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Development of deep learning method for predicting firmness and soluble solid content of postharvest Korla fragrant pear using Vis/NIR hyperspectral reflectance imaging

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ABSTRACT

The objective of this research was to develop a deep learning method which consisted of stacked auto-encoders (SAE) and fully-connected neural network (FNN) for predicting firmness and soluble solid content (SSC) of postharvest Korla fragrant pear (*Pyrus brestschneideri* Rehd). Firstly, deep spectral features in visible and near-infrared (380–1030 nm) hyperspectral reflectance image data of pear were extracted by SAE, and then these features were used as input data to predict firmness and SSC by FNN. The SAE-FNN model achieved reasonable prediction performance with $R_P^2 = 0.890$, RMSEP = 1.81 N and $RPD_P = 3.05$ for firmness, and $R_P^2 = 0.921$, RMSEP = 0.22% and $RPD_P = 3.68$ for SSC. This research demonstrated that deep learning method coupled with hyperspectral imaging technique can be used for rapid and nondestructive detecting firmness and SSC in Korla fragrant pear, which would be useful for postharvest fruit quality inspections.

1. Introduction

Korla fragrant pear (*Pyrus brestschneideri* Rehd) is one of the most popular fruit in China (Wang et al., 2014). This pear is attracting an increasing number of Chinese consumers and is exported to many countries around the world because of its sweet and fragrant taste. Firmness and soluble solid content (SSC) are the most important edible quality attributes of Korla fragrant pear fruit, and they directly employee influence on consumer satisfaction (Fu et al., 2007; Chen et al., 2006; Wang et al., 2017). Thus, they must be taken into account when determining the effect of the postharvest storage period and conditions on fruit quality control. Currently, the industry standard for the determination of fruit firmness is penetrometer test carried out using a Magness-Taylor to penetrate fruit flesh to a depth (Guo et al., 2015). The traditional method used to measure fruit SSC requires juice extracted from the fruit pulp, and is carried out by using digital refractometer. These destructive methods cannot meet the requirements of rapid and automatic monitoring firmness and SSC changes of fruit during postharvest storage. Therefore, there is a considerable need for nondestructive method for the assessment of firmness and SSC in Korla fragrant pear to instruct postharvest handling.

Visible and near-infrared (Vis/NIR) hyperspectral imaging has been one of the most successful techniques for nondestructive detection of firmness and/or SSC of fruit such as apple (Mendoza et al., 2011; Fan et al., 2016), blueberries (Leiva-Valenzuela et al., 2013), banana (Rajkumar et al., 2012), peach (Lu and Peng, 2006) and grapes (Baiano et al., 2012). Recently, Vis/NIR hyperspectral image has also been applied to predict firmness and SSC of pear fruit (Li et al., 2016). The principle for such detections is based on measuring the remission of spectrum from fruit surface in the form of reflectance, interactance or transmission. Since the measured spectrum is related to the composition and structure of the fruit, the relevant wavelength changes in spectrum can thus be utilized to be correlated with the firmness and/or SSC by using some chemometric methods (Huang et al., 2017). However, as Vis/NIR hyperspectral image integrates imaging and spectroscopy to obtain both spatial and spectral information simultaneously from a sample to be measured, the huge amounts of data in hyperspectral image increase the data processing load, resulting in the difficulty of quantitative modeling for the prediction of composition and structure properties of fruit (Liu et al., 2014). In order to reduce the data processing load, the majority of previous studies concerning the application of the hyperspectral imaging to the evaluation of fruit properties used an averaged spectrum or a limited number of representative spectra extracted from region of interest (ROI), which make it difficult to reveal the global information in hyperspectral image relating the differences in composition and structure properties of a

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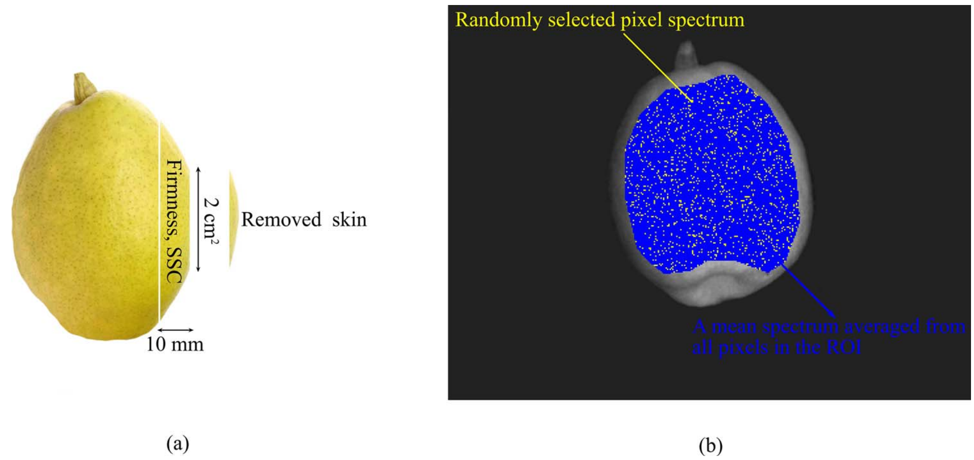

Fig. 1. Spectra extraction and reference measurement positions. Positions for firmness and SSC measurements on pear (a), and hyperspectral image (displayed on 900 nm) of a pear with the selected ROI for spectra extraction (b).

sample (Wang et al., 2016; Roggo et al., 2005). Aiming to deal with large datasets composed of a high number of hyperspectral image data for the early bruise detection on apples, Ferrari et al (2015) recently proposed a hyperspectrogram-based approach, which can reduce each hyperspectral image (both spatial and spectral information) into a single signal. The reduced signals can then be analyzed simply using multivariate analysis methods such as partial least squares regression (PLSR), least-squares support vector machine (LS-SVM) and multilinear regression (MLR). However, in the hyperspectrogram-based approach, multivariate analysis of the reduced signals is made at the image level, and not a pixel level. So far, very little work has been carried out on the big data analysis of hyperspectral image based on a large number of pixel-level spectra for the fruit quality detection.

Deep learning is a new area of machine learning research (LeCun et al., 2015), which has a deep structure of artificial neural networks with capable of processing very large-scale data, and has dramatically improved the modeling performance in many data analysis tasks (Zhao and Du, 2016; Farias et al., 2016; Cole et al., 2017). In the previous study, our research group had confirmed that deep learning classification algorithm coupled with pixel-level spectra in Vis/NIR hyperspectral image (450–1010 nm) achieved satisfactory total classification accuracy of 98.28% for discriminating freshness of shrimp product (Yu et al., 2017). In this work, a novel deep learning regression method is further developed for the prediction of firmness and SSC of postharvest pear fruit. This deep learning method composed of a stacked auto-encoders (SAE) (Suk et al., 2015) and a feed-forward fully-connected neural network (FNN) (Biganzoli et al., 1998), in which SAE is trained by using a large number of pixel spectra to automatically learn spectral features of Vis/NIR hyperspectral image, and the spectral features are fed to FNN to quantitatively predict the corresponding firmness and SSC. To the best of our knowledge, this is the first time that deep learning is applied to the detection of quality attributes of pear fruit. The main object of this study is to investigate the potential of SAE-FNN method together with Vis/NIR hyperspectral imaging technique for detecting firmness and SSC of postharvest Korla fragrant pear fruit.

2. Materials and methods

2.1. Pear samples

Korla fragrant pear fruit at commercial maturity were hand-harvested from an orchard located in Korla, Xinjiang, China (86.10 °N, 41.69 °E) on 4 September 2016. The fruit were picked in different trees and in different canopy layers to get representative samples which contain a wider range of growth conditions, then wrapped in EPE foam fruit nets, put into boxes, and transported to Ningbo city, Zhejiang province of China within 72 h. Upon arrival at the laboratory, a total of 180 pear fruit with uniform size (diameter of 55–65 mm) and weight (120–130 g) were chosen out, then placed in chambers where the temperature (20 ± 1 °C) and relative humidity (90–95%) were controlled to produce a wide distribution in firmness and SSC as the fruit were ripened. Fifteen pear fruit were randomly taken out every other day (from 8 September to 30 September 2016) to be scanned by a Vis/NIR hyperspectral imaging system, and to measure their reference firmness and SSC by traditional destructive methods. The reference measured firmness and SSC of pear fruit were calibrated with the hyperspectral image information using PLSR, LS-SVM and SAE-FNN models, respectively. In the experiments, 135 samples were randomly chosen out and used as calibration set, whereas, the remaining 45 samples were used as prediction set for estimating the performance of the calibration models.

2.2. Reference measurements of firmness and SSC

Firmness and SSC were measured from one side of the pear fruit where spectral acquisition had been carried out. Firstly, a skin of 2 cm^2 was removed around the equatorial section of pear fruit (Fig. 1a). The firmness of the peeled tissue was analyzed destructively using a 3.5 mm diameter Magness-Taylor (M-T) probe, which was attached to a fruit sclerometer (Model: GY-1, Zhejiang Tuopu Instrument, Co. Ltd., Hangzhou, China). A downward pressure with velocity of 1 mm s^{-1} was forced until the plunger has penetrated 10 mm into the peeled tissue. The maximum force was recorded and used as the measurement of pear fruit M-T firmness (Hertog et al., 2004) which expressed in newton (N) with an accuracy of 0.1 N. Then, the juice of flesh whose position was in the same peeled tissue was extracted by using a manual fruit squeezer. The juice was dropped to a digital refractometer (Model: PR-101α, Atago Co., Ltd., Tokyo, Japan) for SSC measurement. The refractive index accuracy is ± 0.1% and the Brix (%) range is 0.0–45.0%.

2.3. Hyperspectral imaging system

Before reference measurements of firmness and SSC, an in-house developed line-scan Vis/NIR hyperspectral imaging system was used to acquire hyperspectral reflectance images from Korla fragrant pears. The hyperspectral imaging system consisted of four components: a spectral imaging system, a lighting system, a translation stage and a computer (Fig. 2). The spectral imaging system was composed of a spectrograph (ImSpectorV10, Spectral Imaging Ltd., Finland) with spectral range of 380–1030 nm, which was connected to the CCD camera (B1621M, Imperx Inc., USA) with max resolution of 1632 pixels in the spatial dimension and 1232 bands in the spectral dimension, and a standard C-