Computer Vision Based Robotic Weed Control System for Precision Agriculture

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Abstract—**India is primarily an agriculture-based country and its economy largely depends upon the agriculture. But, most of the crops grown by the farmer are affected by weeds. Weed identification and control remains one of the most challenging tasks in agriculture. The most widely used methods for weed control is manual spraying of herbicides. But, this method has several negative impacts. Since hand labor is costly, an automated weed control system may be economically feasible. Although there have been many efforts to develop a system to control in-row weeds autonomously, no system is currently available for real-time field use. Further, the Onion is slow-growing, shallow-rooted crop that can suffer severe yield loss from weed competition. In order to overcome the above mentioned problems, the proposed system aims to develop a computer vision based robotic weed control system (WCS) for real-time control of weeds in onion fields. This system will be able to identify weeds and selectively spray right amount of the herbicide. The proposed WCS is an inexpensive and portable wireless system of handheld equipments which can be controlled remotely through a user friendly web interface. It is designed to automate the control of weeds and thus reduces the difficulties of farmers in maintaining the field. The proposed system is based on a combination of image processing, machine learning and internet of things (IoT).**

Keywords—Computer Vision; Image Processing, Robotics, Neural Network; Internet of Things

I. INTRODUCTION

Agriculture plays a significant role in the economic growth of India. Hence, reducing cost and improving crop yield is highly needed. Precision farming technologies have been developed during the last two decades to refine the agricultural management practices. Every field has weeds growing in it throughout the year and in a country like India, the number of such fields are in the hundreds. The weed is a plant that competes with crops for water, food, nutrients and space, therefore reduces crop yield. Along with the increase in food-grain per capita, the need for weed removal also has increased. Identification and removal of weeds for small scale farms in India comes with the difficulty of hiring labor. Acquiring labors for regular crop maintenance has become one of the greatest challenges. The use of IoT, machine learning & image processing to implement human-free interaction with the crops is highly desirable.

Several surveys have been conducted in the past research in order to identify the limitations of the existing weed control systems. Martin et al. [1] proposed a system that identifies weed species using clustering and shape features. But, this method is semi-automatic as images are acquired manually. Riya et al. [2] proposed the system which has various image preprocessing techniques and mainly focuses on accurate identification of weed and not on its removal technique. Weisa et al. [3] proposed that specialized hardware (infrared camera) which can be used to acquire the image as required by the processing algorithms. Here, again the removal technique of the identified weed was ignored. Pusphavalli et al. [4] proposed a robotic system for classification of the weeds and crops based on the visual texture. But, since it uses knives to remove the unwanted plants, there is a risk of interfering with plants along with lots of electrical energy consumption. Further, the uprooting of the weed is not done, which increases the risk of regrowth. Sebastian et al. [5] mainly focuses on plant stem detection and position estimation under natural conditions. Aravinth et al. [6] presented a robotic system which cultivates a plant as per human needs like soil nutrients, climatic conditions and seed topology. These techniques find good solution to the green revolution and not towards weed control. Hossein et al. [7] implemented a weed detection method based on the shape of the leaves with 92% accuracy. However, it works on large crops with big leaves and lacks early weed detection. Astranand and Baerveldt [8] developed robotic weed control system for sugar beets. It consists of machine vision guidance and selective rotary hoe for weed removal. However, this system could detect the weeds when crop emergence rates were high and weed densities low.

Herbicides saving can be done by developing various systems in real time for site specific spraying to the infested areas. These systems use the optical sensors (photodiodes) and are able to discriminate plants and soil by their reflectance. The most famous ones are Weedseeker [9], Detectspray [10] and Sprayvision [11]. However, these systems cannot discriminate between crop and weeds. Jeremie et al. [12] proposed machine vision system for precision sprayer. It differentiates between

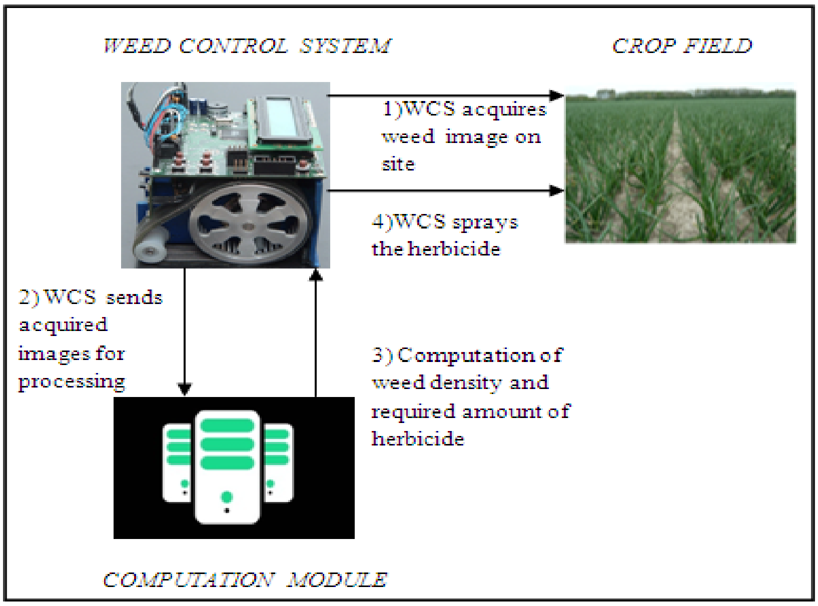

Fig. 1 Proposed robotic weed control system

plant and weed using gabor filter and blob detection. But, this system cannot detect intra-row weeds. There exist several other systems for detection of weed in maize [13], soyabean [14], and wheat [15]. These systems are less accurate in real-time field applications. It was also observed that onion crop is more prone to weeds and it is widely grown in India. Thus, this paper proposes an automatic and effective robotic system which identifies the weed in the field of onion crop and eradicates it by spraying the right amount of herbicide.

II. Proposed Methodology

The proposed system consists of an automated robot for detecting the presence of onion weed (Asphodelus Fistulosus) in the field of onion crop and spraying required amount of herbicide based on the density of the weed. The total cost of the WCS is Rs. 15,000. This is one time development cost and once the system is developed it can be used for many years with less maintenance. Hence, the system can be even used in the developing countries to assist the farmers in weed control. This helps in improving the crop yield. The proposed system is novel as it is autonomous and effective.

The farmer is not required in the field to operate the WCS system. He can control and monitor the system remotely. Further, the quality of images of plants is generally affected by the sunlight and hence this noise in the image may obscure the details. This difficulty is overcome by using image filtering and machine learning techniques in the proposed system. Figure 1 shows the framework of the proposed system. The proposed system is integrated with web services which will provide a web interface for the farmers in order to remotely control and monitor the robot.

The robotic WCS is designed with ATMEGA8 microcontroller, Node MCU Microcontroller, Raspberry Pi, camera and ultrasonic sensor, volt meter, herbicide sprayer. The Raspberry Pi is a single board processor with a 1.2GHz 64-bit quad core CPU. It is also provided with an 802.11n wireless LAN which enables remote access of the device over a simple internet connection. In the proposed system, the Raspberry Pi is a local computing node which hosts Raspbian Operating System. A camera is also attached to the Raspberry Pi for capturing time images of the crops. Node MCU which gives a capability of remotely controlling the WCS is a microcontroller with the open source IOT platform. The proposed WCS also provides the functionality of remotely monitoring the entire system by capturing real time battery status attached to WCS and herbicide level in the sprayer tank with the help of ATMEGA8 microcontroller. Ultrasonic sensor and voltage divider circuit is attached to ATMEGA8 microcontroller for real time data acquisition of these parameters. The captured data is then sent to Raspberry Pi via RS-232 serial communication module. Raspberry Pi establishes a remote connection to the Amazon RDS instance, which hosts MySQL database for storing the real time data captured by WCS. In addition to the above mentioned hardware, the software requirements of the proposed system include Raspbian OS, Java SDK, Python-OpenCV libraries, RapidMiner - Artificial Neural Network, MySQL database.

The former logs in to the system and starts the WCS. Once the WCS is switched on, the image is captured via camera installed on the robot. The captured image may contain only onion plant or weed or plant and weed. Thus, the captured image is then given as an input to the image processing algorithm located on the Raspberry Pi in order to recognize the weed in the image. The flow of data in the image processing module is shown in Figure 2. It consists of image enhancement, feature extraction and classification steps.

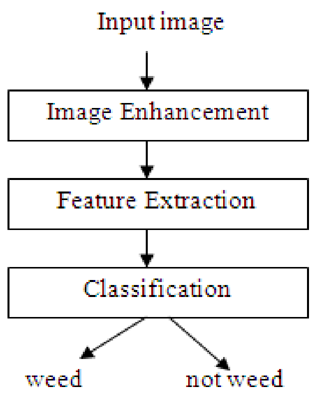

Fig 2. Identification of weed in the image

The acquired image is enhanced by applying a median filter in order to remove noise in the image. Next, the image is divided into 15 sub-images and histogram is computed for Red(R), Green (G), Blue (B) channels in each sub-image. The generated histogram contains 256 intensity levels in each Red, Green and Blue channel. Then, consecutive 12 intensity levels are merged to produce 1 intensity level. This process results in 21 intensity levels for each channel and hence totally 63 intensity levels (21+21+21) are considered as image attributes for each sub-image. These attributes help in identifying the presence of the weed in the sub-image. Here, each attribute represents the probability of having 'n' number of pixels at a particular intensity level '*i*' which is termed as Histogram. The expression given below represents the equation for generating the histogram.

$$P_{x(i)} = (x = i) = \frac{n_i}{n}, \quad i = 1, 2, \ldots\ldots 63 \tag{1}$$

Where, $P_{x(i)}$ is probability of having n number of pixels at a particular intensity level i, n_i is the number of pixels at intensity level 'i' , and n is the total number of pixels in the image. These 63 attributes are given as input to the artificial neural network (ANN) classifier for predicting the presence of the weed in the sub-image. The output of the prediction algorithm is determined by the following equation :

$$y = w_o x_o + \sum_{j=1}^{63} w_j x_j \tag{2}$$

Where,

y = sum of product of synaptic weight and respective attribute value.

w_j = synaptic weight associated with each input attribute.

w_0 = intercept value to generalize the model.

x_j = attribute value.

x_0 = +1 which is an extra base unit.

If the ANN infers that none of the sub-image contain the weed then the system proceeds to acquire the next image.Otherwise, the density of the weed is identified by counting the number of sub-images containing weed. If the sub-image contains the weed then it is assigned a weight 1,otherwise weight 0. Next, the weighted average (*avg*) is calculated considering 15 frames and compared with the threshold 0.3. The value of the threshold is derived based on experiments. If the *avg* > 0.3, then it is considered as high density and the motor is calibrated to run for 5 secs to spray the herbicide. Otherwise, the motor will run for 3secs to spray the herbicide. The herbicide is sprayed using the sprayer mounted on the robot.

III. Experimental Results

The proposed robotic weed control system identifies the weed in the onion crop and controls its growth by spraying the required amount of herbicide. Several experiments were carried out to test the performance of the system. Due to the lifetime of the onion crop and the seasonal unavailability, an artificial field which resembles the fields to a very high extent was fabricated which is as shown in Figure 3. This allowed the datasets to be created with all kinds of environmental conditions, lightings, wind conditions, crop and weed placement. The system is implemented ATMEGA8 and Node MCU micro-controllers, camera, ultrasonic sensors. Motor and battery. In addition to this, Rapid miner open source software is used for learning synaptic weights in ANN and OpenCV image processing python packages for analyzing the image.

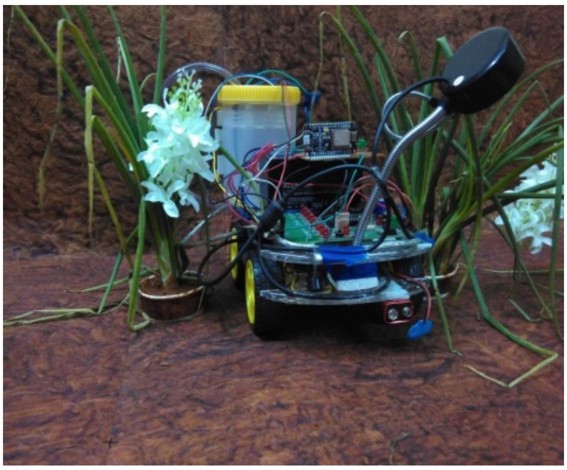

Fig 3. Experimental setup for the proposed system

The farmer controls and monitors the WCS by logging into the web console by giving his valid log in credentials. In the web console, the list of WCS that are administrated by the farmer will be displayed as shown in Figure 4(a). The farmer can initiate the WCS by clicking the ON button.The default WCS information will be displayed on the web console such as battery and herbicide level as shown in Figure 4(b). Whenever, the battery drain out or the herbicide in the container goes below the warning level, the system warns the farmer with the help of buzzer alarm and sends warning message to the registered mobile number of the farmer. The robot is mounted with a camera to capture images of the crop as it moves through the field. The web page will also dynamically show the real time images captured by the WCS in the field. The image captured is given as input to the image processing algorithm. Here, the image is enhanced, divided into 15 sub-images and totally 63 attributes are extracted from the histograms of the sub-image as discussed earlier. These attributes are fed into the ANN to detect the presence of weed in the respective sub-image. Whenever a weed is detected, the required amount of herbicide is computed and sprayed on the weed in real-time.

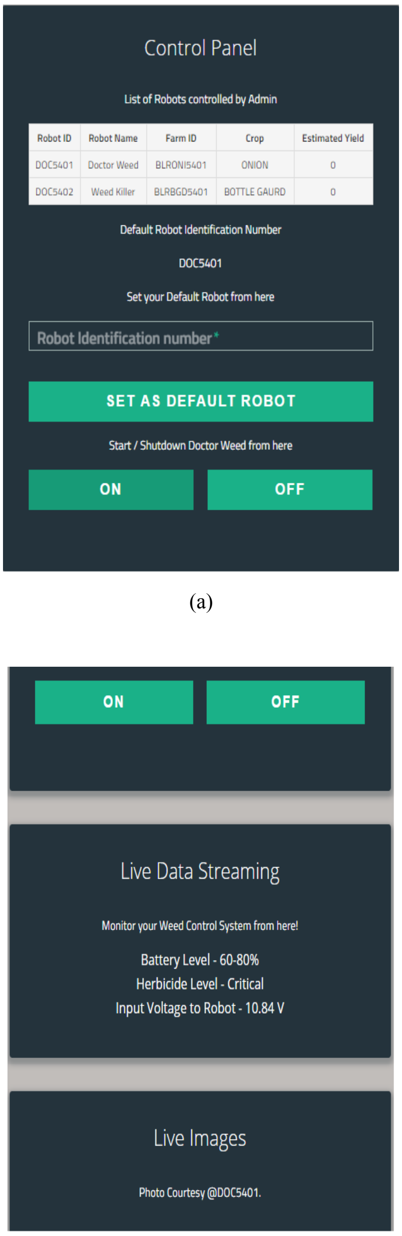

Fig. 4. Web interface: (a) Control panel (b) Live data acquisition

The dataset for the experiments consist of 5305 images of the onion crop captured under different lighting conditions. The captured image was enhanced with median filter and 63 attributes were extracted from the image in order to determine whether the image contains weed. The ANN was trained with 3160 images and tested with 2145 images. The performance of the ANN classifier was analyzed using the following metrics:

$$Accuracy = \frac{TP + TN}{N} \tag{3}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Where, N is the total number of images in the dataset, TP (True Positive) is number of positive samples classified as positive (weed), TN (True Negative) is number of negative samples classified as negative (not weed), FP (False Positive) is number of negative samples classified as positive, and FN (False Negative) is number of positive samples classified as negative. The accuracy metric indicates the overall effectiveness of the system considering positive and negative samples. The sensitivity and specificity metrics show how correctly the ANN can classify the positive (weed) and negative (not weed) samples respectively.

The confusion matrix is shown in Tale I for the ANN used in the proposed system in order to derive the above mentioned metrics. The values of the accuracy, sensitivity and specificity metrics computed considering the ANN classifier are shown in Table II.

Table.1 Confusion Matrix of ANN classifier

Total cases = 2145	**Predicted Class**		
Actual Class		Class = 'Weed'	Class = 'Not Weed'
	Class = 'Weed'	245 (TP)	8 (FN)
	Class = 'Not Weed'	25(FP)	1867(TN)

Table.2 Performance of the ANN classifier in weed identification

Accuracy	**Sensitivity**	**Specificity**
98.64%	96.83%	99.57%

It is observed in the above tables that the ANN identified positive samples (weed) with 96.83% (sensitivity) and negative samples (not weed) with 99.57% (specificity). Overall accuracy of the ANN in classifying the given sample was 98.64%. The system could not attain 100% accuracy due to the varying lighting conditions which created disturbances in the image as shown in Figure 5. Improper lighting affects the features of the images and hence leads to misclassification.

Fig. 5. Image under improper lighting conditions

IV. CONCLUSION

The aim of the proposed robotic weed control system was to detect the presence of the weed in the onion field and control it by spraying the required amount of herbicide on the specific site. The system was designed with various hardware components like microcontrollers, sensors, Raspberry Pi and software components like image processing, machine learning and IoT modules. The system successfully identified the weed in the onion field with 96.83% accuracy. Thus, the proposed system is reliable, saves time, cost, reduces the amount of work the farmer has to do and the herbicides to be sprayed in the farm. This helps in improving the crop yield and also quality of soil. The accuracy of the proposed system can be further improved by incorporating intelligent machine learning algorithms. The module for disease detection can be developed which helps in determining crop yield. Further, the battery usage of WCS must be optimized to increase the battery life. The system can also be tested in the actual onion field to determine its effectiveness under natural conditions.

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