A real-time weed recognition system for selective herbicides using morphological operation

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Abstract—Identifying and categorizing different types of weeds holds significant technical and economic importance in agriculture. Development of a system that can make distinctions based on color, shape and texture is viable. Primary objective of this paper is to develop a machine vision weed control system which is able to identify weed based on its location. A real time robotic system is developed in order to detect plants in the surrounding areas using pattern recognition and machine vision technology. For real-time and specific herbicide applications, the images are categorized in either expansive or precise categories via algorithm following the principal of morphological operation. Different experiments were conducted in order to gauge the efficiency of the aforementioned algorithm in terms of distinguishing between various types of weeds and identifying them as a superlative degree. It also performed admirably amid varying field conditions. The results confirmed that the algorithm exhibited a 95% success rate in terms of categorizing weed samples where a population of 170 samples was used consisting of 85 narrow and 85 broad samples.

***Keywords*—**Weed detection, Image processing, Real-time recognition, erosion, morphological.

I. INTRODUCTION

The term "weeds" is used generally for any plant, the growth of which is mostly detrimental to agricultural progress in any given setting. [1].Weeds effect crop production adversely. Typically herbicides are deployed in a uniform manner, which is not only costly but also proves detrimental to the environment and crop yield. There is evidence based on which methods that target identified sites, can be deemed effective for the purpose of reducing inputs or enabling the use of other non-chemical treatments [2]. However, sensing is of vital importance in such methods in order to target specific areas. The resources available to the crop are apportioned between the crop and the redundant weed which adversely affects crop and machine productivity. Numerous techniques have been employed to thwart weed growth. One of the more common techniques being mechanical cultivation which serves to reduce weed growth, aerate soil and render irrigation more efficient. However, this technique cannot remove weeds on a selective basis. The success of agriculture is directly dependent on the performance of the agricultural chemicals utilized, which is the most common method employed for the purpose of curtailing weed growth.

The use of mechanical methods in agriculture has increased immensely over the past century. Despite the rapid mechanization, there are aspects that have remained unaltered due to various factors including the morphological properties of plants and scarcity of resources etc. For instance, various agricultural processes that remained unaltered since the inception of agricultural methods would still have to be performed manually in the 1990s. One of the most significant objectives for the furtherance of automated farming would be to locate and distinguish between the numerous kinds of weed. Automatic yet accurate performance of agricultural treatments for reduction in weed growth is largely dependent on development of techniques with which different plants can be distinguished and classified accordingly.

Simple techniques for curtailing weed growth typically do not include the use of chemicals. However herbicides can be utilized to thwart weed growth. Selective herbicides are able to target the unwanted herbs or weed, while limiting the adverse effect on the crop to a minimum. The underlying principle in many cases is to tamper with the growth process of the weed.

Overreliance on chemicals between broad and narrow weed can be diminished with the help of a real time automatic weed control system.

The primary objective of this paper is to develop a real time automatic machine vision system that can categorize weeds into narrow and broad classes.

II. LITERATURE REVIEW

In paper [2], a new learning mechanism for machines is introduced in order to distinguish between crops and weed taking their spectral reflectance differences into account. The said mechanism proposes an active approach to learning through a combination of novelty detection and incremental class augmentation. One class classifiers constructed by neural networks provide a basis for novelty detection. Best results for the active learning are obtained for the one-class MOG (mixture of Gaussians) and one-class SOM (self-organizing map) classifiers when compared with one-class support vector machines and the auto-encoder network. Various weed species were experimented on and the success rate for MOG was 31% to 98%, the same being 53% to 94% for SOM.

According to [3], depth cameras are being deployed for added precision in order to analyze the morphological properties of the plant with the classification of smaller plants for identification proving difficult. Crops, weeds and soil can be differentiated from one another by employing dual methodology utilizing height selection and RGB (red, green, blue). 3D point clouds of weed-ridden crops are reproduced in real life conditions by employing Kinect fusion algorithms. The models so constructed were satisfactorily consistent with 3D depth images and soil parameters acquired from actual morphological measurements. RGB recognition is essential in order to distinguish between the weeds with a small height and the soil micro relief of the samples obtaining a correlation of 0.83 with weed biomass. The weed density also correlated well with the volumetric measurements. The results indicate that assessing volume by utilizing kinetic methodology can offer precise results identifying crops and weeds and differentiating between them.

In paper [4], a sophisticated method based on artificial neural network vision is proposed for greater efficiency in production and cost efficiency. In order to identify weed roots in onion crops, multilayer perceptron neural networks technique is employed, which in turn enables the identification of specific areas for spraying, thus decreasing the amount of herbicide utilized. The method in question has been substantiated by practical experiments which provided sufficient evidence regarding saving of resources i-e herbicides due to the active identification and targeting of infected areas.

In paper [5], crops and weeds are distinguished from one another by employing an image processing algorithm which utilizes “wavelet analysis” in order to do so. The textural properties of the crop and weed images are analyzed by the wavelet transform. Data relating to different parameters including Energy, Entropy, Inertia, Contrast, Homogeneity; texture features is extracted. The data so collected is then accordingly classified by the neural network. The location of the weed is assessed based on the classification and the infected area is then treated with the help of herbicides which are sprayed via robotic means.

Article 6 deals with analyzing ground based sensors that can be used for identifying weed and assessing weed levels in a crop. The underlying principles, performance and limitations of the current systems have been discussed.

Paper [7] is concerned with the introduction of weed deduction system based on sensors and its practical use in cereal crops. The weed location is identified by employing an ultrasonic distance sensor. The relevant height of plants is compared to ascertain whether weed containing zones are richer in biomass as compared to normal areas. Two different sets of samples consisting of 80 and 40 spherical-shaped samples with varying weed components were evaluated at two separate dates. To properly assess the heights, the direction of the sensors was kept towards the ground. Grass weeds and broad-leaved weeds were removed. The dissimilarities between weed-ridden and weed free zones were analyzed along with the dry portion of weed and crop smaples. To assess the area covered by weeds and crops, RGB images were obtained the weed removal. Numerous regression based analytical techniques were used to determine the correlation between ultrasonic readings and the coverage of crops and weeds. Difference in heights was observed between weed-ridden and normal samples. The ultrasonic measurements were affected by the presence of weed in the samples. The zones containing weed were differentiated from the normal zones by the ultrasonic readings with a success rate of 92.8%. The cost incurred on weed identification can be decreased by utilizing this system. It can also be applied in non-selective methods for limiting weed growth.

III. OBJECTIVE

Broad leave weeds and narrow leave weed are the two types of herbicides currently in use. We aim to design an algorithm which can:

- Recognize the presence and identify the location of weeds
- Distinguish between the broad leave and narrow leave weed.

IV. MATERIALS

A. Hardware Design:

The concept of the proposed automated sprayer system is illustrated in Fig.1, which includes Camera, Central Processing Unit (CPU), and Decision Box used for controlling dc pumps. The angle at which the images were taken was 45 degree from the ground. In this manner, the protruding portion of the sprayer could be captured in high quality with the image size remaining the same.

The images are relayed to the CPU. The decision box is connected to the CPU via a parallel port which also serves to turn the pumps on or off based on the kind of image that the CPU processes.

B. Software Development:

Microsoft visual C++6.0 is used to prepare the software. The mean and standard deviation between the actual image and the altered image is calculated with the help of a GUI, designed for this purpose with the resolution of the image being 240 pixel rows by 320 pixel columns.

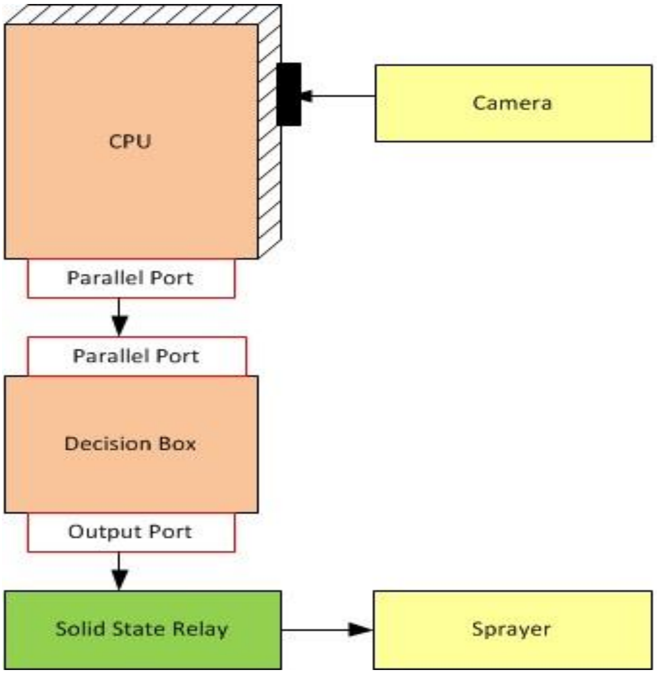

Figure 1: Conceptual flow chart

V. METHODOLOGY

The real time specific weed recognition system is illustrate in figure 2, their purpose being to recognize the broad and narrow weeds [8]. Morphological operation governs the algorithm.

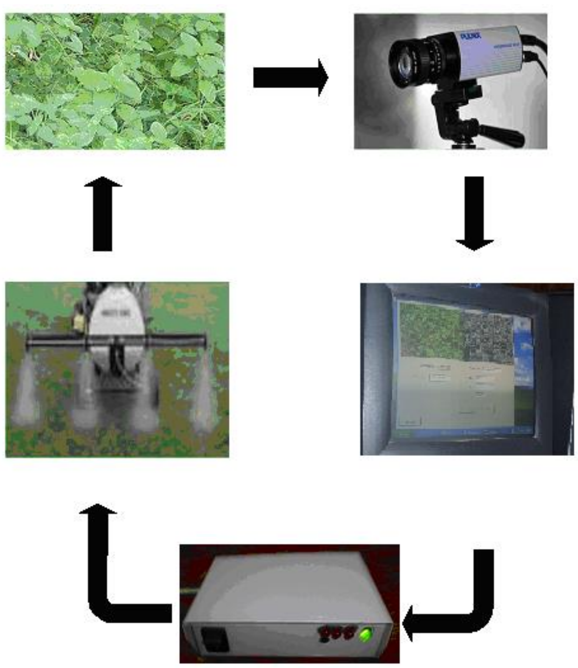

Figure 3: Real-time recognition system

A. Image acquisition

The system we propose can obtain images in RGB format with a resolution of 320*240. The said image can be retrieved from pre-stored images or can be obtained from the images or videos obtained from the camera. Any image that doesn't have the relevant attributes, it can be converted into the relevant format.

B. RGB to Grayscale

With the help of the following transformation, the original image is broken down into red, green and blue constituents and so a binary image is created in this manner.

If G>R and G>B and G>150 then
PIMG = 1
Else
PIMG = 0
End if

R, G and B represent the red, green and blue constituents and PIMG is the binary image obtained after the process.

Weeds are represented by the bright pixels while the other portion of the image is represented in dark pixels in the resultant binary image.

C. Classification by using erosion

Erosion is a morphological image processing procedure that "shrinks" or "thins" objects in a binary image. Mathematically it can be represented as follows:

$$A \ominus B = \{z \mid (B)_z \cap A^c \neq \varnothing \}$$

A represents the binary image and B represents the structuring element.

In other words, erosion of A by B is the set of all structuring element origin locations where the translated B has no overlap with the background of A.

Narrow weeds were eliminated from the binary image by utilizing erosion. The following structural element was utilized in doing so:

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Narrow weed is typically separated from the binary image by the structuring element with minimal effect on the broad weed.

Only broad leaves remain in the after the erosion. The bright pixels which represent the weed are then calculated via the following formula:

$$Percentage = \frac{BP_E}{BP_B} \times 100$$

BP_E indicates the amount of bright pixels in the image after erosion and BP_B denotes the amount of bright pixels in the binary image. Narrow and broad weeds are distinguished based on the value so calculated.

D. Algorithm for classification of Images

The below mentioned procedure is employed to categorize the images.

```
start

If((Broad_Per>=T1&& percentage >=T2) ||

   (Broad_Per>=T3&& percentage >=T4))
       type="Broad Weed";

    else if(Broad_Per>=T5)
       type="Narrow Weed";

    else
       type="Little or No Weed";
end

end
```

T1, T2,T3, T4,T5 are threshold values [9], [10], [11].

VI. Results and Discussion

The conclusions represented in figure 3 were categorized based on morphological operations. 85 images for each category were captured. As illustrated in table 1 and 2, 95% of the little or no weed and 94% of narrow and broad weeds were successfully categorized.

Table: 1

Type of weed	Results in percentage
Broad Weeds	94%
Narrow Weeds	95%
Little Weeds	95%

VII. Conclusion

A real weed-control system that incorporates vision recognition system was designed and various experiments were conducted using it for isolated spraying to limit weed growth. Furthermore, a system based on identification of morphological and other characteristics was developed for identification and categorization of weeds. Images caught by a video camera, were categorized with high rates of success. The four significant stages that constitute the system are: image capturing, image pre-processing, feature extractions and classification.

VIII. Future Work

As far as images which contain only one prevalent weed type are concerned, classification through this system can prove effective. However, samples containing more than one prominent weed types are still difficult to categorize and therefore extensive research is required to categorize such areas of a crop. A promising method for achieving that would be to divide any given population into smaller ones in order to diminish the possibility of there being more than one species of weed in the smaller components002E

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Table: 2
Results of Classification of Narrow, Little and Broad Weeds

Narrow Weed		Little Weed		Broad Weed	
Weed percentage	Broad weed percentage	Weed percentage	Broad weed percentage	Weed percentage	Broad weed percentage
28.92	29.59	15.51	9.69	48.12	47.73
33.04	25.05	7.42	9.30	40.88	40.82
34.96	33.38	6.10	6.49	46.56	33.95
25.88	19.81	0.72	3.62	41.54	28.35
30.60	17.64			39.90	33.10
25.52	28.19			42.26	32.83
24.64	35.08			43.72	28.65
29.46	27.25			42.02	39.56
28.68	24.89				
34.87	28.65			47.08	39.92
32.67	28.40			44.27	29.38
33.83	32.57			40.51	34.54
25.64	19.94			46.20	33.32
28.18	18.56			37.88	46.01
27.96	20.14			38.52	54.08
33.97	24.01			37.82	57.89
30.75	34.70			47.96	55.59
24.07	24.04			37.98	55.35
27.71	34.25			37.82	57.89
30.15	33.06			47.96	55.59
26.10	34.00			35.17	38.22
31.56	36.64				
20.67	23.13				

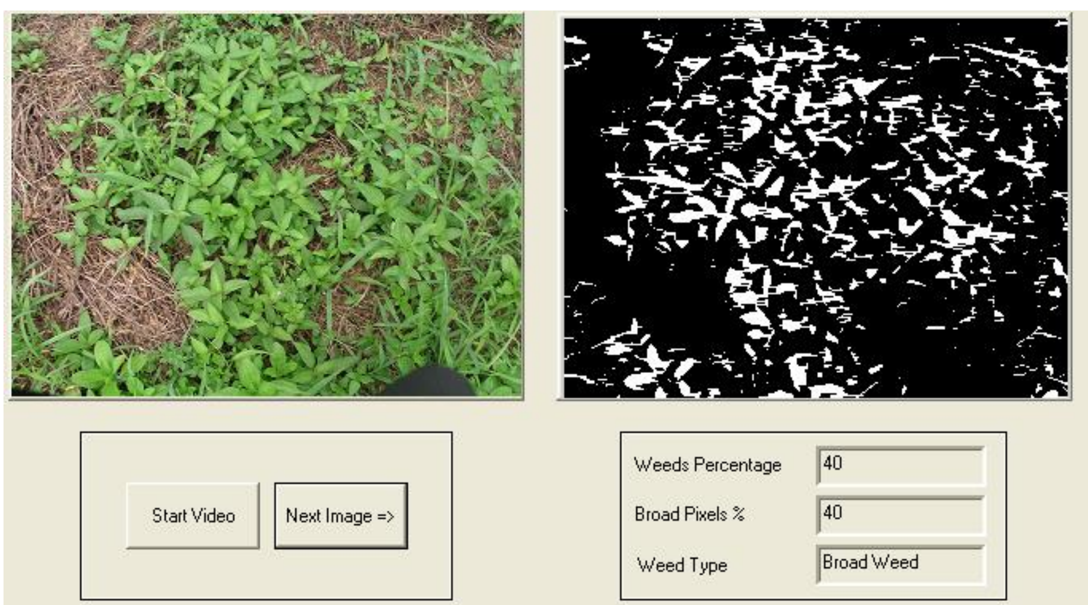

Figure 3: Classified Images
(a) Broad Weed

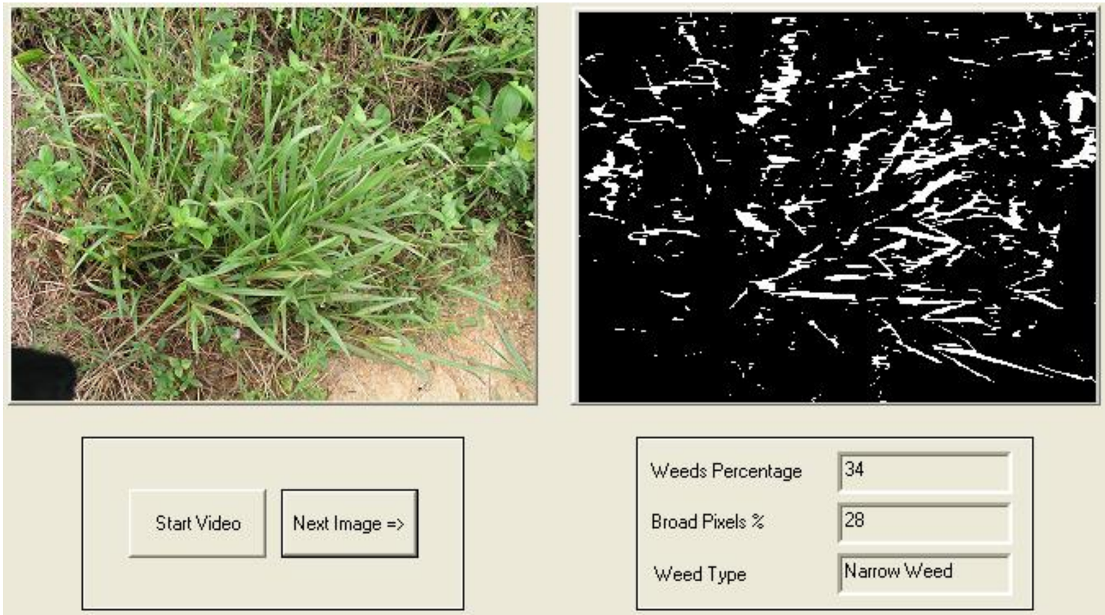

Figure 3: Classified Images
(b) Narrow weed

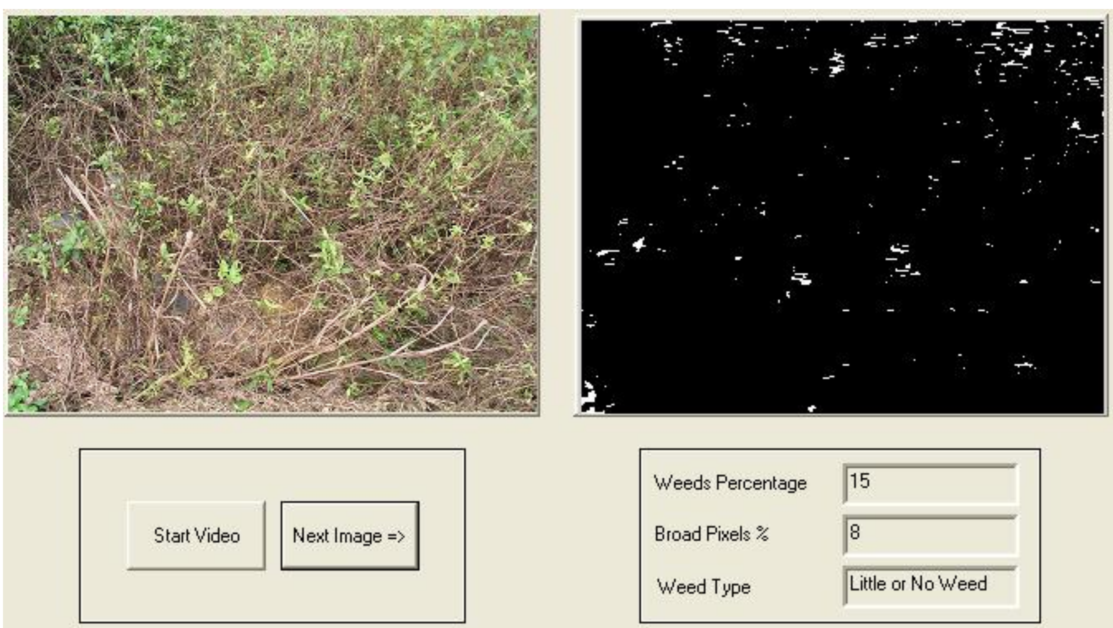

Figure 3: Classified Images
(c) Little weed