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A Novel Technique for Weed Detection using Textural Similarities

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Abstract: *Accurate detection of weeds in farmland can help reduce pesticide use and protect the agricultural environment. To develop intelligent equipment for weed detection, this study used an imaging spectrometer system, which supports micro-scale plant feature analysis by acquiring high-resolution hyper spectral images of corn and a number of weed species in the laboratory. For the analysis, the object-oriented classification system with segmentation and decision tree algorithms was utilized on the hyper spectral images to extract shape and texture features of eight species of plant leaves, and then, the spectral identification characteristics of different species were determined through sensitive waveband selection and using vegetation indices calculated from the sensitive band data of the images. On the basis of the comparison and analysis of the combined characteristics of spectra, shape, and texture, it was determined that the spectral characteristics of the ratio vegetation index of R677/R710 and the normalized difference vegetation index, shape features of shape index, area, and length, as well as the texture feature of the entropy index could be used to build a discrimination model for corn and weed species. Results of the model evaluation showed that the Global Accuracy and the Kappa coefficient of the model were both over 95%. In addition, spectral and shape features can be regarded as the preferred characteristics to develop a device of weed identification from the view of accessibility to crop/weeds discriminant features, according to different roles of various features in classifying plants. Therefore, the results of this study provide valuable information for the portable device development of intelligent weed detection.*

Keywords: hyper spectral imaging; object-oriented; decision tree; corn; weed

Introduction

Farmland weeds are harmful to the growth of crops. They can cause developmental disorders of the plant, such as short seedling, thin stem, and yellow plant leaves. Further, they can cause the reduction of grain yield up to 10% per year. To develop sustainable agriculture to ensure food security, weed detection for variable herbicide application has been an important research topic in precision agriculture.

In recent years, machine vision and remote sensing techniques have been used for weed identification. The machine vision technique captures the intensity of the reflected light from the target plant using a digital camera. Through image processing, plant location, colour, shape, texture, and other features are extracted to identify the target plants. This method can focus on the whole plant or part of the plant and is able to differentiate the weed from other objects in real-time, accurately and automatically. However, the factors such as illumination condition, leaf shape, wind speed, and direction consistently limit the extraction of the color, shape, texture, and other features of the plants from the images, so rapid image processing and accurate weed identification are two major challenges . Compared with machine vision, remote sensing methods can distinguish crops and weeds by reflectance data, especially hyper spectral remote sensing. The hyper spectral sensor with nano-scale spectral resolution can detect the subtle differences of plants using certain feature wavelengths or electromagnetic radiation in the visible and near-infrared (NIR) region. Up to date, there are many studies on identification of weeds from crops using the sensitive spectral bands with encouraging results. However, the identification accuracy is low in cases when the spectral difference between the crop and the weed is not obvious, or the reflection of leaves is affected by factors of water content, plant disease, and growth stage . Therefore, to more effectively discriminate weeds from crops, the combination of multiple features, such as the combination of shape and textural, shape and spectral, and spectral and textural features, should be considered.

The hyper spectral imaging technique with high spectral and spatial resolutions, can be used to extract the spectral, spatial and structural features synchronously. The combination of the extracted features is good for improved identification of weeds from the crop in a complex environment. Studies have been done using spectral and shape features simultaneously for classification of plants based on the analysis of hyper spectral images. Li et al. utilized the method of combination of shape-based analysis and spectral angle match to identify the weeds in a watermelon field, which obtained a good identification accuracy but the shape and spectral features were used separately and the texture features were not included. Tits et al. pointed out that when the shape features were considered, the differences between classes could be enhanced for the recognition of targets. Somers et al. used hyper spectral mixture analysis with spectral and shape features to detect weeds in an orchard field. In addition, textural features are also important in studying spatial information of different targets. Alchanatis et al. considered that spectral and textural features could detect weeds in a cotton field, but the textural features were only used for weed identification after the soiland plants were separated by spectral features.

To promote the development of weed identification technology for designing an intelligent weed identification system and accurately spraying pesticides, the research objectives of this study are:

- To characterize shape, textural and spectral features to differentiate between corn and a number of weeds;
- To compare and validate the identification models of corn and weeds and determine the optimal feature combination to develop an intelligent weed identification system.

DATA MATERIAL

The images used are randomly sampled from previous studies and cover a variety of cameras, plants, soil types and lighting. All images are RGB images. The cameras that have been used are: Samsung EK-GN120, Samsung NX1000, JAI AD080-GE and Canon PowerShot SD1000. The images from the Canon Powershot SD1000 are from [11, 16] and consist of 3,000,816 pixels. The images from the JAI AD080-GE are from [5] and consist of 3,755,808 pixels, the images from Samsung EK-GN120 consist of 2,419,116 pixels and the images from Samsung NX1000 consist of 21,892,117 pixels. Samples from the four cameras are shown in Figure 1. All images have been segmented by hand in order to create a ground truth for the segmentation. The images from [5] come with segmentation masks created using NIR imaging. These masks have not been used in this study. The images are acquired with different backgrounds and under different light conditions. The images from the Samsung EK-GN120 and Samsung NX1000 are acquired outdoors in sunlight without shading. The images from JAI AD080-GE [5] are acquired outdoors in artificial light and the images from the Canon Powershot SD1000 [11, 16] are acquired in indoor in artificial lighting. The plants from [11, 16] are planted in pots trays and photographed against a red plant tray. These images has been cropped in order to remove this red plant tray. The images from the JAI AD080-GE [5] have a severe chromatic aberration, which results in green or purple colours in high-contrast areas and some of the images from the Canon Powershot SD1000 [11, 16] have soil surface covered in green algae. In total, 40 test images are used, which together contain 31,067,857 pixels, of which 4,199,568 are plant pixels.

❖ Materials and Methods

1. Imaging System

In this study, a field imaging spectrometer system (FISS) was used to collect the imaging spectrometer data [18]. The system consists of an enclosed optomechanical subsystem, a computer, and an electronic system. The optomechanical component includes a scanningmirror, a charge-coupled device (CCD) camera (Model INFINITY3-1), a dispersing unit with a “prism-grating-prism” (PGP), and an objective lens. The computer system includes hardware and software for storing imaging data, operating the FISS and processing basic data. The electronic system includes the power supply and the motor control circuit. The FISS has 344 spectral channels in the

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range of 446 nm to 912 nm. The sampling interval of the spectrum is about 1.4 nm and the spectral resolution is 4–7 nm. The signal-to-noise ratio for 60%bands is greater than 500. The spatial resolution of FISS is related to both the parallel and perpendicular directions of the entrance slit. The spatial resolution of the direction parallel to the entrance slit depends on the size of the imaging unit in the CCD camera focal plane and the focal length of the objective lens, and the other one depends on the width of the entrance slit and the focal length of the objective lens. The space resolution of the FISS is better than 2 mm.

2. Data Collection

Sample collection was carried out at the National Demonstration Base for Precision Agriculture (40_10031.600 N, 116_26044.400 E), Beijing, China. Corn and a number of commonly known weeds were chosen as the research targets. Corn was sampled at the 5-leaf stage, an important time for weed control. The two categories of weeds were monocotyledonous and dicotyledonous plants. Monocotyledonous weeds included foxtail (Setaria viridis L., SETVI) and goose grass (Eleusine indica L., ELEIN), and dicotyledonous weeds were round leaf pharbitis (Pharbitis purpurea L. Voigt, PHAPU), lobed leaf pharbitis (Pharbitis nil L. Choisy, PHANI), redroot amaranth (Amaranthus retroflexus L., AMARE), purslane (Portulaca oleracea L., POROL) and lambs quarters (Chenopodium album L., CHEAL). These seven weeds are widely distributed in North China, and are major weeds that impact corn yield.

Whole plants were collected in the field and sent to the laboratory as quickly as possible to minimize analytical errors resulting from the wilting of the leaf blade. In the laboratory, fully expanded leaves were clipped and wiped clean for measurement with FISS. Lighting was achieved by two 500W halogen tungsten filament lamps. Images of white reference were simultaneously acquired with the leaf samples to minimize illumination changes among different measurements and converting the digital number to relative reflectance in every image. A sample image is shown in Figure 1. We collected 10 sheets of imaging spectrometer data when the spectrometer was 1.0 m above the samples.

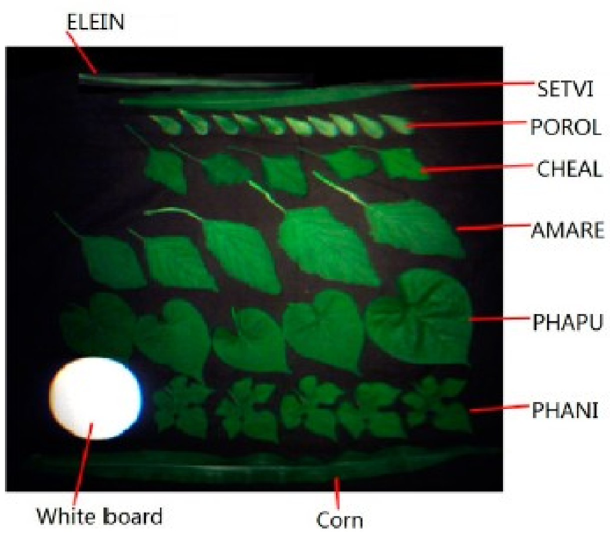

Figure 1. Leaf image for corn and seven weed species. This is one of images acquired by FISS. FISS: Field imaging spectrometer system, SETVI:

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foxtail, ELEIN: goosegrass, PHAPU: round leaf pharbitis, PHANI: lobed leaf pharbitis, AMARE: redroot amaranth, POROL: purslane, CHEAL: lambs quarters.

3. The Process for Crop/Weeds Identification

To extract the image features for identifying the crop and weeds, a procedure of data processing was formulated in sequence as data pre-processing, sample objectivation, feature extraction, identification modeling, and model validation. Data processing included Minimum Noise Fraction (MNF) and data normalization by the imaging spectrometer data of the white reference. The effectiveness of such processing is in removing noises resulting from the instrument and illumination. The imaging data has 344 bands containing both useful and irrelevant information for the corn/weeds identification. Thus, segmented principal component analysis (SPCA) was adopted to extract sensitive bands and calculate the vegetation index for reducing the data dimensionality. Segmentation was then executed on each image in order to obtain leaf object samples and extract spectral, shape, and texture features of the object by the eCognition software (Trimble Navigation Ltd., Broomfield, CO, USA). Finally, a decision tree model for leaf object identification of plants was constructed based on the above optimal features by the C 5.0 algorithm.

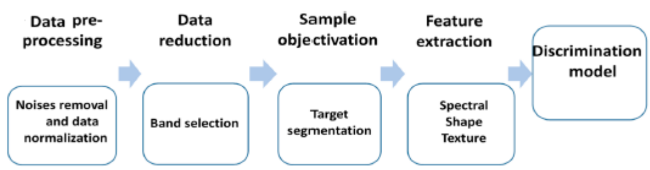

Figure 2. Flow of data processing. The identification process is based on leaf objects except for two parts of image preprocessing and data reduction.

4. Analysis Method

4.1. Data Pre-Processing

Data pre-processing consists of two steps: data noise removal with MNF and filter, and data normalization [14]. Every band of the imaging spectrometer data was checked so as to remove noises using MNF. After MNF, the eigenvalues, which were greater than the slope of the MNF eigenvalue curve, were selected to the adaptive filtering process and transformed back to the original spectral space with the noises removed. To eliminate the impacts of variations in spectral values due to illumination changes among areas of view and spectrometer, we performed data normalization onimaging spectral datasets such that the white reference board was used to calibrate the digital numberto the relative reflectance.

4.2. Data Reduction

SPCA was applied to maintain the most vital and useful information in the imaging spectral datasets of corn/weeds [19]. The complete data set was first partitioned into several highly correlated subgroups by a correlation matrix and then PCA was conducted separately on each subgroup of data. Thirdly, the contribution was calculated of the sum of the square of the correlation coefficient between each band and each important principle component within a subgroup. Finally, the optimal band was selected based on the maximum of the contributions in each subgroup. The method is an effective way to retain desired features for corn/weeds identification, compared with conventionalPCA. In the study, five wavelengths were selected, at 516 nm, 677 nm, 710 nm, 749 nm, and 843 nm.

4.3. Sample Objectivation

Before classifying plant species, plant object samples were obtained by segmentation in theeCognition Developer 8.7 software (Trimble Navigation Ltd., Broomfield, CO, USA). Combination ofmultiresolution segmentation and spectral difference segmentation was studied to subtract thebackground of plants and make a complete leaf of each species an object for sample selection. Images for segmentation were the single-band near infrared image at the wavelength of 910 nm and the NDVI (Normalized Difference Vegetation Index) image calculated from the bands of 710 nm and 762nm. The NDVI image layer weight was set to 2, while the near-infrared image to 1. Scale parameter was set to 0.2 in the multiresolution segmentation while that of spectral difference segmentation was0.19. This was conducted by the rule set in the software.

4.4. Classifier and Validation

Identification of corn and weed species was done with a C 5.0 algorithm based on plant leaf objects. C 5.0 is an extension of the C 4.5 algorithm, and it is more efficient and uses less memory [26]. C 5.0 constructs the classification trees from discrete values based on the “information gain” calculated by the entropy. The C 5.0 model can split samples on the basis of the biggest information gain field. The sample subset that is obtained from the former split is split afterwards. The process continues until the sample subset cannot be split and is usually according to another field. Finally, on examining the lowest level split, those sample subsets that do not have a remarkable contribution to the model are rejected [27]. The decision tree method automatically discovers classification rules by using machine learning techniques. It uses the “information gain ratio” to determine the splits at each internal node of the decision tree [28]. In the study decision tree classifier construction options included 10 trials of boosting and global pruning.

All plant object sampleswere randomly split into two parts, 70%ofwhichwas training dataset and the other was testing dataset. The training setwas useful to build the discrimination model, whereas the testing set was used for validating the classification. The classification quality was quantitatively assessed through the Global accuracy, Kappa coefficients, user’s accuracy, and producer’s accuracy, were all extracted fromthe confusion matrix.

CONCLUSION

The viability of integrating spectral, shape, and texture characteristics to identify corn and seven weed species from the imaging spectrometer data was investigated. The identification approach combines the object-oriented algorithm and the decision tree C 5.0. The former can generate plant leaf objects by segmentation and is used to extract the attributes considered to be most representative of the classes of interest, while the latter is a classifier to identify eight plant species. We selected characteristics among three categories of spectral, spatial, and textural features. Classification results showed that the decision tree model combining these three types of characteristics containing simpler decision rules, had higher levels of exactitude and used less attributes than the ones with combination of two kinds of features. In addition, we observed the importance of various features in classifying plants. It was found that spectral and shape features can be regarded as the preferred characteristic to develop the means of weed identification from the view of accessibility to crop/weeds discriminant features. Additionally, the identification error rate of some weeds was able to be reduced when the texture features were considered. Our preliminary results can provide valuable support for the portable device development of intelligent weed identification. However, many factors may affect the features of extraction of crops and weeds in the natural environment, such as leaf blocking, leaf angle inclination, and solar altitude. As to whether this method could be applied in the field requires further investigation.

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