ANALYSIS AND TESTING OF WEED REAL-TIME IDENTIFICATION BASED ON NEURAL NETWORK

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Abstract: Contrasting the two green strength genes of soil, wheat, corn, and the weed, the paper designed a system to identify the weed from the crop. It used the 2G-R-B and BP neural network, with the help of pixel-position-histogram diagram, to calculate the area and position of weeds. The result showed that it could identify the weed from the field and crop with an accuracy of 93%. The program gave the result that running time of identifying weed in wheat field was 273.31ms. As far as the corn was concerned, the time was 321.94ms, In a word, the system can satisfy the request of real-time.

Keywords: variable spray, weed identify, picture disposal, visual c++

1. INTRODUCTION

Large amounts of pesticides are applied to the field by Chinese farmers each year. By the time of 2006, the Chinese total output of pesticides has reached 2.15 billion pounds. Typically, herbicides are applied with a blanket treatment to a whole field without regard to the spatial variability of the weeds in the field. Automatic target-activated herbicide sprayer can

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selectively target herbicide according to the allocation and the characteristic change of the target. It can increase the efficiency of chemical usage, and reduce the waste of chemical and environment pollution as well. Weed identification system is one essential part of the automatic sprayer (Thornson J.F., Stafford J.V., 1991). So far much of the machine vision weed sensing research has been done. Burks (2000) used the Co-occurrence Matrix and Color Features to identify 5 weeds from the soil. It used the 11 texture-characteristic parameters of tone and saturation to distinguish weeds from plant and soil, the accurate rate was 93%. However, the division arithmetic of texture needs lots of calculation, which slows down the time of identifying. This method is no good for real-time sensing as well. Plant identification had been accomplished with the use of shape features of plant (Guyer et al., 1993a; Woebbecke et al., 1995; Ji Shouwen and Wang Rongben, 2001). In this way, the system could identify weeds from the corn and soil by the projective area. But it couldn't be applicable to the instance that corn is shorter than weed and its accurate rate was influenced by the light and the condition of the soil. The purpose of the study is to develop a weed-identifying system to detect the crop and gather field information. The system bases on investigating the wheat and corn of the east of Shandong Province to identify weed with the program made by visual c++ (VC++) and artificial neural network (ANN). The result showed that the system could satisfy the request of real-time and identify weeds from the wheat and corn.

2. MATIERIALS AND METHOD

The contrast of the two green strength genes of soil, wheat, corn and the weed in the field is shown in Fig. 1 and Fig. 2. The green genes of plant and the non-plant are almost not overlap. The green genes of plant and the non-plant is distinguished well when the threshold value of 2G-R-B are 10-30, or the value of 2G/(R+B) are 1.0-1.15. There is a range of each one of the two threshold value. When the value slows down, the interference in the picture

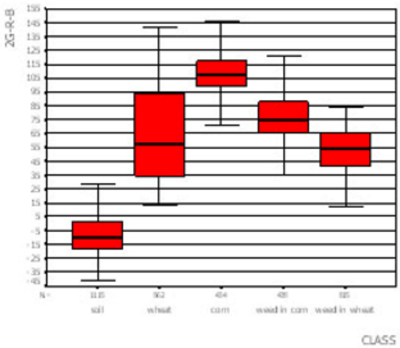

Fig. 1. 2G-R-B

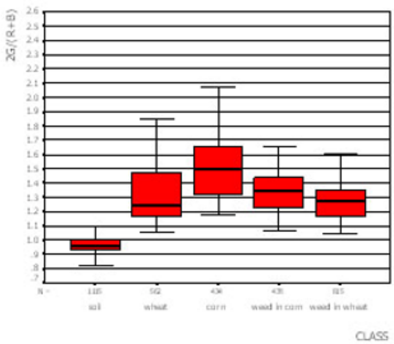

Fig. 2. 2G/(R+B)

grows up and vice versa. The accuracy of the system can be 95% or more when the threshold value of 2G-R-B is 20 or 2G/(R+B) is 1.05.

In order to reduce the effect of illumination, the color component RGB normalized by brightness can be used to show. That is chroma coordinate, and the coordinate is also called 2g-r-b. Though the characteristic of Excess Green and the 2G/(R+B) factor are affected little by the strength of illumination and illumination angle, they has brought certain miscounting and lead partial characteristics of Excess Green between plants and non-plants to fold because that it has the floating number operation in the computation process. Its deviation absolute value is big in using the characteristic of Excess Green 2G-R-B of the RGB space directly, but its relative deviation is small and the folding doesn't exist between two parts. It is more advantageous that the natural environment influence is infirm. It's more effective to use the characteristic of Excess Green 2G-R-B form than other forms, and in this way it can save the time in weed background segmentation. In this paper, the characteristic of Excess Green 2G-R-B was used as parameter to filter the excess green binary, and the image wasn't dealt with before it is filtered the green binary.

2.1 Segmentation of weed and plant

As illustrated in Fig. 1 and Fig. 2, both 2G-R-B and 2G/(R+B) can't be used to detect crop and weed because they fold seriously to each other. Position distributed characteristic method, shape characteristic method, texture characteristic method and other methods can be used to detect crop. The wheat and other drilling crop are planted by men, so its position distribution is regular and spreads in row; but weeds growth naturally and spread irregularly between crop rows. So in this paper, position characteristic method was used for segmentation of wheat and weed. The corn is dibbling crop, which has leaves from 3 to 5 cotyledons stage, and there is certain distance between plants and row space, so crop leaves are not severely occluded. For the corn, their shape characters were firstly extracted and artificial neural network (ANN) was trained to detect the weed.

2.2 Detection of the row

The central line of the plant is the line formed by the scion during the time of growing. There are many methods to sense the line such as Hough switch and pixel decision histogram. The dealing time of Hough switch is longer than that of pixel decision histogram. Thus in this real-time system, the histogram was adopted. The Fig. 3 and Fig. 4 are the center lines in wheat area disposed by VC++. After detecting lines of the plant, the system used

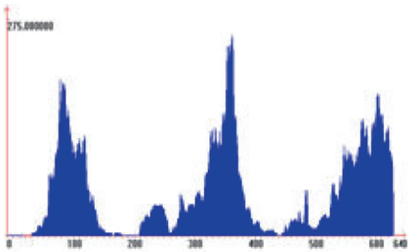

Fig. 3. Chart of plumb projection

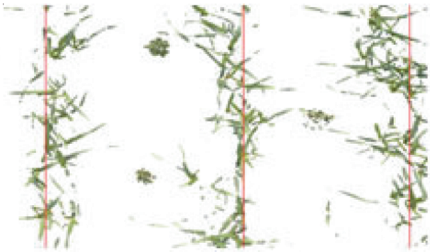

Fig. 4. Center line in wheat area

area planting method to fill the plant area by taking the point in the central line as the seed point. The area connecting with the plant line was considered as plant, and the others were taking for the area of weed.

2.3 Dibbling crop and BP neural network

The framework of neural network is shown in Fig. 5. The network has three layers, and the input layer has 6 nodes. This paper selected 6-20-1 network and tested the neural network by the software of Neural Shell2. The stylebook was suggested as the following: if the S (area) < T1 (threshold value) or the P (perimeter) < T2 (threshold value), the stylebook was regarded as weed, and these stylebooks couldn't be used to train the network. The threshold value is determined by the growing condition of the corn. T1 and T2 were 100 and 50 respectively and the unit was pixel in testing. The result showed that the selected stylebook could improve the training precision and the accuracy of the network.

3. RESULTS AND DISCUSSIONS

3.1 Dibbling crop and BP neural network

The input and output stylebook of the ANN are shown in Table1.

Table 1. Result of input and output

	Input						Output
	Aspect	Roundness	Elongation	PTB	LTP	Compactness	class
1	3.982	2.676	0.597	0.754	0.104	0.667	1
2	1.184	6.464	0.084	1.486	0.130	0.613	0
3	1.140	4.963	0.066	1.127	0.158	0.564	1
4	1.185	4.914	0.084	1.194	0.153	0.629	0

The Table 2 shows the accuracy which the error rate ≤ 0.05 and the error of different network structures. These data were gotten in the condition that the learning rate was 0.5 and momentum gene was 0.5. The number of stylebook was 100.

Table 2. Effect of hidden node (learning rate 0.5 and momentum 0.5)

Number of connotative layer notes	12	16	20	24	26	30
Mean absolute error	17.65	15.01	16.16	17.0	16.78	18.67
STDEV	13.63	12.72	12.05	14.35	14.18	16.24
Min. absolute error	1.48	1.95	1.25	1.35	0.20	0.78
Max. absolute error	69.41	54.34	49.97	70.71	75.06	73.74
Mean related error (%)	3.24	2.76	3.05	3.12	2.94	3.24
STDEV	2.00	1.90	1.80	1.90	1.92	1.89
Min. related error (%)	0.30	0.34	0.21	0.02	0.14	0.16
Max. related error (%)	6.89	7.02	7.51	6.45	7.56	7.31
Percent within 5%	81.82	81.82	87.36	81.82	81.82	81.82

Table 2 shows that the learning rate and accuracy of the stylebook are high in the 6-20-1 network. And the training number is little.

Secondly a test to determine the effect of different learning rate and momentum was performed (Table 3).

Table 3. Effect of identification under different learning rate and momentum

Leaning rate and momentum	0.5, 0.5	0.5, 0.7	0.5, 0.9	0.7, 0.5	0.7, 0.7	0.7, 0.9	0.9, 0.5	0.9, 0.7	0.9, 0.9
Mean absolute error	13.16	13.48	20.27	9.56	5.09	17.03	10.36	15.80	14.70
STDEV	12.05	11.82	15.09	11.99	12.87	13.27	12.01	12.26	13.63
Min. absolute error	1.25	0.65	1.95	1.74	1.53	1.46	0.54	0.93	0.29
Max. absolute error	49.97	48.49	45.40	41.55	38.13	46.97	48.39	54.70	52.59
Mean related error (%)	3.05	3.18	3.85	3.13	3.17	3.27	3.17	3.17	2.70
STDEV	1.80	1.85	3.14	1.72	1.60	2.66	1.91	1.65	2.28
Min. related error (%)	0.21	0.10	0.39	0.30	0.31	0.35	0.09	0.19	0.06
Max. related error (%)	7.51	7.36	14.96	7.21	7.08	9.03	7.35	7.28	8.50
Percent within 5%	87.36	86.36	81.82	89.82	94.91	77.73	88.36	86.36	81.82

Table 3 shows that the accuracy is 94.91% when both the learning rate and momentum are 0.7.

3.2 Design of software

A program was made by VC++. The stylebook was collected in the field of east Shandong Province under different illumination and temperature. We take 321 photos to test. The software runs well and the running time was shown in Table 4.

Table 4. Contrast of consume time

Wheat	Running time (ms)	Corn	Running time (ms)
Pretreatment	61.08	Pretreatment	60.03
Segmentation of plant and the soil	24.14	Segmentation of plant and the soil	26.15
Distill the line	26.39	Unit of areas	65.60
Area planting method	59.07	Distill the characters	98.91
Areas demarcation	41.27	ANN	13.24
Areas calculating	29.90	Areas calculating	26.56
Data save and sending	31.46	Data save and sending	31.45
Total	273.31	Total	321.94

The Table 4 shows that both the dispose time used in corn and wheat are lass than 0.35s. So the system can satisfy the request of real-time.

4. CONCLUSIONS AND FUTURE WORKS

The system runs well in taking the pixel decision histogram to determine the central line of wheat and taking the method of ANN to sense the weed in corn. The software can identify weeds from the plant and soil. It can calculate the area of the weed and satisfy the request of real-time

This paper used the BP neural network and 2G-R-B, with the help of pixel-position-histogram diagram, to calculate the area and position of weed. The result showed that it could identify the weed from the field and crop, and its correct rate was 93% under different illumination. The program gave the result that running time of identifying weed in wheat field was 273.31ms. As far as the corn was concerned, the time was 321.94ms. The test showed that the system could identify weeds from the plant and soil in good condition.

Future work is constructing the platform to do dynamic experiment.

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