The final publication is available at

http://link.springer.com/article/10.1007%2Fs11947-012-1015-2

In-line estimation of the standard colour index of citrus fruits using a computer vision system developed for a mobile platform

A. Vidal[1,2], P. Talens[1], J.M. Prats-Montalbán[3], S. Cubero[2], F. Albert[4], J. Blasco[2*]

[1] Departamento de Tecnología de Alimentos. Universitat Politècnica de València. Camino de Vera s/n, 46022 Valencia, Spain.

[2] Centro de Agroingeniería. Instituto Valenciano de Investigaciones Agrarias (IVIA). Cra. Moncada-Náquera km 5, 46113 Moncada (Valencia), Spain. Email: blasco_josiva@gva.es

[3] Departamento de estadística e investigación operativa. Universitat Politècnica de València. Camino de Vera s/n, 46022 Valencia, Spain.

[4] Instituto Interuniversitario de Investigación en Bioingeniería y Tecnología Orientada al Ser Humano. Universitat Politècnica de València. Camino de Vera s/n. 46022 Valencia, Spain.

Abstract

A key aspect for the consumer when it comes to deciding on a particular product is the colour. In order to make fruit available to consumers as early as possible, the collection of oranges and mandarins begins before they ripen fully and reach their typical orange colour. As a result they are therefore subjected to certain degreening treatments, depending on their standard colour citrus index at harvest. Recently, a mobile platform that incorporates a computer vision system capable of pre-sorting the fruit while it is being harvested has been developed as an aid in the harvesting task. However, due to the restrictions of working in the field, the computer vision system developed for this machine is limited in its technology and processing capacity compared to conventional systems. This work shows the optimised algorithms for estimating the colour of citrus in-line that were developed for this mobile platform and its performance is evaluated against that of a spectrophotometer used as a reference in the analysis of colour in food. The results obtained prove that our analysis system predicts the colour index of citrus with a good reliability

($R^2 = 0.925$) working in real time. Findings also show that it is effective for classifying harvested fruits in the field according to their colour.

1. Introduction

Colour is one of the most important attributes of agrifood products, since consumers associate it with freshness and it is a critical factor in the customer's preference for a particular product over others (Campbell et al., 2004). Producers strive to guarantee that the products they put on the market have the attractive colour typical of mature fruits of the variety, as well as ensuring that individual products are packed in batches with a similar colour (Díaz et al., 2000; Blasco et al., 2009). The analysis of the colour of the whole production can be performed automatically using different optical technologies (Pathare et al., 2012), but in most cases there is a need to use some colour index or criteria to sort the product into different colour categories (Yam and Papadakis, 2004).

When an object is assessed visually, three physical factors must be present: a source of light, the object itself and a light-receiving mechanism, the spectral distribution of the light source having a strong influence on the perceived colour (Sahin and Sumnu, 2006). There are different standard sources of light, but the most widely used in colour measurement of food is the standard D65 (Noboru and Robertson, 2005), which corresponds to the spectral distribution of the midday sun in Western Europe, and is recommended for use as the standard daylight illuminant by the CIE (Commission Internationale de l'Eclairage). Colorimeters are electronic devices for

colour measurement that express colours as 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, digital cameras can provide images in which the colours of the pixels are determined individually, a method that is more suitable for cases where the surface has a heterogeneous colour (Cubero et al., 2011; Lorente et al., 2012). The colour of a particular pixel in an image is expressed by three coordinates in a colour model. 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, and achieved a success rate similar to those obtained by visual inspection.

The biggest drawback is that RGB is a device-dependent colour model. For this reason, other colour models closer to the human perception of colour are frequently employed, like HSI (Kang et al., 2008; Quevedo et al., 2010; Hashim et al., 2011). In addition, RGB or HSI are non-uniform colour models. This means that the same numerical distance between two colours of these models may produce distinct differences in human perception, depending on the position of such colours in the space. Uniform spaces like CIELAB or HunterLab define distances that produce the same differences in perception regardless of the position of the colours (Smith and Guild, 1931), and for this reason they are very well suited for colour comparison. Several works have compared different colour spaces and the conclusion is that the most appropriate for measuring or representing the colour of fruit is CIELAB (Mendoza et al., 2006; Arzate-Vázquez et al., 2011; Lang and Hubert, 2011). In most

cases, however, a better way to give comparable measurements of colour is by using colour indices, which combine these coordinates in one single ratio that is easier for operators to handle (López-Camelo and Gómez, 2004; Quevedo et al., 2011; Cavazza et al., 2012). In this work, the HunterLab system was selected because this is the colour space used to determine the standard citrus colour index (CCI) (Jiménez-Cuesta et al., 1981).

A practical application where the inspection of the colour is needed is the assessment of citrus fruits. Fruits are harvested manually, then loaded in boxes and transported to a packing house, where the fruit is sorted. In the early season, this sorting focuses on classifying by colour, because fruit is treated separately (orange fruits go directly to market, orange-green undergo a 24-hour degreening process, and green fruit is submitted to 72 hours' degreening). The CCI is the parameter used in the citrus industry to determine the harvesting date or to decide which fruit should undergo a degreening treatment (DOGV, 2006).

In this work, the development of a computer vision system for in-line colour assessment (to be used on a mobile harvest-aid platform capable of automatically inspecting and sorting citrus) is described and compared with a reference colour acquisition device. The aim of this comparison is to determine whether the system can potentially be used for this purpose and also the accuracy achieved by this new sorting system when working under some restrictions due to the working in the field.

2. Material and methods

2.1 Hardware used for data acquisition

The computer vision system of the machine was composed of a smart camera (Sony, XCI-SX 100C/XP), which has a built-in microprocessor and therefore does not need an external processing unit, such as a computer. The camera operates under the MS Windows XP operating system[©], and the software to acquire and process the images was programmed specifically for this purpose in programming language C. The main advantage of this camera is that it can be powered directly from the battery of the mobile platform and there is no need to use an external processing unit (computer), since the camera already has this capability. This makes this configuration optimal for working in the field, where there is no external power supply. In contrast, the computational power is very low compared with a standard personal computer and this makes it necessary to develop highly optimised image-processing algorithms.

The light source used to acquire the images was composed of four strips, each 500 mm in length, with 50 LEDs per strip. Each 0.3 W LED produces light with a colour temperature of 6000 K and a colour reproduction of 70 Ra, the Gamma Correction parameter of the camera being set to 1.0. Due to the limited energy sources available in the field, to achieve a sustainable system we powered the LEDs using a stroboscopic mode synchronised with the image acquisition, which allowed a saving of about 90% of the energy in comparison with standard powering using direct current. This was done using the strobe output of the camera and controlled by a specific electronic board designed for this purpose. Polarising filters were used to avoid bright spots.

This mobile platform, which is described in Cubero et al. (2010), is capable of pre-sorting the harvested fruit into three different categories of quality in the field using the computer vision system. To do so, a series of rotating elements individualise the

harvested fruit and separate the pieces into two lanes. Fruit enters the inspection chamber on rollers that allow the fruit to be transported and rotated under the camera while images are captured. The camera captures 1280 x 969-pixel images with a resolution of 0.31 mm/pixel that contain up to eight fruits from the two lanes. Image acquisition is synchronised with the movement of the fruit using an optical encoder that supplies the camera with one trigger pulse each time a new roller enters the scene. In this way, four images of each fruit are acquired in different views while the fruit rolls along under the camera at a speed of 0.4 m/s. To freeze the movement, a shutter speed of 1/500 was set on the camera. Figure 1 shows the image arrangement with the four positions of the fruit where the images are captured.

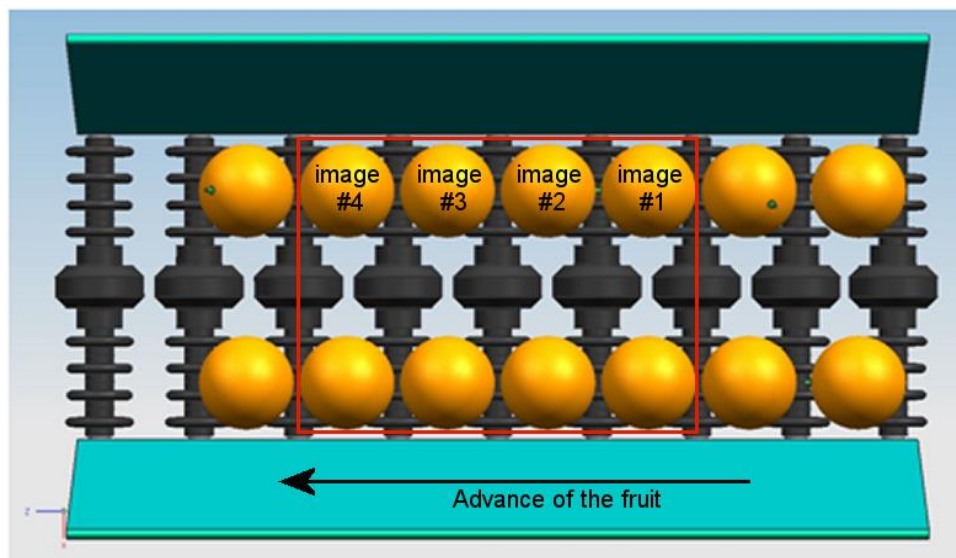Figure 1. The scene captured by the camera is marked in red. The figure shows the positions in which the four images of the fruit are acquired

Once the fruit has been inspected, it is sorted according to the data extracted from the images. Figure 2 shows the actual system built to acquire the images. Even though this system was developed for capturing and inspecting the images in real time, and

to provide results in-line, in this case the four images taken of each fruit were also stored in BMP graphic file format.
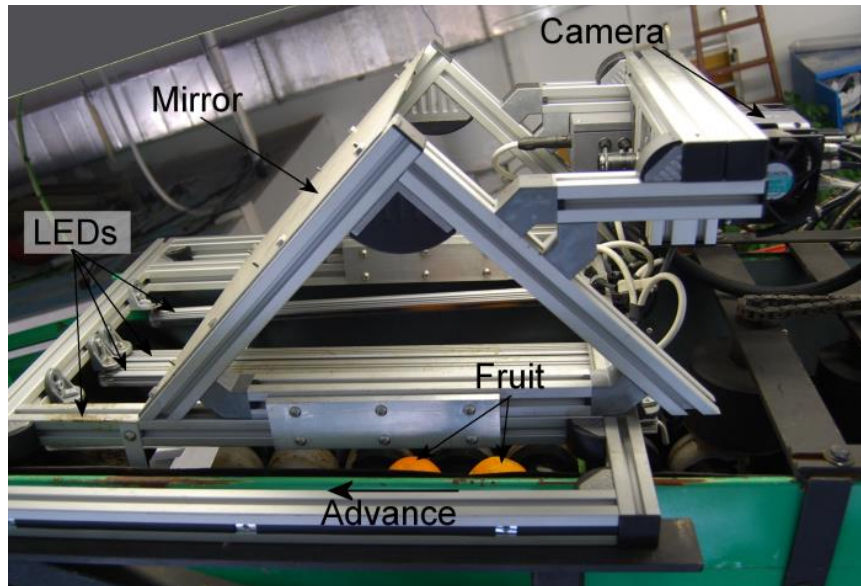

Figure 2. Computer vision system developed for the mobile platform

To take reference measurements, a Minolta spectrophotometer CM-700d was used to obtain the spectral reflection curve of the fruit. The equipment uses a pulsed xenon lamp (with an ultraviolet cut filter) as the light source and a silicon photodiode array as a detector. The instrument utilises the di:8º/de:8º geometry. The instrument was calibrated with a white reference tile ($L = 97.10$, $a = -4.88$, $b = 7.04$) before the measurements.

2.2 Fruit used in the experiments

Experiments were carried out with a set of 225 oranges cv. 'Navelina'. Fruits were chosen randomly from the production line of a packing house and had colours ranging from green to the typical orange colour of the cultivar. Fruit included pieces that presented a homogeneous green colour with yellow spots or a homogeneous orange colour with some green or yellow spots so as to cover most of the possibilities

that can be found in the real world. Each fruit was labelled and the colour measured with the two devices. Figure 3 shows some illustrative samples of the fruit used for the experiments.

Figure 3. Representative samples of the colour of the fruit used for the experiments

2.3 Feature selection

The aim of feature selection is to calculate the CCI, which is defined by equation (1).

$$\mathrm{CCI} = \frac{1000 \times a}{L \times b} \qquad (1)$$

The first step is to separate the fruit from the background, which is achieved using a threshold in the green channel (G), because this colour is high for all possible skin colours in the range of the fruit studied. The threshold was empirically determined by analysing the histogram of the images of fruit. Two clear peaks appear in the green channel of the images, one corresponding to the background and the other corresponding to the fruit. The image is divided into eight areas corresponding to the expected location of each fruit, which is an operation that can be performed since the position of the fruits is known due to the synchronisation mechanism. Areas on the left represent the first view of the fruit while areas on the right show the fourth and last view of the fruit. For the first three images, the data is just acquired and stored in the memory of the computer and only when the last image has been acquired is the CCI calculated.

The colour of the pixels in the image is codified in RGB coordinates and, therefore, they need to be converted to HunterLab coordinates. The first step is to convert the RGB value to XYZ coordinates using the standard equations described in Mendoza et al. (2006). Then, the XYZ values are converted to L,a,b coordinates using the equations corresponding to illuminant D65 and standard observer 10º described in (Hunterlab, 2008). This conversion is computationally very costly in terms of processing time if it is performed for each pixel in the image. As the processing time is a critical restriction for in-line applications, mainly due to the low-power but energetically efficient solution adopted for the mobile platform, in order to speed up the colour space conversion, this operation was performed previously off-line by calculating the CCI of all possible RGB values in the image, these values being stored in a Look-Up Table (LUT). This table is preloaded in the memory of the computer, so that during in-line processing the HunterLab value of each pixel can be obtained just by consulting the LUT, which dramatically reduces the computational cost and makes it very effective for in-line processes.

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

1. The RGB values of all pixels in the image segmented as fruit were converted to HunterLab (the LUT was consulted for each pixel). Then the CCI was calculated for each pixel. The CCI of the image was calculated as the mean of the CCI of all the pixels of the fruit. The result was called LUT-CCI.

2. The mean of all the RGB values of the pixels belonging to the fruit was calculated. The resulting value was transformed into the CCI value using the LUT. The result was called PIX-CCI.

The CCI of the fruit was then calculated as the mean of the CCI of the four partial images of the fruit. Figure 4 shows the flowchart of these two algorithms.
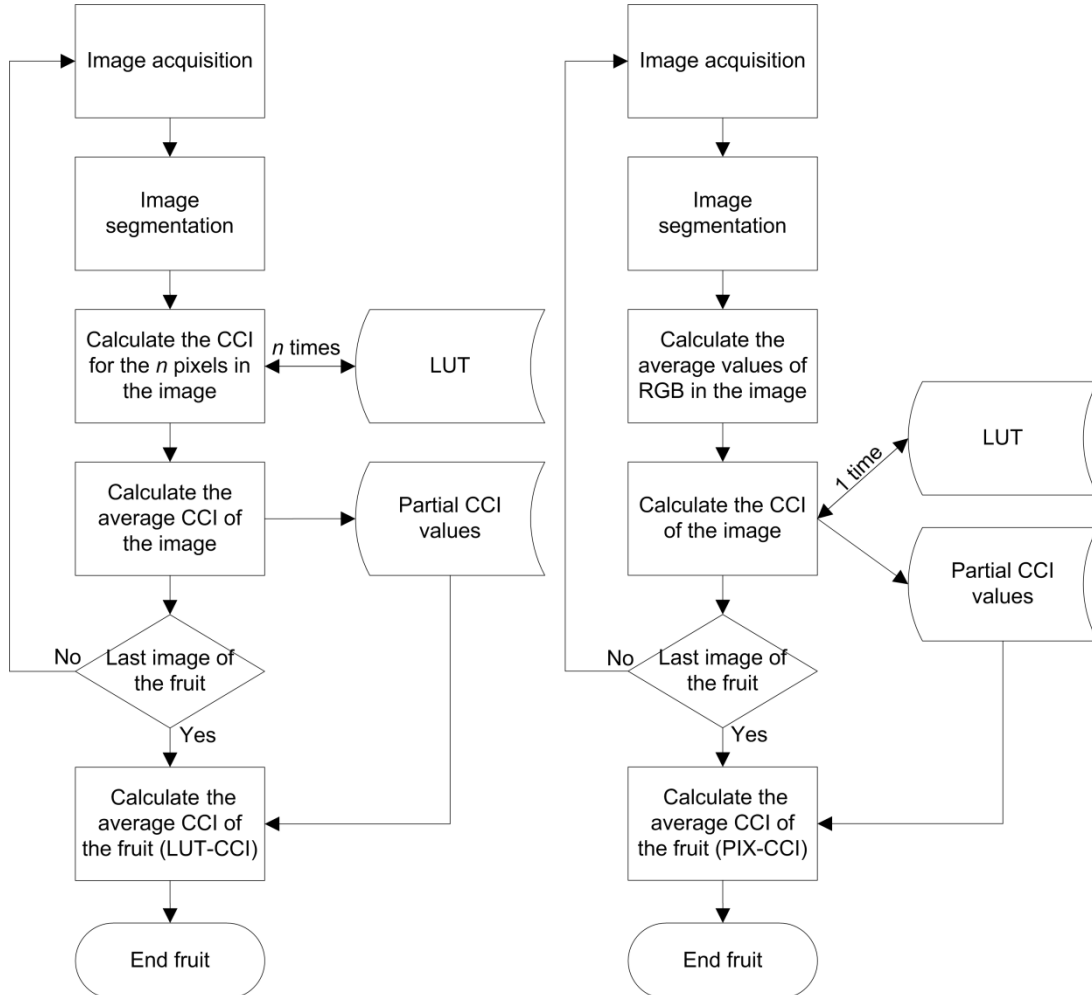
Figure 4. Algorithms developed to estimate the CCI values of the fruit. Left) obtaining the CCI value from the average of the CCI of each pixel (n = total number of pixels in the image belonging to fruit). Right) obtaining the CCI value from the average of the RGB values

To obtain the reference values, the spectral data of six points on each fruit were taken using a spectrophotometer. The acquired areas were chosen randomly in an attempt to cover the whole surface, but including coloured spots when they were present. The average of these spectral data was calculated to obtain the colour reflectance curve of each orange. The data of this reflectance curve were multiplied by a CIE standard illuminant D65 and by the CIE standard observer 10º and converted into the

tristimulus values of XYZ (Hutchings et al., 2002). The XYZ coordinates were converted to HunterLab using the same equations as those implemented in the image processing algorithm (Hunterlab, 2008). Later, the corresponding CCI value is calculated using Equation 1.

2.4 Test

The CCI values 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.

Two tests were carried out during this work:

1. To assess which approach for image analysis provides a more accurate prediction of the CCI.

2. To determine the behaviour of the vision system towards the spectrophotometer.

The statistical analysis of data was performed through multiple regression models using Statgraphics Centurion (StatPoint Technologies, USA).

3 Results and discussion

In terms of processing speed and computational cost, this system cannot be compared with a standard configuration for image processing composed of a camera and a computer, as is commonly used in a packing house. Using this standard equipment would allow more complex algorithms to be implemented, but on the other hand the power supply would become a problem, as a power inverter would be needed to convert the supply from the battery to the standard 220 V used by this equipment. Table 1 shows the processing time needed by the system for each image. By

estimating the average RGB of the fruit and then making just one conversion to HunterLab, an in-line process of eight images per second can be achieved.

Table 1. Time required by the different algorithms to process one image

Operation	Time (ms)
Estimating the CCI of each pixel without using LUT	1171
Estimating the CCI of each pixel using LUT (LUT-CCI)	189
Estimating the CCI from the average RGB (PIX-CCI)	125

3.1 Prediction models for LUT-CCI

In order to assess the goodness of the imaging system developed, a multiple linear regression model (Montgomery, 2005) was built on a training set of 150 out of the 225 oranges. The remaining 75 oranges (all of them of the same colour ranges as the ones used for the calibration set) were used for validation. Table 2 presents the corresponding Regression model and ANOVA table.

The determination of the model can be performed in different ways. In this case, the method chosen was to inspect the statistical significance of both the linear and quadratic effects of the computer vision system, which have a p-value of 0% − a value that gives complete confidence in the model that was built. When a new term (cubic) was included, the R^2 value did not improve from a statistical point of view (general test for hypothesis testing), which meant that this new term should not be included.

The R^2 is very good, which offers confidence in the computer vision acquisition system that was developed. The model for the LUT-CCI algorithm presents statistically significant linear and quadratic coefficients, which means that there is some curvature in the relation between the spectrophotometer and the vision system.

Table 2. Regression and ANOVA analyses for the LUT-CCI implementation

```
                    Multiple Regression Analysis
   -----------------------------------------------------------------------
```

```
                                    Standard            T
Parameter                Estimate     Error      Statistic        P-Value
-----------------------------------------------------------------------------
CONSTANT                  7.85188    0.162265      48.3893          0.0000
LUTCCI-VISION            0.380083    0.00996238    38.1518          0.0000
LUTCCI-VISION^2          0.00227994  0.000495653    4.59987         0.0000
-----------------------------------------------------------------------------

                            Analysis of Variance
-----------------------------------------------------------------------------
Source              Sum of Squares   Df  Mean Square   F-Ratio     P-Value
-----------------------------------------------------------------------------
Model                     4110.14     2     2055.07     775.37      0.0000
Residual                  389.613   147     2.65043
-----------------------------------------------------------------------------
Total (Corr.)             4499.76   149

R-squared = 91.3415 percent
```

In order to validate the models properly, the next step was to use the regression models to predict the colour values of the validation set. Figure 5 presents the corresponding validation results. In this case, the validated R^2 value is even a little bit higher than the one obtained for the calibration set. This result indicates that the vision system developed for working on a mobile platform under field conditions is completely reliable.
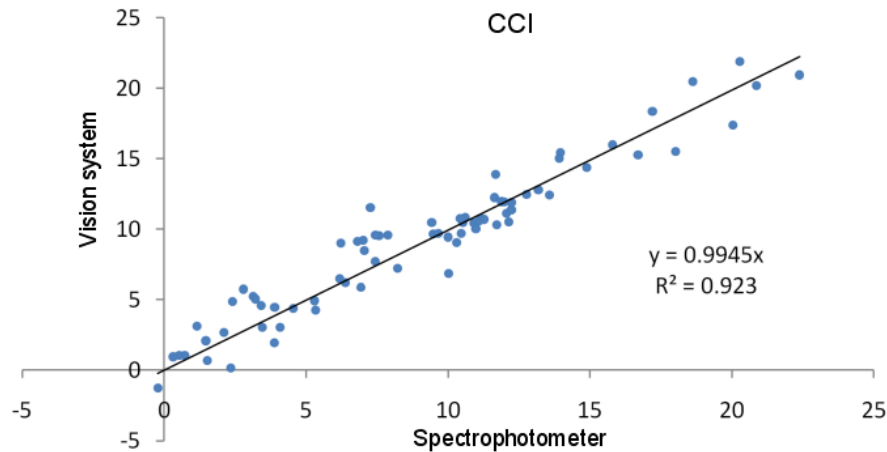

Figure 5. Vision system (LUT-CCI) *vs.* spectrophotometer values plot. The x coordinates correspond to the reference values, whereas the y coordinates relate to the computer vision system

3.2 Prediction models for PIX-CCI

Table 3 presents analogous results for the multiple linear regression model in the case of the PIX-CCI vision algorithm. The R^2 is practically the same in this case, thus giving the impression that both algorithms perform in the same way. The

determination of the model was carried out using the same procedure as previously explained for the LUT-CCI system.

Table 3. Regression and ANOVA analyses for the PIX-CCI implementation

```
                    Multiple Regression Analysis
-------------------------------------------------------------------------
                                  Standard        T
Parameter              Estimate      Error     Statistic        P-Value
-------------------------------------------------------------------------
CONSTANT                9.43425   0.158145       59.6558         0.0000
PIXCCI-VISION          0.370914   0.0093459      39.6874         0.0000
PIXCCI-VISION^2      0.00134088   0.000432616      3.09947       0.0023
-------------------------------------------------------------------------

                       Analysis of Variance
-------------------------------------------------------------------------
Source            Sum of Squares    Df   Mean Square    F-Ratio    P-Value
-------------------------------------------------------------------------
Model                   4117.19     2        2058.6     791.01     0.0000
Residual                382.567   147       2.60249
-------------------------------------------------------------------------
Total (Corr.)           4499.76   149

R-squared = 91.4981 percent
```

When computing the R^2 value for the validation set, we can see in Figure 6, which shows the reference *vs.* predicted values for the vision system, that it is similar to that provided by the LUT-CCI algorithm.
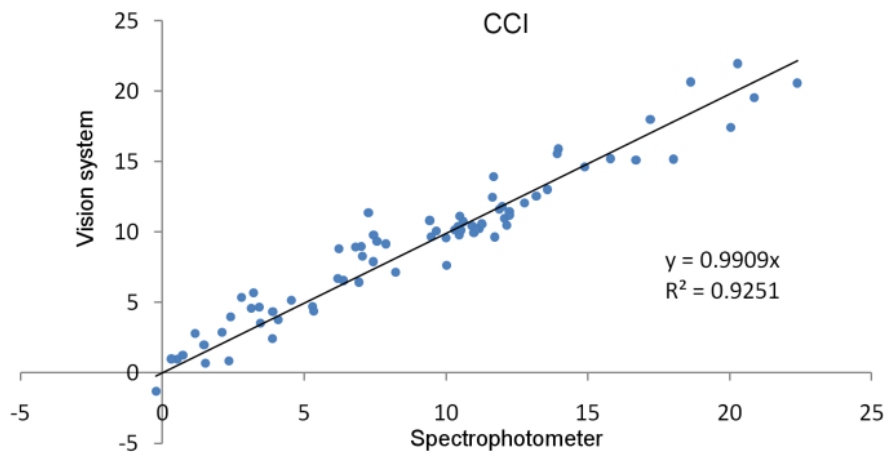

Figure 6. Vision system (PIX-CCI) *vs.* spectrophotometer values plot. The x coordinates correspond to the reference values, whereas the y coordinates relate to the vision system

Finally, Table 4 presents the 95% confidence interval for the comparison of the (percentage) determination coefficient values. From this information, it is possible to

see that all models provide comparable prediction R^2 values, so they can all be used with the same reliability.

Table 4. Confidence intervals (95%) for the comparison of percentages, for the validated R^2

	LUT-CCI		PIX-CCI	
	LCL	UCL	LCL	UCL
Industrial vision system	88.03%	96.57%	88.30%	96.72%

4 Conclusions

A computer vision system allowing the colour index of citrus fruits to be measured automatically while the fruit is being harvested has been developed and tested. This system allows pre-sorting the fruit in the field according to the amount of degreening that is needed. The main advantages are the high speed of processing the fruit using low computational performance equipment and the ability to include the colour of the entire surface of the fruit. To determine the system's capability to reproduce the colour of whole fruits, they were compared with the measurements obtained using a spectrophotometer (reference system in colour measurements of food). The colour of the fruits was measured by the imaging systems using two different algorithms: from the average of the CCI values and from the average RGB values, the latter being faster and more reliable. High correlations were achieved in all cases. In both cases a well-adjusted R^2 value was obtained: 92.30% for the LUT-CCI system and 92.51% for the PIX-CCI system. Being faster the latter, it is the recommended method. 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, which is a valuable step forward for this industrial sector.

References

Arzate-Vázquez I, Chanona-Pérez JJ, Perea-Flores MJ, Calderón-Domínguez G, Moreno-Armendáriz MA, Calvo H, Godoy-Calderón S, Quevedo R, Gutiérrez-López G (2011) Image processing applied to classification of avocado variety Hass (*Persea americana* Mill.) during the ripening process. Food and Bioprocess Technology, 4(7), 1307-1313.

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), 1664-1669.

Cavazza A, Corradini C, Rinaldi M, Salvadeo P, Borromei C & Massini R (2012) Evaluation of pasta thermal treatment by determination of carbohydrates, furosine, and color indices. Food and Bioprocess Technology. DOI: 10.1007/s11947-012-0906-6. In-press.

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.

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.

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. The Avi Publishing Company, Westport, USA.

Gardner JL (2007) Comparison of calibration methods for tristimulus colorimeters. Journal of Research of the National Institute of Standards and Technology, 112, 129-138.

Hashim N, Janius RB, Baranyai L, Rahman RA, Osman A & Zude M (2011) Kinetic model for colour changes in bananas during the appearance of chilling injury symptoms. Food and Bioprocess Technology. DOI: 10.1007/s11947-011-0646-z. In-press.

HunterLab (2008): Applications note, 8(9), http://www.hunterlab.com/appnotes/an08_96a.pdf. Accessed September 2012.

Hutchings JB, Luo R, Ji W (2002) Calibrated colour imaging analysis of food. In: MacDougall, D. (ed.) Colour in Food, pp. 352–366. Woodhead Publishing, Cambridge, England.

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.

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.

Lang C & Hübert T (2011) A colour ripeness indicator for apples. Food and Bioprocess Technology. DOI: 10.1007/s11947-011-0694-4. In-press.

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 September 2012.

Lorente D, Aleixos N, Gómez-Sanchis J, Cubero S, García-Navarrete OL & Blasco J (2012) Recent advances and applications of hyperspectral imaging for fruit and vegetable quality assessment. Food and Bioprocess Technology, 5(4), 1121-1142.

Mendoza F, Dejmek P & Aguilera JM (2006) Calibrated color measurements of agricultural foods using image analysis. Postharvest Biology and Technology, 41, 285-295.

Montgomery DC (2005) Design and Analysis of Experiments 6th ed. John Wiley & Sons. Tempe, Arizona, USA.

Noboru O & Robertson AR (2005) Colorimetry. Wiley. West Sussex, England.

Pathare PB, Opara UL & Al-Said FA (2012) Colour measurement and analysis in fresh and processed foods: A Review. Food and Bioprocess Technology. DOI: 10.1007/s11947-012-0867-9. In-press.

Quevedo RA, Aguilera JM & Pedreschi F (2010) Colour of salmon fillets by computer vision and sensory panel. Food and Bioprocess Technology 3, 637–643.

Sahin S & Sumnu SG (2006) Physical properties of foods. Springer. New York, USA.

Quevedo R, Valencia E, Alvarado F, Ronceros B & Bastias JM (2011) Comparison of whiteness index vs. fractal Fourier in the determination of bloom chocolate using image analysis. Food and Bioprocess Technology. DOI: 10.1007/s11947-011-0729-x. In-press.

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.