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Development of a machine for the automatic sorting of pomegranate (*Punica granatum*) arils based on computer vision

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ABSTRACT

The pomegranate is a fruit with excellent organoleptic and nutritional properties, but the fact that it is difficult to peel affects its commercialisation and decreases its potential consumption. One solution is to market the arils of pomegranate in a ready-to-eat form. However, after the peeling process, unwanted material, such as internal membranes and defective arils, is extracted together with good arils and must be removed on the packing line because the presence of such material shortens the shelf life of the product or deteriorates its appearance. For different reasons, the commercial sorting machines that are currently available for similar commodities (cherries, nuts, rice, etc.) are not capable of handling and sorting pomegranate arils, thus making it necessary to build specific equipment. This work describes the development of a computer vision-based machine to inspect the raw material coming from the extraction process and classify it in four categories. The machine is capable of detecting and removing unwanted material and sorting the arils by colour. The prototype is composed of three units, which are designed to singulate the objects to allow them be inspected individually and sorted. The inspection unit relies on a computer vision system. Two image segmentation methods were tested: one uses a threshold on the R/G ratio and the other is a more complex approach based on Bayesian Linear Discriminant Analysis (LDA) in the RGB space. Both methods offered an average success rate of 90% on a validation set, the former being more intuitive for the operators, as well as faster and easier to implement, and for these reasons it was included in the prototype. Subsequently, the complete machine was tested in industry by working in real conditions throughout a whole pomegranate season, in which it automatically sorted more than nine tons of arils.

1. Introduction

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. This fruit is affected in the orchards by particular physiological disorders, such as sunburn or the splitting of ripe fruit (Melgarejo et al., 2004), which do not influence its internal quality and properties, but do degrade its external appearance and, thus preventing the affected fruits from being marketed. However, manual peeling and extraction of the arils is difficult, and this gives rise to a certain degree of rejection by the consumer in favour of other fruits that are easier to eat. On the other hand, the nutritional and anticarcinogenic properties of pomegranates have been widely demonstrated (Schubert et al., 1999; Gil et al., 2000; Malik et al., 2005; Lansky and Newman, 2007). Furthermore, pomegranate trees do not require water or other agricultural inputs (fertilisers, phytosanitary products and so forth) in large quantities and this makes growing them easier in arid and semi-arid climates.

One way of increasing the consumption of this fruit is to sell ready-to-eat arils, which have a very high added value in an increasingly health conscious society.

Several machines for extracting the arils are already on the market, but their descriptions lie beyond the scope of this work. One of their main problems, however, is that fragments of internal membrane 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. For all these reasons, it is crucial for manufacturers of ready-to eat pomegranate arils to find automatic solutions to inspect and sort the product.

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In current production lines, this raw material inspection has three major objectives: (1) to remove the pieces of internal membranes and skin; (2) to remove unwanted arils, such as those that are too small, broken or have brownish colours; and (3) to sort the quality arils by colour in order to render the appearance of the product uniform in the package. Since manual inspection is too expensive and subjective, computer vision opens up the possibility of constructing an automatic sorting machine.

Machine vision has been largely employed for fresh fruit inspection, and attempts to imitate human operators (Blasco et al., 2003; Brosnan and Sun, 2004). This technology is nowadays available for the automatic sorting of most popular, relatively big fruits, such as oranges (Aleixos et al., 2002; Blasco et al., 2007a, b), apples (Leemans and Destain, 2004), peaches (Miller and Delwiche, 1991; Zwiggelaar et al., 1996) and tomatoes (Edan et al., 1997).

Computer vision systems mounted in sorting machines require auxiliary devices to make the objects enter and leave the field of view of the cameras. They usually work in combination with other devices that split the production into different categories. It is often advisable to separate the objects individually during these processes in order to facilitate both the analysis of the objects in the image and the action of the sorting mechanisms. Large fruits are relatively easy to separate from each other by mechanical means and this allows the computer vision system to inspect each individual object more easily.

However, with the exception of the following, very little information is available on the development of machine vision systems in the case of processed and small fruits: olives (Díaz et al., 2004), dates (Wulfsohn et al., 1993), mandarin segments (Blasco et al., 2007c), raisins (Huxoll et al., 1995) or canned peaches (Vizmanos et al., 1997). Inspection of pomegranate arils has not yet been automated to date because they are particularly difficult to manage due to their small size, and because it is a wet and sticky product that is very difficult to separate. Moreover, arils are more fragile than whole fruits which complicates the way they are handled considerably. All these reasons make it necessary to develop a specific sorting machine.

Additional difficulties such as the range of possible colours of the arils (from white to dark red or brown), the high speed of the conveyor belts, and the bright spots produced by water on the skin of arils, further complicate colour estimation. Supervised segmentation techniques based on statistics, such as Bayesian methods, can facilitate image analysis (Marchant and Onyango, 2003), although they require the participation of an expert to train the system properly. Simpler techniques, such as thresholding, provide faster image segmentation, but they can only be used if the colours of the objects belonging to the different classes are distinctive and well defined (Gunasekaran, 1987; Zion et al., 1995).

The Agricultural Engineering Centre of the Valencian Institute of Agricultural Research (IVIA) and the pomegranate producer Frutas Mira Hermanos, have collaborated over two years in order to design and develop a computer vision based prototype (patent pending) to automatically inspect and sort pomegranate arils depending on their commercial quality, and to remove unwanted materials produced during the extraction of the arils. The results of preliminary trials undertaken during the first season, working on-site the producer facilities, have been presented elsewhere (Blasco et al., 2008). The present paper discusses the technological challenges involved and the engineering solutions implemented in the development of the new prototype.

2. Objective

The objective of this work was to develop an engineering solution for the automatic sorting of pomegranate arils. This task 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.
- Developing communication and control procedures to supervise the whole machine, which included a friendly interface with the user.

The proposed solution had to be developed as a prototype for sorting all the objects that left the extracting machine into up to four categories, while ensuring a minimum production of 75 kg of arils per hour.

Computer vision algorithms had to assess the colour of each object individually, and had to be capable of discriminating between arils and other undesired material, mainly composed of fragmented skin and internal membranes. 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 to achieve the required throughput. Intuitive and fast classification techniques had to be compared in order to decide which one should be implemented in the prototype. The optimal solution had to be the one that consumed less computing time and was easier to operate by a non-experienced user, without compromising quality standards. Moreover, the solution had to be economically feasible and easy to maintain.

3. Materials and methods

The prototype (Fig. 1) basically consisted of three major elements that corresponded to the feeding, inspection and sorting units. These are described below.

3.1. Feeding unit: Separation and transport of the objects

Raw material coming from the extracting machine travelled on a single 250 mm-wide conveyor belt, and then dropped down onto a vibrating, tilted plate. The inclination of the plate and its vibrating movement made the material move forward and disaggregate as it reached the end of the plate. In the following step, it was split into six 30 mm wide conveyor belts that moved at a relatively higher speed (0.75–1.25 m/s). This action produced an individual separation of the different objects that made up the raw input. This step was crucial for subsequent processes, since it allowed the system to use simple image analysis techniques and to expel each object into its corresponding outlet. The narrow size of the belts prevented large accumulations of material and facilitated the separation of the objects.

The colour of the conveyor belts was chosen to enhance the contrast between the belts and arils in order to make segmentation of the images easier. Conveyor belts of different colours were tested before being installed on the prototype. These preliminary tests consisted in acquiring and segmenting images of arils and internal membranes placed over pieces of white, blue, dark green, light green and grey belts and then measuring the ratio of successful classification (Blasco et al., 2008).

3.2. Inspecting unit and computer vision system

The prototype used two progressive scan cameras to acquire 512×384 pixel RGB (Red, Green and Blue) images with a resolution of 0.70 mm/pixel. Both cameras were connected to a

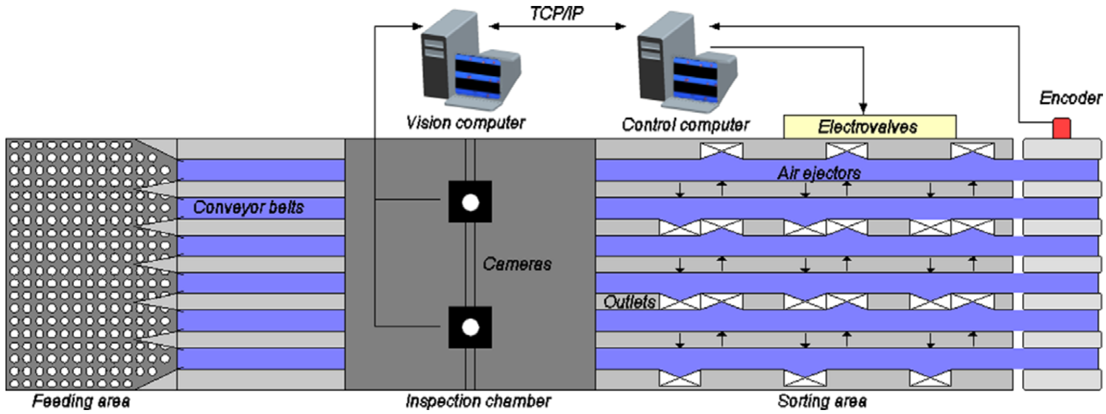

Fig. 1. Scheme of the sorting machine.

computer, the so-called "*vision computer*" (Pentium 4 at 3.0 GHz), by means of a single frame grabber that digitised the images and stored them in the computer's memory. The illumination system consisted of two 40 w daylight compact fluorescent tubes located on both sides of each conveyor belt, thus making a total of 14 tubes. Tubes were used together with high frequency electronic ballast to avoid the flicker effect. This illumination was powerful enough and did not produce shadows. The influence of bright spots in the scene caused by direct lighting on wet surfaces, which could alter the perception of the colour by the inspection system, was minimised by using cross-polarised filters placed above the lamps and on the camera lenses. The scene captured by each camera had a length of approximately 360 mm along the direction of the movement of the objects and a width that allowed the system to inspect three conveyor belts at the same time. The entire system was housed in a stainless steel chamber. A picture of the whole prototype is shown in Fig. 2.

3.2.1. *On-line image acquisition and analysis*

All the image analysis software was programmed in C language. All source codes were specifically written for this application without the use of any commercial library in order to ensure the control of the operations and real-time responses.

One of the major achievements of the software that was developed is the possibility of working with two cameras at the same time, since the acquisition of the images is a very time-consuming process (40 ms per image). The software 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.

Segmentation consists in determining which regions of the image correspond to background and which represent the objects of interest. We opted for a pixel-oriented segmentation algorithm, because these algorithms are normally faster than other approaches (region-oriented algorithms, textural analysis, etc.). The conveyor belts were blue and consequently had high B values and low R values of the RGB coordinates. The colour of pomegranate arils varies between white and red, which correspond to high R values. Internal membranes are mostly white, and hence have high R, G and B values. Consequently, the segmentation algorithm used a pre-defined threshold in the R band. Pixels having R coordinates below this threshold were considered to belong to the background. Fig. 3 illustrates this principle by showing the histogram of the R band of a typical aril surrounded by the blue background. The peak on the left corresponds to background pixels (low R values), while the peak on the right represents pixels from the aril. The value of this threshold was selected manually and at random between the two peaks by an expert.

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

Fig. 2. Prototype developed for the inspection of pomegranate arils.

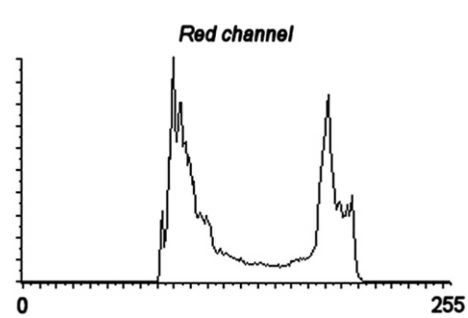

Fig. 3. Histogram of the R component of a small window containing a typical aril (right peak) and the background (left peak).

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.

In order to measure the speed of image processing, an oscilloscope was connected to the parallel port of the vision computer. At the beginning of the image analysis, the machine vision computer triggered the oscilloscope time count. At the end of the image processing, a new signal stopped the clock, thus allowing us to measure the time that had elapsed between the two signals and to determine whether the system reached real-time requirements.

3.2.2. Selecting the way to represent the colour of the objects

Pomegranates (*Punica granatum*, cv. "Mollar de Elche") were used during the tests. The colour of their arils ranged from white–pink (predominant at the beginning of the season) to red–brown (more frequent at the end of the season) (Fig. 4).

Training and validation sets of objects were built from samples obtained from the extracting machine. These objects were sorted into five categories by experienced workers. Following the quality standards of the company, these categories depend on the colour of the objects and were named: *white aril, pink aril, red aril, brown* (rotten) *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 of 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 colour and class of each object were stored. Different methods were used to define the colour of the objects, all of which were based on the average RGB values of their pixels. These methods involved the average RGB values themselves, the R/G ratio, the R value and the G value.

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 re-training 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. For this reason, this technique was one of the methods chosen for implementation in the prototype.

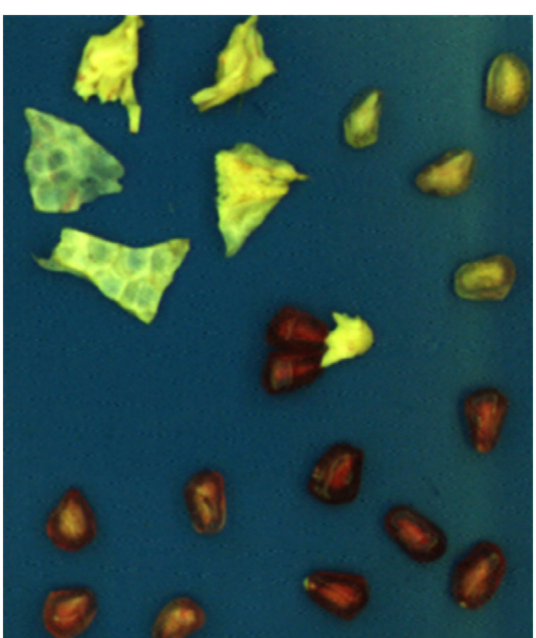

Fig. 4. Unwanted material (e.g. internal membranes) and arils of different qualities (white, pink and red).

Thresholds for each of the object classes were established from percentile 10% and 90% of each of the colour descriptors in each class. When gaps or overlaps between categories were found, the central value of the gap or the overlap was used to define the borders of each class.

Table 1 shows the basic statistics of the R/G ratio for the different categories and the selected thresholds. Percentiles 10% and 90% overlapped only for the red and brown categories, which could cause confusion between these two categories.

However, a simple technique like this is not always the optimal solution to a problem and we decided to compare it with the results obtained with a more sophisticated statistical method, such as Bayesian linear discriminant analysis (LDA). This type of LDA relies on the Bayes theorem (1):

$$P(x|w_i) = \frac{p(x|w_i)P(w_i)}{\sum_{j=1}^{m} p(x|w_j)P(w_j)}, \quad i = 1, \dots m \tag{1}$$

where x was the 3-dimensional observed vector (in our case, the average RGB values of an object), w_i ($i = 1 \dots m$) was one of the m different classes, m is the number of classes (5 in our case), $P(x|w_i)$ was the probability that the observed x belonged to class w_i, $P(w_i)$ was the *a priori* probability of an object belonging to class w_i (this probability was considered to be the same for each class), and $p(x|w_i)$ was the conditional density function of the RGB values in the class w_i (we assumed that all of them were Gaussian with equal covariance matrix).

The assessment of the two classification methods was performed 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 made by human experts, in order to build the confusion matrix for each method. Tests were performed at the beginning and at the end of the season to observe whether there were changes in the performance of the classification algorithms.

3.3. The sorting unit

The sorting area followed the inspection chamber (Fig. 5). Three outlets were placed on one side of each of the conveyor belts. In front of each outlet air ejectors were suitably placed to expel the product.

The separation of the arils was monitored by the control computer, in which a board with 32 digital outputs was mounted. This board was used to manage the air ejectors. The computer tracked the movement of the objects on the conveyor belts by reading the signals produced by the optical encoder attached to the shaft of the carrier roller.

Table 1
Basic statistics of the R/G ratio for each colour category

	Mean	Standard deviation	Percentile 10%	Percentile 90%	Thresholds (R/G range)
Unwanted material	97.8	1.3	96.1	99.5	0–107
White	125.1	8.2	115.0	133.3	108–133
Pink	139.7	7.2	134.6	144.7	134–144
Brown	155.2	8.1	145.8	166.7	145–165
Red	183.1	14.4	164.8	202.0	166–255

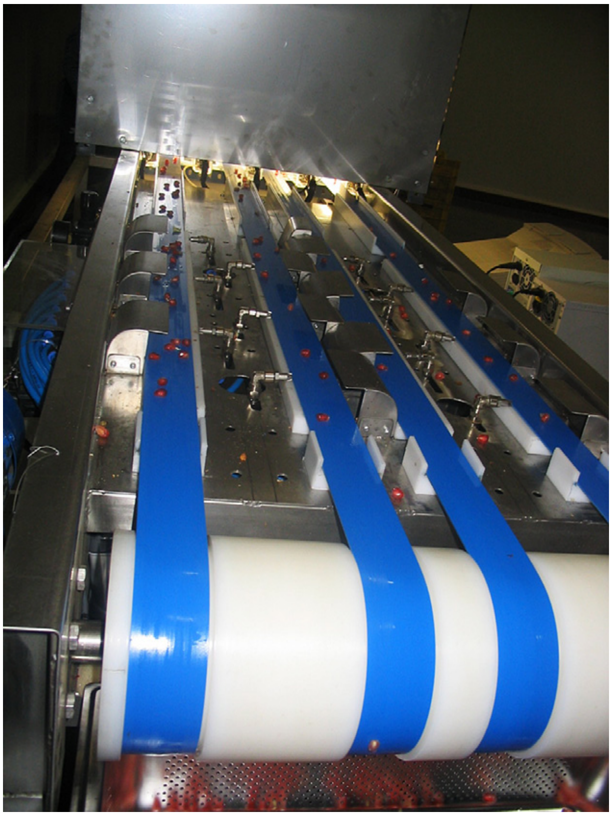

Fig. 5. Details of the grading area showing the air ejectors and the outlets.

The control computer received the category and the position of each object in image coordinates via TCP/IP. The information about the category was used to establish which air ejector had to be used for each object. The positions of both the object in the image and the belt were employed to calculate the moment at which the ejector had to be activated. The control computer stored the number of encoder pulse counts necessary for the object to reach the ejector, and then decreased this value every time it received a pulse from the encoder. When the count reached zero, the object was supposed to pass just in front of the ejector and the computer opened the appropriate electro-valve in order to remove it from the belt. As has been said earlier, since synchronism was based on counting encoder pulses, it was independent of the speed of the belt. This design made it possible to achieve a position tracking accuracy of 0.3 mm.

3.4. Testing the prototype under commercial conditions. Global evaluation of its performance

Once the prototype was ready, it was installed in commercial facilities for industrial testing and configured to separate arils and unwanted material as described above. The prototype was tested in commercial conditions over a period of six months, between September and February 2005/2006, which was the pomegranate season in Spain.

During the tests, the prototype inspected more than nine tons of objects. It was unviable to evaluate the results of the individual classification of each object, since working under commercial conditions made it impossible to stop the line in order to compare the classification of single objects made by the machine and human experts. For this reason, the evaluation was performed on the batches produced by the prototype. A panel of three experts analysed random samples obtained from the different outlets of the machine, each expert giving an overall subjective opinion of the performance of the inspection system for each category. Each expert decided whether the automatic classification was good, regular or poor and the final decision of the panel was considered to be the one on which two or three of them had agreed (Fig. 6).

4. Results and discussion

The main outcome of this work was the implementation of an engineering solution for sorting pomegranate arils under commercial conditions. The development and successful commissioning of the automatic inspection machine constituted an important engineering achievement in itself. The following sections describe some of the key results which contributed to this development.

4.1. Feeding unit

The feeding unit worked properly during the tests conducted under industry conditions. It required precise levelling in order to distribute raw material uniformly on the six conveyor belts. Excessive amounts of raw material on one or several belts proved to have an important influence on the performance of the machine as a whole.

Other solutions had been considered, but the arils were always prevented from rolling freely when they reached the belts. The movement of the objects on the belt produced errors in the synchronism between the inspection and the sorting units and, as a result, some pieces did not reach the proper outlet.

Biconic rollers with a rotational movement have been employed in other machines for small fruit inspection, like olives (Díaz et al.,

Fig. 6. Details of objects of different categories.

2000). These devices allow the system to inspect practically the whole surface of the objects by acquiring images while the object rotates. Moreover, they provide a way to isolate individual objects. However, arils are sorted only by colour, but the colour is distributed uniformly; for this reason a single image provided all the information required to assign the object to a class. The way the feeding unit was designed here is less expensive than if it had been built using biconic rollers.

4.2. Inspection unit and computer vision system

4.2.1. Speeding up image analysis by using thresholds on colour descriptors. Comparison with a LDA method

Table 2 shows the average rate of success obtained on the validation set when using the defined thresholds on single R, G and B values and on the R/G ratio to distinguish between white, pink, red and brown arils and unwanted material. Average success was low (52%) when using the R values alone. This may indicate that all the categories have relatively high red components, which increased the confusion between categories and was not apparent before conducting the experiments. Average success was also low when using the R and G bands alone, reaching values of 61% and 67%, respectively. Although the five categories gave different average values for R, G and B values (Table 1), the high variability of values within the categories prevented them from being separated automatically by this simple method. However, the use of the R/G ratio improved the results considerably (90% success).

Results of this classification method based on the R/G ratio were acceptable both at the beginning and the end of the season. Tables 3 and 4 show the confusion matrix on the validation set using the thresholds defined in Table 2 at the beginning and the end of the season, respectively. These tables also show that unwanted material was the class in which best correct classification was obtained (98%). This can be easily explained by the fact that the colour and the size of foreign material were normally very different from those of the arils (the sorting algorithm considered both parameters in order to produce the final decision of the class). The most sensitive classes from the commercial point of view were red and brown arils; successful classification reached a rate of 90% at the beginning of the season and 85% at the end. Confusion between these two classes was higher than for any other pair of classes, probably due to the overlapping of values evident in Table 1. Better results were obtained for the pair of classes white and pink. It has to be noted that arils experience global darkening as pomegranates ripen throughout the season, although this fact has not been quantitatively demonstrated in this work. This could explain the increase in the confusion between both pairs of classes in the last experiment.

The results of classifying the validation set at the beginning of the season using the LDA-based method on the average RGB value of the object are shown in Table 5. In general, all categories were well classified, and unwanted material detected with a success rate of 100%, although 1% of white arils were wrongly classified in this class. There was a small amount of confusion between white, pink and brown arils, but it has to be taken into consideration that pink and white are secondary qualities. Around 3% confusion was found between the red and brown classes. The average rate of success of this method was close to 92% in all the categories at the beginning of the season. However, tests performed at the end of the season showed that success decreased in all categories, but particularly in the red category and mostly in the brown category, which fell to 83% (Table 6). The confusion between both classes increased to more than 10%.

The analysis of the coefficients of the classification functions allowed us to deduce the parameters that had a higher power to discriminate between the classes (Table 7). Since the span of the

Table 2
Average success rate of classification on the validation set using thresholds on the different colour descriptors

Category	R (%)	G (%)	B (%)	R/G (%)
White aril	48.6	68.1	69.9	92.0
Pink aril	41.8	54.7	64.8	91.4
Red aril	58.1	73.1	62.6	89.2
Brown aril	49.6	61.1	58.0	89.0
Unwanted material	88.9	100	83.7	98.3
Total	52	67	61	90

Table 3
Confusion matrix of the classification performed at the beginning of the season using thresholds on the R/G ratio

Actual	Classified as				
	White (%)	Pink (%)	Red (%)	Brown (%)	Unwanted material (%)
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
Unwanted material	1.7	0.0	0.0	0.0	98.3

Results refer to the validation set.

Table 4
Confusion matrix of the classification performed at the end of the season using thresholds on the R/G ratio

Actual	Classified as				
	White (%)	Pink (%)	Red (%)	Brown (%)	Unwanted material (%)
White aril	89.4	7.3	0.0	2.0	1.3
Pink aril	4.0	88.0	1.7	6.3	0.0
Red aril	0.7	3.0	85.7	10.3	0.0
Brown aril	2.0	5.3	11.3	81.3	0.0
Unwanted material	1.7	0.0	0.0	0.0	98.3

Results refer to the validation set.

Table 5
Confusion matrix of the classification performed at the beginning of the season using LDA on the average RGB values of the objects

Actual	Classified as				
	White (%)	Pink (%)	Red (%)	Brown (%)	Unwanted material (%)
White aril	93.3	3.3	0.0	2.3	1.0
Pink aril	2.0	91.7	4.3	2.0	0.0
Red aril	0.0	5.3	91.3	3.3	0.0
Brown aril	1.0	2.7	3.0	91.3	0.0
Unwanted material	0.0	0.0	0.0	0.0	100.0

Results refer to the validation set.

Table 6
Confusion matrix of the classification performed at the end of the season using LDA on the average RGB values of the objects

Actual	Classified as				
	White (%)	Pink (%)	Red (%)	Brown (%)	Unwanted material (%)
White aril	91.3	6.3	0.0	1.3	1.0
Pink aril	3.0	90.0	1.7	5.3	0.0
Red aril	0.3	2.0	86.7	9.0	0.0
Brown aril	1.3	4.7	10.7	83.3	0.0
Unwanted material	0.7	0.3	0.0	0.0	99.0

Results refer to the validation set.

Table 7
Coefficients of the classification functions obtained using LDA

Class variables	White	Pink	Red	Brown	Unwanted material
Green	0.38	−0.07	−0.38	−0.76	1.80
Red	0.08	0.41	0.61	0.86	−0.81
Blue	−0.04	−0.05	−0.05	−0.02	−0.16
Constant	−34.0	−28.3	−27.7	33.6	−99.3

R, G and B values was similar, the higher the coefficient was, the higher its importance for determining the class would be. Subsequently, the G and R bands proved to have the greatest importance, which reinforced the idea of using the R/G ratio to represent the colour of the arils.

Since the average success rate of both methods (multiple thresholds on the R/G ratio and LDA on average values of objects) were similar (they differed by about 1% in each category), we decided to use the simplest one, which allowed us to increase processing time. Moreover, thresholds are easier to tune by the operators when they want to change the sorting results in real time.

4.2.2. Processing speed

The time consumed by the vision computer to process one image was about 15 ms, which made it possible to analyse 65 images/s. Computer vision algorithms allow the machine to attain a working speed of more than 25 images/s, but it was limited to 12 images/s due to mechanical limitations. This opens up the possibility of including more sophisticated solutions in the prototype, for instance, learning algorithms for automatically adapting the classification parameters to the changes in the colour of the arils, similar to those proposed by Picus and Peleg (2000) for dates. In this sense, a specific study of the evolution of the colour in the arils would be required, but this was beyond the scope of this work.

4.3. Sorting unit

Although the selected design allowed a belt position tracking accuracy of 0.3 mm, tests showed that a larger space was required between objects if they were to be sorted accurately. The jets produced by the nozzles generated a cone-shaped air flow that pushed out all the objects within their volume of influence. Off-line experiments demonstrated that two consecutive objects required a 20 mm separation in order to be correctly ejected when conveyor belt speed was 1000 mm/s. On the other hand, the current design makes it possible to increase the number of categories the product can be sorted into by elongating the conveyor belts and increasing the number of outlets and air nozzles.

4.4. Intensive testing under commercial conditions

The automatic inspection of categories of unwanted material, white arils and pink arils was considered to be *good* throughout the season by the expert panel. However, the classification of red and brown arils was considered to be *good* only during the first four months. At the end of the season, the classification performance decreased, because the confusion between red and brown arils increased. The performance of the prototype was 75 kg of arils per hour, which was considered to be acceptable for commercial purposes.

Although image processing techniques similar to the one described in this paper can be easily found in literature, this work is not focused on the development of a computer vision system, but presents engineering solutions to automate the sorting of pomegranate arils. The technological solutions adopted and the algorithms presented in the paper have proved to be relevant in the application of machine vision in order to automate this task, and have made the marketing of ready-to-eat pomegranate arils a feasible proposition.

The particularities of pomegranate arils make them very difficult to handle and sort. This machine is unique and different from others that have been designed for sorting small or pre-processed fruits that can be found on the market or even in the literature, and this is why the prototype is being patented.

5. Conclusions

This work describes an engineering solution for the automatic sorting of pomegranate arils. A prototype for inspecting and sorting the arils was developed and successfully commissioned, which could handle a maximum throughput of 75 kg/h. The feeding unit, based on a tilted plate and narrow conveyor belts, was an effective device for separating fragments of raw material coming from the extracting machine. The inspection unit, which had two cameras connected to a computer vision system, had enough capacity to achieve real-time specifications and enough accuracy to fulfil the commercial requirements. The sorting unit was able to classify the product into four categories. Synchronisation between the last two systems via an optical encoder made the performance of the machine independent of the speed of the conveyor belts. Intensive testing under commercial conditions gave good results over an entire season.

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