Rapid Nondestructive Defect Detection of Scindapsus aureus Leaves Based on PCA Spectral Feature Optimization

Zhiyun Xiao¹,², a, Jiao Wang¹,²

¹College of Electricity Power, Inner Mongolia University of Technology, Inner Mongolia Hohhot, China
²Inner Mongolia Key Laboratory of Electromechanical Control, Inner Mongolia Hohhot, China

a xiaozhiyun@imut.edu.cn

Abstract. Classification and identification of yellowing, spotted and normal green leaves were performed by using hyperspectral imaging technology. Firstly, three kinds of support vector machine (SVM) classification models were established under different preprocessing methods. The optimal preprocessing method (normalized + SG + first derivative) was obtained by using the pixel as the data set input and the recognition rate of the classification reached 97.4%. However, the amount of data information is large and the detection time is relatively long. In order to further optimize the spectral characteristics and improve the detection efficiency, principal component analysis (PCA) was used for feature selection and feature extraction under this optimal pretreatment method. The experiment shows that the feature extraction method selects the optimal principal component number of 7 in the dimension reduction experiment with the dimension ranging from 3 to 15 and the recognition rate is 97.3% after SVM classification, which is 4.8 percentage points higher than the feature selection method. The method of feature selection speeds up by 22.57s, which is faster than the optimal preprocessing method by 104.07s, which can greatly improve the recognition and detection speed while ensuring the accuracy. The results show that the hyperspectral image technology combined with the support vector machine classification model can achieve the non-destructive rapid detection of green leaf defects under the normalization + SG + first derivative preprocessing method and feature extraction.

1. Introduction

Scindapsus aureus is one of the very excellent interior decorations. It is alive when it meets water. Because of its tenacious vitality, it is called "the flower of life". Environmentalists have shown that a pot of scindapsus aureus is equivalent to an air purifier in a room of 8 to 10 square meters, which can effectively absorb harmful gases such as formaldehyde, benzene and trichloroethylene in the air. It is generally more efficient to use the hydroponic method for planting, and the survival rate will be higher [1]. During the growth and development of scindapsus aureus leaves, it is easy to be affected by light, water, fertilization and other factors causing yellowing or disease spots, which increases the difficulty of detection and classification in actual production. Hyperspectral imaging technology has the
advantages of high resolution, strong anti-interference ability and non-destructiveness. It overcomes the subjectivity of manual detection and improves the detection efficiency. Therefore, it has become the focus of the development of "intelligent agriculture" and the research hotspot in the field of crop detection.

At present, the detection of agricultural products defects and lesions based on hyperspectral analysis at home and abroad has also been rapidly developed and achieved good results [2-12]. Wang Bin et al. used hyperspectral techniques to establish a model for decay, disease and normal pear jujube to qualitatively identify and classify the characteristic damage of pear jujube [13]. Zhou Zhu et al. proposed a combination of band-ratio algorithm and uniform quadratic difference algorithm based on hyperspectral analysis to detect the external defects of potato, which provided a reference for online non-destructive testing of potato [14]. Zhang Hailiang et al. used hyperspectral imaging technology to non-destructively detect citrus defects, and proposed a combination of characteristic wavelength principal component analysis and band ratio algorithm, with a recognition rate of 94% [15]. Tian Youwen et al. used hyperspectral imaging technology to correctly identify apple insects and fruit stems/flower buds, providing a theoretical basis for online quality detection and grading of apples [16]. The above literature shows that the high-spectral technology has achieved good results in the application of crop defects in agriculture, and the feasibility is also very large, but there are few studies on crop leaf defects and lesion detection, and a large amount of image information is used as input. The amount of data and information is large, and there are problems such as increasing the difficulty of data storage and processing thus slowing down the running speed.

The purpose of this study is to extract the region of interest (normal region, yellowing region, and spotted region) of scindapsus aureus leaves by using hyperspectral imaging technique, and establish support vector machine (SVM) under conditions including spectral preprocessing, feature selection and feature extraction. Using pixel point classification of hyperspectral which remotes sensing image for reference. The pixels was used as the input in to model of the data set to achieve the fast nondestructive defects based on spectral feature analysis of scindapsus aureus leaves, so as to realize the rapid classification and identification of scindapsus aureus leaves defects.

2. Materials and Methods

2.1. Experimental Materials
The hydroponic scindapsus aureus used in this experiment was purchased from the flower market in Hohhot. The sample set of normal leaf, yellowing leaf, and spotted leaf were collected to obtain three 512×512 hyperspectral images as shown in Fig.1. Among them, the yellowing leaf should have a larger part of yellowing, and the spotted leaf also should have larger spots.

2.2. Graphic Gathering
This experiment used Specim (Special IQ), a handheld new hyperspectral camera from Specim (Oulu, Finland). Specim IQ is a handheld broom system with an integrated operating system and controls. Allows sensor technology to be transferred to the greenhouse and on-site at the quality level of laboratory equipment without any carrier platform control and storage equipment. The hyperspectral imaging inspection system is shown in Fig.2.

The Specim IQ hyperspectral camera is used to acquire hyperspectral images in the spectral range from 400 to 1000 nm with a spectral resolution of 7 nm and 204 spectral bands. Two Alai-type 575W spotlights are used as the light source, and other auxiliary equipments including a tripod, a pan-tilt, a calibration whiteboard, and a correction color card.

The hyperspectral imaging detection system was placed in a dark laboratory, the leaves were placed on a single background platform, the position of the light source was adjusted, the distance between the platform and the lens was determined to be 20cm, and the exposure time of the camera was adjusted to 15ms. The leaves were placed on the platform to collect hyperspectral images of
normal leaves, yellowing leaves, and spotted leaves. Before collecting samples, you need to select custom mode in the hyperspectral camera to do

Fig. 1 Samples of scindapsus aureus leaves (a) Normal leaf (b) Yellowing leaf (c) Spotted leaf

Fig. 2 Hyperspectral imaging monitoring system. 1. Leaf sample 2, 3. Light source 4. Storage platform 5. The Specim IQ hyperspectral camera 6. Transmission data line 7. Computer 8. Tripod

Black and white correction, and make correction for subsequent hyperspectral images. Calculate the corrected image, the formula as follows:

\[
R = \frac{I - B}{W - B}
\]

\(W\) —— Standard whiteboard gets full white calibration image
\(B\) —— Camera black calibration image
\(I\) —— Original hyperspectral image

The hyperspectral data of the collected leaves were imported into the computer using the hyperspectral camera's own software Specim IQ Studio, The PyCharm operating environments and Matlab R2016a were used for processing and analyzing.

2.3. Spectral preprocessing and analysis method

2.3.1. Spectral preprocessing. Because the spectral information is easily affected by physical factors such as environment, conditions, and instruments during the collection process, it contains many redundant information that interferes with the spectral information. In order to remove noise, eliminate the influence of other factors on the information, and to optimize the spectral range and data processing, the acquired spectral information needs to be preprocessed. In this study, normalization, SG smoothing filtering, and first-order derivative method are used to combine the three pre-processing methods one by one, and the support vector machine (SVM) classification models under different pre-processing were established for comparison.

The data normalized can make the weights of each feature dimension have the same influence on the objective function, and improve the convergence speed of the iterative solution. Converting hyperspectral data to the [0, 1] range using maximum and minimum normalization, the scaling of the original data can be achieved, the formula is:
\[ X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]  

(2)

\[ X_i \] —— Normalized data  
\[ X \] —— Original data  
\[ X_{\text{min}} \] —— Minimum value of original data  
\[ X_{\text{max}} \] —— Maximum value of the original data

The SG smoothing algorithm [17] which is also known as convolution smoothing method is a polynomial smoothing algorithm based on the least squares principle proposed by Savizkg and Golag. This method can improve the smoothness of the spectrum and reduce noise interference. Different window widths will achieve different filtering effects. Generally, the window width is odd. In this study, based on the experimental filtering effect, a secondary smoothing filter with a window width of 7 was selected for spectral preprocessing.

The first derivative method [18] uses a first-order differential derivation, which can improve the spectral resolution, and it is a common spectral preprocessing method. Formula is as follows:

\[ X_{i,1g} = \frac{X_i - X_{i,g}}{g} \]  

(3)

\[ X_i \] —— Discrete spectrum before pretreatment  
\[ X_{i,1g} \] —— First derivative at the wavelength point  
\[ g \] —— Window width

Through multiple experimental comparisons, it can be seen that the best pretreatment effect is achieved when the window width is 7.

2.3.2. Region of interest extraction. In this study, the mask algorithm was used to extract the region of interest from the sample leaves. The basic principle is to determine the pixel position of the normal, yellowing and spotted leaves regions by calculating the variance of the spectral characteristic curves of different regions of interest between 700 nm and 800 nm. Therefore, background segmentation can be achieved basically. The variance of the spectral curve of the normal leaf is \([0.04, 0.08]\), the variance of the spectral curve of the yellowing leaf is \([0.01, 0.04]\), the variance of the spectral curve of the spotted leaf is \([0.002, 0.005]\), and the variance of the spectral curve of the background region all are below 0.002.

2.3.3. Feature selection and feature extraction. Selected the 204 bands of the whole spectrum of the spectral curve, that is, the range of 400 nm to 1000 nm were studied. Before the support vector machine classification and recognition model is carried out, the spectral information of 204 bands are separately selected and feature extracted. Comparison of dimensional methods to reduce information redundancy, reduce data characteristics, and improve classification efficiency.

The feature selection is to select a partial feature from all the extracted features as a training set feature, and the feature does not change the value before and after the selection, but the dimension decreases. In this paper, the feature selection is based on the PCA band selection of the five main components of the three types of leaves images. By comparing the information of the original image in the main component image, the first two principal component average weight coefficient curves were drawn, and five features were selected. Wavelengths 435.0, 548.8, 613.8, 682.6 and 759.4 nm.

Feature extraction [19] is dimension reduction, which essentially maps from one dimension space to another in a certain numerical relationship. The number of features does not change, but the feature values change accordingly. In this paper, the feature extraction is achieved by changing the dimension from 3 to 15 by PCA, and the optimal principal component is 7 dimensions. The optimal principal component number means that the feature recognition rate in this dimension is the highest.
2.3.4. Classification modeling method. Support vector machine classification shows many unique advantages in solving small sample, nonlinear and high-dimensional pattern recognition, and has strong generalization ability and predictive ability.

This study established a support vector machine (SVM) classification model under three different preprocessing methods. In order to compare the recognition rate and improve the recognition speed, the optimal preprocessing method was selected to establish two kinds of support vector machine (SVM) classification models based on full spectrum PCA feature selection and PCA feature extraction. In this study, by using SVC classifier [20] for training, the pixel points of the scindapsus aureus leaves in the normal area, the yellowing area and the spotted area were used as data input to improve the status of pictures’ information occupying large memory, speed up data processing and training speed.

The kernel function selected the RBF Gaussian kernel function, that is, the radial basis kernel function. Compared with the polynomial kernel function, it requires fewer parameters. Compared with the Sigmoid kernel function, its correct rate is higher [21], so the applicability is stronger. Under the comparison of multiple adjustment experiments, when the penalty parameter C=1 and the kernel function parameter g=0.125, the highest recognition rate can be obtained, so the support vector machine classification recognition model was obtained.

3. Results and analysis

3.1. Spectral analysis and region of interest extraction

Spectral information at different wavelengths is present at each pixel of the scindapsus aureus leaves.

![Spectral characteristics of three types of scindapsus aureus leave](image)

**Fig. 3** Spectral characteristics of three types of scindapsus aureus leave

The spectral information of the three types of scindapsus aureus leaves with wavelengths from 400 nm to 1000 nm is shown in Fig.3. Observing the spectral region, it was found that the spectral curves of the three types of leaves varied from 510 nm to 680 nm and 700 nm to 800 nm. Among them, the yellowing leaf reach a spectral reflectance of 0.4 between 510 nm and 680 nm, which is significantly higher than the other two classes. The normal leaf showed peaks between 700 nm and 800 nm, and the reflectance reached 0.88. The yellowing leaf and the spotted leaf showed no obvious spectral absorption characteristics.

The region of interest extraction is mainly determined according to the variance of the spectral characteristic curves of the three types of leaves between 700 nm and 800 nm. The result of three types leaves mask segmentation images are shown in Fig.4.
In this spectral range, there is a large difference between the spectral curve variance of the three types of leaves and the background spectral variance, thus the region of interest can be well separated from the background. The background area was marked as No.0, the normal area was marked as No.1, the yellowed area was marked as No.2, and the variegated area was marked as No.3.

3.2. Spectral analysis under different spectral preprocessing

The study used three different pretreatment methods combined with spectral data preprocessing to improve the signal to noise ratio. The experimental results showed the spectral characteristic curves of three kinds of spectral pretreatments: normalized, normalized + SG, normalized + SG + first derivative, are shown in Fig.5. According to the spectral characteristic curve, the spectral reflectivity after normalization is generally lower than untreated, which makes the data more regular.

And the peak reflectivity of the normal leaf between 700 nm and 800 nm was reduced to 0.65. After the normalized + SG treatment, the wavelength band between 800 nm and 1000 nm gradually became smooth and the noise was reduced. After normalization + SG + first derivative treatment, the spectral characteristic curve was greatly changed. The normal leaf showed trough at 706 nm, the most obvious trough of yellowing leaf appeared at 685 nm, and the spectral reflectance reached a minimum -0.038, the spotted leaf showed trough at 688 nm. Although the trough was similar to the yellowing leaf, the spectral reflectance of the spotted leaf was -0.01, which was much larger than that of the yellowing leaf. Therefore, it can be found that between 666 nm and 764 nm, the first derivative method can make the spectral curves of the three types of leaves exhibited obvious features, so as to facilitate later feature optimization and classification identification.

3.3. SVM classification and recognition results under different spectral preprocessing

In this study, the SVC classifier in the support vector machine was used to classify and recognize the three types of scindapsus aureus leaves.

After the spectral preprocessing of the three types of leaves, the pixel points were used as training data input into the support vector machine model. When testing, a normal leaf, containing yellowing and spotted regions leaf were selected which different from the training samples leaves. It was identified and classified under different spectral preprocessing. The obtained classification and recognition results are shown in Table 1, and the recognition result is shown in Fig.6.

From the classification and recognition results, under the preprocessing method of normalized + SG + first derivative, the overall recognition result of scindapsus aureus leaves was the best, the overall recognition rate reached 97.4%, and the recognition effect of yellowing area was poor, the accuracy rate was 95.2%. According to the SVM classification and recognition results, it is seen that there was a partial misclassification in the yellowing area, the spotted leaf and normal leaf identification was relatively accurate, and the running time was 174.59s.

3.4. PCA feature selection and feature extraction

According to the previous SVM classification and recognition results, the optimal preprocessing method is normalized + SG + first derivative method.
Table. 1 SVM model recognition results under different pre-processing

| Preprocessing method | Recognition rate | Total | Normal | Yellowing | Spotted |
|----------------------|------------------|-------|--------|----------|---------|
| Unpreprocessed       | 0.962            | 0.999 | 0.950  | 0.726    |         |
| Normalized           | 0.967            | 0.999 | 0.925  | 0.992    |         |
| Normalized + SG      | 0.969            | 0.999 | 0.908  | 0.997    |         |
| Normalized + SG+ First Derivative | 0.974 | 0.989 | 0.952  | 0.994    |         |

Fig. 5 spectral characteristic curves under different preprocessing methods

Fig. 6 SVM classification recognition result

Based on this method, PCA feature selection and feature extraction processing are performed on 204 bands of sample spectral information.

Then, the selected five characteristic bands and the optimal principal component number 7 were respectively taken as inputs. These inputs were trained and predicted in the support vector machine (SVM) classifier. The recognition rate and running speed of the two methods were compared.

After the PCA feature selection, the image of the three types of scindapsus aureus leaves under the five principal components are shown in Fig.7. The experiment shows that the cumulative contribution rate of the first five principal components is 99.9%. Combined with the first five principal component images, it can be seen that the normal and yellowing leaves retain most of information for the original image in the PC1 image. However, the spotted leaf contains the most original image information in the PC2 image. It can be seen from the first five principal component images that as the number of principal components increases, the information contained in the image decreases, and the image sharpness also gradually decrease. The first and the second principal component average weight coefficient map was plotted in order to select a representative characteristic wavelength. The generated average weight coefficients map of the first and the second principal component is shown in Fig.8.
Selecting the local extremum points on the image, the five characteristic wavelengths are 435, 548.8, 613.8, 682.6, 759.4 nm. Five characteristic wavelengths were inputted into the SVM classification model. The recognition results are shown in Table 2. From the classification results, the total recognition rate reached 92.7% and the running time of the program was 93.09s when the five feature bands were selected as the input. However, the recognition rate of the yellowing region was poor which reached 83.9%.

| Characteristic wavelength | Recognition rate |
|--------------------------|------------------|
| Total                    | Normal | Yellowing | Spotted |
| 435,548.8,613.8,682.6,759.4 nm | 0.927 | 0.987     | 0.839    | 0.963    |

When the dimension changes within 3–15, the optimal principal component number was 7 after PCA feature extraction and the best total recognition rate was 97.3% after extracting the PCA feature. The experimental results are shown in Table 3.
The experimental results showed that the recognition speed was greatly accelerated after extracting the PCA extraction and the reduction of the dimension. It can be seen from the experimental comparison that the recognition rate after dimension reduction was about 97% and the highest total recognition rate was 97.3% when the number of the principal component was 7, the running time was 70.52s. On the whole, recognition effect of the yellowing leaves was generally lower than that of the other two types of leaves. But they were all maintained above 93%. The recognition rate without PCA dimension reduction reached 97.4%. In this experiment, the reduction of dimension significantly, improved the running speed which was 104.07s faster than that without PCA processing and 22.57s faster than that with PCA feature selection. However, it does not improve the recognition rate distinctly and the difference of recognition rate was only 1% before and after reducing the dimension. This improves the efficiency of classification detection and could basically realize the rapid non-destructive detection of the defects of scindapsus aureus leaves.

The results show that both feature selection and feature extraction can effectively detect the defects of scindapsus aureus leaves. However, in this study, feature extraction has a higher recognition rate and a shorter running time than feature selection. Therebefore, it can improve defect detection efficiency while ensuring accuracy.

| Dimension | Recognition rate |
|-----------|------------------|
| 15        | 0.972 0.989 0.985 0.996 |
| 14        | 0.969 0.989 0.939 0.998 |
| 13        | 0.970 0.989 0.942 0.998 |
| 12        | 0.970 0.989 0.943 0.997 |
| 11        | 0.971 0.988 0.944 0.997 |
| 10        | 0.970 0.988 0.943 0.996 |
| 9         | 0.969 0.989 0.940 0.998 |
| 8         | 0.970 0.989 0.943 0.997 |
| 7         | 0.973 0.989 0.949 0.996 |
| 6         | 0.969 0.989 0.940 0.997 |
| 5         | 0.972 0.989 0.947 0.996 |
| 4         | 0.972 0.989 0.974 0.996 |
| 3         | 0.970 0.989 0.943 0.997 |

4. Conclusion
Based on the hyperspectral imaging system, the following conclusions were obtained by using support vector machine (SVM) classification for three types of scindapsus aureus leaves samples under three different spectral pre-processing, feature selection and feature extraction:

(1) There are significant difference in the spectral characteristics of the three types leaves in the wavelength ranging from 700nm to 800nm. The region of interest can be extracted by calculating the difference in variance between the three types of leaves spectral curves and the background spectral curve within this range.

(2) The experimental results show that the support vector machine has the best classification and recognition result under the pre-processing method (normalized + SG + first derivative) and the recognition rate reached 97.4%. Spectral characteristic of the three types of blades with the wavelength ranging from 666nm to 764nm can be better reflected by using the first derivative method for the spectral pretreatment.

(3) Both feature selection and feature extraction can perform non-destructive detecting on the defects of scindapsus aureus leaves. However, feature extraction can reduce the training time while maintaining a high recognition rate. The characteristic wavelength obtained under feature selection...
does not necessarily represent most of the features of the entire sample, which leads to the low recognition rate.

(4) Compared with traditional image processing, which uses hundreds or even thousands of images as the input of the sample set. Using pixel points as data set input can greatly alleviate data memory and improve running speed while keeping better recognition effect. The feasibility of this method in other plant leaves detection of defects and disease is still being further verified.

In summary, hyperspectral imaging technology combined with support vector machine classification model for the analysis of PCA-based spectral feature extraction can basically achieve rapid non-destructive defect detection of scindapsus aureus leaves. At the same time, it also provides a basis for the study of the application of hyperspectral techniques to the defects of plant leaves elements which are not visible to the human eyes.

5. Acknowledgment

This study was carried out with the support of the National Natural Science Foundation. I would like to thank my teacher Professor Xiao. Mr. Xiao has a professional knowledge and a rigorous academic attitude. He has carefully guided me and patiently taught me throughout the research process so that I can successfully complete this research. I know that there are still many shortcomings in this research. In the future research, I will continue to explore new ideas and methods to make greater progress.

Fund Project: National Natural Science Foundation of China (61661042)

About the author: Zhiyun Xiao (1974—), male, professor, doctor., main research direction: digital image processing, pattern recognition and application E-mail: xiaozhiyun@imut.edu.cn

6. References

[1] Lang Wei. Scindapsus aureus Farming Methond [J]. Science and Technology of Tianjin Agriculture and Forestry, 2017 (01): 20. (in Chinese)

[2] Sun Dawei, Cen Haiyan, Weng Haiyong, et al. Using hyperspectral analysis as a potential high throughput phenotyping tool in GWAS for protein content of rice quality. [J]. Plant methods, 2019, 15.

[3] Guo Wenchuan, Dong Jinlei. Nondestructive Detection on Firmness of Peaches Based on Hyperspectral Imaging and Artificial Neural Networks [J]. Optics and Precision Engineering, 2015,23(6):1530-1537. (in Chinese)

[4] Meng Qinglong, Zhang Yan, Shang Jing. Nondestructive Detection of Defect on Apples Using Hyperspectral Imaging Technology[J]. Food Research and Development, 2019, 40 (5): 168-172. (in Chinese)

[5] Huang Fenghua, Zhang Shujuan, Yang Yi, Man Zun, Zhang Xuehao, Wu Yuxiang. Application of Hyperspectral Imaging for Detection of Defective Features in Nectarine Fruit [J]. Transactions of the Chinese Society for Agricultural Machinery, 2015, 46 (11): 252-259. (in Chinese)

[6] Wang Wanjiao, He Xiaoguang, Wang Songlei, Liu Guishan, Wu Longguo. Detection of Common Defects in Jujube Fruit Using Hyperspectral Imaging. Food & Machinery, 2015, 31 (3): 62-65,86. (in Chinese)

[7] Li Zhiqi. Non-destructive testing of potato external defects based on hyperspectral and multi-information fusion [D]. Ningxia: Ningxia University, 2015

[8] Tian Youwen, Mu Xin, Cheng Yi. Advancement of Nondestructive Detection of Fruit Defects Based on Hyperspectral Imaging [J]. Journal of Agricultural Mechanization Research, 2014, (6): 1-5. (in Chinese)

[9] Fan Y, Wang T, Qiu Z, Peng J, Zhang C, He Y. Fast Detection of Striped Stem-Borer (Chilo suppressalis Walker) Infested Rice Seedling Based on Visible/Near-Infrared Hyperspectral Imaging System[J]. Sensors, 2017, 17 (11): 2470.

[10] Kong W, Zhang C, Huang W, Liu F, He Y. Application of Hyperspectral Imaging to Detect Sclerotinia sclerotiorum on Oilseed Rape Stems [J]. Sensors, 2018, 18 (1): 123.
[11] Rajkumar P, Wang N, Eimasry G, Raghavan G S V, Gariepy Y. Studies on banana fruit quality and maturity stages using hyperspectral imaging [J]. Journal of Food Engineering, 2012, 108 (1): 194-200.
[12] Baranowski P, Mazurek W, Wozniak J, Majewska U. Detection of early bruises in apples using hyperspectral data and thermal imaging [J]. Journal of Food Engineering, 2012, 110 (3): 345-355.
[13] Wang Bin, Xue Jianxin, Zhang Shujuan. Detection of Decay and Disease Pear Jujube Based on Hyperspectral Imaging Technology [J]. Transactions of the Chinese Society for Agricultural Machinery, 2013, 44 (Supp1): 205-209. (in Chinese)
[14] Zhou Zhu, Li Xiaoyu, Tao Hailong, Gao Hailong. Detection of potato external defects based on hyperspectral imaging technology [J]. Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE), 2012, 28 (21): 221-228. (in Chinese)
[15] Zhang Hailiang, Gao Junfeng, He Yong. Nondestructive Detection of Citrus Defection Using Hyper-spectra Imaging Technology [J]. Transactions of the Chinese Society for Agricultural Machinery, 2013, 44 (9): 177-181. (in Chinese)
[16] Tian Youwen, Cheng Yi, Wang Xiaqin, Liu Sijia. Recognition method of insect damage and stem/calyx on apple based on hyperspectral imaging [J]. Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE), 2015, 31 (4): 325-331. (in Chinese)
[17] Chu Xiaoli, Yuan Hongfu, Lu Wanzhen. Process and Application of Spectral Data Pretreatment and Wavelength Selection Methods in NIR Analytical Technique [J]. Progress in Chemistry, 2004 (04): 528-542. (in Chinese)
[18] Yang Renxin,Yang Yan,Yuan Jinjin. The Research and Progress of Hyperspectral Image Preprocessing Methond [J]. Journal of Guangxi Normal University (Natural Science Edition), 2015, 32(01):28-32. (in Chinese)
[19] Yang Renxin,Yang Yan,Yuan Jinjin. Research on Hyperspectral Image Feature Extraction and Feature Selection [J]. Journal of Guangxi Normal University (Natural Science Edition), 2015, (2): 39-43. (in Chinese)
[20] Ma Yan, Zhang Ruoyu. Recognition of fresh apricot defects by support vector machine with different spectral pretreatment methods [J]. Xinjiang Farm Research of Science and Technology, 2017, 40 (4): 39-41. (in Chinese)
[21] Xiao Zhiyun, Liu Hong. Adaptive Features Fusion and Fast Recognition of Potato Typical Disease Images [J]. Transactions of the Chinese Society for Agricultural Machinery, 2017, 48 (12):2 6-32. (in Chinese)