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Real Time Specific Weed Classifier Based on Variation in Environmental Conditions

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***Abstract*— Natural light is an important factor that needs to be considered in the implementation of an automatic sprayer system. This paper evaluates the scalability of real time specific weed recognition system using histogram analysis, and its comparison with two dimensional weed coverage rate (2D-WCR), and Angular Cross Sectional Intensities (ACSI) classifiers based on the variation in the natural lighting conditions to encompass the cloudy and bright shiny outdoor environment. A large image dataset of 1500 images was used as compared to the previously used image datasets (200-1200 image datasets). The dataset images are further subdivided based on different lighting conditions and is termed as normal, dark, and bright. The proposed classifier was applied to classify these images into broad and narrow class for real time selective herbicide application using a single constant threshold. The analysis of the results shows over 94 percent weeds detection and classification accuracy (broad and narrow). The results confirmed the scalability of the proposed classifier to encompass dark cloudy as well as bright light outdoor conditions on the same day of application, while maintaining the same accuracy and 22% - 30% better classification accuracy than Two-Dimensional Weed Coverage Rate and Angular Cross Sectional Intensities classifiers.**

***Keywords*—Image Processing, automatic sprayer system, weed classification, histogram analysis**

I. Introduction

Weed is an unwanted plant that grows in undesirable place and competes with the desirable plants for food, shelter, and water. Herbicides are used to overcome these unwanted plants. Herbicides has greatly improved the crop production by eliminating weeds, but the excessive usage has an adverse effect on the water reservoir, environment, and on the bee colonies. Herbicides are applied uniformly to the whole field without considering the weed density. Weeds are often patchy rather than distributed in the whole field [6, 7].

Herbicides could be reduced if applied based on the density of the weeds. This practice would reduce the overall cost of the herbicides and in turn would result lower the adverse effect on water reservoir and the environment. This new method is termed as selectively spraying, spot spraying, or intermittent spraying [8].

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The purpose of this paper is twofold: firstly is to apply the proposed histogram analysis classifier as in [1] to a dataset of 1500 images. This dataset is much larger than previously used in the studies as in [1, 13, 17, and 23] to distinguish individual weeds into broad and narrow weeds. The dataset is further subdivided into three sub datasets. The first sub dataset is termed as Normal and is taken in the daylight outdoor condition. The second sub dataset is termed as Bright and is 20 percent brighter than the Normal image sub dataset. The third sub dataset is termed as Dark and is 20 percent darker than the Normal image sub dataset. The three image datasets are different in light parameter. The main reason of difference in light parameter is to encompass dark and cloudy as well as the shiny daylight outdoor conditions, and to evaluate the effectiveness of the histogram analysis without any preprocessing step which consumes considerable amount of CPU time during real time outdoor application as used in [23]. A sample broad class weed image from the three image sub datasets is shown in Figure 1. Secondly, the proposed histogram analysis classifier is compared with 2D-WCR, and ACSI classifiers on the same dataset of 1500 images for accurate classification.

II. Related Work

The main focus of research in this field is to control weeds with less herbicide. This will in turn reduce the production cost as well as protect the environment and the underground water reservoir. One simple method is as proposed in [24] for banding herbicide spray on crop rows, while cultivate between the rows.

In the recent years, several methods and algorithms have been developed for real time selective herbicide system as in [1, 12-22]. Two main systems have developed for the implementation of these methods and algorithms that operates on vehicle and suitable for field condition. One system uses the spectral reflectance approach. In this approach optoelectronic sensors are used that measure the light reflected at special wavelengths. Although this method is good for discriminating plants and soil, but discrimination between weeds and crop cannot be accomplished using this method. Reflection at different wavelengths was measured for the discrimination among weeds, crops, and soil [10, 11]. The testing of this spectral analysis systems have been reported only in [3]. The second system uses image analysis approach which uses a CCD camera along with image analysis software for detecting and discriminating weed and crop plants based on their color, shape and texture features [2, 4]. The algorithms and methods used in this system efficiently classify weeds and crops in real time environment as in [1, 12-22].

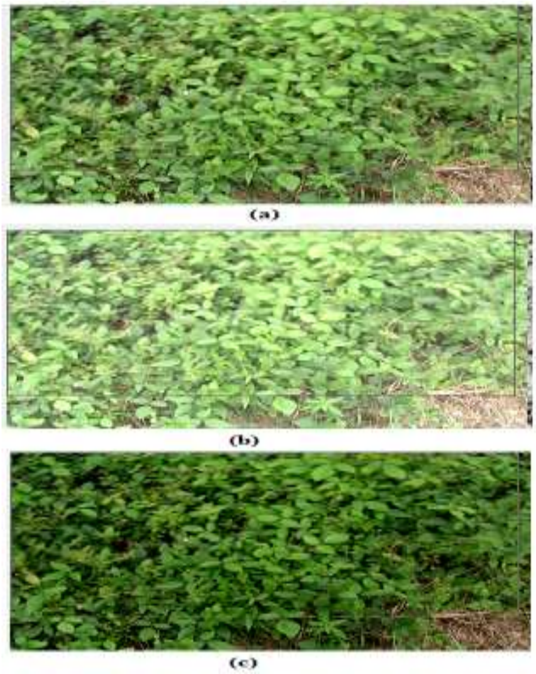


Figure 1. (a) Normal Image (b) Bright Image, and (c) Dark Image

A system that could make use of the spatial distribution information in real-time and apply only the necessary amounts of herbicide to the weed-infested area would be much more efficient and minimize environmental damage. Therefore, a high spatial resolution, real-time weed infestation detection system seems to be the solution for site-specific weed management [9].

III. Material and Methods

A. *Hardware Design*

The concept of the automated sprayer system is shown in Figure 2, which includes digital camera, Central Processing Unit (CPU), and Decision Box controls two DC pumps for spraying. The Normal image dataset was taken at an angle of 45 degrees with the ground. This angle orientation was chosen among many other angles, because using this method, the long, narrow area in front of the sprayer could be captured with high resolution without increasing the image size. Agriculture fields are selected for this type of study.

The images are given to Central Processing Unit. The Decision Box is connected to the Central Processing Unit through a parallel port which ON or OFF the corresponding DC pump, based on the type of image processed by the Central Processing Unit. The results in the lab were obtained using Intel Core i5 with 1.80 GHz Microprocessor and 4 GB RAM [1].

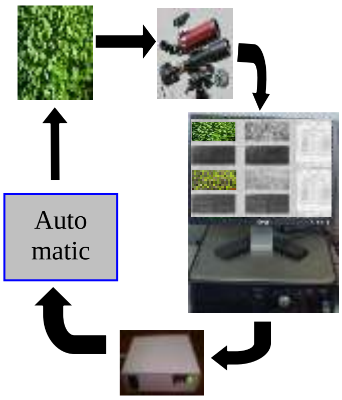


Figure 2. Automatic Sprayer Control

B. *Software Development*

The software is developed in Microsoft Visual C++ 6.0. A Graphical User Interface (GUI) is developed that shows the Original image, processed image, and the histogram. All the three sample image data sets have a resolution of 240 pixel rows by 320 pixel columns.

IV. Methodology

A. *Image Pre-processing*

In weed detection methods, the images are processed in two steps (i) Segmentation of the vegetation from the soil and residue and (ii) detection of the vegetation pixels that represents the weeds. [27]. A vegetation index plays an important role and is used as a first step in weed detection process. The authors in [26] indicated that weeds in field images must be carefully segmented; otherwise the feature extraction will yield unreliable results from analyzing soil and weeds [9]. Different vegetative indices have been used in the literature. The authors in [25], were the first who developed and tested five color vegetation indices using chromatic coordinates r, g ,and b to distinguish plant material from bare soil, corn residue, and wheat straw residue. The five color vegetation indices were (r-g, g –b, g – b, r – g, and 2*g – r –b) [25].

In these five indices Woebbecke found that excess green vegetation index (ExG = 2g - r -b) and modified hue were most efficient in providing a near-binary intensity image out-lining a plant region of interest ,but modified hue were computationally expensive than excess green vegetation index.

Color images were taken from the field. Three arrays were defined to store red, green and blue colors of RGB image in their respective arrays. To distinguish weeds from background objects in a color image, a color segmentation image-processing step using Excessive Green (ExG) is conducted where the background has been segmented from plants for feature extraction.

ExG = 2g – r- b

if(ExG > Threshold)

{

$g_{i+1} = g_i$

$r_{i+1} = r_i$

$b_{i+1} = b_i$

}

else

$g_{i+1} = r_{i+1} = b_{i+1} = 0$

The green pigment of the green part computed is compared with the threshold value which separate soil and residue from the plant as a preprocessing step.

B. *Classification of Images*

In classification phase, the classification of weeds into broad and narrow weeds is based on histogram analysis. The histogram of a digital image having gray levels in the range [0, L-1] is a discrete function $h(r_k)$ such that

$$h(r_k) = \sum_{p=0}^{k} n_p \qquad (1)$$

where r_k is the k^{th} gray level and n_p is the number of pixels in the image having a gray level r_k. After histogram computation, width of histogram (W) is computed with the restriction:

$$T_1 < \mathrm{W} < T_2$$

Where T1 and T2 are the two histogram threshold values.

Next the number of peaks (NP) is calculated with the following restrictions:

$$T_1 < NP < T_2 \ AND \ NP > T_3$$

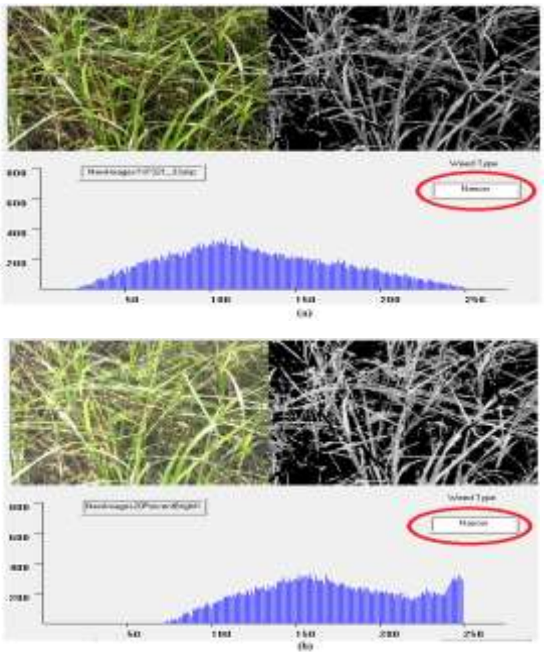
Where T1, T2, and T3 are the threshold values.

The values of W, and NP will then classify the weeds into broad and narrow weeds [1,5].

2D-WCR [13], and ASCI [17] are applied to the image sub datasets for classification into broad and narrow weeds. Each classifier uses a different threshold value for the classification of each sub dataset. Then the three sub datasets were combined into one large dataset and the three classifiers were applied for classification using a constant threshold value.

V. Results and Discussion

Figure 3 and Figure 4 shows weed classification into broad and narrow classes. Figure 3, shows the correct classification of Normal, Bright, and Dark datasets into narrow weeds using the histogram analysis classifier [1]. Similarly, Figure 4 shows the correct classification of Normal, Bright, and Dark datasets into broad weeds, using the histogram analysis classifier [1].



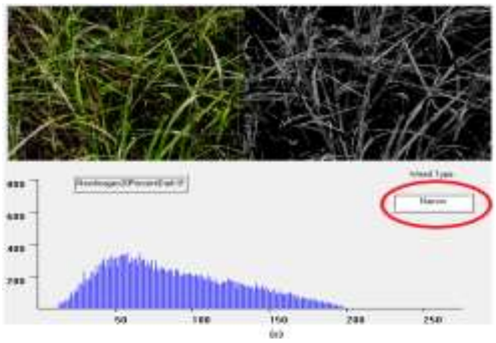


Figure 3. Results of (a) Normal, (b) Bright, and (c) Dark narrow type of weed

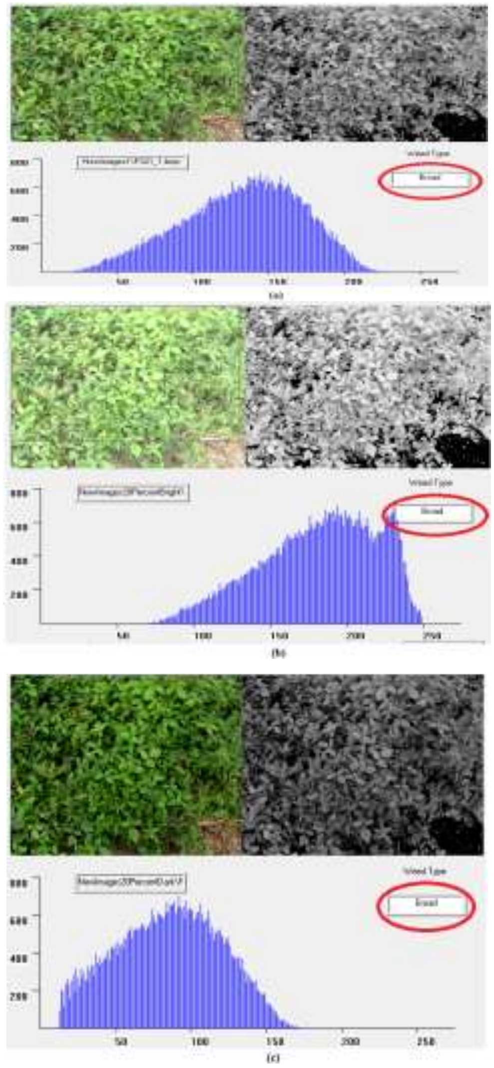


Figure 4. Results of (a) Normal, (b) Bright, and (c) Dark broad type of weed

Histogram analysis, 2D-WCR, and ASCI gives 100% accuracy to detect the presence or absence of weed cover in the entire three image datasets. For areas where weeds are detected, the results of classification of these three methods for normal, dark, and bright image datasets are different. Each dataset contains 500 images, having 250 images from narrow and 250 images from broad class, and a total of 1500 images with different weed densities of both types. Each classifier uses a separate threshold value for each sub dataset (Thresh1, Thresh2, and Thresh3). These threshold values differ significantly across the three image sub datasets. The results are shown in Table 1

The average accuracy of the three sub datasets (Normal, Dark, and Bright) of Histogram analysis is better by 1-10% as compared to 2D-WCR and ASCI for broad weed and (2%- 24%) for narrow weeds.

TABLE I. RESULTS OF CLASSIFICATION USING HISTOGRAM ANALYSIS, 2D-WCR, AND ASCI CLASSIFIERS FOR THE THREE IMAGE DATASETS WITH DIFFERENT THRESHOLD VALUE.

Classifiers	Threshold (different for each image sub dataset	Weed Type / Dataset Type	Percent Accuracy (%) Broad	Narrow	Little Weed
Histogram Analysis [1]	Thresh1	Normal	98%	98%	100%
	Thresh2	Bright	98%	98%	100%
	Thresh3	Dark	97%	98%	100%
2D-WCR [13]	Thresh1	Normal	89%	73%	100%
	Thresh2	Bright	86%	74%	100%
	Thresh3	Dark	88%	75%	100%
ACSI [17]	Thresh1	Normal	97%	96%	100%
	Thresh2	Bright	98%	98%	100%
	Thresh3	Dark	96%	95%	100%

In further experiments, the three classifiers were applied to the combined image dataset of 1500 images. Each classifier uses a single constant threshold value (Thresh1) for the classification in order to reduce the computational cost of dynamic threshold calculation. The results are shown in Table II.

The accuracy of Histogram analysis is better than 2D-WCR and ASCI by 21% to 30% for broad weed and by 23% to 30% for narrow weeds. The average accuracy of histogram analysis for overall classification as compared to 2D-WCR and ASCI is better by 22% to 30% as shown in Table II.

TABLE II. RESULTS OF CLASSIFICATION USING HISTOGRAM ANALYSIS, 2D-WCR, AND ASCI CLASSIFIERS FOR COMBINED IMAGE DATASET WITH SAME THRESHOLD VALUE.

Classifiers	Single Threshold	Weed Type / Data set Type	Percent Accuracy (%) Broad	Narrow	Little Weed
Histogram Analysis [1]	Thresh1	Combined (1500 images)	94.5%	96%	100%
2D-WCR [13]	Thresh1	Combined (1500 images)	65%	66%	100%
ACSI [17]	Thresh1	Combined (1500 images)	74%	73%	100%

Conclusion

Weeds are harmful to plants and needs to be controlled through herbicides. Herbicides in excess are also harmful to the soil and the environment. To remove weeds with the minimum possible application of herbicides, real time weed control machinery is important.

A real time specific weed classifier is developed in [1], are tested on a large dataset of 1500 images with high variation in light parameter in order to reduce the computational cost of preprocessing step and dynamic threshold computation. This classifier was then compared for accuracy with 2D-WCR, and ASCI classifier for soil detection, weed classification into broad and narrow weed types. The classifier shows an effective and reliable classification of images taken by a video camera under extreme lighting conditions, and outperformed 2D-WCR and ASCI classifier using the same threshold for the whole image dataset. The results verified that the classifier is scalable to adapt to the extreme variation of outdoor conditions during real time application.

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