



MEASUREMENT OF COLOUR OF CITRUS FRUITS USING AN AUTOMATIC COMPUTER VISION SYSTEM

MASTER IN SCIENCE AND ENGINEERING OF FOOD

Alumno: Anna Vidal Zaragoza

Directores: Pau Talens Oliag

José Blasco Ivars

Escuela Técnica Superior de Ingeniería Agronómica y del Medio Natural

School of Agricultural Engineering and Environment

MEASUREMENT OF COLOUR OF CITRUS FRUITS USING AN AUTOMATIC COMPUTER VISION SYSTEM.

Anna Vidal¹, José Blasco², Pau Talens¹

ABSTRACT

A key aspect for the consumer to decide on a particular product is the colour. In order to provide as soon as possible fruit available to consumers, citrus begin to be collected before they reach their typical orange and therefore are subject to certain degreening treatments, depending on their initial coloration. Recently, there has been developed a mobile platform that is capable of performing this process in the field while the fruit is harvested. However, due to the restrictions of working in field conditions, the computer vision system equipped in this machine is limited in its technology and processing capacity compared to conventional systems. This work evaluates this automatic inspection system of citrus colour and compares it with two devices; a characterized computer vision system and spectrophotometer used as reference in the analysis of colour on food. The results obtained prove that the industrial image analysis system equipped in the mobile platform predicts the colour index of citrus with a good reliability (R2 = 0.975) and is effective for classification of the fruit according to its colour.

Keywords: colour analysis, citrus fruits, degreening, machine vision

RESUM

Un aspecte fonamental per a que el consumidor es decideixi per un producte determinat és el color. Amb l'objectiu de posar al més aviat possible les fruites a la disposició dels consumidors, els cítrics comencen a recol·lectarse abans que aconsegueixin el seu color taronja típic i per això es sotmeten a determinats tractaments de desverdizació, que depenen de la seva coloració inicial. Recentment s'ha desenvolupat una plataforma mòbil que és capaç de realitzar aquest procés en el camp alhora que es recol·lecta la fruita. No obstant això, a causa de les peculiaritats i restriccions del treball en el camp, el sistema de visió per computador que incorpora aquesta màquina és limitat quant a la seva tecnologia i capacitat de processament respecte d'un sistema convencional. Aquesta tesina avalua aquest sistema

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¹ Instituto Universitario de Ingeniería de Alimentos para el Desarrollo - Departamento de Tecnología de Alimentos. Universidad Politécnica de Valencia. 46022 Valencia, España

² Instituto Valenciano de Investigaciones Agrarias, Carretera Moncada - Náquera, Km. 4,5 Apartado Oficial, 46113 Moncada (Valencia)

d'inspecció automàtica de color de cítrics i ho compara amb altres dos dispositius, un sistema caracteritzat de visió per computador i un espectro colorímetre emprat com a referència en el mesurament de color en aliments. Els resultats obtinguts proven que el sistema d'anàlisi d'imatge industrial amb el que està equipat la plataforma mòbil prediu l'índex de color dels cítrics amb una bona fiabilitat (R2=0.975) i és eficaç per a classificació de les fruites segons el seu color.

Paraules clau: anàlisi de color, cítrics, desverdizació, visió per computador.

RESUMEN

Un aspecto fundamental para que el consumidor se decida por un producto determinado es el color. Con el objetivo de poner lo antes posible las frutas a disposición de los consumidores, los cítricos comienzan a recolectarse antes de que alcancen su color naranja típico y por ello se someten a determinados tratamientos de desverdización, que dependen de su coloración inicial. Recientemente se ha desarrollado una plataforma móvil que es capaz de realizar este proceso en el campo a la vez que se recolecta la fruta. Sin embargo, debido a las peculiaridades y restricciones del trabajo en el campo, el sistema de visión por computador que incorpora esta máquina es limitado en cuanto a su tecnología y capacidad de procesamiento respecto de un sistema convencional. Esta tesina evalúa este sistema de inspección automática de color de cítricos y lo compara con otros dos dispositivos, un sistema caracterizado de visión por computador y un espectrocolorímetro empleado como referencia en la medición de color en alimentos. Los resultados obtenidos prueban que el sistema de análisis de imagen industrial que equipa la plataforma móvil predice el índice de color de los cítricos con una buena fiabilidad (R²=0.975) y es eficaz para clasificación de las frutas según su color.

Palabras clave: análisis de color, cítricos, desverdización, visión por computador.

INTRODUCTION

Colour is one of the most important attributes of agrifood products, since consumers associate it with freshness and is critical in the acceptance of a particular product among others (Campbell et al., 2004). Producers strive to prevent products with defective colorations from reaching the market (Pedreschi, et al., 2000; Abdullah et al., 2004; Hatcher et al., 2004), as well as ensuring that individual products are packed in batches with a similar colour (Díaz et al., 2000; Blasco et al., 2009a). It is also important to measure how post-harvest treatments affect the colour of fruits (Cubero et al., 2010). When an object is visually assessed, three physical factors must be present. There must be a source of light, the object, and a light receptor mechanism. There are different standard sources of light, but the most widely used in colour measurement of food is the standard D65 (Noburu and Robertson, 2005) which corresponds to the spectral distribution of mid-day sun in Western Europe, being recommended as the standard daylight illuminant by CIE (Gilabert, 2002). The light receptor mechanism normally converts the light stimulus into electrical signals that are later interpreted like the numerical description of the response to the colour perceived by the human

Colorimeters are electronic devices for colour measurement that express colours in numerical coordinates. However, colorimeters are limited to the measurement of small regions of a surface or when the object has a homogeneous colour (Gardner, 2007). Instead, still or video cameras can provide images in which the colours of the pixels are determined individually being more suitable for cases where the surface has a heterogeneous colour (Yam and Papadakis, 2004). The colour of a particular pixel in an image is expressed by three coordinates in a colour space. The primary colours red, green and blue (RGB) are the most widely used in computer vision. When inspected objects have very different colours, sometimes simple ratios between RGB values can discriminate between them, thus saving processing time. For instance, Blasco *et al.*, 2009 used the *R/G* ratio to discriminate four categories of pomegranate arils, reaching a success rate similar to the ones obtained by visual inspection.

The mayor drawback of RGB is that is a device dependent colour space, which means that the resultant colour depends on the equipment and set-up used to produce it; different devices produce different RGB values for the same pixels in a scene. For this reason, other colour spaces, closer to the human perception of colour are frequently employed, like HIS (Quevedo et al., 2010). Blasco et al., 2007 compared five colour spaces for the identification of external defects in citrus fruits and obtained better results with HSI. Both RGB and HSI were used by Xiaobo et al., 2007 to classify Fuji apples into four colour categories. Frequently, individual HSI coordinates provide simple means of colour segmentation. Abdullah et al., 2006 converted RGB into HSI coordinates, and used the H component to classify starfruits into four maturity categories.

However, RGB or HSI are non-uniform colour spaces. This means that the same numerical distance between two colours in these spaces may produce distinct differences of human perception depending on the position of such colours in the space. Uniform spaces like CIELAB or Hunter L,a,b define distances that produce the same differences in perception regardless of the position of the colours, and for this reason they are very well suited for colour comparison. Several works have compared different colour spaces and the conclusion being that the most appropriate for measuring fruit colour is CIELAB (Mendoza $et\ al.$, 2006; Leon $et\ al.$, 2006). CIELAB coordinates are L^* (luminosity), a^* (green to red) and b^* (blue to yellow) while HunterLab coordinates are denote by L,a,b (Gilabert, 2002).

Both spaces derives from the CIE 1931 XYZ colour space (Smith and Guild, 1931), but HunterL,a,b is calculated using square roots whereas CIELAB is calculated using cube roots (Hutchings, 1999). Choosing one space colour or another depends on several factors. In this work the Hunter L,a,b system was selected because this is the system to determine the citrus colour index (CCI) (Cuquerella *et al.*, 2004).

For instance, simple algorithms based on a single L^*,a^*,b^* coordinate have been used for the classification of fruits with a characteristic skin colour. The a^* coordinate was used by Liming and Yanchao, 2010 to grade strawberries and the machine vision system achieved a success rate of 89%. Hue angle and chrome are colour features derived from the above-mentioned uniform spaces. Kang *et al*, 2008 quantified the effect of the curvature of the skin on the calculation of hue angle and chrome of mangoes and demonstrated that hue provided a valuable quantitative description of the colour and colour changes of individual fruit and heterogeneous batches. Sometimes standard indexes combine these coordinates in one single ratio that is easier for operators to handle. For instance, colour indexes of tomatoes and their relationship to visual colour classification were compared by López-Camelo and Gómez, 2004.

An application where the inspection of the colour is needed is the assessment of citrus fruits. Fruits are manually harvested, then loaded in boxes and transported to a packing house, where the fruit is sorted. In the early season, this sorting is aimed at classifying by colour, because fruit is treated separately (orange fruits go directly to the market, orange-green suffer a 24 hour degreening process and green fruit suffer a 72 hour degreening). The Citrus Colour Index (CCI) in the citrus industry is used to determine the harvesting date or to decide if citrus fruits should undergo a degreening treatment (DOGV, 2006). In order to reduce the production costs, it has been developed a harvest-aid platform capable of automatically inspect and sort citrus in the field in three colour categories while fruits are harvested, thus, providing valuable data when the fruit arrive to the packinghouse and allowing the optimisation and planning of further operations. Depending on the sorting done by the machine, the fruit is stored or receive a particular treatment when arrives to the packing-house, therefore it is very important to perform an accurate colour classification.

To sort the fruit, a computer vision system has been specifically developed for the inspection of the external quality of citrus fruits. In this work, the potential for in-line colour assessment of the industrial computer vision equipped in the harvest-aid platform is compared with a reference

colour acquisition device to know the accuracy of this new sorting system. However, industrial machine vision systems for in-line inspection are not as reliable as high quality still cameras are in terms of image quality and colour fidelity (Berns, 2000). Therefore, a characterised high quality image acquisition system has been included in the study in order to set the true potential of an automatic imaging system to reproduce the colours of the fruits.

In brief, the aim of this work was to improve the existing harvesting techniques by using colour classification, and show the efficiency of the Machine Vision in colour classification, comparing with a spectrophotometer and a digital camera images.

MATERIAL AND METHODS

Imaging systems

To develop the experiments, three colour measured systems have been used, the first one was composed by a spectrocolorimeter used for reference since this is a device commonly used in the industry to measure colour. The second one was composed by a high resolution still image capture system. The third was an industrial computer vision system to determine if the measurement of colour of citrus fruits can be automated.

Description of the spectrophotometer

Minolta spectrophotometer CM-700d (figure 1) was used to obtain the spectral reflection curve. The equipment uses a pulsed xenon lamp (with ultraviolet cut filter) as light source and a silicon photodiode array as a detector. The instrument utilizes the di:8°/de:8° geometry and offers measurement with automatic specular component included and specular component excluded switching.



FIGURE 1. Measurement with the spectrophotometer CM-700d

Laboratory computer vision system

A digital camera (Canon EOS 550D) was used to acquire high quality images with a size of 2592 x 1728 pixels and a resolution of 16 pixel/mm. The images were taken by placing each sample inside an inspection chamber in which contained the camera and the lighting system. The camera was placed vertically at a distance of 20 cm from the samples. Illumination was achieved using four lamps that contained two fluorescent tubes each (Osram L 18W/965 BIOLUX), with a colour temperature of 6500°K, and a colour index (Ra) greater than 90 %. The angle between the axis of the lens and the sources of illumination it was approximately 45° since the diffuse reflection responsible for the colour occurs at 45° from the incident light (Francis and Clydesdale, 1975; Hutchings et al., 2002), although since the samples have a spherical shape bright spots that can affect the colour measurement are reflected in any case towards the camera. To minimise the impact of these specular reflections, the interior sides of the inspection chamber were coated by anti-reflective material and cross polarisation was used by placing polarising filters in front of the lamps and in the camera lenses. The fluorescent tubes were powered by means of high frequency electronic ballast to avoid the flickering effect of the alternate current and produce a more stable light. Figure 2 shows the laboratory computer vision system used in the experiment.

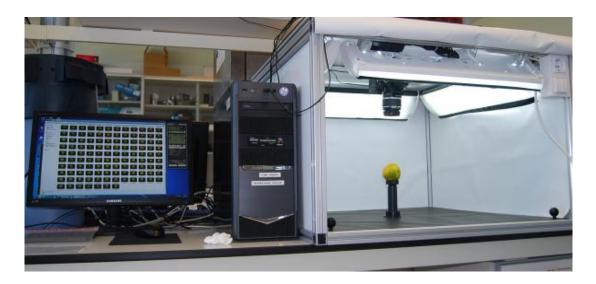


FIGURE 2. Inspection chamber used to capture high resolution images

The application EOS utility[©] (Canon Inc, Japan) was used to capture four images of different position of each fruit (next to the calyx, next to the stem and two along the equatorial perimeter). This software allows tuning all the camera parameters like the ISO, shutter speed or resolution without handling the camera. The settings of the camera used in our experiments are summarized in Table 1.

TABLE 1. Parameters used to capture the images

Variable	Value
Shutter speed	0.5 seconds
Opening	F2 2
Image Recording Quality	Small / Fine
ISO	400
White balance	White fluorescent light
Metering mode	Centre-weighted average metering

Industrial computer vision system

The images taken under industrial conditions have been captured using a mobile platform for harvesting assistance of citrus fruits that is capable of infield sorting the harvested fruit in three different categories of quality using a computer vision system. The machine basically consisted of a central conveyor belt that received the fruit deposited by the pickers on lateral, perpendicular conveyors. The central conveyor is followed by a finger system that elevates the fruit to the upper part of the machine. There, a series of rotating elements individualized the fruit and separated it in two lanes. Fruit entered the inspection chamber on rollers, so fruit was rotated and translated under the camera. Once the fruit is inspected, it is sorted depending on the data extracted from the images (Cubero *et al.*, 2010). A full view of the machine is shown in Figure 3.



FIGURE 3. Mobile platform for citrus fruits harvesting

The computer vision system of the machine was composed of a smart camera (Sony, XCI-SX 100C/XP) which integrates a microprocessor and therefore does not need external processing unit, like a computer. The camera operates under Windows XP operating system, the software to acquire and process the images being programmed in language C. The settings of the camera used in our experiments are summarized in Table 2. The light source used to acquire the images was composed of four strips of 500 mm length with 50 LEDs each strip. Each LED of 0.3 W produces light with a colour temperature of 6000°K and a colour reproduction of 70 Ra. Polarising filters were used to avoid bright spots. The four images taken of each fruit were stored in BMP graphic file format for later analysis.

TABLE 2. Parameters used to capture the images

Variable	Value
Shutter speed	1/125
Opening	F1.4
Focal	Standard fixed focal length lens of 8mm
Distance camera - object	645 mm
White balance	5600°K
Scene size	387 x 290 mm (8 oranges)

Fruit used

Experiments were carried up with a set of 120 oranges of the Navelina cultivar. Fruits were chosen randomly from the production line of a packing house and had colours varied from green and yellow with some green spots to orange. Each fruit was labelled and the colour measured with the three devices. A total of 60 samples were used to perform the regression model while other 60 were use to test the model.

Feature selection

The spectral reflection curve of the six points of each orange was taken using the spectrophotometer, and the average curve of these points was calculated. This average curve was integrated wavelength by wavelength through the visible range, with illuminant spectral emission D65 and standard observer 10°. The areas under the resulting curves yield the values of X, Y and Z coordinates (Hutchings, 1999; Chiralt *et al.*, 2007). The XYZ coordinates were used to calculate the HunterLab parameters (equation 1, 2 and 3) and with them, the corresponding CCI using the equation 4.

$$L = 100 \sqrt{\frac{Y}{Y_n}} \tag{1}$$

$$a = K_a \cdot \frac{\left[\left(\frac{X}{X_n} \right) - \left(\frac{Y}{Y_n} \right) \right]}{\sqrt{\frac{Y}{Y_n}}}$$
 (2)

$$b = K_b \cdot \frac{\left[\frac{Y}{Y_n} - \left(\frac{Z}{Z_n}\right)\right]}{\sqrt{\frac{Y}{Y_n}}}$$
(3)

Where:

$$K_a \approx \frac{175}{198.04} \cdot (X_n + Y_n)$$
 $K_b \approx \frac{70}{218.11} \cdot (Y_n + Z_n)$

Xn, Yn and Zn values depend on the combination illuminant–observer used. For this work, $X_n = 94,811$; $Y_n = 100$; $Z_n = 107,304$ (illuminant D65 and observer 10°).

$$CCI = \frac{1000 \cdot a}{I \cdot b} \tag{4}$$

The images of the fruits were acquired using the digital camera and industrial camera. The colour of the pixels in the image was codified in RGB colour space and, therefore, they had to be converted to HunterLab system. Here they are described the formulas used to convert the RGB value of pixels in the images to the Hunter Lab colour space. The first step is to normalize the RGB values to rgb values, which are values between 0 and 1 (equation 5).

$$r+g+b=1 (5)$$

If R, G or B are greater than 0.04045, equation 6 is applied, otherwise equation 7 is used.

$$r = \left(\frac{R + 0.055}{1.055}\right)^{2.4} g = \left(\frac{G + 0.055}{1.055}\right)^{2.4} b = \left(\frac{B + 0.055}{1.055}\right)^{2.4}$$
 (6)

$$r = \left(\frac{R}{12,92}\right) \quad g = \left(\frac{G}{12,92}\right) \quad b = \left(\frac{B}{12,92}\right)$$
 (7)

Then, it is necessary to transform RGB to XYZ coordinates. It was used the matrix values for the illuminant D65 and observer 10° that it is shown in equations 8 and 9.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = 100 \cdot [M] \begin{bmatrix} r \\ g \\ b \end{bmatrix}$$
 (8)

$$[\mathbf{M}] = \begin{bmatrix} 0,4116694 & 0,3567891 & 0,1796505 \\ 0,2126729 & 0,7151522 & 0,072175 \\ 0,0140739 & 0,113932 & 0,9450441 \end{bmatrix}$$
(9)

Thus, developing equation (8) and using (9) the values of X, Y and Z can be obtained from equation 10, 11 and 12.

$$X = 100 \cdot r \cdot 0.4116694 + 100 \cdot g \cdot 0.3567891 + 100 \cdot b \cdot 0.1796505$$
 (10)

$$Y = 100 \cdot r \cdot 0.2126729 + 100 \cdot g \cdot 0.7151522 + 100 \cdot b \cdot 0.072175$$
(11)

$$Z = 100 \cdot r \cdot 0.0.0140739 + 100 \cdot g \cdot 0.113932 + 100 \cdot b \cdot 0.9450441$$
 (12)

Hunter Lab coordinates were obtained from XYZ values using equation 1, 2 and 3.

This process is computationally very costly in terms of processing time if it is done for each pixel of the image. To speed up the process, the equations described were used to calculate off line the CCI of all possible RGB values, being these values stored in a Look Up Table (LUT). This table is preloaded in the memory of the computer, therefore during the in-line processing it is possible to process the entire image obtaining the HunterLab value of each pixel just by consulting the LUT, which reduces dramatically the computational cost but instead of requiring a greater amount of free memory to store the table.

To decide the CCI of a fruit, two different algorithms were tested in order to know the accuracy of each one:

1) The RGB value of all pixels in the image belonging to fruit was converted to HunterLab (the LUT is consulted for each pixel). Then the CCI was calculated for each pixel. The CCI of the image is calculated as the mean of the CCI of all pixels of the fruit. (Figure 4).

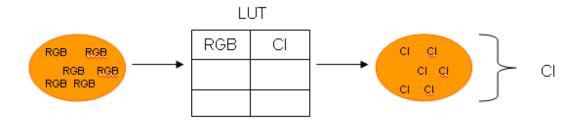


FIGURE 4: Obtaining CCI from the average of the CCI

2) The mean of all the RGB values of the pixels belonging to the fruit is calculated. The resulting value was transformed using the LUT in the CCI value. The result it was called PIXIC. (Figure 5).

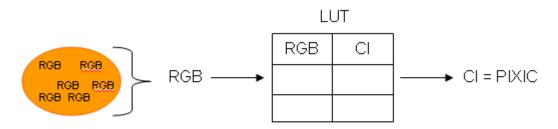


FIGURE 5.Obtaining CCI from the average of RGB values.

The CCI of the fruit was calculated as the mean of the CCI of the four partial images of the fruit.

Test

The values of CCI estimated for each fruit by the laboratory and industrial vision systems were compared with those obtained using the spectrophotometer by means of a quadratic regression and performing a classification.

Three tests were carried on during this work:

- a) To assess which approach for image analysis provides more accurate prediction of the CCI.
- b) To determine the industrial and laboratory vision systems behaviour towards the spectrophotometer
- c) To compare the classification done by the industrial and laboratory vision systems against the classification done by the spectrophotometer.

The statistical analysis of data was performed through analysis of variance (ANOVA) using SPS[©] 17.0 (IBM Corporation, USA).

The classification thresholds to determine if the fruit needs to be treated for degreening is based on the CCI (Jimenez-Cuesta *et al.*, 1981) are summarised in table 3. These values were used to classify the fruit attending the CCI obtained for each system. The success ratio for the industrial computer vision system was obtained from the confusion matrixes from this system and the others.

TABLE 3. Recommendations for the treatment of degreening of oranges and tangerines (Jimenez-Cuesta *et al.*, 1981).

CCI	Mandarins	Oranges
CCI < -13	Not necessary	Not necessary
-13 > CCI < -5	72 h with ethylene	Not necessary
-5 > CCl < +3	48 h with ethylene 72 h without ethylene	72 h with ethylene
CCI > +3	24 h with ethylene 48 h without ethylene	48 h with ethylene 72 h without ethylene
CCI > +7	Not required	Not required

RESULTS AND DISCUSSION

Figure 6 shows the CCI estimated using the three different methods.

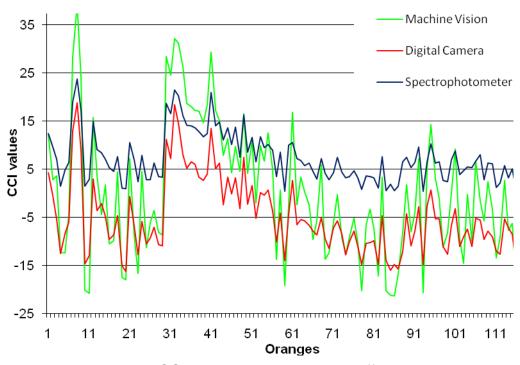


FIGURE 6. CCI estimated by the three different devices

In this figure it is possible to observe how the value of CCI obtained for the different devices for each fruit has the same trend. They are more similar in the case of the imaging systems while the spectrophotometer presents slightly higher values compared to the other two. In order to know the actual relationship between the three measurements, a linear regression was carried out.

For the first algorithm (estimating the CCI for each pixel, then the average CCI), the results show a value a R^2 value of 0.963 between the spectrophotometer and the in-line system and a R^2 of 0.980 between digital camera and the spectrophotometer. These correlations were slightly better than for the second algorithm (estimating the average RGB, then the CCI) that obtained a R^2 value of 0.975 between the spectrophotometer and the inline system and a R^2 of 0.981 between digital camera and the spectrophotometer. In consequence, the second algorithm is more accurate to estimate the CCI.

To determine the industrial and laboratory vision systems behaviour towards the spectrophotometer, regression models were built and analysed using SPSS. Tables 4 and 5 present the corresponding Multiple regression analyses.

TABLE 4. Multiple regression analysis of the industrial vision system (n=120)

	Unstandardised Coefficients		Standardised Coefficients		
	В	Std. Error	Beta	t	Sig.
Industrial system	0.340	0.007	0.959	46.594	0.000
Industrial system2	0.002	0.000	0.083	4.008	0.000
Constant	8.228	0.144		57.073	0.000

TABLE 5. Multiple regression analysis of the laboratory vision system (n=120)

	Unstandardised Coefficients		Standardised Coefficients		
	B Std. Error		Beta	t	Sig.
Laboratory system	0.613	0.011	0.989	53.932	0.000
Laboratory system2	0.002	0.001	0.032	1.755	0.082
Constant	10.293 0.136			75.678	0.000

The quadratic regression was the most significant in the case of the Industrial system, with a p-value < 0.05, but the statistical significance of the quadratic term for the laboratory vision system was doubtful (p-value =0.082).

Tables 6 presents the analysis of variance and the R^2 and adjusted R^2 of the model for the industrial vision system and table 7 the analysis of variance and the R^2 and adjusted R^2 of the model of the laboratory vision system. In both cases R^2 and adjusted R^2 are very similar indicating that the models fit very well.

TABLE 6. Analysis of variance, R² and adjusted R² of Industrial System.

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2996.596	2	1498.298	1148.505	0000
Residual	152.634	117	1.305		
Total	3149.230	119			
				Std. E	rror of the
R	R Square	Adjusted R Square		Est	timate
0.975	0.952	0.951		1	.142

TABLE 7. Analysis of variance, R² and adjusted R² of Laboratory System.

	Sum of Squares	df	Mean Square	F	Sig.
Regression	3033.706	2	1516.853	1536.229	0.000
Residual	115.524	117	0.987		
Total	3149.230	119			
				Std. E	rror of the
R	R Square	Adjusted R Square		Est	timate
0.981	0.963	0.963		0	.994

The industrial and laboratory imaging systems use the same procedure for getting the colour information from the fruits, which could be the reason to present the same behaviour towards the Spectrophotometer. Therefore we assume the type I risk of 8 %.

The quadratic regression model was used for recalculating the CCI values (PIXIC) obtained using the imaging systems, thus obtaining new values so-called "PIXIC transformed". Figure 7 shows the same values of Figure 6 after the transformation, being evident how they fit better after applying the model.

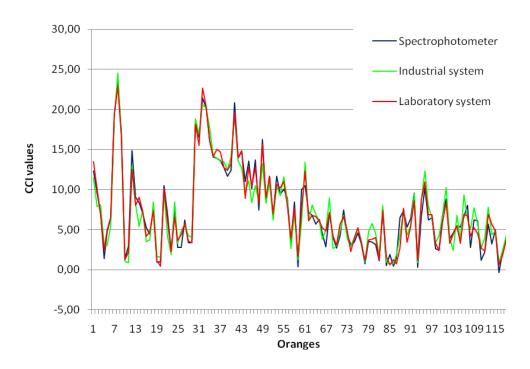


FIGURE 7. CCI estimated by the three different devices after applying the quadratic regression model

Figures 8 and 9 show the scatteplots between the spectrophotometer and the industrial system, and the spectrophotometer and the laboratory imaging system, respectively.

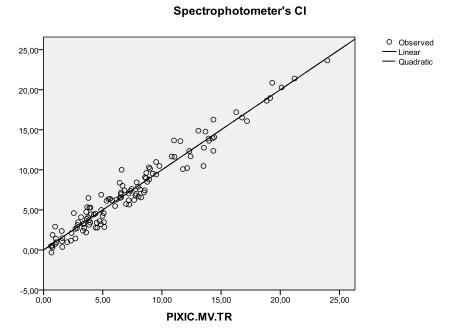


FIGURE 8. Scatterplot between the spectrophotometer and the industrial vision system

Spectrophotometer's CI

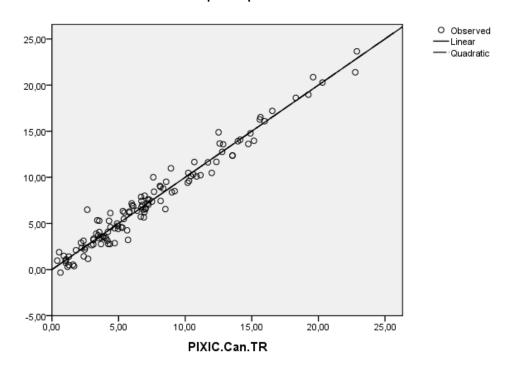


FIGURE 9. Scatterplot between the spectrophotometer and the industrial vision system

Classification of fruit

To compare the different methods in terms of fruit classification, the fruit was sorted using the "PIXIC transformed" values and the CCI obtained using the spectrophotometer. Three categories were set using the recommendations for the treatment of degreening of oranges (Table 1). The range of the values was:

- Group 1: CCI < 3
- Group 2: 3 < CCl < 7
- Group 3: 7 < CCI

A tolerance of ± 0.5 was considered after a personal communication with a specialist in post-harvest, from the IVIA, who states that, in the practice, there are no perceptible differences in colour for variations of even one unit in the CCI. The confusion matrixes for both imaging systems are shown in tables 7 and 8.

As expected, the laboratory system obtains better results than the industrial one, particularly in the case of the middle category which represents those fruits whose colour is changing and have more heterogeneous distribution of the colour. Fruit in group 1 had normally some green and yellow spots randomly distributed which can cause a decrement of the classification performance. On the contrary in the other groups the colours were more uniform. Classification is better when oranges have matured, because the colour tends to become homogeneous. In both cases,

it was obtained more than 84 % success compared with the spectrophotometer, being the average higher than 92 %.

TABLE 7. Confusion matrix between the industrial vision system and spectrophotometer (in %) (Average 92.6 %)

Spectro. Industrial system	CCI < 3	3 < CCl < 7	7< CCI
CCI < 3	84.0	16.0	0.0
3 < CCI < 7	0.0	90.7	9.3
7< CCI	0.0	1.9	98.1

TABLE 8. Confusion matrix between the laboratory vision system and spectrophotometer (in %) (Average 94.2 %)

Spectro. Industrial system	CCI < 3	3 < CCI < 7	7< CCI
CCI < 3	84.0	16.0	0.0
3 < CCI < 7	2.3	95.4	2.3
7< CCI	0.0	1.9	98.1

CONCLUSIONS

Two computer vision systems have been developed and tested to automate the measurement of the colour of citrus fruits in the industry aimed at sorting the fruit depending on the need of degreening. One of them has been built specifically for working in field conditions under limited possibilities of illumination. The second one is developed for working under laboratory conditions. The main advantages are the high speed of processing the fruit and the ability of integrating the colour of the entire surface of the fruit. To know the capability of reproducing the colour of entire fruits, they have been compared with the measures obtained using a spectrophotometer (reference system in colour measurements of food). The colour of the fruits has been measured by the imaging systems using two different algorithms; from the average of CCI values and from the average of RGB values, being the second one faster and more reliable. High correlations were achieved in all cases. Compared with the Spectrophotometer, the results obtained with the laboratory vision system were slightly better than the achieved using the industrial computer vision system. This was expected since the industrial system was not in the optimal conditions due to working limitations, but in

both cases a good R² value was obtained (0.975 for the in-line system and 0.981 for the laboratory system). The capability of the imaging systems to sort the fruit in the same categories than the Spectrophotometer achieved average values higher than 92 %. These results are promising and demonstrate the feasibility of a computer vision system to inspect the colour of citrus fruits in field conditions while the fruit is being harvested, being a valuable advance for this industrial sector.

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REFERENCES

- Abdullah, M. Z., Guan, L. C., Lim, K. C., & Karim, A. A. (2004). The applications of computer vision and tomographic radar imaging for assessing physical properties of food. Journal of Food Engineering, 61, 125–135.
- Berns R.S. (2000) *Billmeyer and Saltzman's principles of color technology*, 3rd Ed., John Wiley & Sons Inc, New York, USA.
- Blasco J, Aleixos N & Moltó E (2007) Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. Journal of Food Engineering, 81, 535–543.
- Blasco J, Cubero S, Gómez-Sanchis J, Mira P & Moltó E (2009) Development of a machine for the automatic sorting of pomegranate (Punica granatum) arils based on computer vision. Journal of Food Engineering, 90, 27–34.
- Campbell BL, Nelson RG, Ebel CE, Dozier WA, Adrian JL, Hockema BR (2004) Fruit quality characteristics that affect consumer preferences for satsuma mandarins. HortScience, 39(7), 1664-166.
- Chiralt A., Martínez N., González Ch., Talens, P., Moraga G. (2007). *Propiedades Físicas de los Alimentos*. Universitat Politècnica de València (Ed).117-120.
- Cubero S, Moltó E, Gutiérrez A, Aleixos N, García-Navarrete OL, Juste F, Blasco J (2010) Real-time inspection of fruit on a mobile harvesting platform in field conditions using computer vision. Progress in Agricultural Engineering Science 6, 1-16.
- Cubero S, Aleixos N, Moltó E, Gómez-Sanchis J & Blasco J (2011) Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables. Food and Bioprocess Technology, 4(4), 487-504.
- Cuquerella J (2004), Levante Agrícola. *Nuevo sistema de medida de colour para cítricos*, Nº. 372, pp. 298-304
- Díaz R, Faus G, Blasco M, Blasco J, Moltó E (2000). The application of a fast algorithm for the classification of olives by machine vision. Food Research International 33, 305-309.
- DOGV (2006). Diari Oficial de la Comunitat Valenciana, 5346, 30321-30328.
- Francis FJ, Clydesdale FM (1975). Food colorimetry: theory and applications.
- Gardner JL (2007). *Comparison of calibration methods for tristimulus colorimeters*. Journal of Research of the National Institute of Standards and Technology, 112, 129-138.
- Gilabert E.J (2002). Editorial UPV . Medida del Color.
- Hatcher, D. W., Symons, S. J., & Manivannan, U. (2004). *Developments in the use of image analysis for the assessment of oriental noodle appearance and colour.* Journal of Food Engineering, 61, 109–117
- Hutchings, J.B., FInstP, FIFST, 1999. Food Color and Appearance. In: Chapman & Hall Food Science Book (Ed). Aspen Publicatio, pp 227-266 (Chapter 8)
- Hutchings, J.B., Luo, R., Ji, W., 2002. *Calibrated colour imaging analysis of food*. En: MacDougall, D. (Ed.), Colour in Food. Woodhead Publishing, pp. 352–366 (Chapter 14).

- Jiménez-Cuesta MJ, Cuquerella J, Martínez-Jávega JM (1981). *Determination of a color index for citrus fruit degreening*. In Proc. of the International Society of Citriculture, Vol. 2, 750-753.
- Kane A.M, Lyon B.G, Swanson R.B, and Savage E.M (2003). *Comparison of Two Sensory and Two Instrumental Methods to Evaluate Cookie Color.* Journal of food science 68(5), 1831.
- Kang SP, East AR, Trujillo FJ (2008) Colour vision system evaluation of bicolour fruit: A case study with 'B74' mango. Postharvest Biology and Technology, 49, 77–85.
- Kit L. Yam, Spyridon E. Papadakis (2004). A simple digital imaging method for measuring and analyzing color of food surfaces. Journal of Food Engineering 61, 137–142.
- León K, Mery D, Pedreschi F, León J (2006) *Color measurement in L*a*b* units from RGB digital images*. Food Research International 39 (2006) 1084–1091.
- Liming X & Yanchao Z (2010) Automated strawberry grading system based on image processing. Computers and Electronics in Agriculture, 71(S1), S32-S39.
- López Camelo AF, Gómez PA (2004) Comparison of color indexes for tomato ripening Horticultura Brasileira 22(3): http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0102-05362004000300006. (accessed February 2012).
- Manresa González A, Ileana Vicente (2007), Editorial Universitaria. El color en la industria de los alimentos. 20-40.
- Martínez-Jávega JM, Salvador A, Navarro P (2007) Adecuación del tratamiento de desverdización para minimizar alteraciones fisiológicas durante la comercialización de mandarinas. En: V Congreso Iberoamericano de Tecnología Postcosecha y Agroexportaciones. Cartagena (Murcia), 29 de mayo al 5 de junio de 2007. Comunicación S3-O106.
- Mendoza F, Dejmek P, Aguilera JM (2006). *Calibrated color measurements of agricultural foods using image analysis*. Postharvest Biology and Technology, 41, 285-295
- Mendoza, F., Aguilera, J.M., 2004. *Application of image analysis for classification of ripening bananas*. J. Food Sci. 69, 471–477.
- Noboru O, Robertson AR (2005). 3.9: Standard and Supplementary Illuminants. Colorimetry. Wiley.
- Pedreschi F, León J, Mery D, Moyano P (2006). Development of a computer vision system to measure the colour of potato chips. Food Research International 39, 1092–1098.
- Pedreschi, F., Aguilera, J. M., & Brown, C. A. (2000). *Characterization of food surfaces using scale-sensitive fractal analysis*. Journal of Food Process Engineering, 23, 127–143.
- Quevedo R. A, Aguilera J. M, Pedreschi F (2010). Colour of Salmon Fillets By Computer Vision and sensory panel. Food Bioprocess Technol 3, 637–643.
- Smith T, Guild J. (1931). The C.I.E. colorimetric standards and their use. Transactions of the Optical Society, 33(3), 73–134.
- Yam KL, Papadakis SE (2004). A simple digital imaging method for measuring and analyzing color of food surfaces. Journal of Food Engineering, 61,137–142.