Lane Detection System based on Hough Transform with Retinex Algorithm

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Abstract

Nowadays, automotive system becomes a great innovation in the world and lane detection system is important to control automobile vehicles. This paper has developed an efficient lane detection system to deal with different types of lighting conditions. Six types of edge detection techniques: canny, sobel, prewitt, Roberts, Laplacian of Gaussian (LOG) and zero-cross methods are analyzed. Line detection based on canny operator is developed. Moreover, Retinex algorithm is employed to normalize input images for all types of illumination. And Hough Transform with Retinex algorithm is developed to solve lighting problem. The proposed method is compared to Hough Transform with Otsu's threshold method. The experimental results show that the proposed method can reduce computation time and improve accuracy for lane detection system.

Keywords- Automotive System, Lane Detection, Hough Transform, Retinex

1. Introduction

Lane detection is the process to locate lane markers on the road and then describe these locations to an intelligent system. In intelligent transportation systems [4], intelligent vehicles cooperate with smart infrastructure to achieve a safer environment and better traffic conditions. The applications of a lane detecting system could be as simple as pointing out lane locations to the driver on an external display, to more complex tasks such as predicting a lane change in the instant future in order to avoid collisions with other vehicles. Some of the interfaces used to detect lanes include cameras, laser range images, and GPS devices [7].

In safety driving assistance system, the correct recognition of lane detection is the most important issue for automobile vehicles to achieve autonomous navigation. The level of autonomy ranges from fully autonomous (unmanned) vehicles to vehicles where computer vision based systems support a driver or a pilot in various situations. Fully autonomous vehicles typically use computer vision for navigation, i.e., for producing a map of its environment and for detecting obstacles.

Researchers have developed various lane detection methods based on computer vision. These detection methods can be divided into two types: model-based and feature-based methods [6, 8, and 10]. In model-based methods, lane boundaries are presented by mathematical models while feature-based methods use segmentation methods to locate road areas. Moreover, model-based methods usually require a very complex modeling process involving much prior knowledge and background. Among model-based and feature-based methods, feature-based algorithms are efficient and popular.

For autonomous vehicle, detection of lane suffers from high computational complexities and poor performance under different lighting conditions. In this paper, we propose Hough Transform with Retinex Algorithm for lane detection to solve lighting problem and compare computational complexity to Hough Transform with Otsu's method.

The remainder of this paper is organized as follows: Section 2 provides review of researches in the literature related to lane detection in automotive systems. In Section 3, our proposed methodology for lane detection is described to solve different lighting conditions. Section 4 presents analysis of results of proposed algorithms. Finally, section 5 describes conclusion and future work.

2. Research Background

With the development of researches on autonomous vehicle, lane detection is becoming a more and more hot topic. Among lane marking detection algorithms, feature-based algorithms are efficient and popular, where many researchers have been done.

Jie Guo et al. [3] proposed an improved random sample consensus (RANSAC) algorithm combined with the least squares technique to estimate lane model parameters based on feature extraction. They achieved comparable results to other algorithms that only worked on detecting the current lane boundaries. However, from experimental results, there are still some difficult lane scenarios to be solved. Moreover, they presented future work that their framework will be integrated with tracking algorithms for improvement.

Hao Yu et al. [1] described a constraint between Sobel operator and Shen Jun edge operator to detect the lane marking points. In addition to, they presented a new vehicle detect algorithm which uses the shadow under the vehicle and the vertical edge to detect the candidate vehicles. Then they used Support Vector Machine (SVM)

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and Histogram of Oriented Gradients (HOG) to verify their system.

Dong-Uk Kim et al. [5] proposed an efficient approach to lane and pedestrian detection by processing sequential images from a camera attached to a moving vehicle. They predicted the left and right lines of the current lane by finding high intensity pixels along multiple horizontal scan lines and connecting the detected pixel points.

Z. Teng et al. [9] proposed an algorithm which integrated multiple cues, including bar filter which has been efficient to detect bar-shape objects like road lane, color cue, and Hough Transform. To guarantee the robust and real-time lane detection, particle filtering technique has been utilized. This algorithm improved the accuracy of the lane detection in both straight and curved roads. It has been effective on a wide variety of challenging road environments. This method fails for the lane tracking when it is to be applied to particle filter in the dashed lane situation.

F. Mariut et.al [2**]** proposed an algorithm that automatically emphasizes the lane marks and recognizes them from digital images, by the use of Hough transform. This method also detects lane mark's characteristics and has the ability to determine the travelling direction. A technique that extracts the inner margin of the lane is used to ensure the right detection of the lane mark. The algorithm works very efficiently for straight roads but fails in some cases of curved roads.

3. Methodology

Our proposed methodology for lane detection to solve lighting problem is shown in Figure.1. This system includes four stages: pre-processing, edge detection, illumination reduction and line detection. In pre-processing step, three sub-stages are described: selection of ROI (Region of Interest), conversion RGB image into gray scale image and noise removal. The major purpose of our system is to detect lanes under different illumination conditions. And another purpose is to improve performance and processing time of lane detection system.

3.1. Preprocessing

This is the most important step in our system. First, we resize input image (as shown in Figure 2) and set ROI (Region of Interest) to reduce memory storage space. Therefore, only region of image which contains relevant information (i.e. lanes' boundaries) is obtained. Next, RGB color image is converted into grayscale image in order to improve processing speed as shown in Figure 3.The last step of preprocessing stage is de-noising. In this case, we apply Gaussian filter to remove noise.

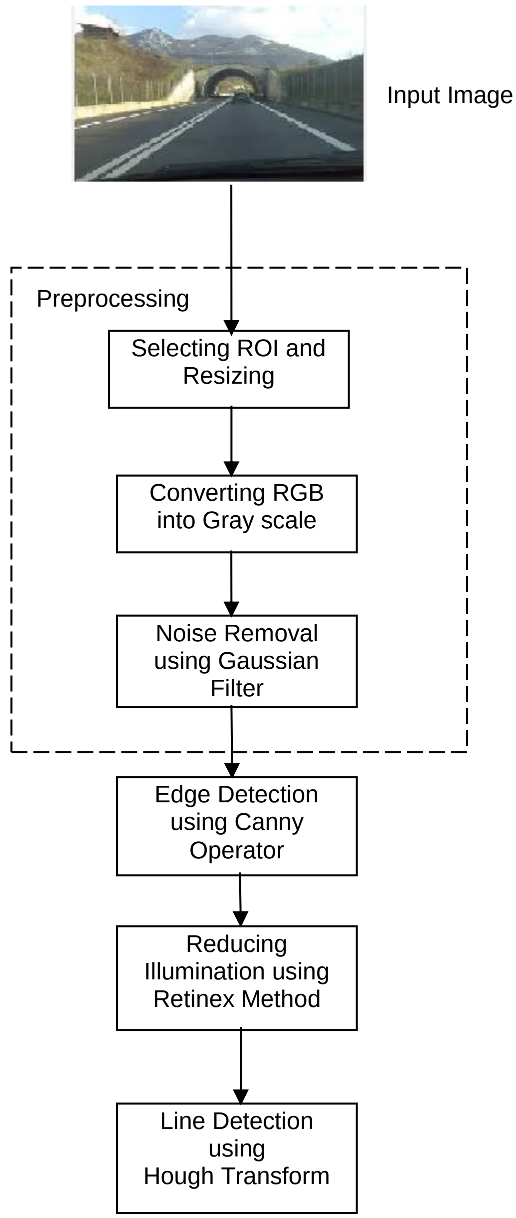

Figure 1. Proposed lane detection system

3.2. Gaussian filter

It is a type of filter which is applied to convolve with the image where the selection of the size of Gaussian kernel will affect the performance of the detector. Typically, it is only needed to calculate a matrix with dimensions $\lceil 6\sigma \rfloor \times \lceil 6\sigma \rfloor$ (where $\lceil . \rfloor$ is the ceiling function) to ensure a result sufficiently close to that obtained by the entire Gaussian distribution.

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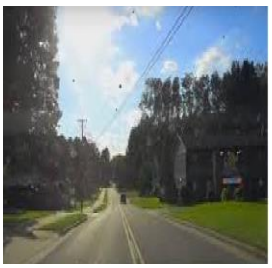
Figure 2. Original image



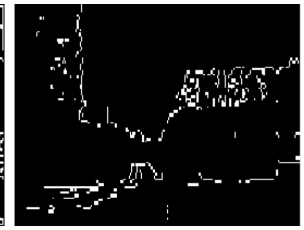
(a) Resized image **(b) Grayscale image**

(c) Noise removal image using gaussian filter

Figure 3. Preprocessing steps of lane detection

3.3. Edge detection

Next, edge detection is performed. Edge information is the most commonly used features in lane detection system. In real-time situations, lane edge features may not be strong and may be affected by shadow. Therefore, the selection of edge detection operator is needed. In this case, sobel operator, canny operator,prewitt operator, Roberts, Laplacian of Gaussian and Zero-cross are individually experimented as edge detection algorithms as shown in Figure 4. From our experiments, canny operator is the most suitable one for next steps of lane detection system. Thus, this operator is accepted as edge detection algorithm for our proposed system.



(b) Sobel operator

(c) Prewitt operator **(d) Roberts operator**

(e) Laplacian of gaussian **(f) Zero-cross method**

Figure 4. Edge detection methods

3.4. Canny operator

The process of canny edge detection algorithm can be broken down to 5 different steps:

(1)Apply Gaussian filter to smooth the image in order to remove the noise

(2)Find the intensity gradients of the image

(3)Apply non-maximum suppression to get rid of spurious response to edge detection

(4)Apply double threshold to determine potential edges

(5)Track edge hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

3.5. Reducing illumination using retinex algorithm

Lighting problem is crucial in Lane Detection System (LDS). In this case, Retinex Algorithm is applied for all types of illumination. The Retinex theory motivated by Land [11] is based on the physical imaging model, in which an image *I*(*x, y*), it could achieve sharpening with compensation for the blurring introduced by image formation process. Moreover, it could improve consistency of output as illumination changes.

$I(x, y)$ is regarded as the product $I(x, y) = R(x, y) \cdot L(x, y)$ where $R(x, y)$ is the reflectance and $L(x, y)$ is the illumination at each pixel (x, y). Here, the nature of $L(x, y)$ is determined by the illumination source, whereas $R(x, y)$ is determined by the characteristics of the imaged objects. Therefore, the illumination normalization can be achieved by estimating the illumination L and then dividing the image I by it. In most Retinex methods, the reflectance R is estimated as the ratio of the image I and its smooth version which serves as the estimate of the illumination L.

$$R_i(x,y) = \log I_i(x,y) - \log[F(x,y) * I_i(x,y)] \quad (1)$$

$$R_i(x,y) = \log \frac{I_i(x,y)}{F(x,y)*I_i(x,y)} = \log \frac{I_i(x,y)}{\bar{I}_i(x,y)} \quad (2)$$

where $I_i(x, y)$ is the image distribution in the i^{th} spectral band and $R_i(x, y)$ is retinex output.

Gaussian function $F(x, y) = K e^{-(x2+y2)/c2}$ where K is determined by

$$\iint F(x,y)dxdy = 1 \quad (3)$$

3.6. Line detection using generalized hough transform

In the final stage of our proposed system, Generalized Hough Transform is applied for lane detection.

To generalize the Hough algorithm to non-analytic curves, Ballard defines the following parameters for a generalized shape $a=\{y, s, \theta\}$ where *y* is a reference origin for the shape, θ is its orientation, and $s = (s_x, s_y)$ describes two orthogonal scale factors. As in the case of initial Hough Transforms, there is an algorithm for computing the best set of parameters for a given shape from edge pixel data. These parameters no longer have equal status. The reference origin location, *y*, is described in terms of a template table called the R table (as shown in table 1) of possible edge pixel orientations.

Table 1. Building R-table

i	ϕ_i	R ϕ_i
1	0	$(Y_{11},\alpha_{11})(Y_{12},\alpha_{12})\ldots(Y_{1n},\alpha_{1n})$
2	$\Delta\phi$	$(Y_{21},\alpha_{21})(Y_{22},\alpha_{22})\ldots(Y_{2m},\alpha_{2m})$
3	$2\Delta\phi$	$(Y_{31},\alpha_{31})(Y_{32},\alpha_{32})\ldots(Y_{3k},\alpha_{3k})$
…	…	…

The computation of the additional parameters *s* and θ is then accomplished by straightforward transformations to this table. The key to generalizing the Hough algorithm to arbitrary shapes is the use of directional information. Given any shape and a fixed reference point on it, instead of a parametric curve, the information provided by the boundary pixels is stored in the form of the R-table in the transform stage.

For every edge point on the test image, the properties of the point are looked up on the R-table and reference point is retrieved and the appropriate cell in a matrix called the Accumulator matrix is incremented. The cell with maximum 'votes' in the accumulator matrix can be a possible point of existence of fixed reference of the object in the test image.

Choose a reference point *y* for the shape (typically chosen inside the shape). For each boundary point *x*, compute $\phi(x)$, the gradient direction and $r = y - x$ as shown in the image. Store *r* as a function of ϕ.Notice that each index of ϕ may have many values of r.

One can either store the co-ordinate differences between the fixed reference and the edge point $((x_c - x_{ij}), (y_c - y_{ij}))$ or as the radial distance and the angle between them (r_{ij}, α_{ij}). Having done this for each point, the R-table will fully represent the template object. Also, since the generation phase is invertible, we may use it to localise object occurrences at other places in the image.

4. Experiments and results analysis

We have evaluated the proposed algorithms with a laptop, in Matlab environment which has Intel(R) Core (TM) i3 CPU @ 2.53 GHz and 2.00GB RAM. Since Caltech's 2008 are available as public database, we have implemented our experiments on it. Four stages are presented in our proposed system: pre-processing, edge detection, illumination reduction and lane detection as shown in Figure 1.

Table 2. Computation time of edge detection algorithms

No.	Edge Detection Methods	Time (seconds)
1	Canny	0.623103
2	Sobel	0.608996
3	Prewitt	0.551883
4	Roberts	0.520003
5	Laplacian of Gaussian	0.660884
6	Zero-Cross	0.543144

The goal of our lane detection system is to solve lighting problem for all types of illumination. In this paper, we proposed an efficient lane detection system based on retinex algorithm which solves different lighting conditions. Region of Interest (ROI) selection, grayscale conversion and removal of noise are applied in preprocessing stage.

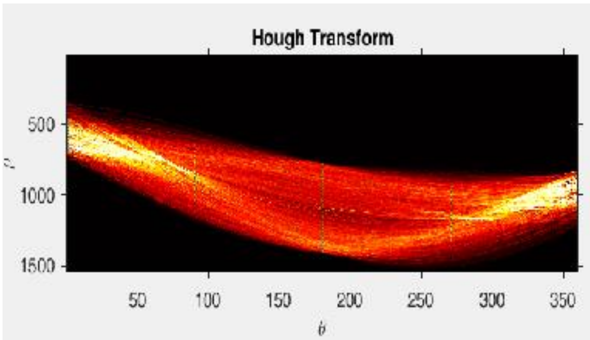


Figure 5. Hough transform using otsu's method

In edge detection, canny operator is the most suitable edge detector for our proposed system. Next, we have tested Otsu's threshold method and retinex method for lighting problem as shown in Figure 5 and 6. In this case, our proposed method gives better computation performance in short time as shown in Table 3.

Table 3. Computation time of illumination methods

Illumination Methods	1	2	3	4	5	6	7	8	9
Otsu's Method	**2.8 (s)**	**0.5 (s)**	**1.2 (s)**	**0.7 (s)**	**0.8 (s)**	**0.9 (s)**	**0.9 (s)**	**1.4 (s)**	**0.8 (s)**
Proposed Method	**1.4 (s)**	**0.3 (s)**	**0.6 (s)**	**0.3 (s)**	**0.8 (s)**	**0.6 (s)**	**0.8 (s)**	**0.7 (s)**	**1.2 (s)**

Moreover, lane detection using Hough transform and edge detection methods (canny, sobel, prewitt, Roberts, LoG, zero-cross and Otsu's threshold) have been tested individually and results are shown in Figure 7.

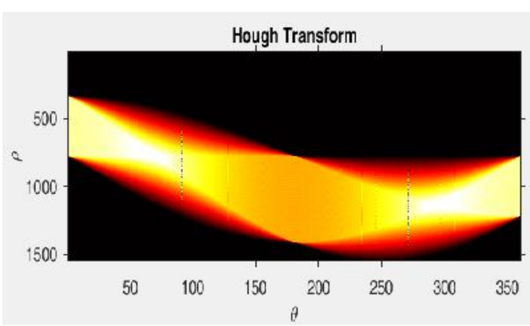
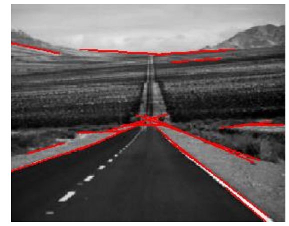


Figure 6. Hough transform using retinex method

(a) **(b)**


(c) **(d)**


(e) **(f)**

(g)

Figure 7. Lane detection using (a) canny, (b) sobel, (c) prewitt, (d) roberts, (e) laplacian of gaussian, (f) zero-cross and (g) otsu's threshold methods

5. Conclusion and future work

In real-time situations, lane detection system faces lighting problem for various types of illumination. Therefore, in this paper, we have especially presented Hough Transform with retinex algorithm for line detection. Moreover, six types of edge detection methods are individually experimented and canny operator is selected as the most suitable edge detection algorithm.

In future work, an efficient method based on Hough Transform and Retinex Method, which is to solve both straight lane detection and curve line detection, will be presented.

6. References

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