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Monitoring spinach shelf-life with hyperspectral image through packaging films

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A B S T R A C T

Different procedures for monitoring the evolution of leafy vegetables, under plastic covers during cold storage, have been studied. Fifteen spinach leaves were put inside Petri dishes covered with three different plastic films and stored at 4 °C for 21 days. Hyperspectral images were taken during this storage. A radiometric correction is proposed in order to avoid the variation in transmittance of the plastic films during time in the hyperspectral images. Afterwards, three spectral pre-processing procedures (no preprocess, Savitsky–Golay and Standard Normal Variate, combined with Principal Component Analysis) were applied to obtain different models. The corresponding artificial images of scores were studied by means of Analysis of Variance to compare their ability to sense the aging of the leaves. All models were able to monitor the aging through storage. Radiometric correction seemed to work properly and could allow the supervision of shelf-life in leafy vegetables through commercial transparent films.

1. Introduction

The consumption of fresh ready-to-eat products and minimally processed foods has increased in recent years (Artes et al., 2009). Ready-to-eat vegetables have a shelf-life between 7 and 14 days (Garcia Gimeno et al., 1997), depending on the type of vegetable, due to microbiology degradations and the loss of physical and organoleptic properties (Toivonen and Brummell, 2008).

The industry demands objective, non destructive and low cost methods to sense the evolution of this product during storage and to evaluate new systems that have been introduced in the ready-to-use processes as UV-C radiations, O_3 treatments, etc.

Modified atmosphere packaging (MAP) is an essential technology for the success of fresh-cut produce. Polymeric films are a key element in MAP. The most commonly used packaging films are a few plastic polymers: polyolefins (polyethylene and polypropylene), vinyl compound polymers (polystyrene and polyvinyl chloride), and polyethylene terephthalate (polyester). For fresh fruits and vegetables, the films need to be "breathable" because the fresh produce inside is still "alive" and "breathing". Micro perforated films are a good solution for this kind of fresh food.

Hyperspectral imaging allows the acquisition of the spectrum of each pixel, in a specific wavelength range, and generates a spatial map of spectral variations. It is a fast, simple and non destructive technology (ElMasry and Sun, 2010). However, the images obtained are very complex to manage directly and need to be preprocessed and then processed (Fernandez Pierna et al., 2009). Hyperspectral imaging has been used on different applications for the characterization of food quality (Cubero et al., 2011; Du and Sun, 2006; Gowen et al., 2007; Sun et al., 2010) or food safety (Del Fiore et al., 2010; Yao et al., 2008). Regarding vegetables Siripatrawan et al. (2011) used hyperspectral imaging for the detection of Escherichia coli contamination in packaged fresh spinach.

Previous research has been done to compare pre-processing methods for scatter correction in spectra: multiplicative scatter correction (MSC), inverse MSC, extended MSC (EMSC), de-trending, standard normal variate (SNV), normalization and spectral derivatives (Fearn et al., 2009; Laxalde et al., 2011; Rinnan et al., 2009; Zeaiter et al., 2005; Zeaiter and Rutledge, 2009). Geometric preprocessing methods are widely carried out to correct spectral data from drift in baseline, non-linearity, curvilinearity, as well as additive and multiplicative effects. All pre-processing techniques have the goal of reducing the un-modeled variability in the data in order to enhance the performance of the model of prediction. However,

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the application of a wrong or too severe type of pre-processing, can remove valuable information. Pre-processing should maintain or decrease the effective model complexity and enhance the model performance.

The objective of the present research was to compare different pre-processing procedures applied to hyperspectral images, regarding their ability to monitor the evolution and spoilage of leafy vegetables under plastic covers during storage. First, the effect of the variation in transmittance of the plastic films that cover the leaves in the measurements was established and corrected. Second, three pre-processing procedures: (a) no pre-process, (b) Savitsky Golay (SG), and (c) Standard Normal Variate (SNV) combined with principal component analysis (PCA), were applied and compared.

2. Materials and methods

Three groups of leaves ($n = 5$ leaves per group) were randomly selected from bags acquired in a local market. Three micro perforated plastic films (polypropylene PPLUS® 160, P1; polypropylene PPLUS® 190, P2; and biaxially oriented polypropylene 30 μm, P3) commonly used in the packing industry of vegetables, were selected. Each group of leaves was assigned one type of plastic film. Each leaf was individually left inside a Petri dish with a piece of grey plastic and covered by the corresponding plastic film. The samples were stored at 4 °C during the whole measurement period. Hyperspectral images were acquired 7 times through 21 days: at 0, 4, 7, 11, 14, 18 and 21 days.

Hyperspectral vision system consisted of a CCD camera with a VNIR spectrometer (Headwall Photonics Hyperspec™) working between 400 and 1000 nm. It was equipped with a progressive line-by-line scan spectrograph with a slit of 25 μm. The selected spectral resolution was 3.2 nm (189 wavelengths), and the spatial resolution was 0.26 mm/pixel. One halogen lamp was used for the illumination. Specific software, Headwall Hyperspec™, was used to control the equipment. Images were acquired according to the conditions shown in Table 1. Samples were scanned acquiring the whole surface of the leaf. A hypercube dataset was obtained from each image.

Relative reflectance hyperspectral images were computed simultaneously to the acquisition, by the software of the camera. White reference (barium sulfate) and dark current signal (acquired with the objective of the camera covered by a black tap) were acquired before each batch of images. Then, each line of the image was corrected pixel by pixel subtracting the dark current and dividing this result by the white reference minus the dark current.

Aiming to obtain a calibration data set completely independent on the validation data set, the 15 leaves were separated into two different groups: a calibration set with three leaves of each plastic, and a validation set with the remaining two leaves of each plastic. The average spectrum of each leaf of the calibration set was computed from the hyperspectral images. Each average spectrum was computed considering all the pixels belonging to the leaf; depending on the size of the leaf the number of spectra range from $n = 7293$ to 85702 (original images without reduction of the spatial resolution). Calibration data set was formed by 63 average spectra (3 leaves × 3 films × 7 dates). Models were generated with the calibration data set. Two types of validations were performed: (a) one applying the models to all the pixels of the leaves of the validation set and (b) a second one considering also all the pixels of the leaves of the calibration set.

Table 1
Configuration of the image acquisition conditions

Spectral binning	4 (189 Wavelengths)
Frames to average	5
Scan length	140 mm
Slit	25 μm
Exposition time	80 ms

2.1. Preprocessing procedures

All the processes described in this section were applied to the calibration set of spectra and also to all the pixels of the hyperspectral images.

2.1.1. Radiometric correction

Radiometric correction (RC) is currently employed in remote sensing for overcoming changes in the measured light due to the atmospheric transmittance and the position of the sun (Sims and Gamon, 2002; Song et al., 2001). In the present study, this correction was used to correct the measured signal for variation in plastic film transmission. A piece of grey plastic of 25 × 25 mm, having a global reflectance similar to a leaf, was inserted in each Petri dish, beside the spinach leaf.

Let be:

- two pixels of grey plastic (position a) and of leaf (position b);
- $S_0(a, t)$ and $S_0(b, t)$ the measured signal from the two pixels *a* and *b* on the white reference before the measurement made at date *t*.
- $F(a, t)$ and $F(b, t)$ the internal gain factor of pixels *a* and *b*.
- $I_0(a, t)$ and $I_0(b, t)$ the intensity of the input light for the two positions *a* and *b* at date *t*.
- $P(t)$ the transmission of the plastic film, at date *t*, supposed independent of the position.
- G the reflectance of the grey plastic supposed independent of the position and the date.
- $R(b, t)$ the reflectance of the leaf at pixel *b* and date *t*.

Fig. 1 illustrates the light path for the two pixels during the measurement. The signals finally collected by the camera are given by:

$$S(a,t) = I_0(a,t) \cdot P(t)^2 \cdot G \cdot F(a,t) \text{ and } S(b,t) = I_0(b,t) \cdot P(t)^2 \cdot R(b,t) \cdot F(b,t)$$

However, assuming a unitary reflectance for the white reference, we have:

$$S_0(a,t) = I_0(a,t) \cdot F(a,t) \text{ and } S_0(b,t) = I_0(b,t) \cdot F(b,t)$$

Then, the values collected for the two pixels are:

$$X(a,t) = S(a,t)/S_0(a,t) = P(t)^2 \cdot G \text{ and } X(b,t) = S(b,t)/S_0(b,t) = P(t)^2 \cdot R(b,t)$$

The average value of $X(a, t)$ was computed over all the pixels of the grey plastic and then divided by the value of G measured before the experiment, yielding an estimation of $P(t)^2$. Each pixel *b* of the leaf was then divided by this quantity, giving an estimation of the true reflectance $R(b, t)$.

2.1.2. Multiplicative and additive effect

Savitsky–Golay smoothing and differentiation algorithm (SG) was applied to the spectra: a polynomial of order three was fitted to 21 wavelengths width and the second derivative function was applied to the smoothed spectra.

After SG algorithm, the multiplicative effect was corrected by Standard Normal Variate scaling (SNV). SNV subtracts to each wavelength of the spectrum (λ_i) the mean value of this spectrum