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Computer vision based methods for detecting weeds in lawns

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Abstract In this paper, two methods for detecting weeds in lawns using computer vision techniques are proposed. The first is based on an assumption about the differences in statistical values between the weed and grass areas in edge images and using Bayes classifier to discriminate them. The second also uses the differences in texture between both areas in edge images but instead applies only simple morphology operators. Correct weed detection rates range from 77.70 to 82.60% for the first method and from 89.83 to 91.11% for the second method. From the results, the methods show the robustness against lawn color change. In addition, the proposed methods together with a chemical weeding system as well as a non-chemical weeding system based on pulse high voltage discharge are simulated and the efficiency of the overall systems are evaluated theoretically. With a chemical based system, more than 72% of the weeds can be destroyed with a herbicide reduction rate of 90–94% for both methods. For the latter weeding system, killed weed rate varies from 58 to 85%.

Keywords Weeding · Lawn · Computer vision · Bayes classifier · Morphology

1 Introduction

A large amount of herbicide has been used for controlling weeds in agriculture fields, lawns, golf courses, sport fields, etc. This causes environmental pollution and economic concerns. To reduce the use of herbicides, hand labor may be the best way of removing weeds. It is, however, costly and time consuming. Fortunately, with advances in computer vision technology, automatic weed control systems become an alternative solution for this problem.

So far, weed control systems have been developed and tested in cabbage, carrot [1], and tomato fields [2,3]. Typically, these systems start by capturing images from a top-view camera, and then the plant area in the captured images can be discriminated by using color information because the color of the plants and the backgrounds is clearly different. Next, the features of each plant are extracted and used to identify the known crop in the fields. After identification, all unidentified plants are treated as weeds. Finally, instead of uniformly spraying herbicide on the entire area, only areas that contain weeds are sprayed, reducing herbicide usage.

Tang et al. [6] proposed a method for classifying broadleaf and grass weeds. This method uses Gabor wave-lets filter bank for extracting texture features and neural network for classification, and it gives fascinating results. However, each image used in the experiment contains only one type of weeds with soil as background. This means the area of weeds can be detected by color information before doing classification.

In this work, we propose methods for detecting weeds in lawns. The task of detecting weeds in the lawns is quite different from the works mentioned before. Due to the similarity of the colors of weeds and grass in some seasons, color information may not be able to be used for segmenting weeds area from background (lawn). Moreover, because the known plants in this situation are grass that has spread over most of the area of captured images,

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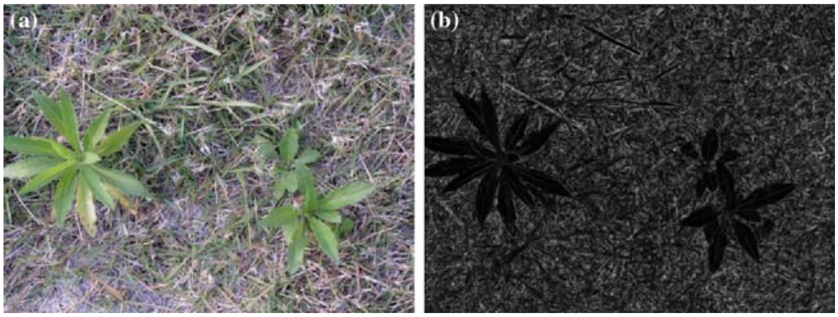

Fig. 1 **a** Example of weed image; **b** its edge image

identifying all blades of grass may be difficult. In this paper, two methods for detecting weeds in the lawns are proposed. The first is based on Bayes classifier while the second is based on morphology operators.

The rest of this paper is organized as follows. Section 2 describes weed image characteristics and the assumptions about them. Then the details of both methods are presented. Section 3 describes the datasets used in the experiments. Section 4 shows the accuracy of the weed detection methods as well as the efficiency of the two simulated weeding systems, and Sect. 5 discusses the results. Finally, Sect. 6 concludes the paper.

2 Weed detection methods

2.1 Weed image characteristics and assumptions

As shown in Fig. 1a, the weed images (pixel size 640 × 480) used in this work are taken from a top-view camera. Generally, an uncountable amount of grass blades is spread randomly in the image. The shape of a blade of grass is quite narrow and small and its color may be green, brown, or yellow, which may resemble the color of some weed species or even the soil. In addition, grass color may be affected by light, season changes, or changes in the camera mode. For that reason, it may be difficult to use color information for discriminating weeds from lawns or even for discriminating plants (grass and weeds) from the soil.

To detect weeds from lawns, the proposed methods are based on the assumption that the grass area should contain a lot of edges while the weed area is smoother than the grass area. Based on this assumption, we use only edge images and ignore color information. Consequently, the methods should be robust against the effect of changing light conditions, etc. To get edge images as shown in Fig. 1b, captured RGB images are converted into gray-scale images and Sobel edge detection operators are applied.

2.2 Bayes classifier based method

This method is based on a well-known pattern recognition technique called Bayes classifier. According to the above assumption, the grass area that has a lot of edges should have higher local mean and variance of edge strength than the weed area. This agrees with the distribution of the local mean and variance of weed pixels and non-weed (grass and soil) pixels, as shown in Fig. 2. In the figure, weed pixels and non-weed pixels are separately distributed.

Figure 3 shows a flowchart of the proposed method. First, we convert RGB images into gray-scale images and calculate the edge images by applying Sobel operators. Then, the local mean and variance of each pixel are calculated from the pixel values in a square window $N \times N$ (in this paper, $N = 17$) whose center is located at the pixel. Next, both the local mean and variance of each pixel are used as features for the Bayes classifier to discriminate weed pixels from the lawn.

The detected images after the Bayes classifier process may contain many small detected areas that are noise

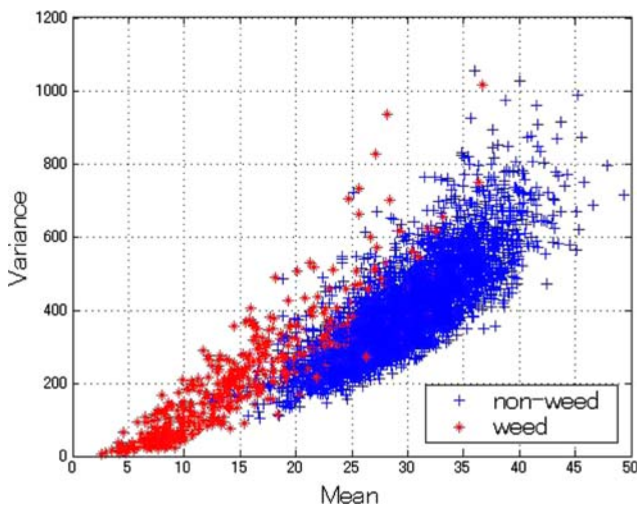

Fig. 2 Distribution of features, local mean and variance of edge strength of weed and non-weed pixels

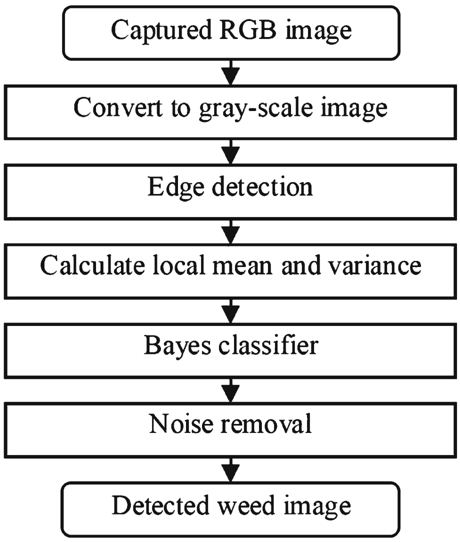

Fig. 3 Flowchart of method based on Bayes classifier

rather than weeds. Therefore, to remove such noise, a closing operator, i.e., dilation with erosion, is employed to connect scattered small areas if they are in the neighborhood. Then, detected areas smaller than threshold value Th1 are removed and a final weed area is obtained. The structuring element used for the closing operation is a square 5×5 and the threshold value (Th1) is 400 pixels determined heuristically in this work. Examples of a detected image before and after noise removal are shown in Fig. 4.

To estimate probability density functions (pdf) of patterns needed by Bayes classifier, we adopted a histogram approximation method. We divide the distribution of features from training images into small blocks. Then the probability of features pattern located in each block can be estimated by the ratio of the number of weed/non-weed patterns to the total number of weed/non-weed patterns. The reason we chose the histogram estimation method is that modeling pdf by using Gaussian distribution resulted in a lot of falsely detected areas, as shown in Fig. 5.

2.3 Morphology operators based method

This approach also uses the differences in the characteristics of the weed and grass areas, but employs morphology operations instead of Bayes classifier. Therefore, this approach does not need a training phase.

The flowchart of the method is shown in Fig. 6. Once the edge image is computed, it is converted into a binary image, as shown in Fig. 6b. Threshold value Th2 used for binarization equals the average of all pixel values. Here we can see that most weed areas consist of black pixels while the background is covered by both white and black pixels. If the white areas are treated as target objects and a closing operator with a properly sized structuring element is applied, most of the background can be connected, as shown in Fig. 6c. However, small black areas caused by some blades of grass still remain. To remove them, areas smaller than threshold value Th3 are replaced by white pixels. In this work, structuring element is a circle seven pixels in diameter, and the threshold value Th3 is 400 pixels determined by heuristics.

Considering the weed area in Fig. 6d there are some edges and small holes that should be removed. Fortunately, the process mentioned in the previous paragraph can be used but the target's object color must be switched. In other words, black pixels are treated as target objects and a closing operator is employed to remove some edges. Next, white areas that are too small are replaced by black. Finally, we get the detected weed images shown in Fig. 6f.

3 Database

The database used in the experiments consists of two sets of lawn images taken from the same place (a lawn at Nagoya University) but in different seasons. Dataset 1 was taken in June, the end of spring in Japan, while dataset 2 was taken in October, the beginning of autumn. Each dataset consists of 30 images. Twenty five images contain weeds while five images contain no weeds. From the images that contain weeds, five images are used in the training step for the Bayes classifier method, while the other 20 images and the five images containing no weeds are used as the test set for both methods. The size of the images is 640×480 pixels, covering a lawn area about 274×205 mm.

Due to the difference in seasons, the color of lawn in each dataset is quite different. As shown in Fig. 7, the lawn in dataset 2 is more green and slightly dense than that of dataset 1. For this reason, in the experiment, they are tested separately to evaluate the robustness of the proposed methods against lawn color change due to changing in season.

4 Experiments

To evaluate the efficiency of the proposed methods, three experiments were done. The first experiment tested the accuracy of the proposed detection methods and their computational times. However, the results from the first experiment do not directly show the

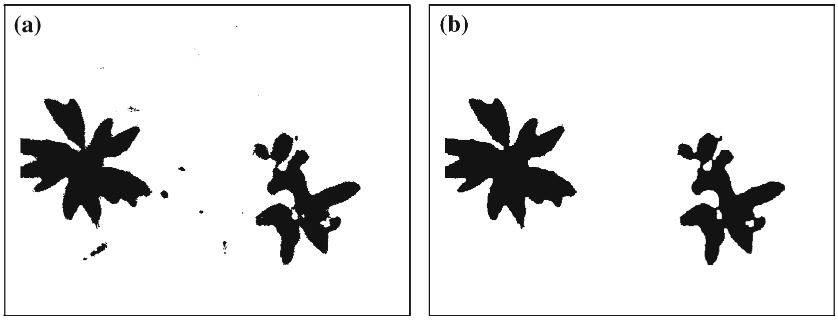

Fig. 4 Detected results of Fig. 1: **a** before and **b** after noise removal

Fig. 5 Detected image of Fig. 1 (after noise removal) by using pdf estimated by Gaussian model

potential of removing weeds from lawns. Hence, in the second and third experiments, we simulate chemical as well as non-chemical weeding systems and theoretically evaluate their weeding efficiency. The experimental results are shown in Tables 1, 2, and 3, respectively. Note that in all tables, BC denotes the Bayes classifier based method and MO the morphology based method.

4.1 Pixel counting and computational times

To evaluate the accuracy of the methods, the weed area in the database images were manually marked and used as ground truth for comparison with detected results. Then the accuracy of methods was evaluated by correct weed detection rate (CWDR) and false weed detection rate (FWDR) defined in Eqs. (1) and (2), respectively.

$$\mathrm{CWDR} = \frac{p_{\mathrm{CDW}}}{p_{\mathrm{weed}}} \times 100, \tag{1}$$

$$\mathrm{FWDR} = \frac{p_{\mathrm{FDW}}}{p_{\mathrm{non-weed}}} \times 100, \tag{2}$$

where p_{CDW} is the number of correctly detected weed pixels, p_{weed} is the total number of true weed pixels, p_{FDW} is the number of falsely detected weed pixels (non-weed pixels detected as weeds), and $p_{\mathrm{non-weed}}$ is the total number of non-weed pixels.

With a Pentium 4 1.60 GHz. PC, the processing times required by the Bayes classifier based and morphology based methods are 0.52 and 0.87 s, respectively.

4.2 Chemical based weeding system

In this experiment, we simulated a system that resemble that proposed by Lee et al. [3] whose system has eight nozzles in the rear used for spraying herbicide. After weed identification, the system divides the image into 8 $\times$ 18 small blocks; each block covers an area about 127 $\times$ 64 mm. Then each row, containing eight blocks corresponding to the number of nozzles, is processed one by one. Only blocks that contain weeds and satisfy certain conditions are sprayed.

In this work, we divided images into 16 $\times$ 40 small blocks (block size = 30 $\times$ 16 pixels) so that each block covers an area 128 $\times$ 68.5 mm. (similar to Lee's block size). So in this case we need 16 nozzles and defined the following four conditions for the simulated system:

1. A block that contains detected weed pixels exceeding 10% of the block area is assumed to be a weed block.
2. All weed blocks are sprayed with herbicide.
3. Weeds whose more than 30% of area is sprayed are assumed to be destroyed.
4. The herbicide is selective herbicide, i.e., it destroys only weeds.

In the simulation, the conditions 1 and 2 are used to define spraying areas. According to the condition 1, it can reduce the number of blocks containing too small weed areas that should not be sprayed. This results in more efficient spraying.

Generally, to destroy weeds with chemical substance, all area of weeds need not be sprayed but only enough areas because herbicide can be absorbed at a part of weeds and moves into another part of weeds, and makes weeds wither. However, if sprayed area is too small, weeds may not be destroyed because the amount

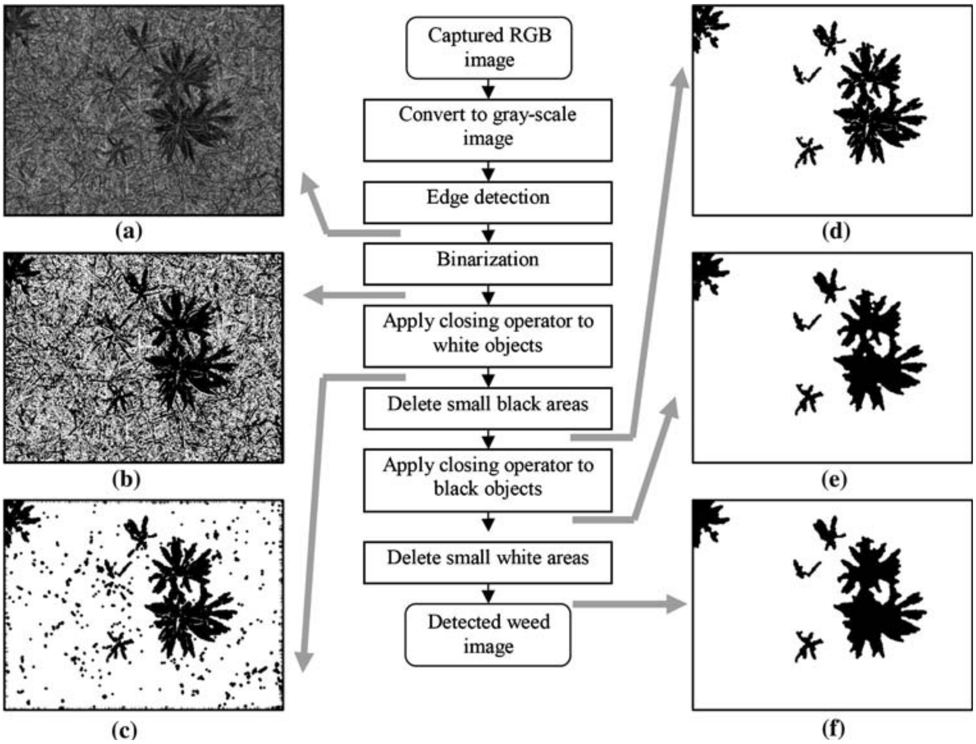

Fig. 6 Flowchart of method based on morphology operations

of herbicide is not enough. In this work, we set the minimum sprayed area enough for destroying weeds in the condition 3.

The condition 4 is set to calculate reduction in usage of herbicide comparing with spraying the overall area. Note that, for a situation which selective herbicide can not be found, sprayed block selection method defined in the conditions 1 and 2 should be modified.

To evaluate this weeding system, killed weed rate, correct spray rate, false spray rate, and herbicide reduction rate are computed as follows:

$$\text{Killed weed rate} = \frac{N_{\text{killed}}}{N_{\text{weed}}} \times 100, \tag{3}$$

$$\text{Correct spray rate} = \frac{N_{\text{CSPB}}}{N_{\text{SPB}}} \times 100, \tag{4}$$

$$\text{False spray rate} = \frac{N_{\text{FSPB}}}{N_{\text{SPB}}} \times 100, \tag{5}$$

$$\text{Herbicide reduction rate} = \left(1 - \frac{N_{\text{SPB}}}{N_{\text{B}}}\right) \times 100, \tag{6}$$

where N_{killed} is the number of killed weeds, N_{weed} is the total number of weeds, N_{CSPB} is the number of sprayed weed blocks, N_{FSPB} is the number of sprayed non-weed blocks, N_{SPB} is the total number of sprayed blocks, and N_{B} is the total number of blocks. An example of spraying results is shown in Fig. 8.

4.3 Pulse high voltage discharge based weeding system

For a non-chemical weeding methods, electrical discharge based weeding is a way that can be used for controlling weeds effectively. Mizuno et al. [4] investigated the performance of weeds destruction using pulse high voltage discharge. They reported that small weeds (about 5 cm in height and 2 mm in stem diameter) can be destroyed with one spark discharge with 135 mJ energy, and a 15 kV, 30 Hz spark discharge for large weeds (80–120 cm in height and 10–15 mm stem diameter). Because the stems and roots of weeds can be damaged by spark discharges, and water transportation is disrupted, weeds wither within a few days after applying spark discharge. In [5], a portable device for controlling weeds using electrical discharge was proposed and tested with a type of weeds often be founded in golf courses.

Although no one reports about automatic weeding system based on pulse high voltage discharge, we think that it is possible to use pulse high voltage discharge instead of chemical substance for controlling weeds in lawns. In the simulation, we assume that one or more spark discharge devices are equipped on a weeding system instead of nozzles and the system applies spark discharges only onto detected weeds areas. Consequently, after detecting weeds, the system needs to select a set of points as the representative of weeds areas.

In the simulated experiments, we set the following conditions:

Fig. 7 Examples of database used in experiments: images of dataset 1 in the *left column* and those of dataset 2 in the *right column*

1. The center of each detected area is calculated by averaging the coordinates of all pixels in its area.
2. The spark discharge is applied at the center of each area.
3. If a part of a weed receives a spark discharge, that weed is assumed to be killed.

The conditions 1 and 2 are defined to select sparking points and the condition 3 is set according to the potential of weeds destruction reported in [4]. To evaluate this weeding system, besides the killed weed rate shown in Eq. (3), correct and false spark rate were also computed.

$$\text{Correct spark rate} = \frac{N_{\text{CSPK}}}{N_{\text{SPK}}} \times 100, \tag{7}$$

$$\text{False spark rate} = \frac{N_{\text{FSPK}}}{N_{\text{SPK}}} \times 100, \tag{8}$$

where N_{CSPK} is the number of sparked weed pixels, N_{FSPK} is the number of sparked non-weed pixels, and N_{SPK} is the total number of sparked points.

5 Discussion

From the first experiment, for both datasets the MO method gave correct weed detection rates, 89.83–91.11%, higher than the BC method 77.70–82.6. However, false weed detection rates of the MO method were also higher. About computational costs, the MO method needs more processing time than the BC method because it has to execute closing operation and small area deletion twice, while BC uses both operations once in the noise removal step. In addition, discrimination with Bayes classifier does not need so much computational time.

In the second experiment, both methods destroyed more than 72% of the weeds of dataset 1 and nearly 100% of dataset 2. Most of missing weeds destruction was caused by hardly detectable small weeds. Because the area of such small weeds is less than 400 pixels which equals Th1 and Th3, it seems impossible in principle to detect such small weeds. In addition, small narrow weeds similar to the shape of grass blades could not be detected either. Both types of weeds fail to satisfy

Table 1 Accuracy of detection methods

Method	Dataset1		Dataset2	
	Correct weed detection rate (%)	False weed detection rate (%)	Correct weed detection rate (%)	False weed detection rate (%)
BC	82.60	0.57	77.70	0.39
MO	89.83	0.89	91.11	1.38

Table 2 Performance of simulated chemical based weeding system

Method	No. of killed weeds	Killed weed rate (%)	No. of sprayed blocks	No. of correct sprayed blocks	No. of false sprayed blocks	Correct spray rate (%)	False spray rate (%)	Herbicide reduction rate (%)
Dataset 1 (total number of weeds = 58, number of weed blocks = 1,533)								
BC	42	72.41	1301	1271	30	97.69	2.31	91.86
MO	47	81.03	1510	1383	127	91.59	8.41	90.56
Dataset 2 (total number of weeds = 27, number of weed blocks = 1,108)								
BC	26	96.29	913	882	31	96.60	3.40	94.29
MO	27	100	1350	1029	321	76.22	23.78	91.56

Table 3 Performance of simulated pulse high voltage discharge (non-chemical) based weeding system

Method	No. of killed weeds	Killed weed rate (%)	No. of sparks	No. of correct sparks	No. of false sparks	Correct spark rate (%)	False spark rate (%)
Dataset 1 (total number of weeds = 58)							
BC	34	58.62	49	44	5	89.80	10.20
MO	40	68.96	70	49	21	70.00	30.00
Dataset 2 (total number of weeds = 27)							
BC	23	85.18	49	42	7	85.71	14.29
MO	22	81.48	105	37	68	35.24	64.76

the assumptions used in the proposed methods. This can explain the large differences between killed weed rate of dataset 1 and dataset 2. As shown in Fig. 9, the number of weeds smaller than 400 pixels is eight for dataset 1 and zero for dataset 2, and dataset 1 also contains more small weeds than dataset 2. Hence, killed weed rate of dataset 1 is lower than that of dataset 2.

From Table 2, the MO method killed more weeds than the BC method because it could detect small weeds

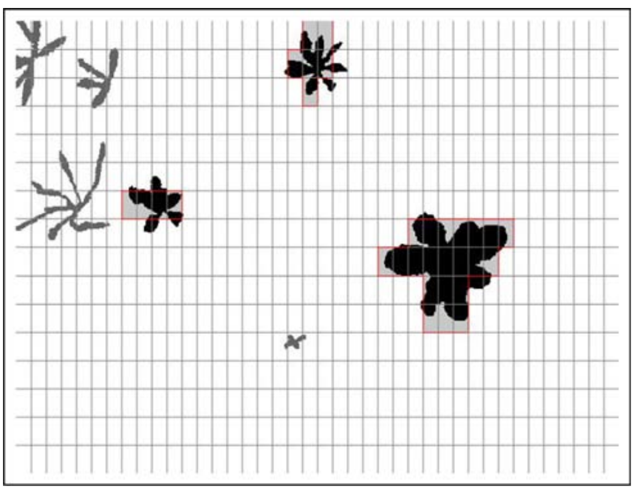

Fig. 8 Example of spraying results. There are seven weeds in the image. Weeds marked by *black color* can be destroyed while weeds marked by *dark gray* cannot be destroyed. *Bright gray* blocks show sprayed area

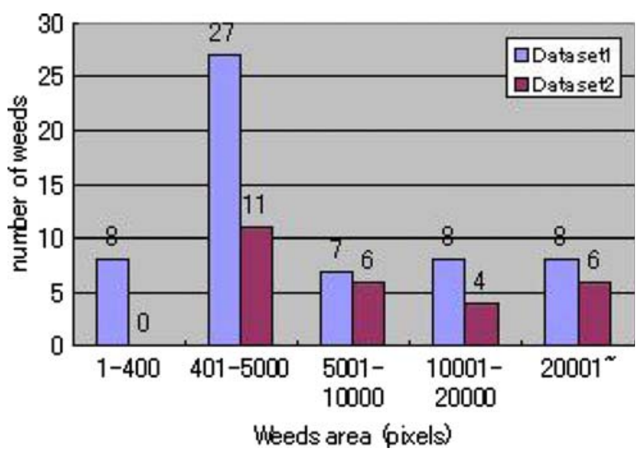

Fig. 9 Comparison of weeds area (pixels) between dataset 1 and dataset 2

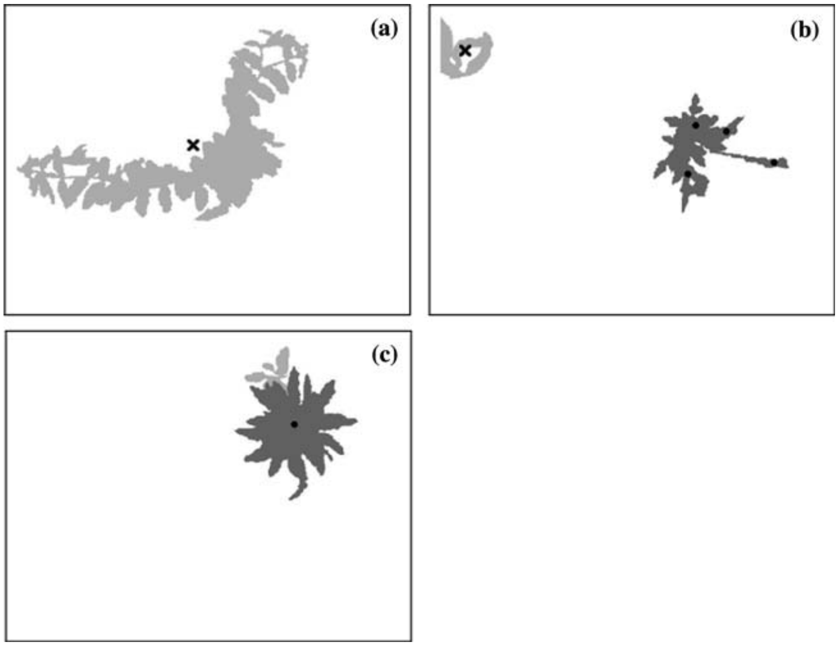

Fig. 10 Examples of mistakenly destroyed weeds for pulse high voltage discharge based weeding system. Dark gray weeds can be destroyed. *Circles* are correctly sparked points and *crosses* marks falsely sparked points

better than the BC method. However, some grass blades were incorrectly detected, increasing the number of false sprayed weeds. According to the condition 4 (using selective herbicide), correct/false spray rates are less important than killed weed rate. The large number in false spray rate shows only inefficiency in spraying. Nevertheless, in the case of non-selective herbicide, i.e., it destroy both weeds and lawns, correct/false spray rates may become more important than killed weed rate because a lot of false sprayings means the lawn receives a lot of damage. For this case, BC method may be better than MO method.

According to the results in Table 2, both methods give more than 90% of herbicide reduction rate, i.e., the system needs herbicide only less than 10% of the amount used for uniform spraying. These numbers show the success of the methods in reducing chemical substance usage.

In the case of the simulated non-chemical weeding system based on pulse high voltage discharge, i.e., the third experiment, the killed weed rates of the pulse high voltage discharge were lower than the chemical weeding system because it not only missed the very small weeds but also because of the error caused by the spark point selection method. In the case of incompact shape weeds or weeds containing holes in their center, the averaging center may be shifted to outside of its area, as shown in Fig. 10a,b. Moreover, error also happened when two or more weeds were connected. As shown in Fig. 10c, only the center of the detected area was sparked, so a small connected area was not killed. On the other hand, the numbers of correct sparkings are higher than the numbers of killed weeds because the stem of some weeds could not be detected. Hence, the areas of those weeds were separated into two unconnected areas or more. To increase the killed weed rate of this weeding system, it needs the spark point selection method that can cope with these problems.

Note that for electrical discharge based weeding, the number of correct/false sparks should be carefully considered because a lot of false sparks means, like the case of non-selective herbicide, a lot of damage to the lawn. For this work, although the number of false sparks of MO method is higher compared with BC method, it is just 68 times, showing only slight but acceptable damage to the lawn.

We discuss the robustness of the proposed methods against season change. Comparing the results of both datasets, CWDR and FWDR of both methods are slightly different in the case of MO. In the case of BC, although CWDR of dataset 2 is lower than that of dataset 1 about 5 points, FWDR of dataset 2 is also lower. These show that the proposed methods are robust against the changing in lawn color due to season change. As mentioned before, although the experiments 2 and 3 show the large differences of killed weed rate between both datasets, it is caused by that the proposed methods missed detecting most small weeds but not by the affect of lawn color change.

According to the results, the assumption we used in this work, i.e., the grass area should contain a lot of edges while the weed area is smoother than the grass area, mostly holds for the lawns except for very small and small thin weeds.

6 Conclusion

This paper proposed two methods based on different techniques for detecting weeds in lawns. The first is based on Bayes classifier while the second is based on morphology operations. The methods can detect weeds from lawns with an accuracy of 77.70–82.60 and 89.83–91.11% for the first and second methods, respectively. In addition, the proposed methods are robust against the change in lawn color due to season change. Also, both methods were applied on simulated chemical and non-chemical weeding systems, and the efficiency of the overall systems were evaluated theoretically. For the chemical based weeding system, more than 72% of weeds were killed, reducing herbicide usage more than 90%. In the case of the non-chemical weeding system, 58.62–85.18% of weeds were destroyed. These results show the possibility of applying the proposed method to automatic weeding systems for lawns.

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