Application of Hyperspectral Imaging Technology in the Identification of Varieties of Zanthoxylum bungeanum

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Abstract: This study used hyperspectral imaging technology to achieve rapid identification of varieties of Zanthoxylum bungeanum. Nine optimal wavelengths are extracted from the spectral range of 400-1000 nm by the random frog (RF) algorithm. The texture features of the first, second and third principal component images are extracted with local binary pattern (LBP). K-nearest neighbor (KNN) and support vector machine (SVM) models were established with spectral features and the combination of spectra and textures, respectively. The accuracy of KNN and SVM models based on the combination of spectral and texture are 100%, but the computational efficiency of KNN model is significantly higher than that of SVM model. It provides a fast and accurate theoretical model for the identification of varieties of Zanthoxylum bungeanum.

1. Introduction

As a seasoning, Zanthoxylum bungeanum can remove the stench of various meats, promote saliva secretion and increase appetite [1]. The nutrient content and price of Zanthoxylum bungeanum in different regions are quite different, and the difference in shape is small. Therefore, it is in line with market demand to establish a rapid and accurate classification method for varieties of Zanthoxylum bungeanum.

Compared with near-infrared spectroscopy and machine vision technology, hyperspectral imaging technology can acquire both spectral information and image information. The texture feature of the image is a global feature that describes the surface properties of the scene corresponding to the image. Combined with the spectral information, the useful information is more abundant, which can effectively improve the prediction accuracy and stability of the model. Fan yangyang et al. used hyperspectral imaging technology to realize the identification of 4 varieties of dried jujube, and the back propagation neural network (BPNN) model based on the fusion features of spectrum and texture achieved the identification accuracy of 100% for prediction set [2]. Deng Xiaoqin et al. used the 23 optimal wavelength combined image texture features to establish a rice seed identification model, which achieved accuracy of 99.22% and 96% respectively on the training set and the prediction set [3]. Based on hyperspectral imaging technology, this study identified 150 samples of three different varieties of Zanthoxylum bungeanum.

2. Materials and methods

2.1 Preparation of samples

The 150 samples used in the experiment were purchased from Hanyuan District in Sichuan Province (50), Wudu District in Gansu Province (40) and Fuping District in Shaanxi Province (60). All samples were individually packaged in sealed, light-proof foil pouches. The sample is divided into a training set and a test set based on the principle of random allocation, wherein the number of training set samples is 120 and the test set is 30.

2.2 Spectral image acquisition

The instrument used to obtain the hyperspectral image was a GaiaSorter hyperspectral sorter (Zolix Instruments Co. Ltd, China) with a spectral wavelength range of 387-1034nm (shown in Fig 1). The sampling interval is 2.8nm and there are 256 bands. In order to eliminate the effects of noise at both ends, spectral data in the wavelength range of 400-1000nm was intercepted for further data analysis. During the acquisition process, the samples were placed in a circular petri dish, the height of the camera lens and the sample surface was adjusted to 255nm, the moving speed of the motorized translation stage was 0.5cm/s, and the exposure time was set to 11ms. In order to eliminate the effects of camera dark current and environmental factors, the original hyperspectral image is corrected by the following formula:

$$R = \frac{I - D}{W - D} \tag{1}$$

where R is the corrected image, I is the original hyperspectral image, and W, D are white reference image and dark reference image, respectively.

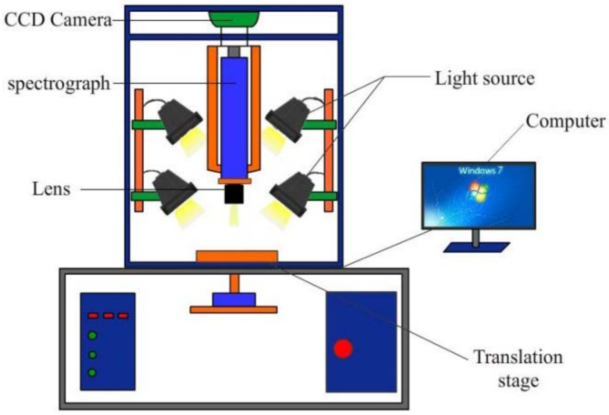
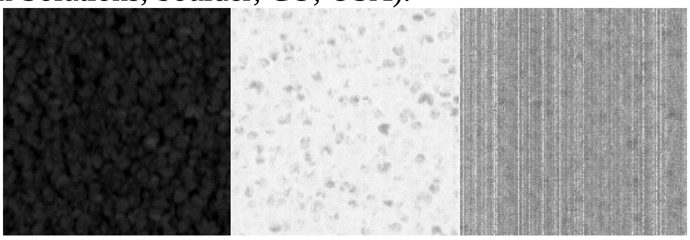


Figure 1. Schematic of the hyperspectral imaging system

After obtaining the corrected image, a circular region of interest (ROI) of 60×60 size is manually selected on the image, and the average spectral data of all the pixels in the area is used as the spectral data of the sample. Then, the principal component analysis (PCA) is performed on the corrected image. Since the cumulative variance of the first three principal components accounts for more than 97%, the 280×280 size ROI of the first three principal component images (shown in Fig 2) are retained for extracting texture features. The above operation is done using the software ENVI 5.1 (ITT Visual Information Solutions, boulder, CO, USA).



PC1 PC2 PC3

Figure 2. PC1, PC2 and PC3 images of ROI

2.3 Data processing

(1) Optimal wavelength selection

In order to reduce the redundant information of spectral data to improve computational efficiency, the random frog algorithm is used to select wavelengths rich in useful information. The RF algorithm works in an iterative manner and serves as a measurement of the importance of variables [4]. After N iterations, the selection probability of each variable is calculated as a measure of the importance of the variable. The selection probability of each variable can be calculated by the following formula:

$$Probability = \frac{N_j}{N}, \quad j=1,2,...p \tag{2}$$

where the N_j is the frequency of the jth variable to be selected in these N iterations.

(2) Texture feature extraction

Local binary pattern (LBP) is an operator used to describe the local texture feature extraction of an image [5]. The original LBP operator is defined in a square area of 3*3, with the center pixel of the area as a threshold, and the gray values of the adjacent 8 pixels are respectively compared with the center pixel. If it is larger than the center pixel, the position of the pixel is marked as 1, otherwise it is 0. The sequence of binary numbers produced by comparison is converted to a decimal number, and then the histogram of the region is counted. In this study, we applied rotation and uniform invariant LBP to obtain LBP textures from principal component images. Ultimately, a total of 10 normalized histogram features of each image were obtained to form a matrix of 150×3×10(samples× images× features).

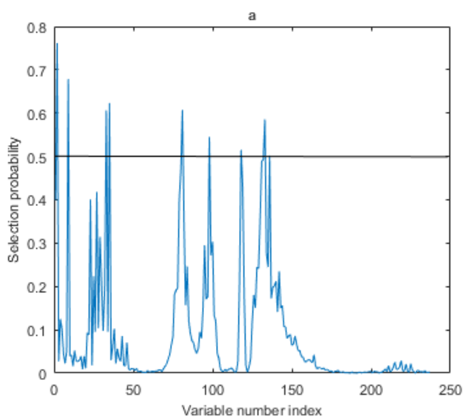
2.4 Classification model

The K-nearest neighbor (KNN) model and the support vector machine (SVM) model are established based on two different inputs, and the discrimination accuracy and computational efficiency of the model are compared. K is a constant. The basic idea of KNN is to calculate the Euclidean distance between test samples and each training set sample, select the nearest K training set samples, and then classify test samples according to the classification decision rule of majority voting. The value of K is determined to be 5 by cross validation. In support vector machine model, radial basis function is used as kernel function, and grid method and 5-fold cross validation are used to find the optimal penalty factor and kernel function parameters.

3. Results and discussion

3.1 Modeling based on optimal spectral

The random frog was implemented to select 9 optimal wavelengths (404nm, 421nm, 479nm, 484nm, 597nm, 639nm, 690nm, 728nm and 736nm) from the full spectral. In Fig 3(a), based on the experience, the threshold was set as 0.5 and the wavebands with probability bigger than threshold were selected. The KNN and SVM identification models are established with these 9 optimal wavelengths as inputs. The results are shown in Table 2. The discrimination accuracy of KNN model is 93.33% and that of SVM model is 96.67%. On the other hand, the computation time of the SVM model is 38.05s, while the KNN model only took 0.22s.



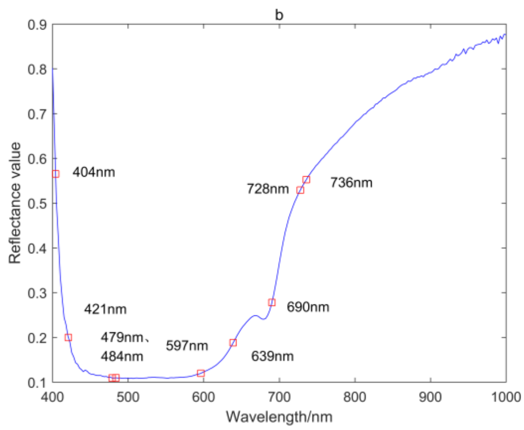


Figure 3. (a) The probability of selected variables by random frog; (b) Distribution of selected wavelengths in full spectrum

Table.1. Results of KNN and SVM models based on 9 optimal wavelengths

Modeling method	Number of variables	Computation time	Number of wrong judgments	Test set accuracy
KNN	9	0.22s	2	93.33%
SVM	9	38.05s	1	96.67%

3.2 Modeling based on a combination of optimal spectral and textural information

The model is established by taking a combination of spectral features and texture features as inputs. As can be seen from Table 2, the performance of model based on the combination of spectral and texture features is better than spectral features alone. The accuracy of the KNN model and the SVM model for the test set reached 100%. The calculation time of the KNN model is 0.27 seconds, only 0.05 seconds more than the model established using the spectral features alone. The computation time used by the SVM model is approximately twice that of the model using spectral features alone. That may be due to the increase in input variables, which increases the computational cost.

Table.2. Results of KNN and SVM models based on a combination of optimal wavelengths and textural information

Modeling method	Number of variables	Computation time	Number of wrong judgments	Test set accuracy
KNN	39	0.27s	0	100%
SVM	39	77.46s	0	100%

4. Conclusion

The rapid identification of varieties of Zanthoxylum bungeanum Maxim based on hyperspectral imaging technology was studied. After collecting the spectral data and image texture features of three varieties of Zanthoxylum bungeanum Maxim, the performance of KNN and SVM classification models with spectral features and spectral and texture features as inputs were compared. The classification accuracy of KNN model and SVM model based on fusion features has achieved satisfactory results, but the computational efficiency of KNN model is much higher than that of SVM model. Therefore, the KNN classification model is more suitable for real-time online classification of varieties of Zanthoxylum bungeanum Maxim.

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