Robust lane detection and tracking for lane departure warning

Yue Dong; Jintao Xiong; Liangchao Li; Jianyu Yang
Sch. of Electron. Eng.,
Univ. of Electron. & Sci. Technol. of China
Chengdu, China

Abstract—**Lane detection is an important component of many intelligent transportation systems. This paper proposes a novel lane departure algorithm for detecting lane markers in images acquired from a forward-looking vehicle-mounted camera. The interested targets of the algorithm are always the nearest two lanes to the automobile, and it can detect the left and right lane separately, which would generate the departure warning more precisely. As the main idea is two sure a straight line, the endpoints of segment lanes of the last image can be used as prior information to estimate lanes in the following one. It's a real-time algorithm for lane detection and tracking, which is also simple to implement. The experimental results on local streets and highways show that the suggested algorithm is very reliable and robust.**

Keywords-lane detection; endpoints of lane markings; tracking; Lane departure warning

I. INTRODUCTION

More than 60,000 people died in car accidents in China in 2011, which often stems from driver inattention or impairment. A system could eliminate many of these crashes if it warned drivers when their vehicle was departing the roadway and controlled the vehicle's steering wheel to keep it in its lane. So lane detection plays an important role in such a system like driver assistant systems and self guided vehicle. In this paper, a novel approach of lane detection which can work robustly in real-time will be proposed.

Lane departure detection has been studied for more than a decade. [1] introduced a method to capture images from two downward side cameras equipped with the front side and the rear side of a vehicle and to estimate lateral position in a traffic lane by detecting a lane marker near a vehicle, and this method was also applied in [2]. However, the approach we are going to present is a more conventional one, which was also been utilized in [3]-[5]. The reasons are as follow: firstly, visual field of a downward side camera is narrow, and only a few information of the lanes can be applied; secondly, instead of testing whether the distance between the initial points of lanes and midline of automobile exceed the threshold or not, it's more complicated to estimate a lateral position in the traffic lane and a yaw angle to the lane, and in [6], low cost, richness of features (color, texture) and non-intrusive nature are also the advantages of using a single camera capturing scene information from the front windshield of the vehicle.

Many approaches have been applied to lane detection, and the recent paper [5] provided a comprehensive summary of existing approaches. The methods are Hough transform [7], dynamic programming [8], along with computational models explaining the structure of the road using deformable contours [5], and regions with piecewise constant curvatures [9]. More recently, there has been an increased focus on building real-time systems [10] on challenging urban scenarios [11]-[12], and on providing functionalities such as lane departure warning [13].

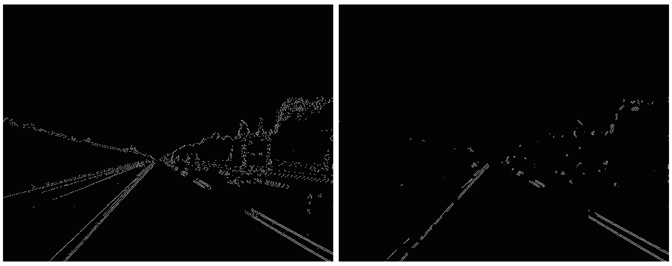
In the paper, we will present a real-time lane-detection and tracking system which is distinguished from the previous ones in the following ways:

1) It uses a more understanding algorithm to deal with the nearest two lanes, in case the typical road which has multiple lanes causes difficulty in generating appropriate departure decision.
2) It detects the left and right lane markings separately, whereas most of the previous work uses a fixed-width lane model. As a result, it can handle challenging scenarios such as merging or splitting lanes effectively， even if one lane is gone, it can also provide warning based on the other lane.
3) It combines lane detection and tracking into a single algorithm, and there is more to be used than the information from a single image that can effectively deal with lane changes, such as emerging, ending, merging, or splitting lanes.

II. DETECTION OF LANE MARKERS

In the approach, the main idea is that two sure a straight line. We'll present how to detect the initial points of lanes in the search-area, and then to generate the terminal points separately to compose line models in the monitoring-area. It's convenient to match the edge vision with a picture of models of lines in it, and the best matched one will be the picture of actual lanes.

(a) Original scene (b) Edge image based on Canny operator



(c) Noise reduction image of phase 1 (d) Noise reduction image of phase 2

Figure 1. Results of edge detection

There are so many papers using Hough transform to solve lane detection, while few of them utilized the prior knowledge which gets from the last image, and that's the biggest difference between the approach in this paper and the other ways. Since it is easy to obtain the initial and terminal points of the last scene, tracking lanes from frame to frame saves a lot of resources, and putting strong constraints on the likely location of the lane increases the accuracy of the algorithm.

A. Edge detection based on Canny operation

Lane boundaries are defined by sharp contrast between the road surface and painted lines. In order to locate the exactly right place of the automobile, it's important to determine the location of lane boundaries. What's more, it also reduces the processing time by simplifying the image considerably.

The canny detector has a very desirable characteristic in that it does not produce noise like the other approaches. Canny operation provides the threshold automatically. However, it often produces far too much edge information including cars ahead and sceneries on the wayside as shown in Fig. 1(b), corresponding to the original image in Fig. 1(a). After observation and experiments, we summarize a scheme to decrease the redundant information. Firstly, delete the points that link with each other horizontally or vertically to reduce the horizontal and vertical line, which has been shown in Fig. 1(c). These lines turn out to be cars ahead and other road signs. Secondly, wipe off the stray points that scattering in the edge image alone as shown in Fig. 1(d).

B. Search the base-points in the search-area

To ascertain the initial points is the key to locate the lane markers precisely. We choose the search-area about a quarter of the image which belongs to the bottom of the scene as shown in Fig. 2(a), and these two points should be selected from the scan-line in the search-area.

(a) Search-area of the original scene (b) Intensity template of a scan-line

Figure 2. Results of the search-area and the template of intensity

(a) Monitoring-area of the scene (b) The final output of lanes

Figure 3. Results of the monitoring-area and the lane detection

It would be appropriate to search from the bottom-line up to the begin-line of the search-area, and if the result is acceptable, stop searching. If no good result is obtained, that means no lane marker is in this area.

We model a scan-line as having an intensity profile as shown in Fig. 2(b), with a uniform intensity I_{marker} distinct from the intensity I_{road}. Although few of the real lanes is exactly the same as the simple template, because of the noise, spot of the road and so on, we can still recognize the lanes from the road based on the intensity as long as we can tell it by eyes in the real word according to the tips below.

Since the interruption of light, color and level of maintenance of roads, the base-line of the intensity changes a lot. The adjustable template $I'_{scanline}$ is obtained from the transformation of $I_{scanline}$, according to (1), and N is the number of pixels in the scan-line.

$$I'_{scanline} = I_{scanline} - \frac{1}{N} \bullet \sum_{i \in R_{saneline}} I_{scanline}(i) \tag{1}$$

There are another three tips to get the right points. Firstly, the orientation of searching in one scan-line is important. It's convenient to look for one point from the midpoint of the line to one side, and then start to search the other point in the opposite direction, which may not worry about the influence from the obstacle in other lane. The next key is how to tell the real lane from the impulse of noise. The situation is normal in the common processing, and the intensity is not the only criterion to judge lane, but also is the width of it. The width of the marker is at least 10 pixels for an RGB image of

620×480 pixels, while the width of spot is much smaller than that. The last tip is about the distance. After finding one initial point, a certain range is set to search the other one to get rid of other road markers in the driveway, such as arrows, and these restrictions of the distance also simplifies the process of detection.

C. Confirm the lane in the monitoring-area

As we all known, the object that is close to us seems large, and the one far away from us seems to be small. These lanes would assemble to one point near the end of the road in the image, and that's what is called the disappearance-point. It belongs to each lane of the image, and it is usually a common one if the CCD is fixed. The lane can be recognized based on two points. In fact, we can obtain the lines after detecting the initial ones. However, in order to prevent the distant scenery disturbing the surveillance of the road markers, the monitoring-area is obtained which is about half of the road surface as shown in Fig. 3(a). We can get the terminal points(B) in the area according to the triangle relationship of the disappearance-point(D) and the initial points(A), and then construct models of left and right lanes separately. Finally, match the models of segment with the edge image.

The line model will be obtained from the initial-point and the terminal point. Given the changeable of road situation, a slightly little shifting of the disappearance-point will cause a bigger change of the kill-point and a distorting lane, which is not expected. Therefore, ranges are offered around these endpoints, and the perfectly matching model is obtained as shown in Fig. 3(b).

D. Tracking the lanes through images

The rule above is suitable to estimate the location of lane in the next image. Since the displacement of the lanes between two successive scenes is small, the actual points of lane change a little. In the result of that, we can utilize the endpoints in the last image to obtain the lanes in the following one, and skip the phases of searching and confirming.

The range of the endpoint is set as follows. The mid-value of the range should be the endpoint from the last one, and the span from the minimum to the maximum is about 10 pixels. In most instances, the endpoints in successive images changes little, so the optical searching choice is to start from the middle of the confines. If the model doesn't fit with the image, choose the one next to the mid-value on the left (or right) to see if this one fits or not, and next time is the one on the right (or left). And the rest can be done in the same manner until the right one is found. If there isn't one to match with the lane, do the searching phase in the next scene.

III. THE FLOWCHART OF THE ALGORITHM

The algorithm would be carried out as the Fig. 4. Z is the flag to indicate the information of whether the lanes has been detected in the last image. If $Z=0$, that means no prior information of last image can be used, and go to the step of searching the endpoints.

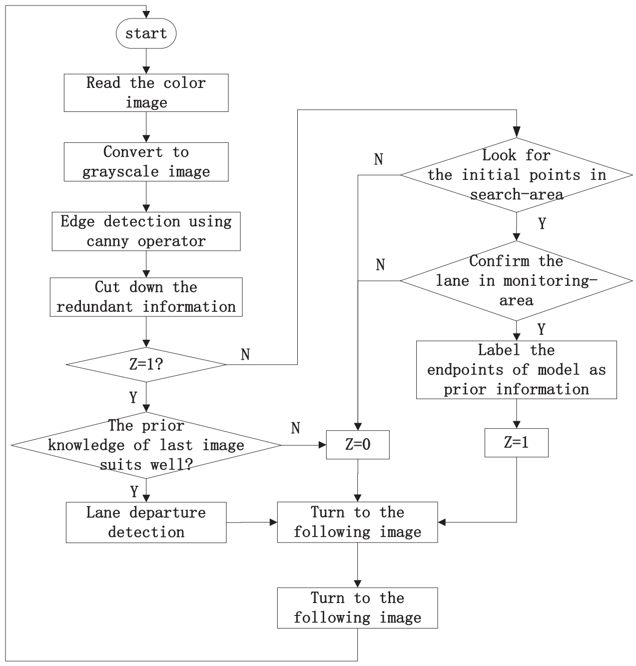


Figure 4. The flowchar of the algorithm

IV. EXPERIMENT AND RESULT

A CCD camera is fixed on the front view mirror to capture the road scene. In the experiment, it was assumed that the input to the algorithm was a 620×480 RGB color image. In order to minimize the processing time to satisfy the need of real-time processing, the first thing of the algorithm is to convert the image to a grayscale image.

The proposed lane departure detection algorithm is implemented in a Pentium(R) Dual-Core CPU E5400 2.70GHz computer using matlab 7.1. As it hasn't been transformed into visual c++, nor transplanted into DSP, the speed of it is limited. We find image down-sampling is a good choice to speed up the processing without affecting the effect of the detection, and in the experiment, we down-sampled the grayscale images.

All the images for experiment are taken in highways and local streets, straight and curved road in different environmental conditions. We choose some typical scenes of three consecutive images to be shown in Fig. 5. One characteristic of the algorithm is to utilize the information of last image to estimate the lanes location of the following one, and that's why we use three consecutive ones to reflect the continuity of the algorithm.

Each experiment scene we choosed has its feature, and they are all very classic. While the road in our campus has spots on it, the highway has more than two lanes,and the lanes of the steet in nightlight are not as clear as the one in daylight. However, the experiment results show that the proposed lane detection methods can work robustly in real-time, and can achieve an average speed of 0.12s per frame with a correct detection rate over 91%.

(a) Campus road (b) Curve way of highway

(c) Urban road in daylight (d) Urban road in nightlight

Figure 5. Results of the lane detection for three consecutive images in each scene

V. CONCLUSION

In the paper, a novel algorithm for lane departure warning system is presented. The location of the endpoints is the key to detect lanes. Once the lanes are detected in one image, the endpoints could be used in the following images as prior information to save resource and time for processing. It is observed that the proposed method has average execution time of 0.12 second in matlab-processing, and if optimized, it will further enhance the speed of operation.

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