COMPUTER VISION BASED NAVIGATION MODULE FOR SUSTAINABLE BROAD-ACRE AGRICULTURE ROBOTS

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ABSTRCT: *In this paper the development of small size low cost interactive robots for precision farming to increase the production of broad acre agriculture is discussed. The major task of robots is to deal with weeds which is one of the critical problem in Pakistan's agriculture. There are two computer vision techniques proposed to automate the process of navigation and weeds detection. In order to maintain the course of action, robot follow the rows of crops in field through image processing algorithm. In this algorithm binary image is first split into several horizontal strips, then with the help of vertical projection method estimates the position of row and finally detect the rows by using Hough transformation. For automatic weeding, image processing is used for detection and differential spraying of weeds. The machine vision algorithm proposed in order to recognize and distinguish types of weeds includes multi-scale filter function with combination of edge maps which generate different filter size to effectively reduce noise. This filtered image is finally feed to continuity estimation (CE)) for feature extraction.*

Keyword – Precision Farming, Machine Vision, Hough Transformation, Continuity Estimation (CE).

I. INTRODUCTION

Now a day's high production in agriculture by means of huge machinery along with controlled strategies of traffic farming is a major concern of farmers. So, researchers have been showing great interest in the development of the automated guidance system for agricultural machinery where the vehicles traverse exactly the same path using precision guidance system. However, due to rapid advancement in precision farming technique results in the increase of weight, size and complexity of farming equipment, also repeated traversing along same pathway has headed towards concentrated soil compaction damage. The problem of soil compaction and target missing failure will ultimately results in the decrease of productivity and yield. So, intelligent path planning technique plays vital role in precision agriculture. In order to achieve the above mention goal researchers and scientists have been involved in the development of automated navigational and farm work guidance for agricultural equipment since early days of tractor invention. Now a day due to the improvement in sensing equipment and embedded technologies give a boost in the efforts of researchers. The basic idea of this paper is to present a new class of equipment for sustainable agriculture which will boost broad acre production and also improve immunity toward environmental uncertainties: light, small, less expensive robotic structure that coordinates as a team to organize the farm field round the clock complete day. The proposed idea is focused on a recent resistant weeds problem facing farms in Pakistan.

Since our whole idea based on multiple robots, to keep our whole system working and affordable, the use of low cost sensors for obstacle detection and motion estimation is the requirement. Cameras are the best choice for low cost monitoring sensor which has an ability to provide much more information of the surroundings as compared to any traditional sensors like laser or ultrasonic sensors. Therefore the goal of this paper is to present a navigational guidance system which can detect crops rows and guide group of agribots to work in the real time even under a huge range of illumination situation using digital image processing techniques.

II. LITERATURE REVIEW

In the development of precision autonomous robots lot of work has been carried out in several areas. [1] Reid et al. made Bayes classifier algorithm to find the optimal threshold point for segmentation of the images of crop rows in order to get information of guidance coordinates. R. Eaton et al. [2] made use of spatial precision to achieve optimal performance of farming system for management of Precision Farming Data Set. Laser based tractor guidance was proposed in [3] and GPS-based [4]. In early stages of the development of the automatic machinery for farm Ollis et al. [5] used the concept of vision to determine the path between cut and uncut crops and the elaborated scheme of harvesting over 48 hectares of crop was presented in [6]. Stentz et al. [7] introduces a semi-autonomous tractor which used to detect obstacles by means of probability density function to limit novel areas in the images obtained. Artificially intelligent robots are developed which are trained by human being once and afterwards by using stereo vision system along with neural network traverse across the field by avoiding obstacles [8]. Tori et al. [9] consider all major task in farming like tillage, planting and plant care etc and develop number of fuzzy logic, neural networks and genetic algorithms to handle these tasks efficiently. Right from the start of automation researcher developed number of robotic farming structure using traditional sensors, especially Johnson et al. [10] present a complete multi-robotic system which can work in number of different environment for a long time. Addition of color cameras along with infrared cameras and nodding laser helps to develop 3D data. Recently Moorehead et al. [11] used a concept of hybrid sensor network to enhance the working of existing robotic structure and at the end of his experimentation he improves the existing structures by 30%. There is also lot of work done on developing customize farm control and management platforms. Bakker et al. [12] gives a great systematic approach to the design of a robotic structure that is able to detect weeds and destroy them, efficient guidance approach, low energy consumption light weight structure. It is a four wheel well balanced structure with both GPS and stereo vision abilities for precise maneuvers of robots in the field.

III. SYSTEM DESIGN

1) *Overview of system*

The overall summary of the proposed system is shown in fig. 1, the farmer communicate with the multi-robot coordination module of robot which further communicates with the remaining system over internet via 3G mobile data connection. Central unit send them complete information of the perimeter of the required target area and also send them the complete information of waypoints in order to cover the area efficiently in less amount of time. Robots continuously feedback their progress and location to the central unit in real time by using 3G mobile data communication. So the communication medium between multi-robots and central unit is internet. Central unit is basically a multi-robot planner which is responsible to traverse multi-robots in the field by using the data of the sensor attached to the robotic structures along with the general sensors like GPS etc. Robots are also equipped with board decision make algorithms which will help them to handle any drop out of communication. The following section will give idea of the sensors and software proposed for the working of this system.

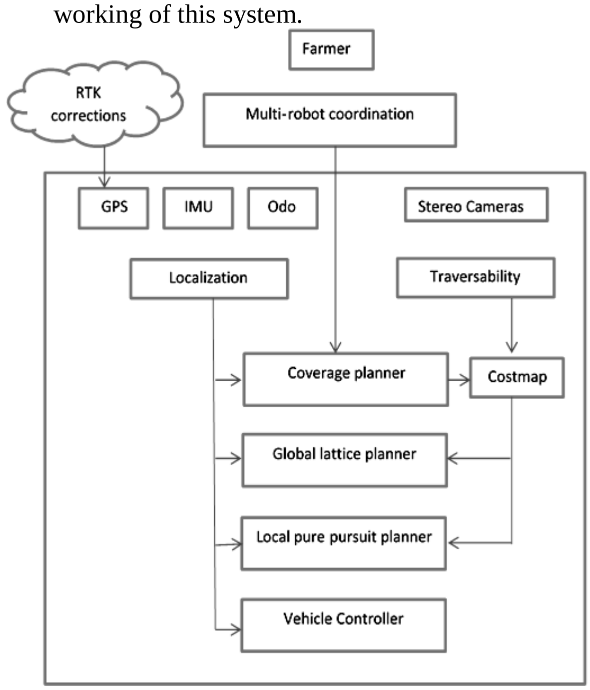

Fig. 1 Block diagram of the System Architecture

Multi-Robot section describes the planning mechanism of subsystem for multiple robotic coverage of large area fields. The major focus of coverage is to plan and find an optimal coverage path through which robot(s) eventually cover all points within a specific area of farm. The proposed system is for basically designed for zero tillage agriculture so in this case cell-decomposition algorithm is used to traverse the agriculture robot(s) parallel to already existing rows in the field. Cell-decomposition algorithm used in this system is boustrophedon decomposition which works efficiently in the field where coverage area is portioned in a lawnmower manner. According to boustrophedon decomposition a field of farm with its known orientation of rows computed by considering sweep line moving orthogonal to the rows. Number of robots are same as the number of rows of the fields which implies that each robot is responsible for single row of the field. Initially allocation of rows to multi-robots and decomposition is computed offline according to given parameters of the field. This is done by calculating complete list of way points located at the start and end of each path first. Then each robot in the field perform the assigned task within its allocated cell or row by using image processing algorithm described later. Along with real robots and simulated robots also operated simultaneously so that farmer can monitor the phenomena at its end.

Software

Simulated environment runs on Ubuntu 12.04 based Robot Operating System (ROS) Fuerte. ROS Point Cloud message along with ROS move_base and cost map frame wok are used to simulate the traversability node and path planning. Mostly 10Hz is used for robot operations at nodes. LabVIEW is used to implement image processing algorithms.

2) *Hardware*

Dedicated PC with specifications core i5, 1.8GHz processor 2 GB RAM is used to run multirobot planner module. Communication is done on 3G based network. Color IP based Wifi camera with 400 × 300 resolution and frame rate of 15fps is used which is located at the height of 110cm from ground and with the tilted angle of 30° with respect to vertical axis. Sensor used other than camera are triple-axis Gyro (ITG-3200), GPS shield for arduino and triple axis accelerometer (ADXL345). Mechanical structure of robot is composed of real time spray gun, wifi ip camera stand, two tanks that carry multiple herbicides and arduino board (embedded board) for interface software with hardware.

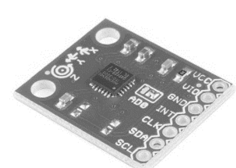

Fig. 2 ITG-3200

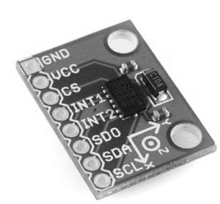

Fig. 3 ADXL345

.proposed method

Coverage planner which runs at robot end ensures that robot follows the motion as planned by central unit. To main the path and target the weed to complete the operations two image processing modules are proposed which are explained the following subsections.

B. Navigation Unit

In order to guide the robot in the field according to the data generated by multi-robot coordination image processing algorithm is used. Rows are detected with the help of line detection technique using Hough Transformation (HT). Hough Transformation works better as compared to other types of line detection techniques due to its ability to absorb noise of surrounding environment [13]. The major issue in detection of rows in the real life problem is the use of vertical projection scheme of camera which absorbs data sets. To handle this issue it is assumed that the orientation of the camera on the robot platform will not exceed the limit of 60° and that is why in are proposed algorithm Hough Transformation calculate the accumulated values of the line which lies between 30° to 150° with maximum variation of 1°. The explanation of this algorithm is described as follows:

1. The first step is Grey scale transformation in which colored object is transformed into grey scale image by minimizing the impact of red and blue value and emphasized mainly on green value content of the image. Transform model used here is 2G – R –B. The complete picture of the transform model is:

$$a(x,y) = \begin{cases} 0 & 2G \le R + B \\ 2G - R - B & \text{others} \\ 255 & 2G \ge R + B + 255 \end{cases} \qquad \text{eq. 1}$$

In above expression R, B, G are the pixel values of red, blue and green value of color image I at (x,y) position respectively and a(x,y) is the pixel value with range [0 -255] transform grey scale image.


Fig. 4 Original Image


Fig. 5 Grey Scale Image

2. After grey scale transform of the image, it is converted into binary form and then split into number of equidistant horizontal strips so that computation complexity of process. Next is Hough Transformation which is used to detect objects through edge detection. Hough Transformation is reduced to estimate the center of the crop rows. In this method number of strips is proximately half of the number of rows of pixels in image. Height of the horizontal strip is h. statistical representation of this step is shown below.

$$v(j) = \sum_{m=1}^{h} G(m,n) \qquad n = 1,2, \ldots .M \qquad (2)$$

$$k = \frac{1}{M}\sum_{m=1}^{M} v(n) \qquad n = 1,2, \ldots .M \qquad (3)$$

Strip size of the image is M * h, while G(m,n) is the value of pixel of grey scale image. “k” is the mean of the whole image strip. v(n) are vertical grey values single image.


Fig. 6 Binary Image

From Fig. 4 it is clear that grey scale value of crops is higher as compared to background values. Compute v(n) for each and every image.

3. Select appropriate grey scale threshold G_T and then set the limit of thresholds as given below:
   $v(n) \ge G_T$ $\quad v(n) = h$
   Otherwise $\quad v(n) = 0$

Here, G_T can be replaced with m.

4. To observe the left hand side and right hand side edges of crops. If $D(n) > 0$, then the column ‘n’ is considered crop’s left edge (up-point), save the value of ‘n’; on the contrary accumulator, if $D(n) < 0$, then the column ‘n’ is considered crop’s right edge (down-point), also, save the value of ‘n’.
5. Given a distance threshold D_T, D_{ud} are the distance constant between crop’s left edge and crop’s left edge.
   If $D_{ud} \ge D_T$, these constants of up and down points are considered as localization points; the midpoint of both points represents localization’s abscissa. In most cases vertical mid points are calculated as follows:
   $$y_i = (m - 1/2) * h, \; m = 1, 2, \quad , N .$$
   From the above expression, calculations for the center of the row can be done; as a plan B, if $D_{ud} < D_T$, the pair of points are not localization points, will be discarded. This step will end after the calculations of up-points and down-points are made.
6. The results are sent to localization unit where center point is computed by taking the average of the line between two edges.
7. When last strip computed end the process.

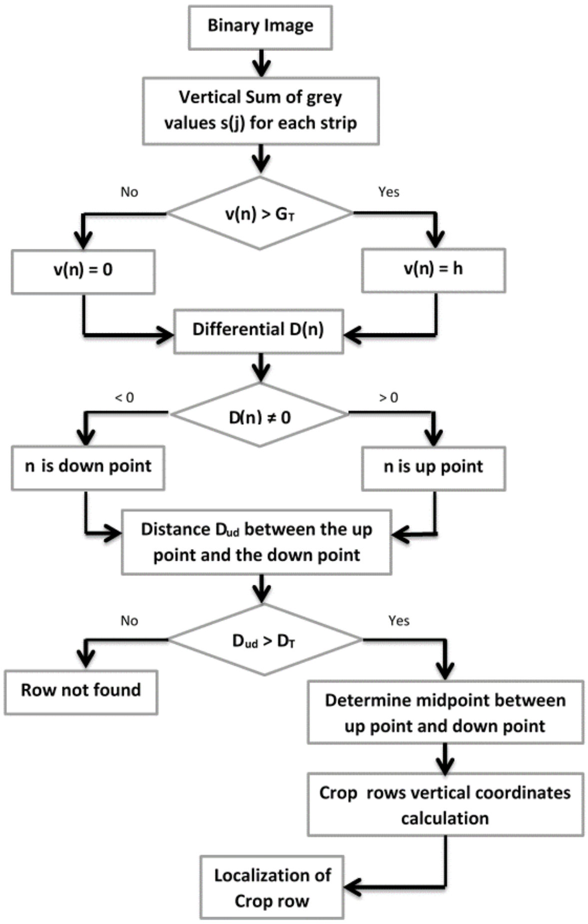

Fig. 7 Graphical summary of Image Processing based Navigation unit

C. Weed detect unit

There are several techniques available for feature extraction now days. To detect weeds in the farms robots are provided with technique which comprises of two main steps first general type filter and second one is a feature extraction technique named continuity estimation (CE). Pseudo code of weed detection unit is presented in Fig. 8.

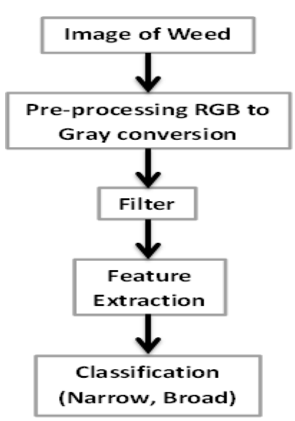

Fig. 8 Pseudo Code for weed detection algorithm

The basic idea of the filter in digital image processing is to make edges of the object prominent. The ordinary filters like low pass, high pass, Gaussian, Prewitt, Sobel etc. are used to enhance the raw image by removing noise in it. In this paper filter is basically a combination of high pass and low pass filter which gives a good analysis of target images. As a first step RGB image of resolution 400×300 is captured and feed to filter after conversion into gray scale image. Gray scale image will help to reduce the computational time required because RGB is a three dimensional array of data while gray scale image is a two dimensional array. Ideally two dimensional low pass spatial filter acts as a smoothing filter which is mathematically represented in the following expression below

$$H(u,v) = \begin{cases} 1 & \text{if} \quad D(u,v) \le D_0 \\ 0 & \text{if} \quad D(u,v) > D_0 \end{cases}$$

Where D_0 represents nonnegative quantity and D(u,v) is the distance between origin of the frequency plane to the point (u,v). In case of two dimensional high pass filter D_0 is the cutoff distance between origin of the frequency plane while D(u,v) is the distance between origin and point at (u,v).

$$H(u,v) = \begin{cases} 0 & \text{if} \quad D(u,v) \le D_0 \\ 1 & \text{if} \quad D(u,v) > D_0 \end{cases}$$

Further modifications are made in order to get better results in weeds detection with the help of above mention high pass and low pass filters. Five different size of scale tested for weed detection and at the end best scaling factor selected before sending the image to the feature extraction section.

$$ha_{hor} = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} \qquad ha_{ver} = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix}$$

$$hb_{hor} = \begin{bmatrix} 1 & -1 \\ 1 & -1 \\ 1 & -1 \end{bmatrix} \qquad hb_{ver} = \begin{bmatrix} 1 & 1 & 1 \\ -1 & -1 & -1 \end{bmatrix}$$

$$hc_{hor} = \begin{bmatrix} 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & -1 \end{bmatrix} \qquad hc_{ver} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 \end{bmatrix}$$

$$hd_{hor} = \begin{bmatrix} 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & -1 \end{bmatrix} \qquad hd_{ver} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & -1 \end{bmatrix}$$

$$he_{hor} = \begin{bmatrix} 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & -1 \\ 1 & -1 \end{bmatrix} \qquad he_{ver} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 & -1 & -1 \end{bmatrix}$$

Fig. 9 Five scales of filter

Next step is to pass gray scale two dimensional arrays from filter to extraction function. Weeds are commonly classified in two types broad and narrow. Feature extraction unit is responsible to generate an output vector which shows the information about type of weed whether it is broad or narrow. Filter does not alter the size or data of the image it only remove the noise to it is difficult and time consuming to go through the whole image therefore the image is minimize by extracting the required area of interest in the image for further process in feature extraction algorithm. The feature extraction technique proposed in this paper is continuity estimation (CE). In this technique significant measure of continuity is done on neighboring pixel of the filtered image in straight line as shown in Fig. 10.

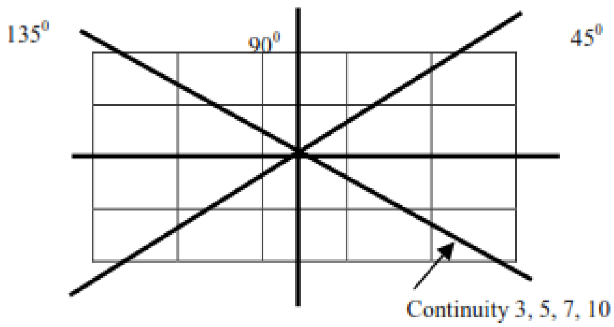

Fig. 10 Technique to measure continuity on filtered image.

The feature vector has different value for both types of weeds which is basically depends on the type of filter used at back end. The plot in fig. 11 show the feature vector values for two different types filters. Horizontal filter is low pass filter while vertical filter is high pass. It can be easily observed that the two types of weeds are grouped in clearly separated regions. This region can be theoretically determined by linear classification tool y = mx + c.

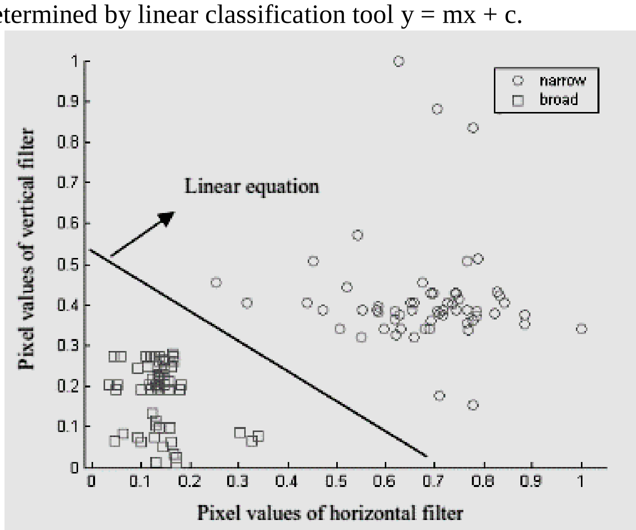

Fig. 11 narrow and broad class weed feature vector.

The above techniques discussed are software oriented. To implement the idea in real life these algorithms are interface with mechanical structure of robots with respond in according to signal received by feature extraction module along with navigational unit. An effective electric circuits are used to transfer information in robotic platform.

IV. RESULTS

To check the functionality of navigational unit image of cabbage field is used which is presented in Fig. 4. The image of resolution 400 * 300 is divided into 10 horizontal strips of size 400 * 30 pixels. Almost more than 50 images has been checked to verify the performance of feature extraction technique proposed earlier in the paper. The feature vector results from combined action of filters and CE are plotted in the graphs as shown below in fig.12 and fig. 13. Minimum error could easily be expected by using linear classification equations. The overall performance of the feature extraction technique is tabulated in the following Table 1 and Table 2.

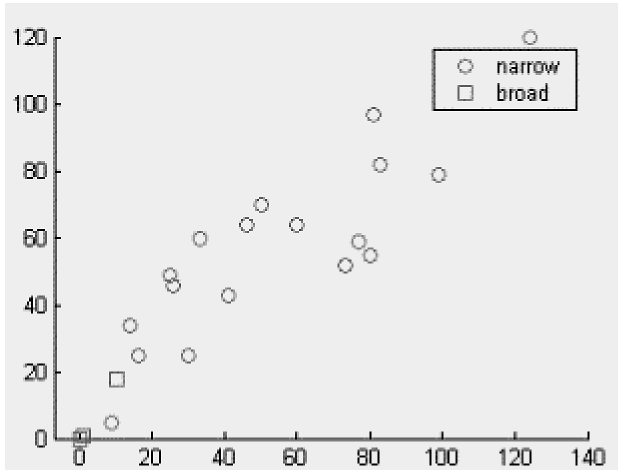

Fig. 12 Feature vectors of CE at scale a

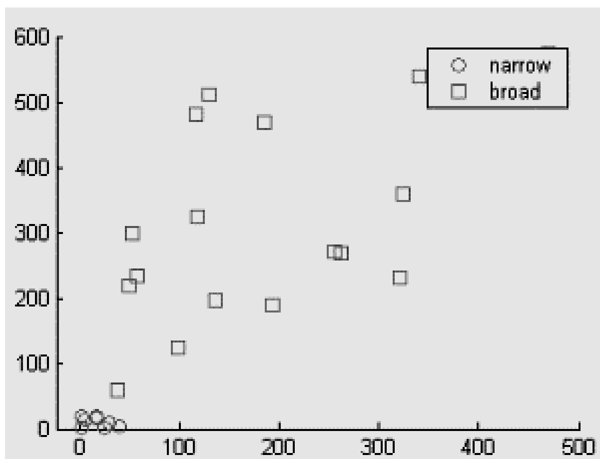

Fig. 13 Feature vectors of CE at scale b

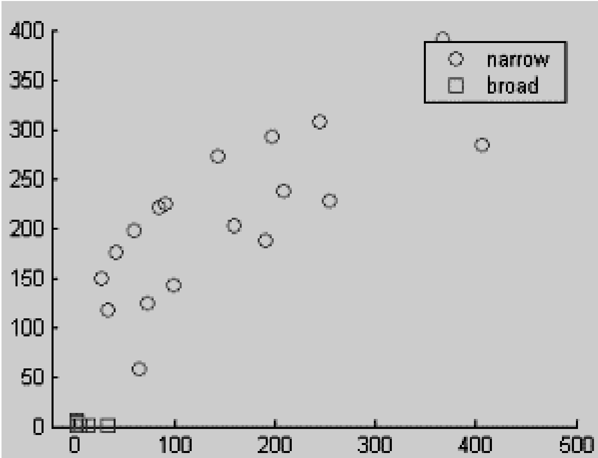

Fig. 14 Feature vectors of CE at scale c

Table 1. Classification rate between Broad and Barrow weeds for 0 degree and 45 degree continuity line

Vertical Horizontal	0 degree		45 degree	
	% of Broad	% of Narrow	% of Broad	% of Narrow
Scale a	39.7	38.7	81.3	80.4
Scale b	40.2	39.2	85.2	83.2
Scale c	41.8	41.1	86.3	88.5
Scale d	43.1	41.4	87.4	89.5
Scale e	44.6	42.3	87.9	89.1

Table 2. Classification rate between Broad and Barrow weeds for 90 degree and 135 degree continuity line

Vertical Horizontal	0 degree		45 degree	
	% of Broad	% of Narrow	% of Broad	% of Narrow
Scale a	60.6	64.5	72.8	71.2
Scale b	60.8	64.8	73.2	74.2
Scale c	59.7	65.4	75.4	75.8
Scale d	62.4	67.1	76.1	74.9
Scale e	63.6	68.4	78.3	75.3

V. CONCLUSION

While dealing with crops in which green color has dominance, the eq 1 2G-R-B gives a good quality gray scale image. In order to enhance the speed of processing gray scale is first converted into binary image, then spilt into horizontal strips and finally using grey level accumulation in vertical direction centers of the crops are extracted. Hough transform is used because is the robust algorithm which works in different environment effectively to detect rows. The Continuity estimation technique with angle of 45 degree and scale c has more success rate as compared to others in order to detect and classify weeds. Future work can be done on feature extraction or classification.

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