International Journal of Natural and Engineering Sciences 5 (2): 15-18, 2011
ISSN: 1307-1149, E-ISSN: 2146-0086, www.nobel.gen.tr

Development and Evaluation of a Guidance-Assistant Algorithm for Agricultural Tractors in Plowing Operation

Sajad KIANI[1]* Saadat KAMGAR[1]

[1]Agricultural Machinery Engineering Dept, Shiraz University, Shiraz, IRAN

*Corresponding Author
e-mail: kiani.sajad@gmail.com

Received: January 21, 2011
Accepted: January 30, 2011

Abstract

This paper describes a robust procedure to obtain a guidance directrix for agricultural tractors in plowing operation with the wide toolbar. The automatic steering algorithm controls the vehicles based on the position of the trajectory results of previous operation on the field. Hough transform method was adapted to process forward view images of a vehicle captured by a digital camera installed at 1.1m height and angle of 35o respect to line of travel. The contrast between disturbed soil and undisturbed soil was the basis for detection of the last track of the machine. This algorithm was tested in the various situations including various illumination conditions and various plant residues. The position of the detected line respect to the furrow was measured by algorithm. The methodology devised to overcome the image noise problems and to be able to determine the proper trajectory for the tractor. The algorithm was able to find the trajectory with high accuracy. Maximum deviation of the detected line from the desired trajectory was measured up to 1.72cm. The suggested algorithm is able to assist the operator during manual guidance of wide plowing tools.

Keywords: Automatic Guidance, Tillage, Hough Transform, Machine Vision.

INTRODUCTION

Potential benefits of automated agricultural vehicles include increased productivity, increased application accuracy, and enhanced operation safety. This paper addresses the problem of assisting the guidance of a tractor in order to control the distance between contiguous passages of work in the tillage operation. Different methods have been studied for automatic guidance for off-road vehicles such as agricultural machines, using a combination of existing solutions including global positioning and computer vision [2,5].

Bell et al. [1], one of the most common types of navigation sensors is the global positioning system (GPS). For example, a four-antenna real-time kinematic-GPS (RTK-GPS)-based navigation system developed that could guide an agricultural tractor following desired paths with a tracking accuracy of 0.04–0.06 m at normal field operating speeds.

To compensate for GPS positioning error associated with machinery attitude, Kise et al., [3,4] integrated an inertial measurement unit (IMU) with an RTK-GPS to provide more accurate navigation information. This integrated navigation system could guide agricultural machinery performing all field operations, including planting, cultivating, and spraying, at a travel speed of up to 3m/s, with a tracking error of less than 0.05m on both straight and curved paths.

Wilson et al. [9], a number of image processing techniques have been investigated to find the guidance course (directrix) from row-crop images. As examples, Machine vision technology can be used to automatically guide a vehicle when crop row structure is distinguishable in a field. Typical applications include guiding a tractor for row-crop cultivation, or guiding a combine for harvest operation. The guidance sensor, i.e., the camera, is a local sensor because only the relative location of the vehicle, with respect to the crop rows, can be determined. Machine vision guidance has the advantage of using local features to fine-tune the vehicle navigation course. It has the technological characteristics closely resembling those possessed by a human operator, and thus has great potential for implementation of a vehicle guidance system.

Tillett et al. [8] describe a vision system for guiding hoes between rows of sugar beet. Image acquisition is done using a camera with near infrared filter. A band pass filter extracts the lateral crop row location at eight scan bands in the image. The position and orientation of the hoe with respect to the rows is tracked using an extended Kalman filter.

Søgaard and Olsen [7] mounted a camera on a hand-operated vehicle and later on a weeder to evaluate the precision of an algorithm based on image analysis. The camera height was of 1.15m and the inclination of the optical axis on the vertical of 56°. The images were also divided into band strip, which were mathematically 'enrolled'. The centre of gravity gave the position and an estimation of the relative accuracy. A weighted linear regression gave the position of the rows. The mean position returned by their algorithm (trueness) was centered with the reference trace, with no statistical differences. The standard deviation (precision) was below 5 mm in the centre of the image and about three times higher under the camera (this was 1.73m at the rear of the image centre). The working speed was of 0.4m/s.

The aim of this algorithm was to detect a trajectory in field for help the operator to guide the vehicle in plowing in order to give more attention to the control of other functions. To reach this aim, a visual perception of the environment was used because this method of sensing gives a solution well-adapted to many situations.

METHODS and MATERIALS

Image Acquisition

Images of the filed were acquired by a camera during tillage operation (whole tillage period) (plowing) Fig.1. However, as the soil has to be sufficiently dry to able to disturb, the weather was always clement. Sunny conditions and drying soils were most encountered. An inexpensive universal serial bus (USB) camera Logitech Quick Cam was used. It was color mono-charge-coupled device (CCD) camera and was a fixed aperture for the USB camera and the aperture of the lens of the camera was set manually. This camera is able to capture digital images with a resolution of 1600×1200 to 320×240 pixels, at a rate of 30 images per second. The digital images were stored as 24 bit color images with a size of 640×480 pixels and saved in RGB color space in the JPG file format. The camera were placed looking downwards, with their optical axis making an angle of 35◦ with the horizontal, in the forward direction. The distance between the ground and the camera was of 1.1 m. The camera was plugged on the USB port of the computer. The programs used for the images treatments were written in MATLAB 7.7 (Math Works, 2008) and then converted to C++ for reducing the processing time.

Pre-Processing and Filtering

The three dimensional image taken by the monochrome CCD camera is converted into a two-dimensional array of pixels, with each pixel represented by a gray level (GL) between 0 and 255. In a typical image scene, the brighter pixels with higher GL represent undisturbed soil and plant residue, and the darker pixels with lower GL represent disturbed soil. Real images of field of view will inevitably contain noise and many parameters, such as the lighting (direct sun or light diffused by clouds, elevation of the sun) and various plant residues change the luminance and the contrast in the image. In image processing it is usually necessary to perform an image enhancement and a high degree of noise reduction in an image before performing processing steps such as edge detection. Image enhancement was done by using point operation. In these images powering was sufficient. The Gaussian filter is a linear filter that is usually used as a smoother. The output of the Gaussian filter at the moment t, is the weighted mean of the input values, and the weights are defined by Equation (1):

$$G(x, y) = e^{-(\frac{x^2+y^2}{2\sigma^2})} \tag{1}$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution, Fig.1. b. shows the results of image enhancement and filtering on GL image.

Point Encoding

The number of pixels used to identify a trajectory is often too high for efficient application of the Hough transform. The objective of edge detection was to substitute the GL image to the binary edge map of image. Indeed, in the detection of trajectory, variations in the soil relief induce differences in the irradiance and consequently clods or tillage furrows add high uncertainty. An edge detector (The Sobel edge detector) was used for data reduction to facilitate further processing. The sharp edge placed

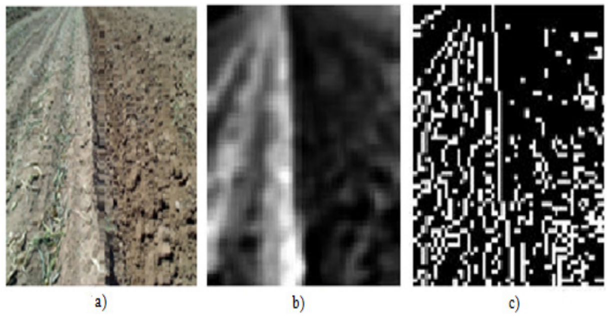

Fig.1. a) Original image with the size of 60*50 pixel, b) image after converting to GL image, applying image enhancement and Gaussian filter and c) point coding by applying Sobel edge detector and getting edge map

approximately at the edge of the trajectory, because it had a high frequency variation, and other edges were boundary of low frequency variation. The Gaussian filter was used to remove all tiny edges in edge map before applying edge detector to reduce processing time of Hough transform. Fig.1 shows the edge map of image after applying median and Gaussian filter.

Detection of the Furrow

The Hough Transform

The Hough transform is widely used for localization of linear objects (straight lines) in images [6]. Such noise will cause some points to be located at a distance from the center of the imaged trajectory. Typically these points, known as outliers, are a constant source of error when a regression analysis is applied to find pathway in a field using machine vision. The Hough transform is quite robust against 'noise' and missing parts, no matter how far it is from the expected position and does not affect the Equation of the line. Rather it is classified as noise and neglected (the result of the algorithm is only slightly sensitive to imperfect data or to interferences). But limitations can be encountered when the 'noise' becomes important compared with the contrast of the objects and when lures are present in the images.

Fundamentals of the Hough Transform

The Hough transform is a non-linear transformation in which, for every pixel (X,Y) of an image, the parameters ρ *and* θ are computed, according to the Equation (2).

$$\rho = X\cos\theta + Y\sin\theta \tag{2}$$

Where X and Y are the position, given in Cartesian coordinates, of the transformed point (white pixel) in the image space, and ρ *and* θ are the parameters represented in the Hough space. The representation of a line by the Hough transform is a mathematical expression where the parameters do not represent physical objects or distances. Unlike X and Y, which carry direct location information within the image, ρ *and* θ do not provide any feature that can be identified in the real scene. The conversion to the ρ *and* θ eases the data processing but, once the calculations have been completed, a back transformation to X and Y coordinates is required.

To perform the transformation effectively, it is necessary to set a boundary for the parameters that define the Hough space and to allocate the required memory. In the image space, X and Y rage from 0 to a maximum value set by the image resolution: 640 for the X coordinate (now denoted X_{dim}) and 480 for the Y coordinate (denoted Y_{dim}) in the present application.

In the parameter space, every line is identified by a unique pair ρ *and* θ. In order to cover the whole range of pixels of the selected portion of the image, the parameter θ must span between $-90°$ *and* 90, whereas ρ will be included in the interval $[-\rho_{max}, \rho_{max}]$. The largest value of ρ, denoted ρ_{max}, can be determined by maximum ρ in Equation (2) as:

$$\frac{\partial \rho}{\partial \theta} = 0 \Rightarrow -X_{dim}\sin\theta + Y_{dim}\cos\theta = 0 \tag{3}$$

Where X_{dim}=640 and Y_{dim}=480 in the situation considered here. The value of θ that produces the maximum ρ denoted θ_m is:

$$\theta_m = \arctan\left(\frac{Y_{dim}}{X_{dim}}\right) \tag{4}$$

Substituting Equation (4) into Equation (2) yields the maximum value of ρ given by:

$$\rho_{max} = X_{dim}\cos\theta_m + Y_{dim}\sin\theta_m \tag{5}$$

An equivalent result can be found based upon geometrical considerations and is:

$$\rho_{max} = \sqrt{X^2{}_{dim} + Y^2{}_{dim}} \tag{6}$$

Where X_{dim} and Y_{dim} are set by the resolution of the image.

The transformation was conducted by applying Equation (2) in the range from $-90°$ *and* 90 with 2^o increments for θ. Plotting the different values of ρ a sinusoid was obtained for very pixel transformed. This transformation method was developed on the basis of the principal that, if points are aligned, all the sinusoids will cross in one single point of the parameter space. The crossing point, denoted by the parameter pair (ρ_L, θ_L) in Equation (2) and solving for Y and is:

$$Y = \frac{\rho}{\sin\theta_L} - \frac{\cos\theta_L}{\sin\theta_L}X \tag{7}$$

In theory, all the points in a row will be collinear, and therefore their sinusoids in the Hough space will meet at one crossing point, whose coordinate in the Hough space will lead to the searched line. Fig.2 graphically illustrates this concept.

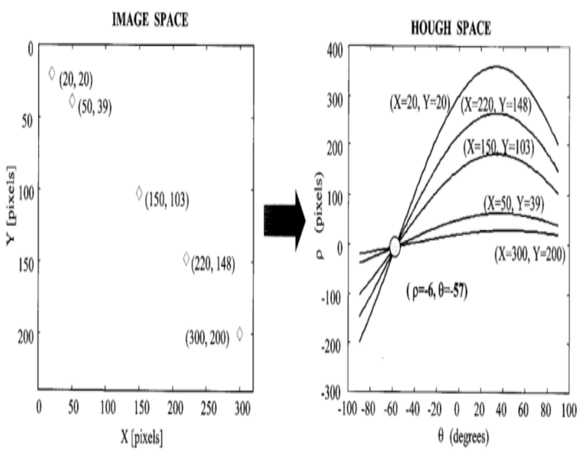

Fig.2. Hough transform for line detection

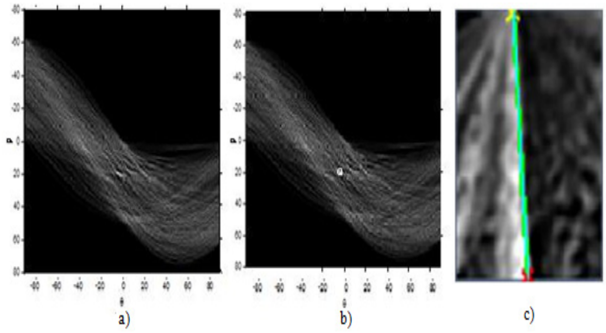

Fig. 3. a) Hough space, b) high picks in Hough space that represents a straight line in the image space (c) detected line of trajectory

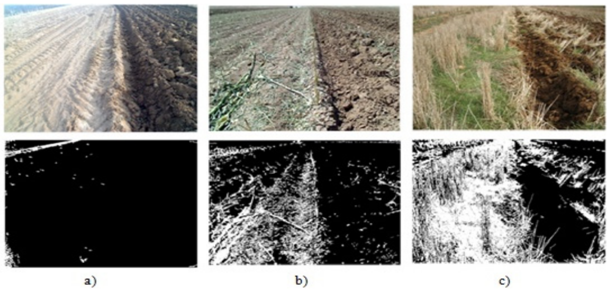

Fig. 4. filed images with a various Plant residue, a) 9%, b) 24% and c) 50% of image area

The outcome from the point encoding operation is a series of points that are somewhat collinear but not aligned in a perfectly straight line, as in the ideal case shown in Fig. 2. As a result, that points yielded by the Hough transform have a cloud-shaped distribution in the parameter space. A high probability that points are aligned is indicated by multiple sinusoids crossing at a specific point and creating certain heavier areas in the parameter space; these areas contain the potential lines. A vote accumulator approach, in which one vote is added every time that a sinusoid crosses a certain location, is used to determine the best estimated cross point of a trajectory in the Hough space. High peaks in the Hough space will represent straight lines in the image space. Connectivity analysis was used to reduce the number of redundant lines yielded by Hough transform analysis. After the Hough space was thresholded, each remaining pair ρ, θ represents a line in the image space. Close points represent similar lines, which in most cases means that the points (pairs (ρ, θ)) identify the just one trajectory. Since the goal is to obtain only one line for each trajectory, neighboring pixels were fused to obtain the best estimation of the sought-after line. Fig. 3 shows results of Hough transform on image of plowing operation.

The Reference and The Measurement

A disturbed soil was formed by the plow, one sharp edge almost vertical and close to the bottom of the furrow, while the other edge was more flared. The camera was located above of the furrow (in this state the furrow is in the center of image). Since a furrow is not necessarily symmetric the position of the trajectory was superimposed at the bottom of the image (at the beginning point of the line detected by Hough transform). The centre of the image is defined as the reference line or target line. The Line Predicting Error (LPE) or the difference between the furrow (center line of image) and the point (beginning of the line) detected by Hough transform were then calculated. The data were measured in pixels but translated in mm.

Table 1. Results of LPE on various plant residues and various illuminations

Fewer residues (9%)			Normal residue (24%)			High residue (50%)			Plant residue
Morning	Noon	Evening	Morning	Noon	Evening	Morning	Noon	Evening	Various illuminations
6/1	72/1	6/1	44/1	52/1	6/1	52/1	7/1	6/1	Mean error (cm)
39/1	34 /1	197/1	1	22/1	232/1	10/1	2 3/1	12/1	Standard deviation

Table 2. shows the analysis of variance of various plant residues and various illuminations on LPE

Source	Sum of Squares	df	Mean Square	F	Sig
Light	2.541	2	1.270	2.789	0.064ns
Residue	0.363	2	0.181	0.398	0.672ns
Light * Residue	0.081	4	0.020	0.045	0.996ns
Error	82.000	180	0.456		
Total	126.152	269			

RESULTS and DISCUSSION

Evaluation of the Algorithm

To validate the algorithm of trajectory detection developed here, laboratory evaluation were carried out to support the development of this method in the early stages of this project, as well as to search for the optimal settings of system parameters. All laboratory tests used image of the actual trajectory scenes recorded by the tractor traveling in the field. One hundred images were acquired. All these images were recorded with the same CCD camera that was installed on the testing tractor, in the various situations including various illumination conditions and various plant residues. All the images were analyzed, one line was found and the position of the detected line respect to the furrow (here is center line of image) was measured by algorithm. Fig.3 illustrates a typical example of this first type of result.

Effects of Various Illuminations and Various Plant Residues

Effects of two factors, plant residue (green and white plant residue on filed) Fig.4 and various illuminations (morning, noon and sundown) for 30 images that randomly selected were tested.

The LPE was measured by the algorithm in pixels but was translated in mm. TABLE I shows the mean error of detected line for 30 images and TABLE II, shows the analysis of variance of effects of various plant residues and various illuminations on LPE.

It can be seen in TABLE II that there is not a significant difference between various illuminations condition and various plant residues at 0.05 significant levels. In fact these results show the robustness of the algorithm in trajectory detection.

CONCLUSION

Working on new equipment increases agricultural productivity, safety and reduces the difficulties of human tasks. A guiding-assistance algorithm for agricultural vehicles in tillage was developed. The adapted Hough transform was applied on grey level images for the detection of lines or alignment clusters.

This method showed one maxima in the Hough space while the classical method gave one local maxima for each line or for each alignment. These maxima presented a good contrast in most conditions. The algorithm utilized the image output from a camera mounted directly above the furrow. The algorithm was evaluated and results show that the algorithm was capable of accurately locating the trajectory in the images. Maximum deviation of the detected line from the desired trajectory was measured up to 1.72cm. The suggested algorithm is able to assist the operator during manual guidance of tillage tools.

REFERENCES

[1] Bell T. (2000). Automatic tractor guidance using carrier-phase differential GPS. Computers and Electronics in Agriculture, 25(1–2), 53–66.

[2] Jahns, G. (2000). Special Issue: navigating agriculture field machinery. Computers and Electronics in Agriculture, 25,1–194.

[3] Kise, M., Noguchi, N., Ishii, K. and Terao, H. (2002). The development of the autonomous tractor with steering controller applied by optimal control. Proceedings of Automation Technology for Off-Road Equipment, Chicago, USA, pp 367–373.

[4] Kise, M., N. Noguchi, K. Ishii and H. Terao. 2001. Development of agricultural autonomous tractor with an RTK-GPS and a FOG. Proceedings of The Fourth IFAC Symposium on Intelligent Autonomous Vehicles, Sapporo, Japan, pp 99-104.

[5] Pilarski, T., Happold, M., Pangels, H., Ollis, M., Fitzpatrick, K. and Stentz, A. (2002). The Demeter system for automated harvesting. Autonomous Robots, 13, 9–20.

[6] Sonka, M ., Hlavac V. and Boyle, R. (1994). Image Processing, Analysis and Machine Vision. Chapman & Hall, London.

[7] Søgaard, H.T. and Olsen, H.J. (2003). Determination of crop rows by image analysis without segmentation". Comput. Electron. Agric. 38, 141–158.

[8] Tillett, N.D., Hague, T. and Miles, S.J. (2002). Inter-row vision guidance for mechanical weed control in sugar beet. Comput. Electron. Agricult. 33 (3), 163–177.2002.

[9] Wilson, J.N.(2000). Guidance of agricultural vehicles—a historical perspective. Computers and Electronics in Agriculture 25, 3–9.