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A Vision System for Autonomous Weed Detection Robot

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***Abstract*—In this paper, a vision guidance system for automated weed detection robot is presented. The developed vision system use series of image processing techniques to detect the inter-row space between the crops and then calculate the current pose and orientation with the help of Hough transform. The dynamic model is used for evolution of values over time and to predict the changes in pose and orientation from frame to frame. The vision system is implemented and simulated in Matlab, and it is observed that the developed system successfully detects and calculates the pose and orientation of the crop boundaries on both real and synthetic images.**

***Index Terms*—weed detection robot, vision system, image processing, Hough transform**

I. Introduction

The economy of Pakistan is largely depends on agriculture. There is approximately 22.14 million hectares area under cropping in Pakistan [1]. During a past few decades, Pakistan has achieved notable agricultural growth. However, this agricultural growth lacks the organic approach in agricultural field, which is the primary concern today in agriculture. Organic approach is a minimization of the adverse impacts on the environments, by avoiding the use of material such as inorganic chemicals that impact on soil health, food safety, cause water pollution and increase population of healthy worms, and other soil organisms. The inorganic chemicals are mainly used to eliminate the weeds in agricultural fields and to increase and protect the crop production. The presence of weeds in agricultural fields has lead to competition between weeds and planted crops [2]. A weed is unwanted plants that limit the growth of the crop by blocking light or using up nutrients and space. Therefore, it is necessary to remove the weeds for better crop growth. The two widely used methods for weed control are chemical weed control and non chemical weed control. The first method is a chemical weed control that use herbicides for immediately eliminated the weeds without replication. It requires less energy input however, the excessive use of herbicides also effects the environments. The second method is a non-chemical weed control that use thermal and mechanical technique for organic food production [7]. All these methods require labors for hand weeding which is expensive, exhausted and often difficult to obtain. Therefore, it is required to develop a system that can automatically detect and control the weed. Due to the recent advancement in technologies, the application of AGV in agriculture, gained tremendous attention [3]. Different autonomous vehicles and guidance algorithms have been developed for agricultural applications [5]. Besides their efforts, the applications of autonomous vehicle for agriculture research is mostly limited to autonomous tractor control and very less work have been done for weed detection and control application. The vision system developed so far for inter row guidance relay on multiple sensor configuration, and the robustness of the system depends on sensor performance [4], [6]. In addition, the image processing techniques used for guidance are computationally expensive or they required supervisory input for automatic guidance [11].

In this paper a vision guidance system for a weeding detection robot is presented. The objective is to enabling the weed detection robot to navigate autonomously between the inter-row spaces of crop for automatic weed control, reduce labor cost and time. The vision guidance system use model based approach and series of image processing techniques that are not only computationally inexpensive, it also provide robust detection and tracking of the inter-row spaces. The main components of the develop vision system are the modified parameterized Hough transform and the dynamic model. The parameters calculated using the Hough transform use for pose and orientation calculation of an autonomous vehicle. The dynamic model is used to evolution of values over time and to predict the changes in values from frame to frame.

The rest of the paper is organized as follows: section II will discuss the Scene model for the navigation purpose. Section III will present the various components of vision systems. Section IV discusses the results and finally section V end the paper with conclusion and future works.

II. Scene Model

The tracking or guidance of any object can be categories either feature based approach or model based approach. The feature based approach utilize feature such as color, edge, landmarks, corner etc., for the tracking purpose. This technique may fail if the features change due to occlusions

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and noise. On the other hand, model based approach based on the prior knowledge of the scene. Model based approach use 2D projection model like straight lines, parabolic curve, or spline model of 3D scene. It requires few features and the extracted features such as edges are match with the scene model for the tracking purpose. In this way, model based approach are more robust against noise, occlusion and missing data and hence selected for navigation of autonomous vehicle. The perspective view of the agricultural field is shown in Fig. 1. This perspective view used as a reference scene model and the measurement obtained using the vision system will be compare with this reference model. If the robot is centered with respect to the left and right crop boundaries and facing forward, θ1 will always less than 90 and θ2 will always greater than 90 along the x-axis in anti-clockwise direction? Where Dr is a distance between the crop boundaries. The distance D_r can be calculated using the equation 1.

$$|D_r| = \rho_1 - \rho_2 \qquad (1)$$

where ρ_1 and ρ_2 are the position of the left and right crop boundaries respectively. The tracking parameters θ and ρ are calculated using the Hough transform and will discuss section III.

III. Vision System

This section will discuss the developed vision system for weed detection robot. Fig. 2 outlined the components of the developed vision system. The brief discussions on these techniques are as follows.

The first stage in any vision-based system is the image acquisition. In this paper, still images from the open sources are used as shown in Fig. 3a [8]. Conventionally, the autonomous vehicle equipped with color camera that can provides color information relative to the local object. Colors are very important feature and used to discriminate between crops, weeds and soil. Color segmentation technique is used next to classify the soil and crop by their color difference in RGB color space. The goal of color segmentation is to provide a partially processed image that includes only crops and soil information. K-mean clustering algorithm is used to perform the color segmentation. To improve the clustering result and reduce the fine details in an image the Gaussian filtering is used. The Gaussian filtering reduces the details in an image by applying the image blurring operation.

After image filtering, the RGB image is converted into the CIELAB space, and then a and b components of the CIELAB space are used for the clustering. The K-mean distribution is used to calculate the segmentation image. The k-mean algorithm uses a two-phase iterative algorithm for minimizing the distance between the members of an output set within the space of the entire data set. To optimize the speed and the processing, the number of iteration is set to 3. The result of the k-mean algorithm is shown in Fig. 3b.

After segmenting the image, ROI is used to restrict the image processing and to reduce the processing time. This ROI selection is set automatic as shown in Fig. 2. Once the crop boundaries have been detected using the Hough transform, the image processing is restricted to the ROI. If the

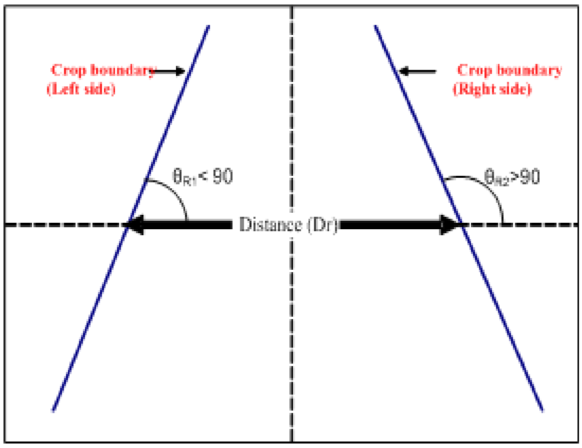


Fig. 1 Perspective view of 2D model of 3D scene

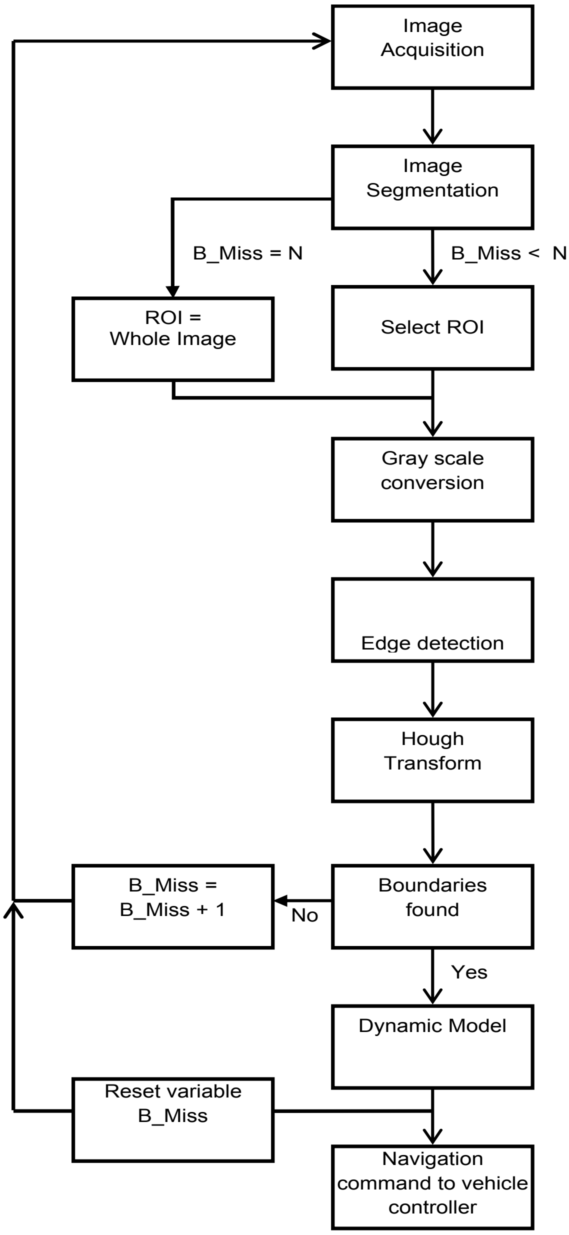


Fig. 2 Flow diagram of the vision system

Figure 3: (a) Crop field image

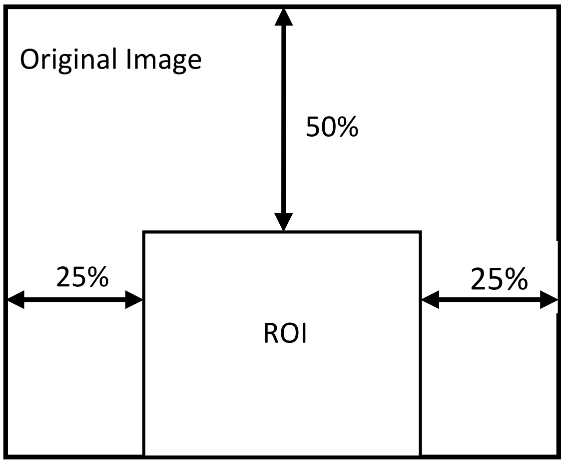


Figure 4: Automatic ROI Selection

Figure 3:(b) Color segmentation using k-mean algorithm

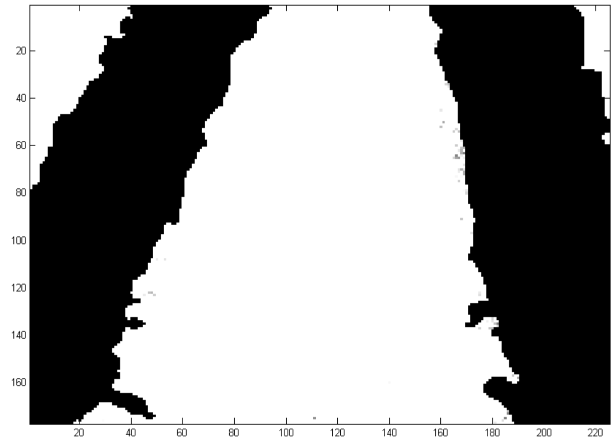


Figure 5: Gray scale conversion on ROI image.

selected ROI does not contain the crop boundaries and the Hough transform fail to detect boundaries N times than the ROI is widen to the whole image. The term B_miss in Fig. 2 refer to the boundary miss and the *N* is set to 5. The ROI is set to 50% to the center bottom of the image and shown in Fig. 4.

After ROI selection, the image is converted into the grayscale as shown in Fig. 5. Grayscale images are typically stored with 8 bits per sampled pixels, which shrinks the number of operation by two third and further simplifies the image processing step. This grayscale conversion is performed using the Intel image processing formula and shown in equation 2.

$$Y = 0.212671R + 0.715160G + 0.072169B \qquad (2)$$

After converting the image into the grayscale, edge detection is performed. To optimize the processing speed and better edge information, Sobel edge detection is used. The Sobel edge detection is computationally simple and easy to implement. The vertical and horizontal Sobel gradient operator is used to perform a spatial gradient measurement in two dimensions. Both gradient operators are slightly modified for better edge calculation and shown in Fig. 6. Finally, the edge detection result is shown in Fig. 7.

To obtain the tracking parameters, parameterize Hough transform is executed [9]. The tracking parameters are (θ_1, ρ_1) and (θ_2, ρ_2) which represent the orientation and position of the crop boundaries with respect to the image center. The Hough transform used is optimized for speed by processing the 1000 edge pixels at a time. After transforming the edge pixels in Hough space, peak detection is performed and all the immediate neighborhood of the maximum found are suppressed to zero. Once sets of candidate peaks are identified in the accumulator, start and end points of line segment associated with those peaks are identified. Two line segments associated but separated by less than predefined gap threshold, are merged into a single line segment. Furthermore the lines that have both θ and ρ parameters within the predefined threshold are also merged to avoid multiple line on the same locations. The start and the end points of line segments computed in this step represent the outline of the crop boundaries. Fig. 8 shows the result of all three steps of Hough transform.

-2	0	2
-5	0	5
-2	0	2

(a)

2	5	2
0	0	0
-2	-5	-2

(b)

Figure 6: Sobel edge detector a) Vertical Sobel Mask
b) Horizontal Sobel Mask

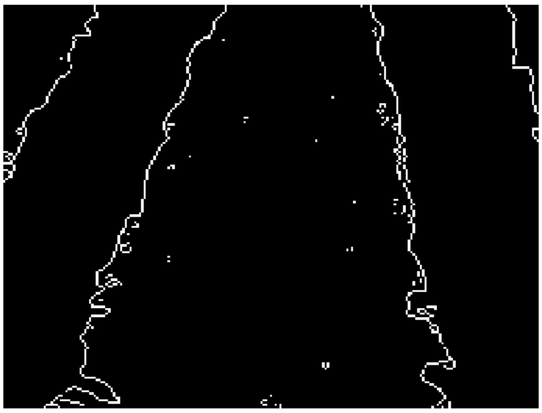
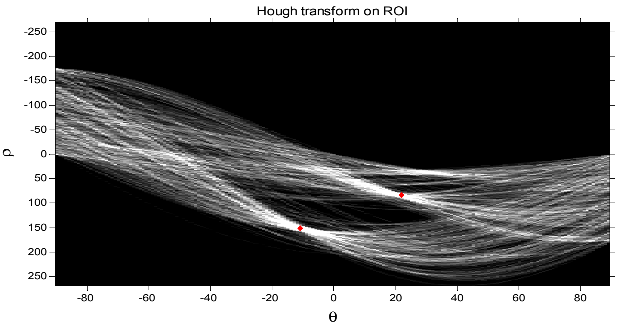
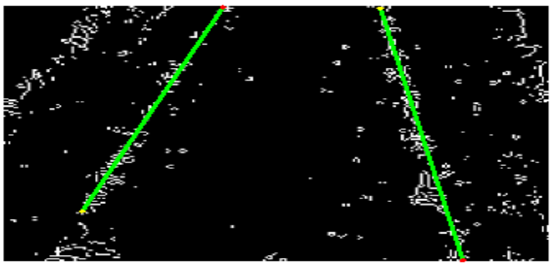


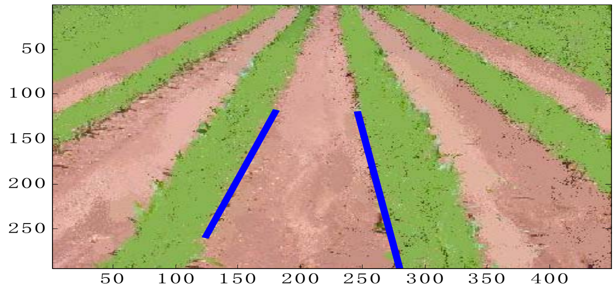
Figure 7: Edge detection result using Sobel edge detector on ROI image Mask.



(a)



(b)



(c)

Figure 8: Steps of Hough Transform

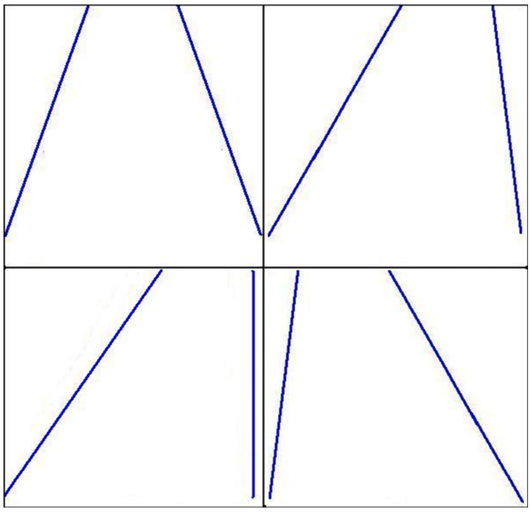
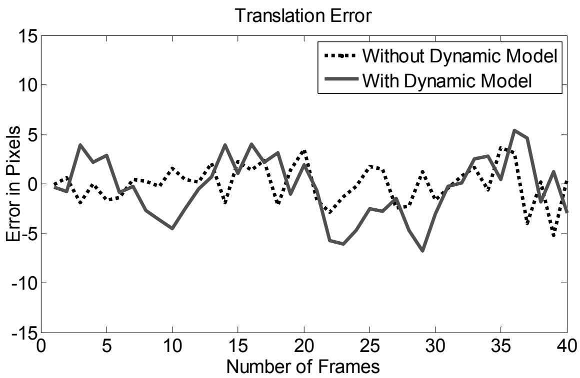
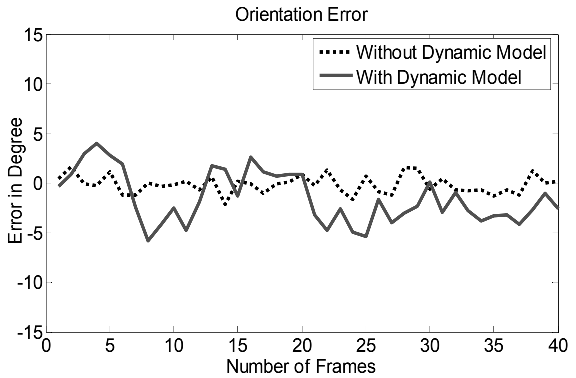


Figure 9: Various scenarios of the crop field



(a)



(b)

Figure 10: Tracking Results (a) Translation Error, (b) Orientation Error.

Once the tracking parameters are calculated, the goal is to guide the weed detection robot in autonomously following the crop boundaries. It required some mechanism to relate the position and orientation of the crop boundaries to the vehicle. The scene model described earlier is used as a reference position and orientation of the vehicle relative to the crop boundaries. It is desirable that the vehicle maintain the position into the center of the crop boundaries. This reference position can be calculated by using the equation 3.

$$P_R = D_r/2 \tag{3}$$

where D_r is the reference distance of the crop boundaries as shown in Fig. 1. Once the reference position is calculated, the parameters ρ_1 and ρ_2 are used to calculate the current position of the vehicle. The current position of the vehicle relative to the crop boundaries is shown in equation 4.

$$P_C = | \rho_2 - \rho_1|/2 \quad (4)$$

The current displacement of the vehicle with respect to the reference position can be calculated using equation 5.

$$T_X = P_C - P_R \quad (5)$$

It is obvious that the positive value of T_X refer to the vehicle as it translates to the right and negative means that vehicle is translating toward the left side.

Similar to the translation measurement, the reference orientation of the vehicle is measure using the scene model. The reference orientation angle θ_R can be calculated using the equation 6.

$$\theta_R = (\theta_{R1} + \theta_{R2})/2 \quad (6)$$

It is observe from the various scenarios of the crop boundaries as shown in Fig. 9 that the reference orientation θ_R is always approximately equal to the 90. The required orientation of the vehicle refers to the crop boundaries are calculated using the equation 7.

$$\theta_X = min(\theta_R - \theta_1, \theta_2 - \theta_R) \quad (7)$$

The minimum value for orientation is select to avoid any big change in one time step. Once the translation and orientation of vehicle with respect to the reference are measured, the vehicle has aligned and orientated itself in crop field. The weed detection vehicle subsequently starts moving in the crop field and begins autonomous navigation.

After calculating the tracking parameters, dynamic model is used to expect the tracking behavior over time. Accurate modeling of the target dynamics can improve the prediction of the location of the target while visual support is insufficient due to occlusion, noise, or visual clustering. In this work, autoregressive process is adopted to model the motion of the vehicle with respect to the crop boundaries in an image sequences. Autoregressive process is a time series modeling strategy that takes into account the historical data to predict the current value. In this model, the current value only depends on the previous states with a deterministic mapping and stochastic disturbance. The simplest autoregressive model is the linear model with the assumption of the constant velocity with respect to the object. Equation 8a and 8b describe the second order autoregressive model for weed detection robot as [10]:

$$T_{X(t)} = T_{X(t-1)} + (T_{X(t-1)} - T_{X(t-2)}) + b\varepsilon_t \quad (8a)$$

$$\theta_{X(t)} = \theta_{X(t-1)} + (\theta_{X(t-1)} - \theta_{X(t-2)}) + b\varepsilon_t \quad (8b)$$

where T_X and θ_X are the translation and orientation of the vehicle respectively, b is the regression coefficient and ε_t is the stochastic disturbance.

IV. RESULTS & DISCUSSION

This section present the results obtained from the developed vision system for the weed detection robot. Although the results of individual image processing components are already presented, this section provides the results of tracking and navigation of the vehicle in the inter row space of crop field. The vision system is implemented in the MATLAB and executed without the code optimization. To check the robustness of the tracking system, synthetic images are used. These synthetic images are not lengthy due to the impossibility of finding long sequences, they contain wide range of scenarios and conditions of the crop field. The output of the vision system has not used to correct the vehicle's course, instead the vision system is tested to calculate the tracking parameters T_X and θ_X, required to generate the navigational command for the vehicle. Fig. 10a and Fig.10b show the result of the tracking system with and without the dynamic model. It can be observed from Fig. 10 that the tracking without the dynamic model shows minim error compare to tracking with the dynamic model. The reason of high error using dynamic model is the stochastic drift. However, this stochastic drift required to predict the position of the vehicle refer to the crop boundaries. If the tracking system fails to detect the crop boundaries, the boundaries position and orientation is predicted using dynamic model. However, if the system fail to detect the crop boundaries B_Miss = N times then the image processing is performed on whole image. Fig. 10a and Fig. 10b also shows that the overall error of the tracking within the envelope of ±5 pixels for translation and ±5 degree for the orientation. These value shows that the proposed tracking system can effectively track the crop boundaries for weed detection robot.

V. CONCLUSION & FUTURE WORK

In this paper, a vision system for weed detection robot is presented. The developed vision system autonomously guides the vehicle between the inter-row space of the crop field for the weed detection. The weed then can be destroy either by using the control spray of herbicides or by using the thermal or mechanical technique. The control spray of herbicides significantly improves the organic approach in the agricultural field. In addition, it reduces the labors cost and save the significant time. The developed vision system successfully detects and tracks the crop boundaries and the errors on synthetic images are less than ± 5 pixels for translation and ± 10 degree for the orientation. The error can further reduce by using the appropriate estimator such as Kalman filter and particle filtering algorithm.

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