Research Paper

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Weed Detection in Lawn Field Using Machine Vision*

—— Utilization of Textural Features in Segmented Area ——

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Abstract

Weeding is an essential operation for maintaining the beauty of lawn fields such as golf course and garden. Since intensive chemical spray is not desirable, it is necessary that the weed area is discriminated from lawn area. However, both weed and lawn usually have similar green color in summer. A method using textural features extracted from an image was investigated for detecting weed area in this paper.

Three textural features, Contrast Angular Second Moment, and Inverse Difference Moment were extracted from 9 or 16 regions in an image with and without image smoothing. The results showed that the features extracted from weeds' size well-fitted segmented image area with image smoothing could discriminate weed regions from lawn regions in lawn field.

[Keywords] weed, lawn, machine vision, textural features, region

I Introduction

Nowadays, maintaining lawn fields could be a hard work since many huge lawn fields should be taken care of. In maintaining lawn fields such as golf courses and gardens, removing or killing unwanted weed is the main activity. For golf courses, removing or killing weed periodically is necessary since some parts of the golf courses need to be freed up from any kind of weeds, even at the early stage. As for gardens, such kind of activity is also necessary to maintain the beauty of the lawn and to eliminate the lawn's competitors. However, it is said that removing or killing weeds in lawn fields periodically is not an easy job if it is done manually. Especially for golf courses, weeds need to be removed or killed at a very young stage but then they are difficult to find. Large working areas also makes this job even slower and harder without special machines. Therefore, the use of an automatic weeding machine to work in the lawn fields, more specifically in golf courses, is desirable.

To develop an automatic weeding machine, a detection system must be considered first before any other factors are taken into consideration. Machine vision or vision system is a useful technology to detect weed parts in lawn fields for this purpose. In recognizing an object as a target in a machine vision system, the system should have an ability to discriminate between the object and its background. Several studies have attempted to discriminate a weed from its background in order to apply spot spraying. For example, shape feature analysis on binary images for ten common weeds

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was conducted by Woebbecke et al.[1] to develop an image processing system that could distinguish between monocots and dicots weeds along with corn and soybean plants. Discrimination between crops and weeds has also been investigated by developing a detecting method in non-herbicidal weeding operations, as reported by Shibata et al.[2]. They used two different cameras, CCD camera and thermal infrared camera. RGB gray-scale histograms obtained with the CCD camera was used for plants discrimination from the ground. Surface temperature histograms obtained with the infrared camera was used for crop plants discrimination from other plants by their sizes. Therefore, the method is complex and expensive.

However, weed and lawn in lawn fields may have the same color, especially in summer when both the color of weeds and lawn is green. So, a color dependent method such as the RGB system cannot be applied for this purpose. Regarding this issue, a study for detecting weeds in golf courses was also conducted by Mashita et al.[3] using two different methods; a color CCD camera and micro wave. Mashita et al.[3] reported that the color CCD camera method is effective for winter, while the micro wave method replaced the color CCD camera in summer. A combination of three different methods, the color CCD camera, the tactile sensor and the photo sensor was developed by Kawamura et al.[4]. The color CCD camera was used to find weed flowers so that weed also could be found, the tactile sensor detected different strains between weeds and lawn when they were traced using a finger-like device and the photo sensor with interference filters was used to detect weeds which have more chlorophyll contents than lawn. Hence, a method to recognize an object which has a similar color as its background, a texture analysis has been introduced by Haralick et al.[5]. According to Haralick et al.[5], texture is one of the important characteristics used in identifying an object or region of interest in an image. From the textural features, a population of lettuce was monitored during their growing period for the population control as reported by Murase et al.[6]. Park and Chen[7], were applying the texture analysis in a multi-spectral image textural analysis for poultry carcasses inspection based on co-occurrence matrices and Kranz et al.[8] were utilizing texture analysis to estimate soil surface storage provided by various tillage practices. Even though the weed and lawn have the same color in summer, the shape and size of most weeds are different with those of lawn, so it is possible to detect the area that has weed using textural features.

So far, we know that textural features introduced by Haralick et al.[5] are very powerful characteristics for identifying different objects in image processing field. Until now, there is no research in image processing field on developing vision system to detect weed in lawn field using these textural features. Otsuka and Taniwaki[9] studied image processing technique for detection of round shape weed in lawn field using texture analysis, but the textural feature used in their study is obviously different with those introduced by Haralick et al.[5]. Moreover, the method provided by Otsuka and Taniwaki[9] is suitable only for big leaves or round shape weeds, not for long narrow shape weeds.

The objective of this study is to develop a machine vision system for weed detection in lawn fields, regardless of the color of weeds and lawn, to be applied in an automatic weeding system to work in lawn fields. The system is expected to be able to detect weed parts of any size and shape even at an early stage as they must to be removed or killed.

II Material and Apparatus

1. Weed

In this study, weeds in lawn fields were grouped into three types, based on their physical appearance round shape weeds (RS) which has wide and short leaves (L-W ratio is 3.2 or less), long shape (LS) which has thin and long leaves (L-W ratio is 6.9 or greater), and medium shape (MS) which is between RS and LS (L-W ratio is greater than 3.2 but less than 6.9). The names of the weeds were *Artemisia princeps* Pampan (RS) *Gnaphalium purpureum* L. (RS) *Paspalum dilatatum* Poir (MS), *Cyperus rotundus* L. (LS), *Gnaphalium japonicum* Thumb (LS), *Poa annua* L. (LS) and *Sysirinchium atlanticum* Bickn (LS).

The weeds observed in this experiment were acquired from their natural habitat (golf course) and at the same stage when they need to be removed manually. Lawn's name is *Zoysia matrella* Merr. (Manilagrass in English, Himekouraishiba in Japanese). No special treatment was applied to the weeds before image acquisition. Minimum and maximum length, minimum and maximum width and length-to-width ratio of the leaves as an important physical properties of the weeds are shown in Table 1.

Table 1. Physical properties of weed leaf used in the experiment

Weed Name	Length (mm)			Width (mm)			L-W Ratio
	Min	Max	Median	Min	Max	Median	
Round Shape							
Artemisia princeps Pampan	16.6	29.6	23.1	9.6	20.3	14.9	1.5
Gnaphalium purpureum L.	10.7	32.0	21.3	4.3	9.1	6.7	3.2
Medium Shape							
Paspalum dilatatum Poir	10.6	57.6	34.1	2.7	7.5	5.1	6.7
Paspalum dilatatum Poir	14.4	53.3	33.9	3.2	7.5	5.3	6.4
Long Shape							
Cyperus rotundus L.	16.5	45.6	31.0	2.1	4.3	3.2	9.7
Gnaphalium japonicum Thumb	14.4	40.7	27.6	2.1	4.3	3.2	8.6
Poa annua L.	6.4	26.8	16.6	1.6	3.2	2.4	6.9
Sysirinchium atlanticum Bickn	28.8	66.4	47.6	2.7	6.4	4.5	10.5
Lawn							
Zoysia matrella Merr.	5.9	18.7	12.3	1.1	2.7	1.9	6.6

2. Experimental apparatus

A video camera (NV-3CCD1 Panasonic Movie Camera, f 1.6 lens vision angle, 1/3 inch CCD Image Sensor for RGB) hanging on a pole supported by two tripods, one of each side. Camera height was adjustable from 40 cm to 70 cm with 10 cm increment. Sunshine illuminance was measured using a brightness meter (MD-28 Takemura Electric Works Ltd.) with measuring range 0−200,000 lx. A video player, a color TV monitor, and an image capture board (NBCC PB9805, Japan Computer Board Co. Ltd.) which has an ability to capture images in 256×256 pixels resolution, RGB color signals were used in image capturing. This board was installed to a personal computer (PC98, NEC) which was also used for image analysis.

III Experimental Method

1. Image acquisition

Image acquisition was done at Sunset Hills Country Club golf course in Matsuyama City, Ehime Prefecture, Japan. The images were acquired from top view, at several camera distances, therefore the covered area and the size of the objects were different (Table 2). The reason of choosing camera distances from 40 cm up to 70 cm is based on the observation that those distances are suitable for the desired physical design of an automatic weeding machine. The weeds' sizes were between 30×30 mm^2 and 95×95 mm^2 in this experiment.

Images data were acquired in June, 1995. Eight types of weed (2 RS weeds, 2 MS weeds and 4 LS weeds) were observed from lawn fields and they were acquired with four different camera distances under sunshine conditions with illuminance ranging from 7,000 lx to 40,000 lx. The result of image acquisition was 32 images (8 different

Table 2 Relationship between camera distance and cover area

Camera Distance (cm)	Cover Area (cm×cm)
40	20.8×29.5
50	26.2×36.5
60	31.6×43.5
70	37.0×50.5

weeds at 4 different camera distances). Sunshine illuminance varied over a large range due to changing weather from clear to cloudy which happened sometimes during the image acquisition.

2. Textural features

The texture-context information is adequately specified by the matrix of relative gray-tone frequencies when two neighboring resolution cells separated by a distance occur on the image. Such matrices of gray-tone spatial-dependence frequencies are a function of the angular relationship between the neighboring resolution cells as well as of the distance between them. The matrix, according to Haralick et al.[5], is called co-occurrence matrix. Three of the textural features introduced by Haralick et al.[5] were applied in this study for texture analysis. By assigning values 1 and 0 to the distance and the angle of the co-occurrence matrix respectively, the following three textural features were calculated and used for region classification of weeds in lawn fields:

(1) Contrast (CON)

This feature measures the local variation of the image. Higher contrast value means higher amount of local variation.

$$f_1=\sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p\ (i,\ j) \right\};\ |\ i-j\ | = n \qquad (1)$$

In the above equations, f_1 is CON, i and j are gray-tones of two neighboring resolution cells, $p(i,j)$ is relative frequencies matrix of two neighboring resolution cells, n is absolut difference of i and j, and N_g is number of distinct gray-tones in quantized image.

(2) Angular Second Moment (ASM)

This feature measures the homogeneity of the image. Higher value of this feature means fewer amplitude or intensity changes in the image that results in much sparser gray-tone spatial-dependence matrix.

$$f_2=\sum_{i}^{n} \sum_{j}^{n} \left\{ p\ (i,\ j) \right\}^2 \qquad (2)$$

Where f_2 is ASM and other notations are the same as in Eq. (1).

(3) Inverse Difference Moment (IDM)

This feature is another way to measure homogeneity value that is local homogeneity. Higher value of this feature means much sparser gray-tone spatial-dependence matrix.

$$f_3=\sum_{i}^{n} \sum_{j}^{n} \frac{1}{1+(i,\ j)^2}\ p\ (i,\ j) \qquad (3)$$

Where f_3 is IDM and other notations are the same as in Eq. (1).

3. Area segmentation in analysis

Before feature extracting, the image area were segmented into several equivalent size of regions to restrict weeds area in an acquired image for minimum chemical spraying or mechanical weeding operation. In the first analysis, the image area were segmented into 9 regions and in the second analysis into 16 regions. Two different numbers of segmentation were chosen in the analysis to find an appropriate regions size for the size of weed in the acquired image. Nine and 16 regions were considerably reasonable for segmentation. Less than 9 for equivalent region sizes is 4, which is considered not efective and more than 16 is 25, which is considered too many and would slowdown the analysis speed. When an image area was segmented into 9 regions, the size of the region occupied 85×85 pixels, while when it was segmented into 16 regions, the size was 64×64 pixels. For an image acquired at an 40cm camera distance, the 85×85 pixels region was approximately equivalent to 69×98 mm^2 area, while the 64x64 pixels region was approximately equivalent to an 52×74 mm^2 area.

4. Analysis method

Every image was analyzed twice using a written program, the first analysis without image smoothing and the second one with image smoothing, which was performed before the features extraction. According to Awcock and Thomas[10], the process of image smoothing seeks to remove unwanted noise from an image while at the same time preserving all of the essential details that an observer would wish to see in the original image. A Weighted Spatial Averaging method was used for image smoothing, mathematically expressed as follows:

$$p = \frac{2p_0 + \sum_{i=1}^{8} p_i}{10} \tag{4}$$

Where p_0 is central pixel, p_i are 8 neighboring pixels and p is result of image smoothing.

The three textural features were extracted from every region in the image being analyzed and were used for classifying whether the region contained weeds or not. Even when some regions in the image are classified as weed regions, it does not mean that the entire region was covered by weeds, but that the minimum action for weeding is required only for the weed regions. The region classification, instead of detecting the center of weed in lawn field, is especially effective for chemical spraying since some of chemicals are able to kill the weeds by treating their leaves. The success rate of the classification results were calculated based on actual classification data obtained manually from the same images. The following rule was used in region classification:

$$\text{IF } (\text{CON} \geqq TL_1 \cap \text{ASM} \leqq TL_2 \cap \text{IDM} \leqq TL_3) \text{ THEN region=weed ELSE region=lawn} \tag{5}$$

where TL_1, TL_2 and TL_3 are threshold levels for CON, ASM and IDM respectively and all were assigned 50% of each maximum value.

The flowchart in Fig. 1 shows step-by-step image analysis for the region's classifications as mentioned above.

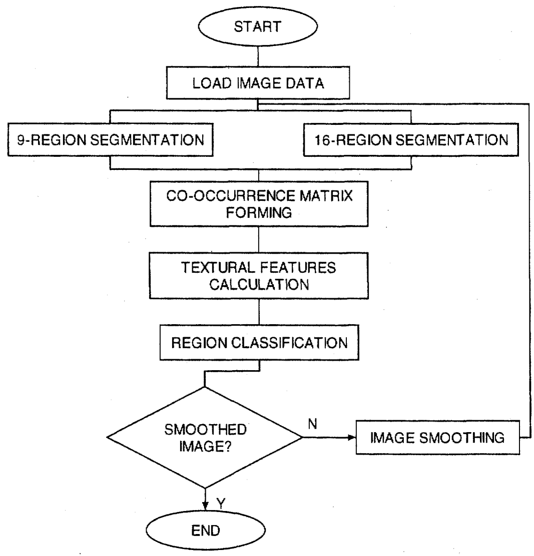

Figure 1. Flowchart of region classification using texture analysis

IV Results and Discussion

1. Results

Image area segmentation and the results of textural features extracted from 9 regions after image smoothing are shown in Fig. 2 and Fig. 3 as an example. In Fig. 2, the acquired image contained an RS weed in regions No. 1, 2 and 5. It was observed from Fig. 3 that the regions with weeds were satisfactorily detected, since the values of CON were higher than TL_1 in the weed regions (No.1, 2 and 5), while the values of ASM and IDM were lower than TL_2 and TL_3 due to the textural difference between the weed and lawn region. In the figure, the values of the textural features were standardized from 0 to 1 by converting the minimum value to 0 and the maximum value to 1 for each characteristic. The example shown here is the extreme good one, many of the images had regions with small part of weeds when they were segmented.

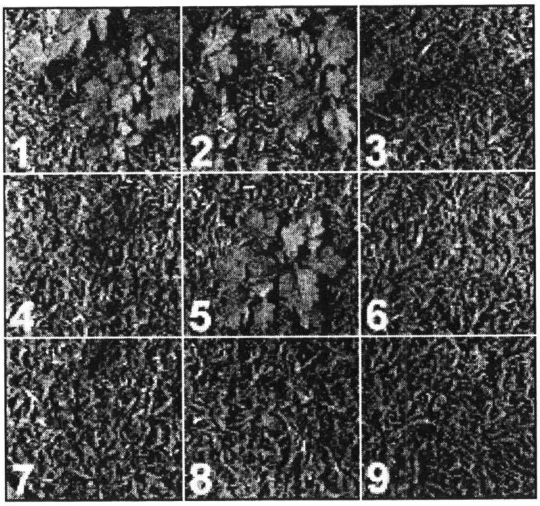

Figure 2. Image area segmentation into 9 regions for image acquired at a 40 cm camera distance

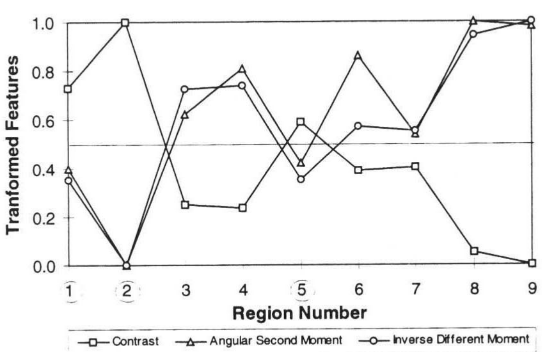

Figure 3. Illustration of region classification for 9-segmented region, smoothed image (regions no. 1, 2 and 5 were classified as weed regions)

The results of region classification shown in Fig. 4 and Fig. 5 are successful classification rates. Successful classification rate is percentage of successful classification regions on the area segmented images (weed regions classified as weed regions and lawn regions classified as lawn regions). From 32 images, in 9 regions, the highest success rate for unsmoothed images (HSR-U) was 76.2% in average (86.4% for RS weed, 91.0% for LS weed and 51.3% for MS weed), which was obtained from a 60 cm camera distance. The highest success rate for smoothed images (HSR-S) was 88.5% in average (100% for RS weed, 96.4% for LS weed and 69.2% for MS weed), obtained from a 50 cm camera distance (Fig. 4).

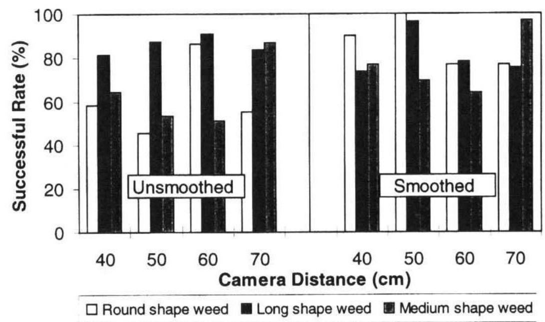

Figure 4. Successful classification rate using texture analysis in 9-segmented region

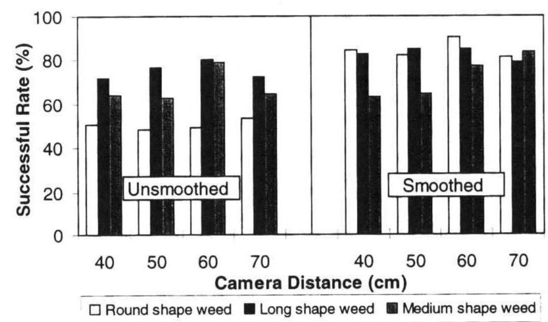

Figure 5. Successful classification rate using texture analysis in 16-segmented region

In 16 regions, HSR-U was 69.3% in average (49.3% for RS weed, 80.0% for LS weed and 78.6% for MS weed), obtained from a 60 cm camera distance, while HSR-S was 83.9% in average (90.1% for RS weed, 84.8% for LS weed and 76.8% for MS weed), obtained from a 60 cm camera distance (Fig. 5). Different numbers in image area segmentation caused different result in weed part isolation which made classification results different. Image smoothing was useful to decrease noises so the results of classification increased.

2. Discussion

In the image analysis, using textural features in region, it was found that image area segmentation affected the result of region classification. Image area segmentation should be able to isolate weed parts from lawn parts without having an ambiguous region. An ambiguous region could appear when a region had a small part of weed surface in it. Nine regions segmentation resulted in fewer ambiguous regions so the region classification results were better than 16 regions segmentation for most camera distances. However, the number of regions segmentation might be changed if the weed size is greatly different from the observed one. Here, most of weed's size were around 80×80 mm^2, when viewing in image became around 69×98 pixels (for 40 cm camera distance), 56×78 pixels (50 cm), 47×65 pixels (60cm) and 41×55. All of the size in pixel are well-fitted in 9 image area segmentation. Also, 40 cm and 50 cm camera distances produced less intersection between weed and lawn area. So, image area segmentation must be large enough to cover weed size, but not too large to make one representative weed surface if exist. The best one is if the weed could occupy entire region in weed area, and no or minimum weed in lawn area.

Camera distances also affected the results of the analysis. The results for the images acquired from 50 and 60 cm camera distances are better since the noises were not very strong and the difference among various small weeds and lawn were still strong enough to be discriminated. In the images acquired for the 40 cm distance, the noises from lawn area were very strong. It was observed that the success rate became slightly lower for the 70 cm distance compared with the results for 50 and 60 cm distances. Here, it was noticed that the change of the camera distance caused a change of number of weed regions in the entire image, because it changed the covered area by the camera so that the result had a fluctuation depending on weed type and size. The number of regions in image area segmentation might also be changed for a large different camera distance.

Image smoothing was effective only for the images acquired in short camera distances due to the elimination of the influence of strong noises. The success rate for images acquired at 40 and 50 cm camera distances increased largely after the image smoothing, while the increased rate was low for the 60 and 70 cm distances. According to the weed type, the smoothed images showed better result than the unsmoothed images for RS and MS weeds images in 9-segmentation. However, the success rate of LS weed slightly decreased after image smoothing. In 16-segmentation, all types of weeds showed better result after image smoothing. Image smoothing decreased noises of the images, so the three features appeared more harmoniously. The noises were caused by white sand used for hardening the land. They became very bright dots with high gray-level values surrounded by relatively dark areas with low gray-level values in images. This condition sometimes confused the texture analysis and produced poor harmony among the three textural features and caused a wrong classification. LS weed showed inconsistent results with the image smoothing, because some weed parts were very thin and disappeared after the image smoothing.

From these reasons, it was also understood from the same images data that the most appropriate camera distance for the condition was 50 or 60 cm without image smoothing, and 40 or 50 cm with image smoothing. These distances were found to be good ones for weed detection in lawn fields for the early stages using texture analysis. However, one disadvantage was found, when using the texture analysis for detecting weed in lawn fields, that is the textural features of lawn field from location to location having great variations, fixed threshold levels for region classification cannot be assigned. Therefore, threshold levels for the three textural features used in this experiment were set to 50% of each maximum value. Since the image was segmented into several equivalent regions, and the regions were thresholded using 50% of maximum values, there was always at least one region classified as weed region even when there was no weed in the entire image. The possible solution for this problem is using lawn characteristics from the previous acquired image to set next threshold level, since the system would capture similar lawn continuously in practice. By this way, lawn characteristics might change gradually but the threshold level also would change gradually to fit the current situation.

VI Conclusion

It was observed that the texture analysis was useful to be applied to perform weed detection in lawn fields during summer season, when the color of weed and lawn are similar. Image area segmentation affected the results of region classification and it was found that 9 segmentation results in fewer ambiguous regions so the classification results were more accurate compared when with 16 segmentation for all camera distances in this texture analysis. Image smoothing helped noise elimination and was good only for images acquired in short camera distances and had a negative effect in far camera distances. The suggested camera distance for weed detection in lawn fields in the early stage, using texture analysis method, based on this experiment were 40 or 50 cm with image smoothing. Reasonable good separation between weed and lawn region might be expected if region size could cover weed with minimum intersection.

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「研究論文」

マシンビジョンによる芝地の雑草検出*
ー分割領域でのテクスチャー特徴量の利用ー

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要　旨

ゴルフ場や庭園などにおける芝地の雑草防除は行わなければならない作業であるものの、最小限の薬剤散布あるいは機械的防除が望まれているため、芝と雑草とを見分ける必要がある。本研究では、類似した緑色を呈する芝と雑草を、画像から抽出されるテクスチャー特徴量で識別する方法について検討した。その方法は、あらかじめスムージング処理をおこなった画像と行っていない画像を9分割および16分割した上で、3つのテクスチャー特徴量（一様性、局所一様性、コントラスト）を抽出した。その結果、雑草の寸法にあった領域分割を行い、スムージング処理を施した画像において、良好に雑草を検出できることがわかった。

［キーワード］雑草、芝、テクスチャー特徴量、分割領域、マシンビジョン

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