A Vision System Based Crop Rows for Agricultural Mobile Robot

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***Abstract*—In a machine vision-based autonomous navigation system for agricultural field mobile robot, obtaining guidance information from crop row structure is the key in achieving accurate control of the robot. This paper presents a new method for robust recognition of plant rows based on the Hough transform. It used a camera to find a path from structured agricultural fields to automatically navigate a mobile robot following crop rows. Firstly, the camera calibration was applied to obtain the relationship between the image coordinates and the world coordinates. Secondly, pattern recognition and image processing were used to obtain quasi navigation baseline. And lastly, the real navigation line was extracted from quasi navigation baseline via Hough transform. Experimental results indicate that this method has a simple robust algorithm, low-level requirements for software and hardware, and ultimately can meet the requirement for agricultural robot's works in the field.**

Keywords- machine vision; camera calibration; Hough Transform (HT)

I. INTRODUCTION

Potential benefits of automated agricultural mobile robot include increased productivity, increased application accuracy, and enhanced operation safety. So a number of different sensor methodologies have been proposed or developed for agricultural machine guidance [1].

However, the guidance researches of agricultural mobile robot mainly concentrate on both machine vision and Global Positioning System (GPS) which are of the most promising methods [2, 3]. In contrast to a real-time differential global positioning system (RTD-GPS), Machine vision is cheaper and has a higher precision. Furthermore, machine vision can provide local or relative information. So machine vision guidance is used in this project.

For a farmland's vision information, in general, crop rows are approximate straight lines and parallel each other. Thus, the crop rows can be used for mobile robot baselines. These baselines can be described by $y = kx + b$ [4]. In fact, they are often called quasi-lines. That's to say, they don't mean real straight lines, because these baselines are approximate straight lines which formed by lots of dots. What's more, some segments of them may be blurry or disconnected.

The main objective of this research is to look for a novel method for robust recognition of crop rows based on Hough transform that is able to navigate agricultural mobile robot effectively.

II. MATERIALS

- *Hardware:* Daheng DH-CG300 Image Acquisition Card; KOKO color CCD camera, the focal length of the camera lens is 16cm; mobile vehicle; computer (PentiumⅣ 1.8GHz CPU, 256M RAM.)
- *Software:* Microsoft Visual C++ 6.0; the platform SDK (Software Development Kit) of DH-CG300 Image Acquisition Card

III. CAMERA CALIBRATION

A. Test Platform

Camera calibration can be considered as a preliminary step for most application in computer vision. The purpose of it is to establish a mapping between the camera's 2-D image coordinate and a 3-D world coordinate system so that a measurement of a 3-D point position can be inferred from its projections in cameras' image frames.

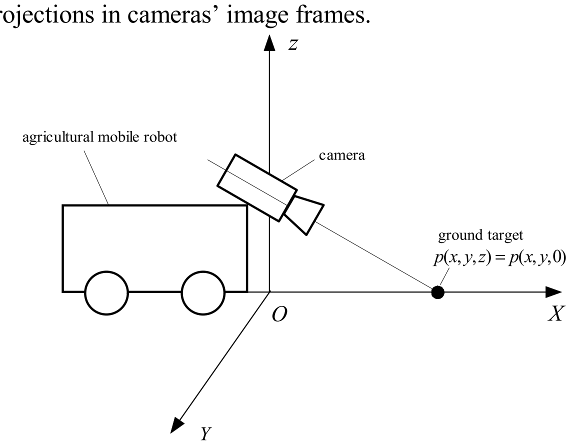


Figure 1. The world coordinate system and a ground target: $O - X - Y - Z$ is the robot coordinate system; $p(x, y, 0)$ is a ground target in the world coordinate system.

In order to localize and navigate the robot using the vision information, the camera has to be first calibrated. The camera is fixed on the top of the robot, and pointing to the ground. The camera calibration is a process that models the relationship between the 2D image coordinates and the 3D reference coordinates Because agricultural robots often operate in farm field with limited elevation changes, it is acceptable to simplify the model from a 3D space to a 2D plane (as shown in Fig. 1) to reduce computational load. We can calibrate the camera using 2D image coordinates and 2D world coordinates.

B. The General Imaging Model of a Camera

The common foundation of the optics triangulation is the theory of the geometrical optics imaging. The camera is used as the eye of a machine, through which realize the mapping from world coordinates to image coordinates (on pixels). Pinhole camera model is shown in Fig. 2.

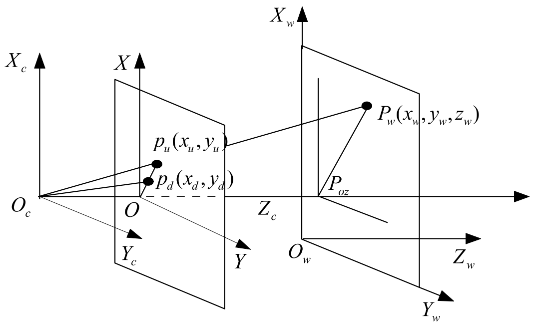


Figure 2. The geometric relation between an object point and its 2D image projection

An object point $p_w(x_w, y_w, z_w)$ is first transformed from the world coordinate system to the camera coordinate system $p_c(x_c, y_c, z_c)$, whose Z_c-axis and origin coincide with the optical axis and optical center of lens, respectively. This transformation of an ideal camera is formulated by

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{d_x} & 0 & u_0 \\ 0 & \frac{1}{dy} & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} \quad (1)$$

$$= \begin{bmatrix} \alpha_x & 0 & u_0 & 0 \\ 0 & \alpha_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} = \mathbf{M}_1\mathbf{M}_2\mathbf{X} = \mathbf{M}\mathbf{X}$$

Where s is proportion coefficient, α_x, α_y, u_0, v_0 are internal parameters of a camera, $\mathbf{R}$, $\mathbf{t}$ are external parameters, $\mathbf{M}$ is a 3×4 matrix, $\mathbf{0} = (0,0,0)^T$ [5]. As we know, using more than 6 given points in space and their image pair-point coordinates, we can get projection matrix through least square method, accordingly get all internal and external parameters.

IV. NAVIGATION BASELINE EXTRACTION

A. Image processing

The digital camera was mounted 1m above the ground and was set 15° downward in order to sample the field image over a wide field of view and to decrease the effects of the background. At the same time, the focal length of the camera lens, 16cm, kept unchanged. Fig. 3a was sampled in early autumn, when the soybean was in an early stage.

In this study, the image processing adopted the following five steps: grey-level transform; OTSU binarization; main crop row's choice; and edge detection.

1) Grey-level transform

Considering the image information between green crop and background have a great difference in green color, we used the '2G-R-B' method to increase green portion, and sequentially separated each other. The principle is shown as follows:

$$pixel(x,y) = \begin{cases} \mathbf{0} & \mathbf{2G} \le R+B \\ 2G-R\text{-}\mathbf{B} & \textbf{\textit{others}} \\ \mathbf{255} & \mathbf{2G} \ge R+B+255 \end{cases} \quad (2)$$

Where $pixel(x,y)$ is the gray value of $po\mathrm{int}(x,y)$ in the gray image, confined to [0, 255]; R,G and B are the red, green and blue values of $po\mathrm{int}(x,y)$ in the color image respectively.

In the resulting image the green crops appear bright in contrast to a dark, almost uniform background where the soil surface, including shadows, stones, straw, etc. has disappeared. This image is well suited for identification of crop. Fig. 3a is a colour image of soybean crops. Fig. 3b is the result of grey-level transform.

2) OTSU binarization

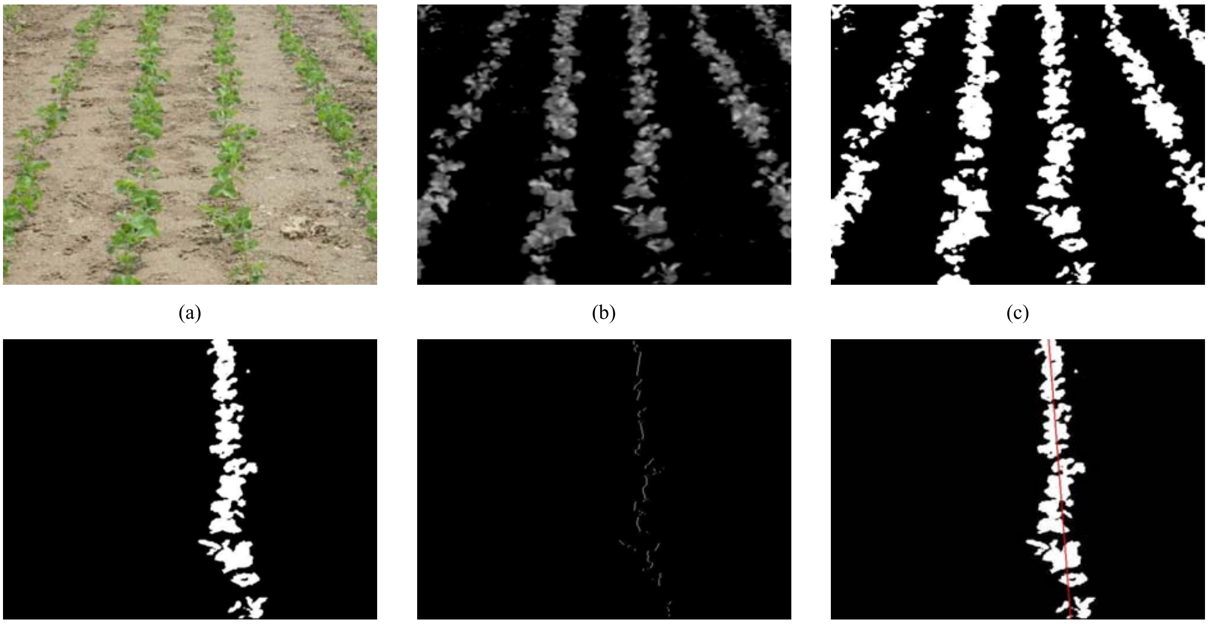
Among the global thresholding techniques, the Sahoo et al. (1988) study concluded that the OTSU method (OTSU, 1979) was one of the better threshold selection methods for general real world images with respect to uniformity and shape measures. The basic principle of OTSU is looking for an optimal threshold value to divide gray-level histogram of an image into two parts on the condition that between-cluster variance is maximal. Fig. 3c showed the result of binarization with OTSU algorithm.

3) Main crop row's choice

From Fig. 3c, we can see several of crop rows are segmented. In fact, one of crop rows is enough to navigate for agricultural robot. Here, the vertical projection method is used to obtain the main crop row [6]. Fig. 3d is the result of processing.

4) Edge detection

We may regard the pixels which gray change from 0 to 1 or 1 to 0 as the left edge or right edge. Without losing generality, the left edge extraction was utilized in this system, as shown in Fig. 3e.



(a) (b) (c)

(d) (e) (f)

Figure 3. Result of image processing

B. Hough transform

In order to obtain the true navigation baseline from quasi navigation baseline, Hough transform was employed in this paper. In Hough transform, each point in a curve votes for several combinations of parameters; the parameters that win a majority of votes are declared the winners. Let us consider the equation of a straight line:

$$y = kx + b \tag{3}$$

In the above equation, x and y are observed values, and k and b represent the parameters. If the values of the parameters are given, the relationship between the coordinates of the point is clearly specified, Let us rewrite the above equation as

$$b = -xk + y \tag{4}$$

Where k and b are variables of interest, and x and y are constants. The equation (3) represents a straight line in the $k-b$ space. The slope and intercept of this line are determined by x and y. A point (x, y) corresponds to a straight line in $k-b$ space. This mapping is shown in Fig. 4.

In practice, the polar form of the line is used rather than the explicit form to avoid problems with lines that are nearly vertical. Then points (x, y) are mapped into the (ρ,θ) parameter space. The mapping equation can be expressed with equation (5):

$$\rho = x\cos\theta + y\sin\theta \tag{5}$$

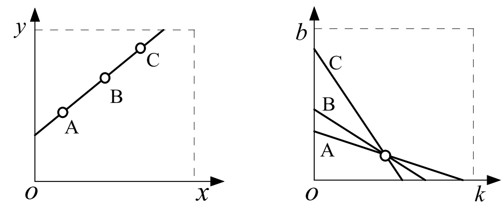


Figure 4. Image-to-parameter space mapping of a point in the Hough transform.

The detailed algorithm of Hough transform works as follows:

Step one. Construct an accumulator array. For straight line detection, the HT maps each edge pixel (x, y) from the image space into a parameter space of (θ,ρ), where contributions from each feature point to each possible set of (θ,ρ) are accrued. For this purpose the parameter space is divided into cells with each cell corresponding to a pair of quantized (θ,ρ). An accumulator array is often used to represent the quantized space.

In this system, for each edge pixel (x y), vary θ from -90° to 90° and calculate $\rho = x \times \cos\theta + y \times \sin\theta$. The total quantizing dots are units of $\theta \times \rho$. Coordinate of each cell array is (θ,ρ). At the beginning, all cells are initialized by 0.

Step two. Scanning the whole binary image, if the current pixel is black, the corresponding elements in accumulator array add 1.

Step three. Scan the accumulator array and search the peaks in accumulator array. The peaks correspond to the parameters of the navigation baseline.

Fig. 3(f) was the real navigation baseline after Hough transform.

C. Path designing [7-9]

When the mobile robot moves, the controller can obtain real-time navigation information after Hough transform and also get position information from the pose sensor on the wheel, so the system regards the vision information as a norm, matching with pose information. When they both match well, the controller make no adjust. As long as both of them do not match with each other any more, according to the deviation angle $\triangle\theta$ and the deviation distance $\triangle\rho$, the system quickly adjusts the pose of robot and guarantee it move forward along the navigation baseline.

V. DISCUSSIONS

Camera calibration had a good result on the condition that the agricultural robot moved in a smoother field. When the field is uneven, the calibration result is unstabilized.

If the rows and inter-row spaces could be segmented clearly, the quasi navigation baseline could also be detected easily. If the field had narrow inter-row spaces or as the crop grew, the rows became overlapped and more and more canopies grew together. This made it difficult to reliably separate from background. As a result, the navigation parameters (deviation distance and deviation angle) would have a bigger error.

VI. CONCLUSIONS

A novel method for robust recognition of crop rows based on Hough transform which would be able to guide agricultural mobile robot was presented. The system is not restricted to a specific crop (such as soybean) and has been tested on other green crops. We presented a new way of modeling the plant rows. The Hough space representation proved to be suitable to obtain navigation parameters in a computationally efficient way. After examination in a laboratory and field, results show that this method can attain navigation parameters in real time and guide the mobile robot effectively.

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