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A Novel Vision Based Row Guidance Approach for Navigation of Agricultural Mobile Robots in Orchards

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***Abstract*— This paper presents a novel vision based technique for navigation of agricultural mobile robots in orchards. In this technique, the captured color image is clustered by mean-shift algorithm, then a novel classification technique based on graph partitioning theory classifies clustered image into defined classes including terrain, trees and sky. Then, Hough transform is applied to extract the features required to define desired central path for robot navigation in orchard rows. Finally using this technique, mobile robot can change and improve its direction with respect to desired path. The results show this technique classifies an orchard image properly into defined elements and produces optimal path for mobile robot.**

Keywords- agricultural robotics; vision based navigation; image classification; mean-shift; graph partitioning; Hough transform

I. INTRODUCTION

Application of mobile robotic systems in agricultural tasks has been increasing vastly. These tasks including harvesting, weeding, spraying, transportation and etc. [1]. Many research has been done in the development of mobile robotic systems for greenhouses [2-3], orchards [4-5] and agricultural fields [6-7]. Path planning and navigation of autonomous mobile robots are one of the most important challenging parts for outdoor environment especially agricultural fields and orchards. This part is in charge of making the desired optimal path for robot to follow and effectively perform the agricultural tasks [8]. Machine vision applications in agriculture can be categorized in three main areas including noninvasive measurement, vision based navigation and behavioral surveillance [9]. Vision based navigation of agricultural mobile robots has had sufficient attention in many research in recent years.

The objective of this research is introducing a novel approach for navigation of autonomous mobile robots in orchards based on machine vision techniques. The output of this approach would be the optimal path extracted by Hough transform algorithm which is obtained from a classified color image. Classification stage includes clustering image by mean-shift algorithm and classification using a novel approach based on graph partitioning algorithm.

This paper is organized as follows. In section 2, the proposed approach is described in different stages. In section 3, experimental results and discussion on the proposed technique are presented and finally in section 4, the conclusion of whole paper is provided.

II. PROPOSED TECHNIQUE

This vision-based technique is based on feature extraction of a classified color image to determine the navigational path for a mobile robot in an orchard row. The algorithm consists following stages as shown in Fig. 1.

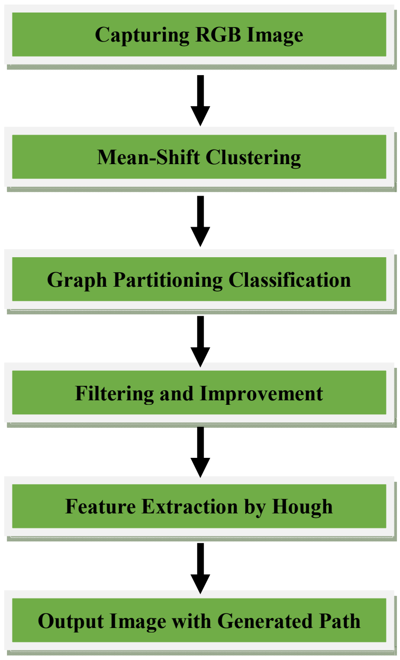

Figure 1. Flow diagram of the proposed approach

A. Image Acquisition and Laboratory Equipment

The images used in the experiments are collected randomly from internet for different environmental situation. The resolution of images are 640 × 480. The image processing

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computer is configured with Intel® Core™ i7-4770 CPU @ 3.40 GHz and 16 GB RAM memory. The simulation platform is Matlab R2014a.

Figure 2. A typical 640*480 size orchard image

B. *Clustering by Mean-Shift Algorithm*

Mean shift is one of the clustering algorithms which is based on operation in feature space. In this method, image is converted into feature space using a nonparametric kernel density function to model the features. Then clustering can be formulated by finding the modes density function and assigning each point to the specific modes [10]. For instance, to approximate the kernel density at point x in a dataset of $\{x_i\}_{i=1}^{n} = R^D$:

$$\hat{f} = \frac{1}{n}\sum_{i=1}^{n} K_H(x - x_i) \tag{1}$$

Thus the kernel density estimation would be:

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} k\left(\left\|\frac{x-x_i}{h}\right\|\right)^2 \tag{2}$$

And the mean shift vector is given by:

$$m(x) = \frac{\sum_{i=1}^{n} x_i k\left(\left\|\frac{x-x_i}{h}\right\|\right)^2}{k\left(\left\|\frac{x-x_i}{h}\right\|\right)^2} - x \tag{3}$$

The reason for clustering image is to reduce computational time by processing on clustered pixels instead of processing on each pixel. Image processing in this case is much more faster and efficient. The clustered output of typical orchard image from Fig. 2 by mean-shift algorithm is shown in Fig. 3.

Figure 3. Clustered image using Mean-Shift algorithm

C. *Classification Using Graph Partitioning*

The method for classification is based on [11] which we developed previously. There are several partitioning algorithm based on graph theory which spectral graph partitioning has attracted so many attention and successfully applied to many problems and applications including image segmentation [12-13], image retrieval [14], object tracking and recognition [15-16] and etc. In image graph partitioning, each pixel is considered as a node in graph network and the adjacent nodes are connected together by a link (edge). Each of the edges has a weight value which is obtained from a formula. This weight value defines similarity or dissimilarity between two nodes. Graph partitioning attempts to form graph nodes into groups with high similarity for intragroup and low similarity for intergroup nodes.

Having a graph $G = (V, E, W)$ where V is the set of nodes, E is the set of edges linked between nodes. W is the edges affinity matrix with $w(u,v)$ as the $(u,v)^{th}$ element [17]. Graph partitioning can be done on this network by several graph partitioning technique. The degree of dissimilarity between two sets of nodes which is needed to be partitioned can be computed as a total weight of the removed edges between two sets:

$$cut(A,B) = \sum_{e\in A, v\in B} w(u,v) \tag{4}$$

The minimum cut value is the best cut that can perfectly partition the graph into two disjoint regions. One of the spectral graph partitioning technique is Normalized Cut method. This technique partitions graph by considering the information of intragroup and intergroup nodes and is formulated as:

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \tag{5}$$

Where $assoc(A,V)$ is the total connection of nodes in part A to all the other nodes in graph and correspondingly the same for $assoc(B,V)$. Therefore, maximizing intragroup association and minimizing intergroup association can be obtained, but the partitioning process is a NP complete problem and requires approximation methods. Shi and Malik at [18] presented a good approximation solution for normalized-cut as a generalized eigenvalue problem.

The image classification using this partitioning technique is based on the approach we developed in [11]. This method is achieved by a change in Normalized Cut algorithm to have image classification instead of image segmentation. As it has been explained, the dissimilarity value w between nodes or clustered regions is defined by a formula. This formula uses the color space features of each node. Then weight matrix W can be computed for all nodes. The weight $w(u,v)$ between regions u and v is defined by:

$$w(u,v)=\begin{cases} e^{-\left[\frac{\|F(u)-F(v)\|_2^2}{d_I}\right]} & \text{if u and v are adjacent, otherwise} \\ 0 \end{cases} \quad (6)$$

Where $F(u)=\{L(u),u(u),v(u)\}$ is the color vector of node u in luv color space, and d_I is a positive scaling factor determining the sensitivity of the $w(u,v)$ to the color differences between u and v. In this case, graph partitioning gives image segmentation based on number of desired segments (i.e. $k=4$, k is the number of segmented regions).

If the adjacency condition does not be considered, then every node is connected by a weighted edge to all other nodes in the graph and the representation of graph will be a complete graph. So $w(u,v)$ and correspondingly the matrix W will be computed by:

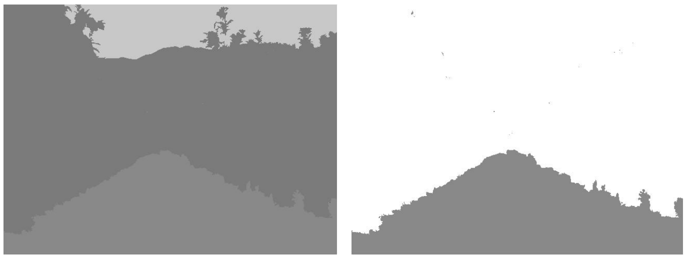
$$w(u,v)=e^{-\left[\frac{\|F(u)-F(v)\|_2^2}{d_I}\right]} \quad (7)$$

By applying this formula, it will give classification of image instead of segmentation. In this case, k is the number of desired classes. The classified orchard image is shown in Fig. 4. Generally, 3 classes are considered as terrain (brown), trees (green) and sky (blue).

Figure 4. Classified image using proposed classification technique

D. 2.4 Optimize Extraction by Filtering Operation

In this stage, some filtering operations are performed to optimize the classified image for better feature extraction by Hough transform. First, it is required to convert the classified image into a grayscale image. With grayscale image, it is easier to just pick the main class which is needed for feature extraction. The main required class is the terrain. That can be done by picking the bottom central pixel color (the location of robot) and compare with the other pixels and just keep the pixels which have the same color code. The results can be seen in Fig. 5.



a b

Figure 5. (a) Converted image to grayscale, (b) Filtered image for having the specific class which is required

Finally, it should be converted to a binary black and white image so it can be processed by Hough transform to extract the border lines between terrain and the trees. This can be done as edge detection on the image using canny filter to have the binary image as it is shown in Fig. 6.

Figure 6. Binary representation of classified filtered image

III. Feature Extraction by Hough Transform

Hough transform extracts the border lines between trees and terrain. Hough transform is a powerful feature extraction technique which basically extracts straight lines in an image by transformation between Cartesian space and parameter space [19-20]. The advantage of Hough transform is that the pixels should not be on one line and neighbors to detect the straight line. Thus, it can extract the lines very well which have breaks in them caused by noises.

The output result of Hough transform would be a two dimensional matrix with the parameters angle θ and displacement ρ, each on one dimension. Each element of matrix defines a value equals to number of points that are positioned on line with a specific angle, so the highest value will be the highest straight line which is surely the border line between terrain and trees. Results after applying Hough transform on orchard image is presented in Fig. 7.

Figure 7. Extracted border lines between terrain and trees by Hough transform

The generated central line can be considered as navigational path for robot from the central bottom point of image (the robot location) to the intersection of two extracted lines (Fig. 8). With the generated path and information provided by other sources (GPS, compass or other tools), mobile robot computes intermediate points to correct its trajectory and navigate itself in the orchard.

Figure 8. Optimal trajectory path from the centre of image (robot location) to the intersection point of two border lines.

IV. EXPERIMENTAL RESULTS & DISCUSSION

In this section, the experimental results are represented to evaluate the performance of the proposed technique for different environmental conditions.

In order to test the performance, tree images of different orchards with different types of environment has been processed and analyzed. The first one, is a well-structured orchard with soil type terrain (Fig. 2). The second image is an orchard with not regulated trees and also a grassy terrain (Fig. 9-a-1). The third image is an orchard with not well structured trees rows and also a fully grassy ground (Fig. 9-b-1).

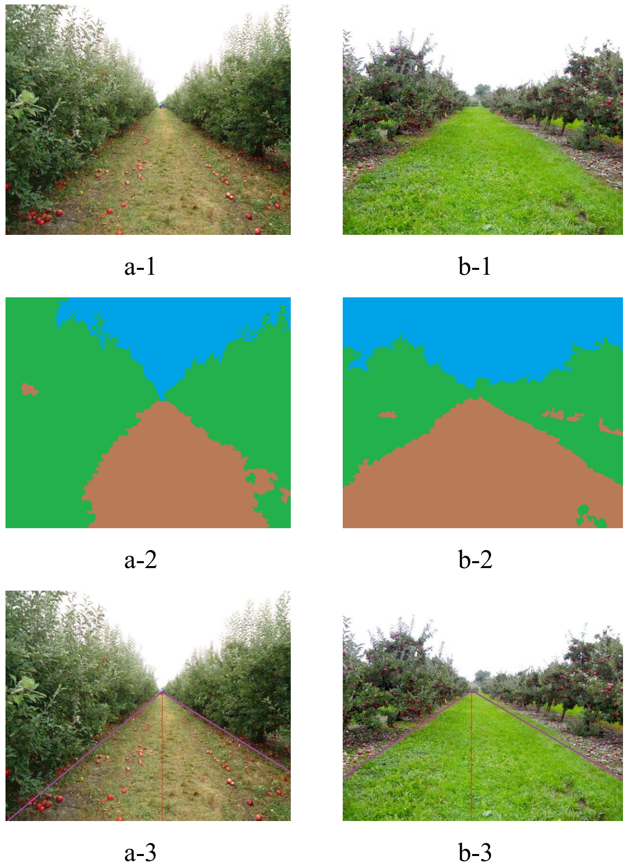


Figure 9. Experimental results on different orchard images

As it can be seen in Fig. 2, the results show that the proposed approach classifies the orchard elements in image (ground, trees and sky) very well (Fig. 4) and extracts the border lines between terrain and trees (Fig. 7) and finally generates the central line as the optimal path which robot should follow (Fig. 8). In second image, the classification is not as well as first image due to the orchard structure (Fig. 9-a-2). The classified image is filtered and optimized in filtering stage and then Hough transform extracts the border lines. As it is shown in Fig. 9-a-3, the generated central path is still very well. The third image, is considered as a not much well-structured orchard, but it is classified into the orchard elements well (Fig. 9-b-2) and by filtering process, it is possible to have the extracted path still fairly well (Fig. 9-b-3).

The proposed approach also has been compared to the technique developed by Torres-Sospedra and Nebot in [8]. In their approach, a color image of orchard is classified into orchard elements by a multilayer feedforward (MF) neural network. Extraction of desired path is done by Hough transform after some filtering operation. MF neural network provides better classification compared to our classification technique but classification based on neural networks requires training, validation and testing on different number of samples.

These stages especially training are time consuming and require several number of training data and patterns for each specific type of environment. Neural network classification is considered as a supervised technique while our approach for classification is unsupervised. Precision of feature extraction by Hough transform is directly proportional to the quality of image classification. The results from two approaches are shown in Fig. 10. Difference in classification provides different results for feature extraction.

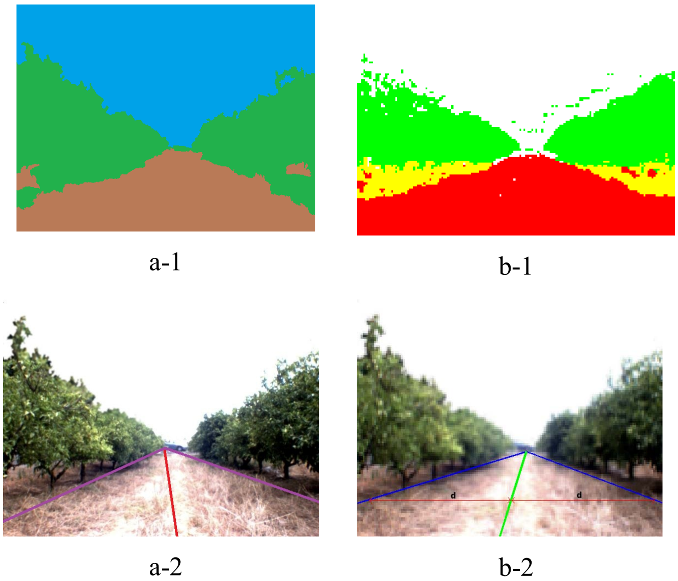


Figure 10: Comparing the results from our proposed technique (a) and the technique proposed in [8] (b).

As this paper introduces a novel approach, the results show effectiveness of the proposed technique in general to produce desired central path for navigation of mobile robots in orchards. It can provide better performance if the focus be on specific type of environment. This technique can be used as a complementary system to the other navigational systems such as LiDAR to provide a robust and reliable navigation system for mobile robots in orchards.

V. CONCLUSION

A novel vision based row guidance approach for navigation of mobile robots in orchards is presented in this paper. Image processing section includes mean-shift clustering and a novel graph classification approach which can perform classification very well. Hough transform is applied to extract the features of classified orchard image and finally generate the optimal path based on that. The experimental results show that the proposed technique is useful to apply on agricultural mobile robots. The future work will be focusing on improving performance and robustness of the technique for different orchard environments and also lighting variations.

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