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Non-destructive grading of peaches by near-infrared spectrometry

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Abstract

This paper describes an experimental study on non-destructive methods for sorting peaches according to their degree of ripeness. The method is based on near-infrared (NIR) transmittance spectrometry in the region between 730 and 900 nm. It estimates the ripeness in terms of internal sugar content and firmness. A station for acquiring the NIR signal has been designed and realized, carefully choosing between several options for each component. Four different stations have been realized and compared during the experimental phase. The signals acquired by the station have been pre-processed using a noise-reducing method based on a packets-wavelet transform. In addition, an outlier detection technique has been applied for identifying irregular behaviors inside each of the considered classes. Finally, a minimum distance classifier estimates the grade of each experimental data. The results obtained in classification show that this early version of the station enables the correct discrimination of peaches with a percentage of 82.5%.

Keywords: Non-destructive fruit grading; NIR transmittance Spectrometry

1. Introduction

Quality evaluation of agricultural products is an important cue for both producers and consumers. In the past 50 years, researchers have developed new technologies enabling the producers to satisfy the consumers which demand a constant and reliable food quality.

The assessment of ripeness represents an important part of quality evaluation and depends on a combination of several factors. Traditionally, ripeness has been estimated by direct perception or by destructive techniques applied to a number of samples [1]. Unfortunately a very common feature of almost all biological products is variability that makes sampling not completely satisfactory. An accurate ripeness assessment requires to test the whole production: generally, firmness and soluble solids content are useful, but their measurement is necessarily destructive.

The development of automatic technologies has enabled new methods for evaluating various ripeness factors on agricultural products.

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Nevertheless, the high cost of their implementation is still a considerable drawback.

This work describes a non-destructive measure of peaches ripeness that uses a low cost station and near-infrared (NIR) spectrometry.

Section 2 presents details about each component of the system; Section 3 describes the signal processing algorithms used and the obtained results. At the end, conclusions and future developments are drawn.

2. Method and devices

The developed station uses spectroscopic analysis of the transmitted NIR radiation to evaluate ripeness of peaches. In the NIR region the organic substances (like glucose, fructose and sucrose) absorb the electromagnetic radiation. The bonds of organic molecules change their vibrational energy when irradiated by NIR frequencies and exhibit absorption peaks through the spectrum [2].

Qualitative and quantitative chemical and physical information is contained within the wavelength spectrum of absorbed energy. The proposed station is composed by lens, a spectrograph, a CCD camera and a PC equipped with a frame grabber (Fig. 1).

The light, irradiated on the fruit by the lamps, diffuses through its flesh and is therefore conveyed by the lenses in the spectrograph (ImSpector V10) which analyzes the radiation coming from a single line of the observed scene. The electromagnetic spectrum associated to each point of the line is spread perpendicularly to the line itself. This produces a two-dimensional image where the x-axis spans the spatial position in the scene while the y-axis spans the analyzed spectrum of frequencies (400–1000 nm). This image is acquired by a CCD camera and digitized by a frame-grabber producing the data that are analyzed by the software modules (Fig. 2). The whole station has a cost of about euro 20,000.

Each component of the station has been chosen on the base of its behavior in the NIR range (specifically from 780 to 1000 nm). Every fruit has been acquired twice, each time with a different half facing the camera with the suture away from the incident light beam. The detector was positioned at about 120° with respect to the incident light beams. The whole measuring station is vertical on

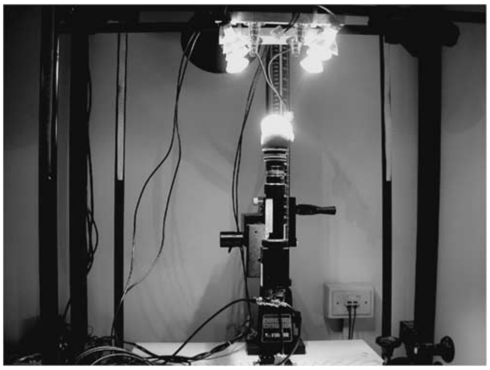


Fig. 2. A picture of the system used for measuring the transmitted NIR radiation. From top to bottom: the light sources, the fruit, the spectrograph and the CCD camera.

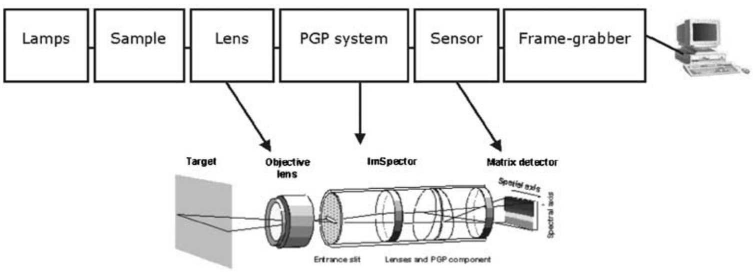


Fig. 1. Scheme of the proposed station. The experiments show the results obtained comparing different configurations of lamps and lenses. Station A uses tungsten–halogen lamps and standard lens. Station B uses infrared rays lamps (with an emission peak around 1200 nm) and standard lens. Station C combines tungsten–halogen lamps with MAF lens (with minimum attenuation in the NIR range). Station D uses infrared rays lamps and MAF lens.

the bench. The fruit is leaned on the set-up with a rubber "fruit-brought".

The acquired signals have been compared with measurements obtained directly via physical–chemical analysis.

The total sugar content in juice fruit is a mixture of glucose, fructose and sucrose and is referred to as total sugar or solid soluble content [3]. It has been measured in Brix degrees with a refractometer by reading the index of refraction of the juice extracted from the samples. Firmness has been measured with a penetrometer that measures the force required for inserting a probe in the fruit.

Both these instruments are normally used for destructive grading fruits. Each parameter has been divided into four intervals whose combination provides sixteen possible grades for each fruit.

3. Processing and results

The system measures a mono-dimensional spectrum of the radiation gone through the fruit. The pattern of attenuation, varying over the considered interval of frequencies of the spectrum, depends on the chemical and physical property of the fruit.

The data analysis assesses the relationship between these observed patterns and the two properties of interest (sugar content and firmness). Techniques for both enhancing the quality of the measured signal and for evaluating this relationship with the ripeness classes are needed.

The signal processing phase involves two parts: pre-processing and classification. The pre-processing aims to improve the signal-noise-ratio (SNR) and to identify samples exhibiting anomalous behaviors (they can affect negatively the training phase of the classifier). The classification uses a minimum distance classifier to assign each sample to its appropriate class.

3.1. Pre-processing

The detected signals are quite noisy and show a poor signal-to-noise ratio (SNR). To characterize statistically the noise we have carried out two kind of experiment. One thousand of acquisitions have been done preventing the light from entering the camera to measure the background noise. Then, one thousand of acquisitions have been done opening the lens in the dark, without any light source, to detect and measure eventual sources of noise in the environment.

These two noises are statistically very similar and can be both considered as white Gaussian. The noise reduction is highly desirable to improve the quality of classification. We have used a packets-wavelet-based approach [4]. The main advantage of wavelets lies in the resolution of the transformed signal in both the frequency and the spatial domains. This transform uses a set of spatial functions $\psi_{a,b}(x)$ called wavelets [5,6], constructed by translating and dilating a *mother wavelet* $\psi(x)$

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{x-b}{a}\right) \quad (a \neq 0)$$

where the scale parameter a plays the role of a frequency and b is the position parameter. By increasing a, the wavelet $\psi_{a,b}(x)$ is broadened while b translates it along the x-axis. The continuous wavelet transform of a function $f(x)$, $W[f(a,b)]$, is defined by

$$W[f(a,b)] = \langle \psi_{a,b}(x), f(x) \rangle = \int_{-\infty}^{\infty} f(x)\psi^*_{a,b}(x)\,\mathrm{d}x$$

The continuous wavelet transform is reversible if the admissibility condition is satisfied

$$c_\psi = \left\{ 2\pi \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\xi)|^2}{|\xi|}\,\mathrm{d}\xi \right\}^2 < \infty \tag{3.1}$$

where $\hat{\psi}(\xi)$ is the Fourier transform of $\psi_{a,b}(x)$ and c_ψ is a constant that depends on the wavelet used. If (3.1) is satisfied, the reconstruction is possible by using the following formula

$$f(x) = \frac{1}{c_\psi^2}\int_a \int_b Wf(a,b)\frac{1}{a^2}\psi\left(\frac{x-b}{a}\right)\mathrm{d}a\,\mathrm{d}b$$

The reversibility implies that even if a signal is transformed several times and decomposed at each transformation it can be recomposed by applying the inverse transform. The scheme of repeated applications of the wavelet transform leads to the

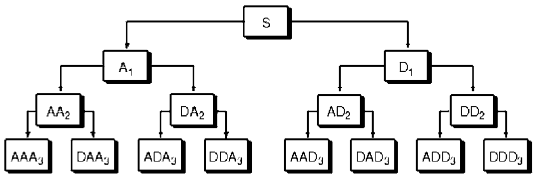


Fig. 3. Binary tree decomposition with packets-wavelet.

splitting algorithm of packets-wavelets used in this application.

In the packets-wavelet framework, the de-noising idea is exactly the same that in the wavelet framework but with a more complex and flexible analysis because at each level both the details and the approximations are split. The complete binary tree is produced as shown in Fig. 3.

The Daubechies filters have been used because they are minimal phase filters that generate wavelets with minimal support for a given number of vanishing moments. A single wavelet packets decomposition gives a lot of bases where the best representation either in high or in low frequency can be found. This has been done by finding the ''best tree'' based on an entropy criterion. We have used the Best-Basis algorithm of Coifman–Wickerhauser described in Wickerhauser' book [7].

Subsequently the coefficients of the best-basis that are significantly near the noisy background are filtered by the method of hard threshold. This method sets to zero those coefficients that are below a certain threshold while the coefficients above the threshold remain unaffected. The hard threshold filter has the following expression

$$W_f = 0 \quad \text{if } |W| < \tau$$
$$W_f = W \quad \text{if } |W| \geqslant \tau$$

We have used the "Stein's unbiased risk estimator" (SURE) to choice the threshold that is found by evaluating the loss associated with each option as the Euclidean distance between the original and the de-noised signals (Scheme 1).

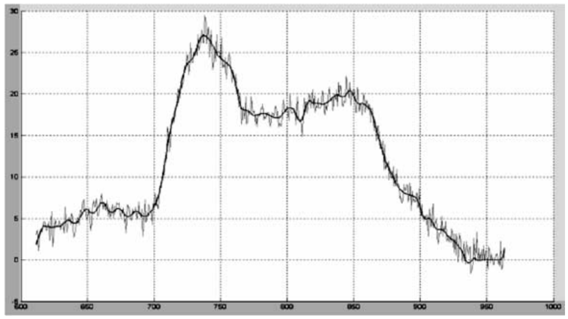
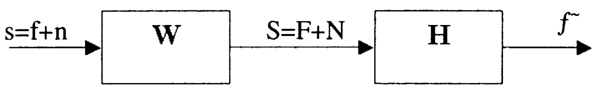


Fig. 4. The figure shows the signal before (gray) and after (black) the de-noising process. The approach based on the packets-wavelets transform allows the removal of most of the noise while keeping the high-frequency components of the signal.

After this filtering, the signal is recomposed and its SNR is calculated again. In our experiments it has become almost twice the original level. The greater advantage is that this method does not affect the signal in the high frequency band. In this application this is important because we expect the useful information to be related also to rapid variations of the signal (Fig. 4).

For classification step, it is necessary to extract from each class the features giving the best representation of its characteristics.

Detecting outliers is important: they can point out critical aspects of the acquisition process not properly considered. In these experiments, due to the seasonal nature of peaches, the detection of outliers has been done at the end of the acquisition. This prevented an immediate investigation about the causes of these outliers: this will be the aim of further experiments. Outlier detection has been based on an iterative algorithm that calculates the Euclidean distance between the samples in a class. A threshold representing the maximum distance allowed among samples of the same class is fixed: its value depends on the application. At every iteration, the distances between samples of the same class are calculated and used for filling a



Scheme 1. The signal f with noise n is decomposed with the transform wavelet block W; the transformed signal S is filtered and then $\tilde{f}$ is reconstructed as a de-noised signal.

square matrix. The sample having the greatest number of distances above the threshold is removed from the class. This step is repeated until all the remaining matrix elements are below the threshold. In this way in each class only the homogeneous samples are kept: that makes the features extracted for the classification phase more representative of its characteristics.

An example of samples removed from or kept in a class is shown in Fig. 5.

3.2. Classification

A simple but effective scheme, the minimum distance classifier, has been used to classify the data. Table 1 shows the discretization of each parameter normally used in the destructive evaluation of fruit firmness. It generates the potential fruit grades shown in Table 2. The dark areas roughly represent fruits with very unripe characteristics against quite fully ripen samples.

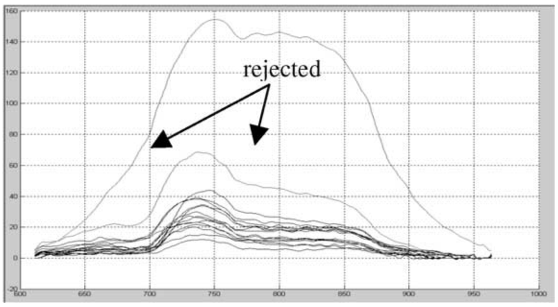


Fig. 5. The figure shows the spectra corresponding to fruits belonging to a same class. The two that have been marked as outliers and rejected by the outlier detection/removal process are evidently different from the remaining elements of the class.

Table 1
The considered intervals for each analytical measure of ripeness

Brix degree	Firmness
Poor [0–10]	Soft [0–2]
Medium [10–12]	Tender [2– 4]
Good [12–14]	Dense [4–6]
Excellent [14–18]	Hard [6–15]

Table 2
The cross product of the considered intervals for the two parameters produces 16 classes of ripeness the fruit can ideally belong to

	Soft	Tender	Dense	Hard
Poor	Cl 1	Cl 2	Cl 3	Cl 4
Medium	Cl 5	Cl 6	Cl 7	Cl 8
Good	Cl 9	Cl 10	Cl 11	Cl 12
Excellent	Cl 13	Cl 14	Cl 15	Cl 16

In our experiments these classes have been grouped (darker areas) in order to check a first level of ripeness discrimination.

The applied template matching can be easily expressed mathematically. Let $\mathbf{x}$ be the feature vector for the unknown input, and let $\mathbf{m}_1, \mathbf{m}_2, \ldots, \mathbf{m}_c$ be the templates (i.e., perfect, noise-free feature vectors) obtained after the outlier detection phase from each of the c classes. Then the error in matching $\mathbf{x}$ with $\mathbf{m}_k$ is given by

$$||\mathbf{x} - \mathbf{m}_k||$$

Here $|| \ldots ||$ represents the *norm* of the corresponding vector. A minimum-error classifier computes $||\mathbf{x} - \mathbf{m}_k||$ for $k = 1, \ldots, c$ and chooses the class for which this error is minimum. Since $||\mathbf{x} - \mathbf{m}_k||$ is also the distance of $\mathbf{x}$ from $\mathbf{m}_k$, this schema represents a *minimum-distance* classifier [8].

Tables 3–6 show, for different configurations of the station, the final classification results obtained

Table 3
Results with different outlier thresholds and the station A

Station A	Outlier threshold = 150	Outlier threshold = 200	Outlier threshold = 250
Set-comparison	74.3%	82.5%	71.4%

Table 4
Results with different outlier thresholds and the station B

Station B	Outlier threshold = 150	Outlier threshold = 200	Outlier threshold = 250
Set-comparison	63.3%	66%	63.3%

Table 5
Results with different outlier thresholds and the station C

Station C	Outlier threshold = 150	Outlier threshold = 200	Outlier threshold = 250
Set-comparison	76.6%	77.5%	71.1%

Table 6
Results with different outlier thresholds and the station D

Station D	Outlier threshold = 150	Outlier threshold = 200	Outlier threshold = 250
Set-comparison	60.4%	61.2%	60.7%

setting different thresholds during the outlier detection. Changes of this threshold affect the number of samples belonging to each class. In fact, a low value keeps in each class only samples very similar to each other while larger values increase the number of samples allowing larger differences between their characteristic.

In order to be meaningful, the comparison of the different configurations of the station has been done only on a set of fruits (set-comparison) that have been acquired using all the four different set-ups. Further acquisitions, made using only some of the four configurations, have not been considered.

It is possible to note that by increasing the outlier threshold from 150 to 200, the percentage of correct classification increases. This is due to the greater number of samples, still really related to their class, that become available for building the templates that become more representative of their class. A further increase causes a reduction of correct classification: the new samples assigned to each class are more likely to be artifacts and to negatively affect the significance of templates.

Furthermore, comparing the configurations using the same lens it is possible to note that the best results are obtained using the tungsten–halogen lamps. This result is due to the better match between the spectrum of the light sources and the sensitivity of the camera: in fact the infrared rays lamps provide greater intensities in a range where the sensitivity of the sensor is very low and vanishes the expected advantage. Furthermore, comparing the results obtained using configurations with the same lamps and different lenses, the better results seem to be obtained with standard lens. This is a quite surprising result that needs further investigation during the next planned experiments. On the base of the available data, the best configuration would be the station A.

4. Conclusions

Quality control, in several fields, requires the design of instruments for approximating the human judgment in a satisfactory way. This task is especially challenging in applications, as the quality evaluation of fruit, that involve product with high variability and requiring the estimation of several parameters that are difficult to measure in a non-destructive way.

Nonetheless, this achievement is important because the fruit market, due to the wide international competition, calls for a reliable and economic assessing of the quality level of the whole production.

There is a strong interest in the development of systems for the non-destructive automatic evaluation of fruit ripeness. Commercial solutions are expensive and are based on technologies that have not reach a full maturity.

This paper describes a low-cost system that enables a significant estimation of parameters related to the internal quality by a non-destructive technique that can therefore be applied to each single fruit: therefore the whole production can be graded.

Several hardware options for its realization have been experimentally verified. Moreover, the signal processing techniques and the data analysis tools required for usefully exploiting the signal provided by the sensor have been identified. Efficient modules have been developed for each of these tasks. The complete systems, in its hardware and software parts, even at its early phase of development, provides definitely interesting results and justify further investigation in this field.

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