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A Novel Lane Detection based on Geometrical Model and Gabor Filter

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Abstract—**Many people die each year in the world in single vehicle roadway departure crashes caused by driver inattention, especially on the freeway. Lane Departure Warning System (LDWS) is a useful system to avoid those accident, in which, the lane detection is a key issue. In this paper, after a brief overview of existing methods, we present a robust lane detection algorithm based on geometrical model and Gabor filter. This algorithm is based on two assumptions: the road in front of vehicle is approximately planar and marked which are often correct on the highway and freeway where most lane departure accidents happen [1]. The lane geometrical model we build in this paper contains four parameters which are starting position, lane original orientation, lane width and lane curvature. The algorithm is composed of three stages: the first stage is called off-line calibration which just runs once after the camera is mounted and fixed in the vehicle. The parameters of camera used for lane detection is accurately estimated by the 2D calibration method [2]; The second stage is called lane model parameters estimation and lane model candidates construction, the first three parameters, starting position, lane original orientation and lane width will be estimated using dominant orientation estimation [3] and local Hough transform. Then the construction of lane model candidates is implemented for the final lane model matching; the third stage is model matching. The proposed lane module matching algorithm is implemented to match the best fitted lane model. The combination of these modules can overcome the universal lane detection problems due to inaccuracies in edge detection such as shadow of tree and passengers on the road. Experimental results on real road will be presented to prove the effectiveness of the proposed lane detection algorithm.**

I. INTRODUCTION

WITH the rapid increase of urban traffic, the traffic safety becomes more and more important. According to the research [1], many accidents of roadway departure crashes are caused by driver inattention. A System called Lane Departure Warning System (LDWS) being capable of warning the driver when the vehicle begins to move out of its lane is desperately needed to eliminate these crashes. Lane detection is a kernel part in LDWS and also key technology for the successful development and employment of that system. In the past few years, several approaches for lane detection were proposed and successfully demonstrated. Some products coming with these approaches not only can be applied to LDWS but also can be used in Autonomous Driving Systems in military. The work presented here focuses on the detection of lane on the marked road, since this aspect represents an essential component of Lane Departure Warning System. Lane detection also can be used to infer the position and orientation of the vehicle within a lane and can provide a reference system for locating other vehicles or obstacles in the path of that vehicle which can be applied to further development of the Obstacle Avoiding System. As most of other lane detection algorithms, the method we are about to present is vision-based lane detection. In principle, vision-based lane detection can be categorized in three main classes: feature-based [4-6], region-based [7-8] and model-based [9].

Claudio Rosito Jung et al. [5] used the edge detection, squares angular estimation, Hough transform to estimate lanes on a road. The results were obtained in his paper using his algorithm. The algorithm mostly runs good except when it comes to shadow or other interference on the road.

Yue Wang et al. [10] used B-Snake spline as a geometric model that can represent the road. Then he processed images with Canny/Hough Estimation of Vanishing Points (CHEVP) to extract the parameters needed by the geometric model. The obtained results were very robust and accurate. As in his paper, the algorithm can overcome the interference of shadows. However, when the system detected the shadow of a tree trunk or a shadow of telegraph pole which has a uniform orientation, an unpredictable result occurred.

The desired properties of lane detection techniques include:

1) Quality of lane detection should not be affected by shadows, which can be cast by trees, buildings, etc.

2) It should be able to handle the curved roads instead of assuming that the roads are straight.

3) It could assume the parallelism of both sides of the lane markings to improve the detection in the existence of noises in the images.

4) It should provide an explicit reliable measurement of the obtained result that we could know whether to abandon the method.

A good lane detection algorithm should satisfy all the properties mentioned above. So in this paper, we will introduce a model-based lane detection algorithm which is robust and satisfies all the above properties.

It has been observed that many road lane detection approaches only use the image processing techniques which loss the road geometrical information. This information, which includes lane geometrical features associated with

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geometrical relationship between camera and road, is useful to improve the accuracy and reduce the computation in the lane detection process. To some extent, loss of the geometrical information not only increases the computation in detection but also make detection unstable. In that case, the proposed algorithm combines road geometrical feature and the lane model matching method is proved to be more stable and accurate.

Our lane detection algorithm presented in the following sections is composed of three parts: lane geometrical model construction, lane model parameters estimation, lane model matching.

II. Lane geometrical model construction

The construction of lane geometrical model contains two components. First, a 2D lane geometrical model in the road planar coordinates system is constructed by some essential parameters. Second, that model is transformed to image coordinates system by camera parameters derived from camera calibration.

A. 2D lane geometrical model in road plane coordinates

Lane model plays an important role in our algorithm. In order to simplify the model, two assumptions have been mentioned above: the road in front of the vehicle is approximately planar; the road is marked road which is often correct in our application of freeway and highway. The 2D lane geometrical model is shown in Fig.1.

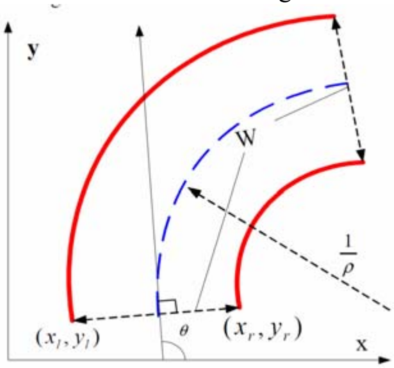

Fig.1 2D lane geometrical model (Red lines are the paralleled marked lanes on the road. Blue dashed line which is used for the representation of road model is the middle line between those two red lines)

Therefore the 2D lane geometrical model can be represented by the middle line and three parameters: θ , W and ρ using the following formulas:

$$\left(x - x_r - R_r \cos\theta\right)^2 + \left(y - y_r - R_r \sin\theta\right)^2 = R_r^2 \qquad (1)$$

$$\left(x - x_l - R_l \cos\theta\right)^2 + \left(y - y_l - R_l \sin\theta\right)^2 = R_l^2 \qquad (2)$$

$$R_r = \left(\frac{1}{\rho} - \frac{W}{2}\right),\ R_l = \left(\frac{1}{\rho} + \frac{W}{2}\right) \qquad (3)$$

where the x, y are the points on road lanes. The W is the lane width. The θ is the lane original orientation. The (x_r, y_r) and (x_l, y_l) are the starting position on both side of lane model. The r is the curvature of lane model. This is the lane model in the road planar coordinate system.

B. Projection of lane model

After the lane model in road planar coordinates system is constructed, the model needs to be transformed to image coordinate system (As shown in Fig.2) through projection matrix given by camera calibration [2] for parameters estimation and lane model matching.

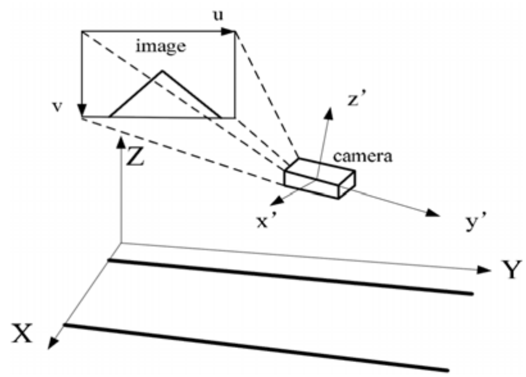

Fig.2 The projection of lane model (The X-Y-Z is world coordinates. The x'-y'-z' is camera coordinates. The X-Y is road plane coordinates. The u-v is image coordinates.)

The relation between the X-Y-Z coordinates system and the image coordinates system can be expressed as the equation below:

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R & T \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \qquad (4)$$

where the s is an arbitrary scale factor, the α and β are the scale factors of image u and v axes, the γ is the parameter indicating the skewness of the image, the R is the rotation matrix from world coordinates to image coordinates and the T is the translation matrix, the point of (x, y, z) is the point in the world coordinates system, the point of (u, v) is the projected point of (x, y, z) on the image coordinates system.

In order to simplify the lane model and diminish the number of model parameters, we use the middle line in Fig.1 to represent the first three parameters of the lane model which are starting position, lane curvature and lane original orientation θ . Fig.3 shows the middle line models in different curvatures.

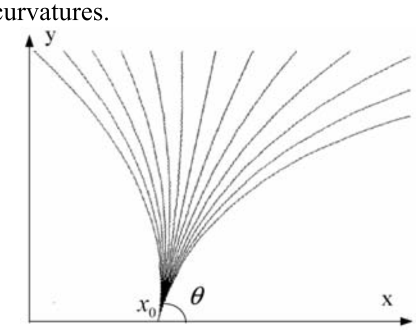

Fig. 3: Middle lane models in thirteen different curvatures

After the middle line models determined, the final lane models only need lane width W to be constructed. The process of transform is shown in Fig.4.

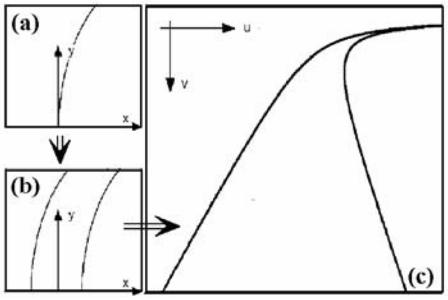

Fig.4: The process of lane model transformation (a) is the middle line model. (b) is the 2D lane model constructed by (a) and lane width W. (c) is the image lane model derived from (b) using equation (4).

III. Lane model parameters estimation

In the last section we have described the structure and transformation of lane geometrical model. This model has four parameters: starting position, lane original orientation, lane width, and lane curvature. Finding four parameters in the whole image is time and computation exhausting. In order to reduce the time and computation, some parameters need to be estimated before the final lane model matching.

As shown in Fig.5, after the vanishing point and road lanes are detected, we could easily estimate the starting position, lane original orientation and lane width. We will demonstrate our method of parameter estimation in detail in following.

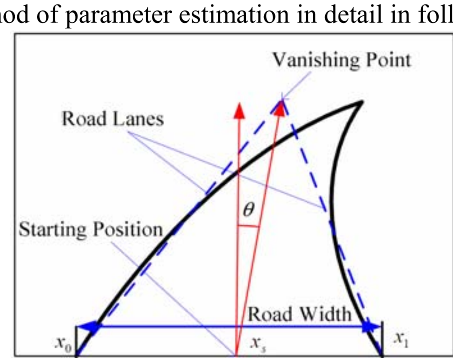

Fig.5 Lane geometric analysis

A. Image Segmentation

As we know, usually the lane in front of the ego-vehicle is not just a single curvature arc. Instead, the lane often is a parabola. According to the highway safety and road geometric design elements mentioned in [11], the perceptive effect of road in near field can be seen as a single curvature arc. In that case, image segmentation according to the relationship between camera and road coordinates systems is implemented to separate the road in front of vehicle into two regions: near field and far field (As shown in Fig.6). In the design of Lane detection in the application of Lane Departure Warning System, one only needs to focus on near field to measure the state of ego-vehicle in current, predict the vehicle location and warn the driver if the vehicle departs the lane. The highway and freeway geometric design rules help us to simplify our lane geometric model and improve the accuracy of our lane detection algorithm.

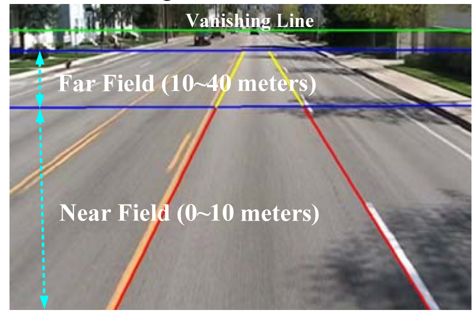

Fig. 6: The definition of the near and far fields

B. Vanishing Point Detection

The vanishing point is the key issue for the model parameter estimation especially in the initial orientation and road width estimation. In that case, the accuracy and stability of vanishing point estimation and robustness to noise must be guaranteed. So in our lane detection, the process of vanishing point detection is separated into two stages: initial stage and online stage.

1) *Initial Stage:*

Vanishing point detection in initial stage is time exhausting. Fortunately, it just happens in the first frame of our lane detection algorithm. In this stage, we use the Group Dominant Orientations algorithm to estimate the location of vanishing point [12]. In this algorithm, the Gabor Filter texture analysis is adopted to estimate orientation in each pixel. Then, the orientations in those pixels vote the finial vanishing point. The Gabor wavelet kernels used in this paper are as follows:

$$G_{im}(x,y,\theta,\lambda,\sigma)=e^{-\frac{1}{8\sigma^2}(4a^2+b^2)}\cos\frac{2\pi a}{\lambda} \tag{5}$$

$$G_{real}(x,y,\theta,\lambda,\sigma)=e^{-\frac{1}{8\sigma^2}(4a^2+b^2)}\sin\frac{2\pi a}{\lambda} \tag{6}$$

$$a=x\cos\theta+y\sin\theta\,,\ b=x\sin\theta+y\cos\theta \tag{7}$$

where the x and y represent the row and column of the Gabor wavelet, the kernel center of Gabor wavelet satisfies x=y=0, the θ is the wavelet direction, the λ is the wave length, the s indicates the support size of Gaussian function. The actual convolution kernel G is then obtained by subtracting its DC component (i.e. mean value) from itself and normalizing the result so that its L^2 norm is 1.

The ROI is extracted in the near field. To save computation, only 345 pixels in the ROI are convoluted with Gabor filter. Actually, each pixel should vote for more than one single vanishing point because there is some noise in texture orientation analyses and the road is not strictly planar road. The original results are shown in Fig.7.

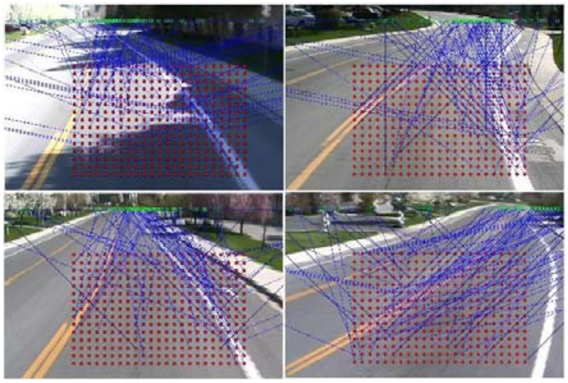

Fig.7: Vanishing Point Voting Result. Red point is pixel in ROI, Green point is vanishing points voted. Blue line is orientation line at every pixel in ROI.

Then we use Gaussian model and maximum likelihood method to estimate the single vanishing point. The results are shown in Fig.8.

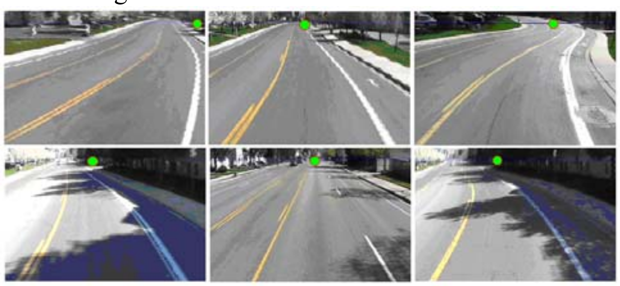

Fig.8 Single Vanishing Point Result

2) *Online Stage:*

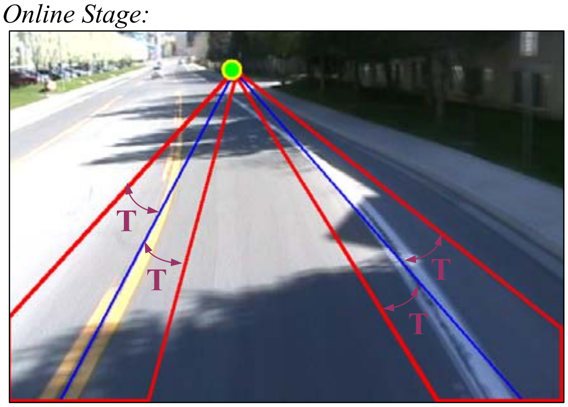

Fig.10 Tracking Region in next frame
The regions included in the red lines are defined as tracking region.

The difference between initial stage and online stage is the Gabor filtering region. In online stage, the detection region is adjusted according to the result of lane boundary detection (Fig.10). Then we randomly choose 100 pixels in each region to apply the Gabor Filter to estimate the orientations in those pixels. The voting method which mentioned above is adopted to vote the finial vanishing point.

C. *Lane Boundary Detection*

After obtaining the vanishing point, the lane initial orientation and lane width need to be estimated for the lane model. First, because of the perspective effect, the lane width can not be directly estimated. In that case, the road boundary should be first detected. The classical method of Canny edge detection and Hough transform are applied to detect the road boundary. Apparently, the road lanes on both sides have more contribution for voting the vanishing point. In other word, most pixels on the edge of each side lane must pass through the vanishing point. The Hough transform in this paper is simplified to restrict the transform to one parameter space which means there is just one parameter q needed to be estimated during the transform process. The transform can be shown as:

$$\theta = \arctan \frac{u - u_{vp}}{v - v_{vp}} \tag{8}$$

where (u_{vp}, v_{vp}) is the vanishing point position in the image and (u, v) is the edge pixel in edge image obtained by Canny edge detector. The results are shown in Fig.10.

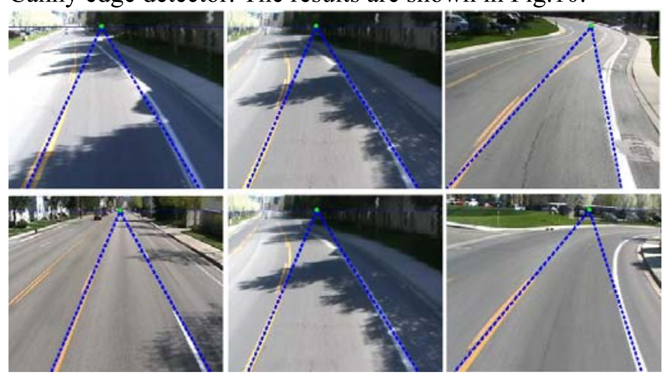

Fig.10: Result of road boundary

According to the geometrical relation as shown in Fig.5, the lane width can be defined as the distance between the two lowest points on the boundary lines. The starting position is the middle point of those two points. The lane original orientation is the angle of the line from the starting point to the vanishing point.

IV. Lane Model Matching

After those three lane model parameters (starting position, lane original orientation and lane width) have been calculated, the four parameters estimation problem now is reduced to one parameter which can easily apply the lane model matching algorithm to get the last parameter: lane curvature (As shown in Fig.3). We use a set of curvatures as candidate lane models. The final issue is how to determine the last parameter by our model matching algorithm.

Every lane model candidate has its unique curvature which means different lane models have different orientations along the line. In that case, we use the Gabor filter to filter the image along the line of lane model (Fig. 11). The best fitted road model will have the maximum voting value.

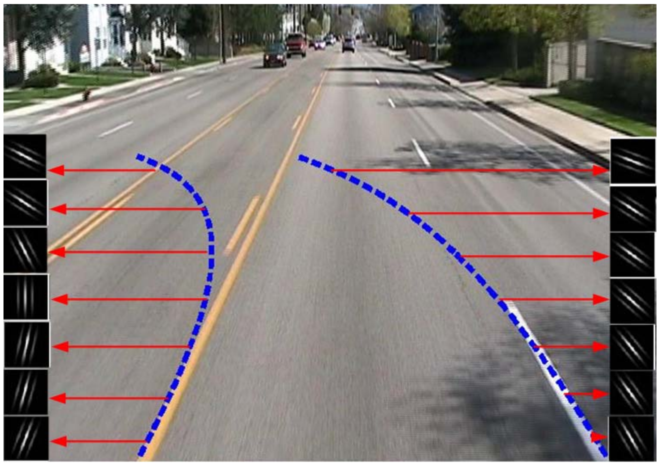

Figure 11: Model Matching Algorithm. Blue lines are the road model. Red arrows indicate the orientations along the road model lines.

The model matching algorithm can be described as following:

$$R_j = \sum_{i=1}^{N} (I * G_{real(j)}{}^i)(u_i{}^j, v_i{}^j)^2 + \sum_{i=1}^{N} (I * G_{im(j)}{}^i)(u_i{}^j, v_i{}^j)^2 \tag{9}$$

$$R_m = \max(R_1, R_2, ..., R_{15}) \tag{10}$$

where R_j is the voting confidence of the j-th lane model, N is the number of equidistance points extracted from the lane model, $G^i_{real(j)}$ and $G^i_{im(j)}$ is the Gabor filter at the direction of the i-th point on the j-th lane model, $(u_i{}^j, v_i{}^j)$ is the i-th point along the j-th lane model line. From (10), the lane model with the maximum voting confidence is selected as the best fitted model. The results of model matching are shown in Fig.12.

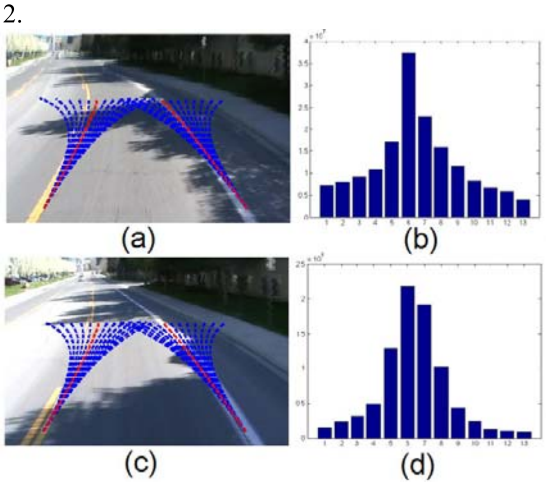

Fig.12: Model Matching Result. (a) and (c) are the lane models. The blue lines refer to the candidates while the red lines refer to the best fitted models. (b) and (d) are the corresponding voting confidence of the lane models.

V. EXPERIMENTAL RESULTS

We tested our algorithm for many different marked roads. It successfully detected road lane even under ill-lighting conditions including shadows.

A. *Result in single frame*

Fig. 13 shows the result of the proposed algorithm in single frame.

Fig.13: Lane Detection Results in single frame

B. *Result in consecutive frames*

We tested our algorithm in consecutive frames in video file and projected the result to 2D road planar coordinates using equation (4). Some frames are shown in Fig.14.

VI. CONCLUSION

We have developed a road detection algorithm on the marked road which can be used for Lane Departure Warning System or other auxiliary driving system. Experiment results in Figure 13 shows that it has robustness in shadow.

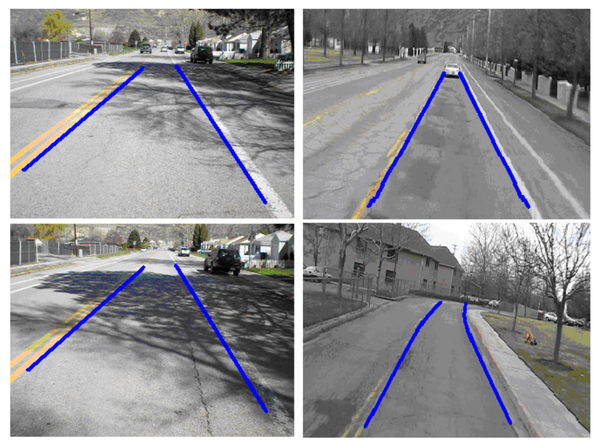

Figure 13: Experimental Result

In order to get a terrain map for the vehicle, we can further transform the result to the 2D road planar coordinates using equation (4). The result of matched road and their terrain maps is shown in figure 13.

In this paper, a novel and robust method was presented to detect the road in images. In this method, the camera parameters are utilized to generate road model. Experimental results show that the algorithm achieves high accuracy and is robust to the noise and other interferences such as shadow.

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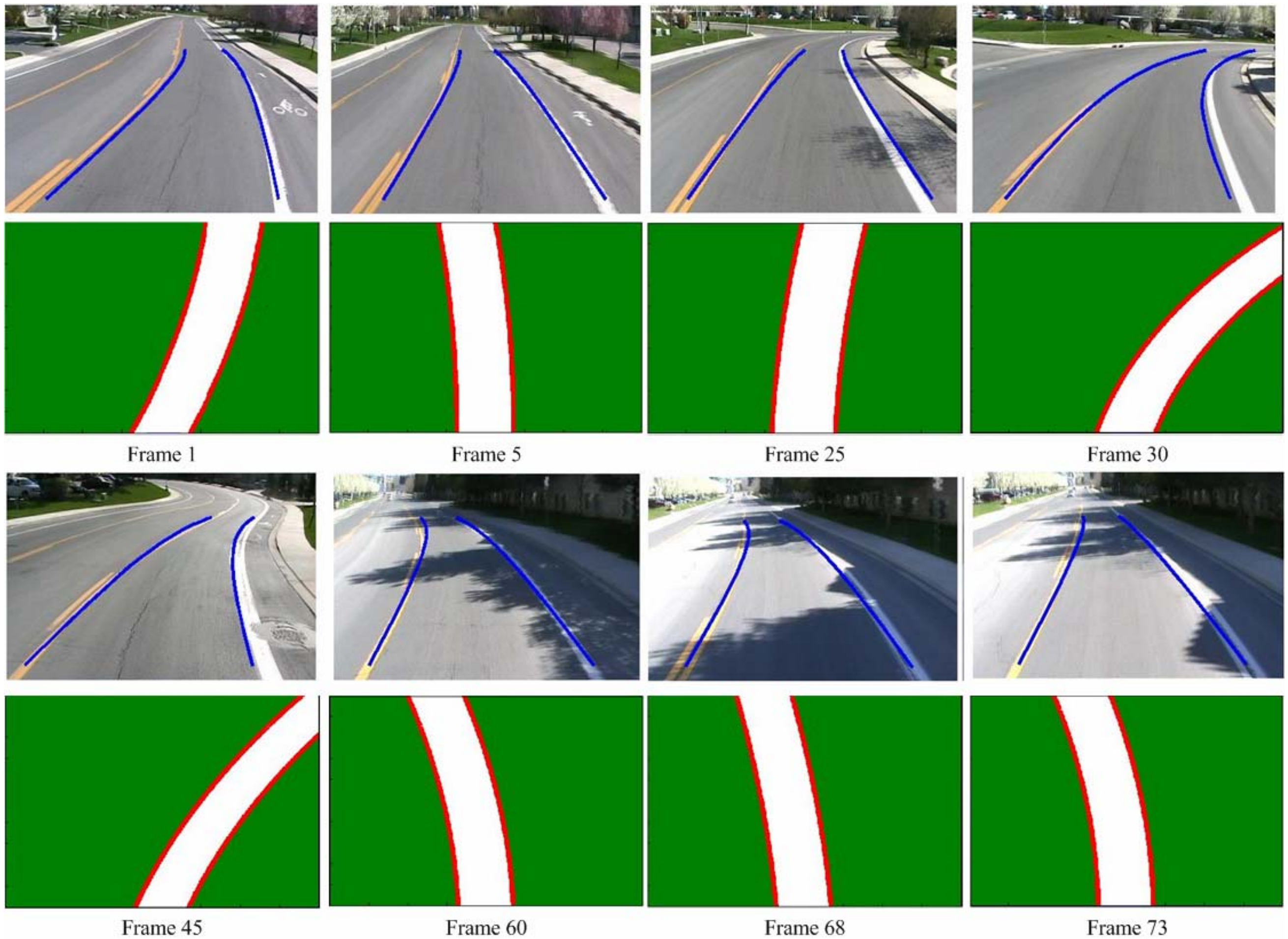

Fig.14 Result in consecutive frames and 2D road map projection. First and third rows are results of our lane detection. Second and fourth rows are results of 2D road map projection in the scale of 15 meter ×15 meter.

REFERENCES

[1] Want, J.S. and Knipling, R.R. *Single-Vehicle Roadway Departure Cranshes: Problem Size Assessment and Statistical Description National Highway Traffic Safety Administration Technical Report DTNH-22-91-C-03121*

[2] Z. Zhang, *A flexible new technique for camera calibration*. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.22, No.11, pages 1330-1334, 2000.

[3] Christopher Rasmussen. *Grouping Dominant Orientations for Ill-Structured Road Following.* In Proc of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2004.

[4] J. Goldbecka*, B. Huertgena, S. Ernsta, L. Kelchb. *Lane following combining vision and DGPS.* In: Image and Vision Computing 18 (2000) 425–433.

[5] Claudio Rosito Jung*, Christian Roberto Kelber. *Lane following and lane departure using a linear-parabolic model*. In: Image and Vision Computing 23 (2005) 1192–1202

[6] Wei Liu, Hongliang Zhang, Bobo Duan, Huai Yuan and Hong Zhao. *Vision-Based Real-Time Lane Marking Detection and Tracking.* In Proc. of the IEEE Intelligent Transportation Systems, Oct. 2008.

[7] Andrew Lookingbill, David Lieb and Sebastian Thrun. Optical *Flow Approaches for Self-supervised Learning in Autonomous Mobile Robot Navigation.* Autonomous Navigation in Dynamic Environments 2007.

[8] J.M. A´ lvarez and A. Lo´pez. *Novel Index for Objective Evaluation of Road Detection Algorithms*. In Proc. of the IEEE Intelligent Transportation Systems, Oct. 2008.

[9] Yue Wang, Dinggang Shen and Eam Khwang Teoh. *Lane Detection Using Catmull-Rom Spline.* In Proc. of the IEEE Intelligent Vehicles 1998.

[10] Yue Wang, Eam Khwang Teoha, Dinggang Shen. *Lane detection and tracking using B-Snake.* In: Image and Vision Computing 22 (2004) 269-28

[11] Iyinam, A.F. *Analysis of Relationships Between Highway Safety and Geometric Standards.* Doctorate Thesis, ITU Institute of Science and Technology, December 1997

[12] C. Rasmussen. *Grouping dominant orientations for illstructured road following*. In: Computer Vision and Pattern Recognition, 2004