Journal of Food Engineering 179 (2016) 11–18

Contents lists available at ScienceDirect

Journal of Food Engineering

journal homepage: www.elsevier.com/locate/jfoodeng

Hyperspectral imaging analysis for ripeness evaluation of strawberry with support vector machine

Chu zhang [a], Chentong Guo [b], Fei Liu [a], Wenwen Kong [a], Yong He [a,*], Binggan Lou [b]

[a] College of Biosystems Engineering and Food Science, Zhejiang University, Hangzhou, 310058, China
[b] College of Agriculture and Biotechnology, Zhejiang University, Hangzhou, 310058, China

ARTICLE INFO

Article history:
Received 19 April 2015
Received in revised form
5 January 2016
Accepted 6 January 2016
Available online 22 January 2016

Keywords:
Hyperspectral imaging
Strawberry
Ripeness classification
Texture features
Data fusion

ABSTRACT

A hyperspectral imaging system covering two spectral ranges (380–1030 nm and 874–1734 nm) was applied to evaluate strawberry ripeness. The spectral data were extracted from hyperspectral images of ripe, mid-ripe and unripe strawberries. The optimal wavelengths were obtained from spectra of 441.1–1013.97 and 941.46–1578.13 nm by loadings of principal component analysis (PCA). Pattern texture features (correlation, contrast, entropy and homogeneity) were extracted from the images at optimal wavelengths. Support vector machine (SVM) was used to build classification models on full spectral data, optimal wavelengths, texture features and the combined dataset of optimal wavelengths and texture features, respectively. SVM models using combined datasets performed best among all datasets. SVM models using datasets from hyperspectral images at 441.1–1013.97 nm performed better with classification accuracy over 85%. The overall results indicated that hyperspectral imaging could be used for strawberry ripeness evaluation, and data fusion combining spectral information and spatial information showed advantages in strawberry ripeness evaluation.

1. Introduction

Fruit ripeness, the key factor for determining the optimal harvest time for fruits, is crucial for fruit growers. Fruit ripeness is a quite complex issue. Traditionally, fruit ripeness is identified by human experience or laboratory based detection of quality parameters (color, texture, chemical constituents, etc.) or their combinations. Usenik et al. (2014) used firmness, soluble solids content (SSC) and color information and taste to evaluate plum ripeness. Fuentes de Mendoza et al. (2013) used fatty acids, triglycerides and sterols profile of olive oil to evaluate olive ripeness. López Camelo and Gómez (2004) used color features to evaluate tomato ripeness. Shinya et al. (2013) studied the fruit mass, soluble solids content (SSC), ground skin color features, the spectral absorbance difference at 670 nm and 720 nm index (I_{AD}), fruit/flesh firmness and uniaxial compression strength related to peach ripeness. Azodanlou et al. (2004) used total volatile compounds, total acidity, total sugar content (degrees Brix) and fruit firmness to evaluate strawberry ripeness. These methods could acquire satisfactory accuracy, but suffer the problems of being time consuming, high cost and the rigorous requirement of operation skills. Advanced techniques, including machine vision, spectroscopy and spectral imaging, have been applied to evaluate the degree of fruit ripeness in a fast, non-destructive, low-cost and convenient way.

Machine vision technique captures the image of the samples, using external features extracted from the images like color, shape, size and texture features combined with the measured reference values of different chemical and physical properties to build models to predict the chemical and physical properties of unknown samples. Changes of external features of fruits during ripening make it feasible to evaluate fruit ripeness with machine vision technique. Machine vision has been proved efficient in fruit ripeness evaluation, and fruit chemical constituents could also be predicted by machine vision. Fadilah et al. (2012) used color features from images captured by a RGB camera to evaluate oil palm ripeness. Tan et al. (2010) used a RGB camera to evaluate oil palm ripeness and oil content. Ji et al. (2013) studied the banana ripeness by a digital imaging method with color feature analysis. Mendoza and Aguilera (2004) studied banana ripeness by computer vision system with color feature analysis, texture analysis and chemical analysis. Velez-Rivera et al. (2014a) used a computer vision system to evaluate mango ripeness with color features, TA, SSC, firmness and ripening index (RPI).

* Corresponding author.
E-mail address: yhe@zju.edu.cn (Y. He).

http://dx.doi.org/10.1016/j.jfoodeng.2016.01.002
0260-8774/

However, machine vision only captures the external information of the targets, uses the external information to evaluate fruit external and internal quality. Spectroscopy technique could obtain internal quality information as a fast and non-destructive method. Changes of internal quality of fruits during ripening make it feasible to use spectroscopy technique to evaluate ripeness of fruits. Studies have been reported of using spectroscopy technique to evaluate fruit ripeness and fruit quality. Larrain et al. (2008) used a portable near-infrared spectroscopy (NIRS) instrument to determine sugar (Brix), pH, and anthocyanin concentration related to ripeness of grape. Giovenzana et al. (2014) used a handheld optical system to determine total soluble solids and polyphenols of grape to evaluate grape ripeness. Tarkosova and Copikova (2000) used NIRS to determine carbohydrate content of banana to evaluate banana ripeness. Qin et al. (2012) used spatially offset Raman spectroscopy to evaluate tomato ripeness.

Both machine vision and spectroscopy could evaluate ripeness without measuring the chemical or physical parameters, they use the predefined ripeness stages as the reference ripeness data to build models and extract the information contributing to fruit ripeness. However, the two techniques focus on different aspects of the samples. Spectral imaging technique is the integration of machine vision technique and spectroscopy technique, acquiring both spatial information and spectral information simultaneously. Hyperspectral imaging (HSI) is one of the common forms of the spectral imaging technique.

HSI has been successfully used to determine fruit quality, fruit ripeness and fruit damage. Wei et al. (2014) used spectral data and texture features from hyperspectral images to evaluate ripeness of Astringent persimmon. Tallada et al. (2006) used hyperspectral imaging system to determine strawberry firmness related to ripeness. Lleo et al. (2011) used spectra indices extracted from hyperspectral images to evaluate peach ripeness. Velez Rivera et al. (2014b) used hyperspectral imaging to detect mango mechanical damages. Each pixel within hyperspectral image contains a spectrum which shows the spectral property of the pixel. Generally, the average spectrum of all pixels of the pre-defined sample region (also called region of interest, ROI) can be used to build regression or discriminant models, and the spectrum of each pixel can be used for prediction to acquire chemical, physical or category information of the pixel by the established models to form a prediction map (also called distribution map).

The main objective of this study is to evaluate strawberry ripeness by HSI at different spectral ranges, using both spectral and spatial information. The specific objectives of this study are to: 1) explore the potential of two different spectral ranges to evaluate strawberry ripeness; 2) establish SVM models to identify strawberry ripeness based on full spectral data and selected optimal wavelengths; 3) extract and apply texture information to identify strawberry ripeness; 4) combine spectral data and texture features to identify strawberry ripeness.

2. Materials and method

2.1. Strawberry samples

Strawberry samples (cv. Hongyan) were collected from a local strawberry park in Hangzhou, Zhejiang province, China. Sixty ripe strawberries, 60 mid-ripe strawberries and 60 unripe strawberries were collected by local experienced strawberry growers, all samples were healthy without bruises. The samples were taken to the laboratory for hyperspectral image acquisition after collection and cleaning.

2.2. Hyperspectral image acquisition

2.2.1. Hyperspectral imaging system

A laboratory based hyperspectral imaging system was used in this study (Fig. 2). The system acquired hyperspectral images by 2 different camera systems covering two spectral ranges (380–1030 nm with 512 bands and 874–1734 nm with 256 bands). The former is acquired by an imaging spectrograph (ImSpector V10E; Spectral Imaging Ltd., Oulu, Finland), a 672 × 512 CCD camera (C8484-05, Hamamatsu, Hamamatsu City, Japan) with a camera lens (OLES23; Specim, Spectral Imaging Ltd., Oulu, Finland), and the latter is acquired by an imaging spectrograph (ImSpector N17E; Spectral Imaging Ltd., Oulu, Finland), a 320 × 256 CCD camera (Xeva 992; Xenics Infrared Solutions, Leuven, Belgium) with a camera lens (OLES22; Specim, Spectral Imaging Ltd.). Above all, the system contained two 150 W tungsten halogen lamps (Fiber-Lite DC950 Illuminator; Dolan Jenner Industries Inc, Boxborough, MA, USA) placed in two sides of the camera symmetrically at a 45° angle for illumination, a conveyer belt driven by a stepper motor (Isuzu Optics Corp, Taiwan, China). The system was placed in a dark room, and controlled by a computer.

2.3. Image acquisition and correction

To acquire clear and non-deformable images containing the full samples, the height between the lens and the sample, the moving speed of the conveyer belt and the exposure time of the camera should be adjusted. For images at 380–1030 nm, the height, the moving speed, and the exposure time were set as 360 mm, 2.05 mm/s and 0.05 s, respectively. For images at 874–1734 nm, the height, the moving speed, and the exposure time were set as 360 mm, 25 mm/s and 5 ms, respectively. The samples were placed in the conveyer belt, and were scanned line by line along the Y-axis with the sample moving along the X-axis at a certain speed.

The white reference image and dark reference image should be acquired under the same experimental conditions of hyperspectral image acquisition for image correction. The dark reference image was captured by turning off the light source and covering the camera lens completely by its opaque cap, and the white reference image was acquired using a piece of white Teflon, and the correction was conducted by the following equation:

$$I_c = \frac{I_{raw} - I_{dark}}{I_{white} - I_{dark}} \quad (1)$$

where I_c was the corrected image, I_{raw} was the raw image, I_{white} was the white reference image, I_{dark} was the dark reference image. The resolution of the acquired images at 380–1030 nm was 92 PPI (pixels per inch) and the resolution of the acquired images at 874–1734 nm was 32 PPI.

2.3.1. Spectral data extraction

For hyperspectral images at 380–1030 nm and 874–1734 nm, ROI should be predefined to extract spectral information. In this study, ROI of each sample was defined as the entire fruit sample region of each strawberry, and the spectral information of the ROI was extracted. Average spectrum of all pixels within the ROI was used to represent the sample.

2.4. Texture feature extraction

The texture features of strawberry hyperspectral images could represent the features of strawberry, like color, roughness, intensities, firmness, chewiness and their arrangements, which could directly or indirectly relate to fruit quality or ripeness. Texture