A New Approach to Lane Detection based on Pattern Recognition Technology

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***Abstract*—This paper proposes a novel image processing algorithm to detect lane markers. In order to improve the accuracy and anti-interference ability the region of interest in source image is determined based on spatial positional relationship. A small size detection window scanner moving in the region of interest to determine whether there is a lane mark at the current position according to the characteristics of image in detection window. This method can improve detection accuracy and noise immunity. The proposed method is proved to be efficient through experiments for various complex environments, and has good real-time performance and reliability.**

***Keywords*—Active safety; Lane marker detection; Local Otsu; Window scanning**

I. INTRODUCTION

Advanced driver assistance systems (ADAS) have received considerable attention in recent decades, because many car accidents are caused mainly by drivers' lack of awareness or fatigue. Lane departure warning system (LDWS) is an important part of ADAS. The core technology of LDWS is accurate detection of lane markers[1,2]. This paper studies the application of machine vision technology to detect lane markers in a complex environment.Currently, researchers have developed a number of lane recognition algorithms based on computer vision[3-8], but for the following reasons the performance recognition technology may be lower in some cases: (1) Shadows: Shadows caused by trees, fences, vehicles, etc. will result in lane recognition fails. (2) Illumination: Image pixel values have great volatility because of the change of sunlight when cloudy, sunny, morning and evening etc.. (3) Climate: Rain, snow, dust storms, fog and other weather will reduce road image quality. (4) Shelter: Other vehicles, leaves and other debris will block lane marker. (5) Real-time: detection algorithm does not particularly complex considering the real-time requirements.

According to characteristics of lane, we have studied lane marker recognition algorithm based on grayscale image features. First, the region of interest(ROI) is divided according to spatial relationship between camera and position of lane, which is important to reduce the amount of data and exclude external interference. To further enhance anti-jamming capability, multiple detection windows(DW) are distributed in the ROI. Due to the small area of each DW, we believe that the range of illumination in this window is uniform and no other interference. Then we analyze the color distribution characteristics for road surface and lane markers. The RGB color image is converted to grayscale image in ROI[9]. Then according to the characteristics of road grayscale image pixels, we use median filtering method to smooth grayscale image[9]. Lane initial detection is the basis of the algorithm in the system which is needed when system is initial working or tracking failure. Using DW scan ROI for location lane line position in image. The gray-scale image is converted to binary image for each DW using Otsu method for segment the background and objectives. According to the properties of background and target to judge whether the target is lane marker. The least square method is used to fit lane markers to a straight line. Because the least square method has poor immunity characteristics, we study using the principle of least square method to remove error points.

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II. PROPOSED METHOD

A. ROI division method

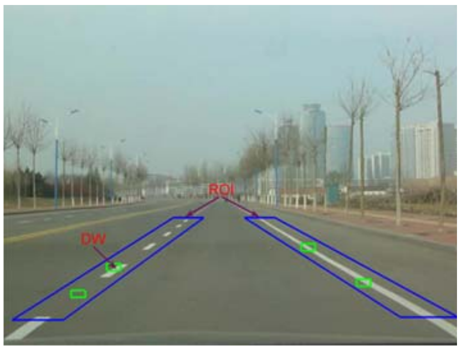


Fig. 1. ROI.

The camera is mounted on the upper center of the front windshield of vehicle to capture image. Due to the installation position and the angle of camera, there are large amounts of irrelevant information in video image. Road area is located under center image position. Lane detection is carried out in this area. Therefore, to consider the detection algorithm reliability, timeliness, accuracy, we detect only in this region, which can greatly reduce amount of calculation and exclude interference of external environment. We call these regions is region of interest(ROI). Fig.1 shows the ROI. Location and size of ROI is obtained by experiment.

Lane marker can be obtained through grayscale image edge detection because of simple texture, less interference and difference gray values between road and lane marker in ROI. Because there may be shadows on pavement, interfering specular reflection, stains, vehicles, etc., so the edge detection for entire unified ROI will fail. So in this paper, the DW is used to scan ROI and edge detection only applied in DW. We can accurately obtain lane marker edges because low probability of outside influence for the small area in ROI. The image processing is performed based on DW. The amount of data of lane detection will be much less than the whole image processing and this method also can save a lot of time cost. According to the principle of relations perspective, the width of lane will be smaller in more distant from the car, so the DW size should be changed accordingly.

B. Initial detection

There will be many problems while removing environment impact on detection by division ROI. For example ROI include surrounding environment for error division, other vehicles in ROI, illumination or shadows. These issues will have an impact on the detection results and even lead to complete failure. Therefore, the algorithm in this paper uses DW scanning ROI for searching lane maker and detection edge. Since DW is small in size and therefore can be considered the external environment(such as lighting or shadows) is the same effect on the region. Although light may be different for each DW but this does not affect detection results. If several windows detection fails, due to the continuity and predictablity of lane marker, the failure does not affect global detection.

1. Image properties of DW

Since there are large difference between road surface and lane marker, and therefore the edge detection is realized by image binarization method. Binarization threshold T_{otsu} is obtained by Otsu algorithm[10] for each DW. Image is divided into two types of background and objectives by the threshold T_{otsu}. The between-class variance δ^2 is a function of T_{otsu}:

$$\delta^2 = \omega_1 \omega_2 (u_1 - u_2)^2 \tag{1}$$

Where ω_1 is the ratio of background area and total area. ω_2 is the ratio of objective area and total area. u_1 and u_2 are the mean values of background and objective.

Each DW at different positions will get one of the best T_{otsu} value used this method that there will be a maximum between-class variance. It is obviously not need to be a binary operation when the DW contain road surface only. This method may fall into local optimum, but can not detect lane marker. If the DW contains lane marker the δ^2 value is large, on the contrary small. According to δ^2 determine whether the value distribution of the DW area is uniform. ξ represents DW area gray value is uniform or not. DW region may exist la*ne marker when* $\xi=1$*. DW is not exists lane marker when* $\xi=0$ because the gray values are uniform that lead to δ^2 small. The calculation formula is as follows:

$$\xi = \begin{cases} 1 & \delta^2 > 50 \\ 0 & \delta^2 \le 50 \end{cases} \tag{2}$$

2. Lane judgment rules

DW grayscale image is divided into two parts of target and background using Otsu algorithm. According to the image properties of target and background we determine whether the target belongs to lane marker.

(1) The average pixel values of target area: if the average pixel values of the detected target small the target may not be lane marker but may be disruptor because lane line pixel values are large.

(2) Target area: the target may be lane marker when the target area reaches a certain value. Small size of the target can not be lane marker.

(3) The average gray values subtraction of target and background: this value can be reflected by δ^2.

(4) Determines whether target edge straight and parallel or approximately parallel. Both side edges of lane marker in real world are parallel. Because of the relationship in perspective projection the both edges in image are not parallel but approximately parallel. The angle between the two edges is small. We can exclude non lane by this condition.

(5) Determines whether target as a whole. If the target dispersion first removing small areas and then judgment the biggest target.

(6) Both sides of DW are road surface and the middle area is lane marker. The pixel values of intermediate region are uniform and greater than both side regions in DW.

(7) Lane marker width within a certain range and it does not change in short time.

(8) Both lane markers on left and right should be parallel and have a distance criterion between each other.

3. Lane fitting

The DW center and the centroid of lane in DW have the same position in X-axis. This ensures that any window can contain all of lane markers in the region. Therefore it is not happen lane can not be completely detected because of the DW position. Lane marker contour is obtained through edge detection. In this paper we fit lane centerline as a straight line. Lane centerline coordinates (x_{iz},y_{jz}) is calculated for each window according to binary image.

$$x_{jz} = (x_{je1} + x_{je2}) / 2 \tag{3}$$

Where: x_{iz}, y_j represents coordinates of lane center line of j row in image, $y_{iz}=j$. x_{ie1} and x_{je2} are X-axis coordinates of edge on both sides of lane line.

Using least square method[11] to fit the center points for a straight line, the linear equation as follows:

$$Ax + By + C = 0 \tag{4}$$

The distance D_j between each lane center point and the straight line:

$$D_j = \frac{|Ax_{jz} + By_{jz} + C|}{\sqrt{A^2 + B^2}} \tag{5}$$

The least square method is fitting line based on the principle of minimum distance square. The error points obtained in lane detected process should be eliminated those can interference fitting line. If D_j>5, we consider that this point deviate from the lane center line, namely the error detection happened, and remove the point.

Also the DW area is very small and can be considered that the influence of external environment on the window is same. But there is still much interference in DW scanning process. Such as shadows boundaries, leaves and other debris in detection window. Those points need to be removed in order to fit lane line right. The proposed elimination algorithm is based on the assumption that most DW can correctly detect lane makers. It is entirely reasonable that most detected points should be located on the same straight line. The exclusion method is designed based on the principle of least square method, the specific steps as shown below:

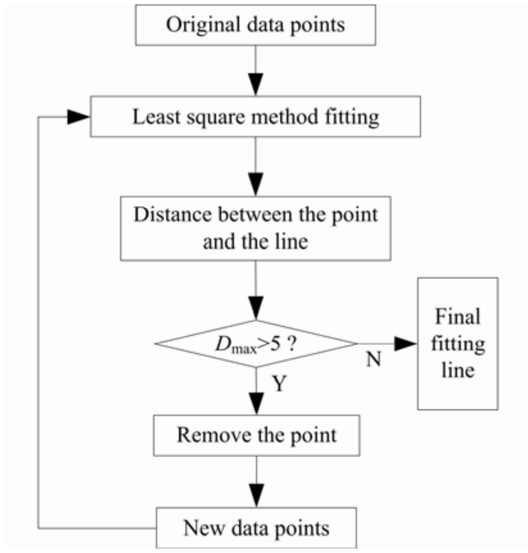
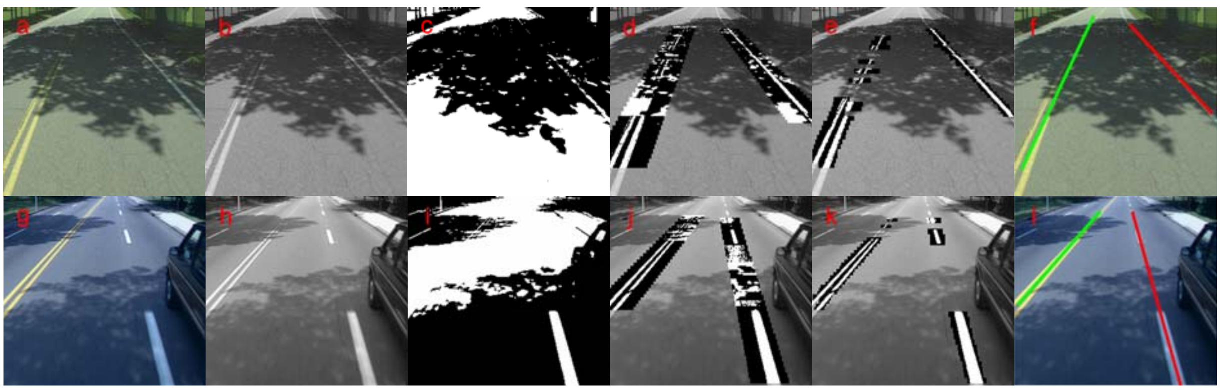


FIG. 2. Flowchart of removing noise points by the least square method.

III. EXPERIMENTAL RESULTS

The offline experiments are carried out on a virtual machine with MATLAB7.1 environment using a computer platform with an Intel(R) i3 3.4GHz core and 4GB of memory. To evaluate the performance of the proposed algorithm, we utilized the proposed algorithm to test a large number of image sequences that contain various complex road environments. The test image sources are come from CMU road sequences and personally collection image video from highway. Note that CMU road video image size is 240×256 and all personal video sequences are captured by car recorder with the setting of 30 fps, a 320×240 frame size. The weather environment in the image includes strong light, shadow, cloudy, night, after snow.

In Fig.3 the a, g, m, s are the CMU original color images. Image a and g contains a lot of shadows and the shaded area has dramatic changes in brightness not only dark. The image m is under normal lighting conditions acquired and the light intensity distribution. The image s is in cloudy environment acquired and the light intensity is weak. The gray images b, h, n, t are obtained by the proposed gray method. The gray values of yellow lane are larger than pavement pixel values. Sign shows very clearly. The sign of yellow lane in the far region for image b shows very unclearly because of shadows and thin. It is also shows unclearly in image a. The images c, i, o, u are binary images obtained by the Otsu method. Because there are a lot shadows that has dramatic changes leads to lane extraction failed using binarization method in image c and i. Illumination is uniform in image o. The gray values of lane and road are quite different. Lane has been successfully detected using binarization method. Image u failed to detect lane with binary image using Otsu method because the whole values in far region are greater than other region. As can be seen from the four images the image segmentation method with Otsu algorithm is easily affected by external environment. If there are ideal external environment the method can divided lane from road successful but if environment is bad such as shadows or non-uniform illumination the method will fail. The image d, j, p and v show lane detection using Otsu algorithm in each independent DW scanning area in ROI. Since each DW scanning area small size, light in area will be greater chances of balanced, suffered outside influence would be more same, so the application Otsu algorithm can get better threshold for segmentation lane. As can be seen from the figure the lane detection results are better than the results that using only one threshold in overall image. Lane can be detected very well in light or shadow but in the shadow of the mottled areas due to the rapid change of light the detection effect is still not ideal. Image e, k, q, w show the results of lane detection which have been obtained by DW scanning and lane attributes judgment method. Because DW width wider than lane, DW will completely contains lane in some positions in the process of DW scanning. Due to the small size of DW, the impact of external environment will be substantially equal to DW. Lane will be extracted exactly based on screening according to lane properties. But in some region detection will still fail or segmentation errors, the failure means no detected lane. Image f, l, r and x show the fitting lines by linear least square fitting method for image e, k, q and w. In DW scanning detection process each DW is independently and the results are independently for each other, so we can accurately fit the lane.



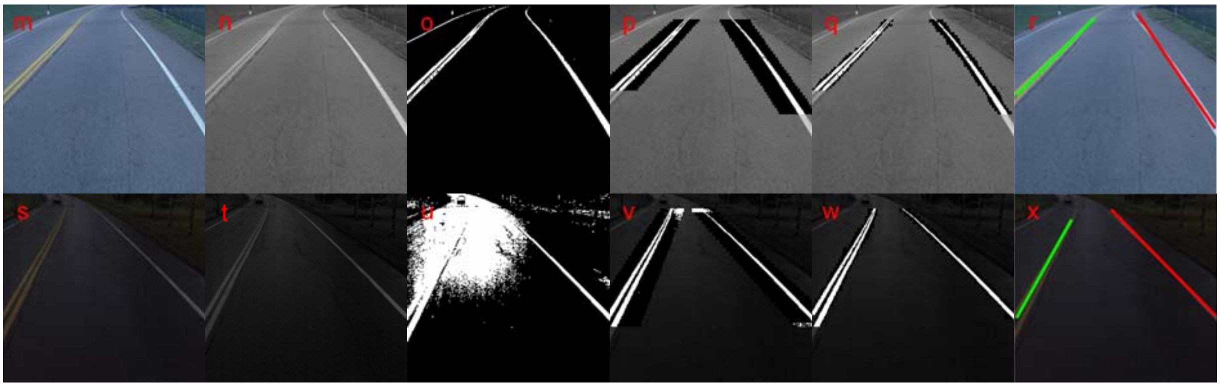


Fig. 3. Lane feature extraction results.

Table 1 shows the lane detection process parameters for each image of Fig.3. The No. of 1, 2, 3 and 4 indicates the image of a, g, m and s in Fig.3. The TT column is the number of scanning area for each side of lane ROI, namely the number of DW. The V column represents the number of DW which can correctly determined lane based on lane properties. The I column represents the number of DW which can't exact lane. The E column represents the number of DW which detected lane error. The T column indicates the computing time for detection lane. The F column shows the detection success or not. The invalid number of left lane of No.1 and 2 is large because of shadows and fuzzy lane in far regions in image e and k. There are many DW which cannot effectively detect lane. The valid numbers of other images close to or equal to the numbers of total scanning number. This shows most DW can correctly detect lane. The error numbers of No. 1, 2, 3 and 4 are small whether there are large shadows or uneven illumination in image e, k, q and w. it Show that the algorithm has strong anti-interference in the detection process, the external interference will not lead to the fitting lane have big error. The computational time shows this algorithm has good real-time performance. The computing time is consumed during the initial detection time, not the tracking phase calculation time. The tracking phase calculation time will be less than the time.

TABLE I. LANE DETECTION STATISTICS

No.		TT	V	I	E	T (ms)	F
1	**LL**	60	32	26	2	30.2	S
	RL	30	28	1	1	25.6	S
2	**LL**	60	47	12	1	22.4	S
	RL	30	20	8	2	21.8	S
3	**LL**	30	30	0	0	20.6	S
	RL	30	30	0	0	21.4	S
4	**LL**	30	30	0	0	19.9	S
	RL	30	30	0	0	21.3	S

Explanation of symbols in table 1 as follows: The LL and RL represent left lane and right lane respectively. The S denotes detection success.

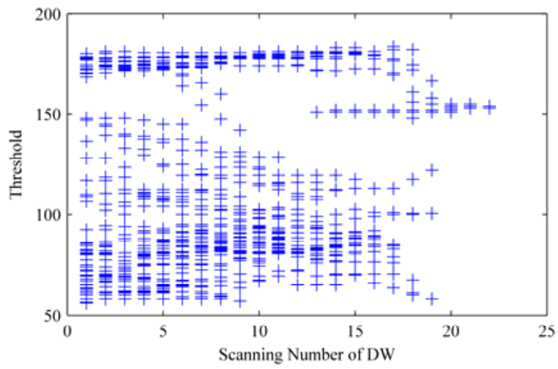


Fig. 4. Thresholds distribution.

Fig.4 is the thresholds distribution in Fig.3(a) those obtained by the proposed method. The thresholds have a large variation range from 50-180 distribution. This shows that the size of detection and calculation region has large effects on the segmentation results in lane detection process. Only select an appropriate threshold in appropriate detection window will be exacted lane completely. The method proposed in this paper for mobile DW scan can just meet the requirements. Fixed window local Otsu segmentation algorithm may be divided lane into different window. The size of lane in each detection window that position is fixed may be very small, and the lane accounting for the secondary effects in the window. This will cause the segmentation threshold error. The mobile DW in this paper proposed will completely contains lane in some positions in the process of DW scanning. At this point the lane occupies the absolute effect in the window. We can accurately exact lane from DW using threshold that obtained from Otsu. The mobile DW scanning detection method has higher accuracy than fixed detection window method.

The relationship between the maximum distances from points to fitting line and iteration times is shown in Fig.5. As Fig.5 shows, with the iteration number increases, the maximum distance is decreasing. The relationship between the lane angle and iteration times is shown in Fig.6. The collected points have more accurate thanks to DW scanning detection. There are only two DW windows error for left lane that affected by light and shadows in Fig.3(a). Therefore, the angle changes significantly in initial iteration process in Fig.6. The distance also changes significantly in Fig.5. Further iterations the angle changes very little. This show that lane has been detected accurately at this time.

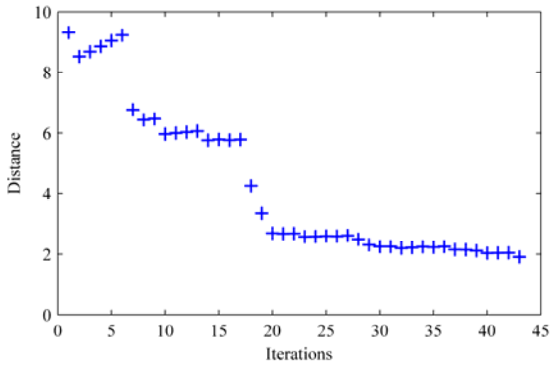


Fig. 5. The distance changes with the number of iterations.

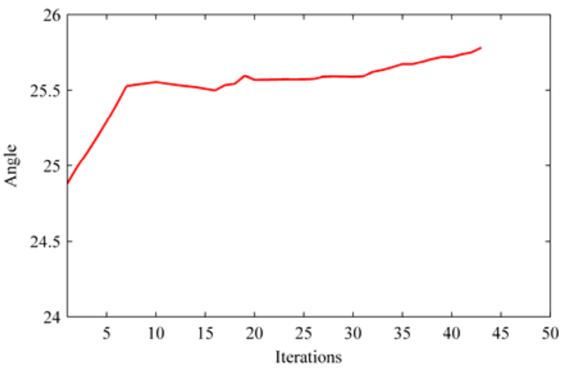


Fig. 6. The angle changes with the number of iterations.

IV. CONCLUSIONS

In this paper, we have presented detail lane detection and tracking method, which can easily be achieved. The experimental results show that the proposed method has high reliability, strong robustness and adaptability for lane detection in complex environment, and can recognize lane markers real-time.

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