Predictive Lane Detection for Simultaneous Road Geometry Estimation and Vehicle Localization

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Abstract — **this paper describes a predictive lane detection method with assistance of road geometry data from digital road map to simultaneously estimate road shape and vehicle localization. In our approach, visual information is not the only source to detect lane and estimate road parameters, the road geometry information derived from digital road map has also been providing important predictive cues for lane detection. Comparing with the conventional vision-only based approaches, our system is able to provide more reliable and stable road geometry estimation result. In addition, a precise longitudinal localization can also be achieved through the piecewise polynomial matching algorithm. Simulative and real road tests under various environmental conditions have shown the effectiveness of the proposed method.**

I. Introduction

WITHIN the last two decades, lane detection is one of the primary research topics in advanced driving assistance systems (ADAS). Lane detection primarily works for vehicle's lateral control systems, namely, Lane Departure Warning System (LDWS) and Lane Keeping Assist System (LKA) to estimate vehicle position and posture relative to road lane. Although some works utilize LIDAR or RADAR to detect roadside boundary, or uses embedded magnetic markers in the road way, the predominant approach by far is the use of video camera and image processing to extract the land and road edge markings from the image – exactly what human drivers do in visually processing the road scene.

So far, exiting works in vision based lane detection literature generally refer to a lane model consisting of camera model and road shape model. Most of the approaches are conduced to calculate related road shape parameters and trace lane boundaries in a recursive prediction-updating loop. Widely adopted methods for road parameters estimation are Kalman Filtering (KF), Extended Kalman Filtering (EKF) and Particle Filtering (PF) techniques. Road model is another argumentative topic in the field of lane detection. Straight line is the simplest road shape model, but is also erroneous for non-straight or non-flat road. Recently most approaches prefer to use piecewise line segments with the assumption of flat road surface, such as piecewise lines, circular [3], clothoid [4], polynomial approximation and so on. Although some more precise models like three-dimensional (3-D) road shape [5] could gain accuracy describing lane variance in both horizontal and vertical, it surfers from the high computational cost and high sensitivity to noise on the contrary.

The most difficult challenge for vision-based approaches is the robustness to different environment condition. Various meteorological and lighting conditions (day, night, sunny, rainy, snowy), road environmental conditions (occlusion, degraded road markings) significantly influence the estimation results. Most of the previous works depend on occupancy rate of proposed road model points and actual road features (edges or lane markers) on the image to evaluate result's accuracy. However, even with high occupancy rate, the estimated road shape model may not be accurate if two or more parameters are problematic. For example, on a curve road, if road width is estimated wider than its true value and road curvature is slightly bigger, we can still observe the image matches perfectly with the estimated road shape model.

To solve the problems mentioned above, a Predictive Lane Detection (PLD) algorithm is proposed in this paper. PLD is a hybrid solution composing of prediction module and visual detection module. The prediction module for road geometry is estimated by vehicle localization and road network, because it performs more reliable and robust for road prediction than the previous vision-only based approaches (example shown in Fig.1). In addition, prediction is also used for lane tracking on noisy image by limiting the detection zone on the image close to camera.

Fig. 1: The result of road geometry estimation projected on real scene without visual detection in stormy weather

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The paper is outlined as follows: section II describes our approach for PLD with constrains, road model and algorithm procedure. Section III discusses road geometry estimation in detail relying on present digital map. And Section IV introduces visual detection modules and how to analyze the parameters in each module. Hybrid results are presented in the finally section.

II. OUR APPROACH

A. Constrains

In our project, we utilize 2-D digital road map to reconstruct front road geometry for lane detection. And roadside variance in vertical plane is ignored here. In order to achieve our goal for PLD, we develop an image-based approach by taking following constrains into account.

i. It must collaborate with vehicle localization module, which is required for high accuracy and real-time performance.
ii. Local road network (2-D map, 3-D map) should be included unless a more precise approach could support for road information in detail.
iii. In our approach, Vehicle Coordinate System (VCS) and Camera Coordinate System (CCS) are regarded as same coordinate system, because we set GPS's antenna, Gyroscope and camera in the same plane.
iv. The algorithm in this paper assumes in a horizontal plane and the road's vertical curve is ignored. But the vertical part could also be recovered as long as 3-D map employing in system.
v. The rolling angle of vehicle is set as constant value.

B. Road Model

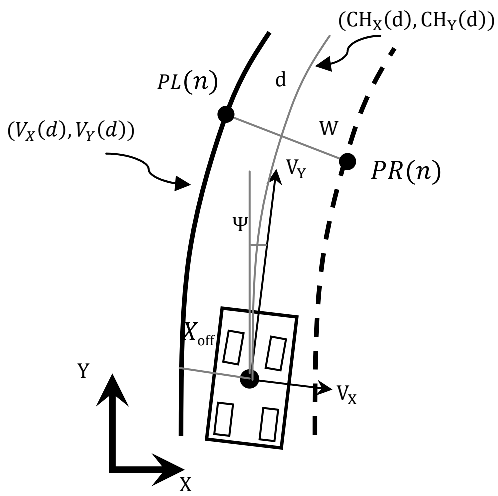


Fig. 2: Relationship between vehicle and road from bird's-eye view

Since road model could figure lane mark's position and its variety in VCS (see Fig. 2), how to define a road model precisely is a key problem for most lane detection. In our approach, we could replace lane's variety part with road geometry estimation. As the original reference information (road width and vehicle's offset) is also included in road model, road model for PLD is defined as following equation:

$$V_X(d) = \pm 0.5W + X_{off} + CH_X(d) \tag{1}$$

- $V_X(d)$: is the position in latitudinal direction of VCS;
- W: is the width of lane;
- X_{off}: is the lateral displacement in vehicle coordinate system;
- $CH_X(d)$: is lane variety in latitudinal direction of VCS;
- d: is the distance along the road network;

$CH_X(d)$ is a crucial part driven from road geometry. Comparing to other models by visual detection, our approach utilizes the reference points from road network in 2-D plane directly, which should be more reliable than points of image-based. The road geometry is recovered relying on vector of distance. It could simulate road geometry not only in latitudinal direction but also in longitudinal direction which used to be ignored by many approaches. Besides, lane width and lateral displacement are detected by visual detection module.

C. Algorithm Procedure

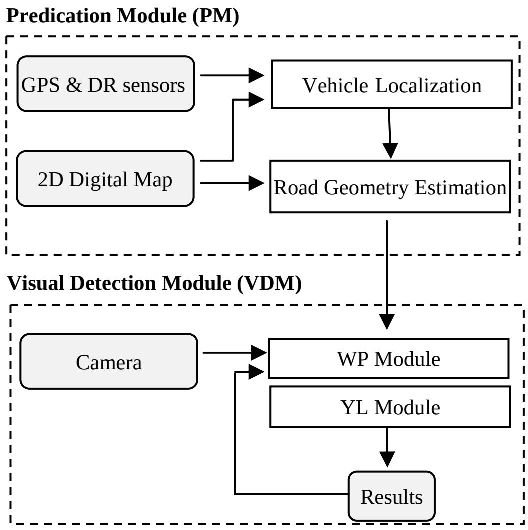


Fig. 3: Procedure chats of Predictive Lane Detection

Figure 3 presents the system block diagram. In prediction module, vehicle localization is estimated based on vehicle motion model with supporting with GPS and DR sensors. Digital road map is not only applied Map Matching (MM), but also provides node points of road network. In the step of road geometry estimation, new reconstruction approach based on route distance is designed for various road networks. Before visual detection, the PM could offer information of road geometry as soon as possible.

In Visual Detection Module (VDM), system will refer to the information from PM first. It will help to confirm the processing area avoiding noise's influence. And the error causing by road geometry should be considered in PW (vehicle Pitch angle and road Width) module and YL (vehicle Yaw angle and vehicle Lateral displacement) module. These two modules are proposed to analyze feature points for related parameters.

III. PREDICTION MODULE

In section II, we have mentioned the road model (Equ.1) as crucial part for lane detection. Lane variety used to be recovered by image-based points with various models, such as circular, clothoid or polynomial ways. Because road parameters are very sensitive from reference points through image processing, we try to rebuild road geometry by utilizing vehicle localization and digital map. It is supposed to be a robust way to acquire the road parameters reliable and stable.

Since vehicle localization and digital map were introduced by many papers [7], [8], [9], it is no necessary to discuss these technologies in detail but know about the information from this module. Position and orientation $(v_x(k), v_y(k), v_ori(k))$are given by localization system with time sequence **k.** Road node points (r_x, r_y) consisting for road network are provided by digital map.

A. *Road Geometry Reconstruction*

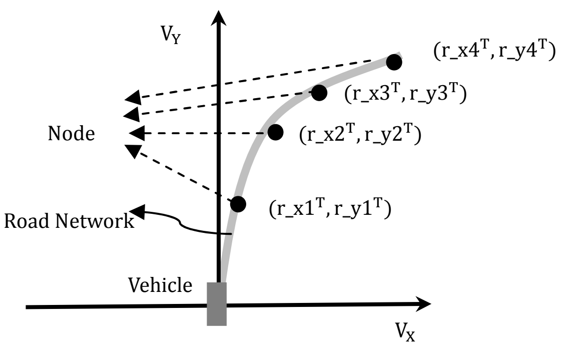


Fig. 4: Road geometry reconstruction in VCS

First of all, the node points should be transformed into VCS (see fig. 4). Vehicle always locate at origin point by tangent with road network. Node points in front of car, could figure out a general road's direction within certain distance. Polynomial method is chosen to approximate to real road because it is flexible to reconstruct any kinds of road. If road points by a selected route, we could simulation any road geometry by polynomial method. Furthermore, road geometry will be changed with vehicle following on the road network. So this method could express the road geometry precisely and timely.

The traditional method for polynomial is set up a relationship between V_x and V_Y directly. It relies on the order of polynomial and the number of node points. So it is hard to recover geometry accurately especially in some situations such as intersection and U-turn.

Here, we consider the polynomial in low-order and route distance is chosen as variety vector for recover V_x and V_Y independently. This method could simulate geometry as to practical situation and be realized easily by the way of mean-square. Although computational expense for $CH_X(d)$ and $CH_Y(d)$ estimation are increases for double, it could recover the geometry in a low-order and high precision.

$$CH_X(d) = \sum_1^n A(i)d^i \quad (2)$$
$$CH_Y(d) = \sum_1^n B(i)d^i \quad (3)$$

- $A(i)$: is the polynomial parameters in latitudinal direction of VCS;
- $B(i)$: is the polynomial parameters in longitudinal direction of VCS;
- d: is the distance along the road network;

The road network near to intersection is selected here and figure 5 expresses the procedure of our approach for road geometry estimation. Fig. 5(a) is the original data of vehicle localization (△) and road node points (*) in local coordinate system. And fig.5 (b) shows the result in VCS after coordinate transformation. According to node points (*) in fig.5 (b) projected into two feature spaces independently with the variety of distance, fig. 5(c) and fig. 5(d) is the feature space of x-d and y-d. The reconstruct route is shown as pink curve in the figure through proposed equation 2, 3 with 3 orders estimation. And the final combination result for road geometry is shown in the fig. 5(e) as green curve.

B. *Prediction for Visual Detection*

The purpose of this section is to provide the precise information for visual detection. In the section II, lane variety in road model is supposed to be given by road geometry estimation. And it could refer to the result of $CH_X(d)$ by equation 2. Furthermore, it could also be utilized in visual detection to eliminate influence causing by $CH_X(d)$ in latitudinal direction.

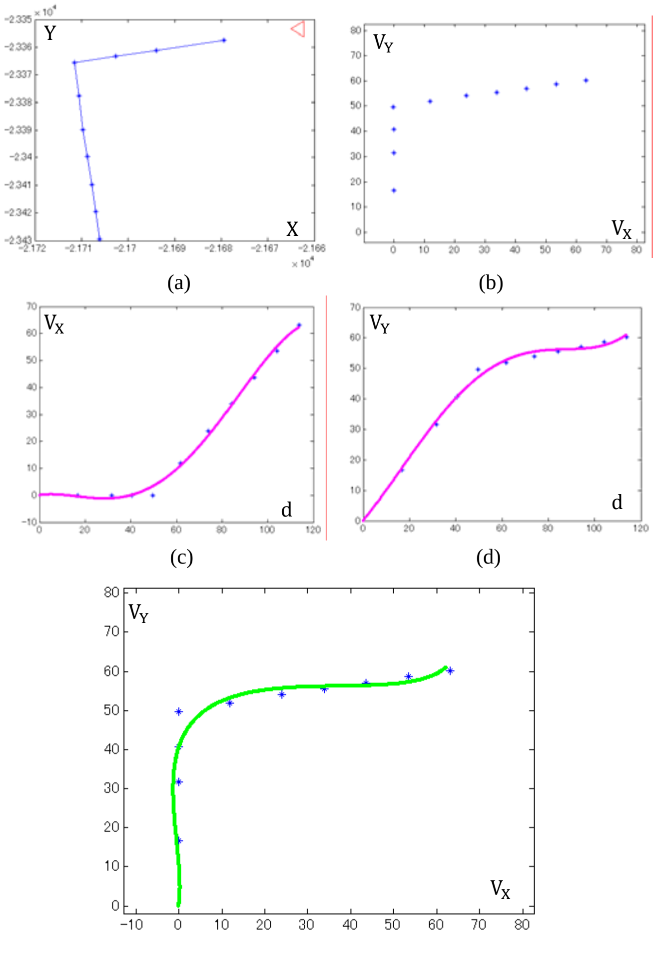
Besides, information $CH_Y(d)$ by equation 3 is also very important. However, it is ignored in the most situations because $CH_Y(d)$is considered as same as distance, which means visual detection model would like to select the feature points by horizontal line. According to point PL(n) and point PR(n) shown in figure 2, these two points are not at same horizontal line in VCS. That is why the road width of curve part is wider than straight one.

The slope k(d) of road geometry is expressed by equation 4. We could estimate the difference between left line and right line in longitudinal direction while the road width is considered the same, like the point PL(n) and point PR(n) in the figure 2. If we refer the right line as the baseline $CH_Y(d)$, the corresponding pair points should locate at

$CH_Y(d) + \Delta y(d)$ of longitudinal direction. So $\Delta y(d)$ could be expressed as equation 5.

$$k(d) = \frac{\partial CH_Y(d)}{\partial CH_X(d)} = \frac{\sum_1^n i*B(i)d^{i-1}}{\sum_1^n i*A(i)d^{i-1}} \quad (4)$$

$$\Delta y(d) = W \cdot \sin(\tan^{-1}(\frac{-1}{k(d)})) \quad (5)$$



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

Fig. 5: Simulation results of road geometry reconstruction

IV. Visual Detection Module

Here we set the right line as the base line and right road line is denoted as equation 8, 9. Left road line could be denoted as equation 6, 7 according to road geometry estimation provided by PM.

$$LX(d) = f_x\left(\frac{-0.5W + X_{off} + CH_X(d)}{CH_Y(d) + \Delta y(d)} + \Psi\right) \quad (6)$$

$$LY(d) = f_y\left(\frac{H}{CH_Y(d) + \Delta y(d)} + \theta\right) \quad (7)$$

$$RX(d) = f_x\left(\frac{0.5W + X_{off} + CH_X(d)}{CH_Y(d)} + \Psi\right) \quad (8)$$

$$RY(d) = f_y\left(\frac{H}{CH_Y(d)} + \theta\right) \quad (9)$$

- $(LX(d), LY(d))$: is the point on the image of left lane marks;
- $(RX(d), RY(d))$: is the point on the image of left lane marks;
- $(CH_X(d), CH_Y(d))$: is the road geometry in VCS;
- H: is the height of camera;
- Ψ: is the yaw angle of car;
- θ: is the yaw angle of car;
- (f_x, f_y): is the focal length of the camera;

A. *PW Module*

PW module shows the linear relationship between vehicle Pitch angle and road width. The difference function (Equ. 10) between right line and left line is acquired by equation 6, 8, where $\Delta y(d)$ is set as zero.

$$\Delta X(d) = RX(d) - LX(d) = \frac{f_x W}{f_y H} LY(d) - \frac{f_x W}{H}\theta \quad (10)$$

$\Delta X(d)$ means the difference between pair points locating on right line and left line and $LY(d)$ is the related point on the vertical direction of image. Normally, $\Delta y(d)$ is close to zero and $\Delta X(d)$ could be estimated by same horizontal line. According to equation 10, the relationship of $\Delta X(d)$ and $LY(d)$ is the linear if two lines are parallel in vehicle coordinate system unless some places such as fork or junction. PW module is relying on this linear relationship and related parameters could be estimated by feature points on the space of $\Delta X(d)$ and $LY(d)$. But it should refer to $\Delta y(d)$ for picking up pair points on a significant curve.

Figure 6 is a typical image after feature extraction. Firstly, we should calculate the difference of feature points based one same horizontal line, which appear in zone belonging to left line or right line. And according to equation 10, the difference is calculated by given space of W and θ. So if we set up a series of reasonable W and θ, the different results could estimate the matching points with actual points from image. Figure 7 shows the matching probability in the space of W and θ. The peak area (shown as red points in fig 7) represents a reliable area with high probability. Finally width and pitch are estimated by statistical results.

The result is given in figure 8, blue points are the actual different points and pink points are given by estimated parameters. Of course, the difference points in figure 8 perform a linear characteristic of PW module. In this way, the lane width could be calculated by the slope of straight line and pitch angle is calculated afterwards by intercept.

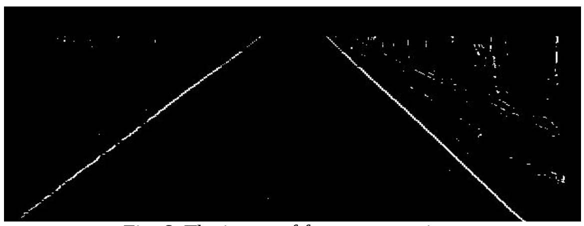


Fig. 6: The image of feature extraction

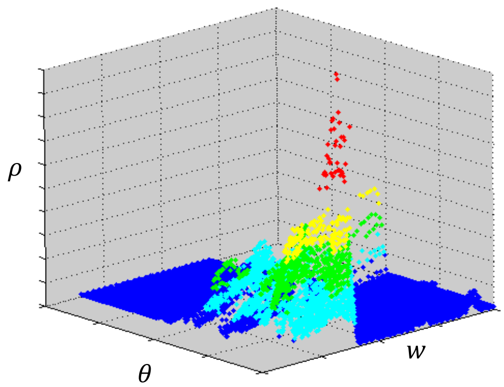


Fig. 7: Matching probability corresponding to W and θ

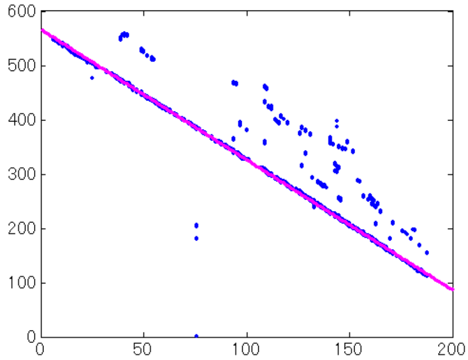


Fig. 8: Feature distribution map of PW module

B. YL Module

YL module is designed to get vehicle lateral displacement and yaw angle by referring to equation 6 or 8. The same as PW module, the parameters in this module should be seen as linear characteristic according to related functions. But we have discussed lane variety $\mathrm{CH_X(d)}$ of latitudinal direction in section 3, which is the prediction vector to eliminate the influence caused by curve part. If the feature points on image are compensated in opposite direction, YL module could search maximal matching probability on image in linear way as PW module. For example, road geometry is estimated by prediction model (see fig. 9). Then it is transformed into image space through camera's parameters. So the original feature points (white points) are compensated by relevant compensation, which are shown as the green points in figure 10.

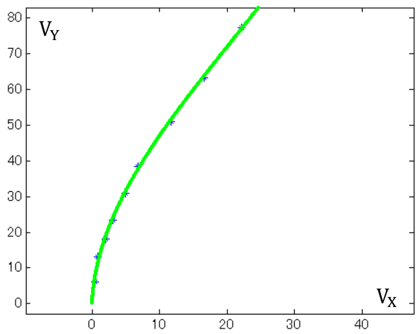


Fig. 9: Road geometry Estimation in VCS

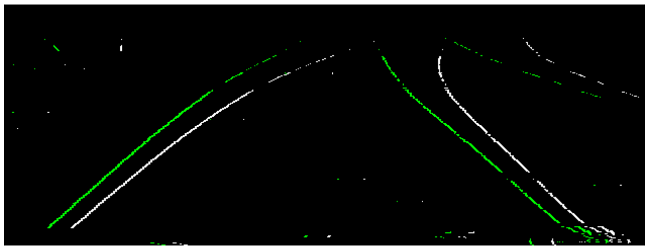
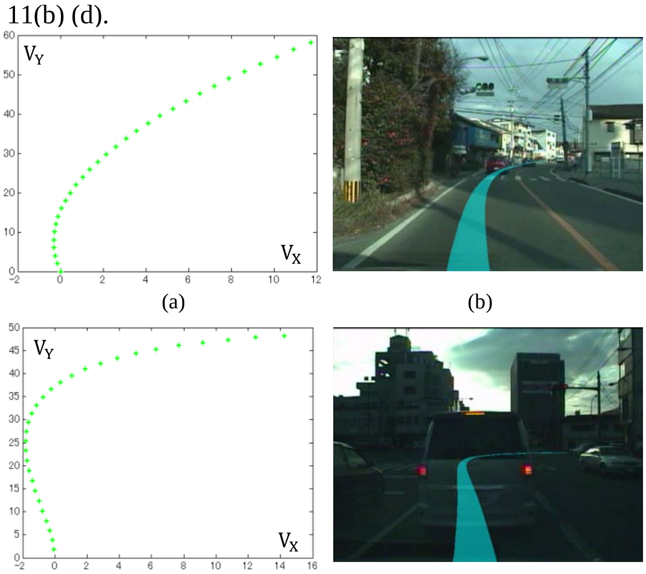


Fig. 10: Feature compensation based on geometry estimation for linear transformation

V. Simulations and Results

Our tests were based on the on-line data collection based on several sensors: a Teli CCD COLOR CAMERA was mounted on the front roof of test vehicle, image sequences were captured in NTSC format at the frame rate of 30fps, GPS data (Pioneer® GPS-M1ZZ) and inertial data (Gyroscope: Datatec®GU-3024 & Nissan LAFESTA CAN Speed) were sent to PC's serial port and recorded at the frequency of 1Hz and 60Hz separately; Shobunsh® Super Mapple ver.6 (1/25,000) was used as the 2D road map. Unfortunately, so far the algorithm has not been implemented by on-line processing. We just record data of vehicle localization and road network with synchronization of video recorder. And all tests are realized in the laboratory.

We have discussed the prediction module in section III and the result of road geometry estimation is shown in figure 5. Firstly, road geometry in VCS should be confirmed if it matches to the road on image or not. The range of geometry results ('*') in fig. 11(a) is 60 meters with interval of 2 meters. According to fig. 11(a), $\mathrm{CH_X(60)}$ is 11.73 meters and $\mathrm{CH_Y(60)}$ is 58.2. Although the error by longitudinal direction in VCS could be ignored, $\mathrm{CH_X(d)}$ by latitudinal direction must be counted for visual detection. But in fig. 11(c), $\mathrm{CH_Y(d)}$ could not be ignored as same as $\mathrm{CH_X(d)}$. And the projected road by estimation results is shown in fig. 11(b) (d).



(a) (b)

(c) (d)

Fig. 11: Road geometry estimation and projection on image

As a result of geometry estimation shown in fig. 12 (a) (c) (e), other parameters are detected by visual detection module introduced in section 4. And all the parameters are included in table 1. Here we choose the 3-order of polynomial for reconstruction road geometry. Furthermore, final lines are plotted on the image based on parameters (shown in fig. 12 (b) (d) (e)). Although the results on the image match to real line mark, there are little excursion between proposed line and real line. The error by vehicle localization, digital map or road reconstruction model might cause the excursion.

VI. CONCLUSION

In this paper we proposed a predictive lane detection method with road geometry estimation that relying on precise localization and digital map. Although some constrains are defined for practical application, this method effectively estimate the reliable parameters and works well in different kinds of condition.

The online processing of this approach is still under evaluation and we are focusing on improving the accuracy and stability of vehicle localization. In addition we are also working on some important applications using this approach, like the classification of different types of lane marks based on different lane width distribution.

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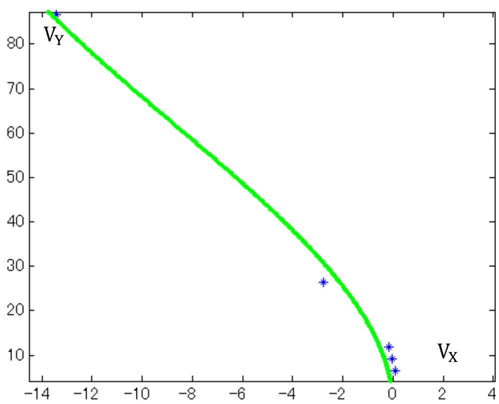
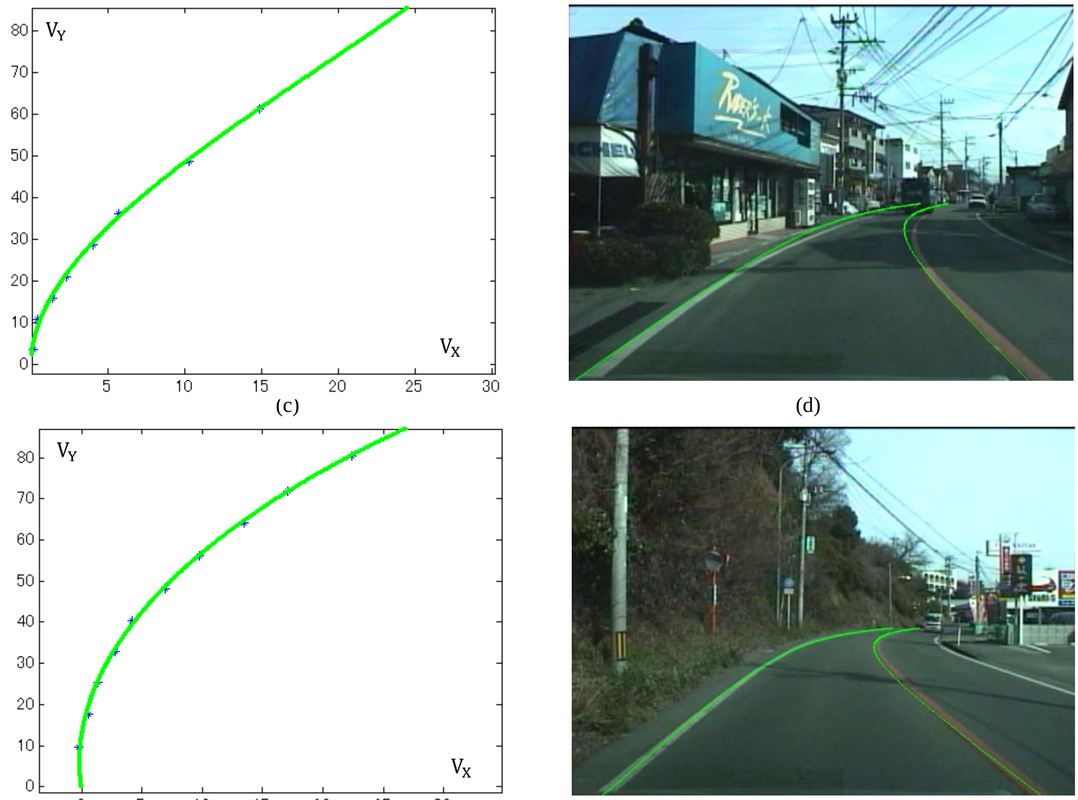
Table 1: Road parameters of figure 12 by proposed approach

Fig	Width (m)	Offset (m)	Pitch (°)	Yaw (°)	CH_X (m^{-1})	CH_Y (m^{-1})
(a)(b)	3.33	1.60	1.28	1.50	-0.00826 -0.00312 1.65e-005	0.99946 -0.00027 1.43e-006
(c)(d)	3.24	1.40	0.00	0.00	0.00592 0.00517 -2.46e-005	1.0044 -0.00057 -6.62e-007
(e)(f)	3.25	1.80	0.77	-1.00	-0.0465 0.004 -4.10e-006	1.0007 4.892e-005 -7.92e-006



(a)

(b)



(c) (d)

(e) (f)

Fig. 12: Road geometry estimation and final detection result on image