Modified Lawn Weed Detection: Utilization of Edge-Color Based SVM and Grass-model Based Blob Inspection Filterbank ⋆

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Abstract. We propose a lawn weed detection method modified from our previous work, i.e., Bayesian classifier based method. The proposed method employs features calculated from not only the edge-strength of weed/lawn textures but also color information of RGB. Instead of using Bayesian classifier, we exploit more sophisticated classifier, i.e., support-vector machine, for detecting weeds. After weed detection, the proposed method uses noise blob inspection for removing misclassified weed areas. The inspection process is based on a bank of directional filters modeled from characteristics of the edge of grass blade. Experimental results show that the performance of the proposed method outperforms the compared methods.

Key words: Lawn weed detection, edge-color information, noise blob inspection, grass-edge model, directional filter

1 Introduction

Using herbicide is one of the popular methods for controlling weeds because it is convenient and does not take too much time. Obviously, using a large amount of herbicide, however, causes environmental pollution and also increases the cost of weeds control. Therefore a weed control method with reduction of herbicide usage or a non-chemical method is preferred. Nowadays, with the advances of image processing techniques and robotics, an automatic weed control system becomes an alternative solution for this problem. Such the system uses a camera for capturing the field or lawn image, and sends the image to a processor for detecting weeds. If the processor found a weed in the image, it controls a nozzle system for selective spraying (sometimes called spot spraying), i.e., it sprays herbicide only onto the area of detected weeds, instead of spraying uniformly the

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entire area. Consequently, herbicide usage can be significantly reduced. Moreover, the system may not use any nozzle system for spraying but it is equipped a non-chemical weeding device for removing weeds, e.g., using a robot arm for picking up, or using flaming or electric current to destroy weeds.

Up to now, there are some works about the methods for controlling weeds in lawn based on both image processing techniques and special sensors. Mashita et al. reported their development of microwave based sensor for discriminating weeds in lawn in summer [1]. In the same work, they also reported a technique that analyzes the intensity of red band for detecting weed in winter. In [2], Kawamura et al. reported the development of tactile and photo diode sensors for detecting lawn weeds. These two types of sensors were developed for detecting weeds in autumn and winter. They also proposed a detection method based on image processing techniques. The detection method was designed for detecting ears of weeds of some species, which form in spring and have different color from lawns. In [3], Otsuka and Taniwaki proposed a lawn weed detection method based on analysis of variance of weed/lawn surfaces. Their research, however, focused on only detection of broadleaf weeds. In [4], Ahmad et al. proposed a technique using three types of classical textural features, i.e., contrast, angular second moment, and inverse difference moment, and they did the detection in block-level instead of pixel-level. In [5], they also proposed another method based on gray-scale uniformity analysis. This method employs the difference of uniformity between weed and lawn surfaces for detecting weed. After the uniformity analysis, image enhancement and blob inspection are done by considering on its area and perimeter ratio, and multiple expansion and contraction are done. They showed that the method can accurately detect weeds of round shape and medium shape groups. In addition, they proposed a method for finding the center location of detected weeds by using a grouping technique [6, 7].

Recently, we proposed two methods for detecting weeds in lawn [8]. The first method, called BC method, is based on well-known Bayesian classifier [9]. It uses two features calculated from the edge image. The second method is called morphological operation based method (denoted by MO). This method exploits morphological image processing operations, e.g., closing and opening [10], for segmenting weed area from background. In [11], the performance of the two detection methods and the gray-scale uniformity analysis method were evaluated and compared using two types of simulated automatic weeding systems and using four datasets taken from four different seasons. Moreover, we proposed the method based on a fast and simple color image processing technique for detecting weeds when the color of weed and lawn are clearly different, especially in winter [12]. This color based method outperforms the compared gray-scale based methods for a winter dataset. We also proposed the method for discriminating input image taken in winter from the image taken in the other seasons. This enables us to realize a hybrid system that automatically selects to use color based or gray-scale based methods, depending on input images.

In this work, we propose a method modified from our BC method by using both edge and color information and inspecting noise blobs based on grass-edge model filterbank. In Sect. 2, we explain the detail of the proposed method. Then, Sect. 3 shows the experimental results and discussion. Finally, we conclude the paper in Sect. 4.

2 Proposed Method

2.1 Modified lawn weed detection method using edge-color information

Bayesian classifier (BC) based weed detection method was designed from the assumption that the texture of weed and lawn surfaces are different; the weed surface is quite smooth, whereas lawn surface contains a lot of edges. The BC method uses two features extracted from edge image, i.e., mean and variance of edge strength, to measure the difference of weed/lawn surfaces. The features are calculated from each pixels in the edge image using a window of size $N \times N$. Then, each pixel is classified into weed or lawn classes using Bayesian classifier.

In this work, we not only use the edge based features but also add up color information from input image. We directly use features from RGB images, i.e., the intensities of red, green, and blue bands. In most related works, to make weed detection be generalized to any seasons, color information is not used as a feature in the detection and only gray-scale based information is used because of the similarity of weed and lawn colors [3–8, 11]. In fact, although the colors of weed and lawn seem to be similar when they are observed by human eyes, they are slightly different when they are observed by a digital camera. Moreover, using color information may reduce the errors caused by the soil and shadow. In the soil and shadow areas, it is possible that their textures are similar to that of the weed areas; however, their colors are clearly different from the color of weeds. In this work, we adopt more sophisticated classifier, i.e., support-vector machine (SVM) [13], for distinguishing the difference in edge and color features. Using more features, SVM can exploit the kernel method to map input features into higher dimension space where input patterns from different classes can be separated. Here we use five-dimensional feature vector as input. Similar to the BC method, each pixel in the image is classified into weed or lawn classes by using trained SVM. After weed detection, noise blob inspection is done for removing noise blobs. The flowchart of the proposed method is shown in Fig. 1.

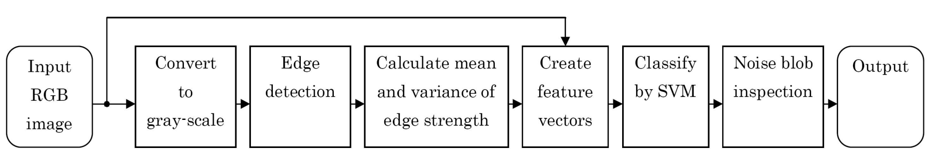

Fig. 1. Flowchart of the proposed system.

2.2 Noise blob inspection using grass-edge model filter

For detecting weeds in agriculture fields, many works attempt to detect only the known plant, i.e., the crop in the field, and consider the other unknown plants as weeds [14, 15]. However, it is quite difficult to do that for detecting weeds in lawn fields, where the known plant is grass. As shown in Fig. 2(left), there are a lot of grass blades in lawn areas. Each of them aligns in different directions, and these alignments seem to be in random-manner. Therefore no one proposes a model of grass blade and does detection in the way mentioned above. However, in this work, we try to model the edge of grass blades and design matching filters corresponding to the model. Figure 2(right) shows an example of edge image calculated by using Sobel operators [10]. We can see two nearly parallel lines caused from drastically changing at the border of grass blade, whereas the inside of the grass blade seems to have no edge due to its smoothness. Therefore there should be two peaks caused by two edge lines in the direction that is perpendicular to grass blade direction. This characteristic of the edge image can be used as a model of grass blade, i.e., composition of two peaks in cross section and two parallel lines in the grass blade direction.

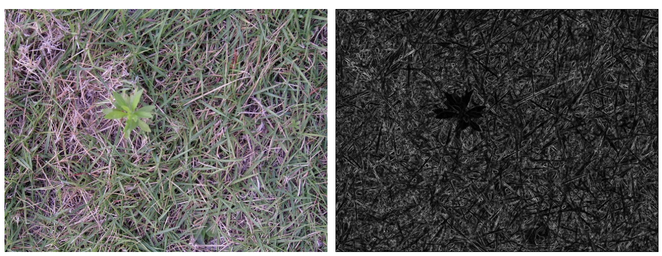

Fig. 2. Example of lawn weed image (left) and its edge image (scaled version) (right).

From the model, we design a matching filter that has the same pattern as the edge of grass blade. The filter consists of one Gaussian distribution in the grass blade direction and two Gaussian distributions in the cross section of grass blade. Such the filter of zero degree direction is shown in Eq. 1. It is a separable filter [10].

$$G(x, y, \sigma_x, \sigma_y, d) = G(x, \sigma_x) \cdot G(y, \sigma_y, d), \tag{1}$$

$$G(x, \sigma_x) = exp\{-0.5 \cdot (\frac{x}{\sigma_x})^2\}, \tag{2}$$

$$G(y, \sigma_y, d) = exp\{-0.5 \cdot (\frac{y - \frac{d}{2}}{\sigma_y})^2\} + exp\{-0.5 \cdot (\frac{y + \frac{d}{2}}{\sigma_y})^2\}, \tag{3}$$

where the parameters x and y are coordinate of the filter and parameters σ_x and σ_y control the shape of Gaussian distributions of Eqs. 2 and 3, respectively.

Parameter d controls distance between the peaks of two Gaussian distributions. Separated components (x and y components) of the proposed filter are shown in Fig. 3. To generalize the proposed filter to any direction θ, we replace x and y in the right terms of Eqs. 2 and 3 by x_θ and y_θ, respectively. The generalized form of the proposed filter can be written as Eq. 4. Figure 4 shows an example of the proposed filter of eight directions by the step of 22.5 degrees.

$$G(x, y, \sigma_x, \sigma_y, d, \theta) = \\ [exp\{-0.5 \cdot (\frac{x_\theta}{\sigma_x})^2\}] \times [exp\{-0.5 \cdot (\frac{y_\theta - \frac{d}{2}}{\sigma_y})^2\} + exp\{-0.5 \cdot (\frac{y_\theta + \frac{d}{2}}{\sigma_y})^2\}], \tag{4}$$

$$\begin{bmatrix} x_\theta \\ y_\theta \end{bmatrix} = \begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}. \tag{5}$$

If the shape of the proposed filter matches an edge of grass blade, the filter should give higher response because the peaks of grass blade are multiplied with two peaks of the filter. However, when the shape of the filter does not match or the filter is convoluted to weed areas, the filter should give lower response because the peaks of the filter are multiplied with non-edge area. This characteristic of the proposed filter is exploited for discriminating noise blobs from real weed blobs. Figure 5 shows an example of filtering results of the edge image in Fig. 2(left).

In noise blob inspection, using Eq. 4, we generate a bank of n filters of various directions and shapes by changing the parameters θ, σ_x, σ_y, and d. This filterbank is convoluted to some detected areas to calculate a feature. That feature is used for discriminating noise blobs from real weed blobs by thresholding method. The noise blob inspection is described as follows:

1. Apply closing operation to connect detected areas located in near distance.
2. Delete all blobs whose area is less than a threshold value Th_1.
3. Apply dilation operation to expand border of the remaining blobs.
4. Consider only the remaining blobs whose area is smaller than a threshold value Th_2, and convolute them with the proposed filterbank.
5. Calculate M_{ij}, i.e., the mean of intensity of the pixels located inside the j^{th} blob convoluted by the i^{th} filter ($i = 1, 2, 3, ..., n$, $j = 1, 2, 3, ..., m$, where m is the number of convoluted blobs).
6. Calculate VAR_j, i.e., the variance of M_{ij} over all n convoluted images.
7. Delete the j^{th} blob if VAR_j is greater than a threshold value VAR_{max}.

The following is the reason that why we can discriminate noise blobs from weed blobs by using VAR_j. In weed areas, no filter matches to the edge of grass blade. Therefore, all values of M_{ij} are low, resulting in lower VAR_j. However, in lawn areas, there are both matched and mismatched filters. Some values of M_{ij} are high, whereas the others are low, resulting in higher VAR_j.

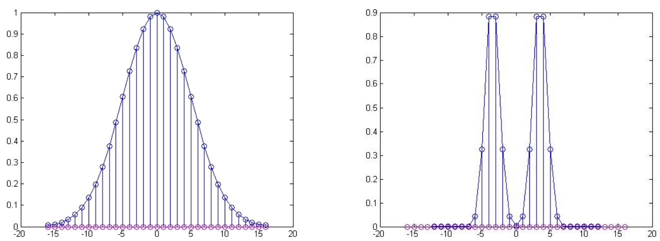

Fig. 3. Separated components of the grass-edge-model filter at direction of zero degrees. x component (left) and y component (right) are corresponding to Eqs. 2 and 3, respectively.

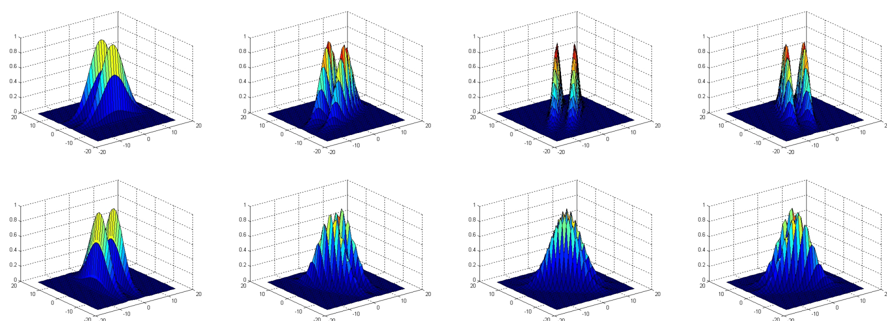

Fig. 4. Examples of eight directional grass-edge model filters. From top-left to bottom-right, the directions of filters are 0, 22.5, 45, 67.5, 90, 112.5, 135, and 157.5 degrees, respectively.

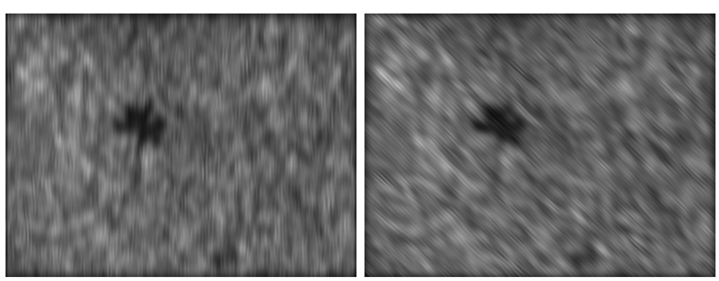

Fig. 5. Responses of the edge image in Fig. 2 filtered by the grass-edge model filters of 0 degree (left) and 45 degrees (right) directions. Note that the origin of x-y coordination is at the top-left.

3 Experimental Results and Discussion

The database used in our experiments consists of four datasets taken from different seasons in Japan. It is the same database as used in [11, 12]. Image size is 640×480 pixels. Each datasets contains 25 images for testing and five images for training. Five images from 25 test images contain no weed, whereas the remains of 20 images contain at least one weed. In the experiments, we combine all four datasets together. Therefore we get total 20 training images and 100 testing images. The total of weeds in the testing set is 188.

In this work, we used a support-vector machine implementation called LIBSVM [16]. It provides support-vector machine source code for both classification and regression, and provides various types of kernel. Because training support-vector machine spends a lot of time if the number of training vectors is too high, we did not extract features from every pixels of the training images but extracted only from the pixels located at cross points of a sampling grid. The size of each blocks of the sampling grid used in this work is 16×16 pixels. By doing that, training time can be significantly reduced into an acceptable time, whereas it still preserved the characteristics of weed- and lawn-pattern models.

In the experiments, we used filterbank of the proposed filters of eight directions (0, 22.5, 45, 67.5, 90, 112.5, 135, and 157.5 degrees), three values of the distance d (8, 10, and 12 pixels), and $\sigma_x = 5$, $\sigma_y = 1$. Therefore the filterbank contains total 24 different filters. The filter size is 33×33 pixels. The threshold values Th_1, Th_2, and VAR_{max} are set to 100, 500, and 15, respectively. The type of SVM is C-SVM, the kernel type is RBF, parameters $C = 10$ and $\gamma = 0.1$. The window size used for calculating mean and variance of edge strength is varied from 3 to 15 with increment of two.

To evaluate performance of the proposed method, we simulate two types of automatic weeding systems. One is a chemical based weeding system. The other is an electrical spark discharge based system, a non-chemical system. The simulation conditions are the same conditions used in [11]. The proposed method is compared with the BC and MO methods proposed in [8] and gray-scale uniformity analysis based method (denoted by UA) proposed by Ahmad et al. [5]. Some parameters of the compared methods are adjusted. For the BC method, the window size is varied from 3 to 17 with increment of two, and the small area deletion threshold (for the electrical spark discharge based system only) is varied from 100 to 400 with increment of 100. For the MO method, structuring element is a circle of seven pixels in diameter, and small area deletion threshold is varied from 100 to 1400 with increment of 100. For the UA method, sensitivity is set to three, the window size is varied from 3 to 9 with increment of two, three pairs of blob inspection thresholds are used; (64, 81), (172, 218), and (466, 590).

In the comparison, performance of weed destruction (killed weed rate and the number of killed weeds), and accuracy performance (correct/false spray rate, the numbers of correct/false sprayed blocks, correct/false spark rate, the numbers of correct/false sparks) are considered as the main factors. To compare the performance of each set of parameters for finding the best one, we set an acceptable error, i.e., acceptable false sprayed blocks for the chemical based system and acceptable false sparks for the electrical spark discharge based system. Then we find the set of parameters that gives error smaller than the acceptable error and gives the best weed destruction performance. If there are two or more sets of parameters giving the same number of killed weeds, the set of parameters giving smaller error is considered to be better than the others. Figure 6(left) shows the comparison of parameters for the chemical based weeding system, whereas Fig. 6(right) shows that of the electrical spark discharge based system. Note that BC NR denotes the BC method with a noise removal step.

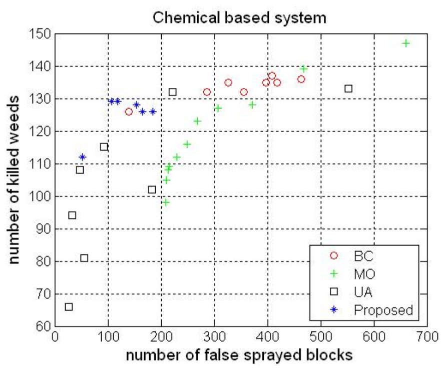

Fig. 6. Performance comparison of the chemical based system (left) and the electrical spark discharge based system (right). Each point shows weeding performance (# of killed weeds) and error (# of false sprayed block or # of false sparks) of each method with a set of parameters.

Table 1. Performance of all gray-scale methods with the best parameters for the chemical based system. The acceptable error (# of false sprayed blocks) is set to 210.

Method	# of killed weeds	Killed weed rate	# of sprayed blocks	# of correct sprayed blocks	# of false sprayed blocks	Correct spray rate	False spray rate	Herbicide reduction rate
BC	126	67.02%	3133	2993	140	95.53%	4.47%	95.10%
MO	105	55.85%	3751	3541	210	94.40%	5.60%	94.13%
UA	115	61.17%	3216	3123	93	97.11%	2.89%	94.48%
Proposed	129	68.61%	3451	3343	108	96.87%	3.13%	94.60%

In the case of the chemical based system, it is quite difficult to compare the proposed method with the BC and MO methods because the error (# of false sprayed blocks) of the proposed method is in lower range than the BC and MO methods and it does not overlap with those of the BC and MO methods.

Table 2. Performance of all gray-scale methods with the best parameters for the electrical spark discharge based system. The acceptable error (# of false sparks) is set to 20.

Method	# of killed weeds	Killed weed rate	# of spark	# of correct sparks	# of false sparks	Correct spark rate	False spark rate
BC NR	123	65.43%	415	399	16	96.14%	3.86%
MO	113	60.11%	201	181	20	90.05%	9.95%
UA	112	59.57%	265	254	11	95.85%	4.15%
Proposed	127	67.55%	538	523	15	97.21%	2.78%

However, it shows the characteristics of the proposed method; it gives accuracy better than those two methods. When we compare the proposed method with the UA method, it is clearly that the proposed method outperforms the UA method. It gives killed weed rate better than the UA method when we select an acceptable error (the number of false spray blocks) in low range. Table 1 shows the comparison of each methods when the acceptable error is set to 210. Clearly, the proposed method gives the best trade-off between weeding performance and error. Note that there is no significant difference in herbicide reduction rate among all four methods.

In the case of the electrical spark discharge based system, as shown in Fig. 6(right), the BC method outperforms the others when we set the acceptable error, i.e., the number of false sparks, to a value less than 15. However, it is clear that the proposed method outperforms the others when the acceptable error ranges from 15 to 50. Table 2 shows the comparison of each methods when the acceptable error is set to 20. The proposed method also gives the best trade-off in this case.

Note that the computational time of this method is longer than that of the other methods. The computational intense step is the weed detection by using SVM because there are a lot of support-vectors got from the training of SVM. Filtering using the proposed filterbank does not spend a lot of time because it is done only on specific areas, some selected blobs, instead of filtering on the entire image. Although increasing the number of filters in the filterbank slows down the proposed method, filtering with the proposed directional filters can be sped up by using separable filtering techniques proposed in [17, 18].

4 Conclusion

In this paper, we have proposed the lawn weed detection method modified from the BC method. Instead of using only features from gray-scale image (the mean and variance of edge strength), we also use the color information as additional features. The classifier was changed to more sophisticated one, i.e., support-vector machine. Also noise blob inspection has been proposed for post-processing. It is based on the proposed directional filterbank design from the model of grass-edge. From the experiments, the performance of the proposed method outperforms the compared methods.

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