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Maize seedling/weed multiclass detection in visible/near infrared image based on SVM

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Abstract: Weed detection play an important role in variables spraying in precision agriculture. This paper presents a new SVM (support vector machine) method using decision binary tree to discriminate crop and weeds in visible/near infrared image. Vegetation is segment from soil according to spectral feature in near-infrared band based on threshold method. The multi-spectral reflectance features of vegetation canopy are combined with texture features and shape features. Then multi-class detection is achieved based on decision binary tree established by maximum voting mechanism. It was tested by discriminate maize seedling and its associated weeds. The validation tests indicated that SVM using decision binary tree could improve classification accuracy significantly, and meet real-time requirements of agricultural applications greatly. The proposed method has produced results superior to other approaches.

Key words: precision agriculture; image segmentation; weed detection; support vector machine
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基于SVM的可见/近红外光的玉米和杂草的多类识别

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摘要:杂草的识别分类在精准农业的变量喷施中具有重要的作用.因此提出了一种新的基于SVM(支持向量机),利用决策二叉树在可见/近红外图像中识别作物和杂草的方法.根据近红外波段的光谱特性,利用阈值法实现了植物和土壤背景的分割.将植物冠层的多光谱反射特征、纹理特征和形状特征相结合,采用最大投票机制算法构造合理的决策二叉树,实现了分类.对玉米幼苗及其伴生杂草的识别结果表明,基于SVM,利用决策二叉树的多类分类,可极大的提高分类精度,满足农业应用的实时性要求,与其他方法相比具有较好的结果.

关 键 词:精准农业;图像分割;杂草识别;支持向量机
中图分类号:TP391.41 **文献标识码**:A

Introduction

Nowadays, there is a clear tendency to reducing the use of chemicals in agriculture. One possible method of achieving this is to minimize the volume of herbicides by using site-specific spraying. Currently, machine vision technologies offer the possibility of image-based weed classification, and thereby open up the potentials for automated weed control [1].

Image-based weed classification has attracted much research attention. Multi-spectral features have been adopted by many researchers recently. Alchanatis

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et al. used the multi-spectral image to identify weeds in cotton fields and achieved an accuracy of about 85% [2]. Borregaard T et al. utilized the features of multi-spectra, ranging from 660 to 1060nm, to detect weeds (fat hen, black bindweed and fools parsley) from crops (sugar beet or potato) achieving 90% correct classification [3]. Gerhards et al. proposed a real-time approach to detect small weed seedlings presented in various crops using three digital bi-spectral cameras with near-infrared and visible channels[4]. Slaughter et al. employed visible light and NIR reflectance spectra to distinguish tomatoes from nightshade (solanum nigrum) weeds and reported a classification rate of 100% [5]. Koger et al. adopted the wavelet decomposition to analyze hyper-spectral signal and achieved 83% accuracy of weed classification in soybean field [6].

Multi-spectral analysis shows distinctive advantages over spatial-domain methods in simplicity and hence can be implemented in real-time [7,8]. Most existing multi-spectral methods focus on the separation of green vegetations from soil background and the classification of two kinds of vegetations. Research has not yet been made to classify intra-class and inter-class weed species.

We proposed a new SVM (support vector machine) using decision binary tree in this paper to discriminate multiclass in visible/near-infrared image. Vegetation canopy multi-spectral reflectance features are combined with texture features and shape features for classification. The perfect features are selected as input vectors of SVM classifier. The proposed method was tested by classifying maize seedlings and its associated weeds in visible/near-infrared image. The proposed method has produced results superior to other approaches, and could improve classification accuracy greatly and meet real-time requirements of agricultural applications.

1 Materials and methods

1.1 Image acquisition and segmentation

Camera MS3100 Duncan Camera (3CCD Camera) was fixed in a cantilever beam shooting frame and was about 75cm above the ground. Optical axis of camera is perpendicular to the ground in order to avoid geometric distortion of captured images and obtain complete shape features of whole plant canopy.

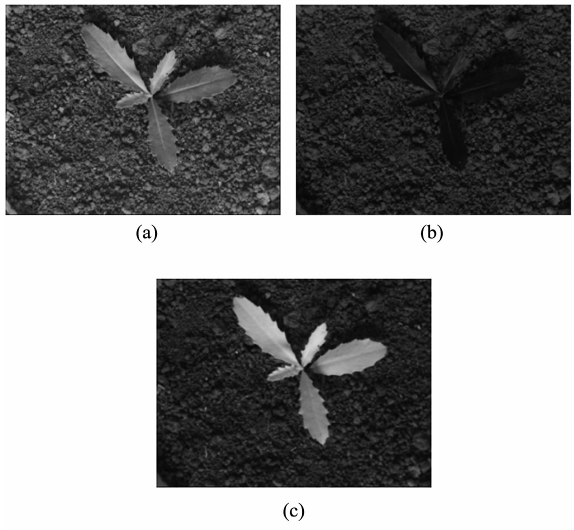

Fig. 1 Sample image of thistle (a) green light image (b) red light image (c) near infrared image
图1 刺儿菜样本各色图像 (a)绿色 (b)红色 (c)近红外

Images used in this study were taken in the experimental field of Northwest A&F University in late March and the first 10 days of April when the maize seedling had obvious features in the stage of 3 ~5 leaves. Its associated weeds in this area are monocotyledon weeds such as goose grass, and dicotyledon weeds such as purslane. The experimental data included 120 maize seedling samples and 120 weeds samples for each class. Each sample was captured at different location. Fig. 1 shows a sample image of thistle.

Study of Vrindts Els shows that spectral curves of different plants have the same shape [9]. The reflectance spectral curves of maize and soil show significant difference at near infrared band. Vegetation can be seperated from soil background easily based on the difference, and the near infrared image is converted into a binary image. However, due to the influence of plant diseases and insects, small black holes may appear on vegetation leaves in the binary image. Moreover, stone, waste and residues in soil may also misclassify soil as vegetation. In order to correct these inappropriate segmentations, morphological dilation and erosion are implemented as a post-processing procedure to refine the obtained binary image. The segmentation results of Fig. 1 are shown in Fig. 2.

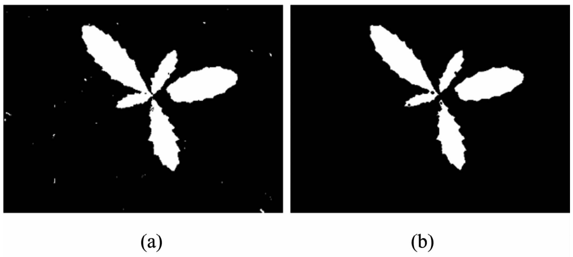

Fig. 2 Segmentation results of thistle (a) binary images (b) binary image after post-processing
图 2 刺儿菜样本图像分割结果 (a) 原二值图 (b) 经后处理的二值图

1.2 Monocotyledon/dicotyledon classification

There are great reflectivity difference between monocotyledons (maize, goose grass and setaria) and dicotyledons (thistle and purslane) at near infrared band (780 ~ 1350nm). Therefore, we can discriminate monocotyledon and dicotyledon using vegetation canopy spectral features combined with the first invariant central moments.

1.2.1 Canopy spectral features extraction

Since the great difference exists in vegetation canopy reflectivity between monocotyledons and dicotyledons at near infrared band, we can detect it using gray mean of vegetation canopy pixel points in near infrared image and red light image. Gray mean of IR is calculated using equation 1:

$$\mu_{IR} = \frac{1}{N}\sum f(x,y) \quad , \tag{1}$$

where, μ_{IR} is the gray mean of vegetation canopy pixel points in near infrared IR image, N is the number of vegetation canopy pixel points, and $f(x,y)$ is the gray value of point (x,y).

As red light image R and near infrared image IR were acquired in the same shooting, their pixels are one to one correspondent. Then we obtained the fused image IR/R from IR image and R image, gray mean of IR/R is defined as follows:

$$\mu_{IR/R} = \frac{1}{N}\sum f_{IR/R}(x,y) \quad , \tag{2}$$

where $f_{IR/R}(x,y)$ is the gray value of coordinate point $\mu_{IR/R}$ in IR/R fused image, N is the gray mean of IR/R image, N is the number of pixel points in fused image IR/R. Fig. 3 shows the IR mean, IR/R mean of monocotyledon/dicotyledon.

1.2.2 The first invariant central moments extraction

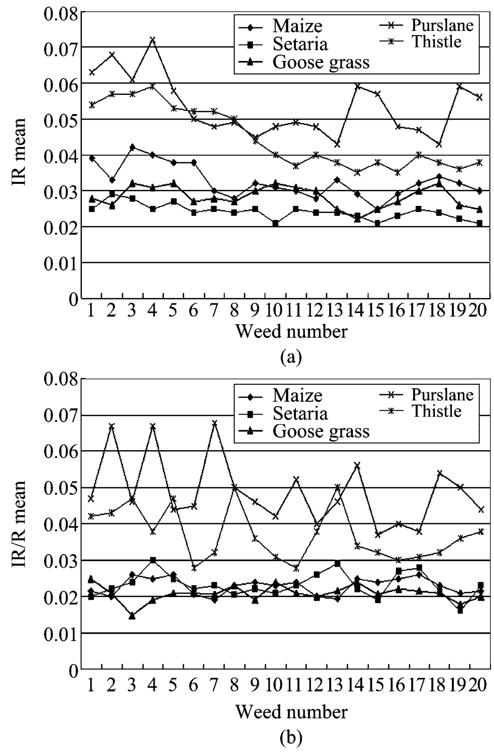

Fig. 3 (a) IR mean (b) IR/R mean of Dicotyledons /monocotyledon
图 3 双子叶植物与单子叶植物的 (a) IR 均值 (b) IR/R 均值

In order to improve classification rate, vegetation canopy spectral features and the first invariant central moments are combined to avoid the influence from illumination and other factors. The mean of central moments is calculated using equation 3:

$$\mu_{ij} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\vec{x})^i(y-\vec{y})^j f(x,y)\,dxdy \quad , \tag{3}$$

where $\vec{x} = M_{10}/M_{00}$, $\vec{y} = M_{01}/M_{00}$ are the coordinates of the centroid. Central moments after area standardization show translation and scale invariance, and it can be defined as follows [10]: $\eta_{ij} = \mu_{ij}/\mu_{00}^{\gamma}$, where $\gamma = (i+j+2)/2$.

First invariant central moments are defined as the sum of second-order central moments η_{02} and η_{20} after area normalization [11]. Fig. 4 shows the first invariant central moments of monocotyledon /dicotyledon. IR mean, IR/R mean and first invariant central moments are selected as input vectors of SVM.

1.3 Maize seedling/weeds classification

As reflectivity difference is not obvious in intra-

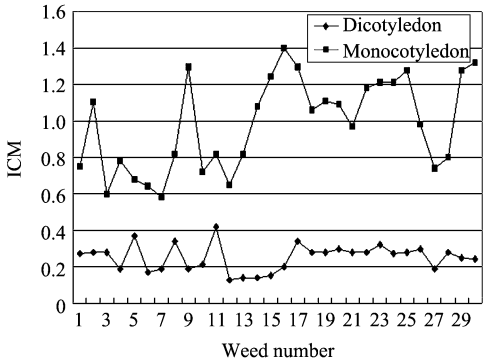

Fig. 4 ICM of dicotyledon/monocotyledon
图4 双子叶植物与单子叶植物的 ICM

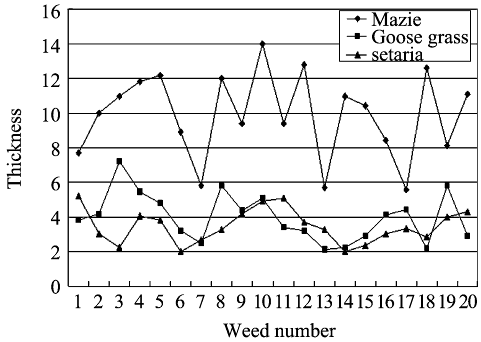

Fig. 5 Thickness of monocotyledon
图5 单子叶植物厚度

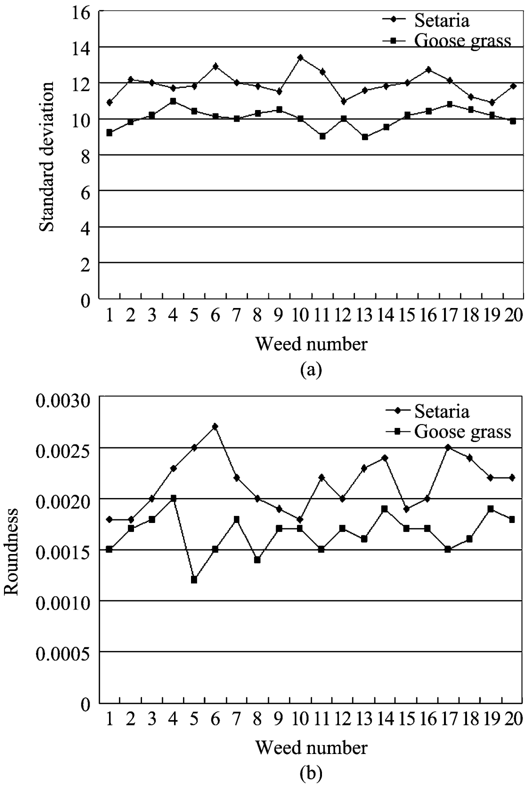

Fig. 6 (a) Standard deviation and (b) smoothness of goose grass and setaria
图6 牛筋草和狗尾草的(a)标准差(b)平滑度

monocotyledon class or intra- dicotyledon class, we need to take other methods to classify intra-class species. Shape features and texture features were used to fulfill this task.

1.3.1 Intra-monocotyledon classification

Shape feature parameters of maize seedling and its associated weeds were compared and analyzed. It was found that their data was intersectional in ratio of width to length, circularity, invariant central moments, roundness and elongation. Also there is obvious difference in their thickness among 3 ~ 5 leaves maize seedling, goose grass and setaria. Therefore, thickness was selected to classify maize seedling, goose grass and setaria, and as input into a vector of SVM. Thickness of monocotyledon is shown in Fig. 5.

Goose grass and setaria have similar shape features and color. Therefore, we extracted texture features base on IR image to classify goose grass and setaria. Standard deviation and smoothness based on histogram are taken as input vectors of SVM. Standard deviation and smoothness of goose grass and setaria are shown in Fig. 6.

1.3.2 Intra-dicotyledon weed classification

Thistle and purslane show significant difference in dimensionless roundness and ratio of width to length, which show RST (rotation scaling translation) invariance. Therefore, roundness and ratio of width to length are taken as input vectors of SVM. Roundness and ratio of width to length of 20 thistle and purslane samples are shown in Fig. 7.

1.4 SVM multi-class classification using binary decision tree

1.4.1 Classification based on SVM

Currently, multi-class support vector machine is structured mainly based on traditional two-class support vector machines. But it still have some deficiencies such as training or establishing classification model, large number of support vector machines need training, the training time shows nonlinear growth with node increasing [13,14]. In this paper, we adopted the decision binary tree classification model as it shows flexibility

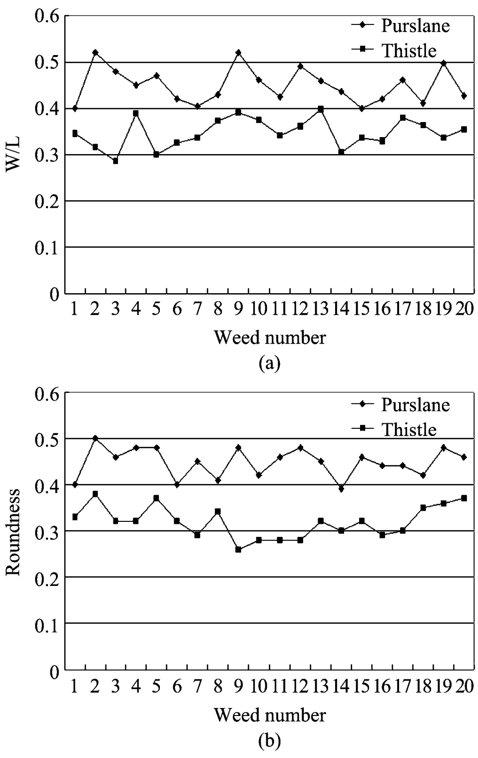

Fig. 7 (a) W/L (b) roundness of thistle and purslane
图 7 蓟和马齿苋的(a) W/L (b)圆度

for different applications.

In this paper, decision node of decision binary tree using approximate optimum method divided multi-class samples into two groups. The maximum voting mechanism is applied to each classifier so that objects are distributed in the most probable class. Class obtaining most votes is the final result. This algorithm is also Baysian optimal. Decision binary tree is shown in Fig. 8.

1.4.2 Classification based on BP neural network

Back Propagation Neural Network (BPNN) provides a general framework for representing nonlinear functional mapping according to a given relation between several input and output variables, where the form of the mapping is governed by the weights. Before the design of this neural network, different construction and parameter values were compared. Construction, training functions, target error and other parameters of this neural network are determined by testing and comparison time after time [15,16], as shown in Table1.

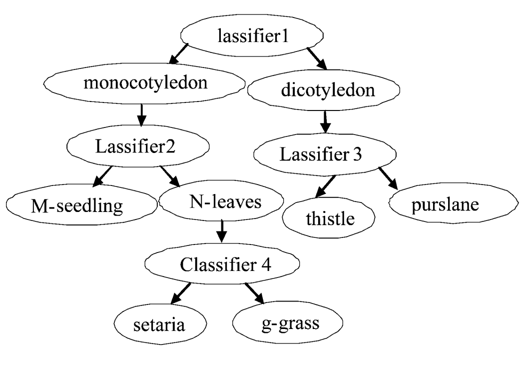

Fig. 8 Decision binary tree
图 8 决策树示意图

Table 1 Parameters setting of BP neural network
表 1 BP 神经网络的参数设定

Parameters	Parameters neural network
Network layer number	3
Hidden layer number	1
Neuronal number of every layer	8 – 14 – 5
Training function	Tranlm
Weight adjust principle	Trangdm
Function type of every layer	Tansig, pureline
Learning rate	0.01
Target error	0.02

1.4.3 One versus rest Method (OVR)

O-v-r method is also used in this classification task for comparison. First, k sub-classifiers of SVM are constructed. Next, the i^{th} sample belonging to the i^{th} class as positive class is marked when the i^{th} sub-classifier of SVM is constructed, while other classes are also marked as negative when they do not belong to the i^{th} class. Finally, all classes were trained using the same SVM based on o-v-r method.

2 Results and discussion

We validated the proposed method based on LibSVM component and achieved classification using VC++. Automatic optimize parameters C and scale parameter σ that influence classifier greatly are obtained based on interactive test. Optimal parameter values are determined towards the highest classification rate and the least training samples.

60 samples of each class were randomly selected as training samples, and the remaining 60 are taken as test samples. Parameter corresponding to the highest classification rate of the test samples is $[\sigma, C] = [0.4, 512]$ in the experimentation. Table 2 shows the results of SVM multiclass classification based on decision

Table 2 Discriminated results by the proposed SVM method
表2 使用SVM方法进行辨别的结果

Artificial classification	M-seedling	Setaria	Purslane	G-grass	Thistle	Classification rate (%)	Classification time(ms)
M-seedling	58	0	0	1	1	96.7	41.2
Setaria	1	55	0	3	1	91.6	42.7
Purslane	0	0	54	1	5	90	39.2
Goose grass	3	7	0	48	2	83.3	43.4
Thistle	1	0	5	2	52	86.7	40.1

Table 3 Discriminated results by BP neural network
表3 使用BP神经网络方法进行辨别的结果

Artificial classification	M-seedling	Setaria	Purslane	G-grass	Thistle	Classification rate (%)	Classification time(ms)
M-seedling	56	1	0	2	1	93.3	42.2
Setaria	2	52	1	4	1	86.7	43.8
Purslane	1	0	53	1	5	88.3	39.4
Goose grass	2	6	0	51	1	85.0	46.7
Thistle	1	2	5	3	49	81.6	40.5

Table 4 Discriminated results by o-v-r method
表4 使用o-v-r方法进行辨别的结果

Artificial classification	M-seedling	Setaria	Purslane	G-grass	Thistle	Classification rate (%)	Classification time(ms)
M-seedling	54	2	1	3	1	90.0	43.4
Setaria	4	47	1	7	1	78.4	46.7
Purslane	1	0	57	1	1	95.3	39.8
Goose grass	2	5	0	52	1	86.7	48.3
Thistle	1	2	5	2	51	85.0	41.9

binary tree. The average correct classification rate was 89.7% and the highest correct classification rate achieved was 96.7%, and the longest classification time was 49.2ms. The validation tests indicated that processing speed was improved under certain correct classification rate condition. With the same experimental data, classification results of maize-seedling and weeds using o-v-r based classification and BP neural network are shown in Tables 3 and 4.

To show the superiority of the proposed method, we used chi-squared test for goodness-of-fit that compares the distribution of the observed counts and the null hypothesis counts based on the same error rate. The comparison of the classifiers using chi-squared test statistic is shown in Table 5.

Table 5 Comparison of the classifiers with the proposed methods using chi-squared test statistic
表5 用卡方检验对分辨结果做统计比较

Type	BPNN	OVR
M-seedling	3.287	4.607
Setaria	89.071	73.064
Thistle	106.18	49.45

It shows that the proposed method is superior that we can reject the null hypothesis based on the values of chi-squared test since it is far greater than 3.841459.

Objects misclassification is mainly due to some weeds grow earlier than maize and misclassified as maize seedling because of their broad leaves. In addition, the mistake is accumulated by deformation and occlusion of crimp leaves of maize seedling or weeds.

Algorithm parameters should be estimated accurately using prior knowledge to improve the classification rate. A general underestimation appears in this algorithm, mainly due to several reasons. For example, there is a lack of periodicity in vegetation geometry, weeds are embedded into maize seedling, and weeds present variability.

3 Conclusions

In this paper, a new SVM method based on binary tree to detect intra-class and inter-class types of monocotyledon/dicotyledon is proposed. Threshold method is applied to segmentation in near-infrared band firstly. Then, multi-spectral reflectance features of vegetation canopy are combined with texture features and shape features for classification. The perfect features are selected as input vectors of SVM classifier. Finally, multiclass classification is achieved based on binary decision tree established by maximum voting mechanism. The average correct classification rate of 89.7% has been achieved and the highest correct classification was 96.7%. The longest and average classification time was 43.4ms and 41.32ms respectively. The validation tests indicated that the multiclass classification model based on decision tree could greatly improve classification accuracy and reduce training time to meet real-time requirements of requirements of agricultural applications. The proposed method has produced results superior to other approaches.

The proposed method is applied to static images. However, in real applications, dynamic images should be shot by walking agricultural robot. These images may be blurred by moving. Therefore, future efforts will be devoted to the investigation of the influence of dynamic image using this algorithm and how to minimize the effect. Furthermore, further work is needed to combine this algorithm with vegetation competition models to assess the misclassification rate objectively.

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