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1 **Computer vision for automatic quality inspection of dried Figs (*Ficus carica***

2 **L.)**

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13 **ABSTRACT**

14 This work develops automated systems based on computer vision to improve the quality

15 control and sorting of dried figs of Cosenza (protected denomination of origin) focusing on

16 two research issues. The first one was based on qualitative discrimination of figs through

17 colour assessment comparing the analysis of colour images obtained using a digital camera,

18 with those obtained according to conventional instrumental methods, i.e. colourimetry

19 currently done in laboratories. Data were expressed in terms of CIE XYZ, CIELAB and

20 HunterLab colour spaces, as well as the browning index measurement of each fruit, that were

21 analyzed using PCA and PLS-DA based methods. The results showed that both chroma meter

22 and image analysis allowed a complete distinction between high quality and deteriorated figs,

23 according to colour attributes. The second issue had the purpose to develop image processing

24 algorithms to achieve real-time sorting of figs using an experimental prototype based on

machine vision, advancing an industrial application. An extremely high 99.5% of deteriorated

figs were classified correctly as well as 89.0% of light good quality figs. 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 for regional and local products and the relationship they

have with their territory 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), where it could contribute significantly to

their sustainable development. According to FAOSTAT (www.faostat.org), fig production in

49   Italy counted 11.520 tons in 2013. In the same year, and according to Istat data (National

50   Institute of Statistics – Italy), Calabria is in second place after Campania (Southern Italy),

51   both in terms of cultivated area (474 ha) and production with 2.839 tons, corresponding to

52   24% of the national total. In Calabria (Southern Italy), fig cultivation is principally located in

53   the province of Cosenza, where the widest-grown cultivar is the 'Dottato'.

54   The expectations and requirements of exigent consumers lead the agro-food industries to

55   increase the marketed product quality, extend its shelf life, reduce the environmental impact,

56   as well as to improve the content in services, but the intrinsic biological variability between

57   individual fruit and vegetable products make it impossible for analytical destructive methods

58   to ensure that each individual fruit meets the high quality standards that constitute a

59   fundamental criterion for a competitive place in a global market. Dried figs should respond to

60   the minimum quality requirements established by UNECE (United Nations, 2014). They

61   should be 'intact, sound, clean, sufficiently developed, free from living pests and any of their

62   damages, free from blemishes, areas of discolouration, free from mould filaments, free of

63   fermentation, free of abnormal external moisture and free of foreign smell and/or taste except

64   for a slight salty taste'. Nowadays, the quality sorting of dried figs is carried out manually by

65   experienced operators, which are usually located on both sides of conveyors belts or rollers

66   transporting fruits to be sorted, but visual methods are slow, subjective and do not guarantee

67   the quality of the whole production. Hence, the agro-food industry has to implement new

68   technologies that provide rapid and reliable results, allowing at the same time a qualification

69   of the product along the entire supply chain.

70   Consumer willingness to purchase often depends on the appearance of the product, which

71   may also influence the expectations relating to the organoleptic properties, and therefore

72   consumer behaviour. Colour perception is subjective and can be considered as an indicator of

73   freshness or maturity state (Valadez-Blanco et al., 2007). Different physical systems have

74   been developed to avoid this subjectivity for colour analysis, which may be evaluated with

75   visual and/or instrumental procedures (González-Miret et al., 2007). In comparison,

76   conventional instruments analyze only a small part of the sample, and therefore are not

77   appropriate for food that often presents a heterogenic surface, and consequently, artificial

78   vision systems have been developed in recent years in order to overcome this problem and to

79   make colour analysis more exhaustive and meticulous including the total surface of the

80   product while carrying out post-harvest operations (Kang & Sabarez, 2009). In this sense,

81   non-destructive technologies for foodstuff quality assessment such as machine vision systems

82   constitute a promising tool for quality control as well as product inspection, sorting and

83   grading (Gómez-Sanchis et al., 2013;Pallottino et al., 2013a & 2013b; Benalia et al., 2015).

84   Indeed, images are both a large data set and a visible entity that can be interpreted at the same

85   time (Grahn & Geladi, 2007). Recent progress in image acquisition techniques allows areas of

86   millions of pixels to be analysed using sophisticated systems (Martin et al., 2007).

87   Even though numerous studies have considered digital imaging employment for the various

88   aspects of food colour assessment in the recent years (Mendoza et al., 2006; Kang & Sabarez,

89   2009; Menesatti et al., 2009), these latter are still at experimental scale. They certainly need to

90   be optimized for large-scale implementation in agro-food industries due to the complexity of

91   such structures. Computer vision systems developed to work at industrial scale are by far

92   more complex than those limited to acquire images of static fruit using still digital cameras.

93   The fruit is in movement and randomly oriented, the image acquisition has to be synchronised

94   with the advance of the fruit and the decision resulting from the image processing must be

95   provided in real time to deliver the fruit to the proper quality outlet. However if optimized for

96   large scale implantation, they are of great interest because of the advantages they present:

97   mainly, rapidness, effectiveness, accuracy and objectiveness; moreover, they are non

98   destructive, do not need sample treatment, and are able to assess the whole area of the product

99   despite uneven features present (Cubero et al.2011). Therefore, they allow cost and labour

100   savings, especially when used in automated processes.

101   The present work deals with the assessment of dried fig skin colour comparing two analytical

102   methods: image analyses and conventional colourimetry, analyzing PDO certified dried figs

103   'Fichi di Cosenza', as well as deteriorated ones. Furthermore, automated sorting of figs using

104   an experimental prototype based on machine vision systems was developed in order to

105   confirm the obtained results and simulate post-harvest processing at industrial scale.

106   **2   MATERIALS AND METHODS**

107   **2.1.   Dried fig colour assessment**

108   Two groups of dried figs belonging to the variety 'Dottato' were considered for trials. The

109   first group consisted of dried figs of excellent quality harvested during the 2012 season,

110   provided by the Consortium of 'Fichi di Cosenza DOP' (European Commission, 2011) in

111   Southern Italy. The second group, however, comprised purchased fruits of the same variety

112   'Dottato', from the previous season, which showed a certain quality loss due to major sugar

113   crystallization, as well as to fungal and insect infestations.

114   Fig skin colour was first measured by means of the chroma meter CR-400 (Minolta Co.,

115   Osaka, Japan), using the CIE illuminant D65 and the 10° observer standard. The instrument

116   was calibrated using a white tile reference (L^* =97.59, a^* = -0.05, b^* =1.65). L^* value

117   indicates lightness when it is equal to 100, or darkness if it is equal to 0. However, a^* value

118   represents the red (positive value) or green (negative value); and b^* value constitutes the

119   yellow (positive value) or blue (negative value) (Rodov et al., 2012). Each fruit with a mean

120   of three measurements in different zones represented a replicate.

121   After the chroma meter measurements, image acquisition of each fig was performed with a

122   digital camera Canon EOS 550D that captured images with a size of 2592 x 1728 pixels and a

123 resolution of 0.06 mm/pixel. Lighting was provided by eight fluorescent tubes (BIOLUX 18

124 W/965, 6500 K, OSRAM, Germany) placed on the four sides of a square inspection chamber

125 in a 0°/45° configuration. The camera was connected to a computer, and image analysis was

126 performed according to a software specially developed for this purpose at the Laboratory of

127 Artificial Vision for Agriculture (IVIA-Spain), which separates the objects (figs) from the

128 background using the RGB.R value, and then converts the obtained R, G, B values from the

129 pixels selected as figs into HunterLab space. The first step consists in the conversion of RGB

130 values to CIE XYZ values, then, from CIE XYZ to *L, a, b* coordinates as described by Vidal

131 et al., (2013) and to *L*, a*, b** coordinates attending the equations in HunterLab (2008), in

132 both cases assuming a D65 (6500 K) illuminant and a 10° observer.

133 Since RGB colour model is device dependent (Menesatti et al., 2012), a previous calibration

134 step was done consisting in the comparison of the colour of each patch of a digital colour

135 checker (Digital ColorChecker SG Card, X-Rite Inc, USA) acquired using the chroma meter

136 and the camera. The colours were then converted from RGB to CIELAB and a linear

137 regression was done between both series of values giving a $R^2 > 0.98$ for the three *L*, a** and

138 *b** components. Hence, it was considered that the camera provided accurate colours.

139 *2.1.2. Data analysis*

140 Data obtained from both conventional colourimetry and image analysis were then expressed

141 in terms of *XYZ.X, XYZ.Y, XYZ.Z, L*, a*, b*, L, a, b* coordinates, and the ratios *L/a, L*/a** in

142 order to look for the best variables among all that permit the best segregation between both

143 groups since that it was the first time that such analyses are done on dried figs. In addition, the

144 browning index (*BI*) that it is considered to be an important parameter where enzymatic or

145 non-enzymatic browning processes occur (Mohammad et al., 2008) was also calculated and

146 considered in the model (eq. 1, Palou et al., 1999).

6

147 $$BI = \frac{100(x - 0.31)}{0.172}$$ (eq. 1)

148 where:

149 $$x = \frac{a + 1.75L}{5.645L + a - 3.012b}$$

150 At the end of the trial, a total of 26 parameters (variables) were obtained and statistically

151 analyzed according to principal component analysis (PCA) and partial least squares -

152 discriminant analysis (PLS-DA), using SIMCA-P v13 (MKS Umetrics AB, Sweden). In order

153 to compress and interpret the internal relationships between variables, and at the same time

154 check whether there are some of these being able to segregate between the two analyzed

155 classes (deteriorated and not deteriorated figs), principal component analysis PCA (Jackson,

156 1991) was applied. PCA is a projection method of the original variables onto new ones, called

157 latent variables, orthogonal and arranged according to their explained variance. This is carried

158 out expressing a matrix X as:

159 $X = TP^{\mathrm{T}} + E$ (eq. 2)

160 where T is the score matrix, P is the loading matrix and E is the residual matrix for X. This

161 way makes it possible to determine the general pattern of any process, and the relevant

162 variables that rule it.

163 However, PCA does not necessarily search for those variables that better discriminate

164 between classes, but only for those gathering the highest variance in the data. Thus, when

165 looking for segregating, another latent-based multivariate projection model, such as PLS-DA

166 (Sjöström et al., 1986) is a more sensible technique to apply. PLS (Geladi & Kowalski, 1986)

167 models the data through the use of eq. 2 and these other following expressions:

168 $T = XW^* = XWP^TW$ (eq. 3)

169 $Y = TC^T + F$ (eq. 4)

170   where T is the score matrix, P the loading matrix for X, C the loading matrix for Y, W and W^*

171   weighting matrices, and F the residual matrix for Y.

172   In the case of PLS-DA, Y is built from as many dummy variables as classes we have to

173   segregate. A dummy variable is a binary variable formed by 1's and 0's, the former linked to

174   the class the dummy variable is related to, and zeros to the rest of observations. Hence, the

175   PLS-DA looks for those internal directions that best segregate the classes of interest, also

176   trying to explain X reasonably.

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

178    $$Y_{pred} = XB_{PLS} = TQ^T = XW(P^TW)^{-1}Q^T \qquad \text{(eq. 5)}$$

179   Where

180    $$B_{PLS} = XW(P^TW)^{-1}Q^T$$

181   When applied to images, these techniques belong to Multivariate Image Analyses, MIA

182   (Prats-Montalbán et al., 2011). Together they make up the most suitable analytical tools for

183   the trials that were carried out, taking into account that each sample was considered regarding

184   its 26 variables.

2.2.   In-line dried fig sorting

186   Due to the high complexity of handling small fruit and the relatively low market in

187   comparison to other fresh fruit, there are not commercial electronic sorters of dried figs to

188   separate them in qualities. Hence, there is a need to develop such sorter. For this purpose,

189   automated sorting trials based on a computer vision system were performed on an

190   experimental prototype, developed at the Laboratory of Artificial Vision for Agriculture

191   (IVIA-Spain) that was originally designed for mandarin orange segment and pomegranate aril

192   in-line sorting (Blasco et al., 2009a; Blasco et al., 2009b) and that was adapted for the sorting

193 of dried figs. It principally consists of three functioning elements: supply unit; inspection unit

194 and separation unit (figure 1).

195

196 Figure 1. *Picture of the in-line sorting prototype*

197 From the supply unit, fruit are spread on a number of conveyor belts, 30 mm wide and 250

198 mm long, moving at a relatively high speed (0.5 m/s). They pass through the inspection unit

199 which consists of two progressive scanning colour cameras (JAI CV-M77), placed at

200 approximately 0.9 m above the subject, that provide RGB images (512 x 384 pixels) with a

201 resolution of 0.70 mm/pixel. Cameras are equipped with 12 mm lens, and lighting is provided

202 by light emitting diode (LED) lamps. The entire system is housed in a frame of stainless steel

203 suitable for agro-food products. After each image processing, the computer sends data about:

204 fruit position, the number of the conveyor belt on which it is located, and the corresponding

205 category (issue) to the computer which is responsible for directing the movement of the

206 inspected fruit to the separation unit and its subsequent categorisation.

207   The trials considered 96 figs, which had previously been classified in the subsequent three

208   categories: 31 light PDO figs, 26 dark PDO figs and 39 deteriorated figs (figure 2). Each fruit

209   in the validation set went through the whole classification process five times in random

210   positions, orientations and sides, thus it was as if 480 figs were categorised. An additional set

211   of 24 figs was used to build the models and train the image processing software.

212   One of the requirements of current quality standards for dried figs is that the contents of each

213   package must be uniform (United Nations, 2014). Moreover, consumers are prone to purchase

214   lots with uniformity of colours and sizes. Hence, the output of each category was established

215   as follows:

216   • Category 0: (Light PDO figs): the fig arrives at the end of the conveyor belt.

217   • Category 1: (Dark PDO figs): the fig is ejected at the first outlet.

218   • Category 2: (Deteriorated figs): the fig is ejected at the second outlet.

a)   b)   c)
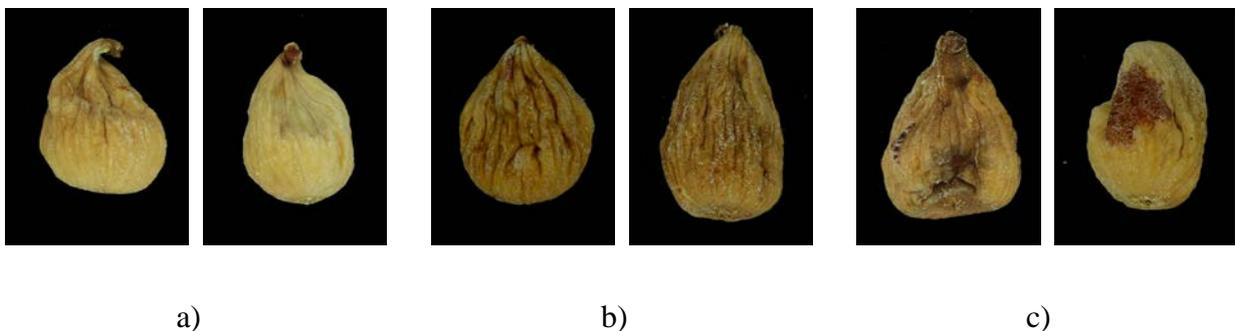
219   Figure 2. *Samples with different colours that should belong to different categories: a) light, b) dark*

220   *and c) defective uneven coloured figs*

221   In-line systems working in real-time have to run very fast image processing algorithms and

222   hence it is not possible to incorporate complex segmentation models although it could be

223   more effective in some cases. On the other hand, it is very important that the quality

224   parameters can be easily controlled by non-experienced workers trough a friendly interface.

225   This means that, the machine has to prioritize easy to handle methods to separate the fruits

226   over other maybe more robust but also more complex statistical methods.

227 Following this principle, image segmentation was developed based on the analysis of the

228 colour that was done on images captured with the mentioned industrial cameras under

229 dynamic conditions. As first step, each pixel in the image was classified as background or as

230 belonging to an object to be analysed. Since there was a great contrast between the white

231 background and the fruit, a threshold was enough to properly remove the background from

232 the image analysis. Preliminary analysis of the histogram of the training images determined

233 that a threshold value of $T_0=100$ in the green band could separate the fruit without error.

234 Therefore, any pixel with a value in the G channel above T_0 could be considered as belonging

235 to the background and removed. This operation was performed only in the regions of interest

236 corresponding to the conveyor belts while the parts of the images outside these regions were

237 not considered.

238 All remaining pixels in the images were considered as belonging to potential figs. Therefore,

239 the RGB values of the remaining pixels were converted into CIE XYZ and CIELAB

240 coordinates to calculate the BI.

241 To separate the pixels in the figs into any of the predefined classes it was necessary a previous

242 analysis. An analysis of the variance (ANOVA) was carried out for each variable using the

243 training samples to determine in which of the different available colour coordinates the figs

244 that belonged to different qualities could be better discriminated, or if it was necessary, a

245 combination of several colour coordinates. Once defined the variables, the thresholds among

246 the three classes initially set in the sorting prototype were established from the data extracted

247 the basic statistics (tables 3 and 4). Once determined the colour indexes and the thresholds,

248 the algorithms were programmed to classify the pixels in the images in one of the three

249 categories as follows, where the thresholds T_1 and T_2 were obtained from the previous

250 analysis:

251   •   If average $BI < T_1$ the pixel was considered deteriorated

252   •   If average $BI \geq T_1$ and average $XYZ.X < T_2$, the pixel was considered a dark PDO;

253   otherwise the pixel was considered as belonging to a fair PDO fig.

254 After the pixels-wise image segmentation, it was necessary to perform a filtering process in

255 order to reduce the noise caused by shadows found in the borders of the fig and by small

256 groups of isolated pixels. This process consisted on a two-iteration erosion of the complete fig

257 followed by a median filter. Finally, the decision about the category of the fig was set based

258 on the number of pixels of each class belonging to the fig, which is equivalent to classify the

259 fig into the class occupying the major area in the fig.

260 The sequence of image processing carried out by the sorting machine in real time is shown in

261 figure 3. The original image captured by the cameras shows the figs while they are

262 transported by the conveyor belts. The first step corresponds to the segmentation based on the

263 thresholds in the regions of interest defined by the known position of the conveyor belts. Then

264 the filtering is performed in order to reduce the noise and the segmentation problems caused

265 by shadows found in the borders of the figs. Finally, the decision is taken by counting the

266 amount of pixels belonging to the different classes. For the case shown in figure 3, attending

267 the decision of the vision system, the figs in blue belonged to the deteriorated class, the figs in

268 red are dark figs, and the fig in green is a light one.

269
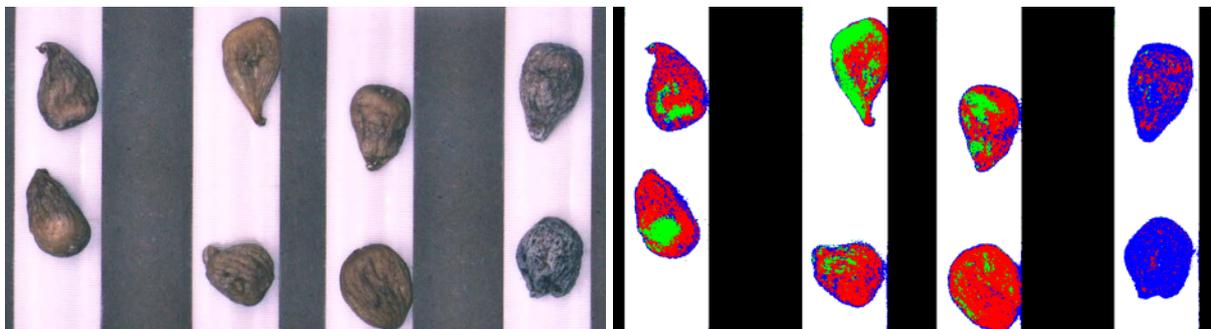
270   a)   b)
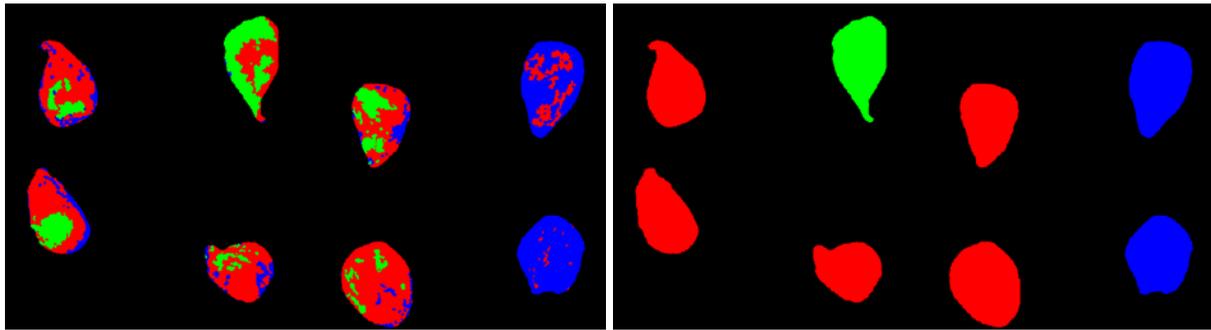
271

272   c)   d)

273 Figure 3. *Steps in-line image processing of the figs sorting machine. A) original image captured by the*

274 *cameras, b) segmented image, c) filtered image, and d) decision image*

275 The tests were carried out by placing the figs into a vibrating platform that guide the fruit

276 randomly to the different conveyor belts of the prototype. Each fruit was transported by the

277 conveyor belts, analysed and sorted by the outlet corresponding to their assigned category.

278 This was done for the different categories of fruit separately for a proper identification and

279 reference of the fruit once it was separated in the outlets, since it would be difficult to

280 properly identify each individual fruit in the outlets after being sorted by the machine if all of

281 the figs would had been tested in the same trial. After each trial, the fruit in the different

282 outlets was accounted and tested again for five times.

283 **3   RESULTS AND DISCUSSION**

284 **3.1.   Dried Fig colour assessment**

285 Figure 4 represents the score plot of PCA (2 PC's, R^2 81%), showing an overview of the

286 behaviour of each fruit belonging to the studied groups with PDO figs of Cosenza in black

287 and deteriorated ones in red. Here, as stated above, the analysis considered the totality of

288 variables (26), that is, those obtained by conventional colourimetry as well as those obtained

289 from image processing. In this case, the PCA model is able to segregate the two classes. In

290 order to assess for which ones are mainly responsible for segregation, the loadings plot (figure

291 5) is inspected.
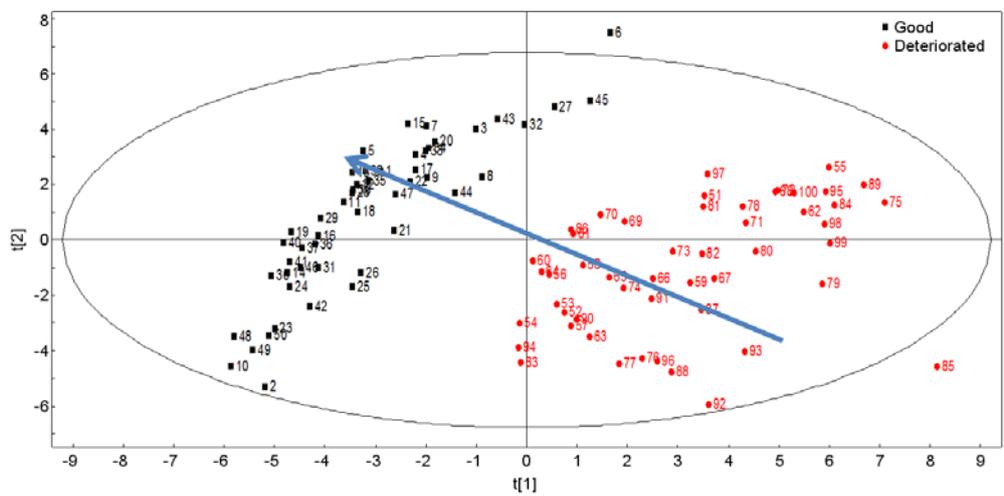
292

293 Figure 4. *Score plot of PCA results considering all the variables (image analysis and conventional*

294 *colorimetry). The ellipse represents 95% confidence interval.*

295 The segregation between class 1 (sound figs represented by black points) and class 2

296 (deteriorated figs represented by red points) is mainly characterized by the variables

297 XYZ.Zcol, XYZ.Zimg and L/a on one hand, and CIEb_img, Huntb_col, and CIEb_col, on the

298 other hand.

299
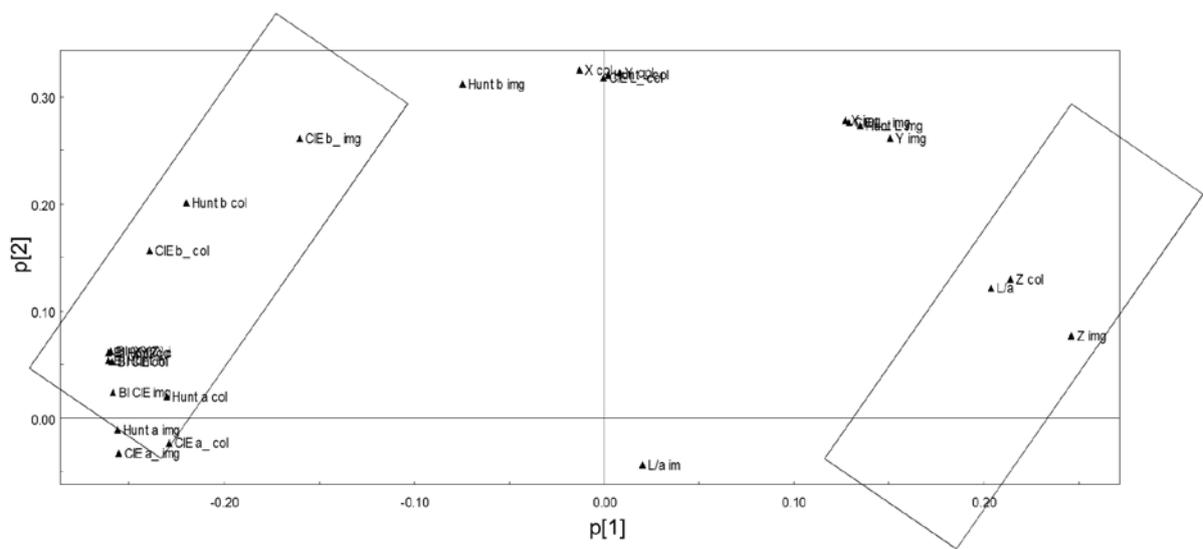
300 Figure 5. *Loading plot of PCA results considering all the variables (image analysis and conventional*

301 *colorimetry). The rectangles include the most segregating variables.*

302 PLS-DA results highlight two clusters, each one corresponding to one of the assessed groups

303 of figs (figure 6). The plot shows that the first component is able to segregate between the two

304 classes. From the PLS-DA weights of the first component (figure 7), the variables responsible

305 for the segregation can be derived. Note that, in the case of having more than one discriminant

306 component in the model, other approaches (e.g. VIP's) would be more sensible. Nevertheless,

307 in this case, since the discriminant direction is mainly related to the fist latent variable, both

308 approaches provide equivalent results (see figure 8), with the advantage that the weights

309 provide the positive or negative correlation of each variable with each of the classes to be

310 segregated. It must be stated that, for classification purposes, the model was built with 5 latent

311 variables and an R2Y value of 96.5% and a Q2Y value of 95%, which in practice means that

312 all figs where correctly classified in a 7-blocks cross-validation procedure. However, this was

313 not the goal of the analysis, but selecting the most discriminant variables and comparing them

314 with the ones used in the already built in-line sorting machine.

315 On the other hand, the score plots of PCA and PLS-DA show similar clusters for the two

316 studied groups, and PCA confirms that the XYZ.Z coordinate is one of the best discriminant

317 variables. The difference between the two score plots lies in the fact that PCA does not look

318 for segregating both classes, but for maximizing the variance, as previously stated. Anyway,

319 since the rotation in the components is not very large, the variables indicated by the loadings

320 barplot (figure 9) are almost the same as the ones outlined by the first component weights of
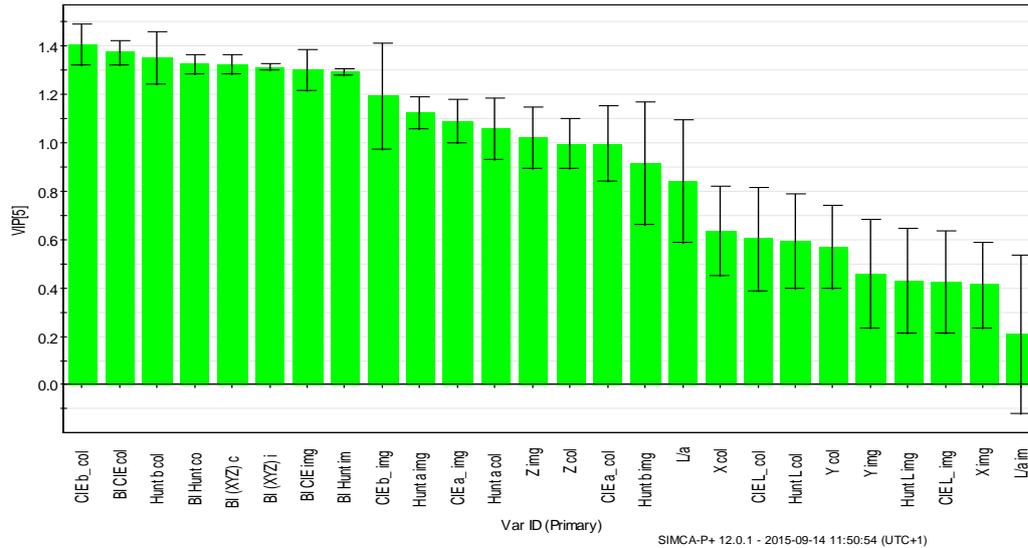
321 the PLS-DA model (figure 7).

322
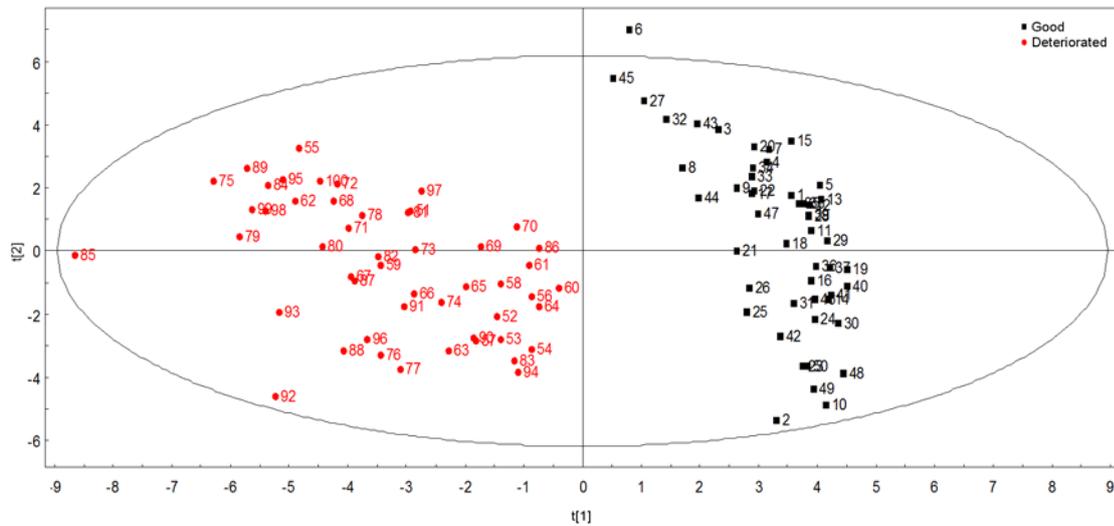
Figure 6. *Score plot of PLS-DA results considering all the variables (image analysis and conventional colorimetry). The ellipse represents 95% confidence interval.*
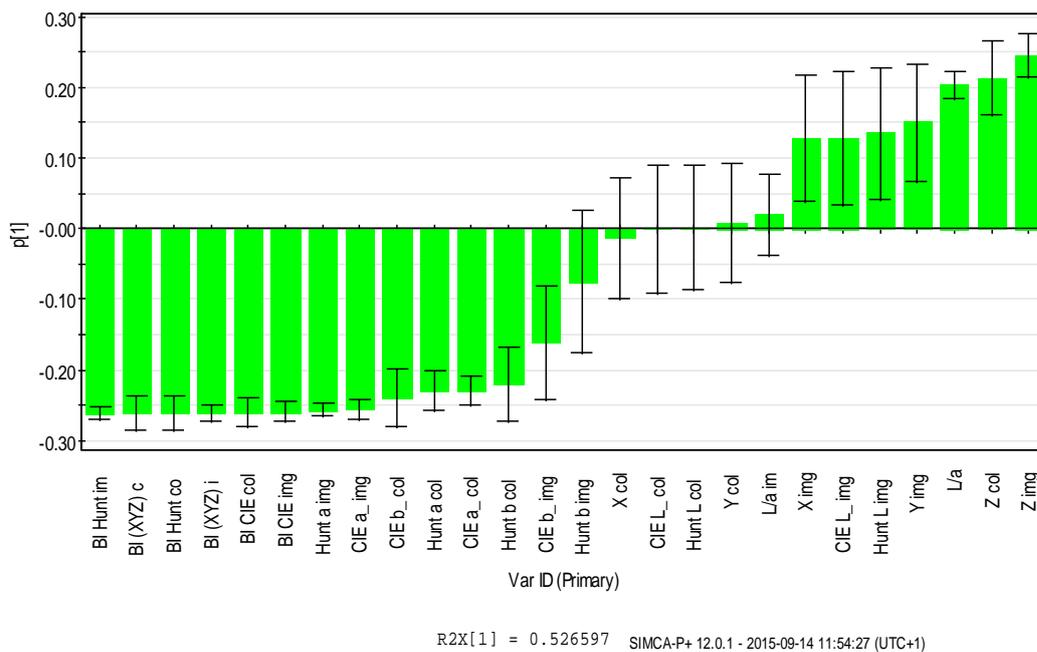

325
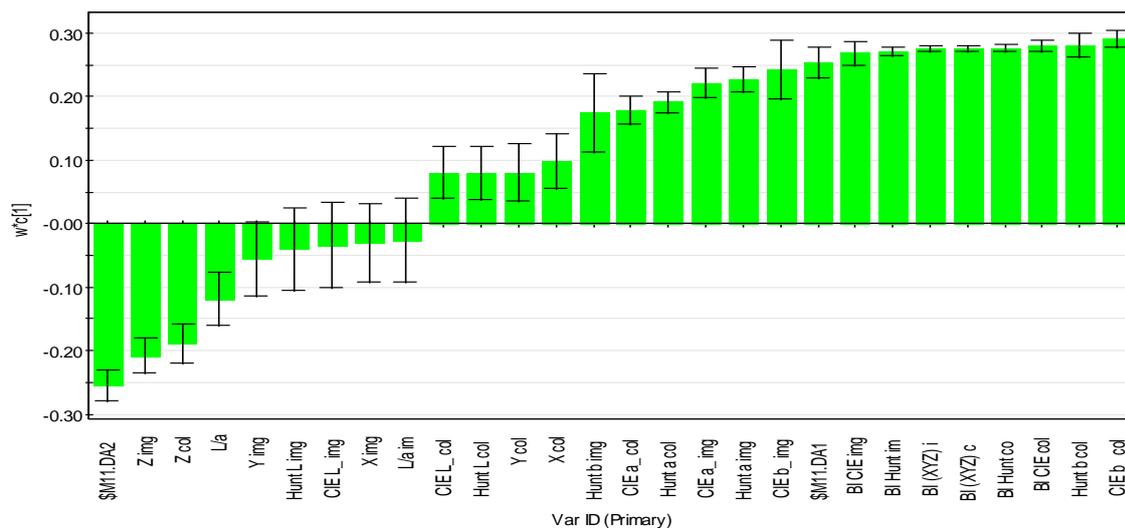
Figure 7. *Weights plot of the first component of the PLS-DA model considering all the variables (image analysis and conventional colorimetry)*

328

Figure 8. *VIP's plot of the first component of the PLS-DA model considering all the variables*

(image analysis and conventional colorimetry)

331

Figure 9. *Columns plot of PCA for the first component considering all the variables (image analysis*

and conventional colorimetry)

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 currently destructive methods

338 based on sampling for this purpose. The browning index seemed to be an interesting index

339 that showed this distinction, and therefore a valid indicator for dried fig quality assessment

340 but the colour measurement in some different spaces did not present significant differences.

341 Nevertheless, note that, depending on the study, the discriminant directions in PCA (if any)

342 might not be necessarily on the first components, hence being mandatory to look for them

343 throughout the ones gathered in the model (Prats-Montalbán et al., 2006).

3.2. In-line dried fig sorting

345 The methods, conditions, aims and equipment used for classifying the fruit in real-time using

346 and industrial machine are different from those used to assess colour using a standard

347 colorimeter and hence new variables need to be selected. ANOVA's carried out on the main

348 discriminant variables highlighted by the PLS-DA and PCA analyses achieved similar results

349 in terms of significance. From these analyses, variables *BI* and *X* were selected for

350 segregating the different categories of figs during the in-line real-time inspection using the

351 machine since the study of the basic statistics clearly determined that it was possible to set

352 thresholds to separate among the different categories. Tables 1 and 2 show the ANOVA for

353 these variables while tables 3 and 4 show the summary of the statistics. Browning index could

354 be clearly used to separate between good and defective figs and it was decided from these

355 data to use a threshold value of $T_1=35$. On the other hand, dark and light figs could be

356 separated using the *X* colour value and hence, using the data in table 4, a threshold value of

357 $T_2=7$ was configured in the machine.

358 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

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

371   according to the colour of the side showing as they randomly passed. It has to be remarked

372   that the results correspond to the inspection of the validation set of the figs five times, but

373   each time they fall down in a random position, orientation and side on the conveyor belts and

374   were captured in a different and random location in the image. This means that for each time,

375   the conditions and lighting of each particular fig were different.

376   A certain degree of confusion is normal using the fast classification method implemented.

377   However, the main confusion occurred between classes light and dark which could be

378   acceptable since both are good quality figs separated only for commercial reasons. On the

379   other hand, a little confusion happened between good and deteriorated figs that are more

380   important from the point of view of the final quality. An aspect to improve is that the machine

381   classified 3.8% deteriorated figs as dark, which, even it could be under a tolerance of 5%,

382   should be reduced. On the contrary, it would be of less importance if dark figs were classified

383   as deteriorated. These results illustrate that fig sorting, using the above-described system, was

384   achieved successfully. The highest percentage was obtained each time for deteriorated figs,

385   followed by light PDO ones, and then dark PDO figs.

386   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%

387

388   To identify a specific index to determine accurately the quality for PDO dried figs of

389   Cosenza, the achieved analysis has to be consolidated by further research, taking into account

390   additional parameters i.e., colour change according to ripeness, drying status as well as the

391   correlation of skin colour with the contents of anthocyanins (Rodov et al., 2012). This may be

392   achieved and incorporated in the future to the in-line sorting machine with the use of faster

393   computing units.

394   Some of the problems found could be resolved using, instead of conveyer belts, bi-conic roller

395   conveyors (ElMasry et al., 2012) which turn the fruits as they progress, allowing the system to

396   inspect their whole surface. On the other hand, a complex analysis of the colour or the texture

397   of the figs would result in a better accuracy of the classification, but the computing

398   requirements would not ensure actual real-time processing at a commercial speed.

399   Image processing time was about 15 ms, permitting an analysis of up to 65 images/s.

400   However, due to mechanical limitations of the prototype, and also because a very high speed

401   could damage the product when it is expelled by the outlets, the speed of the conveyor belts

402   was limited to 0.5 m/s, obtaining then 10 analysed images per second. Considering an ideal

403   distance of 0.1 m between two consecutive figs, at the highest speed of the conveyor belts

404   (0.5 m/s), the tested prototype has the productivity of about 40 figs/s, corresponding

405   approximately to 2160 kg/hour. The system has been proved on a prototype with several

406   mechanical limitations, it is expected that the performance in terms of accuracy and capacity

407   of fruit process is higher when the system will be developed into an industrial machine.

408   **4   CONCLUSIONS**

409   As currently carried out, dried fig inspection and grading methods are labour intensive and

410   unreliable due to machine speed and inspector fatigue. Therefore, the development of an

411   effective integrated inspection system that can detect quality according to previously

412   established parameters of the whole fruit would be valuable for the fig industry. The present

413   work showed that the combination of computer vision systems and latent-based multivariate

414   statistical projection models used for this purpose allowed these objectives to be reached

415 under laboratory conditions for manual quality inspection which can be suitable for small

416 productions or when only the control of a few number of samples is required. These results

417 are interesting because they illustrated that both, chroma meter and image analysis allowed an

418 effective distinction between high quality dried figs and deteriorated ones, based on colour

419 parameters, being the photographic camera much cheaper and easy to use than the chroma

420 meter.

421 A system for in-line sorting of figs in real-time was developed based on computer vision and

422 colour parameters providing reliable results. This is the first attempt to create a machine

423 capable of sorting dried figs in real-time using computer vision and a machine with capability

424 of separating the fruit into different categories. The system could classify correctly between

425 three classes of figs using the browning index and the X colour coordinate. The test were

426 carried out in dynamic conditions with the figs being transported under the camera at high

427 speed, and later separating the figs into different categories by different outlets depending on

428 the decision of the vision system. This was repeated five times achieving always good results,

429 having the major confusion between the two classes of sound figs but a little confusion of

430 only 0.5% was done between sound and defective figs which is the most important from the

431 commercial point of view.

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