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Automatic Lane Keeping of a Vehicle Based on Perception Net.

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ABSTRACT

The objective of this research is to monitor and control the vehicle motion in order to remove out the existing safety risk based upon the human-machine cooperative vehicle control. A predictive control method is proposed to control the steering wheel of the vehicle to keep the lane. Desired angle of the steering wheel to control the vehicle motion could be calculated based upon vehicle dynamics, current and estimated pose of the vehicle every sample steps. The vehicle pose and the road curvature were calculated by geometrically fusing sensor data fro*m camera image, tachometer and steering wheel encoder though the Perception Net, where not only the state variables, but also the corresponding uncertainties were propagated in forward and backward direction in such a way to satisfy the given constraint condition, maintain consistency, reduce the uncertainties, and guarantee robustness. A series of experiments was conducted to evaluate the control performance, in which a car like robot was utilized to quit unwanted safety problem. As the results, the robot was keeping very well a given lane with arbitrary shape at moderate speed.

Keywords: Perception Net, Sensor Fusion, Vehicle Motion Control, Image Processing

1. INTRODUCTION

The traffic accidents have been increasing as the volume of traffic has been increasing, which requires the vehicles with intelligence to remove out the existing and/or future safety risk, if any, based on the human-machine cooperative vehicle control. The safety can be guaranteed by prevention of a driver from losing control of the vehicle, e.g., the skidding or overturn at a curved road due to excessive speed and the drifting away of the vehicle from the lane due to mistake or sleepiness of the driver. In the case where a safety risk is detected, the system may give the driver a proper warning to alert him/her for the safety risk. Furthermore, the system may automatically modify the control input of the vehicle, issued by the driver, in such a way as to ensure the safety while optimally compromising with the freedom of driving. To implement such a system, it is most crucial to detect the vehicle position relative to the road and the curvature of the upcoming road.

To this end, there have been advances for the last decade. One of methods to detect such information is to construct the road with identifiers such as magnets. [2] Even though this method has high reliability, it requires high cost to construct such roads. The other one is to utilize camera vision system and some additional sensors. In this method, the road need not have identifier but have some lane boundary markers. [3,4,5] From the survey on the conventional results, we come up with that there are two issues to be considered in development of the system for detecting the vehicle pose and road curvature. One is to reduce the computational burden. Most of conventional results utilizing vision algorithms such as Hough transform [2,3,4] or IPM [5] are suffering from the heavy computational burden. Reducing the image resolution as an alternative to overcome this drawback, may decrease accuracy or robustness. The other is to increase robustness. External environments such as the weather condition and the illumination condition, or internal environments such as CCD camera and electrical devices mounted to the vehicle, may cause noise or uncertainties in the image to be processed. Moreover, some of lane boundary markers are dotted lines or lines or may be missing, which also requires robustness of the system.

So, in this paper, Perception net based estimation method [7,8] is used to estimate the vehicle pose relative to the road and the road curvature in such a way as to reduce the computational burden and increase robustness. In order to reduce the computational burden, we modeled the lane on the road to be three commented rectangular plates. Since we have to investigate only the area defined by three plates, we could get efficient computation for real-time processing. In order to increase reliability and robustness, an algorithm so-called "Perception-Net" for estimating the vehicle pose and the road curvature was used. In this algorithm, not only variables to be estimated but also the corresponding uncertainties are propagated forward and backward through the Perception-Net in such a way as to satisfy the given constraint condition,

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maintain consistency, reduce the uncertainties, and guarantee robustness. If we have precise estimated values for plate pose and vehicle pose parameters, a control strategy for the vehicle to keep given lane can be obtained straight forward. That is, the objective of the lane keeping control is to reduce a predicted tracking error of the vehicle, while the vehicle is traveling along the given lane. In this paper, we calculated a required steering angle for lane keeping based upon a kinematic relation ship in a vehicle among the steering angle and the vehicle pose parameters. Main idea in lane keeping control is how to calculate predictive steering angle required to quit a estimated prediction error of the vehicle in lateral direction from center of a given lane.

To evaluate the performance of the proposed control algorithm, we conducted a series of experimentation on a test road which has straight and curved lane. The vehicle used in this experimentation is a kind of robot with shape of a car in which its travel speed and direction are controlled via a serial wiring port connected to a personal computer and a CCD camera is installed to take pictures of the front view of a car while traveling along the given lane.

2. MODELING OF VEHICLE POSE AND UPCOMING ROAD

First, we define a series of connected rectangular plates which are supposed to cover the lane around and ahead of the vehicle. This series is like a chain of rectangular plates each of which has certain degrees of freedom of motion relative to the adjacent plates and its size is set in such a way that the lane inside the plate can be approximates as a pair of straight and parallel lines as shown in Fig.1. In order to define the coordinate frames in each plate, we set the center points of the bottom line of the plates as the corresponding origins. And we define the x axis as the bottom line with the positive direction in the left side. Then the corresponding y and z axes are automatically defined. For details, see Fig.1. In this paper, we assume that the number of plates is 3. the pose of the plates and the vehicle is determined by the coordinate transformation relationships which can be obtained using the homogeneous transformation chain rule. We assume that the vehicle is always located on the bottom line of the first plate with a direction which may be different from the direction of the corresponding z axis. Hence, the pose relationship between the vehicle and the first plate is determined by the lateral distance d from the vehicle to the origin of the first plate, the angle β_c between the vehicle direction and the z axis of the first plate, and the height h of the camera from the ground. The pose relationships between the plate and the adjacent plate are determined by rotation angles α_i (pitch), β_i (yaw), and γ_i (roll), which show degree of freedom of the plates.

The above three plates are projected to the image frame via a perspective project as three trapezoids. Throughout this paper, these trapezoids will be called windows and used as image processing zones. In other words, we have only to concern these windows in order to extract the lane boundary, which remarkably reduces computational burden.

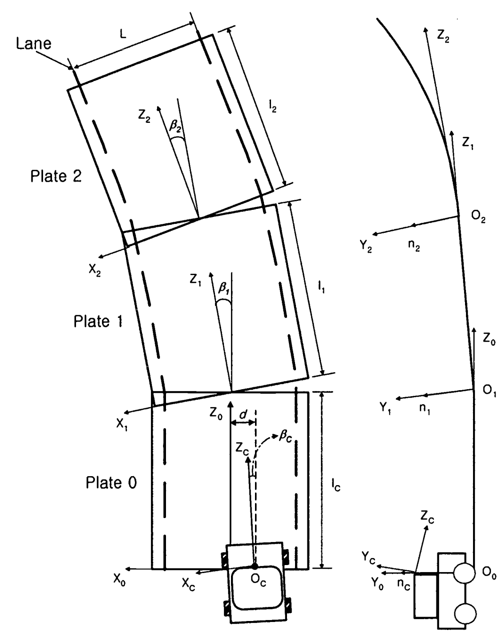


Fig. 1 Rode model via connected plates

3. ESTIMATION OF THE PLATE AND VEHICLE POSE PARAMETERS

3.1 Estimation of Pose Parameters Based Perception-Net

The perception net connects logical sensors or features of various levels of abstraction that can be identified by the sensor system. The perception net is formed by the interconnection of logical and physical sensors with three types of modules: feature transformation module (FTM), data fusion module (DFM), and constraint satisfaction module (CSM). An FTM transforms a set of primitive features into a more abstract and a higher level of feature. A DFM takes multiple data of a feature to generate an optimal estimate of the feature. A CSM represents system knowledge which imposes a constraint upon a set of feature values given as input variables. The net is operated in such a way that a state change at a logical sensor propagates to adjacent logical sensors, triggering a chain of state changes throughout the net. It is noted that the propagation of state change is bi directional, forward and backward: the net automatically updates, and maintains the consistency of its state not only through the forward propagation of state change but also through the backward propagation of state errors in such a way as to satisfy the constraints.

Fig.2 shows the Perception-Net used in this paper to estimate the pose parameters and road curvature. Suppose that the current time instant is described by $t=k\Delta t$, where Δt denotes the sampling time and k denotes the time index. At the current time instant, the current predicted pose parameter $\phi(k|k-1)$ is computed, based on the estimated pose parameter $\phi(k-1|k-1)$ at the previous time step, the current sensor data from velocity meter and steering wheel encoder, and the non-holonomic constraint of the vehicle. This procedure is performed through FTM1 in Fig.2. Then the plates determined by the predicted pose parameter are projected to the image frame, and the corresponding windows are determined in the image frame. In these windows, both sides lines which are supposed to linearize the lane boundaries, are extracted and projected to the corresponding plates. This procedure is performed through FTM2-FTM6. Through FTM2, the pixels (P_L,P_R) which are supposed to comprise the lane boundary markers are extracted. Through FTM3 and FTM4, both sides lines (X_L,X_R) are calculated from the extracted pixels using the least square method. Through FTM5 and FTM6, the extracted lines are projected to the plates to get both lines (Y_L,Y_R) in plate frames. Then, we adjust the pose parameters and both side lines from the predicted pose parameters and projected lines in such a way that the given constraints are satisfied. As a method to obtain the optimal estimates $\phi(k|k)$ for such parameters and lines, we utilize a geometric data fusion method, where not only the given constraints but also the ellipsoidal uncertainty bounds are taken into consideration. This procedure is performed on CSM. Then, the estimated pose parameter is utilized to predict the pose parameter at the next time step, and the procedure is repeated.

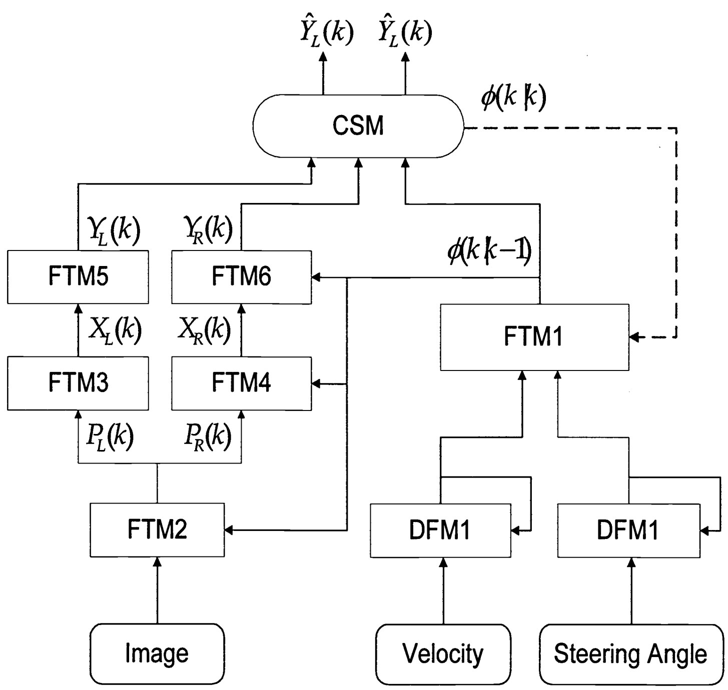


Fig. 2 Perception-Net for estimation of vehicle pose and road curvature

3.2 Forward Propagation

First, we investigate how the velocity and the steering wheel angle affect the plate and plate pose. Let $\Delta\beta_c$ denote the variance of β_c and Δd_c denote the variance of the lateral vehicle position along the x_c axis of the camera frame during the sampling period (Δt). Then, from the Ackerman Angle, we obtain

$$\Delta\beta_c = v\Delta t \frac{\delta}{L_v} \tag{1}$$

$$\Delta d_c = \begin{cases} (1-\cos(v\Delta t \frac{\delta}{L_v}))\frac{L_v}{\delta} & \text{Where } \delta \text{ is large} \\ \frac{1}{2} v^2 \Delta t^2 \frac{\delta}{L_v} & \text{Where } \delta \text{ is small} \end{cases} \tag{2}$$

where L_v demotes length of the vehicle between front and rear wheels, v is the measured travel speed and δ is the measured steering wheel angle. Through the coordinate transformation, we obtain

$$\begin{aligned} \Delta d &= \Delta d_c \cos\beta_c + v\Delta t \sin\beta_c \\ \Delta L &= -\Delta d_c \sin\beta_c + v\Delta t \cos\beta_c \end{aligned} \tag{3}$$

where Δd denotes the variant of the lateral position in the plate frame and ΔL demotes the approaching distance along the z axis in the plate frame during the sampled time interval.

Variable update equation for forward propagation are obtained by using a linear interpolation method as following:

$$\begin{aligned} & d(k \mid k-1) = d + \Delta d + n_d \\ & h(k \mid k-1) = h \\ & \beta_c(k \mid k-1) = \beta_c - \beta_1 \frac{\Delta L}{L_0} + v\Delta t \frac{\delta}{L_v} + n_{bc} \\ & \beta_i(k \mid k-1) = \beta_i + (\beta_{i+1} - \beta_i)\frac{\Delta L}{L_i} + n_{bi}, i = 1,2 \end{aligned} \tag{4}$$

where n_d, n_{bc}, n_{b1} and n_{b2} denote the corresponding white noise induced from process noise or modeling error. β_3 denotes the predicted angle between plate 2 and a virtual plate 3. Update equations for other variables (α_i, γ_i) can be obtained similarly. Now, we assume that the measured data v, δ have the additive noise n_v, n_δ.. Then the updated weighting (uncertainty) matrices for the lateral distance d can be obtained by $W_d(k \mid k-1) = (J^t W^{-1} J^{t'} + Q_d)^{-1}$ where

$$\begin{aligned} & W = diag(W_d, W_{\beta_c}, W_v, W_\delta) \\ & J_v = \cos\beta_c(\frac{\partial \Delta d_c}{\partial v}) + \Delta t \sin\beta_c \\ & J_\delta = \cos\beta_c \frac{\partial \Delta d_c}{\partial \delta} \\ & J = \begin{bmatrix} 1 & -\Delta d_c \sin\beta_c + v\Delta t\cos\beta_c & J_v & J_\delta \end{bmatrix} \\ & Q_d = E\{n_d^2\} \end{aligned} \tag{5}$$

The other uncertainties can be similarly updated.

3.3 Backward Propagation

In constraint satisfaction module, all parameters associated with plate pose ϕ, and line equations on the image $X_L(k)$ and $X_R(k)$, are estimated in such a way that minimizes the weighted distance from the parameter ϕ^P predicted in

FTM1 and the line equation parameter $X^m_L(k)$ and $X^m_R(k)$ obtained through FTM2 and FTM4 to the constraint manifold. The optimization for parameter estimation is defined by

$$\underset{\phi}{Minimize} \quad J_m(\phi), \tag{6}$$

where $J_m(\phi) = \frac{1}{2}\left[\left\| \phi^P - \phi \right\|^2_{W_\phi} + \left\| X^m_L - gl(\phi, Y_{LC}) \right\|^2_{W_L} + \left\| X^m_R - g_R(\phi, Y_{LC}) \right\|^2_{W_R} \right]$

Once the optimal solution is found, new line equation parameters and hence the upcoming lane boundary can be estimated while satisfying the constraint. Not only pose parameters but also the corresponding uncertainties need to be updated.
For instance, consider that two variables, x and y with uncertainty bound W_x and W_y respectively, are constrained by $f(x, y) = c$. In CSM, we obtain the estimated value x* and y* in such a way as to minimize the weighted distance from the predicted or measured value to the constraint manifold $f(x, y) = c$. the propagated uncertainty bounds through CSM can be obtained by projecting them to the linearized constraint manifold. The uncertainty bound $W_\phi(k|k)$ for the pose variable $\phi(k|k)$ is propagated from the predicted uncertainty bound $W_\phi(k|k-1)$ in the forward propagation module and the measured uncertainty bound W_L, W_R in the lane boundary identification procedure. Based on the propagation relationship and the constraint, we obtain the following back propagation equation for uncertainty bound :

$$W_{\phi(k|k)} = W_{\phi(k|k-1)} + \left(\frac{\partial gL}{\partial \phi}\right)' W_L \left(\frac{\partial gL}{\partial \phi}\right) + \left(\frac{\partial gL}{\partial \phi}\right)' W_R \left(\frac{\partial gR}{\partial \phi}\right) \tag{7}$$

4 LANE KEEPING CONTROL

The position of a vehicle relative to lanes, especially lateral distance from the center of lanes and orientation of the vehicle (β_c, camera angle), can be calculated by the above estimation algorithm based upon perception net. As shown in Fig.1, in the case that there is lateral distance d, the objective of the lane keeping control is to make lateral distance, d, zero. An estimated lateral distance based upon current measured information like as lane boundaries a vehicle speed, and an angle of a steer wheel, can be calculated by equation(4). To reject the lateral distance while as the vehicle is passing through the plate 0, a variation of the lateral distance should be

$$\Delta d(k|k-1) = -\frac{v\Delta t}{Lo} d(k|k-1) \tag{8}$$

by turning a steer wheel.
Thus, we can calculate the control angle of a steer wheel from eq(2), (3) and (8) as the following equation.

$$\delta(k) = -\frac{zLv}{v\Delta t \cos\ \beta c(k|k-1)} \left(\frac{d(k|k-1)}{Lo} + \sin\ \beta c(k|k-1)\right) \tag{9}$$

Equation(9) shows that the steer wheel could be controlled based upon predicting vehicle pose parameters.

5 EXPERIMENT

A vehicle used in this experimentation is a robot having shape of a car as shown in Fig.3. A CCD camera is installed on a bone net of the car. The front view of the car can be taken by this CCD camera. The captured image is transmitted to an image processing board in a computer through a wireless transmitter. When the car is traveling, the travel speed of the car and an angle of the steer wheel are also measured and transmitted to the computer via a serial port every 1/12 seconds. In the computer, the plate pose parameters of the road and vehicle pose parameters are calculated based upon the measured travel speed, steering wheel and lane boundaries which are also detected in the computer by the image processing algorithm, then the calculated control command for the steer wheel is transmitted back to the car through the serial wire during the sampling duration. Fig.4 shows a test road used in this experimentation. The test road has straight line and curved one and some other lines or characters which produce image noise in processing the road image in the computer. Control experiments are performed at various vehicle travel speeds. In the experiments, the vehicle travels along the straight line first, then along the curved lane with counter clockwise direction.

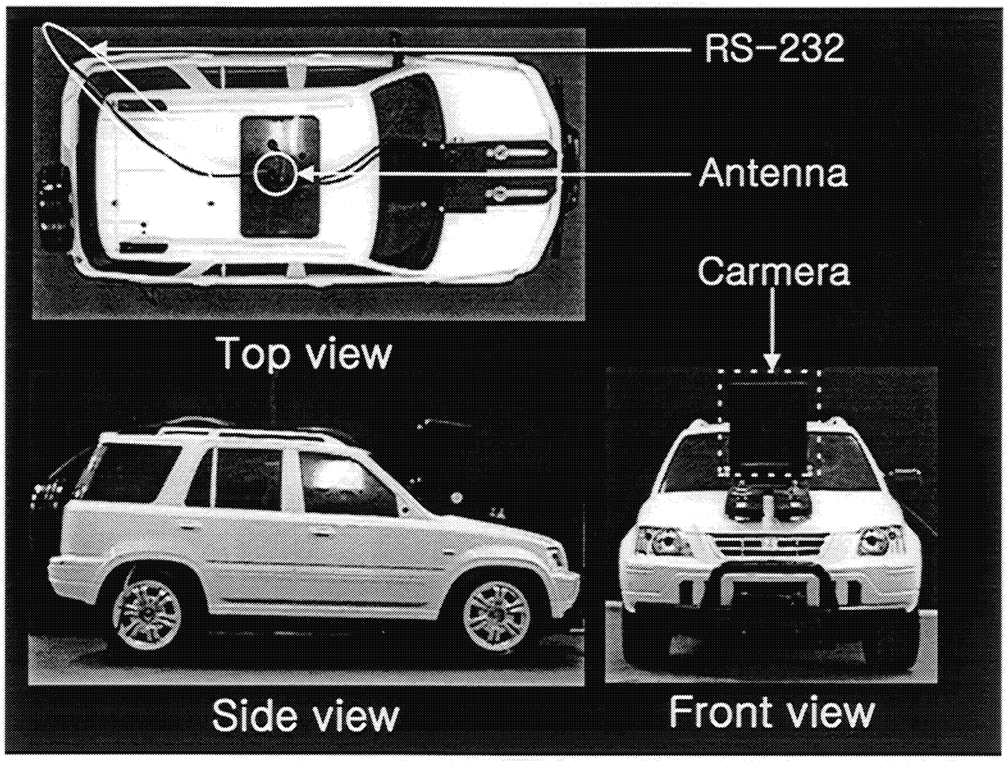


Fig. 3 car like robot for experimentation

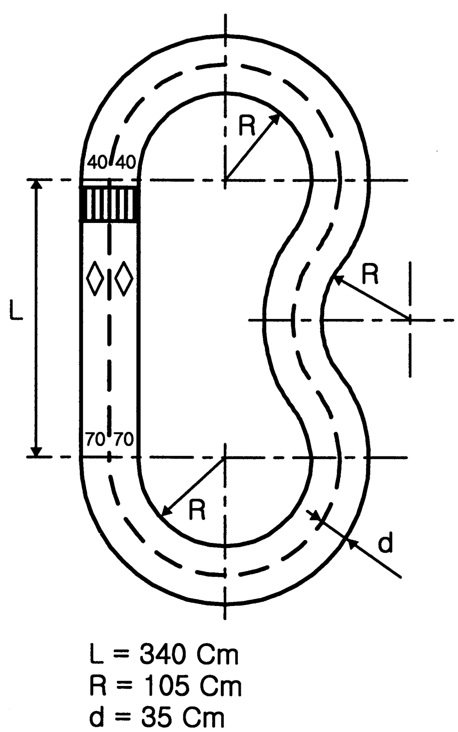


Fig. 4 Configuration of a test road

6 EXPERIMENTAL RESULTS AND DISCUSSION

Fig.5 shows an estimated plate and lane boundaries on the road image on the curved lane. In this figure, the plates are virtual ones only on the image plan, not real ones on the road. So, the lane boundaries can be detected in real time by processing the data within the virtual plates, so called windows in this paper. This figure shows that the virtual plates on the curved lane are rotated to adjacent plates each other so that the lane on the plates can be considered to be straight lines.

Fig.6 shows the experimental results for lane keeping control on the test road. As the results, we can see that the vehicle is keeping within ± 5Cm from the centerline of the lane from considering the variation of the lateral distance in Fig.6(b). We could get the similar performance for all levels of vehicle travel speed used in this experiments. But we can see that the large deviation of the lateral distance from the lane center to out of the circular along the curves lane, while the precision lane keeping is performed along the straight lane. This could be occurred by centrifugal force to the vehicle while traveling on the curved lane. Because the vehicle dynamics was not considered in designing the control method in this research, the lateral distance along the curved lane could not be reduced in this experimentation. Thus, in the further work, the vehicle dynamics should be considered to get the accurate lane keeping of the vehicle even along the curved lane. Fig.6 (a) shows the variation of the steering angle during traveling of the vehicle. We can see how to adjust the steering wheel for the vehicle to keep the lane along the lane on the test road in this figure. The figure shows that the oscillating amplitude of the steering angle is high, ± 3degree. This is induced by the inaccurate estimation of the vehicle pose parameters as well as the inaccurate control algorithm in which the vehicle dynamics is not considered in current research.

Fig. 7 shows the estimated results of the plates and vehicle pose parameters in this experiments. In Fig. 7(a), we can get the results that the orientation of the vehicle is maintained with small deviation, within ± 5 degrees, from the travel direction of the vehicle along the lane. It can be known that the steering angle is also controlled by this control algorithm. But, we can see the large variation of the vehicle orientation in this figure. This may be induced from oscillation of the steer wheel to control the lateral distance of the vehicle. Fig. 7(b) shows the variation of the rotation angle, b1 between the plate 0 and plate 1. In this figure, we can see that the vehicle travels along the straight lane first, and approaches to the curved lane. This figure also shows that, after traveling of the vehicle to 5m along the straight lane, the vehicle is driving in keeping the lanes along the curved lane. In this figure, if can be shown that the estimation of the plate pose parameters is performed very well by using the perception-net based algorithm. Especially, from comparision of the results between Fig. 6(a) steering angle and Fig. 7(b), we can conclude that the steering wheel is controlling for the vehicle to keep the straight or curved lane.

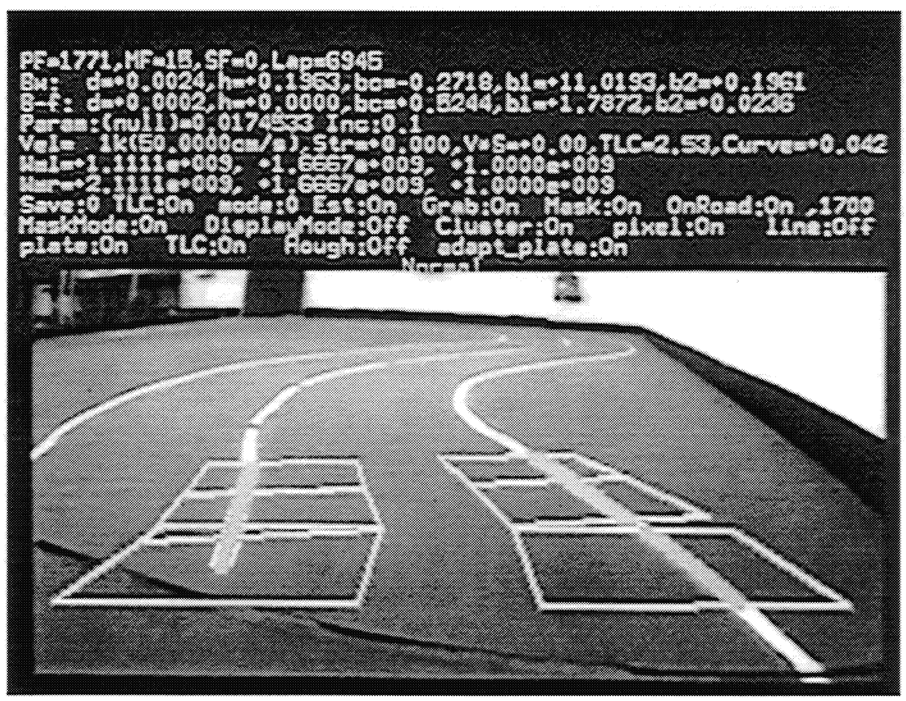
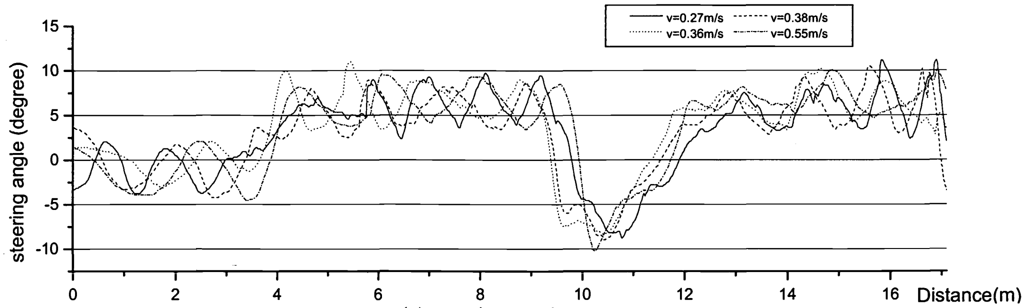
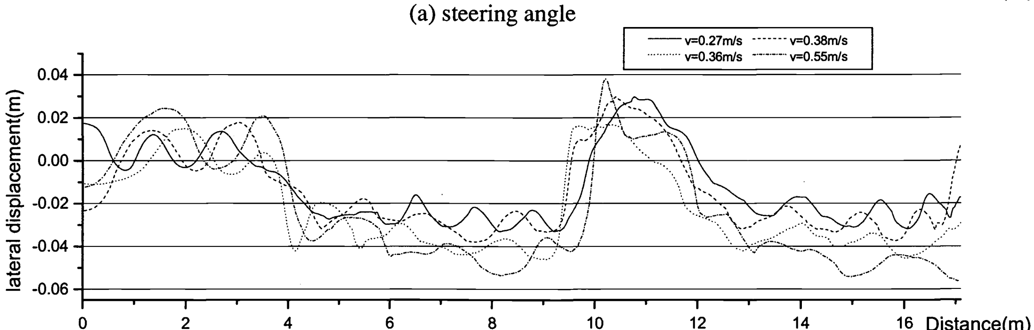


Fig. 5 Estimated plates and lane boundaries

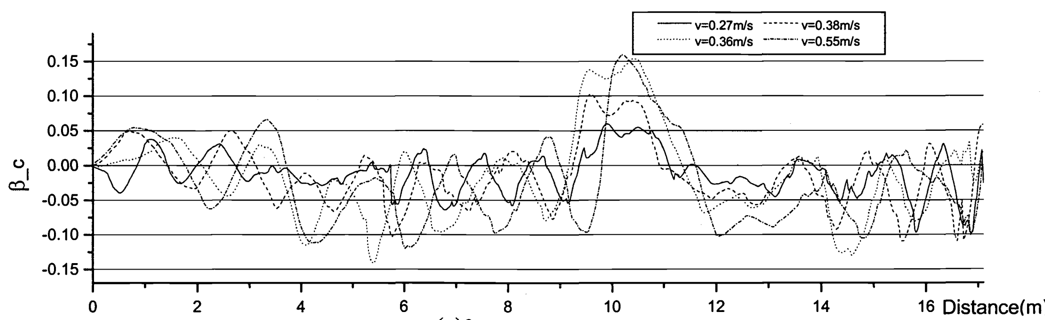


(a) steering angle

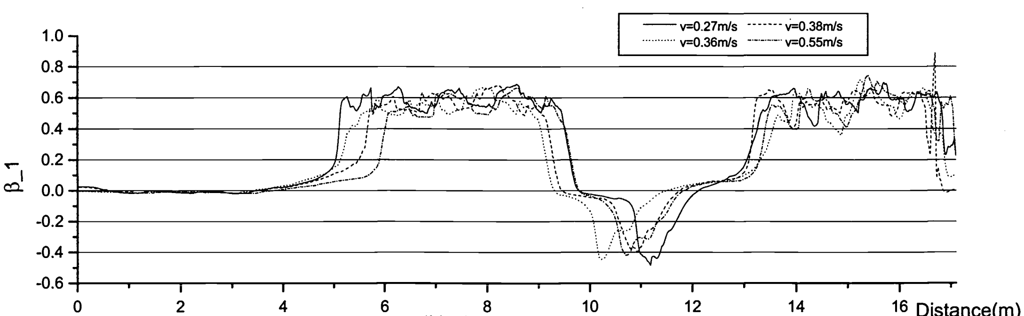


(b) lateral displacement from center of lane

Fig.6 Experimental results of the lane keeping control



(a)βc



(b)β1

Fig.7 Estimated pose parameters

7 CONCLUSIONS

In this paper, proposed is a method for controlling the vehicle to keep a given lane. The control algorithm is calculated based upon the estimated vehicle pose and road curvature, which is obtained by using Perception-Net. The lane on the road is modeled as multiple connected rectangular plates in order to achieve computational efficiency. The vehicle pose parameters are estimated in a systematic way through forward and backward propagation and using to calculate the adjust angle of the steer wheel. The lane keeping is achieved with satisfying accuracy in the proposed control algorithm in which the steering angle is calculated via the predicted lateral distance of the vehicle. In this current research, the vehicle dynamics is not considered and make the large lateral deviation of the vehicle from the centerline in traveling along the curved lane. This should be considered to get a more accurate performance in the future work.

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