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Region-of-Interest Generation for Lane Detection Using High-level Information

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Abstract

Vision-based lane detection is still a challenging task in real application with a variety of complex road scenes. What makes the problem even more difficult is the requirements of real time implement with on-board processor. To speedup the lane detection processing, the Region-of-Interesting (ROI) method was widely used to narrow the candidate searching range for local road features. In this paper, a continuous form of the ROI is first deduced from the lane model and the perspective projection. Then the factors that contribute to the appearance of the ROI are discussed. Lastly, an approximated form of the ROI is given for fast computing. In the proposed model, ROI is considered as a probability map, in which the value is corresponding to the possibility of the lane-markings to appear in a certain location in the scene. Moreover, the model takes the running manner of the vehicle and vibration of the vehicle into account. Experiments show that the proposed algorithm is very efficient in removing the outliers of local features in complex road scenes.

Keywords:

lane detection; region of interest; vanishing point; lane model

1. Introduction

There are many Activity Safety Systems (ASSs) such as Lane Departure Warning System (LDWS) and the Driver Assistant System (DAS) [6, 9] in the market to improve the safety of driving, and most of them require clear lane-markings in a well-illuminated freeway environment. However, it is still a challenging work for such a system to be used in various road environments to achieve real-time requirement, especially in complex road scenes, such as complex shadowing, occlusion by proceeding vehicles and so on [1,3, 6, 10]. To speedup the lane detection processing and improve its robustness, ROI was always generated to narrow down the searching range for road feature detection. In [2], the ROI was defined as a searching boundary along the lane markings detected by the previous frame. Only the features inside the boundary were generated as candidates of the feature points. However, why should it make sense to set such parallel boundary and how to get the parameter were not discussed. In [3] the local feature selection processing was performed based on dynamic Bayesian network, taking into account the temporal coherence across frames and the spatial continuity of the lane-markings themselves. However, the explicit expression of such a processing was not deduced. To generate the ROI, usually a lane model is needed. Although a variety of different lane-modeling techniques have been used, all of them can be classified into two categories. The first category tries to model the lane markings in the vehicle coordinate. Bertozzi and Broggi assumed that the road markings form parallel lines in an inverse-perspective-warped image [12]. Others have used approximations to flat roads with piecewise constant curvatures [13]. The second category tries to model the appearance of the lane marking directly in the frame buffer. For example, deformable contours such as B-snakes have been used to parameterize the appearance of the curved lanes[14]. Most of the models mentioned above have the same assumption that the extrinsic parameter of the camera mounted on the vehicle is constant during the application. Once the lane-markings in the frame buffer is got, with the calibrated extrinsic parameters, the relation of the vehicle with the lane marking in the real road can be got with high precision.

In this paper, to take into account all the possible aspects that can influence the appearance of the lane-markings in the image buffer of the on-board camera, the explicit expressions of the perspective projection of the on-board camera and the lane-markings in the vehicle coordinate are given in the first section. The ROI can be viewed as all the possible appearance of the lane-markings considering the variation of all the related factors. Unlike other works trying to setup boundaries along the detected lane-markings,

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we model the ROI as a possibility distribution of the lane-markings at certain locations. There are several advantages of the ROI with this form. Firstly, the ROI can be influenced by the running manner of the vehicle, the variation of pitch angle of the on-board camera and the variation of geometry of the lane-markings. All those factors can be investigated as a whole or individually. This will be especially useful in lane tracking. Secondly, with the appearance likelihood of the ROI, it will be easy to use the ROI as a feedback to the local feature detection. Lastly, the parameters of the ROI can be initialized differently for tracking and searching. Comparison studies show that the proposed algorithm is very efficient in removing the outliers of local features in complex road scenes.

This paper is organized as follows. In section II, the appearance of the lane markings in the road scenes is deduced, which gives an explicit expression of the high-level information about the lane markings. The factors which can affect the appearance of the vanishing point are discussed as well. Then a novel ROI generating method is proposed in section III, in which the details of the proposed continuous form of ROI are discussed with real parameters setting and a simple approximation ROI. In section IV, experiments are done in the real road scenes with heavy shadows to show the effects of the continuous ROI in outlier removing. Conclusion is drawn in section V.

2. Mapping from the world coordinate to the image frame buffer

To get an explicit description of the appearance about the lane-markings in the frame buffer, we first define the needed coordinates and then deduce the parametrical expression of the lane-markings.

2.1. coordinate definition

The main idea of vision-based lane detection system is to get the relationship between the current lane and the ego vehicle. To illustrate the orientation of the camera in the vehicle coordinate and the projection from 3D space to the 2D space in a simple way, we defined four coordinate systems here: the frame buffer (C, R) in pixels, the image coordinates (X_I, Y_I) in meter, the camera coordinates (X_C, Y_C, Z_C) in meter, and the vehicle coordinates (X_V, Y_V, Z_V) in meter. Here we use the ENU-system (East-North-Up) as the positive direction of the vehicle coordinates. The origin is the intersection of X_V-axis with the plane, which passes the origin of the camera coordinates and is perpendicular to X_V-axis. The definitions of other coordinates are straightforward, which are omitted here.

The appearance (coordinate values) of the lane-markings in the digital image of road scene can be got as a transform from the 3D Euclidean space of the vehicle coordinate to the 2D Euclidean space of the frame buffer. In practice, such a transform can be divided into two stages: the first stage is the transform from the world coordinate system to the camera coordinate system, and the second stage is the projection from the camera coordinate system to the image frame buffer.

The transform from the vehicle coordinate to the camera coordinate can be expressed as:

$$^{C}P =^{C}_{V} R(^{V}P + ^{V}P_C) \tag{1}$$

The rotation transform $^{C}_{V}R$ can be achieved by the Euler angles with three steps. The shift transform $^{V}P_C$ is the offset of optical center in the vehicle coordinate. All the parameters considered here are determined by the way how the camera mounted on the vehicle, but have nothing to do with the camera. They are extrinsic parameters of the on-board camera.

If we omit the distortions of the lens, the projection can be expressed in the transformation matrix form:

$$\begin{bmatrix} t_2 x_I \\ t_2 y_I \\ 0 \\ t_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & -1/f & 0 \end{bmatrix} \begin{bmatrix} x_C \\ y_C \\ z_C \\ 1 \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} t_3 c \\ t_3 r \\ 0 \\ t_3 \end{bmatrix} = \begin{bmatrix} N_c & 0 & 0 & ^{B}C_I \\ 0 & N_r & 0 & ^{B}R_I \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_I \\ y_I \\ 0 \\ 1 \end{bmatrix} \tag{3}$$

Usually the onboard camera of the lane-detection system is mounted on the vehicle with careful design. It is reasonable to assume the offset of optical center in the vehicle coordinate to be $(0, 0, h)$ and the rotation angles form the vehicle coordinate to the camera coordinate to be $(pi/2+\phi, pi/2+\theta, 3pi/2)$. Further more, if we combine all the steps of transformation into one transform expression, the perspective projection from the 3-D vehicle coordinate to the 2-D frame buffer can be expressed as:

$$\begin{cases} c =^{B} C_I + \frac{x_v cos(\phi)+y_v sin(\phi)}{c_f((h-z_v)sin(\theta)+cos(\theta)(y_v cos(\phi)-x_v sin(\phi)))} \\ r =^{B} R_I + \frac{(h-z_v)-sin(\theta)(y_v cos(\phi)-x_v sin(\phi))}{r_f((h-z_v)sin(\theta)+cos(\theta)(y_v cos(\phi)-x_v sin(\phi)))} \end{cases} \tag{4}$$

Where, $c_f = \frac{1}{N_c f}$ represents the real length of one pixel divided by the focus length and N_c is the distance between two adjacent pixels in the sensor in horizon direction. $r_f = \frac{1}{N_r f}$ represents the real width of one pixel divided by the focus length and N_r is the distance between two adjacent pixels in the sensor in vertical direction. $^{B}C_I$ and $^{B}R_I$ are the coordinate values of the optical center in the frame buffer.

2.2. parameter representation of the lane-markings in the vehicle coordinate

To get an explicit description of the appearance about the lane-markings in the frame buffer, we need a lane model about the lane-markings in the vehicle coordinate first. Here, we represent the lane-markings in the vehicle coordinate as parameter function of a certain variable t. This means the lane-markings can be expressed as $(x_v(t), y_v(t), z_v(t))$. To analyse the lane-markings with certain shape, we expand this parameter function of the lane-markings with the Taylor's series at the original point.

$$\begin{cases} x_v(t) = c_0 + c_1 t + c_2 t^2 + c_3 t^3 + O[t^4] \\ y_v(t) = l_0 + l_1 t + O[t^2] \\ z_v(t) = h_0 + h_1 t + O[t^2] \end{cases} \tag{5}$$

Here, if we look on the parameter t as the arc length along the running direction of the vehicle in a local area, it makes sense to express the $x_v(t)$ with more items because we care more about the shape of the lane-markings along the lateral direction. c_0 is the lateral offset of the vehicle relative to the lane-marking. $c_1 = tg(\phi_v)$ is the tangent of the heading angle of the vehicle relative to the local direction of the lane-marking. c_2 and c_3 are the curvature parameters of the lane-marking. l_0 is the offset of the arc length of the lane-marking in the vehicle coordinate. It makes sense to set l_0 to 0 and l_1 to 1 without loss of generality. h_0 is the variation of the vehicle's height due to the soft suspension system of the modern vehicles. $h_1 = tg(\theta_v)$ is the tangent of the vehicle's pitch angle, also caused by the suspension system. Thus, we can rewrite the parameter function of the lane-marking and omit the infinite items of higher orders.

$$\begin{cases} x_v(t) = c_0 + tg(\phi_v) t + c_2 t^2 + c_3 t^3 \\ y_v(t) = t \\ z_v(t) = h_0 + tg(\theta_v) t \end{cases} \tag{6}$$

To get a simpler form of the lane-marking, the yaw angle and pitch angle of the vehicle can be combined with the corresponding angle of the camera, so the influence of those two items can be considered in the perspective projection transformation. Moreover, the height of the vehicle can be combined with the height of the camera in the vehicle coordinate and be considered in the perspective projection transformation. Thus we get the parameter function of the lane-marking as:

$$\begin{cases} x_v(t) = c_0 + c_2 t^2 + c_3 t^3 \\ y_v(t) = t \\ z_v(t) = 0 \end{cases} \tag{7}$$

The refined perspective projection transformation from the 3-D vehicle coordinate to the 2-D image frame buffer is:

$$\begin{cases} c =^B C_I + \frac{x_v cos(\phi_p) + y_v sin(\phi_p)}{c_f((h_p - z_v) sin(\theta_p) + cos(\theta_p)(y_v cos(\phi_p) - x_v sin(\phi_p)))} \\ r =^B R_I + \frac{(h_p - z_v) - sin(\theta_p)(y_v cos(\phi_p) - x_v sin(\phi_p))}{r_f((h_p - z_v) sin(\theta_p) + cos(\theta_p)(y_v cos(\phi_p) - x_v sin(\phi_p)))} \end{cases} \tag{8}$$

Where $h_p = h + h_0$, $\phi_p = \phi + \phi_v$, $\theta_p = \theta + \theta_v$. In real condition, the combined pitch angle θ_p and the combined yaw angle ϕ_p are very slight. It is very common to keep them less than 0.1rad. In this condition, we can expand all the sinusoidal function with Taylor series, and ignore all the items over the second orders. The simplified perspective projection transformation can be rewritten as:

$$\begin{cases} c =^B C_I + \frac{x_v y_v}{c_f y_v^2} + \frac{x_v z_v - h_p x_v}{c_f y_v^2} \theta_p + \frac{x_v^2 + y_v^2}{c_f y_v^2} \phi_p \\ r =^B R_I + \frac{(h_p - z_v) y_v}{r_f y_v^2} + \frac{-y_v^2 - (h_p - z_v)^2}{r_f y_v^2} \theta_p + \frac{(h_p - z_v) x_v}{r_f y_v^2} \phi_p \end{cases} \tag{9}$$

Substituting the simplified parameter functions (7) into the above perspective projection transformation (9), the final appearance of the lane-markings can be got as a parameter function form as:

$$\begin{cases} c =^B C_I + \frac{c_0}{c_f} \frac{1}{t} + \frac{-c_2 h_p \theta_p + \phi_p + 2 c_0 c_2 \phi_p}{c_f} + \\ \frac{c_2 - c_3 h_p \theta_p + 2 c_0 c_3 \phi_p}{c_f} t + \frac{(c_3 - c_2^2 \phi_p)}{c_f} t^2 + \frac{2 c_2 c_3 \phi_p}{c_f} t^3 \\ r =^B R_I + \frac{h_p}{r_f} \frac{1}{t} + \frac{-\theta_p + 2 c_2 h_p \phi_p}{r_f} + \frac{c_3 h_p \phi_p}{r_f} t \end{cases} \tag{10}$$

3. Possibility distribution of lane-marking as the ROI for local feature detection

Having the parameter function form of the lane-marking in the image frame buffer, we can analyze the factors that can affect the appearance of the lane-marking. If we consider the factors as random variables and model them with certain distribution form, we can get the distribution form of the lane-marking in the frame buffer. This is exactly the ROI that we want to detect for local feature selection.

3.1. factors that affect the appearance of the lane-marking in the frame buffer

From the above parameter function of the lane-markings, we can find that there are three kinds of factors that affect the appearance during running. The first kind is related to the running manner of the vehicle. Here we have the lateral offset of the vehicle relative to the lane-markings $c0$, and the heading angle of the vehicle relative to the lane-markings just in the near front of the vehicle ϕ_v . The second kind is corresponding to the variation of the vehicle caused by the roughness of the road surface. Here we have the pitch angle of the vehicle θ_v and the height of the vehicle h_0. They all because of the soft suspension system of the modern vehicles. The third kind is about shape parameter of the lane-marking. In our special case, it is c_2 and c_3. Although there are other parameters appeared in the function, they are looked on as constant after the on-board camera was mounted on the vehicle. For simplification, here we model those factors as the i.i.d. random variables with normal distribution.

3.2. getting the distribution of lane-marking in the frame buffer using Monte Carlo method

In our vision-based driver assistance system, all the images were captured by a camera having the frame size of 1024 columns with 512 lines. The parameters of our LDWS prototype can be summarized in Table 1.

Table 1. THE PARAMETERS OF OUR LDWS PROTOTYPE

Parameters	Quantity (Unit)	Description
${}^{B}C_I$	512 (pixel)	The column index of the center of the sensor in frame buffer.
${}^{B}R_I$	512 (pixel)	The row index of the center of the sensor in frame buffer.
c_f, r_f	0.000875	The optical element is square 7um x 7um. The focus length is 8mm. This two parameters are identical. They are 7um divided by 8mm.
h	2 (meter)	The height of the camera mounted on the vehicle.
h_0	0 (meter)	The height of the vehicle, changing as a normal random variable.
θ	0.1 (radian)	The camera's pitch angle.
ϕ	0.1 (radian)	The camera's yaw angle.
θ_v	0 (radian)	The vehicle's pitch angle, changing as a normal random variable.
ϕ_v	0 (radian)	The vehicle's heading angle, changing as a normal random variable.
c_0	$\pm$ LD/2 (meter)	Lateral offset of the vehicle relative to the lane-markings. It is half of the width of the lane for the left lane-marking.
c_2	0	Shape parameter about the lane-marking.
c_3	0	Shape parameter about the lane-marking.

To get a deep insight about final appearance form of the lane-marking, we assume the shape parameters c_2 and c_3 to be zeros. Then we can get the simplest form of two parallel straight lines as lane-markings in the frame buffer:

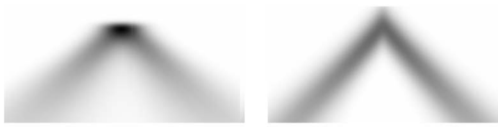
$$\begin{cases} c = {}^{B}C_I + \frac{c_0}{c_f}\frac{1}{t} + \frac{\phi_p}{c_f} \\ r = {}^{B}R_I + \frac{h_p}{r_f}\frac{1}{t} + \frac{-\theta_p}{r_f} \end{cases} \tag{11}$$

This is the simplest lane model used in many LDWSs. There are four parameters that can be modeled as normal distribution variables, and we have two set of parameters for them: the parameters for searching stage and the parameters for lane tracking.

We can have a glimpse of the lane-markings in the frame buffer using Monte Carlo method. Having the parameters as random variables, we can get one instance of the lane-markings in the frame buffer with the observed instance of the variables. Setting the values of the points that on the lane-markings to be 1 and others to 0, we get an image of the lane-markings. With another instance of the parameters, we can get another image about the lane-markings. We repeat this procedure for a huge number of times (1000000) and overlap all the images in one image. Then we get an image about the possibility of every pixel to be a point on the lane-markings, as show in Fig.1. Those pixels have higher values have a higher possibility to be points on the lane-markings.

Table 2. THE PARAMETERS OF THE RANDOM VARIABLES

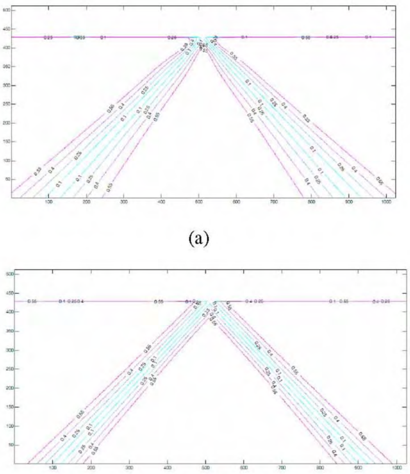
Random varibles	Searching stage μ	Searching stage σ	Tracking stage μ	Tracking stage σ
c_0	$\pm$ LD/2	$\pm$ LD/5	$\pm$ LD/2	$\pm$ LD/10
ϕ_p	0	0.05	0	0.01
h_p	2	0.01	2	0.05
θ_p	0.15	0.01	0.15	0.05



(a) (b)

Figure 1. appearance of the lane-markings with different distribution parameters a) result using distribution parameters for searching stage, b) result using distribution parameters for tracking stage.

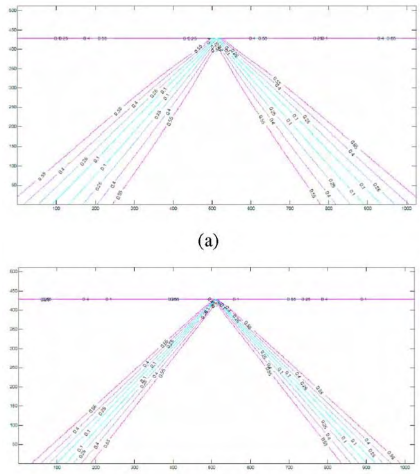
If we consider the possibility distribution along the scan line of the frame buffer, we can find that the peak value should appear on the lane-marking which is determined by the mean values of the parameters in Table-II. Here we define the relative possibility ratio of every pixel in the certain scan line as: $R_c = \frac{P_c}{P_{peak}}$, where $_{peak}$ is the column index of the nearest peak value. We show the contour map of the relative possibility ratio map in Fig.2. All the points between the two contours with the same value have the possibility to be points on the lane-markings above than the value marked on the contours. This means if we search the pixels in this region, the possibility that we can meet the points on the lane-markings will be higher than the value. This is really what we want to do for setting up the ROI during local feature points searching.



(a)

(b)

Figure 2. contour plots of the relative possibility ratio map for searching stage and tracking stage.



(a)

(b)

Figure 3. contour plots of the approximated relative possibility ratio map for searching stage and tracking stage.

3.3. A simplified approximation of the distribution about the lane-marking

From Fig. 2, we can find out that for the vision-based lane detection system, we care more about the possibility distribution of the lane-markings along the scan lines. This possibility distribution can be approximated by a normal distribution along the scan lines. For a certain scan line, the possible column passion of the pixel on the lane-marking can be written as:

$$c = {}^B C_I + \frac{c_0}{c_f}\frac{1}{t} + \frac{\phi_p}{c_f} \tag{12}$$

Here we take θ_p and h_p as constant, and get r using (11). If we consider c as one instance of a random variable C, C still follows the normal distribution, $C \sim N(\mu_C(r), \sigma_C(r))$. $\mu_C(r)$ and $\sigma_C(r)$ can be expressed as:

$$\begin{cases} \mu_c(r) = {}^B C_I + \frac{r_f}{\mu_{h_p} c_f}\mu_{c_0} r + \frac{\mu_{\theta_p}\mu_{c_0} - r_f \mu_{c_0} {}^B R_I}{\mu_{h_p} c_f} + \frac{\mu_{\phi_p}}{c_f} \\ \sigma_C^2(r) = (\frac{r_f}{\mu_{h_p} c_f}\sigma_{c_0} r)^2 + (\frac{r_f \sigma_{c_0} {}^B R_I}{\mu_{h_p} c_f})^2 \\ +(\frac{\mu_{\theta_p}\sigma_{c_0}}{\mu_{h_p} c_f})^2 + (\frac{\sigma_{\phi_p}}{c_f})^2 \end{cases} \tag{13}$$

Again, we can plot the ROI contour map of the approximated relative possibility ratio. Obviously, this map can approximate the original one rather well, and it has the advantage of having all the parameters fixed before tracking or searching.

4. Experimental results for outlier removal

Once we have the parameters of the lane-markings in previous frames or a rough estimation, we can setup the ROI as described in section III. For the ROI is a continuous distribution about the possibility about where the lane-markings should appear in the frame buffer, we can use it as a mask for pre-selection of the local feature in the frame buffer. This can be done with different parameters for the initial stage of searching for the lane-markings and for the lane following stage of tracking for the lane-markings.

4.1. searching mode with complex shadowing

Here we test the proposed ROI setup method for lane-detection in complex shadowing scenes. As shown in Fig.4, there are the original road scene image, the approximated ROI, the road scene masked by the ROI and the final result after local edge feature detection.

4.2. tracking mode with occlusion by preceding vehicle

During lane-tracking mode, we use different parameters for the random variables. As shown in Fig.5, there are the ROI setup and feature detection result.

Figure 4. searching mode with complex shadowing.

Figure 5. tracking mode with occlusion by preceding vehicle.

5. Conclusion

In this paper, we propose a ROI setup method using high-level information about the lane-markings to speedup the local feature detection process. We use the parameterized description of the lane-markings and deduce the appearance of the lane-markings in the frame buffer. Then, we discussed the factors that can affect the appearance of the lane-markings in the frame buffer, and model those factors as i.i.d. random variables. The possibility of certain pixel in the frame buffer to be a point on the lane-markings can be gotten. This is the prior-knowledge about the appearance of lane-markings, and can be used as the ROI to search for local features of the lane-markings in the image.

The factors that are considered in this paper are only the parameters about the extrinsic parameters about the on-board camera and the variation of then cause by vibration of the vehicle and running manner. Those factors about the shape of lane-markings are not considered in this paper.

References

[1] H.-Y. Cheng, C.-C. Yu, C.-C. Tseng, K.-C. Fan, J.-N. Hwang, and Jeng B.-S. Enviroment classification and hierarchical lane detection for structured and unstructured roads. IET computer vision, 4(1), pp: 37-49, 2009.

[2] Wu, B.F. and Lin, C.T. and Chen, Y.L. Dynamic calibration and occlusion handling algorithms for lane tracking. Industrial Electronics, IEEE Transactions on, pages 1757-1773, 2009.

[3] D. Kim, S.H. Jin, N.T. Thuy, K.H. Kim, and J.W. Jeon. A real-time finite line detection system based on FPGA. In Industrial Informatics, 2008. INDIN 2008. 6th IEEE International Conference on, pages 655-660. IEEE, 2008.

[4] K. Kluge and S. Lakshmanan. A deformable-template approach to lane detection. In Intelligent Vehicles 95 Symposium., Proceedings of the, pages 54-59. IEEE, 1995.

[5] Q. Li, N. Zheng, and H. Cheng. Springrobot: A prototype autonomous vehicle and its algorithms for lane detection. Intelligent Transportation Systems, IEEE Transactions on, 5(4):300-308,2004.

[6] J.C. McCall and M.M. Trivedi. Video-based lane estimation and tracking for driver assistance: survey, system, and evaluation. Intelligent Transportation Systems, IEEE Transactions on, 7(1):20-37, 2006.

[7] G.P. Stein, E. Rushinek, G. Hayun, and A. Shashua. A Computer Vision System on a Chip: a case study from the automotive domain. 2005.

[8] T. Veit, J.P. Tarel, P. Nicolle, and P. Charbonnier. Evaluation of road marking feature extraction. In Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on, pages 174-181. IEEE, 2008.

[9] S. Vitabile, S. Bono, and F. Sorbello. An embedded real-time lane-keeper for automatic vehicle driving. In International Conference on Complex, Intelligent and Software Intensive Systems, pages 279-285. IEEE, 2008.

[10] Joel C. McCall, and Mohan M. Trivedi, Video-based lane estimation and tracking for driver assistance: Survey, system, and evaluation. Ieee Transactions on Intelligent Transportation Systems, 2006. 7(1): p. 20-37.

[11] Meng Wu, and Xiangjing An, An automatic extrinsic parameter calibration method for camera-on-vehicle on structured road, IEEE International Conference on Vehicular Electronics and Safety. 2008. Beijing, China.

[12] Massimo Bertozzi and Alberto Broggi, GOLD: A Parallel Real-Time Stereo Vision System for Generic Obstacle and Lane Detection. IEEE Transactions on Intelligent Transportation Systems, 1998. 7: p. 62-81.

[13] Mo Wu, Xiangjing An, and Hangen He. On vision-based lane departure detection approach. in 2005 IEEE International Conference on Vehicular Electronics and Safety Proceedings. 2005. Shaan'xi, China.

[14] Yue Wang, Eam Khwang Teoh, and Dinggang Shen, Lane Detection Using B-Snake. 1999.