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Computer vision for automatic quality inspection of dried figs (*Ficus carica* L.) in real-time

Souraya Benalia [a], Sergio Cubero [b], José Manuel Prats-Montalbán [c], Bruno Bernardi [a,*], Giuseppe Zimbalatti [a], José Blasco [b]

[a] *Dipartimento di Agraria, Università degli Studi Mediterranea di Reggio Calabria, Loc. Feo di Vito, 89122 Reggio Calabria, Italy*
[b] *Centro de Agroingeniería, Instituto Valenciano de Investigaciones Agrarias (IVIA), Cra. Moncada-Naquera Km 5, Moncada, Spain*
[c] *Departamento de Estadística e Investigación Operativa, Universitat Politècnica de València, Camino de Vera s/n, 46022 Valencia, Spain*

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ABSTRACT

This work reports the development of automated systems based on computer vision to improve the quality control and sorting of dried figs of Cosenza (protected denomination of origin) focusing on two research issues. The first was based on qualitative discrimination of figs through colour assessment comparing the analysis of colour images obtained using a digital camera with those obtained according to conventional instrumental methods, i.e. colourimetry currently done in laboratories. Data were expressed in terms of CIE XYZ, CIELAB and HunterLab colour spaces, as well as the browning index measurement of each fruit, and then, analysed using PCA and PLS-DA based methods. The results showed that both chroma meter and image analysis allowed a complete distinction between high quality and deteriorated figs, according to colour attributes. The second research issue had the purpose of developing image processing algorithms to achieve real-time sorting of figs using an experimental prototype based on machine vision, simulating an industrial application. An extremely high 99.5% of deteriorated figs were classified correctly as well as 89.0% of light coloured good quality figs A lower percentage was obtained for dark good quality figs but results were acceptable since the most of the confusion was among the two classes of good product.

1. Introduction

The growing attention of consumers towards regional and local products and the relationship these products have with their place of origin represents an interesting opportunity for agricultural and rural development. The promotion of these high quality food products, which can contribute considerably to rural development and agricultural diversification, could be realized through designations of origin and geographical indications labels (European Commission, 1996; De Luca et al., 2015). The designation of the protected denomination of origin (PDO) 'Fichi di Cosenza DOP' (European Commission, 2011) exclusively regards naturally dried fruits of the domestic fig "*Ficus carica sativa*" (*domestica* L.) belonging to the variety 'Dottato' or 'Ottato', and presenting specific physical, chemical and organoleptic features.

Very nutritional and healthy, dried figs constitute a popular food for local populations of the Mediterranean area because of their content in sugars, mainly fructose and glucose, in essential amino-acids, in carotene (vitamin A), thiamine (vitamin B1), riboflavin (vitamin B2), ascorbic acid (vitamin C), and minerals such as K, P, Fe, Mg, Ca and Cu. They represent an important source of fibre, and their high content in phenolic compounds strongly contribute to their definition as functional fruits (Hatano et al., 2008; Farahnaky et al., 2009; Vallejo et al., 2012). Nevertheless, this strategic cultivation often remains marginalized in many rural areas, as reported by IPGRI and CIHEAM (2003), whereas it could contribute significantly to their sustainable development. According to FAOSTAT (www.faostat.org), fig production in Italy was 11,520 tons in 2013. In the same year, according to Istat data (National Institute of Statistics – Italy), Calabria (Southern Italy) is second only to Campania (Southern Italy), both in terms of cultivated area (474 ha) and production with 2839 tons, corresponding to 24% of the national total. In Calabria, fig cultivation is principally located in the province of Cosenza, where the widest-grown cultivar is the 'Dottato'.

* Corresponding author.
E-mail addresses: soraya.benalia@unirc.it (S. Benalia), cubero_ser@gva.es (S. Cubero), jopramon@eio.upv.es (J.M. Prats-Montalbán), bruno.bernardi@unirc.it (B. Bernardi), gzimbalatti@unirc.it (G. Zimbalatti), jblasco.ivia@gmail.com (J. Blasco).

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Consumer expectations and requirements lead the agro-food industries to increase the marketed product quality, extend its shelf life, and reduce the environmental impact. However, the intrinsic biological variability between individual fruit and vegetable products make it impossible for analytical destructive methods to ensure that each individual fruit meets the high quality standards that constitute a fundamental criterion for a competitive place in a global market. Dried figs should reach the minimum quality requirements established by UNECE (United Nations, 2014). They should be 'intact, sound, clean, sufficiently developed, free from living pests and any of their damages, free from blemishes, areas of discolouration, free from mould filaments, free of fermentation, free of abnormal external moisture and free of foreign smell and/or taste except for a slight salty taste'. Nowadays, the quality sorting of dried figs is carried out manually by experienced operators, who are usually located on both sides of conveyors belts or rollers transporting fruits to be sorted, but visual methods are slow, subjective and do not guarantee the quality of the whole production. Hence, the agro-food industry has to implement new technologies that provide rapid and reliable results, at the same time boosting product value along the entire supply chain.

Consumer willingness to purchase often depends on the appearance of the product, which may also influence the expectations relating to the organoleptic properties, and therefore consumer behaviour. Colour perception is subjective and can be considered as an indicator of freshness or maturity (Valadez-Blanco et al., 2007). Different physical systems have been developed to avoid this subjectivity for colour analysis, which may be evaluated with visual and/or instrumental procedures (González-Miret et al., 2007). Conventional instruments analyse only a small part of the sample, and therefore are not appropriate for food that often presents a heterogenic surface. As a consequence, artificial vision systems have been developed in recent years in order to overcome this problem and to make colour analysis more exhaustive and meticulous including the total surface of the product while carrying out post-harvest operations (Kang and Sabarez, 2009). In this sense, non-destructive technologies for foodstuff quality assessment such as machine vision systems constitute a promising tool for quality control as well as product inspection, sorting and grading (Gómez-Sanchis et al., 2013; Pallottino et al., 2013a, 2013b; Benalia et al., 2015). Indeed, images are both a large data set and a visible entity that can be interpreted at the same time (Grahn and Geladi, 2007). Recent progress in image acquisition techniques allows areas of millions of pixels to be analysed using sophisticated systems (Martin et al., 2007).

Even though numerous studies have considered digital imaging for the various aspects of food colour assessment in recent years (Mendoza et al., 2006; Kang and Sabarez, 2009; Menesatti et al., 2009), they are still at an experimental scale. They certainly need to be optimized for large-scale implementation in agro-food industries due to the complexity of such structures. Computer vision systems developed to work at an industrial scale are far more complex than those which acquire images of static fruit using still digital cameras. The fruit is in movement and randomly oriented, the image acquisition has to be synchronised with the advance of the fruit and the decision resulting from the image processing must be provided in real time to deliver the fruit to the proper quality outlet. However if optimized for large scale implantation, they are of great interest because of the advantages they present: mainly, rapidness, effectiveness, accuracy and objectiveness; moreover, they are non destructive, do not need sample treatment, and are able to assess the whole area of the product despite uneven features present (Cubero et al., 2011). Therefore, they allow cost and labour savings, especially when used in automated processes.

The present work deals with the assessment of dried fig skin colour comparing two analytical methods: image analyses and conventional colourimetry, analysing PDO certified dried figs 'Fichi di Cosenza', as well as deteriorated ones. Furthermore, automated sorting of figs using an experimental prototype based on machine vision systems was developed in order to confirm the obtained results and simulate post-harvest processing at an industrial scale.

2. Materials and methods

2.1. Dried fig colour assessment

Two groups of dried figs belonging to the variety 'Dottato' were chosen for trials. The first group consisted of dried figs of excellent quality harvested during the 2012 season, provided by the Consortium of 'Fichi di Cosenza DOP' (European Commission, 2011) in Southern Italy. The second group, however, comprised purchased fruits of the same variety 'Dottato', from the previous season, which showed a certain quality loss due to major sugar crystallization, as well as to fungal and insect infestations.

Fig skin colour was first measured by means of the chroma meter CR-400 (Minolta Co., Osaka, Japan), using the CIE illuminant D65 and the 10° observer standard. The instrument was calibrated using a white tile reference ($L^* = 97.59$, $a^* = -0.05$, $b^* = 1.65$). L^* value indicates lightness when it is equal to 100, or darkness if it is equal to 0. However, a^* value represents the red (positive value) or green (negative value); and b^* value constitutes the yellow (positive value) or blue (negative value) (Rodov et al., 2012). Each fruit with a mean of three measurements in different zones represented a replicate.

After the chroma meter measurements, image acquisition of each fig was performed with a digital camera Canon EOS 550D, which captured images with a size of 2592×1728 pixels and a resolution of 0.06 mm/pixel. Lighting was provided by eight fluorescent tubes (BIOLUX 18 W/965, 6500 K, OSRAM, Germany) placed on the four sides of a square inspection chamber in a 0°/45° configuration. The camera was connected to a computer, and image analysis was performed according to a software specially developed for this purpose at the Laboratory of Artificial Vision for Agriculture (IVIA-Spain), which separates the objects (figs) from the background using the RGB.R value, and then converts the obtained R, G, B values from the pixels selected as figs into HunterLab space. The first step consists in the conversion of RGB values to CIE XYZ values, then, from CIE XYZ to *L*, *a*, *b* coordinates as described by Vidal et al. (2013) and to L^*, a^*, b^* coordinates attending the equations in HunterLab (2008), in both cases assuming a D65 (6500 K) illuminant and a 10° observer.

Since RGB colour model is device dependent (Menesatti et al., 2012), a previous calibration step was done consisting in the comparison of the colour of each patch of a digital colour checker (Digital ColorChecker SG Card, X-Rite Inc, USA) acquired using the chroma meter and the camera. The colours were then converted from RGB to CIELAB and a linear regression was done between both series of values giving a $R^2 > 0.98$ for the three L^*, a^* and b^* components. Hence, it was considered that the camera provided accurate colours.

2.1.1. Data analysis

Data obtained from both conventional colourimetry and image analysis were then expressed in terms of *XYZ.X*, *XYZ.Y*, *XYZ.Z*, L^*, a^*, b^*, *L*, *a*, *b* coordinates, and the ratios L/a, L^*/a^* in order to look for those variables that permit the best separation between both groups since it was the first time that such analyses had been done on dried figs In addition, the browning index (*BI*), which is considered to be an important parameter where enzymatic or non-enzymatic browning processes occur (Mohammad et al., 2008), was also calculated and considered in the model (Eq. (1), Palou et al., 1999).

$$BI = \frac{100(x - 0.31)}{0.172} \quad (1)$$

where

$$x = \frac{a + 1.75L}{5.645L + a - 3.012b}$$

At the end of the trial, a total of 26 parameters (variables) were obtained and statistically analysed according to principal component analysis (PCA) and partial least squares – discriminant analysis (PLS-DA), using SIMCA-P v13 (MKS Umetrics AB, Sweden). In order to compress and interpret the internal relationships between variables, and at the same time check whether some of these are able to separate the two analysed classes (deteriorated and not deteriorated figs), principal component analysis PCA (Jackson, 1991) was applied. PCA is a projection method of the original variables onto new ones, called latent variables, orthogonal and arranged according to their explained variance. This is carried out expressing a matrix X as:

$$X = TP^T + E \quad (2)$$

where T is the score matrix, P is the loading matrix and E is the residual matrix for X. This makes it possible to determine the general pattern of any process, and the relevant variables that rule it.

However, PCA does not necessarily search for those variables that better discriminate between classes, but only for those gathering the highest variance in the data. Thus, when aiming to separate, another latent-based multivariate projection model, such as PLS-DA (Sjöström et al., 1986) is a more sensitive technique to apply. PLS (Geladi and Kowalski, 1986) models the data through the use of Eq. (2) and the following expressions:

$$T = XW^* = XWP^TW \quad (3)$$

$$Y = TC^T + F \quad (4)$$

where T is the score matrix, P the loading matrix for X, C the loading matrix for Y, W and W^* weighting matrices, and F the residual matrix for Y.

In the case of PLS-DA, Y is built from as many dummy variables as classes we have to separate. A dummy variable is a binary variable formed by 1's and 0's, the former linked to the class the dummy variable is related to, and zeros to the rest of the observations. Hence, the PLS-DA looks for those internal directions that best separate the classes of interest, also trying to explain X reasonably.

This way, it is possible to compute, from any matrix X, the prediction of Y as:

$$Y_{\text{pred}} = XB_{\text{PLS}} = TQ^T = XW\left(P^TW\right)^{-1}Q^T \quad (5)$$

where

$$B_{\text{PLS}} = XW\left(P^TW\right)^{-1}Q^T$$

When applied to images, these techniques belong to Multivariate Image Analyses, MIA (Prats-Montalbán et al., 2011). Together they make up the most suitable analytical tools for the trials that were carried out, taking into account that each sample was considered regarding its 26 variables.

2.2. In-line dried fig sorting

Due to the high complexity of handling small fruit and the relatively small market in comparison to other fresh fruit, there are not commercial electronic sorters of dried figs to separate them into qualities. Hence, there is a need to develop such a sorter. For this purpose, automated sorting trials based on a computer vision system were performed using an experimental prototype, developed at the Laboratory of Artificial Vision for Agriculture (IVIA-Spain). It was originally designed for mandarin orange segment and pomegranate aril in-line sorting (Blasco et al., 2009a,b) and subsequently adapted for the sorting of dried figs It principally consists of three functioning elements: supply unit; inspection unit and separation unit (Fig. 1).

From the supply unit, fruit are spread on a number of conveyor belts, 30 mm wide and 250 mm long, moving at a relatively high speed (0.5 m/s). They pass through the inspection unit which consists of two progressive scanning colour cameras (JAI CV-M77), placed at approximately 0.9 m above the subject, which provide RGB images (512 × 384 pixels) with a resolution of 0.70 mm/pixel. Cameras are equipped with a 12 mm lens, and lighting is provided by light emitting diode (LED) lamps. The entire system is housed in a frame of stainless steel suitable for agro-food products. After each image processing, the computer responsible sends the following data: fruit position, the number of the conveyor belt on which it is located, and the corresponding category to a second computer which is responsible for directing the movement of the inspected fruit to the separation unit and its subsequent categorisation.

A set of 24 figs was used to build the models and train the image processing software. This was done by manually dividing the figs into the three different categories and passing each category separately through the in-line prototype. The trials considered 96 figs, which had previously been classified in the subsequent three categories: 31 light PDO figs, 26 dark PDO figs and 39 deteriorated figs (Fig. 2). Each fruit in the validation set went through the whole classification process five times in random positions, and orientations and sides, thus it was as if 480 figs were categorised.

One of the requirements of current quality standards for dried figs is that the contents of each package must be uniform (United Nations, 2014). Moreover, consumers are prone to purchase lots with uniformity of colours and sizes. Hence, the output of each category was established as follows:

- Category 0: (Light PDO figs): the fig arrives at the end of the conveyor belt.
- Category 1: (Dark PDO figs): the fig is ejected at the first outlet.
- Category 2: (Deteriorated figs): the fig is ejected at the second outlet.

Fig. 1. Picture of the in-line sorting prototype.

Fig. 2. Samples with different colours that belong to different categories: (a) light, (b) dark and (c) deteriorated uneven coloured figs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In-line systems working in real-time have to run very fast image processing algorithms and hence it is not possible to incorporate complex segmentation models although it could be more effective in some cases. On the other hand, it is very important that the quality parameters can be easily controlled by non-experienced workers through a friendly interface. This means that the machine has to prioritize easy to handle methods to separate the fruits over other maybe more robust but also more complex statistical methods.

Following this principle, image segmentation was developed based on the colour analysis of images captured with the aforementioned industrial cameras under dynamic conditions. As a first step, each pixel in the image was classified as background or as belonging to an object to be analysed. Since there was a marked contrast between the white background and the fruit, a threshold was enough to properly remove the background from the image analysis. Preliminary analysis of the histogram of the training images determined that a threshold value of $T_0 = 100$ in the green band could separate the fruit without error. Therefore, any pixel with a value in the G channel above T_0 could be considered as belonging to the background and removed. This operation was performed only in the regions of interest corresponding to the conveyor belts while the parts of the images outside these regions were not considered.

All remaining pixels in the images were considered as belonging to potential figs Therefore, the RGB values of the remaining pixels were converted into CIE XYZ and CIELAB coordinates to calculate the *BI*.

To separate the pixels in the figs into any of the predefined classes a previous analysis was necessary. An analysis of the variance (ANOVA) was carried out for each variable using the training calibration samples to determine into which of the different available colour coordinates the figs belonging to different qualities could be best placed, or if necessary, a combination of several colour coordinates. Once the variables had been defined, the thresholds among the three classes initially set in the sorting prototype could be established from the data extracted from the basic statistics (Tables 3 and 4). Once the colour indices and the thresholds had been determined, the algorithms were programmed to classify the pixels in the images in one of the three categories as follows, where the thresholds T_1 and T_2 were obtained from the previous analysis:

- If average $BI < T_1$ the pixel was considered deteriorated.
- If average $BI \geqslant T_1$ and average $XYZ.X < T_2$, the pixel was considered a dark PDO; otherwise the pixel was considered as belonging to a fair PDO fig

After the pixelwise image segmentation, it was necessary to perform a filtering process in order to reduce the noise caused by shadows found at the edges of the fig and by small groups of isolated pixels. This process consisted of a two-iteration erosion of the complete fig followed by a median filter. Finally, the categorisation of the fig was based on the class of pixel which covered the largest part of the fig

The sequence of image processing carried out by the sorting machine in real time is shown in Fig. 3. The original image captured by the cameras shows the figs while they are transported by the conveyor belts. The first step corresponds to the segmentation based on the thresholds in the regions of interest defined by the known position of the conveyor belts. Then the filtering is performed in order to reduce the noise and the segmentation problems caused by shadows found at the edges of the Figs Finally, the decision is taken by counting the number of pixels belonging to the different classes. For the case shown in Fig. 3, according to the decision of the vision system, the figs in blue belong to the deteriorated class, the figs in red are dark figs, and the fig in green is a light one.

The tests were carried out by placing the figs into a vibrating platform that guided the fruit randomly to the different conveyor belts of the prototype. Each fruit was transported by the conveyor belts, analysed and sorted by the outlet corresponding to their assigned category.

3. Results and discussion

3.1. Dried fig colour assessment

Fig. 4 represents the score plot of PCA (2 PC's, R^2 81%), showing an overview of the behaviour of each fruit belonging to the studied groups with PDO figs of Cosenza in black and deteriorated ones in red. Here, as stated above, the analysis considered the totality of variables (26), that is, those obtained by conventional colourimetry as well as those obtained from image processing. In this case, the PCA model is able to separate the two classes. In order to assess for which components are mainly responsible for separation, the loadings plot (Fig. 5) is inspected.

The separation between class 1 (sound figs represented by black points) and class 2 (deteriorated figs represented by red points) is mainly characterized by the variables *XYZ.Z*col, *XYZ.Z*img and *L*/*a* on one hand, and *CIEb_img* (b^**_img*), *Huntb_col* (*b_col*), and *CIEb_col* (b^**_col*), on the other hand.

PLS-DA results highlight two clusters, each one corresponding to one of the assessed groups of figs (Fig. 6). The plot shows that the first component is able to separate the two classes. From the PLS-DA weights of the first component (Fig. 7), the variables responsible for the separation can be derived. Note that, in the case of having more than one discriminant component in the model, other approaches (e.g. VIP's) would be more sensitive. Nevertheless, in this case, since the discriminant direction is mainly related to the fist latent variable, both approaches provide equivalent results (see Fig. 8), with the advantage that the weights provide the positive or negative correlation of each variable with each of

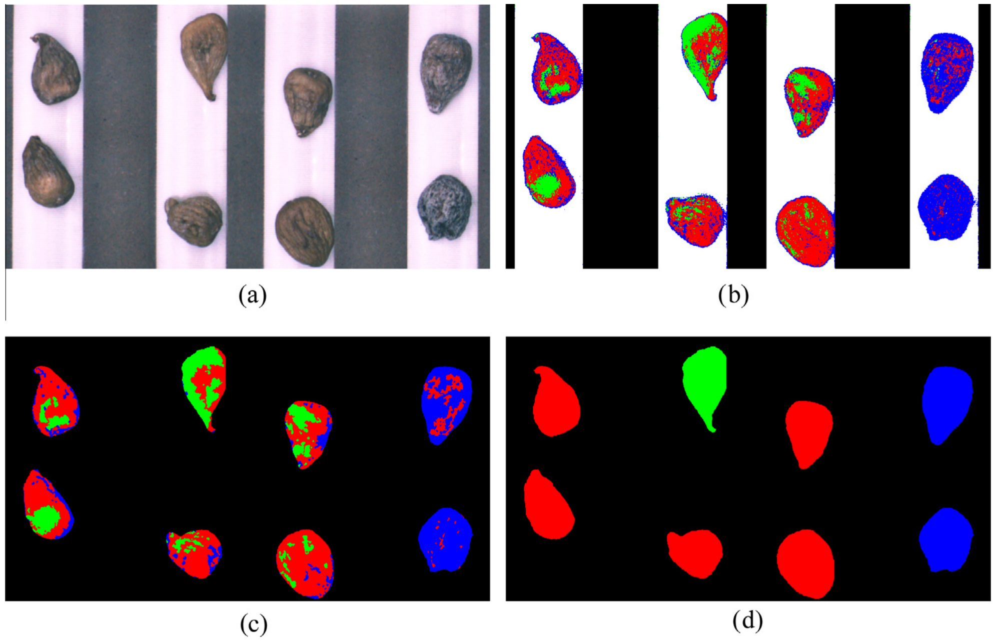

Fig. 3. Steps in the in-line image processing of the figs sorting machine. (a) Original image captured by the cameras, (b) segmented image, (c) filtered image, and (d) decision image.

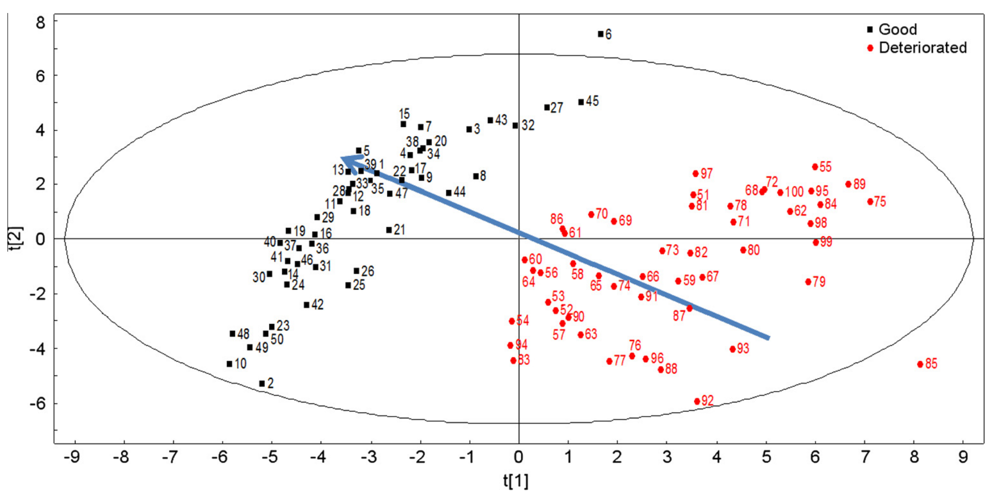

Fig. 4. Score plot of PCA results considering all the variables (image analysis and conventional colourimetry). The ellipse represents 95% confidence interval.

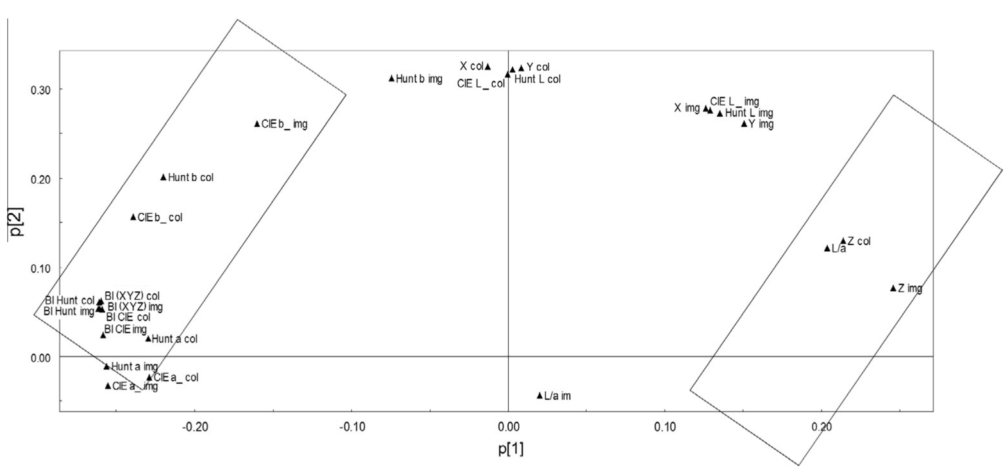

Fig. 5. Loading plot of PCA results considering all the variables (image analysis and conventional colourimetry). The rectangles include the best separating variables.

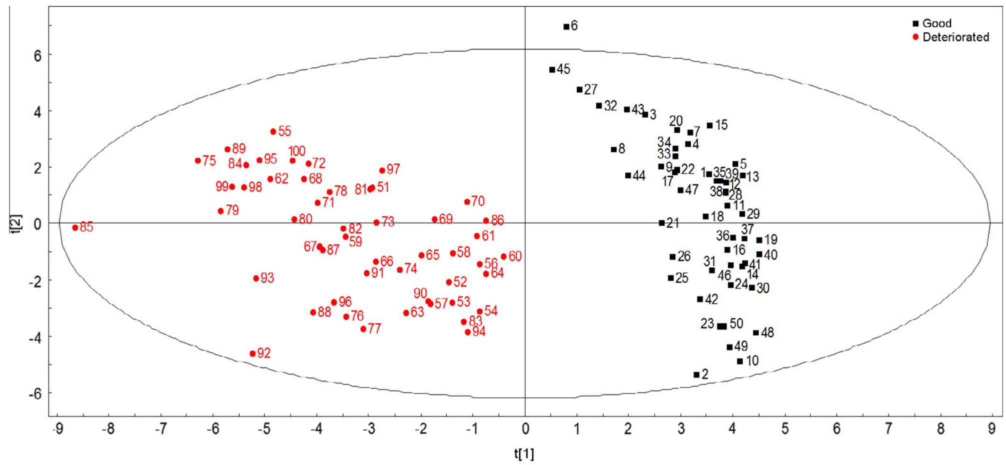

Fig. 6. Score plot of PLS-DA results considering all the variables (image analysis and conventional colourimetry). The ellipse represents 95% confidence interval.

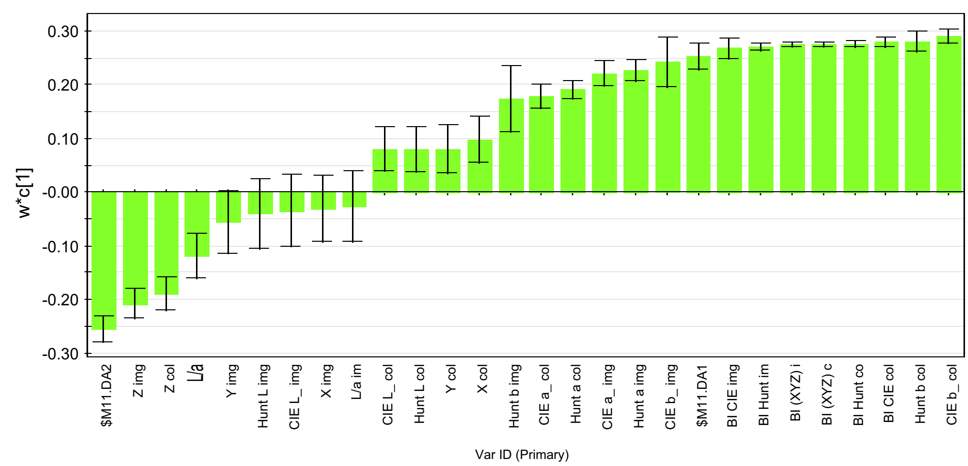

Fig. 7. Weight plot of the first component of the PLS-DA model considering all the variables (image analysis and conventional colourimetry).

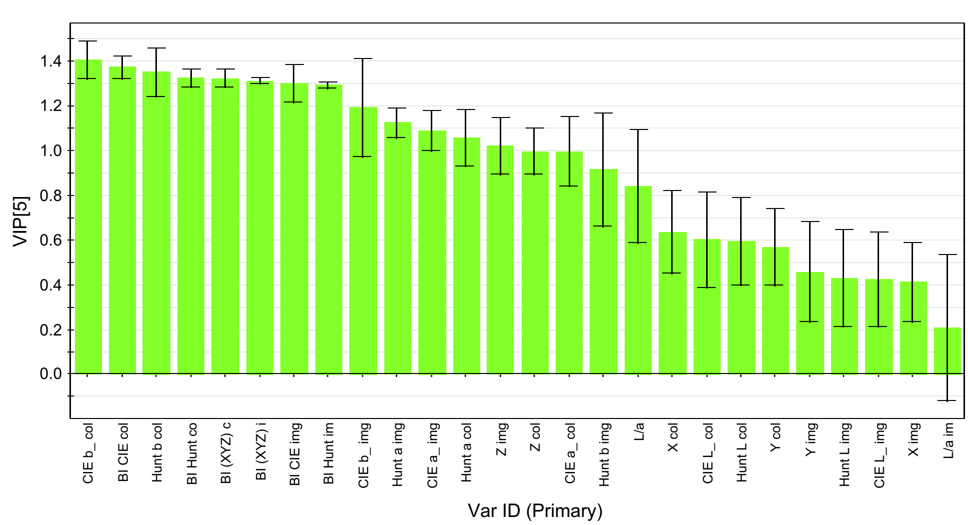

Fig. 8. VIP's plot of the first component of the PLS-DA model considering all the variables (image analysis and conventional colourimetry).

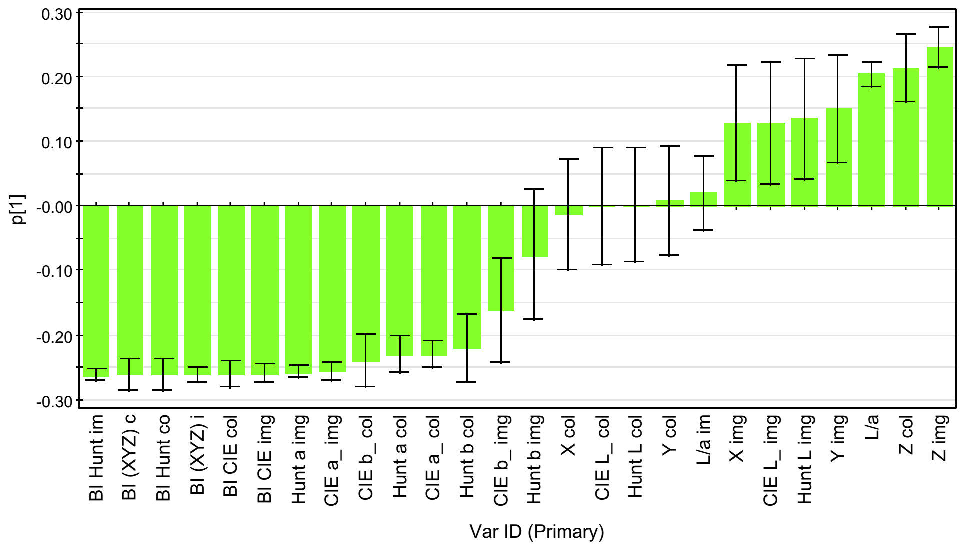

Fig. 9. Column plot of PCA for the first component considering all the variables (image analysis and conventional colourimetry).

Table 1
Analysis of variance for browning index.

Source	Sum of squares	Df	Mean square	*F*-ratio	*P*-value
Between groups	9435.52	2	4717.76	83.03	0.0000
Within groups	5284.36	93	56.82		
Total (Corr.)	14719.90	95			

Table 2
Analysis of variance for *X*.

Source	Sum of squares	Df	Mean square	*F*-ratio	*P*-value
Between groups	311.73	2	155.86	53.48	0.0000
Within groups	271.04	93	2.91		
Total (Corr.)	582.77	95			

Table 3
Summary statistics for browning index.

Class	Average	Standard deviation	Coeff. of variation (%)	Min	Max
Light	48.27	5.43	11.24	36.58	59.54
Dark	43.13	8.43	19.90	31.56	61.71
Deteriorated	25.93	8.31	32.04	8.48	41.70

Table 4
Summary statistics for *X*.

Class	Average	Standard deviation	Coeff. of variation (%)	Min	Max
Light	8.81	1.89	21.78	6.32	14.53
Dark	5.63	0.90	15.90	4.08	7.75
Deteriorated	10.08	1.94	19.26	5.56	13.15

the classes to be separated. It must be stated that, for classification purposes, the model was built with 5 latent variables and an R2Y value of 96.5% and a Q2Y value of 95%, which in practice means that all figs were correctly classified in a 7-block cross-validation procedure. However, this was not the goal of the analysis: the goal of the analysis being the selection of the most discriminant variables and comparing them with the ones used in the already built in-line sorting machine.

On the other hand, the score plots of PCA and PLS-DA show similar clusters for the two studied groups, and PCA confirms that the *XYZ.Z* coordinate is one of the best discriminant variables. The difference between the two score plots lies in the fact that PCA function is not to separate both classes, but to maximise the variance, as previously stated. Anyway, since the rotation in the components is not very large, the variables indicated by the loadings barplot (Fig. 9) are almost the same as the ones outlined by the first component weights of the PLS-DA model (Fig. 7).

The study carried out highlights that, in this case, both statistical analyses, PCA and PLS-DA, could distinguish clearly between high quality PDO figs and deteriorated ones, showing the effectiveness of both techniques used for fig colour assessment as a qualitative parameter. Hence, analysis of high quality images could perfectly replace current destructive methods based on sampling for this purpose. The browning index seemed to be an interesting index that showed this distinction, and therefore a valid indicator for dried fig quality assessment but the colour measurement in some different colour spaces did not present significant differences. It is important to consider all components in the model, and not only the first, to determine which indicate the discriminant direction (Prats-Montalbán et al., 2006).

3.2. In-line dried fig sorting

The methods, conditions, aims and equipment used for classifying the fruit in real-time using an industrial machine are different from those used to assess colour using a standard colourimeter and hence new variables need to be selected. ANOVAs carried out on the main discriminant variables highlighted by the PLS-DA and PCA analyses achieved similar results in terms of significance. From these analyses, variables *BI* and *X* were selected for separating the different categories of figs during the in-line real-time inspection using the machine since the study of the basic statistics clearly determined that it was possible to set thresholds to separate the different categories. Tables 1 and 2 show the ANOVA for these variables while Tables 3 and 4 show the summary of the statistics. Browning index could be clearly used to separate between good and deteriorated figs and it was decided from these data to use a

Table 5
Results of automated sorting.

Machine\Vis	Light PDO figs (%)	Dark PDO figs (%)	Deteriorated figs (%)
Light PDO figs	89.0	26.9	0.5
Dark PDO figs	11.0	69.2	0.0
Deteriorate figs	0.0	3.8	99.5

threshold value of $T_1 = 35$. On the other hand, dark and light figs could be separated using the X colour value and hence, using the data in Table 4, a threshold value of $T_2 = 7$ was configured in the machine.

Results of the performance of the machine are shown in Table 5. At the end of the trials, 99.5% of deteriorated figs were correctly classified, as well as 89% of light PDO figs; however, just 69.2% of accurate classification was reached for dark PDO figs This decrease of accuracy is related to the unevenness of the figs' skin colour. In fact, some fruits had a lighter colour on one side than on the other; consequently, the machine classified them according to the colour of the side showing as they randomly passed. It has to be remarked that the results correspond to the inspection of the validation set of the figs five times, but each time they fall randomly onto the conveyor belts and were captured in a different and random location in the image. This means that for each time, the conditions and lighting of each particular fig were different.

A certain degree of confusion is normal using the fast classification method implemented. However, the main confusion occurred between the light and dark figs which could be acceptable since both are good quality figs separated only for commercial reasons. On the other hand, there was little confusion between good and deteriorated figs, which is more important from the point of view of the final quality. An aspect to improve is that the machine classified 3.8% deteriorated figs as dark, which, even though within a 5% tolerance, should be reduced. On the contrary, it would be of less importance if dark figs were classified as deteriorated. These results illustrate that fig sorting, using the above-described system, was achieved successfully. The highest percentage was obtained each time for deteriorated figs, followed by light PDO ones, and then dark PDO figs

To identify a specific index to determine accurately the quality for PDO dried figs of Cosenza, the achieved analysis has to be consolidated by further research, taking into account additional parameters i.e., colour change according to ripeness, drying status as well as the correlation of skin colour with anthocyanin content (Rodov et al., 2012). This may be achieved and incorporated in the future to the in-line sorting machine with the use of faster computing units.

Some of the problems found could be resolved using, instead of conveyer belts, bi-conic roller conveyors (ElMasry et al., 2012) which turn the fruits as they progress, allowing the system to inspect their whole surface. However, although a complex analysis of the colour or the texture of the figs would result in a better accuracy of the classification, the computing requirements would not ensure actual real-time processing at a commercial speed.

Image processing time was about 15 ms, permitting an analysis of up to 65 images/s. However, due to mechanical limitations of the prototype, and also because a very high speed could damage the product when it is expelled by the outlets, the speed of the conveyor belts was limited to 0.5 m/s, obtaining then 10 analysed images per second. Considering an ideal distance of 0.1 m between two consecutive figs, at the highest speed of the conveyor belts (0.5 m/s), the tested prototype has the productivity of about 40 figs/s, corresponding approximately to 2160 kg/h. The system has been tested on a prototype with several mechanical limitations, and it is expected that the performance in terms of accuracy and capacity of fruit processing will be higher when the system is developed industrially.

4. Conclusions

As currently carried out, dried fig inspection and grading methods are labour intensive and unreliable due to machine speed and inspector fatigue. Therefore, the development of an effective integrated inspection system that can detect quality according to previously established parameters of the whole fruit would be valuable for the fig industry. The present work showed that the combination of computer vision systems and latent-based multivariate statistical projection models used for this purpose allowed these objectives to be reached under laboratory conditions for manual quality inspection which can be suitable for small-scale production or when the control of only a limited number of samples is required. These results are interesting because they illustrated that both chroma meter and image analysis allowed an effective distinction between high quality dried figs and deteriorated ones, based on colour parameters, a camera being much cheaper and easier to use than the chroma meter.

A system for in-line sorting of figs in real-time was developed based on computer vision and colour parameters providing reliable results. This is the first attempt to create a machine capable of sorting dried figs in real-time using computer vision and a machine with the capability of separating the fruit into different categories. The system could classify correctly between three classes of figs using the browning index and the X colour coordinate. The test was carried out in dynamic conditions with the figs being transported under the camera at high speed, and subsequently separating the figs into different categories by different outlets depending on the decision of the vision system. This was repeated five times, each time achieving good results, the major confusion being between the two classes of sound figs, but a minimal confusion of only 0.5% was found between sound and deteriorated figs: this distinction being the most important from the commercial point of view.

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