** shows images of an advanced decaying fruit acquired with the different vision systems.

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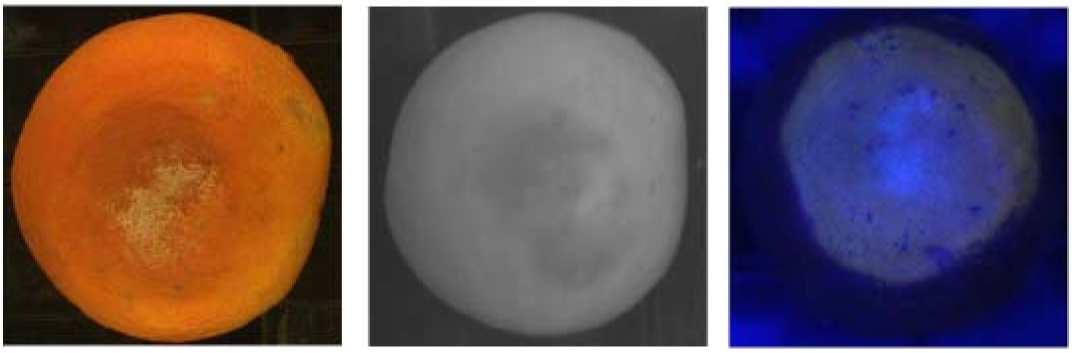

Figure 3: Image of an advanced decay damage acquired using the three acquisition systems. From left to right, visible image, NIR image and UVFL image

Using only colour information, the system can process the images very quickly, since detection can be performed together with the segmentation process. However, there are defects with very similar colours that can be confused. Typical cases are defects caused by scales, which are most commonly confused with thrips (29% of misclassification), or scarring (5% of misclassification). BLASCO *et al.* (2007a) showed that about 65% of defects could be properly identified using colour information alone. Once the morphological parameters described above had been introduced, the correct classification rate reached 82%. By introducing NIR and UVFL images in the analysis, the success rate increased to 86%. However, beyond the numerical results, the greatest increase is achieved in the identification of anthracnose and green mould (95% and 97% respectively), which are dangerous defects that spread these diseases to sound fruits.

A major problem concerning the implementation of this algorithm on line is the large amount of processing time it requires. Although the images should be acquired by different cameras, these tasks can be overlapped in time in such a way that while one image is being acquired, another can be processed. The algorithm that was developed allows this methodology to be used if the order is UVFL, NIR and RGB. But processing all the images is still time-consuming and expensive. NIR and RGB images can be acquired simultaneously, as demonstrated in ALEIXOS *et al.* (2002), by implementing a camera capable of acquiring both images at the same time. In the case of UVFL images, the importance of detecting decay is very high because it can spread to other fruits during their storage or transport.

5 Hyperspectral imaging for detection of fruit decay

Early detection of fungal infections is especially important in packing houses because a very small number of infected fruits can spread the infection to a whole batch, thus causing great economic losses and affecting further operations, such as storage and transport.

The most important post-harvest damage in citrus packing houses is caused by *Penicillium sp* (ECKERT & EAKS 1989). Nowadays, the detection of decaying fruit on citrus packing lines is carried out visually under UVFL illumination, and decaying fruits are removed manually. This procedure, however, may be harmful for operators and operationally inefficient, since the operators must work in shifts of just a few hours. This rate of staff rotation affects the assessment of the quality.

Machine vision systems based only on RGB cameras are unable to detect decaying fruit correctly. The use of hyperspectral sensors makes it possible to acquire a set of images corresponding to particular wavelengths. One of the main problems of these systems is the huge amount of redundant data that is generated and must be removed (CHANG 2003).

In this study, we examined the feasibility of detecting green decay in citrus fruits in the early stages of infection, but avoiding the use of UV illumination. We employed a hyperspectral vision system based on liquid crystal tunable filters (LCTF) similar to the one used by EVANS *et al.* (1998). The system consisted of a monochrome camera (Photometrics CoolSnap ES) with a high level of sensitivity between 320 nm and 1100 nm. It was configured to acquire 551×551 pixel images with a resolution of 3.75 pixels/mm. Two LCTF were used, one sensitive to the visible between 460 nm to 720 nm (Varispec VIS07) and one sensitive to the near-infrared from 730 nm to 1020 nm (Varispec NIR07). Each fruit was illuminated individually by indirect light from halogen lamps inside a hemispherical aluminium diffuser.

The acquisition software was configured to use a different integration time for each particular band that was acquired. Hence, we compensated for the differences in efficiency by calculating a customised integration time for each band (thus, the ones in which the system was less efficient had greater integration times). This compensation was derived from measurements observed from a white reference. For this reason we assumed a flat response over the whole spectral range in all the acquired images. The effect of the reflection of the light over spherical objects was corrected following the work of GÓMEZ-SANCHÍS *et al.* (2008a). We designed a manual fast filter changer that holds and guides the tunable filters, so that images of the same scene could be acquired at visible and near-infrared wavelengths without having to move the camera (GÓMEZ-SANCHÍS *et al.* 2008b). Images were acquired by manually placing the fruit in the inspection chamber and then presenting the damage to the camera. The hyperspectral image was composed of 57 monochrome images of each fruit.

Tests were oriented towards selecting the minimum set of bands that maximise the correct classification of pixels. For this purpose, we studied the evolution of the success rate of classification against the number of bands, once the LDA and CART classifiers had been applied, using the labelled training set and the feature selection methods. The four feature selection methods were: Correlation analysis (CA), Mutual information (MI), Stepwise multivariate regression (SW) and genetic algorithms (GALDA). All four were implemented using Matlab 7.0 (Mathworks, Inc.). All bands present in the labelled train-

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ing set were normalised using mean and variance (standardisation) in order to minimise the effect of the scale on data. A labelled training set was used to generate the models. The four selection methods were programmed to iteratively increase the number of selected bands (*k*) from 4 to 57. The bands obtained in each of the iterations were used to classify the pixels using the two above-mentioned classification methods (LDA and CART) and the average classification success rate was calculated for each number of bands.

Mandarins cv. "Clemenules" (*Citrus clementina* Hort. ex Tanaka) were selected because of their economic importance in Spain. Fruits were chosen randomly from the packing line of a trading company. A total of 200 fruits were used: 150 were inoculated with a suspension of *Penicillium digitatum* spores with a concentration of 10^6 spores/ml (PALOU *et al.* 2001); the rest were inoculated with water for control purposes. The fruits were stored for three days in a controlled environment at 25ºC and 99% relative humidity. After this period, all the inoculated fruits presented a circular area of decay with a diameter between 10 mm and 25 mm. The colour of the damage is similar to the colour of the sound skin around it, therefore making it difficult for a human inspector to detect it.

GALDA achieved better success rates for both LDA and CART classification than the other band selection methods. Moreover, when using LDA the maximum success rate reached 92% when using the 57 bands, while in the case of CART this rate rose to 95% using only 20 bands. The bands selected for use with GALDA are (in nm) 460, 480, 520, 560, 590, 600, 620, 630, 680, 730, 740, 760, 800, 820, 870, 880, 950, 960, 980 and 1010. The use of more than these 20 bands did not increase the success rate to any significant degree, the increment being about only 1% after including all 57 bands. **Figure 4** shows the result of the segmentation of a decaying fruit using CART and LDA.

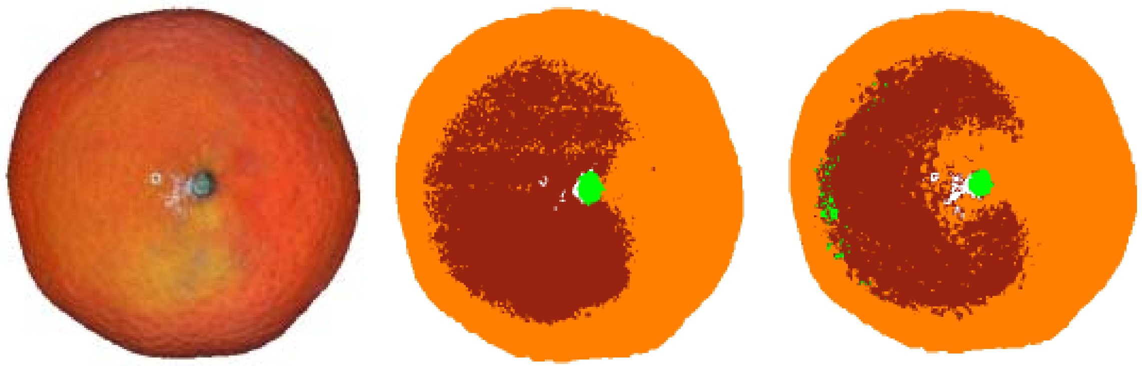

Figure 4: Image of a fruit with decay damage (left). Segmentation using CART (middle). Segmentation using LDA (right)

In general, the best results were obtained with the non-linear classifier (CART), the success rate being above 90% for all classes. **Table 3** shows the confusion matrix obtained with this model. An average success rate of 95.18% (κ=0.9358) was achieved. The most difficult task in the pixel-classification problem is to discriminate the “sound” class from the “decaying” class, although good results were achieved for all classes.

Table 3: Confusion matrix for the classification of pixels using CART and the 20 bands given by GALDA. (Cohen’s kappa =0.9358, average success=95.18%)

Classified / Actual	Sound	Decaying	Decaying with spores	Stem
Sound	90.96%	5.56 %	0.31%	1.48%
Decaying	7.58%	93.63%	0.69%	0.88%
Decaying with spores	0.48%	0.54%	98.74%	0.25%
Stem	0.98%	0.27%	0.26%	97.39%

6 Conclusions

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