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IDENTIFICATION OF NANGUO PEAR MATURITY BASED ON INFORMATION FUSION **

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Maturity is not only an important factor affecting the internal quality of the Nanguo pear, but also an important theoretical basis for grading online fruit. Based on the hyperspectral imaging technology, in this paper, back-propagation neural network and support vector machine models are established to identify Nanguo pear maturity by information fusion of spectral features and image features. The results show that the identification results of the support vector machine based on information fusion of spectral features and image features are the best, and the recognition rate is above 95%. Among them, the recognition rates of immature and mature samples reach 100%.
Keywords: *hyperspectral imaging, maturity, information fusion, support vector machine, back-propagation neural network.*

ИДЕНТИФИКАЦИЯ ЗРЕЛОСТИ ГРУШИ NANGUO НА ОСНОВЕ СЛИЯНИЯ ИНФОРМАЦИИ

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На основании метода гиперспектральной визуализации путем объединения информации о спектральных характеристиках и особенностях изображения для идентификации зрелости груш Nanguo предложены модель нейронной сети с обратным распространением и модель опорных векторов. Результаты идентификации с помощью метода опорных векторов оказались лучше, степень распознавания зрелости >95%, в том числе степень распознавания незрелых и зрелых образцов достигает 100%.
Ключевые слова: *гиперспектральная визуализация, зрелость, объединение информации, метод опорных векторов, нейронная сеть с обратным распространением.*

Introduction. The Nanguo pear is one of the species of autumn pear. It is not only a famous fruit in Anshan, Haicheng and other regions but also one of the characteristic fruits in Liaoning Province. It is also often exported abroad. The Nanguo pear is a precious variety in the world of pear fruit. In the pear fruit introduced in the book entitled “The Third Volume of Chinese Fruit Research,” the Nanguo pear ranks the first. With its unique aroma, it is one of the four pear species among 517 pear species in China. It is known as the “king of pears.” The Nanguo pear is not a single species. It is divided into many types, such as small-type

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fruit, middle-type fruit, big-type fruit, rust-colored type, red type, Nanguo pear-Pingguo pear series, cold-red pear, and so on. Moreover, the Nanguo pear pollination varieties are Pingguo and Huagai pears. It can be seen that the study of the Nanguo pear has certain universality; it provides a theoretical foundation for the investigation of other similar varieties of pears which are of great significance.

In recent years, with increasing production, good and low quality Nanguo pears are mixed together. So, maturity is an important standard for the quality and nutrition of the Nanguo pear, and the main basis for its classification. Identification of the Nanguo pear maturity can avoid the disadvantages of laborer classification such as low efficiency, long sorting time, and ease of destroying the epidermis of the fruit, which ensures the appearance, taste, commodity value, and export quality of the Nanguo pear. At the same time, it provided a theoretical basis for the development of multispectral online quality detection and grading system of the Nanguo pear.

In recent years, hyperspectral imaging technology has become a research hotspot. It is used in nondestructive testing of fruits [1], vegetables [2], meat [3], and crop quality [4]. Hyperspectral imaging technology permits one to obtain information about maturity [5, 6], freshness [7], pigment content [8], surface color [9], texture [10], different damages [11], pollutant treatment [12], pulp hardness, and soluble solids [13] of fruit. It can fuse image features with spectral information [14], which can detect the properties of a test sample during the process of collecting hyperspectral image. Therefore, we call it a perfect combination of image features and spectral information.

The recent research of the Nanguo pear mainly focuses on the physiological and biochemical processes of the fruit, the trace elements contained in the Nanguo pear, and the storage methods. Research on the maturity and quality grading of the Nanguo pear is still rare. The purpose of this paper is to study the information fusion methods of spectral features and image features based on hyperspectral imaging techniques for testing the Nanguo pear maturity. It provides a theoretical basis for the subsequent development of Nanguo pear quality online detection and grading system based on hyperspectral imaging technology.

Experimental. The test materials were purchased from the Fruit Tree Farm, Datun Town, Haicheng City, Liaoning Province. In this study, a total of 280 Nanguo pear samples were selected. The appearance and corresponding maturity of Nanguo pear are shown in Table 1. All fruit are divided into four mature levels: immature, semi-mature, mature, and over-matured ones.

According to the maturity of the Nanguo pear, it is divided into four mature levels: immature, semi-mature, mature, and over-matured. Some images of the Nanguo pear samples were collected by the hyperspectral image system. First, we set the parameters of the hyperspectral image system and adjusted the focal length of the lens of the camera and the distance between the sample and the lens. Then, after repeated adjustments, test parameters were as follows: the distance between the sample and the lens was 272 mm, the moving speed of the carrier platform was 1 mm per second, and the exposure time of the camera was 76 ms. Second, we corrected the hyperspectral image with whiteboard and blackboard so that it would eliminate noise because of the influence of the dark current of the system, the uneven light source, and so on. The hyperspectral curves of the region of interest (ROI) of all samples at different mature levels were collected to obtain the average value of the spectral reflectance of each sample. After denoising and smoothing, the relative reflectance differences of these spectral curves were compared and analyzed to determine the characteristic bands and feature images. After collecting hyperspectral curves data, physicochemical indexes were detected: the detection of soluble solids content (SSC), titratable acid content (TAC), and hardness.

Maturity is the combined result of the changes in physicochemical indexes during fruit growth. First, the Pearson correlation is analyzed between maturity and three indexes, including SSC, TAC, and hardness. We explore the correlation between the above physicochemical indexes and the maturity of the Nanguo pear. Second, the physicochemical indexes of the different maturity samples are tested by the methods of mathematical statistics, that is, the u test between the two sets of data.

TABLE 1. The Maturity of Nanguo Pear

Stored time, days	Appearance	Maturity
6	Peel is mainly green, rough, the points on the peel are obvious	Immature
12	Peel is mainly yellow-green, the points on the peel are a little obvious	Semi-mature
18	Peel is golden yellow with some bright red, the texture of peel is fine and smooth, the points on the fruit peel become unclear	Mature
24	Peel is dark yellow, thin and smooth	Over-mature

In this paper, successive projections algorithm (SPA) and stepwise multiple linear regression (SMLR) are used to select the characteristic wavelengths of SSC and the characteristic wavelengths of maturity. A partial least squares model is established to compare and determine the best characteristic wavelengths.

Color features and texture features are used as image features to describe these differences in the surface areas of the Nanguo pear at different maturity levels.

In image processing, HSV is more similar to the human visual sense. The three components H, S, and V are independent of each other, and they are more sensitive and easy to quantify the color. The H parameter represents the color information. It is more suitable as a color feature than S or V parameters. The H parameter is represented by an angle ranging from 0 to 360°. The H parameter of immature fruits is mainly concentrated in the ~105–140° region. The H parameter of semi-mature fruits is mainly concentrated in the ~70–100° region. The *H* parameter of mature fruits is concentrated in the ~45–70° region. The H parameter of over-mature fruits is ~0–35°, ~40–70°, and ~350–360°. However, there are overlapping parts of the H parameters of the mature and over-mature Nanguo pear. Therefore, the value of the H-parameter histogram is used as the variable, and the Mahalanobis distance is used as the multi-feature discriminant standard to separate two types of the samples in a multi-dimensional space [15].

Let us assume that the sample matrix is X_B:

$$X_B = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \tag{1}$$

where m is the number of matrix rows and n is the number of matrix columns. The average value of the sample is μ:

$$\mu = \left[\frac{1}{n}\sum_{i-1}^{n} \mathrm{x}_{1\mathrm{i}} \cdots \frac{1}{n}\sum_{i=1}^{n} x_{mi}\right]^{\top} = [\mu_1 \cdots \mu_m]^{T}. \tag{2}$$

The data matrix after the centralization is X'_B:

$$X'_B = \begin{bmatrix} x_{11}-\mu_1 & x_{12}-\mu_1 & \cdots & x_{1n}-\mu_1 \\ x_{21}-\mu_2 & x_{22}-\mu_2 & \cdots & x_{2n}-\mu_2 \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1}-\mu_n & x_{m2}-\mu_n & \cdots & x_{mn}-\mu_n \end{bmatrix}. \tag{3}$$

The covariance matrix of the sample is S:

$$S = X'_B X'^{T}_B. \tag{4}$$

The square of the distance from sample X to class B is D_B^2:

$$D_B^2 = (x-\mu)^T S(x-\mu) + \ln|S|. \tag{5}$$

The probability that the sample X belongs to the class B is $P_B(x)$:

$$P_B(x) = \frac{e^{-0.5D_B^2(x)}}{\sum_{k=1}^{2} \mathrm{e}^{-0.5D_k^2(x)}}. \tag{6}$$

Taking into account accuracy and preventing computer overflow, $P_B(x)$ will become

$$P_B(x) = \left\{1 + e^{0.5\left[D_B^2(x) - 0.5D_k^2(x)\right]}\right\}^{-1}, \tag{7}$$

were $B \neq k$, $B = 1,2$.

The above probabilistic analysis method can be used to determine whether the sample is mature or over-mature.

The gray-level co-occurrence matrix (GLCM) is a common method for describing textures by studying the spatial correlation properties of gray scales. In this paper, the contrast, correlation, entropy, homogeneity, and energy of different varieties of the Nanguo pear are extracted by the method of GLCM as the texture feature parameters. The GLCM of four directions (0, 45, 90, 135°) are extracted from each PC image. Then, five texture feature parameters are extracted from 20 GLCM for establishing the maturity discriminant model along with other features.

Back-propagation (BP) neural network is a multilayer feed-forward network trained by error back propagation, with input, hidden and output layers. There are 200 training samples of Nanguo pears, including 50 samples of each maturity level, four maturity levels. Test samples are 80 Nanguo pears, including 20 samples of each maturity, four maturity levels. In this paper, we take the number of feature quantities that fuse spectral features and the image features as the number of input nodes of the BP neural network. Eight maturity characteristic wavelengths selected by the SPA method (described later in the manuscript, by comparison, the characteristic wavelengths extracted by this method are the best) are used as spectral features. That is, eight characteristic wavelengths and five image texture information are fused and modeled. Therefore, the number of BP neural network input layer nodes is 13. The types of maturity in this paper is four, and the number of output nodes of BP neural network is four. The number of hidden layer nodes is calculated from the empirical formula

$$l = \sqrt{m + n} + \alpha , \qquad (8)$$

were l is the number of hidden layer nodes; m is the number of input layer nodes; n is the number of output layer nodes; α is a constant between 1 and 10.

The Nanguo pear samples of four different maturities are assigned as 1, 2, 3, and 4, respectively. If the difference between the predicted and the hypothetical category values is within ±0.5, it indicates that the sample is correctly discriminated. That is, if the predicted result of the immature Nanguo pear sample is 0.5–1.5, the discrimination is correct. The predicted result of the semi-mature Nanguo pear sample is 1.5–2.5, then the discrimination is correct. If the predicted result of the mature Nanguo pear sample is 2.5–3.5, the discrimination is correct. If the predicted result of the mature Nanguo pear sample is 3.5–4.5, so the discrimination is correct. On the contrary, the discrimination is an error. The samples with predicted category values less than 0.5 or greater than 4.5 are removed. The BP neural network is trained according to the above method. Then the maturity of the test samples is identified by the trained BP neural network.

The basic idea of the support vector machine (SVM) is to establish an optimal classification hyperplane. SVM can analyze the data, identify patterns, and classify them. Similarly, 200 fruit were selected as the training samples, and 80 fruit were used as the prediction samples. The spectral features and the image features are fused as the input of the SVM model. Moreover, four samples with different maturities are output as the SVM model. Then the SVM model is trained to identify the Nanguo pear maturity of the prediction samples.

In this study, the two methods are used to identify the Nanguo pear maturity by using information fusion technology.

Results and discussion. We collected the data of hyperspectral image acquisition system every 6 days. Hyperspectral curves were smoothed and denoised, as shown in Fig. 1. As can be seen from Fig. 1, the shapes of the hyperspectral curves of the Nanguo pear for different mature levels were similar, but there were differences in the values of reflectivity. The higher the maturity, the greater the reflectance in the 400–700 nm range. The spectral curve of the over-mature level was at the top. The absorption peak appeared at 675 nm, which was mainly due to the absorption of chlorophyll in the Nanguo pear pulp and epidermis. Due to the different mature levels of fruit, the chlorophyll content was not the same. Therefore, the values of the absorption peak were different. The hyperspectral curves of the samples had the biggest difference and did not overlap at the wavelength of 637 nm, and the contrast ratio was higher at this wavelength. The images for this wavelength were selected as the feature images.

The Pearson correlation and u test results are shown in Tables 2 and 3. As can be seen, the three types of physicochemical values of different maturity samples had significant differences. The difference of SSC was the largest, followed by the hardness, and the difference of the TAC was the smallest. In addition, it could be seen from the correlation analysis of SSC, TAC, hardness, and maturity that the correlation between SSC and maturity was the most significant, so the characteristic wavelength of SSC could be used to identify the maturity of the Nanguo pear.

In this paper, characteristic wavelengths were selected based on maturity and SSC.

Selected characteristic wavelengths based on maturity. The full-wavelength spectrum was used as an input variable, and the number of days (6, 12, 18, 24) was used as a temporary variable. The minimum effective wavelength was set as 5, and the maximum effective wavelength was 20. As shown in Fig. 2, when the number of characteristic wavelengths was 8, the RMSE curve showed an inflection point, and the curve behind the inflection point tended to be stable. Therefore, the number of characteristic wavelengths was determined to be 8. The full-wavelength spectra were selected by the SMLR to determine the optimal characteristic wavelength of maturity.

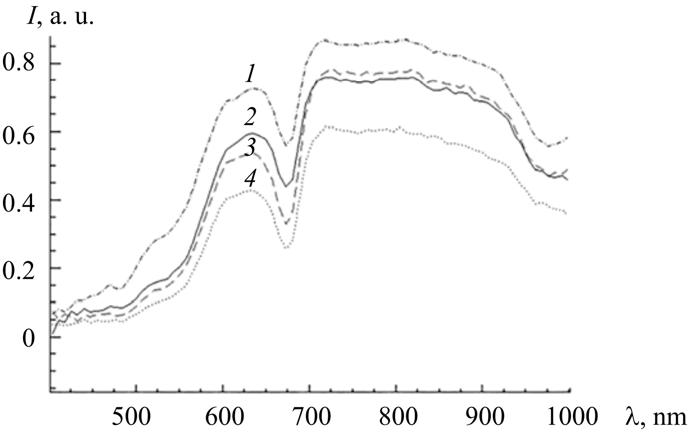

Fig. 1. Hyperspectral reflectance curves of the Nanguo pear for different values of maturity, over-mature (1), mature (2), semi-mature (3), and immature (4).

TABLE 2. Correlation Analysis between the Physicochemical Index and Maturity of the Nanguo Pear

Indexes	Soluble solids content	Titratable acid content	Hardness
Maturity	0.816*	–0.521**	–0.596**
Soluble solids content		–0.382	–0.414**
Titratable acid content			0.288

N o t e: * indicates significant correlation at the 0.01 level; ** indicates significant correlation at the 0.05 level.

TABLE 3. *u*-Test of Physicochemical Indexes of Different Maturity Samples of the Nanguo Pear

Mathematical statistical test (u test)									
Category	Soluble solid content			Titrate acid content			Hardness		
	Semi-mature	Mature	Over-mature	Semi-mature	Mature	Over-mature	Semi-mature	Mature	Over-mature
Immature	1.986**	3.142*	3.558*	1.948	2.142**	2.865**	2.201**	3.263*	3.601*
Semi-mature		2.012**	3.116*		1.944	1.997**		2.121**	2.241**
Mature			1.971**			1.902			1.946

N o t e: * indicates significant correlation at the 0.01 level; ** indicates significant correlation at the 0.05 level; $u_{0.05}$=1.959964; $u_{0.01}$=2.575829.

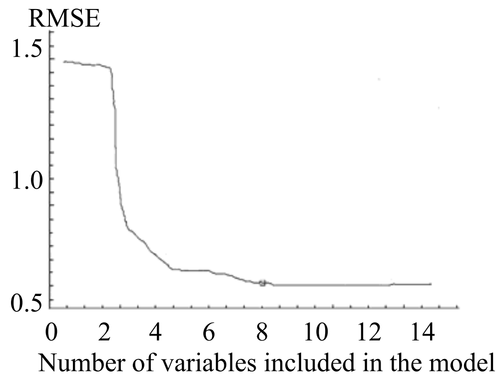

Fig. 2. RMSE distribution of SPA of the Nanguo pear for different values of maturity.

Selected characteristic wavelength based on SSC. The full-wavelength spectra were used as an input variable, and the SSC information was used as an output variable. The characteristic wavelengths of SSC of the Nanguo pear were determined by the SPA and SMLR methods described above, as shown in Table 4.

It can be seen from Table 4 that the characteristic wavelengths of maturity were better than the characteristic wavelengths of SSC, and SPA was better than SMLR. Therefore, in this paper we selected the characteristic wavelengths of maturity 8 by the SPA method.

The BP neural network and the SVM model were established to identify the maturity of the Nanguo pear based on spectral and image features and information fusion of spectral and image features. The spectral features here refer to the optimal feature variables extracted by the SPA algorithm, that is, eight characteristic wavelengths. The model effect was shown in Table 5.

TABLE 4. PLS Model Effect Based on Different Characteristic Wavelengths

Characteristic wavelengths	Selection method	Number of characteristic wavelengths	Characteristic wave-lengths, nm	Calibration set		Prediction set	
				R_C	RMSEC	R_P	RMSEP
Characteristic wavelengths of maturity	Successive projections algorithm	8	482,515,550,647, 690,775,810, 892	0.957	0.216	0.946	0.224
	Stepwise multiple linear regression	12	482,486,515,550,595,647, 690,722,775,810, 892,906	0.944	0.245	0.937	0.265
Characteristic wavelengths of soluble solids content	Successive projections algorithm	9	465, 498, 512, 557, 644, 679, 771, 811, 883	0.926	0.389	0.908	0.423
	Stepwise multiple linear regression	14	455, 488, 502, 562, 598, 663, 715, 767, 842, 866, 922, 947	0.905	0.435	0.887	0.502

TABLE 5. Model Effects of the Nanguo Pear Maturity Based on BP Neural Network and Support Vector Machine

Feature category	Back-propagation neural network				Support vector machines			
	Calibration set		Prediction set		Calibration set		Prediction set	
	R^2_C	RMSEC	R^2_P	RMSEP	R^2_C	RMSEC	R^2_P	RMSEP
Spectral features	0.785	0.424	0.707	0.523	0.862	0.319	0.811	0.407
Image features	0.796	0.401	0.733	0.499	0.889	0.303	0.867	0.386
Spectral and image features	0.901	0.201	0.886	0.304	0.915	0.158	0.898	0.198

As could be seen from Table 5, the effects of the BP neural network and the SVM model, which fused spectral features and image features, are greatly improved, and the predictive ability of the model is greatly strengthened. It was indicated that the spectral characteristic data and image feature data had greater influence and decision-making power on the maturity of the Nanguo pear. Moreover, the model effect of SVM was better than that of the BP neural network model. It showed that two kinds of data were fused to play a synergistic effect and resulted in a better model result. As can be seen from Table 5, the SVM model effect of the information fusion of spectral and image features was the best.

Therefore, it is better to identify the maturity of the Nanguo pear based on the information fusion of spectral and image features. The maturity identification results of the information fusion of spectral and image features are shown in Fig. 3 and 4 and Table 6. As can be seen, the identification rates of immature, semi-mature, mature, and over-mature samples based on BP neural network were 100, 90, 95, and 90%, respectively. The identification rates of immature, semi-mature, mature, and over-mature based on SVM were 100, 95, 100, and 95%, respectively. Semi-mature and over-mature samples had relatively low recognition rates. The identification effect of the SVM model was better than that of the BP neural network model. Among them, the recognition rates of the immature and mature Nanguo pear reached 100%. Therefore, the SVM modeling method is more effective than BP in identifying the Nanguo pear maturity.

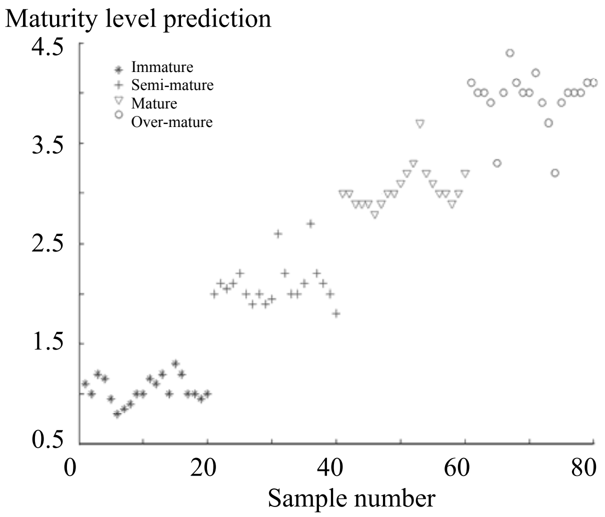

Fig. 3. The predicted values of the Nanguo pear maturity based on the BP neural network.

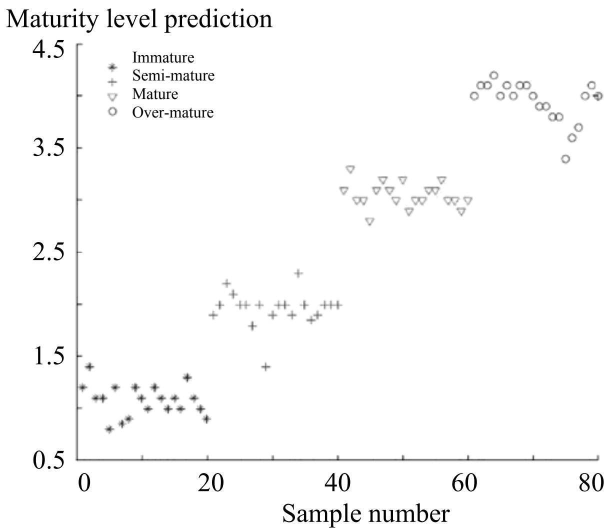

Fig. 4. The predicted values of the Nanguo pear maturity based on the support vector machine.

TABLE 6. The Nanguo Pear Maturity Identification Results of the BP Neural Network and the Support Vector Machine Based on the Information Fusion of Spectral and Image Features

Maturity	Back-propagation neural network				Support vector machines			
	Immature	Semi-mature	Mature	Over-mature	Immature	Semi-mature	Mature	Over-mature
Immature	20				20	1		
Semi-mature		18				19		
Mature		2	19	2			20	1
Over-mature			1	17				19
Number of samples	20	20	20	20	20	20	20	20
Correct rate, %	100	90	95	90	100	95	100	95

Conclusions. The characteristic wavelength of maturity based on SPA selection is selected as the spectral feature. Color and texture features are selected as the image features. Identification of the Nanguo pear maturity by the BP neural network and the SVM model is based on the information fusion of spectral and image features. It shows that the result of the SVM model based on the information fusion of spectral and image features is the best, and the recognition rate is above 95%. Among them, the recognition rates of immature and mature samples reach 100%.

Therefore, it is feasible to identify the Nanguo pear maturity based on the method in this paper. The method based on the information fusion of spectral and image features improves the model effect. Moreover, the accuracy of the SVM model has been greatly improved compared to the existing research. The recognition rate of immature and mature samples reaches 100%. The recognition of maturity can ensure the taste, commodity value, and internal and export quality of the Nanguo pear. At the same time, it provides a theoretical basis for the development of multi-spectral online quality detection and classification system of the Nanguo pear.

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