2010 3rd International Congress on Image and Signal Processing (CISP2010)

Navigation Line Detection Based on Robotic Vision in Natural Vegetation-embraced Environment

Feng Gao, Yi Xun, Jiayi Wu, Guanjun Bao
Key Laboratory of Special Purpose Equipment and Advanced Processing Technology of Ministry of Education
Zhejiang University of Technology
Hangzhou, China

Yuzhi Tan
College of Engineering
China Agricultural University
Beijing, China

***Abstract*—In order to detect navigation line for agricultural vehicles in natural vegetation-embraced environment, a method was presented based on robotic vision. Firstly, an improved region growing algorithm was introduced to segment path. Then the two edges of path were extracted and an array of points through the center was computed. Lastly, the guidance line for vehicles to follow was obtained by Hough transform. The method was also extended to forestry environments and tall-crop fields where planting is discretely spaced. Difference was that the two edges of a path were square-fitted to offset edge imperfections. Batch processing of images under Matlab shows logicalness and steadiness of this method and its extensive appliance in various scenarios.**

Keywords- robotic vision; region growing; Hough transform; navigation line

I. INTRODUCTION

Satisfactory of steady recognition of paths that lead an autonomous vehicle in vegetation-embraced environments are usually lowered by the natural complex of the scenes such as fields and forests. Image segmentation is troubled by the noises from sunlight and shadow [1] [2]. Zhou proposed an extended FloodFill algorithm with a ring-style learning pattern of RGB features to archive region of interest (ROI) [3]. Zhang applied an improved mean shift algorithm to road segmentation [4]. Zhang and Du made a summary about visual information characteristics of a farm that ribbings, furrows and seedling lines on the well-structured field could be used as benchmarks for robotic guidance [5]. Therefore line detection methods are important to solve the key problem. Since point-line duality was introduced by Hough in 1962 to detect straight lines in an image, Straight-line detection has been applied to several fields such as robotics, remote sensing, and imagery [6].In one of the early implementations, Marchant and Brivot used the Hough transform for real-time row tracking [7]. Hough transform is also suited for situations where the crop stand is incomplete with gaps in the crop rows due to poor germination, insect damage or other factors that result in missing crop plants in the row [8][9]. B. Åstrand (2005) reported a robust recognition method of plant rows by fusing information from two rows or more based on Hough transform [10]. Sun analyzed natural cotton field images to study the feasibility of lane detection for agricultural robots, using Hough transform to locate guidance lanes [11]. Zhao developed fast detection of suspended furrows with advanced Hough transform of passing a known point as its candidate [12]. Hou modeled a weeding robot with its weed detection and navigation software in VC++. Image segmentation was done in RGB color space while crop lines were identified by Hough transform [13].

However, researches on path guidance for autonomous robots for robots to follow in other vegetation covered environments such as groves, forests and tall-crop fields are comparatively rare. Difficulty of identifying a possible lane in these scenes lies in discrete planting which breaks visual continuity of a row from overview and hampers path segmentation. In order to solve these problems, a method based on robotic vision was presented in this paper.

II. IMAGE SEGMENTATION

A. Studying Overall Image in Different Color Spaces

Color space is a useful tool to distill a color image into different layers like a spectrum splitting a drop of ray. An image is often set in RGB and HSI color spaces to help find which channel most distinctly shows the objective. We take scenario in a canal park (Hangzhou, China) for example and study the "path" in the two color spaces shown as Fig. 1.

Figure 1. Color channels under RGB and HSI Color Spaces. (with "a" to "f" respectively presenting R, G, B, H, S and I)

It's obvious that the paths are relatively clearer in channel B and S. Thus segmentation under either of the two channels could be properly easier.

B. Selecting Representative "Seed" of the Path

Traditional region growing method processes with a pre-acquired "seed" image. Therefore, initial image segmentation is needed and time of the growing operation is lengthened by huge seed amount.

We simplify the preliminary stage by selecting "seeds" directly from the color image. First, samples representing several path features are obtained by selecting windows shown as Fig. 2(a). These areas are chosen across the path-and-vegetation boundaries where drastic image intensity changes possibly happen according to the B or S channel split above. This helps decide value of the seed in order to completely segment the object "path" from its surrounding. Next, values of the selected seeds are quantified with a three-dimensional view of the sample area. We take the feature sample (L×L, pixel) in window 1 under S channel shown as Fig. 2(b). The 3D intensity map of the boundary between the path and its surroundings under S channel is evident like plateau and plain shown as Fig. 2(c), where "plateau" symbols the "path" and "plain" demonstrates the surrounding vegetation in accordance with HSI value ranges. Third, the 3D sample map is sliced uprightly along each pixel array to show every detailed plateau-and-plain in one plane layered with L pieces shown as Fig. 2(d). This left-view shows an array of curves characterizing the feature with a measuring scale and value of the seed could be limited in a belt Other 2 samples are analyzed in the same way and shown as Fig. 2(e) and Fig. 2(f), which illustrate similar result.

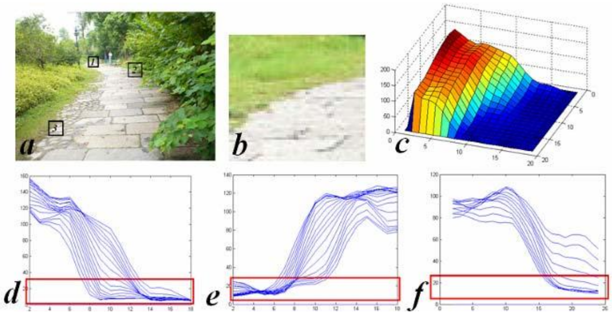

Figure 2. Preparation for region growing. (a). Windows selecting "path" features. (b). A magnified sample of feature 3. (c). Three-dimensional view of the sample. (d). Left-view of the 3D sample and the feature 1 "seed" value range. (e). Left-view of the 3D sample and the feature 2 "seed" value range. (f). Left-view of the 3D sample and the feature 3 "seed" value range.

C. Region Growing

The improved algorithm can be explained as the "seed tank" evolves into object-feature samples in the beginning and continues the growing routine. It is started with a false logical matrix G. Each growing process marks the pixel location of the original image with a True into a logical matrix S_i (i=1, 2,…, k), and perform exclusive-or with G and S_i as (1):

$$G=G \mid S_i \quad i=1, 2,\ldots, k \tag{1}$$

where k is seed-amount, G and S_i are the same size as the original color image. When i is equal to k, all of the selected features are manifested. Result of the 3-time growing of the full image is shown as Fig. 3. Obviously, visual satisfaction for robotic path guidance has been achieved early at the first growing operation, which means object features are similar; hence the seed amount could be reduced to save computing. Actually, in a monotonous vegetation scenario, a few seeds are enough to satisfy segmentation while complex scenes require more.

Figure 3. Complete region growing by the object-feature base. (a) 1st region growing. (b) 2nd region growing. (c) 3rd region growing.

A group of segmentations using the same "seed" are shown as Fig. 4. Results obtained report steadiness of the algorithm.

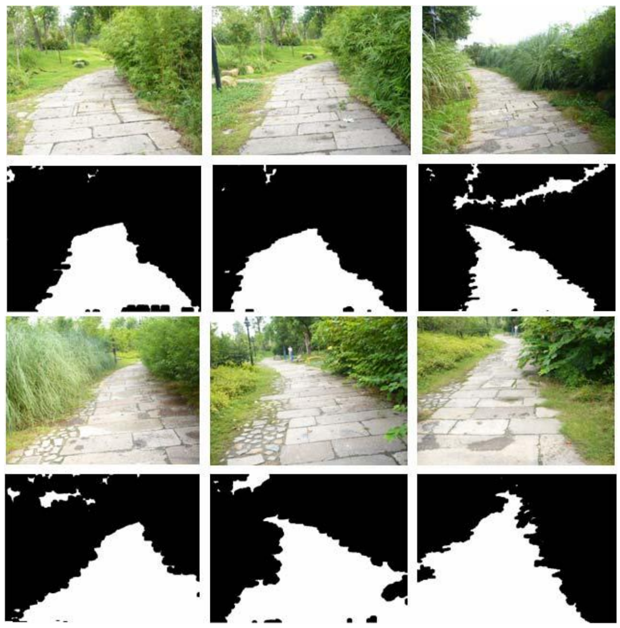

Figure 4. Path segmentation of images taken of a canal park

III. Generating Guidance Line by Hough Transform

A. Obtaining Path Information

Now the path has been separated, it's important to acquire edge information. Notice that there is remain of sky brim in upper part of the binary image. This is caused by the intensity closeness of path and sky which are not connected to each other. But processing followed is not disturbed by the incomplete segmentation. The two edges of a path are obtained by scanning the binary image pixel by pixel where "0" and "1" switch; the position couples (x, y) are memorized in empty arrays (X, Y) respectively. Then an array of points through the center is computed as candidates for the later Hough transform to detect a straight line among them. There is space between the remained sky brim and the vanishing point of the path, and this discontinuity can be harnessed to skip the unwanted part before scanning by just setting the start from the bottom line of this discontinuous belt with perpendicular boundary conditions of the binary image (m×n, pixel) which helps make automatic judgment. Besides, there are times when part of one or both path edge exceed(s) camera aperture. This is solved by defining a boundary parameter similar to the previous incomplete segmentation. Then the path edge scanning is stopped automatically when either side reaches camera aperture. This is to avoid misjudgments of the road side. A group of path edges and center point arrays through the center are shown as Fig. 5. Results above report robustness and logicalness of the method.

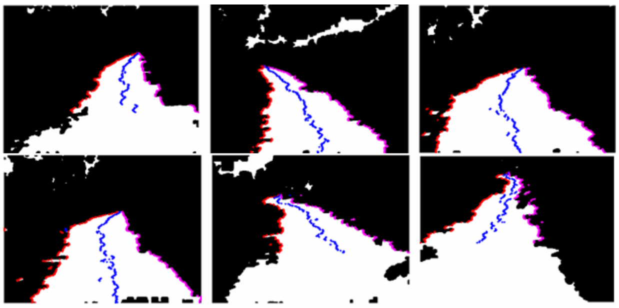

Figure 5. Path edges and point arrays through the center

B. *Line-detecting Out of Point Arrays by Hough Transform*

With the point array computed between the two path edges, information of the central winding lane is visible. The array is extracted then for Hough transform in the $\theta - \rho$ coordinates shown as Fig. 6(a) and (b). We set one peak in line detection to obtain a straight line as the robot's guidance lane shown as Fig. 6(c) and (d).

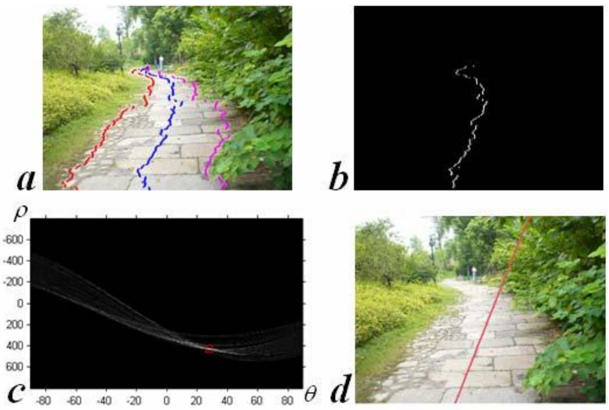

Figure 6. Process of guidance line generation. (a) Path edges and central point array. (b) Separated central array. (c) Hough transforming and peak detection. (d) A straight-line shaped as the guidance line.

Both Hough transforming and detecting process saves time because only the key points concerning the path are calculated as candidates to be operated. Theoretically peaks could be more with straight lines out of many curve segments as the road winds itself. Although it marks all guiding information in one image at once, turmoil comes when windings are several. Practically, only one peak is set to detect the longest lane visually nearby the camera sight, which conforms to perspective principles. A group of path edges and center point arrays with detection results are shown as Fig. 7.The results report steadiness and satisfaction of this algorithm, according to common sense of human vision.

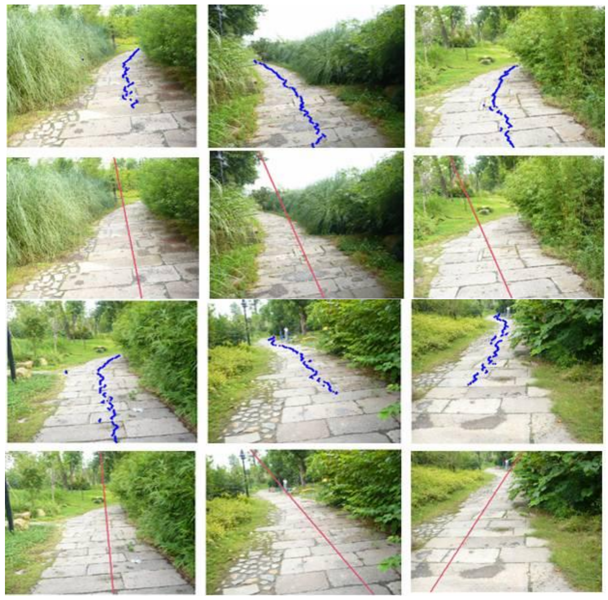

Figure 7. Point arrays through the center and path guidance lines

C. *Analysis of the Guidance Line in Steering Robots*

The path guidance line is to offer updated orientation data for the robot to adjust its steering. The two parameters of this guidance line, the guiding angle α (angle between the path guidance line and a vertical line) and the horizontal deviation e (distance between the path guidance line and central bottom line of camera aperture), are the key information shown as Fig. 8, with positive and negative symbols defining coordinates and angle.

Figure 8. The two parameters of this guidance line, the guiding angle and the horizontal deviation.

The relation between the path guidance line and the steering adjustment is as follow:

1) When $0° < \alpha < 90°$, it should steer towards the right;
2) When $-90° < \alpha < 0°$, it should steer towards the left;
3) When $e < 0$, it should move towards the right and
4) When $e > 0$, it should move towards the left.

Especially, when the path guidance line and the vertical line become one, it means the robot is currently in good position and needs no or little change of steering. Besides, e is much instructive when proportioned against the image width.

In some vegetation environments similar to the above park scene when plants are closely spaced, the algorithm can also be applied. Customized changes only occur in the segmentation stage. A group of path guidance line generating simulation in five scenarios taken of forestry areas in Longjing is shown as Fig. 9. Results of the same appliance in these scenes are rational according to human vision judgment.

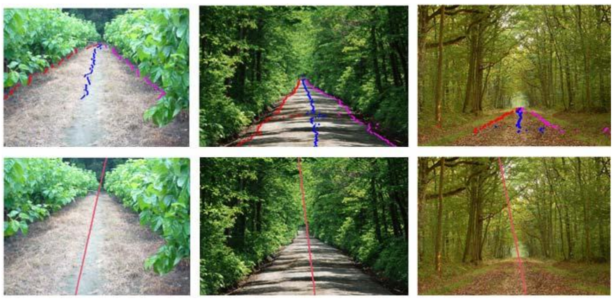

Figure 9. Path edges, central point arrays and path guidance line in scenarios

IV. Extention of the Algorithm in Forestry Scene

Other forestry scenes show no path themselves: discrete planting breaks visual continuity of a row from overview and hampers path segmentation, an example of a firry land shown as Fig. 10(a). Here the object is alternated to tree trunks with the same segmenting process shown as Fig. 10(b). The “path edge” here is actually shaped by intersection points of the trunks and the earth on both sides shown as Fig. 10(c). These positions are scanned and memorized as the method proposed before. Difference comes when path guidance line is generated. By square-fitting the two arrays of intersection points into straight lines, a splitting line through their space in the center is soon figured as the guidance line shown as Fig. 10(d). This alteration of the algorithm happens because the shape of intersection point arrays is improper for direct Hough transform.

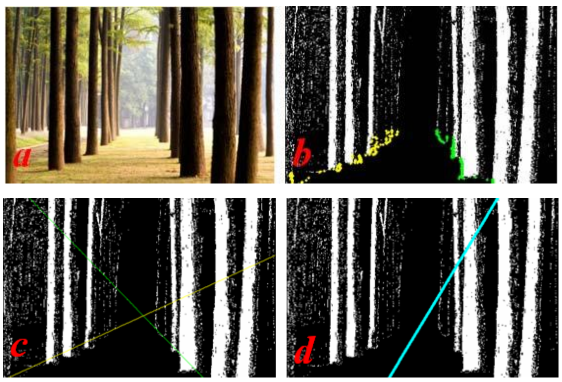

Figure 10. Guidance line of a firry grove. (a).A firry grove in a park, Tonglu, Zhejiang. (b). Intersection point arrays of trunks and the earth on both sides. (c). Square-fitted straight-lines. (d). A splitting line through the embraced space through the center as the guidance line.

The extensive use of the guidance line generating algorithm can also be applied to tall-crop fields much alike forest scenarios. A group of mulberry images are processed shown as Fig. 11.

Figure 11. Path guidance lines in a mulberry field

V. Generating Guidance Line by Hough Transform

A method for detecting navigation line for agricultural vehicles in natural vegetation-embraced environment was presented based on robotic vision. The followings were obtained.

(1) The improved region growing algorithm proposed to segment paths works steadily under the same environments and can be applied to similar circumstances.

(2) The guidance line generating algorithm by Hough transform works robustly in simulation. It can also be used to other scenes with a clear path insight.

(3) The algorithm, with some alteration, can be extended to scenarios where plating is discretely spaced. It gives reasonable results in both the forestry environment and a tall-crop mulberry field.

Future work will be focused on quantifying the relation between the path guidance line and the steering adjustment in practical robot’s driving system.

Acknowledgment

This work is supported by Key Laboratory of Special Purpose Equipment and Advanced Processing Technology of Ministry of Education, Zhejiang University of Technology. (2009EP025).

References

[1] Franke U, D.Gavrila, S. Gorzig, F. Linder, F. Puetzold, C. Wohler. “Autonomous driving goes downtown,” IEEE Intelligent Systems, November-December, 1998, vol. 13, pp.40-48.

[2] Goldbeck J, Huertgen B. “Lane Detection and Tracking by Video Senors,” IEEE/IEEJ/JSAL International Conf. Intelligent Transportation System, Tokyo, Japan, 1999, pp.74-79.

[3] P. Zhou, Q. Zhong, Y. Wang, Y. Zhou. “Fast segmentating ROI of field scenario based on RGB combination and bit-masked reduction”. Journal

of Nanjing University of Science and Technology (Engineering Science) 2007, vol. 41, pp. 656-660. (in Chinese)

[4] L. Zhang, X. Tian, W. Zhou, J. Liu. “Improved mean shift algorithm and its application”. Journal of Nanjing University of Science and Technology (Natrual Science) 2008, vol. 32, pp. 86-70. (in Chinese)

[5] W. Zhang, S. Du. “Hough Transform Applying in Vision Navigation of Farming Machine,” Chinese Journal of Scientific Instrument. 2005, vol. 26, pp.706-707. (in Chinese)

[6] S. El Mejdani, R. Egli, F. Dubeau. “Old and New Straight-line Detectors: Description and Comparison,” Pattern Recognition, 2008, vol. 41, pp.1845-1866.

[7] J.A. Marchant, R. Brivot. “Real-time tracking of plant rows using a Hough transform,” Real-time Imaging, 1995, vol. 15, pp.363-371.

[8] R.O. Duda, , P.E. Hart. “Use of the Hough transformation to detect lines and curves in pictures,” Commun. ACM, 1972, vol.15, pp. 11-15.

[9] S.W. Searcy, J.F. Reid. “Detecting crop rows using the Hough transform,” ASAE Summer Meeting, College Station Texas, 1986, pp.30-42.

[10] B. Åstrand. Vision based perception or mechatronic weed control. Doctor of Philosophy Thesis, Chalmers and Halmstad Universities, 2005, Sweden.

[11] Y. Sun, S. Zhang, W. Li. “Guidance Lane Detection for Pesticide Spraying Robot in Cotton Fields,” Journal of Tsinghua University (Sci & Tech), 2007, vol. 47, 206-209. (in Chinese)

[12] Y. Zhao, B. Chen, S. Wang, F. Dai. “Fast Detection of Furrows Based on Machine Vision on Autonomous Mobile Robot,” Transactions of the Chinese Society for Agricultural Machinery, 2007, vol. 38, pp.84-86. (in Chinese)

[13] X. Hou, Y. Chen, W. Guo. “Machine Vision-based Navigation for a Weeding Robot,” Transactions of the Chinese Society for Agricultural Machinery, 2008, vol. 39, pp.106-109. (in Chinese)