Lane Detection Algorithm based on Local Feature Extraction

Guorong Liu[1,2]
[1] College of Electrical and Information Engineering
Hunan University
Changsha, People's Republic of China
lgr745@hotmail.com

Shutao Li[1,2] and Weirong Liu[1,2]
[2] The State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body
Hunan University
Changsha, People's Republic of China
shutao_li@hnu.edu.cn, liu_weirong@163.com

***Abstract*—An effective local feature extraction algorithm for lane detection is proposed in this paper. First, a lane region of interest (ROI) is determined by the location of road surface appeared in an image. Then, the light intensity and width of lane markings are taken as the local feature. A local threshold segmentation algorithm is utilized to extract lane-marking candidates followed by a morphological operation to obtain the accurate lane. An edge refining procedure is used to eliminate the interference and reduce computational cost. Finally, the lane marking is detected using Hough transform with some subsidiary conditions. With the proposed method, the lane can be accurately detected in conditions of fluctuating and poor illumination, as well as the interference from reflected light can be avoided effectively. The experimental results demonstrate the efficiency of the proposed method.**

Keywords—Lane detection; local threshold segmentation; morphological operation; Hough transform

I. Introduction

The Driver Assistant System (DAS) is mainly designed to improve safety and efficiency for drivers. Lane detection is a significant part of DAS, including Lane Departure Warning System (LDWS) and Lane Keeping Assistance System (LKAS). The LDWS and LKAS can locate lane markings and estimate the vehicle position relative to the road lane. Lane detection is the procedure of estimating the location of lane markings, which can be forwarded to an intelligent system for further processing, such as lateral control assistance[1].

In recent decades, numerous vision-based approaches have been proposed to detect lanes in various conditions. The most commonly used method is mapping an edge image to Hough space to find the best fitting lines[2]. However, in this method, the detection process relies heavily on the outcome of the edge detection process. If there are some interference on the road surface, such as cracks and shadows, the edge of lane markings will not be obtained accurately. To avoid these scenarios, the color-based methods, such as HSI[3], $L*a*b*$ [4] or a custom color space[5], are introduced to better distinguish lane markings from the paved road. He Y. *et al.*[6] used the average of three color channels to represent the intensity image. Cheng H.-Y. *et al.*[7] utilized linear operation on the individual color channels of RGB image to analysis the color distribution of road and lane markings. However, in different lighting conditions the color of lane markings will be various and unlikely to remain in a fixed range. In this case, color-based methods may cause a wrong segmentation result and affect subsequent analysis. In addition to detecting lanes in the image plane, another way is to generate a bird eye view of the road using inverse projection mapping (IPM) [8, 9]. After applying the IPM, all the objects outside the road surface are removed and lane markings are nearly parallel to each other. The drawback of this approach is that it is based on the flat ground assumption and requires an accurate camera calibration. Since the road scene varies with vehicle moving, the flat ground assumption is not appropriate and camera's external parameters are variable. As a consequence, this approach may generate unreliable detection results.

Most of the above mentioned techniques require clear lane markings and a well-illuminated scene [10]. In poor illumination scenes, lane markings are unobvious and noises may appear on the image. Moreover, vehicle headlights, taillights, road lamps and reflected light appear in scenes and will disturb the detection result. To overcome these drawbacks, a local threshold segmentation and morphological operation based lane-marking extraction algorithm are proposed in this paper. Using the local threshold segmentation can overcome the impact of low light and morphological operation can eliminate the interference from light.

The rest of this paper is organized as follows: Section 2 introduces the lane detection algorithm including local threshold segmentation, morphological operation, edge refining, and the modified Hough transform algorithm. Experimental results are given in Section 3 and the work is concluded in Section 4.

This paper is supported by the National Natural Science Foundation of China (No. 61172161) and the Independent Research Funds of the State Key Laboratory of Advanced Design and Manufacturing for Vehicle Body (Hunan University, No.71165002).

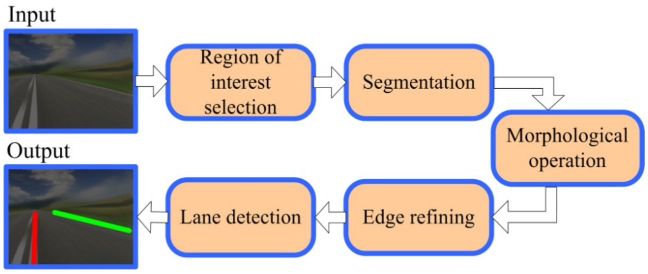


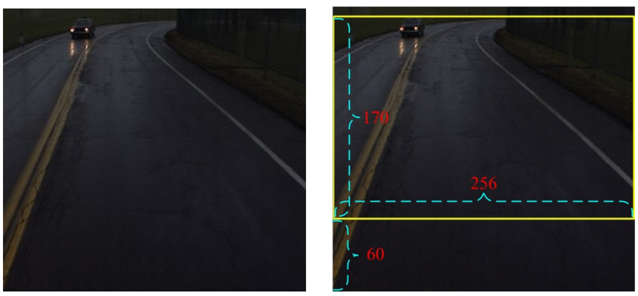
Fig. 1. Block diagram of the proposed lane detection method.

II. The Proposed Method

In this paper, our lane detection algorithm shown in Fig.1 consists of five steps. Each step of the process can be described as follow: First, the lane region of interest is selected with a fixed-ratio rectangle according to the priors of camera and road images. Second, all lane-marking candidates are extracted by the median local threshold segmentation algorithm. Third, the interference of reflected light is removed using a morphological operation and then accurate lane markings are obtained. Fourth, edge refining is performed to eliminate the noise interference and reduce the computational cost. Finally, a restricted search in Hough space is carried out to get the exact location of lane markings.

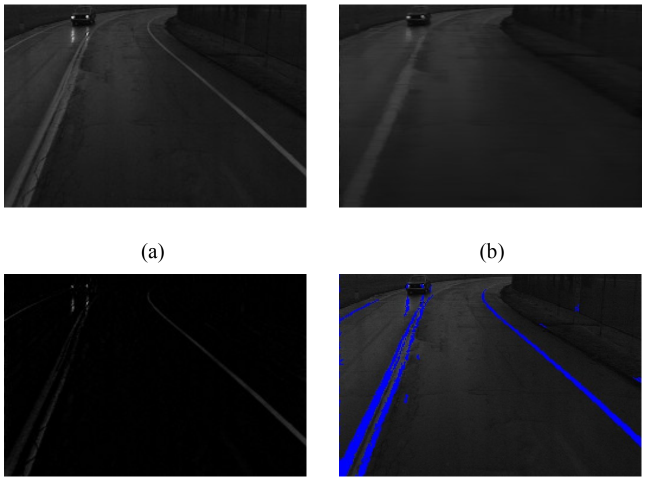
A. Region of Interest Selection

In order to enhance the accuracy and reduce the computational cost of the detection algorithm, the region of interest (ROI) is located first. Let $I \in \mathbb{R}^{m \times n}$ be the original image and let $I_{ROI} \in \mathbb{R}^{m_{ROI} \times n}$ be the ROI, where $m \times n$ and $m_{ROI} \times n$ are the size of the original image and the ROI respectively. Generally, the road area is always located in the frontage of the vehicle and not far from it when it is moving forward. So the bottom region of a road image contains most information of lane markings. Based on some priors such as the position of camera and large number of statistical results, we initialize the ROI with a fixed ratio. The size of ROI is 256×170 when the image resolution is 256×240 . As shown in Fig. 2(b) with yellow box, the ROI is under the vanishing line and upon the useless part.



(a) (b)

Fig. 2. ROI selection. (a) Original image. (b) The selected ROI.



(a) (b) (c) (d)

Fig. 3. The lane-marking candidates extraction. (a) Grayscale image of ROI I_{ROI} . (b) Filtered image $\hat{I}_{ROI}$. (c) The difference between I_{ROI} and $\hat{I}_{ROI}$. (d) The segmentation result (the extracted lane-marking pixels are in blue).

B. Segmentation by the Median Local Threshold (MLT) Algorithm

After the ROI was selected, the next step is to extract lane-marking candidates. Obviously, the process of lane extraction is crucial to the whole process: the better it is, the more accurate the lane description will be. The feature used for the lane extraction is the image pixel directly. The Median Local Threshold (MLT) algorithm[11] is utilized to convert the ROI into a binary image. Compared with the global threshold method, the local threshold method uses the local characteristic of the image and achieves better results in non uniform lighting conditions.

Based on the local threshold extraction algorithm described in [12], we filter the ROI line-by-line to produce a filtered image without bright and dark highlighted objects. Firstly, the grayscale of ROI $I_{ROI}(x, y)$ is convolved with a 1-D median filter with a horizontal width S_x , i.e.,

$$\hat{I}_{ROI}(x, y) = I_{ROI}(x, y) \otimes \hat{f}(x, y), \tag{1}$$

where $\otimes$ denotes the convolution operator and the median filter $\hat{f}$ is defined as:

$$\hat{f}(x, y) = \underset{(s,t)\in S_x}{\text{median}}\left\{I_{ROI}(s,t)\right\}. \tag{2}$$

From [13], it has been demonstrated that taking the minimum over three color channels instead of a gray-level image will generate better results. Generally, the lane marking in road scenes is drawn in yellow or white which corresponds to (255, 255, 0) and (255, 255, 255) in RGB color space. So we use the minimum over two color channels to obtain the grayscale image $I_{ROI} = \min(R, G)$.

Taking into account of the perspective effect, S_x is linear modulated according to the vertical coordinate x. According to the width of lane markings, the range of $S_x \in [S_{min}, S_{max}]$ is determined by the size of image. According to the experimental data analysis, we set $S_{max} = 0.1 * n$ and $S_{min} = 0.01 * n$, where n is the number of columns in I_{ROI}.

Then a binary image I_{BW} is generated by segmenting the difference between the grayscale image I_{ROI} and the filtered image $\hat{I}_{ROI}$ with a threshold value T_G as follows:

$$I_{BW} = \begin{cases} 255 & I_{ROI} - \hat{I}_{ROI} \geq T \\ 0 & I_{ROI} - \hat{I}_{ROI} < T \end{cases}. \tag{3}$$

The value of T is defined according to the statistical properties of pixels in the ROI:

$$T = \sum_{k=0}^{L-1} u_k \times p(u_k), \tag{4}$$

where L is the gray level of the ROI, u_k is the kth gray level and $p(u_k) = n_k / N$ is the probability of occurrence of gray level u_k. n_k is the number of pixels with gray level u_k, and N is the total number of pixels in the ROI.

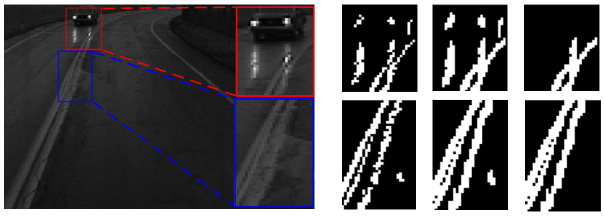
The extracted bright pixels are considered to be lane-marking candidates. As illustrated in Fig. 3, our local threshold segmentation algorithm can find all lane-marking candidates in low contrast light conditions.

C. Interference Removed by Morphological Operation

In order to locate lane markings accurately and eliminate the interference of reflected light effectively, the result extracted above need to be further processed. In low light scenes, lane markings will become discontinuous. Considering the coherence of lane markings, a morphological dilation operator in vertical direction is used to connect the cracked lane-marking. The binary dilation of image I_{BW} by structure element B denoted $I_{BW} \oplus B$ is defined by:

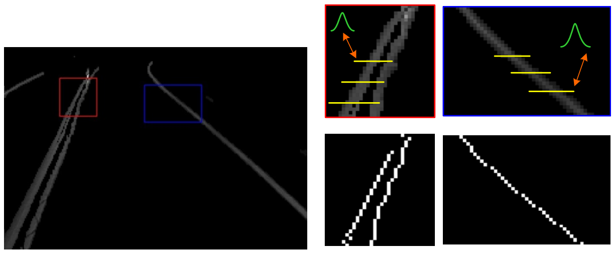
$$I_{BW} \oplus B = \{ z \mid (B)_z \cap I_{BW} \neq \varnothing \}. \tag{5}$$

Then we eliminate the interference caused by the light sources such as car light and reflected light. Since the light sources appeared in the image look like bilateral symmetry, it will turn out to be an approximate vertical strip after the



(a) (b) (c) (d)

Fig. 4. Intermediate results of removing the interference. (a) Grayscale image of ROI I_{ROI} and partially enlarged view. (b) Segmentation result. (c) Morphological dilation result. (d) Interference removed result.



(a) (b)

Fig. 5. The result of edge refining. (a) Grayscale profile of lane markings. (b) Detail with enlarged scale (The upper part: Gaussian shape for the 1-D grayscale profile within the yellow window. The lower part: Result of edge refining).

morphological dilation operation. Therefore, according to the orientation of each connected region, the vertical strips can be ignored. The orientation is defined as the angle (in degrees ranging from -90 to 90 degrees) between the x-axis and the major axis of the ellipse that has the same second-order moments as the region.

The intermediate results are shown in Fig. 4. Fig. 4(a) shows two zoomed portions of the ROI with reflected light and a cracked lane. Fig. 4(b) shows the output of the proposed local threshold segmentation algorithm. The upper and lower lane markings are separated into several parts due to damage. Fig. 4(c) shows the output of the morphological dilation operation. As shown in Fig. 4(d), broken lane markings are connected and the interference of reflected light is removed.

D. Edge Refining

For easy implementation, the grayscale profile of extracted pixels can be obtained by integrating extracted results and the grayscale image with a logical AND operation. The intensity values transition along the horizontal grayscale profile is quite similar to Gaussian shape. We convolve the grayscale profile with a smoothing Gaussian kernel in horizontal direction, i.e., $f_u(x) = \exp(-x^2 / 2\sigma_x^2)$, whose σ_x is adjusted according to the width of lane markings (the same as S_x in Section Ⅱ. B).

Seeking local maxima of each row can achieve the purpose of edge refining. The local maxima are chosen as the best estimate of the lane-marking center pixels. Fig. 5 shows the result of edge refining. With this process, the noise interference is decreased and the computational speed can be increased in the next step.

E. Lane Detection using Hough transform

Because of the limited field of vision, the lane shape can be regarded as straight-lines. Therefore, the well-known Hough Transform (HT), which is robust to noises, is used to detect lanes. The classical HT votes for every point to sinusoid in the polar parameter space (ρ, θ) and uses a larger accumulation array. Here the modified HT with smaller accumulation array of parameter space (ρ, θ) is employed to reduce the required memory and the computational cost.

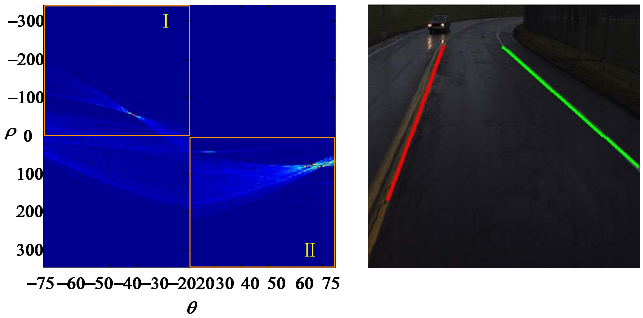
It is assumed that the vehicle is moving within the lane so that lane markings appeared on the image keep in a certain direction. The restriction on θ is utilized to generate the polar parameter space. Using an empirically determined range, θ is given from $-75°$ to $-20°$ and $20°$ to $75°$. Hough space with smaller accumulation array is shown in Fig. 6 (a). According to the sign of θ, lines on the image can be divided into two classes. We search the peak point in each subspace (within orange box shown in Fig. 6 (a)) to find the location of lines corresponding to lane markings. The left and right line segments are defined by:

$$L_l = \{x_l^1, y_l^1, x_l^2, y_l^2, \rho_l, \theta_l, n_l, s_l\}, \quad \theta_l \in [20°, 75°], \qquad (6)$$

$$L_r = \{x_r^1, y_r^1, x_r^2, y_r^2, \rho_r, \theta_r, n_r, s_r\}, \quad \theta_r \in [-75°, -20°], \qquad (7)$$

where (x_*^1, y_*^1) and (x_*^2, y_*^2) are the starting and ending point of line segments respectively, (ρ_*, θ_*) is the coordinate of line segments in Hough space, n_* is the number of selected points contained in a line segment, and s_* is calculated by $s_* = n_* \Big/ \sqrt{\left(x_*^1 - x_*^2\right)^2 + \left(y_*^1 - y_*^2\right)^2}$, which represents a saturation degree.

In order to detect the ego-lane, all the other lane markings need to be considered as outliers. The detected line segments are verified by two criteria: length n_* and saturation degree $\mathbf{s}_* s_*$. The lane markings have a certain length, so the value of n_* and $\mathbf{s}_* s_*$ should meet the requirement. By analyzing the experimental data, two loose conditions ($n_* > 20$ and $s_* > 0.2$) are defined to select valid line segments. The final detection result shown in Fig. 6(b) demonstrates that the HT with subsidiary conditions can accurately detect lane markings. The red line is the detected left boundary, and the green line is the detected right boundary.



(a) (b)

Fig. 6. Result of lane detection. (a) Hough space. (b) Result of line detection.

III. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed lane detection algorithm, we collected a series of real-world road sequences with different types of illumination conditions. The data sets cover three kinds of road scenarios, including the night scene, the rainy scene and the fluctuating illumination scene. The images of set 1 are obtained from [14], set 2 and set 3 provided by the Vision and Autonomous Systems Center of the Robotics Institute in Carnegie Mellon University (at the website http://vasc.ri.cmu.edu/idb/html/road/index.html). From the data set of [14], we selected one scene at night, totaling 15 clips of preview containing 4122 frames(640×480). From CMU/VASC image database, images of rainy scenes and fluctuating illumination scenes containing 75 and 163 frames (256×240) were selected respectively. The experiments are implemented in MATLAB R2010b with 2.30 GHz CPU and 4.0 GB RAM. The average computation time is under 0.2s for processing one image of size 256 × 240 without optimization.

We evaluate performance of the proposed detection algorithm on three different scenes. The method of Borkar *et al.* [14] which used temporal blurring and adaptive threshold to extract lane markings at the night scene, is used for comparison. The results of lane detection algorithms are shown in Table 1. The correct rate is the average percentage of correct detections for each scene, while the false rate and missing rate represent the average percentage of incorrect and undetected lanes respectively. As can be seen from the table, the Borkar's method[14] and our approach perform well at the night scene. The performance of Borkar's method[14] is degraded when tests on the data sets that contains fluctuating illumination and curve lane. This method may cause false results if there are curvature lane markings (Fig. 7 a) and black tracks on the road (Fig. 7 b). Our algorithm correctly finds lane boundaries from the same images (Fig. 7 c and d). These data demonstrate that our approach can work well in various illumination conditions.

TABLE I. THE COMPARISON RESULT OF LANE DETECTION ALGORITHMS

Illumination type	Method	Correct rate	False rate	Missing rate
Night scene	Our method	94.06%	3.98%	1.96%
	Borkar's method[14]	92.09%	6.98%	0.93%
Rainy scene	Our method	98.67%	1.33%	0%
	Borkar's method[14]	86.67%	10.67%	2.67%
Fluctuating illumination scene	Our method	87.36%	5.75%	6.89%
	Borkar's method[14]	74.71%	10.34%	14.95%

(a) (b) (c) (d)

Fig. 7. Examples of comparison result. (a)- (b) False detections by the Borkar's method[14]. (c)- (d) Correct detections by our method.

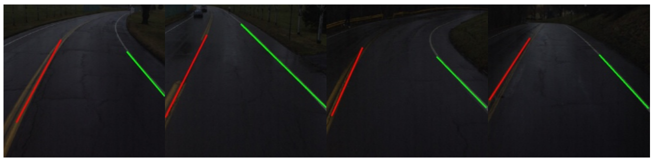
Fig. 8 shows examples of applying our method to sceneries with different illumination conditions. Fig. 8 (a) is a night scene with reflected light, artificial markings, vehicles, curve lane markings and crossing on road images. Fig. 8 (b) demonstrates detection results of upslope, large curvature lanes, dashed and faded lanes in the rainy scene. Fig. 8 (c) shows experimental results in the fluctuating illumination scene. In this clip, the ego-vehicle moves through a tunnel and there are multiple illuminations. The results illustrate that our method can robustly deal with low contrast and curve lane boundaries in various road situations.

However, our algorithm will perform poorly if there is a cover by proceeding vehicles or a similar color between lane markings and surroundings. It is because that the proposed method only uses the spatial information of a single image without considering the temporal information. Moreover, the results may be disturbed if there are something else that meets the condition of lane markings, such as white tracks and multiple lanes on the road. Some false detection results are displayed in Fig. 9.

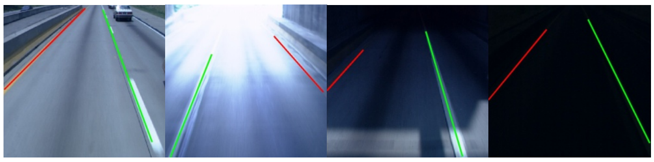
IV. CONCLUSION

In this paper, we provide an effective lane detection algorithm for local roads and freeways of various lighting conditions. By using the Median Local Threshold (MLT) method and a morphological operation, lane markings can be extracted accurately. The final location of lane is determined by Hough transform and a judgment strategy. Without any assumptions on the flat ground or the camera calibration, we demonstrated some results on challenging day and night road scenes. The algorithm was tested on three data sets and experimental results show an effective performance.

(a) Night scene.



(b) Rainy scene.



(c) Fluctuating illumination scene.

Fig. 8. Examples of correct detection result.

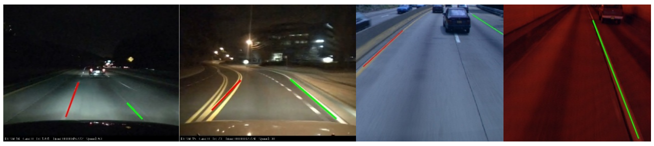


Fig. 9. Examples of false detection result.

Our approach was focused on low-contrast road scenarios, and there were some abnormal results achieved. Since using contextual information for lane detection will lead to more accurate detection results, future work will integrate the temporal information and geometric transformations of the image to improve the performance of the lane-detection module and accomplish the lane-tracking module.

REFERENCES

[1] J. Navarro, F. Mars, and M.S. Young," Lateral control assistance in car driving: Classification, review and future prospects," IET Intell. Transp. Sy., vol. 5 (3), pp. 207-220, 2011.

[2] Y. Wang, E.K. Teoh, and D. Shen," Lane detection and tracking using b-snake," Image and Vis. Comput., vol. 22 (4), pp. 269-280, 2004.

[3] T.-Y. Sun, S.-J. Tsai, and V. Chan," Hsi color model based lane-marking detection,"In: IEEE International Conference on Intelligent Transportation Systems pp. 1168-1172, 2006.

[4] C. Ma and M. Xie," A method for lane detection based on color clustering,"In: 3th International Conference on Knowledge Discovery and Data Mining, pp. 200-203, 2010.

[5] S.-J. Tsai and T.-Y. Sun," The robust and fast approach for vision-based shadowy road boundary detection,"In: 8th International IEEE Conference on Intelligent Transportation Systems, pp. 486-491, 2005.

[6] Y. He, H. Wang, and B. Zhang," Color-based road detection in urban traffic scenes," IEEE Trans. Intell. Transp. Syst., vol. 5 (4), pp. 309-318, 2004.

[7] H.-Y. Cheng, B.-S. Jeng, P.-T. Tseng, and K.-C. Fan," Lane detection with moving vehicles in the traffic scenes," IEEE Trans. Intell. Transp. Syst., vol. 7 (4), pp. 571-582, 2006.

[8] A. Borkar, M. Hayes, and M.T. Smith," A novel lane detection system with efficient ground truth generation " IEEE Trans. Intell. Transp. Syst., vol. 13 (1), pp. 365-374, 2012.

[9] G. Liu, F. Wörgötter, and I. Markeli," Stochastic lane shape estimation using local image descriptors," IEEE Trans. Intell. Transp. Syst., vol. 14 (1), pp. 13-21, 2013.

[10] J.C. McCall and M.M. Trivedi," Video-based lane estimation and tracking for driver assistance: Survey, system, and evaluation," IEEE Trans. Intell. Transp. Syst., vol. 7 (1), pp. 20-37, 2006.

[11] E. Pollard, D. Gruyer, J.-P. Tarel, S.-S. Ieng, and A. Cord," Lane marking extraction with combination strategy and comparative evaluation on synthetic and camera images,"In: Proc. IEEE Conf. Intelligent Transportation Systems, pp. 1741-1746 2011.

[12] T. Veit, J.-P. Tarel, P. Nicolle, and P. Charbonnier," Evaluation of road marking feature extraction,"In: Proceedings of the 11th International IEEE Conference on Intelligent Transportation Systems, pp. 174 - 181 2008.

[13] P. Foucher, Y. Sebsadji, J.-P. Tarel, P. Charbonnier, and P. Nicolle," Detection and recognition of urban road markings using images,"In: Proc. IEEE Conf. Intelligent Transportation Systems, pp. 1747-1752, 2011.

[14] A. Borkar, M. Hayes, M.T. Smith, and S. Pankanti," A layered approach to robust lane detection at night,"In: IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems, pp. 51-57, 2009.