A NOVEL HYPERSPECTRAL FEATURE EXTRACTION ALGORITHM BASED ON WAVEFORM RESOLVING FOR RAISIN CLASSIFICATION

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ABSTRACT

Near infrared hyperspectral imaging technology was adopted in the paper to determine the variety of raisins produced in Xinjiang Uygur Autonomous Region, China. There are three varieties of raisins taking part in the research and the wavelengths of the hyperspectral images are from 921nm to 1680nm. A novel waveform resolving method was proposed in the paper to reduce the hyperspectral data and extract features. The waveform resolving method compresses the original hyperspectral data for one pixel into 5 Amplitudes, 5 frequencies and 5 phases, 15 feature values in all. Neural network was established to determine the variety of raisins. The accuracies of the model which are presented as sensitivity, precision and specificity which are higher than the accuracies of model of traditional PCA feature extracting method combined with neural network. The result indicates that the proposed

waveform resolving feature extracting method combined with hyperspectral imaging technology is an efficient method to determine variety of raisin.
Keywords: spectral feature extraction; waveform resolve; Hyperspectral imaging;neuron network; raisin; classification

INTRODUCTION

Raisin is a kind of popular product because it is delicious and nutritious. Raisins contain large amounts of glucose, calcium, phosphorus and iron, and also a variety of vitamins and amino acids which are beneficial to humans. Xinjiang Uygur Autonomous Region is the most famous raisin producing area in China. In the process of grape into air-dried raisin, it will darken in color and decrease in size, all varieties normally in three kinds of color: green, black and deep yellow. Thus it is very hard for ordinary consumers to identify the variety of raisins. Normally, the product of raisins which is indicated the variety is sold in higher price in the market than the product which is not indicated the variety. Therefore it is necessity to develop a variety identification system for automatic raisin classification.

Hyperspectral imaging can sense wider range of wavelength than human eyes. Human eyes can only sense the wavelength of light in visible range from 400nm to 700nm while a special hyperspectral camera can sense the light in invisible range. These invisible ranges of light can affect the Ingredient information of object. One hyperspectral image is consisted of hundreds of successive wavebands and there is a gray image for each waveband and a spectrum for each pixel of specific position on sample [1]. Generally, hyperspectral sensors acquire images of waveband regions of visible and infrared differently according to the specification [2]. This technology has been wildly applied in agricultural field.

Extensive research on hyperspectral technology focusing on food classifications has been conducted, which include separating products with defects from flawless ones, grading according to the products quality, classification according to the variety or brand of products. Defects detection is implemented by classifying the pixels of defect parts and flawless parts. Some researches have separated ‘Golden Delicious’ apples with bruises from good quality products by spectral technology [3-4], detected apple surface defects and contaminations by hyperspectral imaging technology [5], used hyperspectral technology to detect rottenness on mandarins [6], detected Citrus canker based on hyperspectral imaging [2], recognized external skin damage in citrus by spectral data [7], detected common eight kinds of defects on Citrus hyperspectral reflectance imaging [8]. Some researchers applied hyperspectral technology to detect products contaminated by aflatoxin [9-10]. Some researches applied hyperspectral imaging system to classify maize kernels [11]. These researches combined hyperspectral, imaging analysis, data mining and machine learning technologies to realize a variety of different food classification applications with ideal performance. More applications for food quality and safety control by these analytical technologies were summarized by Gowen [12].

The purpose of the paper is to model an optimized method to extract effective information from raisin hyperspectral data and consequently detect the varieties.

MATERIALS AND METHODS

Sample preparation

There are three varieties of raisins were adopted in this research, Bing-tang-xin(BTX), Hei-jia-lun (HJL), Hong-ti (HT), All the samples were produced in Xinjiang Uygur Autonomous Region, China. RGB images of the samples are shown in Figure 1a-1c. For each variety, 150 raisins were chose in the experiment and they were laid on three to five glass dishes and dishes were put on white papers for image acquisition. There are 1200 raisins used totally. For the variety with larger particles, such as Xiang-fei, 5 dishes were needed and for the variety with smaller particles, such as Hei-jia-lun, 3 dishes were needed. Twenty nine dished were needed in the experiment totally.

Image acquisition and preprocessing

The structure of the proposed imaging framework for raisins classification was based on near-infrared hyperspectral imaging technology and line light source was applied. The light shines on sample and reflects to lens. The range of the wavelengths the hyper-spectrograph applied in this research can sense was from 921 nm to 1680 nm. The smoothing process was necessary for the further classification. The Savitzky-Golay algorithm which is a famous smoothing method adopted in this research for better performance. Actually, there are 226 single band images, from 921nm to 1680nnm were restored for each object scanned by the hyperspectral imaging system.

a. b. c.

Figure 1 Images of three varieties of raisins. a Bing-tang-xin (BTX). b. Hei-jia-lun (HJL). c. Hong-ti (HT).

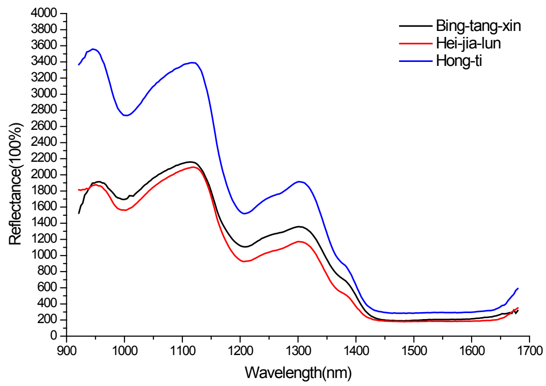

Figure 2 The smoothed spectrum for eight varieties of raisins. a Smoothed spectra for eight varieties of raisins, each curve for each variety. b Spectrum of one pixel (coordinate: X 151, Y 286) on BTX hyperspectral image.

a b

Figure 3 Original image and mask. a Original image. b Mask image.

After capturing the hyperspectral images of the three kinds of raisins, the background including uncovered part of the glass dishes and white paper on the images elimination is necessary. Because the pixels of raisins and background have very different spectral information, we chose a part of raisin pixels as region of interest (ROI), and grow the ROI to make it covering all the pixels of raisins. The portion of the pixels didn't covered by the ROI should be masked, thus the pixel data of ROI parts were set as 255 and background were set as zero and mask image generated consequently. The mask of MGZ image is shown in Figure 3 to illustrate the effect.

METHODOLOGY

Algorithm of spectral feature extraction based on waveform resolving (SFEWR)

Fourier Transform is the core technology for the SFEWR algorithm. Each kind of waveform is consisted of several different sinusoidal wave, sawtooth wave or square wave. Any periodical waveform can be resolved into different sinusoidal waves (harmonic signals) with various frequencies, amplitudes and phases by principle of Fourier transform. Discrete Fourier transform (DFT) is a traditional procedure for determine the components of discrete sequence.

Let us assume that there is a variable $x(t)$ which is the continuous function of time t. In order to apply DFT on the variable $x(t)$, discrete sampling is necessary. The sampled discrete sequence of $x(t)$ is $x(n)$. Consequently, the DFT equation is below:

$$X(m) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi nm/N}, \quad j = \sqrt{-1} \qquad \text{Eq. 1}$$

where $x(n)$ is the discrete sequence in time-domain which will be transformed by DFT, "e" is the base of natural logarithms, N is the number of discrete points sampled and also the number of frequency points. For $x(n)$, the input sequence, the horizontal axis is time and the vertical axis is amplitude. For $X(m)$, the mth output component, the horizontal axis is frequency and the vertical axis is amplitude. The "m" is the transformed output index from 0 to N-1 and $X(0)$ to $X(N-1)$ are the N components resolved from the original sequence $x(n)$.

The defect of DFT is that it is straightforward and inefficient. As the number of discrete points increase, the number of redundant operations increases too. Fast Fourier transform (FFT) is an innovation and it was developed by Cooley and Tukey to reduce the number of arithmetic operations which are necessary in DFT. For an N-point DFT, the number of arithmetic operations is N^2 while the number of N-point FFT is approximately $(N/2)\log_2 N$. And the result of FFT is exactly the same as the result of DFT. The key reason for the high efficiency of FFT is that it subdivides N-point DFT into an array of 2-point DFTs and the number of necessary multiplications is reduced consequently.

In the proposed algorithm of spectral feature extraction based on waveform resolving (SFEWR), Fast Fourier Transform was adopted. First of all, the smoothed raisin spectrum curve is reconstructed as periodical function by repeating the spectral data. The discrete spectral data consists the spectrum curve are regarded as input discrete sequence $x(n)$. Fast Fourier Transform will be applied on $x(n)$ to obtain the resolved components, $X(m)$. Each of $X(m)$ should be sinusoidal function with various amplitude, frequency and phase angle. The first five sinusoidal functions with greatest amplitudes were chose for further analysis. The five sinusoidal functions are called as $X(1)$, $X(2)$, $X(3)$, $X(4)$, $X(5)$. $X(1)$ contains the most useful information of the original spectral data sequence $x(n)$. The $X(2)$ is secondary to the $X(1)$, $X(3)$ comes third, and so forth. For eight kinds of raisins, the amplitudes of $X(1)$ are around 1000 and $X(6)$ are smaller than 100. According to validating results, the information of $X(1)$ to $X(5)$ is enough to express the total useful information in the spectral data sequence $x(n)$. Thus, for each spectrum, $X(1)$ to $X(5)$ are valid for further analysis. But there are also a lot of discrete points in each of the sinusoidal signals from $X(1)$ to $X(5)$ which cannot reach the purpose of simplifying data. The combination of amplitude, frequency and phase angle can be used to illustrate the sinusoidal signal precisely. The five combinations for each spectral data sequence which are fifteen feature values are extracted consequently for further mathematical modeling.

Classification modeling method

Modeling approach depending on artificial neural network (NN) is powerful for complex, nonlinear and parallel tasks. An artificial neural network is designed to implement particular tasks by using several simple processing units which store experiential knowledge known as learning process. The trained weights and thresholds of neurons express the acquired knowledge.

In this research, the 15 features extracted during SFEWR procedure were used as inputs of the neural network classification model. For each kind of raisin, there are 500 pixels were scanned as samples for calibrating the classification model and 100 pixels were scanned to construct validation dataset. Thus there are 4800 samples in calibration dataset and 800 samples in validation dataset. The size of the matrix of calibration dataset was 15×4800 and the size of the matrix of validation dataset was 15×18. The output of the model is the code of the classes the sample belonged to. One represents BTX, 2 represents HJL, 3 represents HT.

Performance evaluation standard

The performance of the method proposed by the paper should be determined by the accuracy of the classification. The classification accuracy indices include sensitivity, precision and specificity. The equations for the three indices are shown as below:

$$Sensitivity = \frac{d}{c+d} \qquad Eq.2$$

$$Precision = \frac{d}{b+d} \qquad Eq.3$$

$$Specificity = \frac{a}{a+b} \qquad \text{Eq.} 4$$

where ‘a’ is true negative, the number of negative samples which are detected as negative; ‘b’ is false positive, the number of negative samples which are detected as positive; ‘c’ is false negative, the number of positive samples which are detected as negative; ‘d’ is true positive, the number of positive samples which are detected as positive.

In this research, for each category of samples, the three indices were calculated. As an example, for BTX raisins, pixels of BTX are positive and pixels of the other 2 categories are negative. ‘a’ is the number of the pixels of the other 2 categories which are detected as the other 2 categories, ‘b’ is the number of the pixels of the other 2 categories which are detected as BTX, ‘c’ is the number of the pixels of the BTX which are detected as the other 2 categories, ‘d’ is the number of pixels of BTX which are detected as BTX. For the overall performance of the 3 categories, true negative, false positive, false negative, true positive are the sum of each ‘a’, ‘b’, ‘c’ and ‘d’ for 3 categories respectively.

RESULTS

The raisin samples which were placed in test plates separately according to the varieties like the manner in Fig. 1 were used for constructing the classification model. For each variety of raisins, 500 pixels were used to calibrate the model and 100 pixels were used to validate the model. Thus there are data of 4000 pixels in calibration data set and data of 800 pixels in validation data set. After image acquisition and preprocessing procedure, the classification model training process was executed based on the spectra of the 4000 pixels. Than the extracted feature of the spectra of 800 pixels (validation data set) were classified by the trained model for evaluating the performance of the model.

Spectral feature extraction by waveform resolving (SFEWR)

The pixels of 3 kinds of raisins were extracted and reconstructed as periodical functions in which the independent variable (horizontal axis) wavelength was regarded as time with unit of second, and the dependent variable (vertical axis) reflectance was regarded as amplitude. After fast Fourier transformation procedure, the reconstructed function should be divided into several sinusoidal functions and the number of them should be equal to the number of the sampling points (discrete points) on one period of periodic function. In this research, the sampling number is 226 and sampling frequency is 100. The larger the amplitude the resolved sinusoidal functions has, the more the useful information the resolved function concludes. The first five sinusoidal functions with largest amplitudes contain enough information to illustrate the original spectrum. Each of them has specific amplitude, frequency and angle. There are fifteen feature values for one pixel (one spectrum). The first one with largest amplitude contains the most information of the original spectrum. The feature values of this Bing-tang-xin pixel are listed in Table 1.

Classification model

The fifteen extracted feature values (three frequencies, three amplitudes and three phases) for each pixel were used as input data and code of the categories as output data to calibrate classification neuron network (NN) model. In order to compare the performance of the proposed method with conventional one, principal component analysis (PCA) was applied to classify these varieties. The accuracy of SFEWR combined with neuron network and PCA combined with neuron network are shown in Table 2. The sensitivity index measures the proportion of positives which are correctly identified as such; specificity index measures the proportion of negatives which are correctly identified as such and precision index measures the proportion of true positives to the detected positives.

CONCLUSION

The three varieties of raisins spectra information of wavelength from 921nm to 1680nm were acquired by hyperspectral image system and the varieties of raisins were classified with ideal performance by the proposed SFEWR and neuron network method. After fast Fourier transform, the neuron network model was established based on the 15 features. The raisins can be classified according to the varieties and the performance of the proposed SFEWR combined with neuron network is better than PCA with neuron network.

Table 1. The feature values of one pixel (spectrum) of BTX.

Frequency	Amplitude	Phase
0.44	890.25	-1.61
0.88	283.34	-1.35
1.77	198	-0.79
2.21	137.66	-1.57
1.33	119.83	-3.05

Table 2. The detection accuracy of the combination of SFEWR and neuron network

	SFEWR+NN			PCA+NN		
	sensitivity(%)	precision(%)	specificity(%)	sensitivity(%)	precision(%)	specificity(%)
BTX	96	91.25	98.97	92	90.9	98.59
HJL	93.8	94.18	99.12	93.6	94.35	99.13
HT	91.4	93.27	99	91.8	91.8	98.74

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