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Machine Vision System for Automatic Quality Grading of Fruit

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Fruit and vegetables are normally presented to consumers in batches. The homogeneity and appearance of these have significant effect on consumer decision. For this reason, the presentation of agricultural produce is manipulated at various stages from the field to the final consumer and is generally oriented towards the cleaning of the product and sorting by homogeneous categories. The project ESPRIT 3, reference 9230 'Integrated system for handling, inspection and packing of fruit and vegetable (SHIVA)' developed a robotic system for the automatic, non-destructive inspection and handling of fruit. The aim of this paper is to report on the machine vision techniques developed at the Instituto Valenciano de Investigaciones Agrarias for the on-line estimation of the quality of oranges, peaches and apples, and to evaluate the efficiency of these techniques regarding the following quality attributes: size, colour, stem location and detection of external blemishes. The segmentation procedure used, based on a Bayesian discriminant analysis, allowed fruits to be precisely distinguished from the background. Thus, determination of size was properly solved. The colours of the fruits estimated by the system were well correlated with the colorimetric index values that are currently used as standards. Good results were obtained in the location of the stem and the detection of blemishes. The classification system was tested on-line with apples obtaining a good performance when classifying the fruit in batches, and a repeatability in blemish detection and size estimation of 86 and 93% respectively. The precision and repeatability of the system, was found to be similar to those of manual grading.

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1. Introduction

The use of machine vision for the inspection of fruits and vegetables has increased during recent years. Nowadays, several manufacturers around the world produce sorting machines capable of pre-grading fruits by size, colour and weight. Nevertheless, the market constantly requires higher quality products and consequently, additional features have been developed to enhance machine vision inspection systems (*e.g.* to locate stems, to determine the main and secondary colour of the skin, to detect blemishes).

Size, which is the first parameter identified with quality, has been estimated using machine vision by measuring either area (Tao *et al.*, 1990; Varghese *et al.*, 1991), perimeter (Sarkar & Wolfe, 1985) or diameter (Brodie *et al.*, 1994). Colour is also an important quality factor that has been widely studied (Singh *et al.*, 1992, 1993; Hahn, 2002; Dobrzanski & Rybczynski, 2002). Some fruits have one colour homogeneously distributed on the skin surface, which we call primary colour. The averaged surface colour is a good quality indicator for these fruits. However, other fruits (*e.g.* some varieties of peaches, apples, tomatoes) have a secondary colour that can be used as a good indicator of maturity. In this case, it is not possible to rely only on the global colour as a quality parameter.

In oranges, peaches and apples there is an interest in detecting long stems in order to avoid damage to other fruit, or because their absence could imply a quality loss. Several solutions have been proposed to determine the position of the stem, such as: the use of structured lighting to detect concavities in apples (Yang, 1993); colour segmentation techniques to differentiate the calyx and stem in citrus fruits (Ruiz *et al.*, 1996); or the study of light reflection in apples (Penman, 2002).

Sometimes, the stem can be confused with defects or blemishes on the skin. Damage and bruise detection is a crucial factor for quality evaluation. One of the first approaches for bruise detection in apples was based on the use of interferential filters (Rehkugler & Throop, 1986). Other studies treated blemishes together with colour estimation (Miller & Delwiche, 1989; Lefebvre *et al*., 1994; Cerruto *et al*., 1996; Leemans *et al*., 1999, 2002; Blasco & Moltó, 2002). More recent techniques combine infrared and visible information to detect blemishes (Aleixos *et al*., 2002) or use hyperspectral imaging (Peirs *et al*., 2002).

The aim of this work is to report the image analysis techniques developed in the project ESPRIT 3, reference 9230 'Integrated system for handling, inspection and packing of fruit and vegetable (SHIVA)', which is described elsewhere (Moltó *et al*., 1997, 1998), and the results achieved in the test performed during March 1998 at the Instituto Valenciano de Investigaciones, Agrarias (IVIA). The vision system was developed for on-line measurement of several parameters related to the quality of oranges, peaches and apples, such as size, identification of secondary colour spots (required for some varieties of peaches and apples), stem location or presence of blemishes. The fruits had to be inspected in four different views in less than 1 s. In order to evaluate the efficiency of the vision system, the performance and repeatability of the automatic inspection were compared with a manual inspection made by experts.

2. Material and methods

2.1. *Hardware*

The machine vision system was composed of a three charge coupled device (CCD) colour camera (Sony XC003P) and a frame grabber (Matrox Meteor), connected to a compatible personal computer [Pentium 200 MHz, 48 Mb random access memory (RAM)]. The system provides images of 768 per 576 pixels with a resolution of $3{\cdot}5\,\mathrm{mm\,pixel^{-1}}$. The frame grabber digitised and decoded the composite video signal from the camera into three user-defined buffers in red, green and blue colour coordinates (RGB).

The lighting system was composed of a ring-shaped fluorescent tube inside of a semi-spherical chamber painted matt white inside, with a hole in the top to place the camera. Direct light to the fruit was avoided by means of a reflecting surface protection placed between the fluorescent tube and the scene.

The vision system was part of the robotic system for automatic inspection, handling and packing. Before entering the inspection chamber the fruit was individualised, then passed to a set of moving vacuum cups, capable of rotating and translating, allowing the fruit to be presented to the camera in four different, non-overlapped positions, in order to inspect as much of the fruit surface as possible (*Fig. 1*).

2.2. *Image analysis*

The image analysis was performed by a specific software application developed at IVIA using the programming language C, run under disk operating system (DOS). The software was divided into two modules: an application for training the system; and another to command the acquisition, process the images and provide the estimated quality parameters of each fruit to the robotic control.

The system required a previous off-line training. Using recorded images of fruit, an expert selected the different regions on the images and assigned all the pixels in every region to one of the pre-determined classes: background, primary colour, secondary colour, general damage type 1, general damage type 2, specific feature, stem and calyx. The classes were chosen in such a way that they could be used for all types of fruit used. To train the system to segment those fruits with a single homogeneous colour, the secondary colour class was not used. The use of two classes for the general damages is justified because for each species of fruit there were defects having different colours that could be separated as light and dark defects. Another pre-defined class was employed for detecting specific features of fruits, such as 'russeting' for *Golden delicious* apples.

Once representative regions of every class had been selected, a Bayesian discriminant model was created, using the three basic colour components of the pixels: red, green and blue (RGB) as independent variables. Bayesian discriminant analysis involves the calculation of the probabilities for each combination of RGB values to belong to any of the above-described classes. An algorithm based on the one described by Harrel (1991) was applied, using different covariance matrices for each class, which results in a quadratic discriminant model. This process enables a reference table to be produced. The table, which is stored in the memory of the computer and consulted during on-line operation allows each pixel of the image to be assigned to the closest matching class.

The colour of the fruits, even in fruits of the same species, can slightly vary depending on many factors, as the maturity state. Since this segmentation method strongly depends on the colour of each individual pixel, it is very sensitive to these changes. For this reason, the

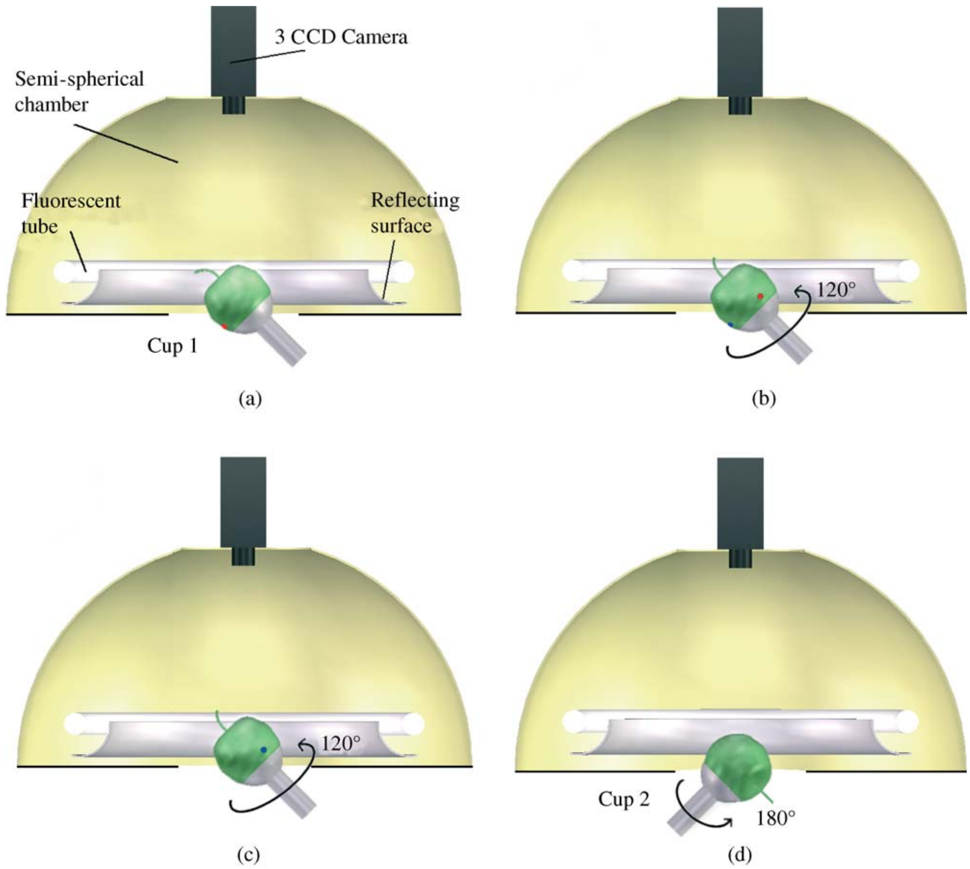


Fig. 1. (a) Acquisition of the first image; (b) acquisition of the second image—cup 1 rotates the fruit 120°; (c) acquisition of the third image—cup 1 rotates the fruit other 120°; and (d) acquisition of the fourth image—cup 2 captures the fruit and rotates 180°

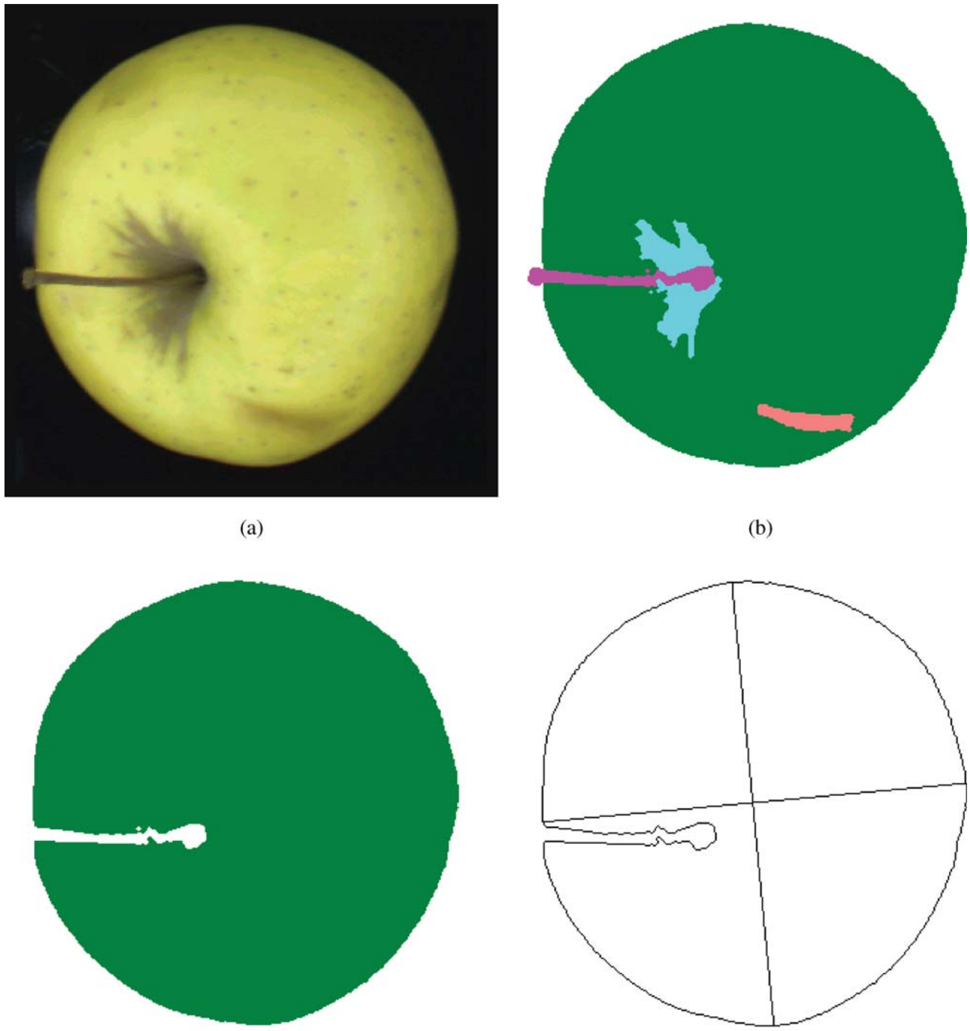
system needed to be trained and a new table created for every test session.

On-line operation started with the acquisition of the first image [*Fig. 2*(*a*)] and the segmentation of its pixels into pre-defined classes by means of the above-mentioned table. Each of the eight-connected pixels of the same class was considered as an independent region. Then, to speed up the process of the contour extraction, a smoothing procedure based on a mode filter was applied to the segmented image in order to smooth the boundary between adjacent regions and to eliminate isolated bad classified pixels [*Fig. 2*(*b*)].

The second step consisted of extracting features to classify the fruits by size. The image was treated as a binary image in which the foreground was the fruit, considered as formed by all the regions, except those considered as background or stem. The stem was not considered as belonging to the fruit since long stems could cause erroneous size measurements [*Fig. 2*(*c*)]. Then, the boundary of the 'fruit' region was extracted and codified by using a chain-code-based algorithm (Freeman, 1961) to calculate the area and the size measured as the length of the principal axis of inertia [*Fig. 2*(*d*)].

In a third step, the regions were not considered as a single fruit and the area of each independent region was measured [*Fig. 3*(*a*)]. To correct errors produced by the segmentation procedure, those regions having less surface than a certain threshold were considered as bad classified pixels. For the valid regions, different parameters were calculated, depending on the class in which their pixels were included. For instance, in the regions composed of pixels of any of the damage classes, the length and the area were calculated. In the case of the regions assigned to stem, only the co-ordinates of the centroid were determined. In the case of multiple stem detections, the longest region was chosen as the 'true' stem, and the others considered as noise [*Fig. 3*(*b*)]. In the regions assigned to primary and secondary colours, the centroid and the average RGB colour were calculated.

The scheme of the whole process is shown in *Fig. 4*. It was repeated for each of the four views of the fruit.



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

Fig. 2. (a) Original image captured by the camera; (b) segmented image showing the sound skin, the russeting, the stem and the damage regions ; (c) region containing all the classes except the stem and the background, used to calculate the size; and (d) image showing how the size was estimated

When the last image was processed, the following features were measured for each fruit:

(1) the length of the major damage—defined as the length of the major region, classified as damage, found in any of the four views;
(2) the damaged area—equal to the sum of all the areas damaged, found in the four independent views;
(3) the stem and calyx—considered to be present if found in any of the views;
(4) the primary colour—calculated as the average of the primary colour estimated in each independent view;
(5) the secondary colour—calculated as the average of the secondary colour estimated in each view;
(6) the fruit size—in accordance with current standards, the size was measured in the equatorial part of the fruit.Since the fruit was not oriented, the size was calculated from the view in which the stem was located nearest to the centroid of the fruit. If the stem was found in less than two images, the size of the fruit was calculated as the average of the size calculated in the four views.

Although several space models used for colour description, as the HSI or La*b*, describe the colours closely to our perception, the RGB system was used because the frame grabber directly provides the colours of the pixels of the image in this system, so further conversions that could consume computational resources are not needed.

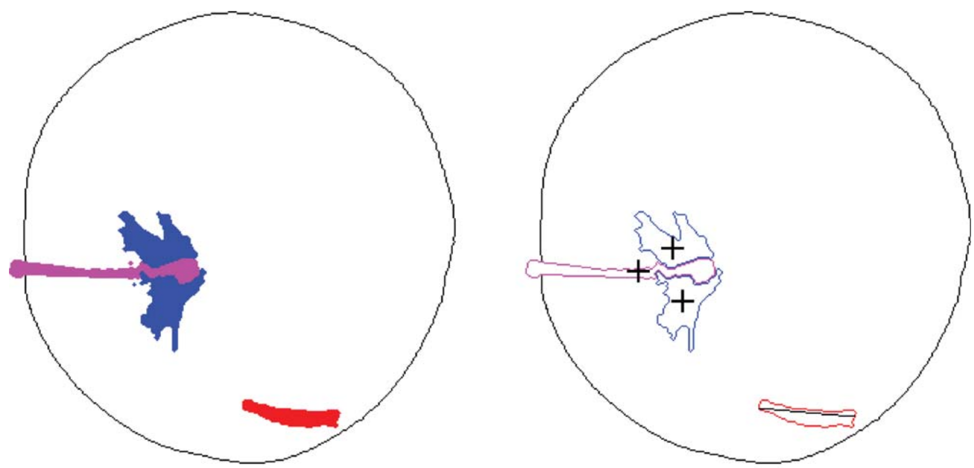


Fig. 3. (a) Segmented image showing the russeting, the stem and the damaged regions and (b) image showing the perimeter and centroid of the russeting and stem regions and the length of the longest damage region

2.3. *Evaluation of the system performance*

2.3.1. *Segmentation procedure*

Although the robustness of the segmentation method can be deduced from the results and repeatability obtained by the system, a preliminary test was done in order to analyse the segmentation procedure on images of fruits. In these tests, representative groups of pixels in images of oranges, peaches and apples, corresponding to the background, sound skin, damage and stem (except for peaches) were selected manually to generate the discriminant functions by means of a Bayesian non-linear discriminant analysis. These functions were tested over an independent set of pixels, belonging to different images, also selected manually. The use of two independent sets of pixels ensures that the estimated performance of the classifier is not biased.

2.3.2. *Colour estimation*

To evaluate the accuracy of colour estimation by the developed sensor, colour measurements were taken from 22 surface sectors of several tomatoes. These sectors varied from a red-greenish colour to red. The ability of the machine vision system to determine fruit colour was evaluated by comparing several standard colour indices that are commonly used for different fruits. These indices were calculated from Hunter Lab co-ordinate values provided by a colorimeter in three random circular areas (8 mm diameter) in each of the selected sectors.

2.3.3. *Stem location*

For assessing the performance of the algorithm for the stem location, images of single, random views of 100 oranges and 100 apples were used. In the case of peaches, two images in random orientation were taken from 76 fruits, which made a total of 152 images. The image analysis algorithms were applied and the centroid of the stem was shown on the computer screen. Then, an operator decided if the system had correctly detected the stem in each image.

2.3.4. *Repeatability of the experts*

Before determining the precision of the vision system in measuring the size and detecting blemishes, a simple test was carried out to estimate the precision and repeatability of the human operators, which is the current reference in commercial packing houses. Apples were used in these experiments because of the more irregular shape. Peaches and oranges are more spherical and easier to be sized by the vision system.

In a first experiment, 40 apples with circumferences between 63 and 86 mm were randomly selected. The size of each apple was measured twice by the experts using a calliper. Both measurements were compared and the precision was calculated by averaging the differences.

To estimate the repeatability of the human operators when detecting blemishes, another test was performed: 48 apples were selected after having been classified by the machine, 24 of them were classified as 'with defects' and the other 24 as 'without defects'. Then, three experts manually classified them in the same two classes. After 15 min, they re-classified the same apples. The similarities and dissimilarities between the two classifications were recorded.

2.3.5. *On-line repeatability of the vision system*

On-line tests to check the repeatability of the machine working under commercial conditions were conducted using 1247 *Golden Delicious* apples, with size ranging

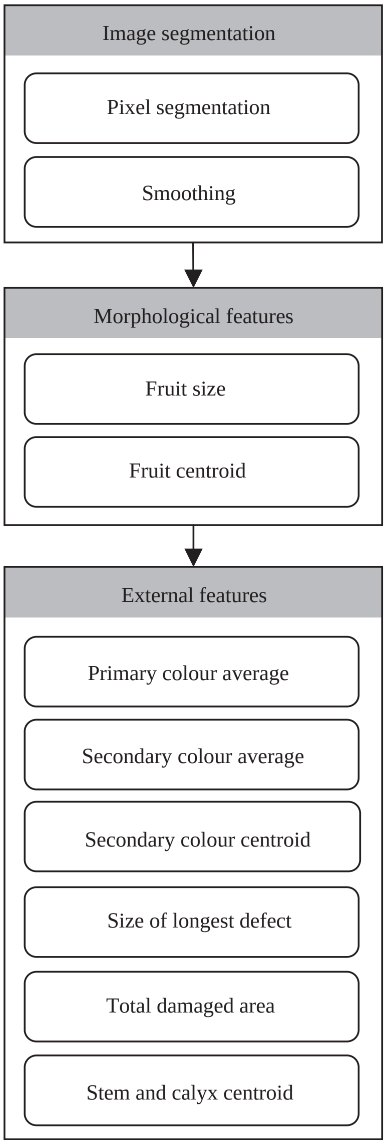


Fig. 4. Scheme of the image analysis procedure

between 64 and 92 mm. The fruit was divided in three categories based on Spanish standards (MAPA, 1992), depending on their size and the presence of external blemishes. Tests consisted of passing the fruit through a machine, which boxed the fruit corresponding with the categories. The respective boxes were passed repeatedly through the system and the changes produced in the classification were observed and counted.

3. Results and discussion

3.1. *Evaluation of the segmentation procedure*

Table 1 presents the pixel segmentation performance of images of oranges, apples and peaches, pointing out

Table 1
Percentage of correct pixel classification for each fruit type

Class	*Pixel classification accuracy, %*		
	Oranges	*Apples*	*Peaches*
Peel	99	95	80
Defect	87	100	89
Stem	84	85	—
Background	100	100	100

an optimal separation of class background (100%) from the rest of classes, which allows a good estimation of the centroid and the size of the fruit.

Most of the errors found in the pixel segmentation procedure are due to isolated or small clusters of pixels, mainly located at the boundaries of adjacent regions. These errors can be detected and corrected when the features of each segmented region are calculated, since these clusters are segmented as regions that are discarded because of its small area.

3.2. *Stem detection*

The performance of the system detecting the stem was measured using 93 images of oranges, 95 images of apples and 140 images of peaches, all of them acquired on-line. The experiments showed that in five images of oranges stems were not detected, while in a further two, bruises were confused with the stem. For peaches, the stem was not detected in one of the 73 images in which it was present, while in 11 of the 79 images without stem, there was a misdetection. In apples, the stem was not detected in two of the 87 images in which it was present, whilst it was misdetected in three out of 13. For the rest of the images of the three fruits, the stem was correctly detected and located (Table 2).

The different colour and shape of the stem or each type of fruit, cause different results in the stem detection. However, there is little confusion between the stems and the bruises, most of the errors being due to bruises detected as stems in fruits without stem.

3.3. *On-line performance and repeatability*

The average precision of the experts when measuring the size of the same apples in two respective experiments was 0·6 mm, which represented a relative error of about 0·8%. However, considering the correct size of the fruit as the average of the six measurements (two valid measurements per expert), the average precision was 1·4 mm (a relative error of 1·9%). These figures can be related to the maximum expected precision of the vision system, which will not be capable of outperforming the

Table 2
Results of the automatic stem detection and location procedure

	Oranges		*Peaches*		*Apples*	
	Correct	*Error*	*Correct*	*Error*	*Correct*	*Error*
Fruits without stem	43	2	68	11	10	3
Fruits with stem	50	5	72	1	85	2
Total	93	7	140	12	95	5

Table 3
Results of the on-line repeatability of the system estimating the size of apples

Size	*Range, mm*	*Repeatability, %*
Very small	0–67	89·4
Small	68–74	94·4
Large	75–88	92·2
Extra large	89–110	100·0
Global repeatability		93·3

precision of the expert, which is the reference measurement. So, an error of 1 mm can be allowed to the vision system when analysing the results of the on-line repeatability tests.

When the experts classified the fruit in the described size categories, they showed an average repeatability of 94%. The repeatability of the vision system varied from 89% for the fruit with the smallest size to 100% for those with an abnormal, large size, averaging 93% (Table 3). Considering that the standards allowed a misclassification of 10%, results can be considered as good. A source of error is due to the fact that most of the apples were of size 72–74 and 79–82 mm, and 74 mm was chosen as the threshold between the small and large categories.

The repeatability of the experts when estimating the degree of damages on the fruit skin ranged between 85 and 90%, averaging 88% (Table 4). Since the system has been programmed and trained by experts, theoretically, its performance is limited by their repeatability. Therefore, the maximum expected repeatability of the vision system would be about 88%. Table 5 shows that the system, working on-line, has 86% repeatability when detecting the external defects. The errors were due to the fact that three factors were considered to estimate the quality: the longest defect, the damaged area and the russeting area. If the estimation of only one of these parameters varied, the quality changed from one pass to another, and the fruit was classified in a different category. This fact particularly affected category I, where the repeatability was found to be lower because this category includes only fruit with an extremely low level of damage, and there were defects that were confused with sound skin due to its light colour. It is very important to point out that the results of this type of experiments strongly depend on the distribution of the fruit sizes and the colour and sizes of the blemishes on the fruit.

Regarding the time employed by the system for inspecting the fruit, using the hardware configuration described, the time required for acquisition and image analysis is less than 300 ms, which is lower than the initial requirements, that were of 1 s. With newer and faster computers, and improving the algorithms to let overlapping between the acquisition and the image processing, this time could be reduced below 50 ms.

4. Conclusions

The segmentation method is fast and appropriate for on-line processes, but depends much on the colour of the objects to be inspected. For this reason, the system needs to be trained frequently by an expert operator.

The machine vision system showed good results when positioning the stem of oranges, peaches and apples, detecting most of them, with few confusions with skin blemishes. Damaged area is properly detected in apples, but the algorithms need to be tested more extensively in oranges and peaches. Further work should be done in order to detect the defects that were not correctly discriminated, mainly because of its light colour, similar to the colour of sound skin.

Size repeatability in on-line operation ranged between 91 and 95%, having an average value of 93%. The repeatability of the machine during on-line detection of external defects was about 86%, mainly influenced by the results obtained in the category I. Comparing these results with the average repeatability of human estimation of the size and the degree of skin damage, that were of 94 and 88%, respectively, and considering that the decision algorithm was trained and tested also by

Table 4
Repeatability of the manual estimation of the grade of blemishes in apples

Expert	*Fruit classified 'with bruises' in both tests*	*Fruit classified 'without bruises' in both tests*	*Fruit whose classification changed*	*Repeatability, %*
1	27	16	5	89·6
2	30	12	6	87·5
3	32	9	7	85·4
Machine	24	24	—	—

Table 5
Repeatability of the on-line fruit classification in categories

Category	*Attributes of the categories*			*Repeatability, %*
	Longest defect, mm	*Maximum allowed surface of defects, cm^2*	*Maximum allowed russeting, %*	
I	Less than 3	Less than 1	Less than 3	53·8
II	3–19	1–9	3–9	88·2
III	More than 19	More than 9	More than 9	83·2
Average				85·6

human operators, we consider that the results are acceptable.

The experiments showed that the consideration of small or decoloured skin regions as defects depends on the subjective criterion of each expert. For this reason, the performance of the machine was measured by estimating the global content of each box, instead of inspecting the fruits individually, as the results of the machine classification were considered to be correct by all of the experts.

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