Identification of seedling cabbages and weeds using hyperspectral imaging

Deng Wei[1,3,4,5*], Yanbo Huang[2], Zhao Chunjiang[1,3,4,5], Wang Xiu[1,3,4,5]

(1. *Beijing Research Center of Intelligent Equipment for Agriculture, Beijing Academy of Agriculture and Forestry Science, Beijing 100097, China*; 2. *United States Department of Agriculture, Agricultural Research Service, Crop Production Systems Research Unit, Stoneville, Mississippi, USA*; 3. *National Research Center of Intelligent Equipment for Agriculture, Beijing 100097, China*; 4. *Key Laboratory of Agri-informatics, Ministry of Agriculture, Beijing 100097, China*; 5. *Beijing Key Laboratory of Intelligent Equipment Technology for Agriculture, Beijing 100097, China*)

Abstract: Target detection is one of research focuses for precision chemical application. This study developed a method to identify seedling cabbages and weeds using hyperspectral imaging. In processing the image data with ENVI software, after dimension reduction, noise reduction, de-correlation for high-dimensional data, and selection of the region of interest, the SAM (Spectral Angle Mapping) model was built for automatic identification of cabbages and weeds. With the HSI (Hyper Spectral Imaging) Analyzer, the training pixels were used to calculate the average spectrum as the standard spectrum. The parameters of the SAM model, which had the best classification results with 3-point smoothing, zero-order derivative, and 6-degrees spectral angle, was determined to achieve the accurate identification of the background, weeds, and cabbages. In comparison, the SAM model can completely separate the plants from the soil background but not perfect for weeds to be separated from the cabbages. In conclusion, the SAM classification model with the HSI analyzer could completely distinguish weeds from background and cabbages.

Keywords: hyperspectral imaging, weed identification, cabbage, seedlings

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1 Introduction

The ever-increasing world population needs sound technology to guarantee adequate food supply that can only be achieved through greater agricultural productivity, but the higher yields cannot be obtained without effective weed management even under ideal management practices[1]. The chemical applied between crops would cause issues with economic losses, environment pollution, and unsafe foods, which are concerned by many countries in the world being associated with living standards[2,3]. In this sense, precision application of chemicals over crops has great significance. In order to reduce the dosage of ago-chemicals for minimizing environmental pollution, herbicides should be applied accurately to the needed locations in the field. Therefore, rapid access to the information of spraying targets is a critical process in precision chemical application. Many approaches to weed detection and identification have been reported in literature, such as photoelectric detection technique[4,5], ultrasonic detection technique[6], remote sensing detection

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Biographies: Yanbo Huang, PhD, Research Agricultural Engineer, Research interests: soft computing, decision support, and remote sensing for precision agriculture, Email: yanbo.huang@ars.usda.gov; **Zhao Chunjiang**, PhD, Research professor, Director of Chinese National Engineering Research Center for Information Technology in Agriculture, Research interests: agricultural information technology, Email: zhaocj@nercita.org.cn; **Wang Xiu**, PhD, Professor; Research interests: intelligent machinery of precision agriculture and automatic control; Email: wangx@nercita.org.cn.

***Corresponding author: Deng Wei**, PhD, Associate Research Professor, Research interest: precision chemical application, precision agriculture, and soft computing. Address: Beijing Nongke Mansion, No. 11, Shuguang Huayuan Middle Road, Haidian District, Beijing, 100097, China; Email: dengw@nercita.org.cn.

technique[7], and image processing detection technique[8-11], X-ray weed detection technique[12], and spectral weed detection technique[13,14]. The image processing technique can detect the target's profile and determine the coverage and amount of smart spray, but mostly this technique is still used in the laboratory instead of being used in field because of its poor stability, large amount of data processing, relatively slow response, and the high costs. In comparison, spectral detection has been widely used in real-time detection system because of its fast response, availability for non-contact detection, strong anti-interference, high reliability, low cost, simple and small configuration, and low power consumption.

Most of the target detection methods can be categorized as being spatial, spectral, and hybrid of the two methods. Spatial methods are normally based on plant morphology, texture, color. Spectral are usually based on the light reflected from the plant surfaces. Each of the two methods has its advantages and disadvantages. The hybrid of the two methods has been studied in many researches. The combination of spatial and spectral methods was reported more and more recently because proper fusion of various technologies can improve the real-time access to information on spraying targets.

Karimi et al.[15] analyzed the hyperspectral data for identifying weed and nitrogen stresses in cornfield in early growth stage. The study provided an acceptable classification accuracy of 69% for combined herbicide and nitrogen applications and more accurate classification results were obtained when herbicide and nitrogen treatments were investigated separately (86% and 81%, respectively). Alchanatis et al.[16] reported that, using an acousto-optic tunable hyper-spectral sensor and a segmentation algorithm based on texture features, the weeds were detected in all images. The weed-infested area was estimated with 14% error, and the false detection rate was 15%. Using artificial light, Borregaard et al.[17] applied a line-imaging NIR spectrometer to record reflectance spectra in the wavelength range 660-1060 nm for the plants (potato, sugar beet, and three kinds of weeds) in the early growth stage and background (soil). Pattern recognition methods, like linear and quadratic discriminant analysis, principal component analysis with soft independent modeling of class analogy, and partial least-squares regression with several *Y*-variables, were applied in discrimination of crops and weeds on the reflectance characteristics. Among these methods, the bilinear methods showed the highest classification performances of 70%-80% on the populations of four species (one crop and three weed species), and up to 90% when divided into two target groups (crop and weeds). Feyaerts and Van Gool[18] developed a spectrograph with a low spectral resolution (35 nm) and used it to discriminate beets from five weeds. The classification accuracy was so good as up to 86%. However, six narrow spectral bands (441 nm, 446 nm, 459 nm, 883 nm, 924 nm and 988 nm) were needed for the classification, which is impractical for field work. Zhu et al.[19] used a 3CCD multi-spectral camera to capture pictures of soybean and two common weeds (*Alternanthera philoxeroides* and *Eleusine indica*) in the laboratory. Based on the image from IR channel of multispectral images with image segmentation and morphological processing, the soybean leaves were extracted. Although the two weeds were similar in size and color, they differed from each other by shape. So, parameters like length, width, areas of the images were calculated and two simple rules were used to identify them. The correct recognition rate was 90.5%. A spectral image can provide not only a single band image but also the spectral curve of each pixel within the image. Thereby a three-dimensional data cube can be formed in which the two-dimensions coordinate of X and Y is normally used to present the spatial position information and Z-axis features the information of wavelength spectrum[20].

In this study, a hyperspectral imaging system named SWIR-N25E was used to acquire the NIR hyperspectral images of two seedling cabbages ('No.8398' and 'Zhonggan No.11') and five weeds (Barnyard Grass, Green Foxtail, Goosegrass, Crabgrass, and Small Quinoa) in the range of 1000-2500 nm. Using the image-spectrum merging technology, the SAM (Spectral Angle Mapper) classification method was respectively applied to discriminant analysis of the spectral images in two spectral-image data processing software, ENVI (The Environment for Visualizing Images) (ITT Visual Information Solutions Company, Boulder, Colorado, USA) and HSI Analyzer (Hyper Spectral Imaging Analyzer) (National Instruments Corporation, Austin, Texas, USA).

2 Materials and methods

2.1 Hyperspectral imaging system

The NIR hyperspectral imaging system named SWIR-N25E was used in the study and shown in Figure 1, which acquires hyperspectral images in 1000-2500 nm. Besides the optical imaging unit, the system also includes data acquisition device, display device, storage device, reflecting mirror scanner, mounting bracket, and power supply. In addition, corresponding to the hardware devices, the system also contains some software for setting parameters, enabling data acquisition, pre-selecting spectral bands, viewing hyperspectral image data, and performing radiometric calibration and other functions.

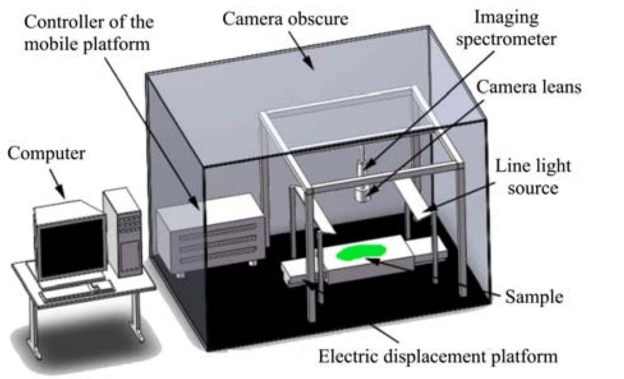


Figure 1 Hyperspectral imaging system and its main components

2.2 Collecting NIR hyperspectral images

The canopy hyperspectral imaging data of five weeds and two cabbages were collected using the SWIR-N25E hyperspectral imaging system in the laboratory of Beijing Research Center for Information Technology in Agriculture on April 26, 2012. Each plant was imaged five times and the image data were saved as the format .raw and .hdr which can be imported into the HSI Analyzer and ENVI software for subsequent processing and analysis.

2.3 SAM classification

Spectral angle mapping (SAM) classification method is a spectral matching technique to investigate the similarity between two spectral vectors at the pixel level, which is based on the similarity between spectra of predicting and training samples or between predicting sample and the sample in spectral library to distinguish the spectral curve of each pixel. The principle of SAM classification is that in the N-dimensional space (N is the number of spectral bands selected in the experiment) each spectral curve is considered as a vector with length and direction. After projecting the spectral vector of each pixel to the N-dimensional space, the spectral angles between the spectra of predicting and training samples (or samples in spectral library) can be calculated to characterize the matching degree between the two spectral vectors. Wherein the smaller the spectral angle is, the more similar the spectra curve of the predicting sample is to the training sample, which indicates higher similarity of the features of the two compared samples and higher probability and accuracy of classification. This method just considers the direction of spectral vectors regardless of the length of the vectors, so it is insensitive to differences in image brightness value associated with the length of spectral vectors so that it is not easy to misclassify the same species under different lighting intensities[21]. This paper applies the SAM method to classify spectral images of cabbage and weed canopies.

2.4 Data processing software

2.4.1 ENVI spectral data processing software

The Environment for Visualizing Images (ENVI) is an advanced tool for processing, analyzing, and displaying multispectral, hyperspectral, and radar data, which can not only provide a flexible function of displaying and browsing images but also simplify the comprehensive interactive processing and classification methods for image sizes, massive multi-band date sets, spectra and spectral image libraries, and the region-of-interest images. Using fitting techniques for spectral data, the spectra of spectral images in training sets or in libraries can be compared so as to identify vegetation, minerals, rocks, and so on[22].

The process flowchart for building the SAM identification model in ENVI is shown in Figure 2.

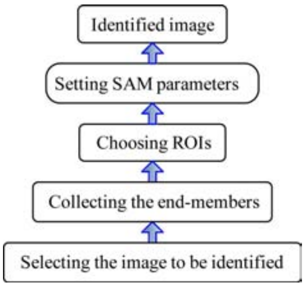


Figure 2 Process flowchart of SAM identification in ENVI

2.4.2 Hyperspectral Imaging Analyzer (HSI Analyzer)

HSI Analyzer is a powerful software to process hyperspectral images fast and effectively. In HSI Analyzer, hyperspectral images can be shown with spectral curves. Various parameters for preprocessing and classification modeling can be conveniently set up in the Analyzer dialog box. With the function of Reporting Setting, the processing results can be exported to Excel spreadsheet. In addition, the starting and terminal bands can also be set so the hyperspectral images within different bands will be dynamically shown.

In order to realize recognition of cabbages and weeds, the process flowchart of classification process using the SAM identification method in HSI Analyzer is shown in Figure 3.

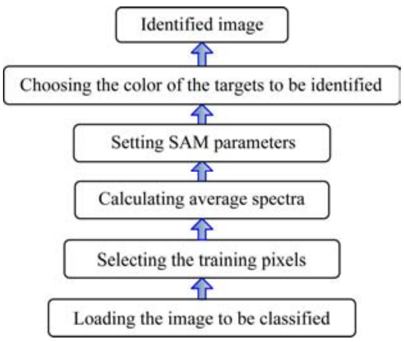


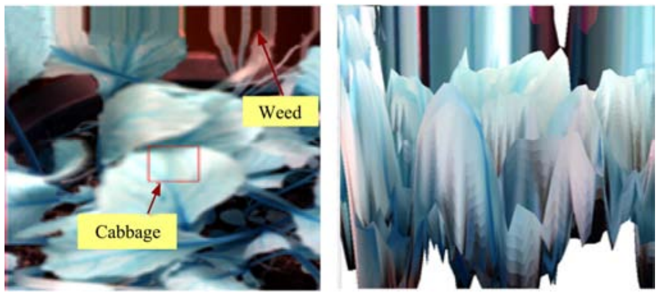
Figure 3 Process flowchart of SAM identification in HSI Analyzer

3 Results and discussion

3.1 Classification of weeds from cabbages in ENVI

3.1.1 Image display

One of the measured spectral images was imported to ENVI and its ordinary spectral image and 3-D spectral image are respectively shown in Figure 4. The 3-D spectral image contains both image information and spectral information, from which not only the spectral data of each pixel can be extracted but also the images of the measured target at each band can be obtained. It contains the concept of image-spectrum merging in spectral imaging technology.



a. Original spectral image b. 3-D image

Figure 4 Display of the images of cabbages and weeds in ENVI

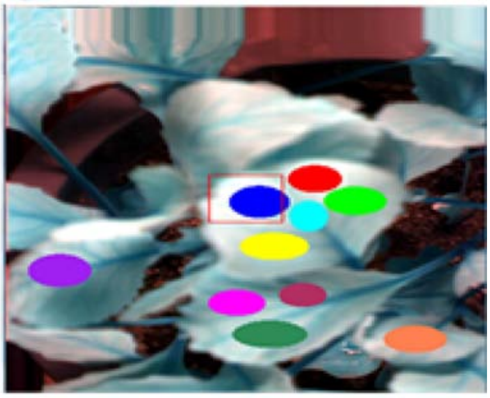
3.1.2 Extraction of the region-of-interest (ROI)

After selecting the ROIs on the images of each plant, the average spectra and some statistic data were calculated for the ROIs. The average spectra of the ROI can be saved as the spectra in spectral library and then directly used for comparison with predicting spectral data.

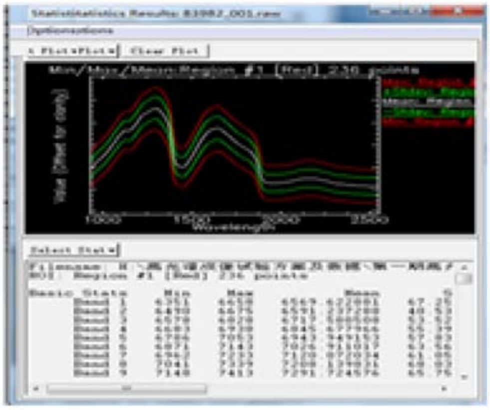
Ten ROIs were firstly selected on the image of each pot of plant shown as the image in Figure 5a. According to the statistic information of the ROI, the average spectral curve (white) was plotted, up and down of which are the spectral curves of standard deviations (green) and the spectral envelope curves of the minimum and maximum values (red). The spectral curves of the ROI#1 for a spectral image sample of Cabbage No. 8398 are shown in Figure 5b. The same operation was repeated for five pots of sample of each plant so fifty average spectra data were obtained for each kind of plant and saved as the .txt files in the spectral library, shown in Figure 5c. All the average spectral curves for each plant can be acquired similarly for cabbage Zhonggan No.11, barnyard grass, Small pigweed, goosegrass, crabgrass, and green foxtail.

3.1.3 Image recognition

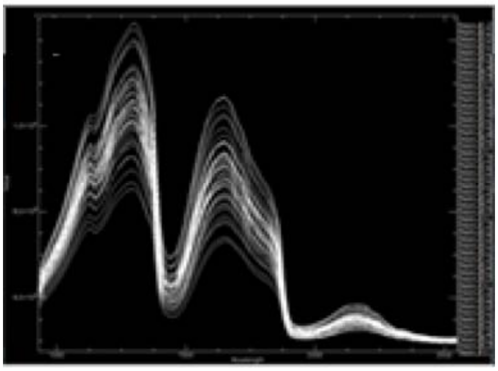
The original image of cabbages and the mixed-placed weeds are shown in Figure 6a and regarded as the image which is going to be identified. The average spectral data of the previously-defined ROI in Section 3.1.2 were selected as the standard spectra in the endmember collector. After selecting the ROI of the image, and at the same time with the parameter ‘Spectral Angle’ set as ‘Single Value’ and ‘Maximum Angle’ set as 0.1 radians in parameter setting dialog of SAM, the measured images were identified and the resulting images are shown in Figure 6b.



a. ROIs on the image

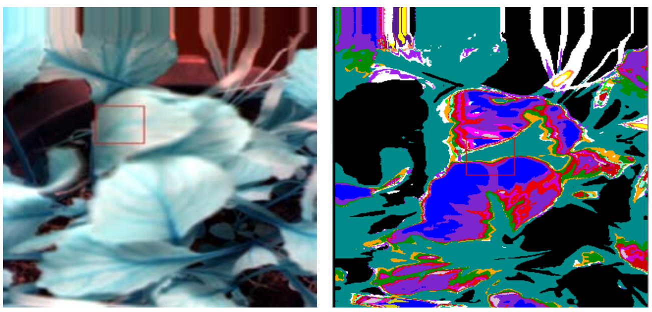


b. Spectral curves of ROI#1



c. Average spectral curves of all ROIs

Figure 5 ROIs and its spectral curves of Cabbage No.8398



a. Original image b. Image after classification

Figure 6 Classification results of cabbages and weeds in ENVI

Comparing the images before and after recognition processing (Figure 6), it can be seen that the background like pots and soil in the original image appears to be black in the identified image, the weeds were white, and the cabbages were presented to be a color completely different from black background and white weeds. As a whole, the results showed good identification effects using the SAM method, where the plants are completely separated from the background and the cabbages can be distinguished from the weeds as well. However, some places on the upper left part of the identified image which should be cabbages actually present to be white. It is probably because directly setting the average value of ROI as the center can't well reflect the angle relation between the vectors of predicting spectrum and standard spectrum.

3.2 Identification of cabbages and weeds in HSI Analyzer

3.2.1 Image display

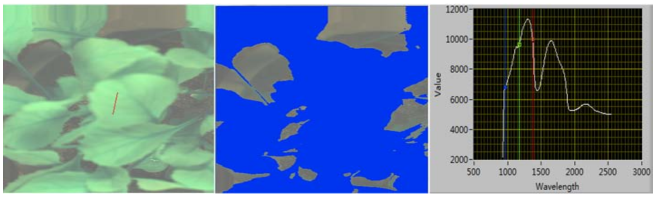
All the measured image data of various kinds of plants were loaded into HSI Analyzer and cabbage No. 8398 and goosegrass were chosen as representatives to be shown in Figure 7. It can be seen from Figure 7 that the spectral images of all species of plants shown in HSI Analyzer look similar to the images which are taken using normal digital camera and their color are close to the color of real plants, whereas the images shown in ENVI present lower-color compared with the real color.

a. Cabbage No. 8398 b. Goosegrass

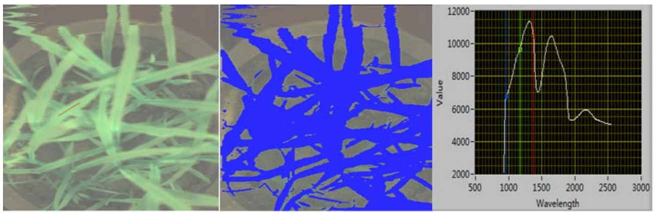
Figure 7 Spectral images of cabbages and weeds displayed in HSI Analyzer

3.2.2 Identification of plants from background

The spectral angles of the spectral curves of all the pixels on the predicting image were calculated when they are compared with the training spectrum of specified pixels. If a calculated spectral angle is less than the set threshold value (9 degrees), then the spectral curve of the pixel is considered as a standard curve and the pixel was colored with the specified color (blue). The spectral angle calculation and comparison involve all the pixels on the predicting image. The spectral angle mapping of each kind of plants were obtained and shown in Figure 8. It can be seen that all kinds of plants are able to be obviously distinguished from the background.



a. Cabbage No.8398



b. Barnyard grass

Figure 8 Original spectral images, SAM mappers and training pixel spectra for cabbages and weeds

3.2.3 Identification of cabbages and weeds

The method and process of recognition of cabbages and weeds were similar to the process of separating plants from background stated in Section 3.2.2. One of the spectral images of mixed-placed cabbages and weeds was loaded into HSI Analyzer and the spectral data on weed pixels in the image were selected as standard training spectra, shown in Figure 9. Then some important parameters were set, such as Smoothing Points, Derivative Order (dt), and Spectral Angle (Angle limit). After the unrecognized targets were set as blue color, the recognizing process was carried out in HSI Analyzer.

a. Original spectral image b. Marked training pixels

Figure 9 Original spectral image and training pixels of mixed cabbages and weeds

Different parameter settings will result in different effects of recognizing cabbages and weeds. Table 1 shows the different parameter settings used in the analyzing and Figure 10 shows the corresponding images of recognition results for the image shown in Figure 9.

Table 1 Various parameters in HSI Analyzer

Model	Parameter setting		
	Smoothing point	Derivative order	Spectral angle
a	0	0	5
b	0	0	4
c	1	0	4
d	1	1	4
e	2	0	5
f	2	0	6
g	3	0	6

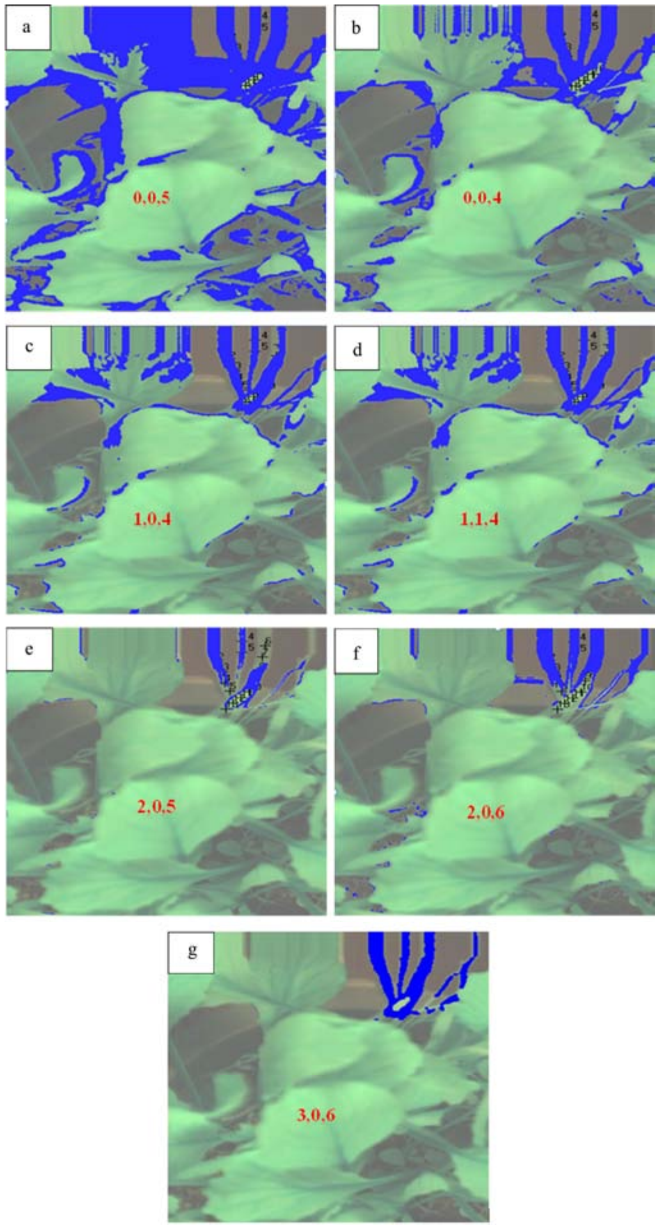


Figure 10 Recognition results of model a, b, c, d, e, f, and g

It can be seen from Figure 10 that the identification effects have no change when the Spectral Angle and the Smoothing Point were separately set to a certain value and just the Derivative Order was changed, which indicated that derivation operation has little effect on identification results and the results were mainly affected by the smoothing point and spectral angel. A plenty part of pots and cabbages were mistaken for the weeds when the Smoothing Point and the Derivative Order were set as 0 and the Spectral Angle was set as 5 degrees, which demonstrated that the matching range was too large. The background was effectively removed in the identified image when the Smoothing Point, Derivative Order and Spectral Angle are respectively set as 2, 0 and 5, but large parts of the weeds had also been removed. Therefore, adding the Spectral Angle to 6, a small part of cabbages and pots were included into the weeds. And increasing the Smoothing Point from 1 to 3, only the weeds in the analyzed identification image appear to be blue, which means that almost all the weeds have been identified.

Comparing the SAM identification methods in ENVI and HSI Analyzer, the selection of training pixel spectra and the setting of parameters like Smoothing Point and Spectral Angle are very critical in both softwares. However, compared with the SAM method in ENVI, the SAM method in HSI Analyzer can achieve better identification effects.

4 Conclusions

1) In ENVI, using SAM spectral image analysis method to identify seedling cabbages and weeds, the plants can be completely separated from the background and the weeds can be roughly identified from cabbages.

2) In HSI Analyzer, also using SAM method to distinguish seedling cabbages and weeds, the better identification results were obtained when parameters were set as the Smoothing Point was 3, Derivative Order was 0, and Spectral Angle was 6, in which of the situation weeds were almost completely distinguished from the background and cabbages.

3) In comparison of the SAM classification methods in ENVI and HSI Analyzer, selecting the spectral of the training pixels and setting the parameters of Smoothing Point and Spectral Angle are both very critical. However, the SAM method in HSI Analyzer results in better recognition results.

4) The analysis results showed that it is feasible to utilize the SAM classification method to identify seedling cabbages and weeds.

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[References]

[1] Towa J J, Guo X P. Effects of irrigation and weed-control methods on growth of weed and rice. Int J Agric & Biol Eng, 2014; 7(5): 22–33.

[2] Sun H, Li M Z, Zhang Q. Detection system of smart sprayer: Status, challenges, and perspectives. Int J Agric & Biol Eng, 2012; 5(3): 1–15.

[3] Wang J W, Tao G X, Liu Y J, Pan Z W, Zhang C F. Field experimental study on pullout forces of rice seedlings and barnyard grasses for mechanical weed control in paddy field. Int J Agric & Biol Eng, 2014; 7(6): 1–7.

[4] Biller R H. Reduced input of herbicides by use of optoelectronic sensors. Journal of Agricultural Engineering Research, 1998; 71, 357–362.

[5] Andújar D, Àngela Ribeiro, Fernàndez-Quintanilla C, Dorado J. Accuracy and Feasibility of Optoelectronic Sensors for Weed Mapping in Wide Row Crops. Sensors, 2011; 11, 2304–2318.

[6] Andújar D, Weis M, Gerhards R. An Ultrasonic System for Weed Detection in Cereal Crops. Sensors, 2012; 12, 17343–17357.

[7] Thorp K, Tian L. A Review on Remote Sensing of Weeds in Agriculture. Precision Agriculture, 2004; 5, 477–508.

[8] Weis M, Sökefeld M. Precision Crop Protection - the Challenge and Use of Heterogeneity; Springer Verlag: Dordrecht/Heidelberg/London/New York, 2010; Vol. 1, chapter Detection and identification of weeds, pp. 119–134.

[9] Christensen S, Søgaard H, Kudsk P, Nørremark M, Lund I, Nadimi E, Jørgensen R. Site-specific weed control technologies. Weed Research, 2009; 49, 233–241.

[10] Burgos-Artizzu X P, Ribeiro A, Tellaeche A, Pajares G, Fernández-Quintanilla C. Improving weed pressure assessment using digital images from an experience-based reasoning approach. Computers and Electronics in Agriculture, 2009; 65, 176–185.

[11] Piron A, van der Heijden F, Destain M F. Weed detection in 3D images. Precision Agriculture, 2011; 12, 607–622.

[12] Haff R P, Slaughter D C. X-ray based stem detection in an automatic tomato weeding system. In: ASAE Annual

Meeting. 2009. Paper Number: 096050.

[13] Vrindts E, De Baerdemaeker J, Ramon H. Weed detection using canopy reflection. Precision Agriculture, 2002; 3(1): 63–80.

[14] Sui R, Thomasson J A, Hanks J, Wooten J. Ground-based sensing system for weed mapping in cotton. Computers and Electronics in Agriculture, 2008; 60(1): 31–38.

[15] Karimi Y, Prasher S O, Patel R M, Kim S H. Application of support vector machine technology for weed and nitrogen stress detection in corn. Computers and Electronics in Agriculture, 2006; 51(1): 99–109.

[16] Alchanatis V, Leonid R, Amots H, Leonid Y. Weed detection in multi-spectral images of cotton fields. Computers and Electronics in Agriculture, 2005; 47(3): 243–260.

[17] Borregaard T, Nielsen H, Nørgaard L, Have H. Crop–weed discrimination by line imaging spectroscopy. Journal of Agricultural Engineering Research, 2000; 75(4): 389–400.

[18] Feyaerts F, Van Gool L. Multi-spectral vision system for weed detection. Pattern Recognition Letters, 2001; 22(6): 667–674.

[19] Zhu D, Shao Y, Pan J, He Y. Identification of crop and weed in seedling stage based on multi-spectral images. Journal of Zhejiang University (Agriculture and Life Sciences), 2008; 34(4): 418–422.

[20] Cao L, Wu C, Hou Q, Zhang W. Survey of target recognition technology based on spectrum imaging. Optical Technique, 2010; (001): 145–150.

[21] Xie J, Pan T, Chen J, Chen H, Ren X. Joint optimization of Savitzky-Golay smoothing models and partial least squares factors for near-infrared spectroscopic analysis of serum glucose. Chinese Journal of Analytical Chemistry, 2010; 38(3): 342–346.

[22] Li H, Gu H, Zhang B, Gao L. Research on hyperspectral remote sensing image classification based on MNF and SVM. Remote Sensing Information, 2007; 5: 12–15.