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Multispectral inspection of citrus in real-time using machine vision and digital signal processors

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Abstract

Citrus are one of the major fruits produced in Spain. Most of this production is exported to Europe for fresh consumption, where consumers increasingly demand best quality. Nowadays, Spanish producers have to compete with other countries with lower production costs. Moreover, inspection and classification tasks in these countries are made manually, which is subjective and varies among different experts or along the day. For these reasons, automatic inspection means, as machine vision, are a priority in Spain, in order to ensure products with an excellent quality. Current commercial sorters based on machine vision only solve the problems that require less computing time, as for instance, sizing or classification in colours. Sometimes they work with low resolution images, in order to achieve high processing speeds. However, this approach reduces the accuracy of the system when estimating the size of the fruit. Another important fact that needs consideration is the possibility of detecting defects on the skin surface using wavelengths that are outside the visible spectrum. This work includes the development of a multispectral camera, which is able to acquire visible and near infrared images from the same scene; the design of specific algorithms and their implementation on a specific board based on two DSPs that work in parallel, which allows to divide the inspection tasks in the different processors, saving processing time. The machine vision system was mounted on a commercial conveyor, and it is able to inspect the size, colour and presence of defects in citrus at a minimum rate of 5

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fruits/s. The hardware improvements needed to increase the inspection speed to 10 fruits/s are also described. The experiments, carried out with oranges, mandarins and lemons, demonstrated that the software is able to single the fruit before estimating the size, which is calculated with an error less than 2 mm. To check the performance in colour estimation, mandarins in different maturity grades were used. Results compared with human classification allow 94% coincidence in the worst case (when the fruit is changing colour from green to orange). The system is also capable of correctly classifying lemons and mandarins, attending to the external defects in 93 and 94% of the cases, respectively, following the Spanish citrus standards.

Keywords: Machine vision; Real-time; Inspection; Fruit quality; Near infrared; Colour space

1. Introduction

Citrus are one of the major fruit products in Spain (about 5 Mt). For a long time, the agro-industry has attempted to automate fruit selection in order to decrease production costs and to compete with countries that have much lower production costs. Due to the fact that most part of the external quality attributes are currently inspected visually, machine vision provides a means to perform this task automatically (Moltó et al., 1998; Diaz et al., 2000). New technologies, such as new hardware architectures, are making possible the implementation of these kinds of application in real-time (Growe and Delwiche, 1996; Aleixos et al., 1999).

Current commercial systems classify the fruit based on parameters such as size, shape, colour or external defects (Lefebvre et al., 1994). However, because these machines need to work at a very high production speed, the resolution of the images must be low enough to analyse the image in the least time possible, so the low quality of the images makes it almost impossible to detect correctly any skin defects or diseases and to distinguish the stem from the defects (Yang, 1993). It is interesting to identify the stem of the fruit in order to eliminate it (Ruiz et al., 1996), or to orient the fruit in a pre-defined way when packing the fruit (Moltó et al., 1996).

Size is one of the first parameters that the consumer identifies with the quality of the product. Size can be estimated in different ways using image analysis (Sarkar and Wolfe, 1985; Tao et al., 1990; Okamura et al., 1991; Varghese et al., 1991). Irregular fruits can be detected by comparing measurements of length, width, perimeter, area, inertia axis, etc. (Guyer et al., 1993) or by using more sophisticated methods such as Fourier transforms (Tao et al., 1995). All these parameters can be calculated from grey images, but for sorting fruit by colour or skin defects, colour information is needed. Several authors also have combined colour with infrared or ultraviolet information (Rehkugler and Throop, 1986; Miller and Delwiche, 1991; Alchanatis et al., 1993), which involves larger amounts of data per fruit and requires higher processing time. Even though size was one if the first parameters estimated automatically, there are still unsolved problems that can cause wrong estimations, mainly due to an excess of fruit in the sorter input, that cause several fruit to travel on the same cup.

Normally, in a standard automatic inspection system there are two cameras: one is sensitive to near-infrared radiation and is used only to discriminate between the fruits and the background, and the other is a colour camera used to classify fruits by colour. Since they are different cameras, the scenes acquired are also different, so infrared information cannot be used together with the visible information to inspect the fruit on a pixel by pixel basis.

This paper describes a new machine vision system for citrus inspection, including a parallel hardware and software architecture, able to determine the external quality of the fruit in real-time at a speed of 10 fruits/s. The work carried out involves the development of optimised algorithms running in parallel, which solve the individualisation problems and estimate the size, shape and colour of the fruits, detecting also the external defects. It also includes the development of a multispectral camera able to acquire visible and near infrared information from the same scene.

2. Description of the system

The vision system has been placed on a commercial fruit sorter having four independent inspection lines. As the first step, the sorter singles the fruit before they enter into the inspection site by means of bi-conic rollers. In principle, each individual fruit is located in a space between two rollers (what is called a cup), although sometimes, when there is an excessive loading, two or more fruits are located in the same cup or fruit are located between two filled cups. The inspection site (Fig. 1) provides adequate lighting to the scene by fluorescent tubes, incandescent lamps and polarised filters that remove reflections from the surface of the fruit. The scene is composed of three complete fruit, imaged with a multispectral camera that simultaneously captures four bands: the three conventional colour bands (R, G and B) and another centred at 750 nm (near infrared, denoted I).

The camera (Fig. 2) has two CCDs, one a colour CCD that provides RGB information and the other monochromatic, to which has been coupled an infrared filter, centred on 750 nm (± 10), that provides I information. The light coming from the scene reaches a semi-transparent mirror that refracts 50% of the light towards the infrared (A) CCD and reflects the other 50% to a second mirror (B), which reflects all the light towards the colour CCD. The system guarantees at least three whole fruits on each image with a resolution of 0.7 mm/pixel.

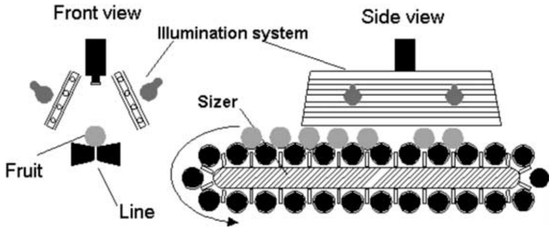

Fig. 1. Scheme of the sorter and lighting system.

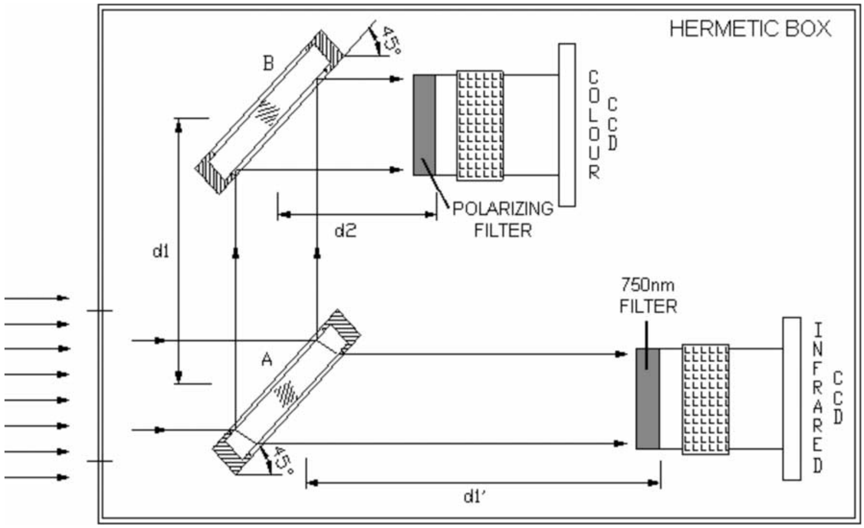

Fig. 2. Scheme of the multispectral camera.

The fruit rotates while passing below the camera due to a forced rotation of the rollers. To single the fruits and estimate their size and shape, the system uses only the I information, but for colour estimation and defect detection it is necessary to work also with the colour bands. This fact has been used to set up a parallel strategy based on dividing the inspection tasks between two digital signal processors (DSP), so during on-line work, two image analysis procedures are performed by the two DSP running in parallel in a master/slave architecture. The master processor calculates the geometrical and morphological features of the fruit using only the I band, and the slave processor estimates the fruit colour and detects the skin defects using the four RGBI bands. After the image processing, the master processor collects the information from the slave and sends the result to a control computer.

The system was tested under laboratory conditions at two common sizer speeds: 300 and 600 fruits/min (5–10 fruits/s). Because the time required to capture one image is 40 ms and the scene contains three complete fruits, at a speed of 300 fruits/min the camera acquires 15 images from each fruit with different rotation angles (Fig. 3), and at a speed of 600 fruits/min it obtains seven images. The fruits used for the test were oranges, lemons and mandarins.

3. Analysis of the size and shape of the objects

The analysis of the shape and size is performed after thresholding and filtering the I image. This algorithm has to single the objects, handling cases that can provide wrong size information, i.e. double fruit on the same cup or fruit touching in adjacent cups.

The first step is to segment the image to separate the fruit from the background, then the contour of the objects is extracted and analysed to detect a possible wrong allocation of the fruit. Finally, the size and shape is estimated.

3.1. Segmentation and edge filtering

Each I image is binarised with a threshold and the boundaries of each of the objects are extracted, applying a convolution mask.

3.2. Contour extraction

First, it has to be checked if there is fruit in the cup. This is carried out by inspecting a logical window in the centre of each cup (Fig. 4)(1), whose positions are known from the encoder of the sizer. If the detected grey level signifies an object, it is placed a bigger logical window fitting the whole cup, and scanning of the border image begins (2). The object is previously smoothed for a faster boundary extraction. After extracting the first contour pixel, the algorithm keeps searching pixels belonging to the contour of the fruit, until it reaches the first contour pixel again (3).

The algorithm extracts an eight-connected contour by using the chain code described by Freeman (1961), so each pixel has eight neighbours and eight directions to check.

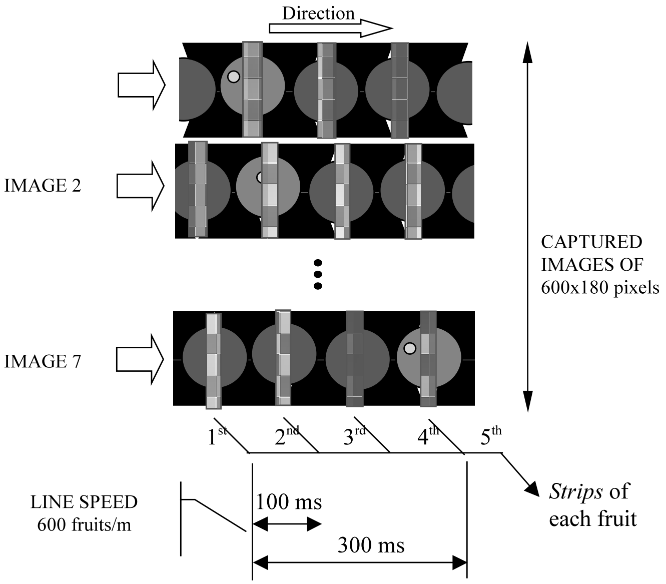

Fig. 3. The central strip of each fruit is obtained and stored to compose the strips image.

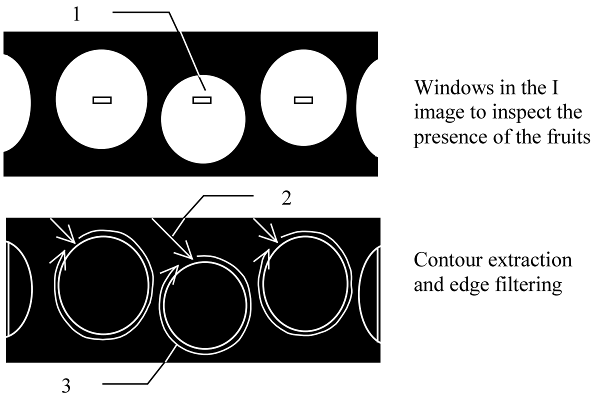

Fig. 4. Fruit contour detection: (1) window to detect the fruit presence, (2) contour searching, (3) contour extraction.

3.3. Singularisation

When a high throughoutput of the line is required, the mechanisms that individualise the fruits do not work efficiently, thus, allowing that several fruit travel on the same cup while passing under the inspection system. Moreover, a large fruit could touch one or both of its neighbours. In these cases, a conventional algorithm to determine the boundaries of the fruit could misinterpret the image, if it only locates the pixels that lie between the fruit and the background. In these cases the fruits that are in contact could be identified as one large fruit.

These errors occasionally occur in three situations (Fig. 5): (a) when a large fruit is in contact with a neighbouring fruit, (b) when a fruit travels between two fruits that are correctly positioned on their cups, or (c) when two or more small fruits travel in the same cup. In all these cases, calculation of size from the apparent boundaries leads to an over-estimation of the fruit size. We have to impose on our algorithm the ability of distinguishing between these three circumstances because any commercial mechanical sorter situated after the inspection system must react in a different way depending on the case. In case (a), because the fruits travel in different cups, they can be adequately separated by any conventional sorting device, so our algorithm must calculate the real size of each fruit, in order to assign each of them to their respective size class. However, in cases (b) and (c), the sorting system will not be able to separate the fruits, because they travel in the same cup or outside of a cup. In these cases, the fruit must be redirected towards the input of the line, in order to be reclassified.

For this reason, a specific algorithm was designed for separating the individual fruit in the image and to determine the case. The algorithm detects the contact points between fruits, by locating unexpected changes in the tangent of the extracted boundary. Sudden changes of the tangent on the X-direction are used to detect cases (a) and (b), while large changes in the Y-direction are used to detect case (c) (Fig. 5).

3.4. Size and shape estimation

Using the information extracted from the boundaries, the following parameters are calculated: centroid, maximum and minimum diameters, perimeter and circularity. All these parameters are calculated for each image of the fruit. Since several images are acquired from each fruit depending on the sizer speed, the size is determined by averaging the maximum diameter estimated for oranges and mandarins and the minimum diameter for lemons.

Shape is estimated by relating the maximum and minimum diameters of the fruit.

4. Surface inspection

The analysis of the whole surface of each fruit in each image would give redundant information, because there are overlapping regions of surface in consecutive images. This also would lead to an enormous consumption of time. Because the fruit rotates while translating below the camera, it is possible to create a new image, composed by the central window of each of the images of the same fruit. Each of these windows is called a *strip* and is properly positioned in the image by reference to the encoder of the sizer. The width of the strips depends on the velocity of the cups. The resultant image obtained by joining the strips represents practically the complete surface of the fruit (Fig. 6).

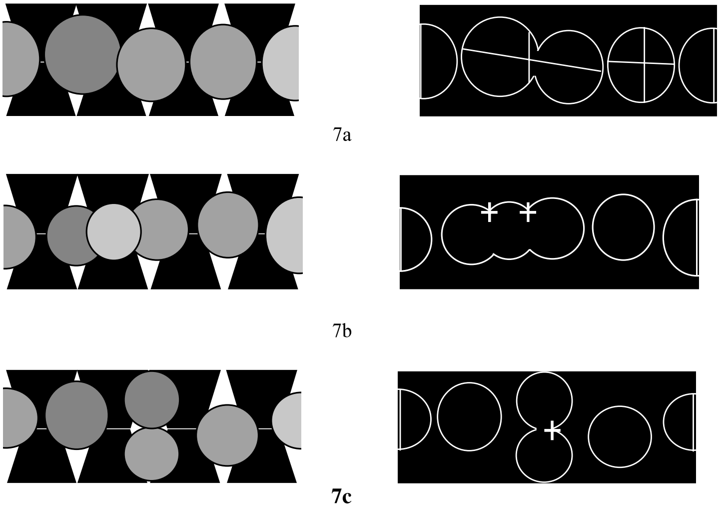

Fig. 5. Anomalies in the transport of the fruits. Fruits in (a) contact or (b) mounted are detected by analysing changes in the X-direction (horizontal). (c) Fruit travelling on the same rollers are detected analysing changes in the Y-direction (vertical).

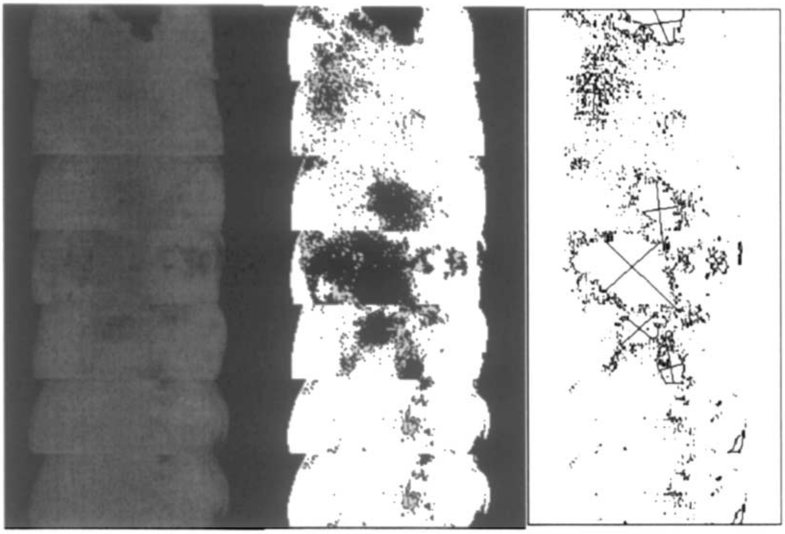

Fig. 6. Raster-scan algorithm applied to an orange surface with defects: (a) original image, (b) segmented image, and (c) detected defects.

4.1. Defect detection

Before the on-line processing, the system needs to be manually trained. Using a specially developed MS Windows-based program, an operator selects different windows in fruit images, representing the pre-established classes (background, primary and secondary colour of the sound skin and blemish). A Bayesian discriminant model (Harrel, 1991) is then generated and stored in a *look up table* (LUT). The independent variables are the grey levels of the RGBI bands. For testing how the I information improves the defect detection, other two models were also generated using only the RGB and RGI (assuming that the blue signal is negligible) bands.

The inspection of the image of strips is partially based on the raster-scan algorithm (Capson, 1984), in such a way that the image is scanned only once. At the end of the scanning, the blemishes are segmented from the rest of the image and their boundaries are extracted. For each fruit, the number and distribution of defects are calculated. Algorithms employed for describing the geometric characteristics of the blemishes of the fruit are the same as those used to calculate the size of the fruit.

4.2. Colour classification

The colour classification is done at the same time as the defect detection. Using the Bayesian discriminant model generated, using the RGB bands, pixels belonging to sound skin are classified as *ripe* or *unripe*, rejecting those belonging to any defect.

Depending on the percentage of ripe and unripe pixels in the fruit image, it is classified as ripe, unripe or varying.

5. System architecture

Because the image analysis procedures have been divided into two logical tasks, the architecture of the software has been developed to run over two DSPs, in a master/slave configuration, working in parallel (Fig. 7). Each of the DSPs has an independent, local memory.

The algorithms were implemented, and the application was simulated on the development board TMS320C4x parallel processing development system (PPDS) from Texas Instruments, which has a 32 MHz clock and four DSPs interconnected in a ring architecture, sharing the system memory. Only two of the DSPs were used for the simulations.

The logic chart of the board is shown in Fig. 8. The system has a 60 MHz clock and a *read only memory* (ROM) to perform the initial program and data load in the

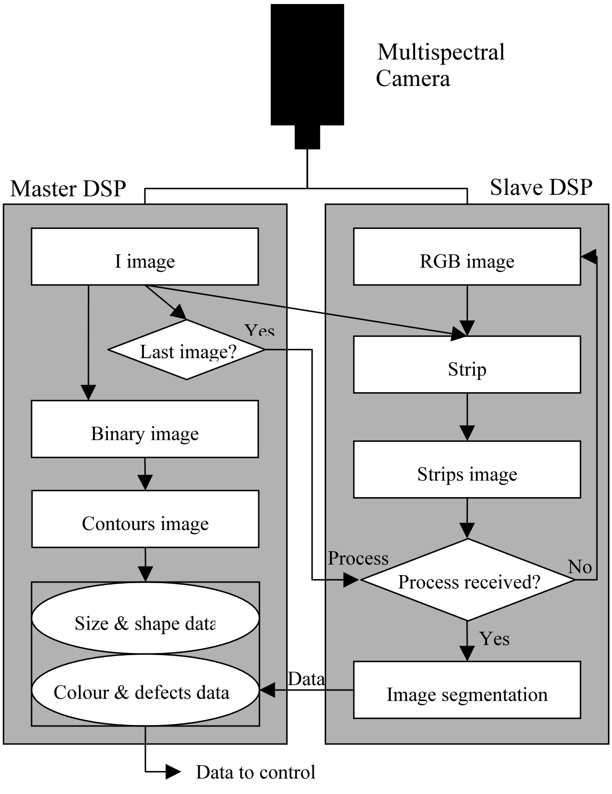

Fig. 7. Image analysis using two DSPs in a master/slave architecture.

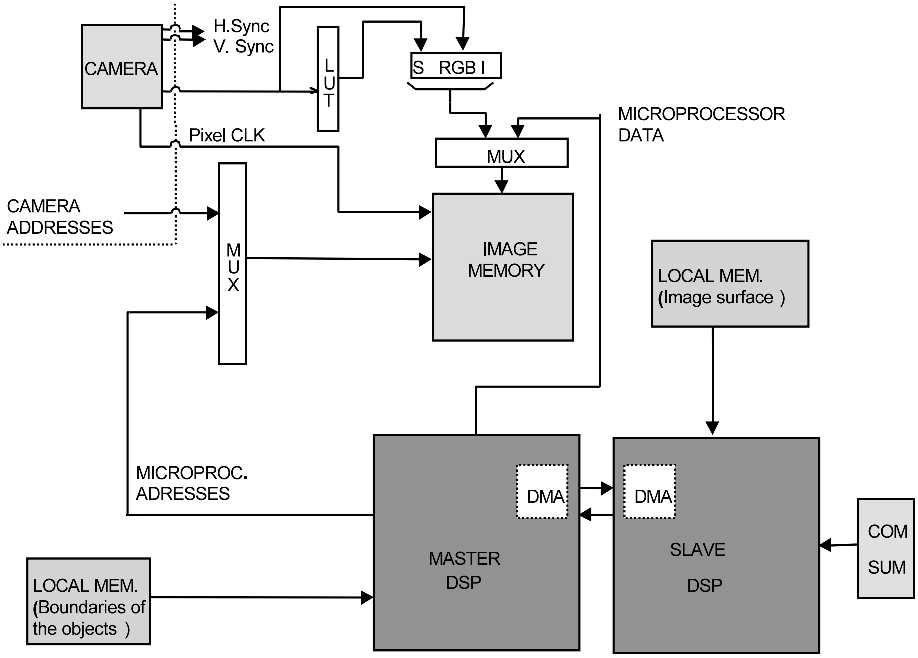

Fig. 8. Implemented hardware architecture.

master processors. The program and data load for the slave processor is done by means of a *direct access memory* (DMA) from the master processor.

5.1. Tasks carried out by the master processor

The multispectral image arrives from the camera, it is segmented using a LUT and stored into the master local memory. At the same time, the I band is thresholded and the contours of the fruits extracted and used to singularise the fruit and estimate their size.

This DSP also sends the strips of each fruit to the memory of the slave DSP. This process does not use processing time because it is done through a DMA and a *first in–first out* (FIFO) buffer.

The number of images used to estimate the size of the fruits depends on the conveyor speed. At greater speeds, fewer images will be acquired. For all the images, minimum, maximum and average diameter of the fruits are calculated and stored. Finally, after taking the last image of each fruit, the possible bad placement of the fruit over the rollers is detected and their size is estimated using the information contributed by all the images.

Further, this processor must transfer to the slave processor the strip images of each fruit from the original multispectral image captured, in order to perform a surface analysis. Once the master processor has sent the last strip of the fruit to the slave processor, it awaits for the results of the surface analysis to pass all the data to the system control, which decides the quality and delivers the fruits to the corresponding boxes.

5.2. Tasks carried out by the slave processor

The slave DSP receives, links and saves the strips in its local memory. It also receives the command to start the image analysis after receiving the last strip. The task assigned to the slave DSP is to detect the blemishes, determine their size and how they are dispersed, and estimate the primary and secondary colour. The biggest part of this work is done by the hardware (counters and comparators).

At the same time that a fruit is being analysed, the slave processor continues receiving and storing in memory the strips of the fruits that travel immediately behind. The strip transference and memory storage does not impose a time penalty for the processors because they are assisted by specific hardware.

Once the individual data of each fruit are obtained, they are supplied to the master DSP upon request. The maximum processing time of each DSP has to be less than 100 ms to reach the objective of inspecting 10 fruits/s.

6. Results

Under laboratory conditions, tests were carried out to estimate both the performance and the accuracy of the designed system. The fruit chosen for the experiments were oranges, mandarins and lemons, selecting always the most complex, depending on the experiment.

6.1. Singularisation results

For singularistation tests, mandarins were used because bad allocation is infrequent in oranges and highly unusual in lemons. Table 1 summarises the performance of the size and shape defect algorithm. All the isolated fruits were correctly found. The same occurred when two or more fruit occupied the same cup. More than 80% of the cases in which adjacent fruits touched or in which the fruit was out of the cups were detected.

Table 1
Bad allocation detection results

Cases	Number of fruits	Correctly classified	Success (%)
Singled fruit7070100	70	70	100
Adjacent fruit in contact605693	60	56	93
Fruit out of cups383387	38	33	87
Two fruits sharing a cup	33	33	100

Table 2
Size estimation using the minimum, maximum and average diameters

Parameter	Minimum diameter		Maximum diameter		Average diameter	
	R^2	ε	R^2	ε	R^2	ε
Mandarins *Nour*	0.96	1.22	0.97	1.05	0.97	1.01
Mandarins *Hernandina*	0.86	2.05	0.86	2.10	0.87	1.98
Lemons *Eureka* (length)	0.98	1.28	0.99	0.76	0.99	0.86
Lemons *Eureka* (size)	0.97	0.99	0.89	2.03	0.93	1.63

Comparison between system and manual measurements in lemons and mandarins.
(R^2: correlation coefficient; ε: standard error).

6.2. Size results

The aim of the experiment was to check how correctly the system measured the size of the fruits, as well as estimating the error, in order to evaluate the ability of the system for classifying fruits in relation to their size.

Because of their irregular shape, the experiments were carried out using 50 mandarins *Nour*, 50 mandarins *Hernandina* and 50 lemons *Eureka*. The size of the mandarins was measured by the equatorial diameter. For lemons the polar size was measured. Before the experiments, an expert manually measured the sizes of the samples using a calliper, showing that all of the mandarins had a size between 41 and 72 mm and lemons between 62 and 99 mm.

For the measurement, seven images of each fruit were taken using the infrared band of the multispectral camera while the fruit were transported below the camera at a speed of 10 fruits/s. The algorithm for calculating the size and shape was applied to each image of the fruit, and maximum and minimum diameters were calculated for each image. Finally, the maximum and minimum diameters of all the images were averaged for determining the size of the fruit.

To check the accuracy of the estimation, the linear regression between the expert and the vision system measurements was calculated. Best results, shown in Table 2, were achieved using the maximum diameter.

6.3. Colour estimation

Table 3 shows the coincidence between the vision system with the manual classification. The results obtained show that in both the cases, mandarins and lemons, this coincidence was higher than 94% in all of the categories, rising to 100% coincidence in the *unripe* category.

When discriminating fruits by colour, a 98% success rate was achieved when the colour was homogeneous. A small decrease (95% success rate) in the performance was observed when the fruit had different hues simultaneously. This high percentage of success is crucial for separating fruits that require ripening (as it is the case in early mandarins) or need to be separated into colour categories (lemons).

Table 3
Fruit classification by colour (comparison with an expert classification)

Category	Expert classification	System classification			Coincidence (%)
		Ripe	Varying	Unripe	
Lemons					
Ripe	50	49	1	0	98
Varying	19	0	18	1	95
Unripe	31	0	0	31	100
Mandarins					
Ripe	50	49	1	0	98
Varying	31	0	29	2	94
Unripe	19	0	0	19	100

6.4. Defect detection

To test the influence of the image bands on the segmentation procedure, the images were manually segmented and compared with the system segmentation to evaluate the coincidence between both segmentations at pixel-level. The results shown in Table 4 demonstrated the feasibility of the RGI bands for segmenting the sound skin, but for defect detection, the use of the four bands is more suitable. Although the blue band only contributes some lightness to the images of fruits, the discrimination capability of the models that include this band is very sensitive, so it can contribute to improve the fruit classification. This improvement is bigger for the defect class, since values of infrared, red and green bands are lower, and so the blue band acquires a greater relative importance.

For evaluating the performance of the system, 160 mandarins and 150 lemons with different sorts of defects on their skin were used. Based on the Spanish citrus standards (MAPA, 1993) an expert first classified a set of fruit to train the system. The vision system decision was assumed to be correct if its decision equalled the expert's decision, and erroneous when it did not. Table 5 shows the results for lemons and mandarins.

Category Extra was composed of fruit with less than 2% of skin area with defects, category I for those fruits with more then 2% and less than 5% of their skin

Table 4
Comparison of different combinations of image bands for segmentation in strip images (% of coincidence with manual segmentation)

Class	RGBI	RGI	RGB
Sound skin	99.4	100.0	99.8
Defect	99.1	81.5	67.6
Stem	100.0	100.0	100.0
Background	99.8	99.8	98.5

Table 5
Results for fruit classification in commercial categories

Category	Expert classification	System classification			Coincidence (%)
		Extra	I	II	
Lemons					
Extra	97	92	5	0	95
Class I	33	3	27	3	82
Class II	20	0	0	20	100
Mandarins					
Extra	95	87	8	0	91
Class I	42	2	40	0	95
Class II	23	0	0	23	100

with defects and category II for the rest of the fruit. The standards allow a tolerance up to 10% between contiguous categories, and as the results for mandarins show in Table 5, the system meets these tolerances and is considered acceptable. In the case of lemons, the category I only had a coincidence of 82%, but this error was shared with the Extra and I categories, that is 8.5% of lemons were classified as Extra and 8.5% were classified as category II. In any case, the tolerances were met.

6.5. Measurement of the processing time

The behaviour of the designed architecture was tested implementing and executing the algorithms onto the simulation board, in order to carry out the estimation of the computation time of the vision application and the time consumed by each processor.

Fruit with different sizes and defects were analysed. At the beginning of the analysis, a ‘start’ event was generated by the simulation card and used by an oscilloscope as a trigger input to start the measurement. When all the processes executed in both processors finished, an ‘end’ event was also generated. With the oscilloscope, the time elapsed between the two events was measured with an

Table 6
Measurement of the time consumed by the inspection operations

Task	Minimum time (ms)	Maximum time (ms)	Average time (ms)
Size estimation (I images, master DSP)	18	62	31
Colour and defect analysis (IRGB images, slave DSP)	98	185	124
Application time	98	185	124
Inspection speed (fruits/s)	10	5	8

accuracy of 0.01 ms. Table 6 shows the maximum and minimum times consumed in each process.

For singularisation and size estimation, the minimum execution time was of 18 ms, which happened when the fruit was well positioned on the rollers. The maximum execution time, 62 ms, was achieved when all of the fruits were badly allocated on the rollers. For defect detection and colour estimation, the minimum execution time was due to fruit with a small size (less surface to inspect) and no defects on the skin, and the maximum was measured in an extremely big fruit with many defects. These times would allow the sizer to work in the worst conditions at a minimum speed of 5 fruits/s. Since in real conditions most of the fruit have a medium size and few defects, the developed system could normally work at a speed of 8 fruits/s. This result has been achieved measuring the inspection time for a batch of oranges with different sizes, colours and defects and is shown as average time in Table 6.

7. Conclusions

This paper describes a parallel system capable of estimating the size of oranges and inspecting almost the whole skin surface of the fruit. Although for correct functioning of a commercial sorter it is important not to input excessive fruit into the machine, because this increases the probability of not allocating a single fruit to each cup, the system is capable of detecting and correcting this malfunction.

Thresholding the infrared image provided a simple and effective means for segmenting the fruit from the background. This fact has been employed both for estimating the size of the fruit and for facilitating the detection of, at least 93%, badly located fruit, which is important to avoid size misclassifications.

The system has achieved a high rate of blemish detection and has been capable of adequately discriminating fruit with non-uniform hue. The experiments also showed that the quality of the inspection was improved by employing the near infrared band. This has been achieved thanks to the relative high resolution of the images (0.7 mm/pixel), the high number of images for each fruit and the simplicity of the algorithms that allowed fast processing.

We can also conclude that the use of more information than just the traditional colour bands RGB, as is the use of the near infrared band, increases the correct classification of the fruit. The contribution of the blue band to improve this classification is especially important to detect the external defects.

The application times were obtained using the simulation board, which is limited by a system clock of 32 MHz and wait states due to shared memory. Since distributed memory is proposed, the processing speed depends only on the clock frequency. With these results, it seems reasonable that using a commercial board with a 60 MHz system clock and distributed memory instead, the time estimation will be approximately half of the times obtained here, that is, the system could reach a minimum speed of 10 fruits/s in those cases where all the fruit to be processed is unusually big and defective, and a speed of 16 fruits/s in standard cases where the fruit have diverse size and a variable number of defects.

The system was able to reproduce the Spanish quality standards. The viability of the system has been demonstrated.

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