2014 IEEE 17th International Conference on
Intelligent Transportation Systems (ITSC)
October 8-11, 2014. Qingdao, China

An Approach of Lane Detection Based on Inverse Perspective Mapping

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Abstract— **Urban lane detection is an essential task for unmanned vehicle system.This paper describes an approach of lane detection algorithm based on Inverse Perspective Mapping, first using overall optimal threshold method to obtain binary image for reducing noise; next using Inverse Perspective Mapping to transform binary image space to top view space; then using k-means clustering algorithm to analysis linear discriminant for reducing interference affect; finally, fitting lane discontinuous on the top view space according road models. Experimental results are presented to demonstrate the effectiveness and superiority of the urban lane detection algorithm.**

Keywords: binary image, overall optimal threshold method, Inverse Perspective Mapping, K-means clustering algorithm, road models

I. INTRODUCTION

With the rapid development of society, drive safety and operation simplifications has been paid more and more attention. Active safety based on on-board intelligence in the vehicles has been regarded as the final solution to avoid traffic accidents. Many unmanned vehicles have been developed to demonstrate and verify the ability of active safety and on-board intelligence. After the "DARPA Grand Challenge" held in 2004 and 2005, and the "DARPA Urban Challenge" held in 2007[1,2,3], a series of annual competitions called "Future Challenge of Intelligent Vehicles in China" has been organized by National Nature Science Foundation of China since 2009.

Urban roadway detection is an essential task for unmanned vehicle system. Up to present, various vision-based roadway detection algorithms have been developed. Vision has been widely used for road boundary detection. Some methods detect road and lane boundaries directly, while others first detect road regions using, for example, color information to determine the road boundaries. They usually utilized different lane patterns (solid or dash white painted line, etc.) or different road models (2D or 3D, straight or curve), and different techniques (Hough, template matching, neural networks, etc.). Basically, there are two classes of approaches used in roadway detection: the feature-based technique and the model-based technique. The feature based technique localizes the lanes in the road images by combining the low-level features, such as painted lines[4,5,6,7,8,9] or lane edges[10], etc. lane segments that are detected by traditional image segmentation. Accordingly, this technique requires the studied road having well-painted lines or strong lane edges, otherwise it will fail. Moreover, as it has the disadvantage of not imposing any global constraints on the lane edge shapes, this technique may suffer from occlusion or noise.This paper describes an approach of lane detection algorithm based on Inverse Perspective Mapping, which transform image space to top view space for analysis. It can use reality road models on the top view space, such as lane length, road width and road shape and etc.The flow of algorithm is shown below figure:

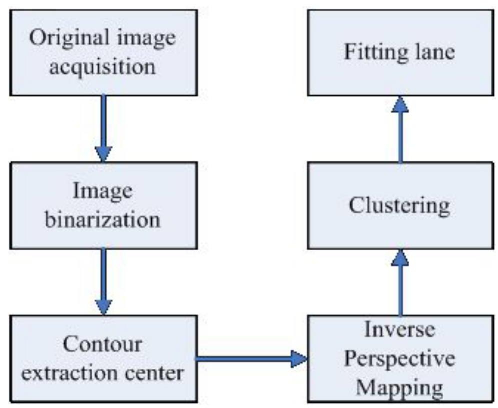

Fig 1 The flow of algorithm

II. BINARIZE IMAGE BY OVERALL OPTIMAL THRESHOLD *METHOD*

Urban roads are structured roads that have some white or yellow lane markings, those markings are special model of roadway. Sequentially, the question of roadway detection translate into detect the lane markings from one image. The most common method is the image segmentation [11,12].Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The simplest method of image segmentation is called the threshold method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value (or values when multiple-levels are selected).This paper describes a method of a overall optimal threshold binarization algorithm. In order to reduce the influence of road edge and distant scenery in lane marking detection, this algorithm removed the sky portion of the image, which made the roads image area accounted for the majority. Taking into account the sensitivity to noise and speed of the algorithm, this paper adopts a holistic optimal threshold method for image binarization.

The principle of overall optimal threshold is statistics distribution of each image gradation characteristics, make use of the variance as a criterion category, select the maximum between-class variance as the selected threshold.Assume an image is divided into 1~m level, the number of pixels for gray values m is n, the total number of pixels is:

$$n = \sum_{i=1}^{m} n_i \tag{1}$$

The probability of each pixel is:

$$P_i = \frac{n_i}{N} \tag{2}$$

Then use an integer K divided it into two groups C_0 and C_1 , namely:

$$C_0 = \{1,2,3\cdots K\} \tag{3}$$

$$C_1 = \{K+1, K+2, \cdots m\} \tag{4}$$

The probability of C_0 is :

$$w_0 = \sum_{i=1}^{k} P_i = w(K) \tag{5}$$

Corresponding to the mean is:

$$u_0 = \frac{\sum_{i=1}^{K} iP_i}{w_0} = \frac{u(K)}{w(K)} \tag{6}$$

The probability of C_1 is :

$$w_1 = \sum_{i=K+1}^{m} P_i = 1 - w(K) \tag{7}$$

Corresponding to the mean is:

$$u_1 = \frac{\sum_{i=K+1}^{m} iP_i}{w_0} = \frac{1-u(K)}{1-w(K)} \tag{8}$$

Where $u = \sum_{i=1}^{m} iP_i$ is the statistical mean of the overall image intensity，then

$$u = w_0 u_0 + w_1 u_1 \tag{9}$$

The variance between two groups is:

$$\sigma^2(k) = w_0(u_0 - u)^2 + w_1(u_1 - u)^2 \tag{10}$$

Change the value of K among 1,2, ..., m, find the value of k for maximum variance, namely the value of K is optimal threshold when $\sigma^2(k)$ is maximum.

Image binarization result is shown below figure, fig 2 is binary image by OTSU, the binarize image by overall optimal threshold method, it can be concluded using overall optimal threshold method binarized image is further reduced noise.

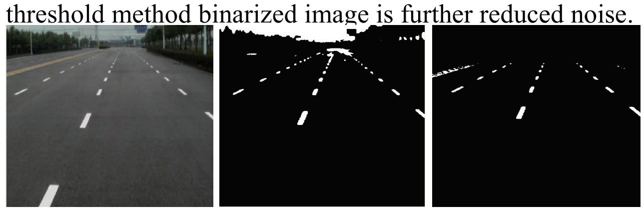

Fig 2 Binary image by overall optimal threshold method

III. INVERSE PERSPECTIVE MAPPING

Two parallel lane of the road is mapped to two intersecting lines in the image space due to the perspective effect of the optical imaging system[13], which is presented from the Fig 3. Since the perspective effect, geometric information of road image is lost during the imaging process. Assume the road is absolute level, the roadway features can be detected through overhead view of binary image by Inverse Perspective Mapping, which can take advantage of the road geometric characteristics to detect the lane marking.

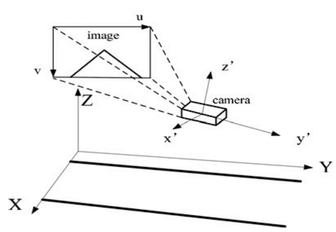

Fig 3 The projection of lane model

Target in camera plane imaging can be seen as a target in camera perspective projection plane, perspective projection is a projection method to form a projected onto the projection plane to obtain a relatively single projection close to the visual effect.

According to the principle of perspective projection:

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & u_0 & 0 \\ 0 & f_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & t \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix} = M_1 M_2 X_w = M X_w \tag{11}$$

(u, v) is image coordinate, X_W is world coordinate s is scale factor. Since we assume the road is absolute level, the value of s is fixed, M is transfer matrix that can be computed through calibration. For this reason, the question of compute Inverse Perspective Mapping matrix convert to solve the equation: $Ax = b$ .The equation can be easily solved through SVD (singular value decomposition).

In addition, the intrinsic (focal length, center, and distortion) and extrinsic (vehicle-relative pose) parameters of the cameras have been calibrated ahead of time[14]. The transform results of figure 4 by Inverse Perspective Mapping shown below figure.

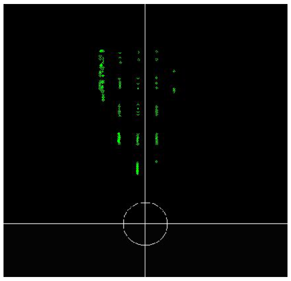

Fig 4 Inverse perspective mapping of lane detection

IV. K-MEANS CLUSTERING ALGORITHM

In data mining, k-means clustering is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. This results in a partitioning of the data space into Voronoi cells.

The problem is computationally difficult; however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both algorithms. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation maximization mechanism allows clusters to have different shapes.

Given a set of observations $(x_1, x_2, \cdots x_n)$, where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets (k ≤ n) $S = \{S_1, S_2, \cdots S_k\}$,so as to minimize the within-cluster sum of squares :

$\arg\min_{s} \sum_{i=1}^{k} \sum_{x_j \in s_i} \left\| x_j - u_i \right\|^2$,where u_i is the mean of points in S_i .

Given an initial set of k means $m_1^{(1)}, m_2^{(1)}, \cdots m_k^{(1)}$, the algorithm proceeds by alternating between two steps:

Assignment step: Assign each observation to the cluster whose mean is closest to it.

$$S_i^{(t)} = \{x_p : \left\| x_p - m_i^{(t)} \right\| \le \left\| x_p - m_j^{(t)} \right\| \forall 1 \le j \le k\}, \quad (12)$$

where each x_p is assigned to exactly one $S^{(t)}$, even if it could be is assigned to two or more of them.

$$m_i^{(t+1)} = \frac{1}{\left| S_i^{(t)} \right|} \sum_{x_j \in S_i^{(t)}} x_j \quad (13)$$

The algorithm has converged when the assignments no longer change. The clustering results of figure 6 by k-means clustering algorithm shown in figure 5.

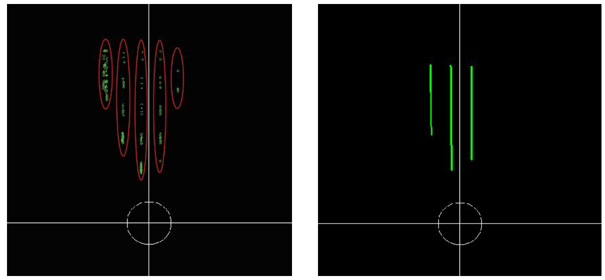

Fig 5 Effect of k-means clustering and fitting

V. FITTING USING ROAD MODELS

Commonly used road models are based on the expression road model straight road model, parabolic road model, hyperbola road model and spline road model etc. In this paper, open uniform B-spline model is selected due to characteristic of flexibility and stability etc.

All points of each clustering as control points for spline, and K-order B-spline curve expression below:

$$A(x) = \sum_{i=0}^{n} P_i N_{i,k}(x) \quad (14)$$

where $N_{i,k}(x)$ is basis functions, m_i is node value, it can be defined as below:

$$N_{i,k}(x) = \frac{x - m_i}{m_{i+k-1} - m_i} N_{i,k-1}(x) + \frac{x_{i+k}}{x_{i+k} - x_{i+1}} N_{i+1,k-1}(x) \quad . \quad (15)$$

In this paper, cubic B-spline curve is selected as the road models shown below, the fitting effect shown in fig 5.

$$A(x) = \frac{1}{6}[x^3, x^2, x, 1] \begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 0 & 3 & 0 \\ 0 & 4 & 1 & 0 \end{bmatrix} \begin{bmatrix} P_{i-1} \\ P_i \\ P_{i+1} \\ P_{i+2} \end{bmatrix} \quad (16)$$

VI. EXPERIMENTAL RESULTS

Experiments were carried out on unmanned vehicle called "Intelligent Pioneer", designed by CASHIPS (Hefei Institutes of Physical Science, Chinese Academy of Sciences). The vehicle attended the Future Challenge of Intelligent Vehicles in China organized by National Nature Science Foundation of China from 2010 to 2013. "Intelligent Pioneer" finished all of the competition programs and get top three in three consecutive years. Analyze the experimental results from the following aspects.

A. The effectiveness of detection high-curvature lane shown in Fig 6.

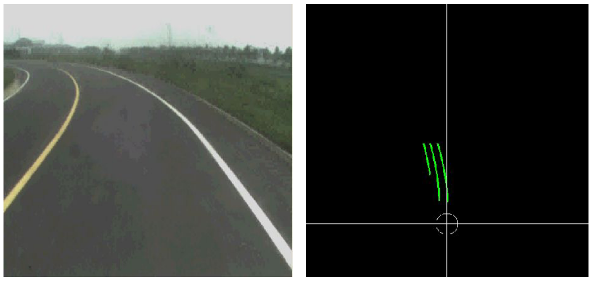

Fig 6 High-curvature roadway detection

B. The effectiveness of lane detection on undulating road surface shown in Fig 7.

Fig 7 Lane detection with the road up and down

C. The effectiveness of lane detection with ambient bright ness change, algorithm is not exposed to strong illumination changes affect.

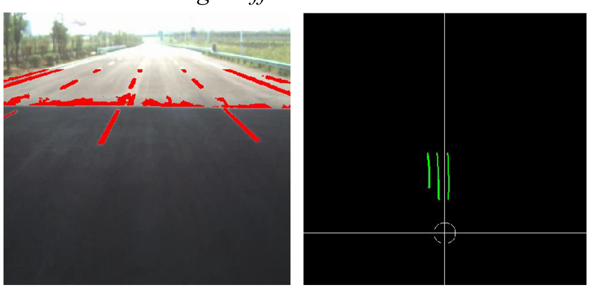

Fig 8 Lane detection with ambient brightness change

D. The effectiveness of lane detection with many road surface disturbances shown in Fig 9.

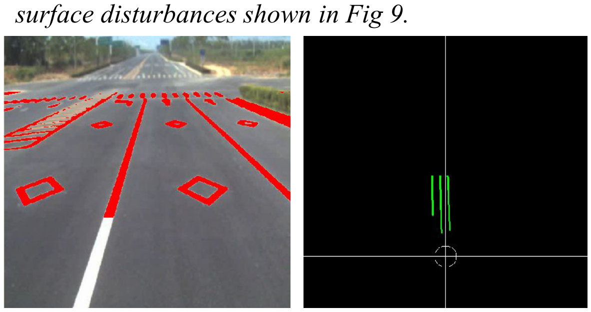

Fig 9 Lane detection based on vision with interference

VII. CONCLUSION

Urban roadway detection is an essential task for unmanned vehicle system. This paper describes an approach of lane detection algorithm based on Inverse Perspective Mapping for detecting urban lanes. This method not only solves many kinds of lane detection but not susceptible to interference affect. The discussion and experimental results are presented to demonstrate the effectiveness of the urban lane detection. Our future intention is to generalize the vision methodology to detect all kinds of lane.

ACKNOWLEDGMENT

This work is supported by The Major program of National Natural Science Foundation "Unmanned vehicle key technologies and platforms face integrated urban environment"(No. 91120307).

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