Non-parametic Model for Robust Road Recognition

Zheng Tian, Cheng Xu, Xiaodong Wang, Zhibang Yang
School of Computer and Communication, Hunan University, Changsha, 410082, China
Email: jt.tianzheng@gmail.com

***Abstract*—Road recognition is one of the key technologies in the vision-based intelligent navigation system. In this paper, we present a novel non-parametric estimation model and a robust approach for the unstructured road recognition. The model keeps a set of sample for both road region and off-road region, and then estimates the probability of a newly pixel based on color information. For improving the real time capability and ruling out the interferences caused by variances of illumination and shadows, the image is divided into several small blocks, and a segment method is used to extract the lane boundaries from the mixed block areas. Finally, the boundaries of the lanes are fitted by the B-spline curve in which the best control points are searched by the least square method. Both field tests and simulation show that the proposed algorithm is effective and robust.**

Keywords-Intelligent navigation system; Unstructured road recognition; non-parametric estimation; Block-segment; B-spline curve

I. INTRODUCTION

Road recognition is one of the key technologies in the vision-based intelligent navigation system, which is recently the hottest research topic of machine vision. A robust road recognition algorithm can provide accurate road position and direction information for the navigation system. Currently, the researches for the structure roads have been highly developed, but the detection of unstructured roads need to be further studied, since the unstructured roads do not have obvious feature, and there exist a variety of interfering factors (such as light, shadow, etc.) from the external environment.

There are mainly two kinds of methods to deal with the detection of unstructured road: the feature-based method and model-based method. The feature-based[1,2] method obtains the road region by clustering or region growing approach based on the differences of gradient, color or texture between road region and off-road region. The main advantage of such kind of method is not sensitive to the shape of the road. But it is sensitive to the shadows, water areas and need more computational resources. The model-based[3] method begins with the hypothesis of the road model, and then matches the road edge with the road model. Such kind of method is more comprehensive, since only few parameters are needed to model the road edges, and it is more robust against noises, but the result of such method is dependent on the hypothesis of the road model, so they cannot fit to the situation that the shape of road changes greatly.

A good solution for unstructured road detection in non-homogeneous environment is to combine the two kinds of methods together[2-5], but how to achieve the trade-off between the complexity and robustness is a difficult problem. In this paper, we present a nonparametric technique for modeling the road and off-road. The approach is based on kernel density estimation of the probability density function which uses the color information of each pixel given a sample, and combines the both advantages of the feature-based methods and model-based methods. Field tests and simulation show that the proposed approach is effective and robust.

II. NON-PARAMETRIC ESTIMATION MODEL

The road recognition problem can be described as a process of image binarization. Each pixel in the image can be marked as road or off-road according to the binarization algorithms. An effective way to carry out the binarization process is to solve the probability density function (pdf) of each pixel in image based on the given sample sets of road and off-road. The methods to solve the pdf mainly include parameter estimation and non-parametric estimation.

Gaussian mixture model (GMM)[2,3] is the representative of the parametric estimation method for road recognition. This method is based on training samples. The road samples and off-road samples are selected firstly. Then the samples are classified by k-nearest methods[4], and each road class is identified by (m_r,C_r,N_r), where m_r represents the mean value of a sample set and C_r indicates how the individual colors elements are interrelated and the number of pixels is N_r. Then the Gaussian pdf and Bayes rule are used to calculate the probability that each pixel x in the image is from a road region or an off-road region. Previous works show that GMM based unstructured methods is effective in non-homogeneous environments where other algorithms fail, such as heavy shadow conditions, barriers on the road etc. However, such kind of parametric estimation method always needs to give a hypothesis that the data samples in each possible classification should be subject to a specific distribution, but sometimes the hypothesis is far from the actual physical model, so these kind of method do not always obtain satisfactory results.

Since these defects, Rosenblatt[6] and Parzen[7] proposed a non-parametric estimation method, the kernel density estimation. This method studies the characteristics of data distribution only from the data samples itself, and does not make any assumptions or use any priori knowledge about the data distribution. As its universality and robustness, the non-

This work is supported by the NSFC grant (No. 60973030) and the Unmanned Ground Vehicle project of Hunan University.

978-1-4244-5900-1/10/$26.00 ©2010 IEEE

parametric estimation is widely used in many statistical application fields.

To process road recognition using the kernel density estimation, let $X_1,\ldots,X_N$ be the recent road (or off-road) samples of color values (e.g. RGB values). Using these samples, the probability density function that each pixel in the image which has color value X_t at time t can be non-parametrically estimated using the kernel K_H as:

$$\Pr(X_t)=\frac{1}{N}\sum_{i=1}^{N}K_H(X_t-X_i) \tag{1}$$

If choosing the kernel estimator function, K_H, to be a Gaussian kernel, $K_H = N(0,H)$, where H is a symmetric positive definite d×d kernel function bandwidth matrix, and we assume diagonal correlation matrix H with a different kernel bandwidths s_j^2 for the j^{th} color channel, then the density can be estimated as:

$$\Pr(X_t)=\frac{1}{N}\sum_{i=1}^{N}(2\pi)^{-\frac{d}{2}}\left|H\right|^{-\frac{1}{2}}e^{-\frac{1}{2}(X_t-X_i)^T H^{-1}(X_t-X_i)} \tag{2}$$

Where d is the dimension of the kernel function. Using this probability estimate, we can respectively calculate the probability that a newly observed pixel value is from the road and off-road regions, the pixel is then considered as a road pixel if $\Pr(road|X_t)>\Pr(off\text{-}road|X_t)$, and vice versa. Practically, the probability estimation can be calculated in a very fast way using pre calculated lookup tables for the kernel function values given the color value difference, $(X_t - X_i)$, and the kernel function bandwidth.

To estimate the kernel bandwidth, s_j^2, for the j^{th} color channel for a given pixel we compute the median absolute deviation over the sample for each consecutive intensity values of the pixel. That is, the median, m, of $|x_i-x_{i+1}|$ for each consecutive pair (x_i, x_{i+1}) in the sample, is calculated independently for each color channel. Since we are measuring deviations between two consecutive intensity values, the pair (x_i, x_{i+1}) usually comes from the same local-in-time distribution and only few pairs are expected to come from cross distributions. If we assume that this local-in-time distribution is Normal $N(m,s^2)$, then the deviation (x_i-x_{i+1}) is Normal $N(0,2s^2)$. So the standard deviation of the first distribution can be estimated as:

$$x\approx N(\mu,\sigma^2)\Rightarrow x_i-x_{i+1}\approx N(0,2\sigma^2)\Rightarrow\sigma=\frac{m}{0.68\sqrt{2}} \tag{3}$$

Since the deviations are integer values, linear interpolation is used to obtain more accurate median values.

III. THE ROAD RECOGNITION APPROACH

In order to improve the real time capability and rule out the interferences due to variances of illumination and shadows, we propose a block-segment approach based on kernel density estimation for detection road regions and use the B-spline curve model for fitting the boundaries of the road lanes. We describe the details of the proposed approach in the following.

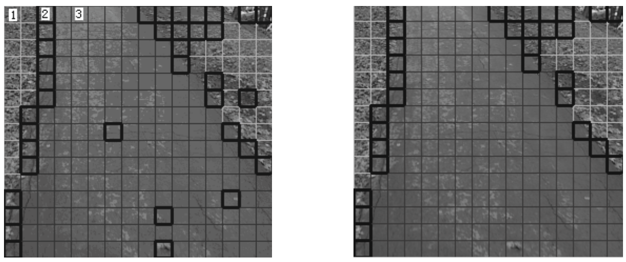
A. *Block classifying*

The adjacent pixels in road or off-road regions are generally continuous and similar, so we don't need to judge every pixel by using kernel density estimation. Based on the block-classifying theory in the literature [8], a discrimination method that classifies blocks by its four corner regions is proposed to improve the flexibility and accuracy.

Firstly the method divides image to some blocks, then uses kernel density estimation to identify the four corner areas of every block to road and off-road region. If most pixels in the corner area are road-pixel, the corner is defined as road region, otherwise, off-road region. Finally we can classify every block according to the corner's classification. The detail process as follows: (1) If all corner areas are road region, the block is defined as road region; (2) If all corner areas are off-road region, the block is defined as off-road region; (3) Others the block is defined as mixture region.

In the process of blocking, blocks and corner areas can be set to different size according to the different scene. The larger block is helpful to eliminate interference points and can reduce the processing time. The larger corner regions are conducive to improving the stability of results, but it will increase the processing time. Our experiments have proved that, in general, setting the size of corner area to the block's 1/67 can be taken to achieve the most stable results.

Fig. 1 shows a block-classifying result, in which the thin-black blocks are road region (label 3), the white blocks are off-road region (label 1), and the thick-black blocks are mixture region (label 2). We can see that some road blocks are misjudged as mixture regions. To fix such error, we make a connectivity detection for the blocks. If all the adjacent blocks of the current mixture region block are road blocks, we modify the block to road block region; if all of the adjacent blocks are off-road blocks, we change it to off-road block region.



(a) Before denoising (b) After denoising

Figure1. Result of block-classifying

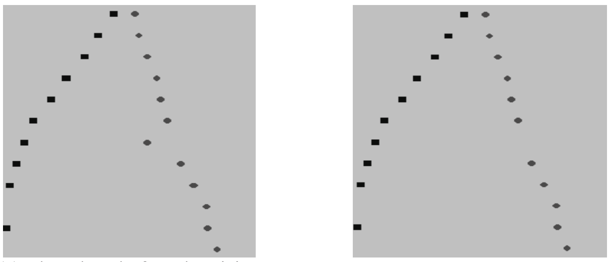
B. *Edge extracting*

It can be sure that the current road boundaries only exist in the mixed region blocks, so we only need to process such kind of blocks. For each mixed block, let the pending line (the line to be processed) be the line that connecting the mid-points of block's left and right border, and then judge each pixel in the pending line to be road or off-road. Algorithm flow is as follows:

- Firstly, identify the pixels in pending line of all mixed region blocks in image;

- Then, scan each pixel on the scan line from image's left to right, where the scan line is defined as the line having the same coordinate of Y-axis as the corresponding pending line. Take the continuous road pixels set in the scan line to be a candidate sub-segment line. Process all the scan lines in image by the same way;
- After that, merge the close candidate road sub-segment line in the scan line. Deal with all scan line's candidate road's sub-segment, and get the road line set;
- Finally, for the road segments on each scan line, extract the line segment's left and right boundary point and obtain the boundary points set of image.

From the Fig. 2(a), we can see there are still some incorrect diagnosed boundary points. In actual situation, the location of the adjacent roads' boundary points and the width of the road change little[9]. Therefore, we can analyze the changes of the road's boundary points, if the location of one boundary point took great changes to the others, or it caused great changes on road width, it would be excluded. Fig. 2(b) shows the result after excluding noise point.



(a) The edges before denoising （b）The edges after denoising

Figure2. Result of edge extracting

C. Model updating

The samples set of road and off-road needs to be updated continuously to adapt to changes in the scene. In this paper, combining with the block-classifying, we update the model by a block credibility based method.

Let C_i be the size of corner area in block, $road_{Ci}$ be the number of road region pixels of block, and $offroad_{Ci}$ be the number of off-road region pixels of block. The credibility of current block's road and off-road region is respectively denoted as W_r and W_o:

$$W_r = \frac{1}{N}\sum_{i=1}^{N}\frac{road_{C_i}}{C_i},\ W_o = \frac{1}{N}\sum_{i=1}^{N}\frac{offroad_{C_i}}{C_i} \tag{4}$$

Where N=4 represents four corner areas, and $0 \leq W_r, W_o \leq 1$, where the $W_r = W_o = 1$ represents the best credibility.

In order to reduce the effect to the model updating from shadows, light and so on, we calculate the average value of every block's current and history credibility in the image. Then, we add these blocks to a update queue, and at every update time we select the N best credibility blocks to displace the samples, where N is depending on the number of blocks in samples set.

D. B-spline fitting

1) Road model selection

The selection of road model plays an important role in the road recognition approach. The commonly used road model includes: straight-line road model, the parabolic road model, hyperbolic road model and spline curves road model. Among these model, the three B-spline curve model has the advantage that changes in local control points will not affect the overall curve, which making the construction of curves with high stability.

An cubic B-Spline curve with n+1 control points P_i (i=0,1,…,n) can be expressed as[10]:

$$C(u) = \sum_{i=0}^{n} P_i N_{i,4}(u) \tag{5}$$

Where $N_{i,4}(u)$ is the base function, and the matrix format is:

$$C(u) = [u^3, u^2, u, 1] \cdot \frac{1}{6}\begin{bmatrix} 1 & 3 & 3 & 1 \\ 3 & 6 & 3 & 0 \\ -3 & 0 & 3 & 0 \\ 0 & 4 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} P_{i-1} \\ P_i \\ P_{i+1} \\ P_{i+2} \end{bmatrix}, u \in [0,1] \tag{6}$$

2) Road boundary fitting

As most of the road shape is not complicated, we can use only three control points to obtain B-spline curve model[11], where the first interpolation point and the end interpolation point are selected as the first and the last control points of the interpolation sequence $[P_1, P_2, \ldots, P_n]$. To let the fitting curve pass by the first and the end interpolation points, the node vector in the first three nodes are set to the same as the last three nodes. To get the optimized position of the second control point, we use the least square method (LSM) to search the interpolation sequence $[P_2, P_3, \ldots, P_{n-1}]$ and select the best one. Thanks to the small number of node in sequence, the search process is not time consuming.

IV. RESULTS

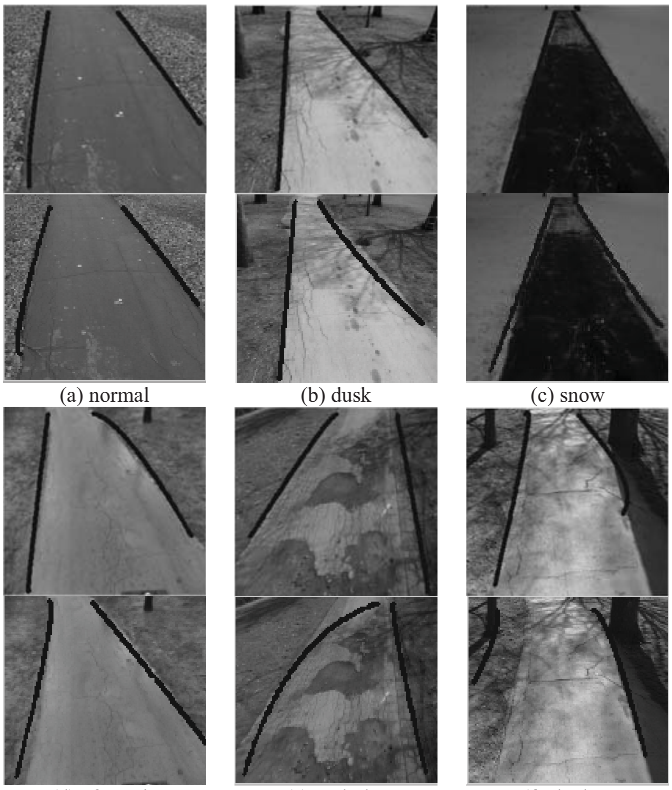
In this section, the experiment was performed on a personal computer which equipped the Intel (R) Pentium ® 4 CPU 3GHz with 512MB memory. The proposed approach was realized using the lib of OpenCV and the code was complied in VS2005. Both field tests and simulation can show the effectiveness and robustness of the proposed algorithm.

（a）Garden scene （b）Cross country scene

Figure3. Results of field tests

Fig. 3 shows two snapshots of video sequence captured during unmanned vehicle field testing, in which the black line represents the road boundaries recognized by proposed approach. In (a) there exist some pedestrians, and the algorithm can successfully rule out these interfering factors and fit the road boundary. (b) contains a cross country road scene of the 2009 "Future of Intelligent Vehicle Challenge". There are many shades of cracks and rutting blots on the road, besides the color and position distribution of grass on both sides of the road is uneven. Our approach can still accurately fit the road boundary. Errors occurred only on the top of the image or on the location of continuous corners, which is because only three control points are used to solve the road model.

As the limitations of the test environment, we carried out a variety of simulation experiments on video images provided by the Vision and Automation System Center (VASC) in Carnegie Mellon University (CMU), the test set of road pictures can be downloaded from: http://vasc.ri.cmu.edu/idb/images/road/. We compared the results of proposed approach with the max_edge algorithm[3]. Materials used in our study include 521 pictures, which contain dawn, dusk, snowy, shade and other test environments.



(a) normal (b) dusk (c) snow

(d) after rain (e) potholes (f) shadow

Figure4. Results of simulation comparison

Fig. 4 shows a part of test results. The first row is the results of our algorithm, and the second row is the results of max_edge. In the Fig. 4, (a) is a image with less interference, both sides of the road is covered with dry leaves; (b) is a dusk scene, the road surface is covered by a number of shadow; (c) is a snow scene, the road surface is covered with snow; (d) is a scene after the rain, it is hard to distinguish road and off-road regions even by eyes. We can clearly see that max_edge and our algorithm both accurately extract the boundary of the road. In scene (e), there are many potholes in the roads, and the road surface is covered by shade. Our algorithm uses block-classifying method to exclude noises, and can accurately finish the fitting. The max_edge can also roughly fit the road boundaries, but due to the interference caused by the shadow, some mistakes occurred on the top of the image. In scene (f), the max_edge algorithm encounters a big problem, the shadow of the tree on both sides of the road are identified as the road boundaries, this is because when there is much interference in the image, the updating method of max_edge becomes instability, but our algorithm can still work well.

V. SUMMARY AND OUTLOOK

In this paper, we present an unstructured road recognition algorithm using the block-segment based non-parametric model combined with B-spline curve. The algorithm use kernel density estimation combined with the block-classifying method to segment road and off-road regions. The block-classifying method not only guarantees the robustness of the mixture model method, but also reduces the computational complexity. Meanwhile, the proposed approach incorporates a model of B-spline curve to fit road boundary, which enhances the capability against the interference from shadows, light changes and other factor. Field tests and simulation experiments show that the algorithm is effective and robust.

ACKNOWLEDGMENT

Beyond the financial support, the authors are also grateful to the opened road image test set provided by the Robotics Institute at Carnegie Mellon University.

REFERENCES

[1] Ceryen Tan, Tsai Hong, Tommy Chang, and Michael Shneier. Color Model-Based Real-Time Learning for Road Following[C]. In: Proceedings of IEEE Intelligent Transportation Systems, 2006:939-944.

[2] Jill D. Crisman, Charles E. Thorpe. A color vision system that tracks roads and intersections[J]. IEEE Transactions on Robotics and Automation, 1993, 9(1):49-58.

[3] O. Ramström, H. Christensen. A Method for Following Unmarked Roads[C]. In:Proceedings of IEEE Intelligent Vehicle Symposium. 2005:650-655.

[4] CHEN Zuoping, YE Zhenglin, LIU Ming. An Algorithm for Fast K-mean Clustering Based on EPDS[J]. 2006, 32(12):191-195.

[5] Liu jia-hai,Bai hong-huan,Huang wei-ao.Lane segmentation based on fusion of color and edge information [J]. Journal of Zhejiang University (Engineering Science), 2006, 40(1):29-32.

[6] M. Rosenblatt. Remarks on some nonparametric estimates of a density function[J]. Annals of Mathematical Statistics. 1956, 27(6):832-837.

[7] E. Parzen. On estimation of a probability density function and model[J]. Annals of Mathematical Statistics. 1962, 33(8):1065-1076.

[8] Guan Yan-ping, He Yue, Liu Pei-zhi, and Lü Lin. Lane and road detection based on colorful image[J]. Computer Applications, 2005, 25(12):2931-2934.

[9] Jingang Huang, Bin Kong, Bichun Li, and Fei Zheng. A New Method of Unstructured Road Detection Based on HSV Color Space and Road Features[C]. In:Proceedings of IEEE Information Acquisition, 2007:596-601.

[10] SUN Jia-guang, YANG Chang-gui. Computer graphics (New Version) [M]. Beijing, Tsinghua University Press, 1995:284-289.

[11] Wang Yue, Eam Khwang Teoh, Shen Ding-gang. Lane Detection and Tracking Using B-Snake[J]. Image and Vision Computing, 2004, 22(4):269-280.