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Multispectral imaging for predicting sugar content of 'Fuji' apples

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ABSTRACT

This research investigated a usage of multispectral imaging to predict sugar content of 'Fuji' apples. A visible/near-infrared spectroscopy (350–1200 nm) was used to select optimal wavelengths for the multispectral imaging system. The spectral data were analyzed using the backward interval partial least square to generate a subset composed of several most sensitive wavebands. Four optimal wavelengths (461 nm, 469 nm, 947 nm and 1049 nm) were determined from this subset using stepwise multiple linear regression. A multispectral imaging system was developed based on these effective wavelengths. The scattering areas of the multispectral images were extracted by using the image histogram and the camera response function. The scattering profiles were calculated from the scattering areas by radial averaging. The modified Lorentzian distribution function was used to fit the scattering profiles. The parameters of the Lorentzian functions were used as the data base of multiple linear regression to create the prediction model. The multiple linear regression model predicted sugar content with r = 0.8861 and RMSE (root-mean-square-error of calibration) = 0.8738° Brix.

1. Introduction

The sugar content is one of the most important characteristics of fruits for better customer experience and repeat purchases. This makes it a main standard of the quality grading of fruits [1]. Among all the sugar content measurement technologies, the optical methods have received widespread attention because they are non-contacting, non-destructive, highly automated and accurate [2]. Near-infrared (NIR) and visible-NIR spectroscopy are the most widely used techniques. A considerable amount of research has been reported on the measurement of sugar content of apples [3,4], pears [5,6], oranges [7], kiwifruits [8] and many other fruits [9–12]. Hyperspectral imaging is another popular technology [13,14]. The hyperspectral images record the intensity distribution of the backscattered light on the fruit skin in contiguous wavebands. The prediction can be applied using the combination of the spectral and spatial information [15,16].

Compared with hyperspectral imaging, multispectral imaging captures images in several separate wavelengths instead of in many contiguous wavebands [2,17]. The major advantages of multispectral imaging are lower cost and faster data acquisition, which makes it more suitable for industrial applications.

Several studies have shown that multispectral imaging can be used for estimating the chemical content of fruit. Lu [18] reported the use of multispectral imaging to measure firmness and soluble solids content (SSC) of the red delicious apples. Ratios of scattering profiles across different spectral bands were used as input data for backpropagation neural network modeling. Two years later, an improvement of firmness detecting method was reported [19] by Peng and Lu. The input data and the modeling approach were replaced by parameters of a modified Lorentzian distribution function and multiple linear regression (MLR) separately for better precision. In 2007, Lu and Peng developed a multispectral imaging prototype for real-time detection of apple firmness using a multispectral imaging spectrograph with four filters [20]. The same system was also used for simultaneous measurement of the firmness and soluble solids content of Golden Delicious apples [21]. The measurement of firmness and maturity of peaches were also investigated [22]. Khodabakhshian et al. [23] developed a multispectral imaging system for the assessment of the total soluble solids (TSS), titratable acidity (TA) and pH in pomegranate. Multispectral images of five wavelengths were used by Qing et al. [24] to analyze the SSC and the firmness of 'Elstar' and 'Pinova' apples. Several multivariate calibration methods using the frequency of light intensities of backscattering images were tested.

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Hashim et al. [25] investigated the detection of chilling injury in bananas by multispectral imaging using the changes in the pigment contents (660 nm) and texture of the exocarp (785 nm).

The main objective of the present work is to test the ability of multispectral images at four selected effective wavelengths (461 nm, 469 nm, 947 nm and 1049 nm) to predict sugar content of ‘Fuji’ apples. A multispectral imaging system is developed for this purpose. There are three specific procedures in this research. (1) The optimal wavelengths used for multispectral imaging are determined based on the visible/near-infrared spectroscopy by using the combination of the backward interval partial least square (BiPLS) analysis and the stepwise MLR algorithm. (2) The scattering areas are segmented by using the image histogram and the camera response function and, only the scattering areas of the images are used for the prediction. (3) The comparison of the predictive effects using different combinations of the optimal wavelengths is also investigated.

2. Materials and methods

2.1. Preparation of samples

A total of 560 fresh ‘Fuji’ apples were purchased from a local farmers’ market in Tianjin, China. The apples were selected according to their appearance in order to ensure that they were free from visual defects. The whole maturity range was represented by the samples used in this study. The samples were washed with cold water to eliminate the effect of surface contamination, put on the desk to dry and then stored in refrigerated air at 4 °C. The apples were moved to the laboratory and stored there to reach room temperature (25 °C) before the experiments were performed. The samples were separated into two groups. The first group of 280 samples was used for the selection of optimal wavelengths. The other group was used for multispectral imaging. These two groups of samples were both divided into two subsets for purposes of calibration (100) and validation (180) separately [26].

2.2. Selection of optimal wavelengths

The absorption spectrum of the juice extracted from the samples was collected by a spectrometer (OmniAS, 350–1200 nm, Zolix Co., Beijing, China) in transmission mode using air as a reference to select optimal wavelengths. The standard pro-processing procedures were applied using OMNICV software (version 6.1, Nicolet Co., Boston, USA) before modeling. A few drops of the juice were separated for the determination of sugar content using a digital refractometer (model PR-201, Atago Co., Tokyo, Japan) in Brix.

Wavelength selection was the intermediate step which connected the spectral data and multispectral images. In the spectral data, the number of wavelengths was 552, which was much more than the number of the samples. Among all the variable selection methods, partial least square (PLS) analysis was reported to be suited well when there were more variables than observations [15]. The wavelengths used for multispectral imaging were usually less than ten [2]. The MLR method was more suitable for dealing with the problem of variables far less than samples [26,27]. In this case, the combination of these two methods was used in the present work.

The absorption spectrum was turned to spectral absorbance for PLS modeling. The BiPLS algorithm was applied using the Matlab iToolbox package downloaded from the website (version 2.1, Department of Food Science, Faculty of Science, University of Copenhagen, Denmark). The leave-one-out cross-validation was used to determine the numbers of latent factors and wavelength intervals for PLS modeling by the lowest root-mean-square-error of cross-validation (RMSECV). The wavelengths were divided equally into 12, 24, 46, 69, 92 and 138 intervals separately according to the divisors of 552. Prediction models were generated using different number of intervals with the number of latent factors from 1 to 20 one by one. The best numbers of wavelength intervals and latent factors were chosen according to the comparison of the predictive effects among these models. A subset of the spectral data was then generated using these most sensitive wavebands.

The final optimal wavelengths were selected using stepwise MLR based on this subset. The stepwise regression was performed using the DPS software (version 9.5, Zhejiang University, China). The wavelengths were selected iteratively according to their significance. A significance test was also performed with a threshold of 5% during processing.

2.3. Multispectral image acquisition

A multispectral imaging system was developed based on the selected wavelengths. As shown in Fig. 1, the system consists of five main components: a 150 W bromine-tungsten lamp (Model LSH-T150, Zolix Co., Beijing, China) emitting parallel light with a diameter of 36 mm, an optical beam shaping component, a sample holding platform, a VIS–NIR identical Gigabit Ethernet (GigE) monochrome camera (Model acA2000-50gmNIR, Basler, Ahrensburg, Germany) with a filter wheel containing four bandpass filters (FWHM = 10 nm, Xintianborui Co., Beijing, China) and a computer (Dell E6520, Intel Core i5-2520 M@2.5 GHz, RAM 8G). The diameter of the incidence light was 1.5 mm, while the incident angle was 15° [28]. The equatorial region of the sample was selected as the imaging volume. All the experiments were performed in a dark chamber.

Generally, the multispectral images could be divided into two parts according to the grey level, including the saturation and scattering areas (Fig. 2a). The grey scale of the pixel in the saturation area was not the full response of the intensity of the backscattered light, since a part of the intensity was dropped. Thus, only the pixels in the scattering area were used for modeling in the present work. The scattering area was segmented from the image using the image histogram and the camera response function. The details of the usage of the histogram had been fully described by Qing et al. [28]. The camera response function (Fig. 2b) expressed the relationship between the light intensity received by each pixel and the corresponding pixel grey scale. This function was measured using the images captured under several different exposure-times following Debevec and Malik [29]. In this function, the linear part was more appropriate for linear modeling. The range of the linear part was analyzed using the second-order derivative of the camera response function (see Fig. 2d). The upper limit of the second-order derivative of the camera response function was set as 0.001. The curves of the image histograms at different wavelengths were similar to each other, and so did the camera response functions. The inflection of the histogram related to the scattering area was found near the grey scale of 55 with a difference of ±5 for all images at four wavelengths. The lower threshold of the second-order derivative of the camera response function was 30 ± 3, while the higher one was 235 ± 4. A range of 60–230 was finally chosen as a comprehensive assessment using these two methods to segment the scattering area.

The center of light scattering profile was calculated following Qing et al [28]. Next, the images were corrected according to the surface curvature. The Lambertian Cosine Law was used to recalculate the reflectance intensity using following equation [21,28]:

$$I_R = \frac{I_c D}{\sqrt{D^2 - x^2}}, \tag{1}$$