Lane Detection Method Based on Improved RANSAC Algorithm

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***Abstract*—Lane detection based on computer vision is a key technology of Automatic Drive System for intelligent vehicles. In this paper, we propose a real-time and efficient lane detection algorithm that can detect lanes appearing in urban streets and highway roads under complex background. In order to enhance lane boundary information and to be suitable for various light conditions, we adopt canny algorithm for edge detection to get good feature points. We use the generalized curve lane parameter model, which can describe both straight and curved lanes. We propose an improved random sample consensus (RANSAC) algorithm combined with the least squares technique to estimate lane model parameters based on feature extraction. Expriments are conducted on both real road lane videos captured by Tongji University and Caltech Lane Datasets. The experimental results show that our algorithm is can meet the real time requirement and fit lane boundaries well in various challenging road conditions.**

Keywords-Lane detection; Improved RANSAC; Lane feature extraction

I. INTRODUCTION

The correct recognition of lane is the core issue of safety driving assistance system such as lane departure warning system for intelligent vehicles to achieve self-autonomous navigation. Lane boundaries can be considered as a visual information feedback of the road environment to the drivers. Compared to other measurement methods, visual sensors are low cost and easy to construct an application system, and thus computer vision-based lane detection methods [1-5] have been widely used to obtain the position information of the lane. The main content of computer vision-based lane detection is extracting and identifying the lane boundary information from images which are obtained from the on-board camera. Lane recognition is an essential precondition for obtaining the trend information of the lane and for getting the distance between vehicles and lane boundaries.

In recent years, researchers have developed many lane detection methods based on computer vision. Generally, these methods can be divided into two categories: feature-based and model-based methods [6-10]. The feature-based methods locate the road areas using segmentation methods whereas the model-based methods represent the lane boundaries by mathematical models. While on the condition of urban streets and highway roads, the most commonly used methods are model-based methods. Various lane models have already been proposed, ranging from straight line segments to flexible splines [3, 8, 9, 10]. Simple models such as straight line model cannot represent the lane shapes accurately, especially in the far-field. On the other hand, sophisticated lane models result in much heavier computational costs and may increase the rate of false detection. Recently, some researches integrate tracking strategy or learning algorithm and propose more robust lane detection methods which can deal with curved roads[2,4,6,9] and achieve satisfied detection results on challenging scenarios, such as distracting shadows or leading vehicles. However, most of them work with high computational complexity and is hard to meet real time requirement.

Taking the characteristics of various lane models and the actual needs of lane detection into consideration, we propose a fast and efficient lane detection algorithm that can detect lanes appearing in urban streets and highway roads. The proposed algorithm is distinguished from the previous ones in the follow ways. Firstly, the generalized curve model we have adopted can fit both straight lines and curve ones. Second again, we use the canny algorithm for edge detection which has a better performance in extracting feature points. And the most prominent point is that we propose an improved RANSAC algorithm which is combined with the least square technology to calculate the lane model parameters. Through all of the methods above, we have improved the accuracy of the lane detection and our lane detection method can work well in real time conditions.

The rest of the paper is organized as follows. Section II introduces image preprocessing methods and lane feature extraction algorithm. Section III proposes the implementation of improved RANSAC algorithm. Section IV illustrates the lane detection experiments and the analysis of the results. Finally, a conclusion is given in section V.

II. IMAGE PREPROCESSING AND LANE FEATURE EXTRACTION

A. Image Preprocessing

There is not only the lane information, but also a lot of noise and interference information shown in the images collected by on-board camera (some sample images as shown in Fig. 1). In order to strengthen the impact of lane information and remove the interference and noise information, we have applied some image preprocessing approaches to make preparations for better lane detection. These approaches are listed as follows. First, we set a region of interest (ROI) on the video frames. Secondly, we introduce a special way of graying the image to better detect

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Figure 1. Example road images

worn yellow lane markings. At the last step, we de-noised the gray-level images.

As we can see from Fig. 1, when the on-board camera optic axis is basically parallel to ground, the region which contains lane boundaries is located in the lower section of the images due to image perspective projection. Owing to the perspective projection transformation, the two lanes that are parallel to each other in real world will intersect at a vanishing point in the image plane. Assuming a flat road, the position of vanishing line can be calculated from the fixed camera parameters. In this paper, we consider the position is known and set the ROI to be a rectangle region that is located in the middle of the images just below the vanishing line.

In view of the collected images are RGB images, we convert color images into gray-scale images in order to improve the processing speed. In this paper, the gray-scale images were generated by weighted-summing RGB values, previous research[8] have proved that the edge detection algorithm achieves a better result using gray-level pixels with 5: 4: 1 weight.

And the last step of image preprocessing we use is image de-noising. In order to meet the real-time need, we have applied the median filtering method. It will set the gray value of a pixel to be the mid-value of all pixels in its neighborhood window. It has received a good inhibition effect on removing pulse interference and salt and pepper noise, it can also reduce the degrade details of images brought by general linear filters. This ensures image edge preservation.

B. Lane Feature Extraction

In the existing lane detection system, the most commonly used features are image gradient and edge information. These feature extraction need small amount of calculation and can extract position information where the image pixel intensities have a strong change. Well-painted lane markings produce strong edges, which benefit the detection of lanes. Depending on the change of environment, the lane edge features may not be strong and may be affected by shadow or other uncertain factors. Thus we need to select a powerful edge detection operator.

Compared to other edge detection algorithms, the Canny edge detection algorithm is an accepted excellent edge detection algorithm which can achieve the most complete extraction of the edge. Applying the above methods, the results are shown in Fig. 2.

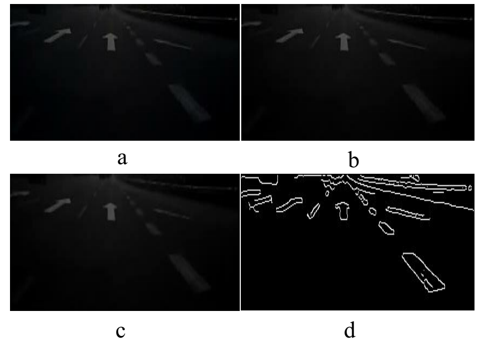

Figure 2. a. ROI region of RGB image, b. image of gray-level, c. image after de-noising, d. edge image

III. Lane Model and Model Parameters Estimation

After the completion of the lane feature point extraction, lane detection process is separated into two parts: the lane modeling and model parameter estimation. We will discuss the two parts in detail in the following subsections.

A. Lane Modeling

From the straight line segment to the flexible spline curve, lane model gets lots of application. The simple lane model cannot describe lane shape accurately. On the other hand, the complex lane model results in heavier computational consumption and may increase the detection error rate.

In this paper, the left and right lane boundaries are described by generalized curves. The classical model has been widely applied in already existed lane detection system [10]. This lane model has taken into consideration the parallel lines and planar ground surface constraints which are applicable in most highway roads and urban streets. In addition, the model requires only a few of parameters which lead to a more precise and faster parameter estimation. The deficiency is a lack of flexibility in fitting complex lane shapes. According to these characteristics above, we adopt this model. The detailed derivation of the lane model is available in [10].

Assuming that the collected images have y rows and x columns. The generalized curve can be described by (1).

$$x = \frac{a}{y - vp_y} + b\left(y - vp_y\right) + c \qquad (1)$$

Here, parameter a controls the curvature of the curve, parameter c representing the vanishing point positions, parameter b correspond to the horizontal positions (this controls the positions of the intersections between the curves and the lowest row of the image) of the left and right curves, parameter vp_y denotes the vanishing line position on the image. Assuming a flat road, the parameters vp_y can be calculated by computing the vanishing points or by fixed camera parameters, in this paper this parameter vp_y is considered to be known.

The parameters a of the two lane boundaries are set to be identical. Also, as an effect of perspective projection, the two lines intersect the vanishing line at the same point. The parameters c are set to be identical as well. However, the parameters b of the two lane boundaries are different. It is of great significance that we use this lane model, since it can both fit straight line and curves. We should notice that equation (1) represents a straight line when a equals to 0.

B. Lane Model Parameter Estimation

After determining the lane model, our task is now to estimate the parameters of the lane model and to optimize the estimation in order to describe the lane boundaries accurately. Lane detection result can be featured with the model parameters we introduced in previous subsection.

RANSAC algorithm is a robust fitting algorithm that has successfully been applied to various computer-vision problems [11]. The RANSAC algorithm can adapt to the complex conditions of lane estimation of model parameters and it does not need training process compared to the Hough transform and template matching method. As a result, it's widely used in lane model parameter estimation in recent years.

The Lane feature points extracted by canny algorithm contains not only valid points but also a lot of noisy points caused by various of reasons (such as the damaged road surface, illumination changes, shadows, covered stains , weather changes). And the distribution of the feature points is irregular. It's very difficult to calculate the lane model parameters correctly because of so many noisy points are existent. There are two main problems we need to take into consideration: on the one hand, the feature points RANSAC algorithm selected in the model initialization is totally random and without using constraint rules, which leads to the real-time reduction of the algorithm; on the other hand, because the RANSAC iterative process are not independent with each other, i.e. feature points used in previous model may still be applied to calculate the next new model, the re-usage of certain feature points can seriously affect the real-time performance and robustness of the algorithm.

To solve the problems mentioned above, we have proposed a real-time, robust and improved RANSAC algorithm. Considering the properties of RANSAC algorithm and real-time requirements, we detect the left and the right lane independently. Our RANSAC fitting procedure is as follows.

1) Initial lane model parameter vector *Mod=NULL*, iterator *i*=1, get lane boundary feature points set *P*, inlier points set *I=NULL, Modbest=NULL*, S=0.
2) Random select *n* (n=3) points from *P* (these points should located in different rows of image), calculate *Mod* by theses points.
3) For any point $p_i(y_i, x_i)$ $p_i \in$ P, if $Dist(p_i) < D_{threshold}$, add p_i to inlier points set *I*.
4) If *number(I)*< $Num_{threshold}$ or *Mod* doesn't meet the constraints, *P=P-I*, *I=NULL*, goto step 2), end If.
5) Recalculate *Mod* by function *LeastSquareFit(I)*, If *Score(I)>S*, *S=Score(I), Modbest=Mod, P=P-I, I=NULL,* i++, end If.
6) If (*i*< *numIterations*), goto step 2).

Here vector *Mod* = [*a, b, c*], function $Dist(p_i)$ is defined by (2). $D_{threshold} = 1$, $Num_{threshold} = 12$. Function *Score(I)* is defined by (3).

$$Dist(p_i) = |x_i - \frac{a}{y_i - vp_y} + b(y_i - vp_y) + c| \quad (2)$$

$$Score(I) = \sum_{p_i \in I} t(p_i) \quad (3)$$

In (3), $t(p_i) \in [0,1]$, if $Dist(p_i) < 1$, $t(p_i) = 1$, else $t(p_i) = 0$.

LeastSquareFit(I) is a function which takes points of set *I* and fits the lane model using a least squares method.

IV. EXPERIMENTS AND ANALYSIS

The algorithm has been tested on the normal PC, Intel(R) Corei5-2430 CPU @ 3.0GHz and 4.00GB RAM. We have collected a number of video clips with a resolution of 480x856, which named as Tongji Lane Dataset. Clip1 and Clip 2 were taken in highways, the rest clips were taken in urban streets. These clips are quite challenging, for clip 1 and clip 2 both are under bad illumination and the weather is cloudy, clip 3 has many complex scenes such as culverts, shadows and passing cars, clip 4 has lots of shadows (at the beginning), different pavement types, street writings and passing vehicles as well, clip 5 has many cure lanes and old lane markings. A total of 12637 frames were tested. The algorithm runs at the rate of 25 frames per second.

Two important evaluation criteria we use are as follows. A true positive rate (TPR) and a false positive rate (FPR) are calculated as TPR = (the number of detected lanes) / (the number of target lanes), FPR = (the number of false positives) / (the number of target lanes). The performance of our algorithm is shown in Table I.

TABLE I. RESULTS OF TONGJI LANE DATASET

Clip	Frames	Lanes	Detected	TPR	FPR
1	3001	5876	5847	86.84%	12.49%
2	3001	4124	4034	93.89%	3.92%
3	3002	5144	5268	88.18%	14.23%
4	1501	1838	2115	83.08%	31.99%
5	2132	2264	2332	94.79%	7.77%
total	12637	19246	19596	88.82%	12.21%

Example lane detection results are shown in Fig. 3 (bad detection results) and Fig. 4 (good detection results) to make more explicit explanation and description. It shows that the proposed algorithm works robustly on various distractions (shadows, non-lane-marking lines or passing vehicles) and on low illumination. Most of the misdetection was caused by fuzzy lane boundaries failure or lack of actual lane markings. Further research is required to improve the lane-marking detection in such cases.

We compare our results with M. Aly's [9] using the Caltech Lane Datasets (http://www. vision. caltech. edu/ malaa/ research/ iv08) to verify the validity of our algorithm.

As the criteria differ, the statistics of M. Aly's are slightly different from the published results. The results do not show the strong points of our algorithm, however our algorithm still achieve a effective performance while Aly's algorithm just work on still images without taking real-time requirements into consideration, as shown in Table II.

TABLE II. RESULTS OF CALTECH LANE DATASETS

Datasets	Aly's		Our method	
	TPR	FPR	TPR	FPR
1	97.21%	3.00%	96.37%	3.17%
2	96.16%	28.78%	97.24%	25.39%
3	95.70%	4.72%	94.64%	7.23%
4	93.13%	5.21%	94.73%	3.85%
total	95.34%	11.50%	95.17%	10.68%

V. CONCLUSION

We have proposed an efficient, real-time, and robust method for detecting lanes in highways and urban streets. Initially, a combination of setting ROI region, special method of image graying and median filtering is used to enhance intensity changes in the video scenes. Next, canny edge detection algorithm is applied to extract lane boundaries feature points. Final an improved RANSAC curves fitting technique is used to detect lanes in the street. The experimental results show that it works efficiently and correctly in various road conditions. We achieved comparable results to other algorithms that only worked on detecting the current lane boundaries. Observing from the experimental results, there are still some difficult lane scenarios to be solved, so future work will integrate tracking algorithms to our framework for improvement. And we will apply it to a vision-based lane departure warning system.

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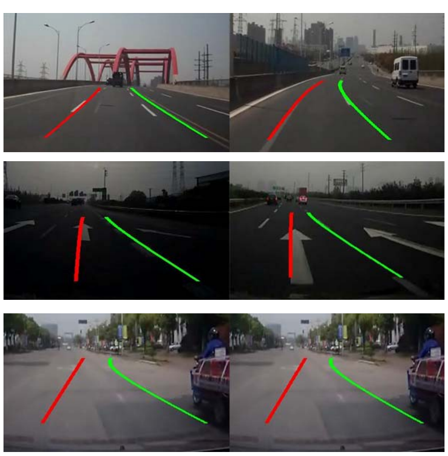

Figure 3. Examples of bad detection results

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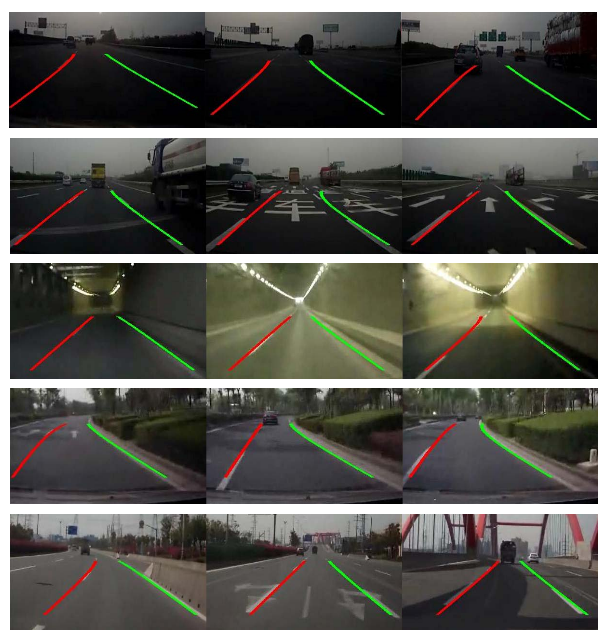

Figure 4. Example of good detection results