Multispectral and hyperspectral imaging for monitoring banana ripeness

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Abstract

Monitoring of the ripening stages of banana fruit is a need for their optimal management at distribution, exportation and market places. In commercial practice, ripening status assessment is usually based on the comparison of samples with a color standard chart by visual inspection. However, this grading process is very subjective and the sector is demanding an objective procedure to replace it. The Present research proposes an objective method of classification based on two optical indexes extracted from hyperspectral images. Hyperspectral images (400-1000 nm) were acquired on two sets of bananas along storage period (six days). Huge number of spectra of the calibration set (classified according to COPLACA standard), allowed to identify the main ripening changes: the chlorophyll absorption band hole (680 nm) disappears and simultaneously an overall decline in the intensity of the NIR region occurs. These effects were sensed by two multispectral indexes centered on the wavelengths in which it has been observed the higher variability: IndexVIS and IndexNIR. Both indexes have demonstrated a high ability to discriminate ripening COPLACA classes from 1 to 5 (usually used in for final retail). A non-supervised cluster analysis has confirmed the spectral pattern of categories of COPLACA, and it has allowed identifying and considering an additional spectral pattern named C8, corresponding to over-ripeness. The projection of the hyperspectral images onto the generated indexes and the assignation of each pixel to one of the 8 categories defined according to the distances to the centroids, allowed the identification of regions with different states of evolution in the bananas.

Keywords: *Musa Acuminata* AAA, maturity inspection, optical indexes, image systems

1. Introduction

Banana is one of the most important fruits consumed all over the world. European bananas are mostly grown on the Canary Islands (Spain), where production of *Musa Acuminata* AAA (Cavendish subgroup) reached 371 000 tons in 2012.

Optimum harvest date, or flowering-harvest interval, is determined from flowering, according to the climate zone and variety and taking into account the fruit size. Bunches can be harvested mature-green, i.e. well developed, mature but still green, which, together with the fact that the banana is a climacteric fruit, allows to manage ripening by applying controlled atmospheres with exogenous ethylene and appropriate temperature and humidity (Aurore et al., 2009). Along banana ripening, the peel color changes, the pulp softens, the flavor develops and moisture is lost (Li et al., 1997). Once ripening begins, it is an irreversible process leading banana peel color changes from green to yellow, with brown spots appearing at the end of the ripening.

Especially for export, the harvesting time and post-harvest conditions need to be correctly managed, in order to extend shelf life up to 60 days for Cavendish bananas. Competition between exporters of dessert bananas from different producer countries makes commercial quality of the products a critical marketing factor, and decision support tools can contribute to improve management of fruits.

There are several methods to determine banana maturity, among them peel color is preferable because is simpler and non-destructive. In commercial practice, visual examination carried out by a human observer, who matches peel color to a standard color chart and assign a score is very usual, although many commercial operators are not able to obtain highly consistent and accurate results. During postharvest, the ripeness status of banana can be checked in different moments. Of remarkable importance is the arrival of the fruit to ripening facilities and distribution centers, where the quality and level of ripeness is checked and the bananas are accordingly stored under controlled conditions based on statistics and appropriate experience of the experts to achieve the desired color at the right time. However, this grading process, based on comparison, is very subjective and the sector is demanding an objective procedure to replace it.

Instrumental assessment of peel color can be performed by measuring the surface reflectance of the peel using spectrophotometers or colorimeters. However, these instruments report only information related to a small surface of the sample. In the ripening of banana the spatial heterogeneity is relevant, so, image systems are appropriated to overcome this drawback (Quevedo et al., 2008). In previous works (Rajkumar et al., 2014) quality parameters like moisture content, firmness and total soluble solids were determined and correlated with the spectral data from a hyperspectral image system.

In recent years, hyperspectral imaging technique has been regarded as a tool for analyses conducted for quality evaluation of food products in research, control, and industries. The hyperspectral imaging system allows integrating spectroscopic and imaging techniques to enable direct identification of different components or quality characteristics and their spatial distribution in the tested sample (Lara et al., 2013; Lleó et al., 2011). Because hyperspectral imaging techniques overcome the limits of spectroscopic techniques and vision techniques, they have emerged as a powerful technique in agricultural and food systems. Based on hyperspectral imaging techniques, multispectral imaging system can be built for real-time implementations (ElMasry and Sun 2010). It involves measuring the intensity of diffusely reflected light from a surface at one or more wavelengths with relatively narrow band passes. Since image data are considered two-dimensional, by adding a new dimension of ‘‘spectrum’’ information, the hyperspectral image data is analyzed as a three-dimensional data cube.

One of the main challenges in the hyperspectral vision is the management and analysis of large and complex databases to extract relevant information contained in them. The starting point for these are the methods of spectral pre-processing (normalization, smoothing, etc.) and multivariate analysis (correlation techniques, principal component analysis, discriminant analysis, etc.) traditionally applied to spectroscopy. In the case of hyperspectral vision these procedures can be applied to the whole image or to sub-populations of pixels representative of the variability of the samples. The projection of the whole images onto new spaces generated by multivariate analysis or the computation of indexes based on selected wavelengths, generate virtual images that must be analyzed searching for similarity.

The aim of this work is to propose a procedure based on a specific multispectral vision system for objective assignment of banana fruits to a maturity level. The first phase is based on hyperspectral imaging multivariate analysis, which produced two indexes with the ability to be implemented in automatic classification equipment. The ripeness references used are based on a commercial visual classification chart.

2. Materials and Methods

2.1. Materials

Two sets of bananas comprised by 7 (set A -calibration) and 14 (set B- validation) fruits respectively, coming from the Canary Islands were selected in the reception area of a company devoted to ripening services and distribution. The color of each banana was evaluated subjectively by comparing the fruit with the standard color chart of COPLACA (Cooperativa Platanera de Canarias), inspired in the Von Loesecke and Willard ripening scale, to obtain banana maturity rating for each fruit. The visual color score of each banana peel was assessed on this seven point scale, where 1 is described as totally green, 2 green with yellow lines, 3 more green than yellow, 4 more yellow than green, 5 yellow with green tip, 6 full yellow, and 7 yellow with brown spots. Fruits are usually marketed with a rating of 5 or less; bananas are not commercially marketed at a 6 or 7 ripeness level.

Banana fruit ripening stages were studied along the storage period in a chamber maintained at 12ºC and 80-90 % RH (without supply of exogenous ethylene). Hyperspectral images of each fruit belonging to set A were taken beginning at time zero and after 5 and 6 days of storage; for set B images were acquired at time zero and after 3 and 6 and 9 days of storage.

The hyperspectral vision system consists of a push-broom CCD camera (Andor Luca) equipped with a spectrograph Headwall Photonics HyperspecTM VNIR (spectral range: 400 to 1000 nm). The spectral binning was configured to obtain 189 wavelengths (spectral resolution 3.17 nm). The acquisition and the storage of the images were made through specific software (Headwall HyperespecTM). The illumination was provided by two halogen lamps with regulated and variable intensity. Each individual banana was placed on a platform that moved under the camera (Micos-MOCO motor). The sample was scanned line by line according to the movement (push-broom system). The spatial resolution was 260 µm. Once the raw images were acquired, the corresponding relative reflectance hypercube was computed, containing the relative reflectance spectrum of each pixel of the image with respect to a reference (mean spectrum of a barium sulfate white reference).

2.2. Methods

A population of spectra for calibration purposes was extracted from set A at day zero, by selecting manually the 90% of the area of each banana; spectra were classified considering the maturity grating assigned by the expert to fruit from which comes each spectrum (65000 spectra). Average spectra for each ripening level were computed in order to identify the main changes along the ripening process. In addition, in order to verify the characteristic and differential spectral patterns present in the populations of bananas studied, a non-supervised cluster analysis was performed in an extended calibration set composed by the original one plus spectra of the banana of set A after the storage period and spectra of set B (at time zero and after 6 days of storage). From the dendrogram, representative classes were selected and the average spectra of each generated class was computed and considered further on. Analyzing spectral patterns the wavelengths showing the maximum variation between ripening levels along storage periods were identified. Indexes based on these relevant wavelengths were proposed; their ability to discriminate ripeness stage of bananas was assessed by analysis of variance. The generated model was applied to the totality of the pixels of the hyperspectral images, computing the artificial images of the indexes. Each pixel of which images was assigned to the class with the maximum membership degree computed according to the Mahalanobis distance to the centroid of the class. Artificial images of the assignation of the pixels to the classes were computed.

All analyses were performed using MatLab® software (MathWorks Inc., Natick, MA, USA).

3. Results and Discussion

Preliminary analysis (data not shown) showed that the best performance of the models was obtained considering normalized spectra, computed by dividing the raw spectra by the integral of intensities along the own spectra; further on, this pre-processing technique was applied to the spectra before the multivariate data analysis.

3.1. Spectral signatures

Figure 1 shows the whole population spectra of calibration and the average spectrum for each ripening class of the calibration set A at time zero. The reflectance spectra in the whole NIR region (from 700 to 1000 nm) present a general decrease from class 1 to class 7, which is according with Rajkumar et al. (2012), who also observed the same effect in bananas with different ripening stages stored at different temperatures; it could be explained considering that moisture contents increase from green to ripe fruits as it was reported by Ramly et al. (2010). Other remarkable band in the spectra is located in the 550–700 nm wavelength region, where a valley that decreases from class 1 to class 7 is observed. Li et al. (1997) demonstrated a strong negative correlation between reflectance at this region with peel chlorophyll content.

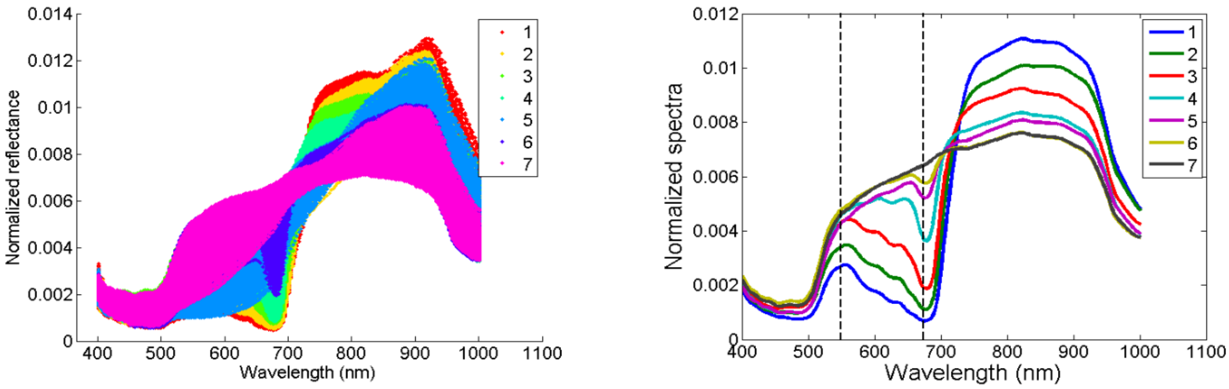


Figure 1. Normalized spectra of calibration set A for each class of COPLACA at time zero (left); average spectrum for each class (right).

Along the storage period, fruits of set A classified originally as 4-6 showed spectral signature similar to class 7, with low reflectance level at NIR region and without the valley centered at 680nm, but with additional distinctive characteristics such as a low reflectance at 550 nm and (Figure 2).

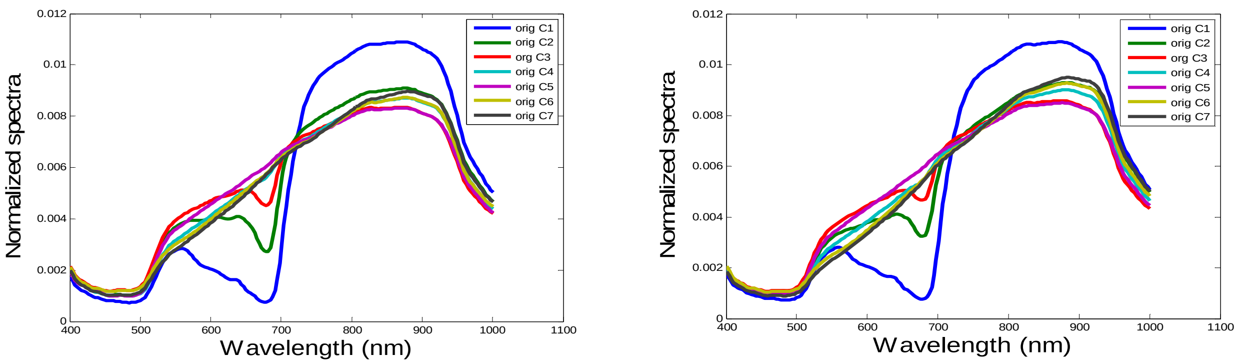


Figure 2. Average of normalized spectrum for each COPLACA class of bananas belonging to set A, after 5 (left) and 6 (right) days of storage.

From the dendrogram obtained of the cluster analysis based on Ward's method, and considering Euclidean distance, groups containing representative spectra of COPLACA classes (from 1 to 7) were identified and selected. Besides, an additional group containing spectra with a particular spectral pattern was observed and considered such as a new class, namely Class 8 (Figure 3, C8). It was verified that spectra pattern of Class 8 corresponded to over-ripened areas of the fruits. The average spectra were computed for the eight groups. These eight spectra were considered as the centroids of each category; further analyses (virtual image computation of membership degree) were made taking into account these centroids.

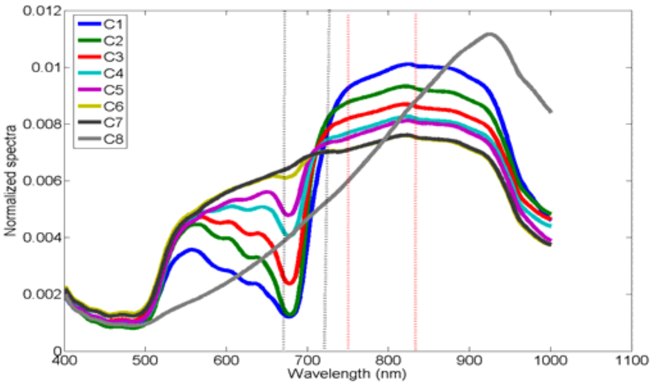
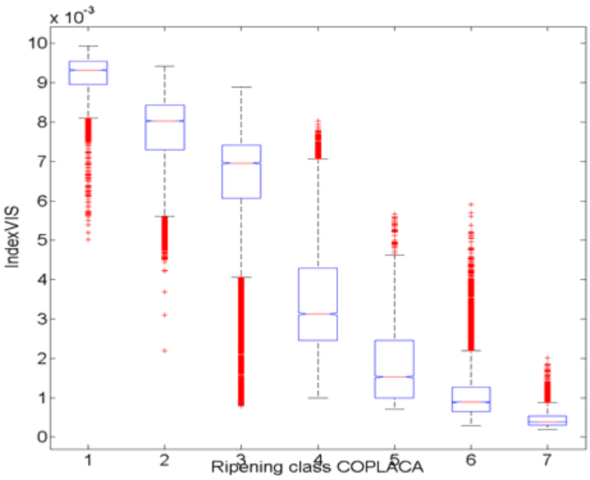


Figure 3. Average spectra of groups obtained in the non-supervised cluster analysis

3.2. From hyperspectral analysis to multispectral indexes

3.2.1. Indexes for sensing ripening evolution

Several indexes were tested (data not shown) and finally two of them were proposed based on the average spectra of calibration set (set A at time zero, Figure 1). The first one (named IndexVIS) was defined for reflecting the variation in the slope in the region comprised between 688 and 750 nm (black vertical lines in Figure 3) and it was computed as the difference between the normalized reflectance at 750 and 688 nm; this slope decreases along ripening process from C1 to C7. The second index (named IndexIR, red vertical lines in Figure 3) was established for sensing the evolution in the NIR region, and it was computed as the sum of normalized reflectance at 780 and 880 nm. For the calibration set, analysis of variance performed on IndexVIS and IndexNIR, showed significant differences between ripening classes, although C6 and C7 resulted practically indistinguishable for both indexes (Figure 4). A large number of pixels appears as outliers, it is usual in images of ripening fruits. (red dots).



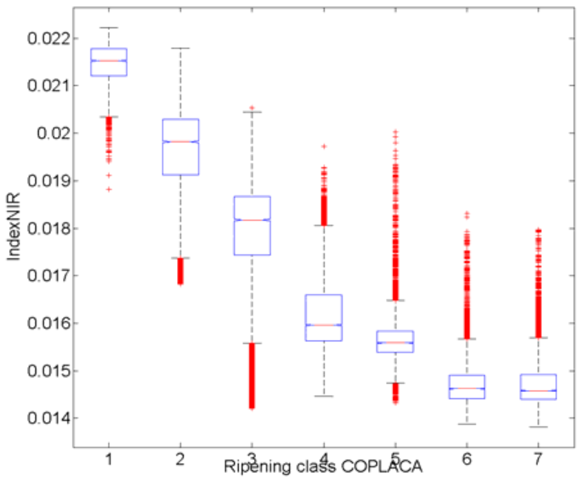


Figure 4. Box and Whisker plots of IndexVIS and IndexNIR for the set A at time zero.

Figure 5 presents IndexVis vs. IndexNIR scatter plot for set A. The average values of the indexes of each category at time zero are plotted in the left and right graphs (black points) to show up the migration of the data points of each original category along time. At time zero both indexes decrease towards increasing maturity categories, distinguishing clearly between C1 to C6. After storage, a movement of the points to the left is observed, although C1 remain practically at the same original area (time zero). In addition, points from category 1 appear close to the centroid of category 2 (at time zero), after six days of storage. Similarly the points of category 3 appear close to the centroid of category 4 after evolution. However, it is observed that the main part of the points of categories originally classified as C5, C6 and C7 migrated to higher values of both indexes (to the right and up), reflecting an inversion in the tendency of the evolution in the over-ripen and non-commercial stages. The main part of these points correspond to pixels with spectral patterns similar to those of the category C8.

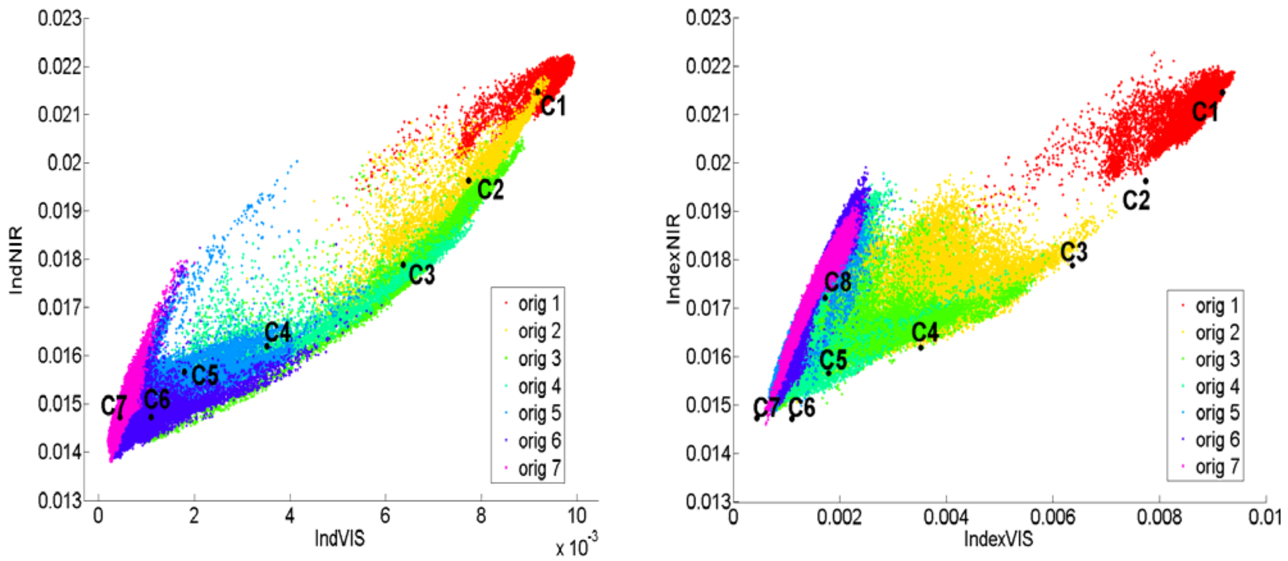


Figure 5 IndexVis vs. IndexNIR scatter plot computed on n = 65000 spectra of set A. Different colors are assigned to the original categories. Average value of each category at time zero are marked with black points. Left: scatter plot for time zero; right: scatter plot after 6 days of storage.

3.2.2. Virtual images

Virtual images of the values of IndexVIS (Figure 6) and IndexNIR (Figure 7) corresponding to bananas of set A are shown. Each column corresponds to one of the 7 bananas of set A, and each row to one period of storage (zero time, 5 and 6 days of storage). At time zero progression to lower values of both indexes from ripening class C1 to ripening class C7 is clear. Along the evolution, at the early stages of ripening (C1-C3) the values of indexes decreased as it could be expected, however for the rest classes of ripening, an involution to higher values can be observed after 5 or 6 days of storage, denoting that over-ripen stage has been reached. This fact is in accordance to the tendencies observed in the Figure 5.

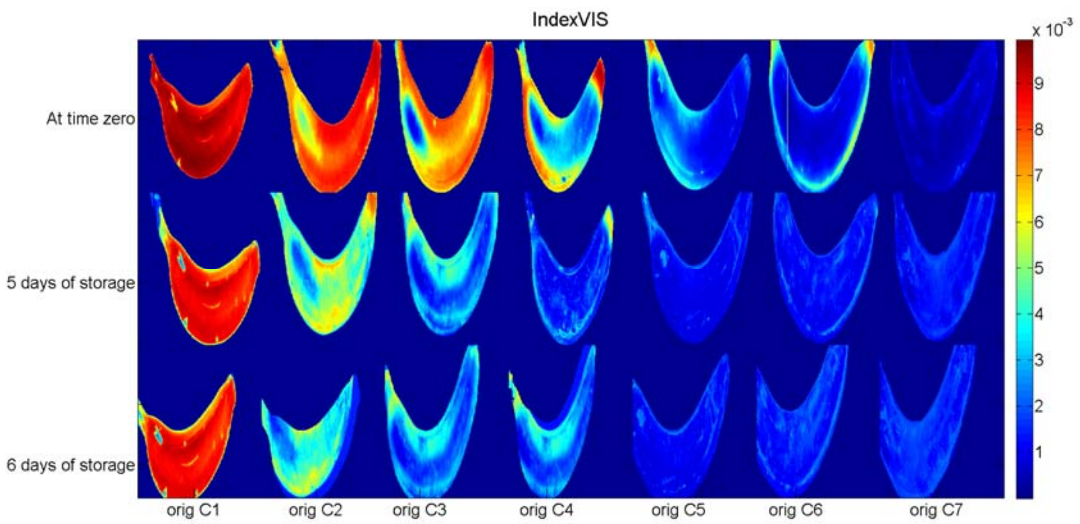


Figure 6. Virtual images of IndexVIS of set A (7 bananas, in columns) along storage period (in rows); in each column, the class to which the banana was originally assigned visually by the expert (C1-C7) orig C1 to orig C7

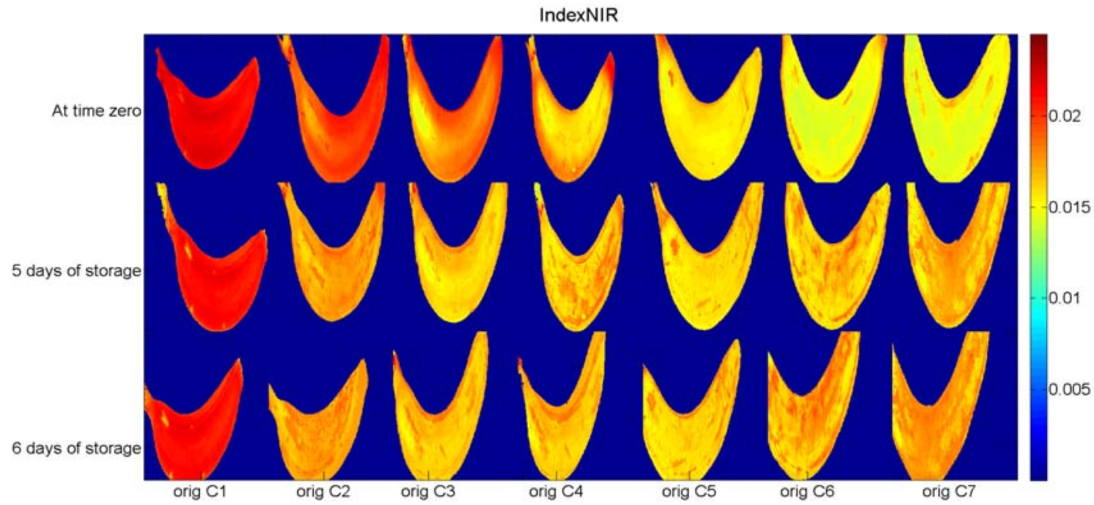


Figure 7. Virtual images of IndexNIR of set A (7 bananas, columns) along storage period (rows); in each column it is consigned the class to which the banana was originally assigned (C1-C7)

Trying to overcome the drawbacks of classification based on a fixed threshold of IndexVIS or IndexNIR, a procedure for the classification of pixels was applied considering both indexes simultaneously. Firstly, eight class centroids for the two indexes were computed as the average of each of the eight groups identified on the cluster analysis showed in Figure 3. Secondly, eight Mahalanobis distances were calculated between each pixel of the virtual image of indexes to each of the eight centroids. Finally, each pixel was assigned to the category which showed the highest membership degree, according to these Mahalanobis distances.

Figure 8 and Figure 9 show the virtual images of the assignation of the pixels of each fruit (in columns) to one of the 8 classes along the dates of evolution (in rows). The evolution of the classification is shown for 7 bananas of set A (monitored through three dates) and 14 bananas of set B (monitored through 4 dates). Generally for each fruit, it can be observed pixels successively assigned to higher levels of ripening, except for fruit classified into C1 (Figure 8, set A at time zero). Pixels of fruits originally classified as C7 (first row, last column) were classified into class C8 after 5 days of storage in set A and after 3 days of storage in set B showing an evolution to over-ripened stages. These proposed virtual images are able to sense the evolution within commercial categories and also to over-ripened stages, and permits automatic classification.

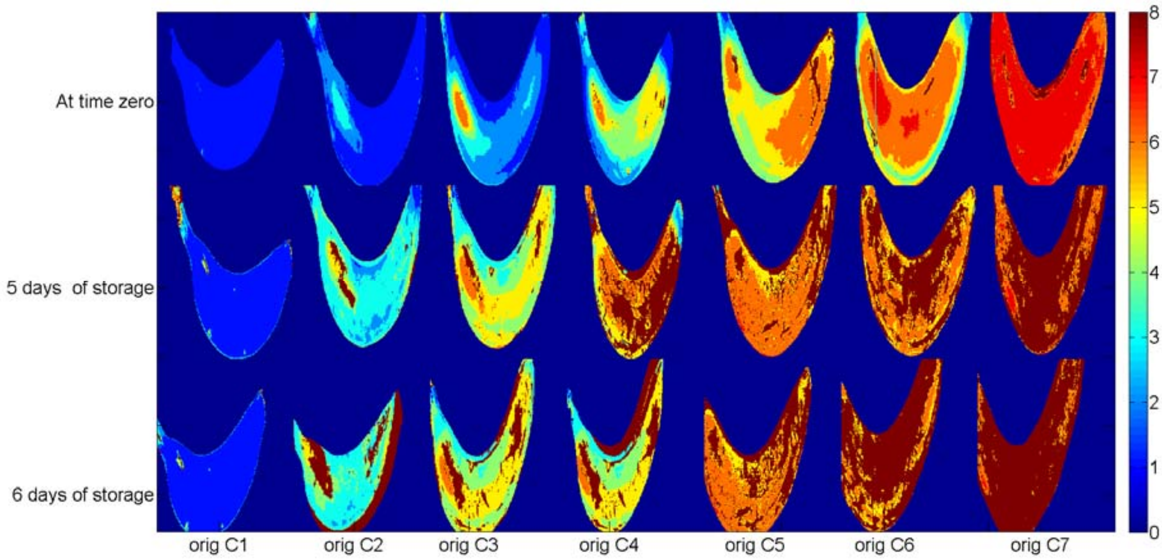


Figure 8. Visualization of the assignation of each pixel of the banana of set A (left) to one of the 8 quality classes (C1-C8) considering the maximum membership degree. Blue: green

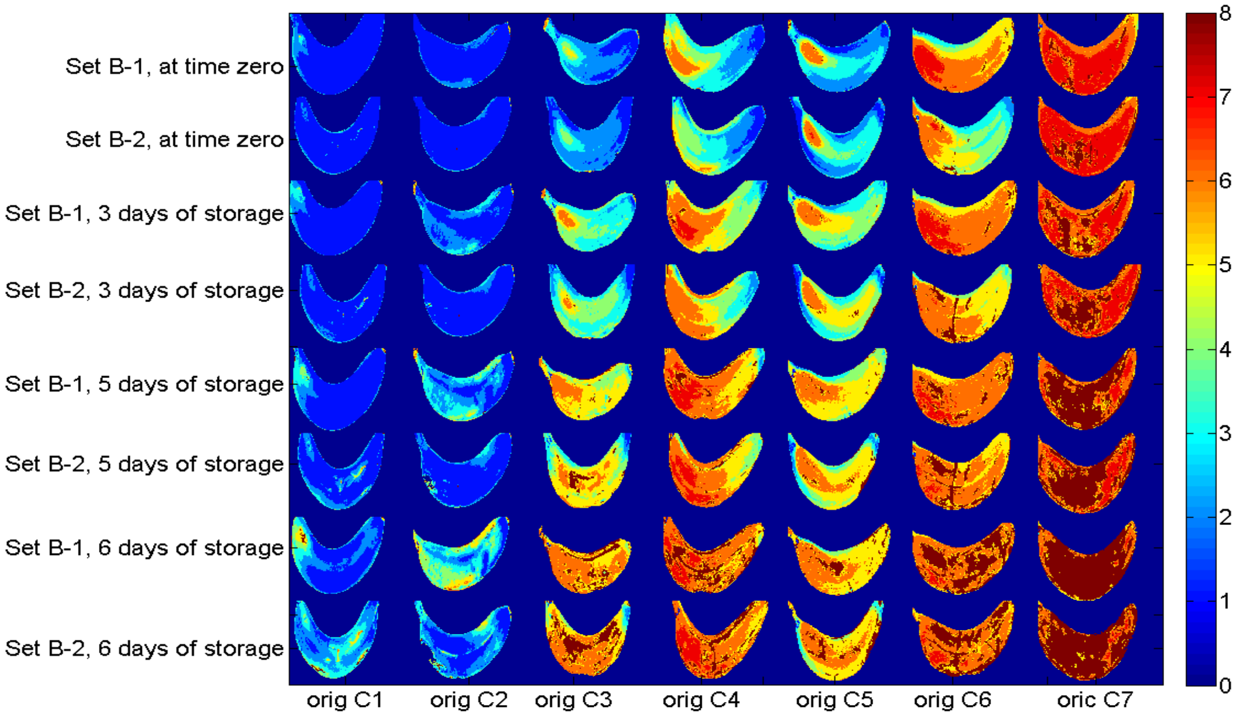


Figure 9. Visualization of the assignation of each pixel of the banana of set B (14 bananas, 2 groups of seven fruits Set B-1 and Set B-2) to one of the 8 quality classes (C1-C8) considering the maximum membership degree.

4. Conclusions

A non-supervised cluster analysis based on Ward method confirms the spectral pattern of seven commercial categories based on human visual classification. This analysis allows to identify an additional spectral pattern related to stages of over-ripeness, with presence of black spots and evolution of brown areas; consequently an additional class corresponding to over-ripeness is proposed. Centroids of the 8 groups conformed by cluster analysis were computed.

Ripening is sensed by two multispectral indexes based on the wavelengths in which it observed the higher inter-class variation is observed IndexVIS (688 and 750 nm) and IndexNIR (780 and 850 nm). Both indexes demonstrate a high ability to discriminate ripening classes from 1(totally green) to 5 (yellow with green tip), which are the ripening states in which the fruit is usually managed and issued for final retail.

The projection of the hyperspectral images onto the generated indexes and the assignation of each pixel to one of the 8 categories defined according to the distances to the centroids, allows the identification of regions with different states of evolution in the bananas. The system proves the feasibility to determine the percentage of the areas of the categorical regions and to establish decision rules about the overall state of the individual fruits. The proposed solution is a clear advantage as compared to the spectrophotometric methods, which analyze just small area of the sample. The proven concept is that multispectral image systems based on three or four wavelengths can be used to accurately monitor banana peel color and can replace the human expert color determination by comparison with standard charts, which shows the usual subjectivity in the assignation of fruits to adjacent categories.

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