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Ранняя идентификация *Curvularia Lunata* с использованием гиперспектральных изображений

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По мере того, как все более популярными становятся методы загущенной посадки и интенсивного внесения удобрений, год от года растет приносящее серьезный ущерб поражение растений *Curvularia Lunata*. Для снижения загрязнения окружающей среды и повышения качества зерна весьма важна разработка методов ранней идентификации поражений. Для быстрой и неинвазивной идентификации ранних стадий заболевания на листьях кукурузы использовалась технология обработки гиперспектральных изображений. В эксперименте листья подвергались инокуляции *in vitro* и через 11 временных интервалов (2, 4, 6, 8, 12, 24, 32, 40, 48, 60, 72 час соответственно) регистрировались гиперспектральные изображения в видимом и ближнем инфракрасном диапазонах. Сравнительный анализ листьев двух типов через 48 час после инокуляции показал наличие хлоротических пятен с различными спектральными характеристиками. Используя смешанный метод расстояний, обнаружено, что наилучшими с точки зрения идентификации *Curvularia Lunata* являются спектральные полосы 465,1, 550,7 и 681,4 нм. Используя данные этих полос как входные параметры, построена модель нейронной сети с обратным распространением. С ее использованием обработаны данные образцов (по 160 образцов каждой из указанных выше временных точек), причем точность идентификации инокулированных листьев составила 97,5%, подтвердив возможность использования такой сети для быстрого и неинвазивного определения *Curvularia Lunata*. Реализован новый метод раннего определения заболеваний кукурузы.

Ключевые слова: гиперспектральные изображения, *Curvularia Lunata*, характеристические спектральные полосы, раннее обнаружение, неразрушающие методы детектирования.

Early identification of *Curvularia Lunata* based on hyperspectral imaging

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With the popularizing of close planting and high fertilizer technology, the occurrence of *Curvularia Lunata* has been increasing year after year, has caused a very serious harm. The early identification method of the disease is of great significance to reduce the environmental pollution and improve the quality of crops. In order to identify the disease quickly and non-damage, we studied on maize leaves, then propose an early identification of *Curvularia Lunata* method based on hyperspectral imaging technology. The experiment leaves are *in vitro* inoculation, at 11 time's points after inoculation (2, 4, 6, 8, 12, 24, 32, 40, 48, 60, 72 hours respectively), we collect hyperspectral images in the visible and near infrared bands of normal leaves and inoculation disease leaves respectively by hyperspectral imaging system. By comparative analysis between two types of leaves, small chlorotic spots are been found after inoculation with 48 hours, spectral information has obvious difference. Based on mixed distance method, we find that the best bands of identification *Curvularia Lunata* are 465.1,

550.7, 681.4 nm. We use these bands as the input quantity and build back-propagation neural network detection model. We make experiments on samples (160 samples for each time point above mentioned) by the model, the accuracy rate of identification inoculation leaves is above 97.5%. The result show that, the BP neural network detection model with characteristic bands can identification *Curvularia Lunata* quickly and non-destructive. It provides a new way for early detection of maize diseases.

Key words: hyperspectral imaging technology, *Curvularia Lunata*, characteristic band, early identification, non-destruction detection.

OCIS codes: 100.4145, 150.1135, 170.0110, 300.6280, 300.6550, 000.5490

INTRODUCTION

Maize is widely grown in the tropical and the temperate zone, and it is one of the most widespread cereals in the world. China is the second largest country to produce and consume maize, where a great deal of maize has been planted. So, the maize is widely distributed in China, and it has become one of the most important cereals of the north and southwest China. The trend is obvious that the main maize regions in China have been expanding since the late 1970s. So that the maize has become the most important cereals from the third important cereal in China [1].

Many ingredients may often influence the growth and development of maize. As a result, some diseases may infect the maize. *Curvularia Lunata* (Wakker) Boedijin is a disease that became widely popular in the northeast and north of the maize regions of China in 1990s [2]. The disease can occur in adult plant and it mainly hurts the blades. The disease can also hurt leaf sheaths and bracts. The virus will spread quickly after the heading stage. So that the lesions will cover the whole maize, and the leaves will dry in advance, even the leaves may die. In recent years, the compact maize acreage has been expanding, close planting and high fertility technology are widely used and the climate is changing. These ingredients have been making the *Curvularia Lunata* (Wakker) Boedijin become more and more serious. And the *Curvularia Lunata* (Wakker) Boedijin has become a serious catastrophic disease after the leaf blight and small spot in China.

To apply pesticides properly can control effectively the spread of it when the disease happens. However, it is usually not easy to find the early symptoms. When the maize shows prominent features of the disease, we may miss the best time to apply pesticide. What's more, agricultural producers may overuse pesticide sometimes to prevent the disease. And it will degrade the quality of the agricultural products, affect the food safety and harm health. To distinguish the disease early can control the further development of the disease. It also plays an important role in reducing the pollution and the use of the pesticide.

Hyperspectral imaging technology is a general technology that is used to make nondestructive de-

tection. Recently, this technology is widely used to test the internal quality and the external quality of the agricultural products [3–5], the pesticide residues of the vegetables [6] etc. The categories to which the technology can be applied include vegetable and fruit [7–12], livestock and poultry meat [13–15], eggs [16] etc. In recent years, some scholars put the technology into practice to detect the plants pests and diseases and has made some progress. Moshou and others [17–18] have used hyperspectral and multi-spectral to identify the Wheat Stripe Rust based on the self-organizing map and neural networks. Feng Wei and others [19] used the hyperspectral to estimate the density of wheat canopy chlorophyll under the powdery mildew infection. And it is made sure that NDAI (α , β) is a reliable quota to estimate the density of wheat canopy chlorophyll. Zheng Zhixiong and others [20] combined the qualitative analysis with the quantitative analysis, to analyze the spectral features of the rice leaf blast area and the normal leaf area, analysed the the spectra that is different a lot with others by using the 2-Dimensional scatter plot. Then he extracted the hyperspectral images of the lesions, using the principal component analysis to classify the degree of the disease of the rice leaf blast by combining these functions with elongation and injury. Tian Youwen and others [21] used the hyperspectral image data of cucumber downy mildew to choose the images of characteristic of wavelength, and to extract the vectors of the texture of the chromaticity moments of the sick leaf, then to classify the cucumber diseases by using support vector machine. Li Bo and others [22] classified the rice white tip and the *cnaphalocrocis medinalis* by probabilistic neural network. Before drawing the conclusion, Li Bo and others analyzed the spectra of rice leaf, and they gained the spectrum of principle component by using principal component analysis (PCA) through choosing the visible band and short-wave infrared (IR). Yuan Ying and others [23] tested the *Aflatoxins* on the maize seed by PCA and factor analysis with discriminant analysis. Before reaching the conclusion, the team preprocesses the data with use of the 400–1000 nm Visible/near IR Hyperspectral Imaging System and standard normal variable correction.

The research selected the maize leaves that were inoculated *Curvularia Lunata* (Wakker) Boedijin as the study object, used the hyperspectral imaging system to continuously gain the hyperspectral images of the maize leaves that were inoculated the *Curvularia Lunata* (Wakker) Boedijin for 72 hrs. We contrasted inoculum leaves and normal leaves and extracted the characterized bands that can identify the leaves that was inoculated the disease correctly. And we provided a theoretical basis for early detection of maize diseases.

1. MATERIALS AND FUNCTION

1.1. Experiment materials

Maize leaves are the study objects in this research. And the type of the maize is DongDan6531, provided by Special Corn Institute of Shenyang Agricultural University. The bacterial strain used in the research is *Curvularia Lunata* A0523, provided by Laboratory of Molecular and Physiological Plant Pathology of Shenyang Agricultural University. The maize was planted in Greenhouse Experimental Base of Shenyang Agricultural University in May 10, 2016. We planted 30 maize seeds per rows and 10 per cols uniformly. The row spacing is 60 cm and the plant spacing is 30 cm. Every plant grew in the environment that has plenty of sunshine, good ventilation and has the same temperature and humidity. The maize was inoculated *Curvularia Lunata* (Wakker) Boedijin in July 10, 2016 when the maize was in 7–8 leaf stage. So, we can start the experiment. We used the vitro inoculation, before the inoculation, we collected the fourth leaf of every maize. 220 leaves were collected totally. While inoculating, we used the scalpel to scrape the *Curvularia Lunata* A0523 from the bacterial colony. Then we washed the bacterial with distilled water and used three layers of lens wiping paper to filter. After that, we made up the spore suspension that contains 10^6 spores per milliliter. And then, we inoculated by artificial inoculation. The 220 leaves were divided into 11 groups, every group contains 20 leaves. We regarded the main vein as the boundary, in the left of it, we inoculate the *Curvularia Lunata* bacterial and in the right of it, we didn't inoculate the *Curvularia Lunata* bacterial to be the contrast. After that we can avoid the difference between different leaves and make the observation of the virus's development more accurately. The maize leaves that were inoculated would keep damp in the culture dish whose diameter is 15 cm. Samples would be taken at 2, 4, 6, 8, 12, 24, 32, 40, 48, 60, 72 hrs after inoculation and the hyperspectral image data of the leaves were collected.

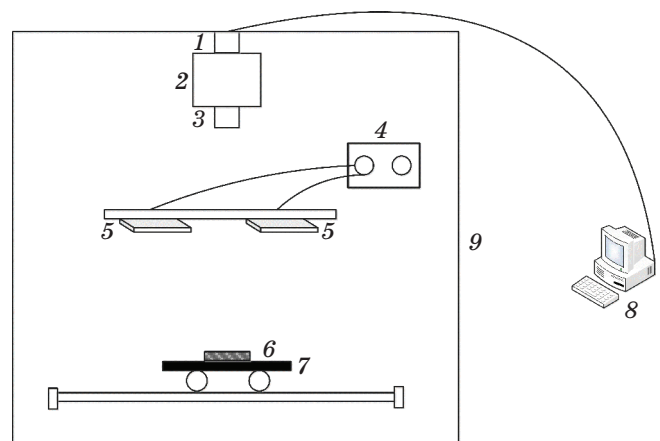


Fig. 1. Hyperspectral imaging system. 1 — EMCCD camera, 2 — imaging spectrometer, 3 — lens, 4 — lighting controller, 5 — halogen lamp concentrator, 6 — samples, 7 — mobile carrier platform, 8 — computer, 9 — black box.

1.2. Hyperspectral imaging system

This study used the hyperspectral imaging system to collect the data of the hyperspectral images. As Fig. 1 shows, the system consists a hyperspectrometer (ImSpector V10E), a EMCCD camera Raptor EM285CL), a halogen lamp (IT 3900, 1500W), a concentrator, a mobile carrier platform and a computer. The spectrum whose wavelength is 400–1000 nm will be collected. The spectrum collected has 512 bands and its resolution is 2.8 nm. The whole system was put into a closed black box in order to avoid the effect of the other light and to improve the accuracy.

1.3. Collection of hyperspectral image

In order to increase the accuracy of spectral information that was collected, we put one leaf on the black and smooth platform each time. And we collected 220 samples in 11 points of time. For each time, we collected 20 leaves that have been inoculated before. In order to improve the definition, we need to adjust the exposure time and the speed of the platform according to the height of the lens, focal length and the brightness of the light source before we collected the hyperspectral images. After many corrections we defined the exposure time is 7.4 ms, the distance is 430 mm and the speed of the platform is 2.85 mm/s. While we collecting, the leaves can move at a uniform speed with the platform. The high spectral camera and the image spectrometer got the image data in different bands and the spectral information of every pixel when the leaves were in every wavelength.

2. DATA PROCESSING AND ANALYSIS

The study chose Spectral-image developed by ISUZU OPTICS as the data acquisition software, used ENVI5.1 (ResearchSystem Inc., Boulder, Colo., USA),

Matlab2012a (The MathWorks Inc., Natick, USA), Excel2013 (Microsoft, USA) and Microsoft Visual Studio 2013 to deal with data.

2.1. Reflection spectral correction

The images need to have reflection spectral corrections before being collected in order to eliminate the impact of the dark current and the image noise in the bands where the light is weak. Firstly, we scanned the white board, which has a high reflectivity and extracted the white labelled image I_W whose reflectivity is 100%. Then we closed the lens to collect the black labelled image I_D whose reflectivity is 0. Next, we put the maize leaves on the platform to collect the spectral images I_S of the samples. Finally, we used the formula (1) to calculate the reflectivity R that was corrected in band i

$$R(i) = \frac{I_S(i) - I_D(i)}{I_W(i) - I_D(i)}. \quad (1)$$

2.2. The *Curvularia Lunata* (Wakker) Boedijin leaves feature band selection

The maize can infect the *Curvularia Lunata* (Wakker) Boedijin quickly. Small leaf spot can be found after 48 hrs of the inoculation. We used the hyperspectral imaging system to collect 11 time's points of leaf samples every 2, 4, 6, 8, 12, 24, 32, 40, 48, 60, 72 hrs later after calculation. In every time point, the images were collected in different bands of 400–1000 nm from 20 leaves in the former 9 time's points. 900 regions of interest from inoculated leaves were collected while 720 regions of interest from normal leaves were collected. The size of every region of interest is 50×50 pixel. After 48 hrs of inoculation, the leaves can have small chlorosis leaf spots. We chose the spectral information in 60, 72 hrs leaf spot area. In every leaf, 6 leaf spot areas were chosen from 40 inoculated leaves in the two time's points. The regions of interest are 240 totally when the 160 of them are in the normal leaves.

The average spectra were calculated respectively where inoculated and normal leaves showed interest at each detecting time point. Figure 2 shows the contrast of the spectrum curve between the normal leaves and the inoculated areas every 2, 4, 6, 8, 12, 24, 32, 40, 48 hrs later. Figure 3 shows the contrast of the spectrum curve between the normal leaves and the leaf spot areas 60, 72 hrs after the leaves were inoculated. Figure 4 shows the contrast between the spectrum curve of the regions of interest between the inoculated leaves and normal leaves.

As the Fig. 2 shows, during continuous 48 hrs after inoculated, the average spectra of the inoculated leaves is lower than the leaves not inoculated during the intervals in 400–700 nm. The difference is remarkable at around 550 nm.

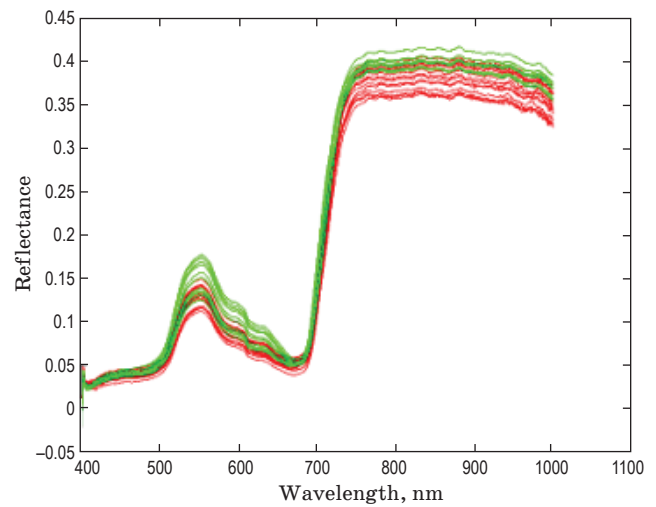


Fig. 2. Reflectance spectrum of normal leaves (green) and inoculation (red) without chlorotic spots.

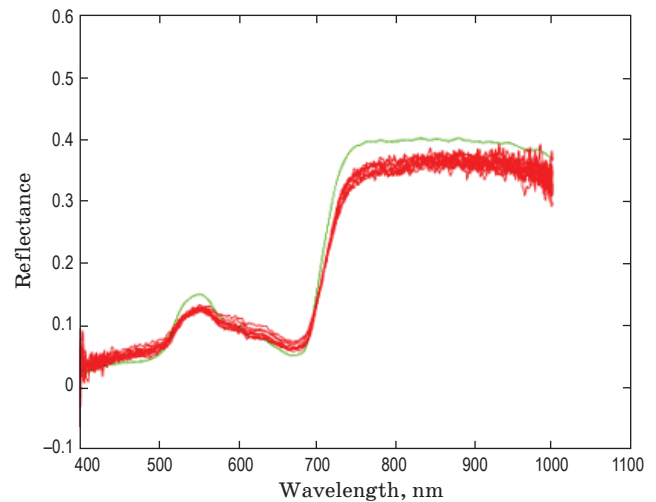


Fig. 3. Reflectance spectrum of normal leaves (green) and chlorotic (red) spots.

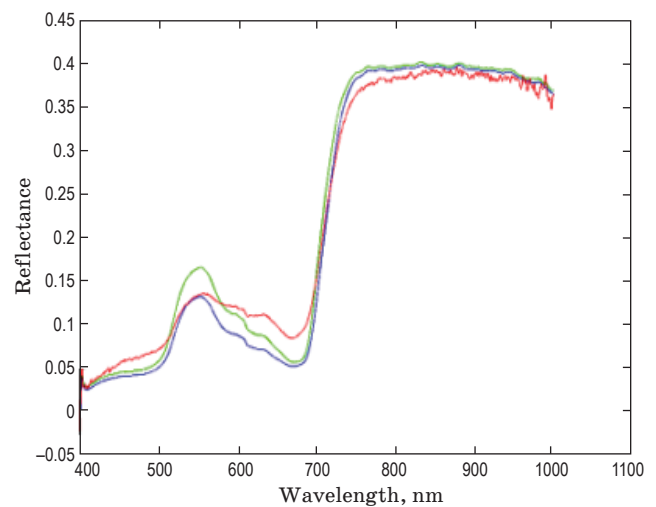


Fig. 4. Reflectance spectrum of normal leaves (green), leaves following inoculation but without chlorotic spots (blue), and with chlorotic spots (red).

Small spots were found 48 hrs later after inoculation. We compared the average spectra between the normal leaves and the inoculated leaf spots. As the Fig. 3 shows, the obvious difference between the normal leaves and the spot area in intervals was found at 400–500, 500–600, and 600–700 nm. A lot of noise was detected at 700–1000 nm.

Figure 4 gives the average contrast curves of areas between the normal leaves and the inoculated leaves that was not found spots 48 hrs after inoculated. As the Fig. 4 shows, the reflectivity reached the highest level 48 hrs after inoculated at the interval of 400–510 nm. Little differences were found between the normal leaves and inoculated leaves of 48 hrs before inoculated. In the interval of 510–610 nm the reflectivity of the inoculated leaves is lower than the normal leaves, especially at 550 nm. The reflectivity of the leaves inoculated 48 hrs later is lower higher than that of the normal leaves. And the change is remarkable in the absorbing valleys at 680 nm. According to what have been mentioned above, we concluded that the best choice of bands are 420–500, 510–610, 610–700 nm. The amount of data of the hyperspectral image is very large. And the strong relativity exists between the adjacent bands. So, we need to extract the bands with separability furtherly from the best area to choose bands. On the base of that, we can reduce the redundant data and detect the disease better. According to the expression of the blend distance method (2), we can get the characterized bands in 420–500, 510–610, 610–700 nm.

$$D_{i,j} = |x_{ik} - x_{jk}|. \quad (2)$$

In this expression, x_{ik} represents the reflectivity of i in the band k , x_{jk} represents the reflectivity of j in the band k . The bands with maximum blend distance was selected in the candidate intervals, and the feature band was confirmed. As the Table 1 shows, according to the result of calculation, the maximum blend distance among 420–500 nm is at the 465.1 nm band, the maximum blend distance among 510–610 nm is at the 550.7 nm band, the maximum blend distance among 610–700 nm is at the 681.4 nm band. 465.1, 550.7, 681.4 nm are thought to the characterized bands of the *Curvularia Lunata* (Wakker) Boedijin.

Table 1. Result of blend distance

No.	420–500 nm / blend distance	510–610 nm / blend distance	610–700 nm / blend distance
1	465.1/0.016327	550.7/0.039495	681.4/0.024807
2	467.6/0.016313	553.2/0.039428	680.1/0.024728
3	476.2/0.016223	548.2/0.039067	682.7/0.024276
4	477.4/0.016201	551.9/0.039001	685.2/0.024217

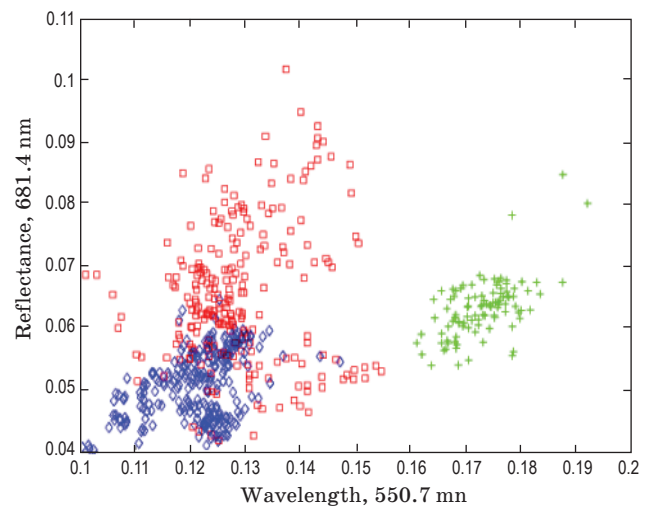


Fig. 5. 2-Dimension scatter plot. Normal leaves (green), the spectrum of the leaves following inoculation between 0 and 48 hrs (blue), the spectrum of the leaves following inoculation after 48 hrs (red).

2.3. Extract inoculated leaves

We selected the characterized bands of the hyperspectral image of the normal leaves, the inoculated leaves and the spectrum of the 550.7 nm and the 681.4 nm of the leaves to analyze the data by 2-Dimension scatter plot. As the Fig. 5 shows, hyperspectral images of the inoculated leaves were got by separating the normal leaves and the inoculated leaves.

2.4 The result of the *Curvularia Lunata* (Wakker) Boedijin test

We have built the model to test the *Curvularia Lunata* (Wakker) Boedijin based on the back-propagation (BP) neural network by Matlab. We used EVEI to take samples of the maize leaves collected by the hyperspectral imaging system. And we took samples 2, 4, 6, 8, 12, 24, 32, 40, 48, 60, 72 hrs after inoculation. In each time point, we took 120 regions of interest for training and 40 for testing. The accuracy of the testing result is shown in Table 2.

The BP neural network was built by analyzing the samples taken in different time points. Then we found that the recognition rate of the spot areas can reach 97.5% when the small chlorosis spots were observed. From the result of the study, we can conclude that it is effective to detect the *Curvularia Lunata* (Wakker) Boedijin in early time by using the hyperspectral imaging system.

Table 2. Test results of *Curvularia Lunata*

Time's point, h	2	4	6	8	12	24
Accuracy, %	86.25	90	90	86.25	90	92.5
Time's point, h	32	40	48	60	72	–
Accuracy, %	92.5	95	97.5	97.5	97.5	–

3. CONCLUSION

Based on the study of the early recognition of the *Curvularia Lunata* (Wakker) Boedijn by using the hyperspectral imaging system, we can come to the conclusions.

(1) The hyperspectral image can show a lot of spectral information and image information. But the strong relativity of information among the adjacent bands was found. And there is also some redundant information. For the test of the objects, it is important to extract the characterized bands. According to the blend distance method and the result of the analysis between the normal leaves and inoculated leaves, we can conclude that the characterized bands of the *Curvularia Lunata* (Wakker) Boedijn distributes at 465.1, 550.7, 681.4 nm.

(2) People can observe the process of the disease from the time dimension by extracting the hyperspectral information of the leaves collected by time

according to the observation and the study of the process of the *Curvularia Lunata* (Wakker) Boedijn infection from the view of the histology.

(3) The recognition rate of the inoculated leaves can reach more than 97% through the test in different time point for samples and the spectral difference of characterized bands between the normal leaves and the inoculated leaves. This result can provide a research foundation for detecting the *Curvularia Lunata* (Wakker) Boedijn in early time. And it can detect the *Curvularia Lunata* (Wakker) Boedijn quickly, losslessly and automatically. So, this study provided a new idea for detecting the maize disease in its early stage.

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