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A VISION BASED CONTROL APPROACH TO HIGH SPEED AUTOMATIC VEHICLE GUIDANCE

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ABSTRACT

The last ten years, automatic outdoor vehicle guidance by computer vision has raised up a great interest from the robotic communauty. This paper proposes the analysis and synthesis of a closed loop control scheme based on vision data which has been successfully implemented on a vehicle. This scheme focuses on two main aspects : **Vision aspect:** The use of efficient image processing algorithms allows us a robust detection of the road lines even in case of bad atmospheric conditions (cloudy weather, shadows...). It has been implemented on a real time vision hardware. **Vehicle aspect:** A road vehicle is a complex dynamic system. Fortunately, it is not useful to take into account the whole complexity of the model for computing robust and efficient control laws. We studied the behaviour of various control laws (continuous and discrete) based on different degrees of complexity of the model. Results which have been obtained in simulation, have been confirmed in our real experiment.

INTRODUCTION

Research on automatic vehicles using cameras has being conducted in many countries, in particular in the United States [3, 6] and in Germany [2]. An effort is made to demonstrate that machine vision systems are able to run with the infrastructure developed for the human drivers. Mainly two kinds of applications have been pointed out : navigation in unconstrained outdoor environment and road following. The first case focuses on Artificial Intelligence techniques and needs to acquire and to reason on a 3D model of the environment. The second case assumes a certain knowledge about the 3D environment (road geometry) and addresses the problem from the point of view of control. This paper deals with this second approach and proposes a complete analysis and synthesis of a closed loop control scheme based on vision data which has been successfully implemented on a vehicle. The paper is divided in three parts. The first one is devoted to the vision aspect. A perception system is responsible for the road detection and vehicle localization. Our algorithm is able to give estimation of five parameters from monochromatic images, at video rate. These parameters are : lateral offset of the vehicle, heading offset (difference between the direction of the road, and the direction of the vehicle), camera height, camera pitch, horizontal road curvature. In the second part, we discuss the vehicle aspect. We establish the dynamic model of the vehicle and of its steering system. Then, the parameters of this model are identified from the real vehicle values. This step allows us to obtain the mathematical model used in simulation. The last part presents the experimental vehicle and results.

VISION ASPECT

We use vision as a sensor giving the relative 3D position of the vehicle on the road. This section explains how this measurement is possible. The reader can find more precise informations on that subject in [1].

The method is based on the reconstruction of two models : the first one describes the 3d attitude of the vehicle, the second one is about the state of the world surrounding the vehicle. Measurements are made by the use of a on-board camera directed toward the road. Both models are written in the sensor reference frame, by applying rotations, translations and perspective projection. Identification and prediction are given by an Extended Kalman Filtering.

The method

Let us first define the various references used. The first R_f is an absolute reference in which the scene model is given. The second R_m is a 3D reference tied to the camera. At last R_i is a 2D reference which is the sensor reference (we suppose the optical center is at the center of the ccd matrix). A point P in $R_f = (X, Y, Z)^t$ is noted $p = (x, y, z)^t$ in R_m and its projection in R_i is $p_e = (xe, ye)^t$.

The first task is to define the geometric model of the scene in R_f. It is defined as a set of N elements E_i :

$$M = E_0 \cup E_1 \cdots \cup E_N \qquad (1)$$

And the model may be written as :

$$E = \{P \in \Re^3 / \exists i \in 1..N and F(P, \underline{M_i}) = 0\} \qquad (2)$$

Each part of the model is described by a parameter vector $\underline{M}_i$. We note $\underline{M}(t) = (\underline{M}_1^t(t), \ldots, \underline{M}_N^t(t))^t$ the complete dynamic parameter vector to be estimated.

The model description in R_i is produced from its description in R_f (2) by applying : translations, rotations and perspective projection.

We note it :

$$Ep = \{P \in N^2 / F_p(P, \underline{M}, \underline{T}) = 0\} \tag{3}$$

where F_p depends on : $\underline{T}$ vector including translations and rotations, and $\underline{M}$ vector which is the state model.

Then we have to take into account a model of the system dynamics being estimated : $\underline{T}$ follows the vehicle evolution, $\underline{M}$ is depending on the evolution of the scene.

These evolutions are often non-linear functions. Let k be a discrete variable ; the state vector is :

$$\underline{X}(k) = (\underline{T}^t(k), \underline{M}^t(k))^t \tag{4}$$

Then the Φ function is including the evolution of $\underline{X}(k)$:

$$\underline{X}(k+1) = \Phi(\underline{X}(k), \underline{W}(k)) \tag{5}$$

The noise covariance matrix Q is : $E[\underline{W}(k)\underline{W}^t(k)] = Q$.

The updating of the model is based on the *innovation* which is the difference between image primitives predicted and actual measurements. The measurements are predicted by using caracteristics $h_i, i \in [0..N]$ of the measurement process and the predicated state :

$$y_i = h_i(\underline{X}(t_k), V(k)) \tag{6}$$

with $V(k)$ the measurement noise. The noise covariance matrix $V(k)$ is : $E[\underline{V}(k)\underline{V}^t(k)] = R$.

We also note, for all observations/measurements :

$$\underline{Y}(k) = h(\underline{X}(k), \underline{V}(k)) \tag{7}$$

Then the problem can be written in the state formalism :

$$\underline{X}(k+1) = \Phi(\underline{X}(k), w(k)) \tag{8}$$

$$\underline{Y(k)} = \underline{h}(\underline{X}(k), V(k)) \tag{9}$$

With : $E[\underline{W}(k)\underline{W}^t(k)] = Q$ the prediction noise covariance matrix and $E[\underline{V}(k)\underline{W}^t(k)] = 0$.

Then an extended Kalman filtering is able to produce an optimal estimation $\hat{\underline{X}}(K)$ of $\underline{X}(k)$.

The application

Now, let us describe our application within the previous formalism :

- The scene model is 3 bands between circulation lanes. The only parameter is the local curvature C of the road (the road is supposed to be locally flat, and the lanes supposed to have a constant width.
- 4 parameters gives the attitude of the car on the road. Two translations : x_0 (lateral position) and z_0 (camera height). The third translation is taken as null. We also take into account the 2 rotations : α (camera inclination) and ψ (lateral deviation). The third rotation is taken as null.

The references are taken as shown in Figure 1.

The equation $F_p(pe, \underline{M}, \underline{T}) = 0$ which is the projection of the three bands road model (Cf relation (3)) is after many simplifications :

$$\begin{aligned} E_p &= \{p_e = (x_e, y_e)^t / - x_e \\ &\quad + e_u\left(\frac{e_v z_0}{2(y_e - e_v\alpha)} C \right. \\ &\quad \left. + \frac{y_e - e_v\alpha}{e_v z_0}(x_0 + b.e) - \psi\right) = 0\} \end{aligned} \tag{10}$$

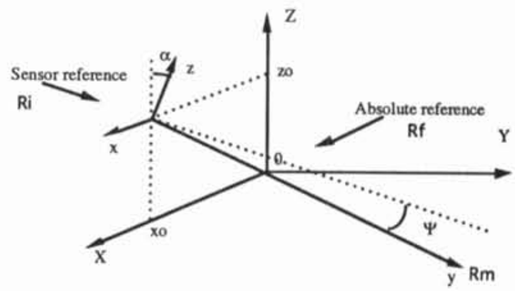

Figure 1: Absolute and sensor references.

Where : (x_e, y_e) are the coordinates of a point in the image, and (e_u, e_v) are sensor scaling factors, assuming $(b = 0)$ for the middle band, $(b = -1)$ for the left band, $(b = 1)$ for the right band.

We propose in [1] an algorithm for detecting bands in the images.

Then we pose : $\underline{X}(k) = (\underline{T}^t, \underline{M}^t)^t = (x_0(k), C(k), \psi(k), \alpha(k), z_0(k))^t$ the state vector to be estimated.

The predictable evolution of the vehicle is included in $\Phi(k)$). It allows, for example to take into account the relationship between (x_0), (ψ) and the speed (V) by :

$$x_0(k) = \Delta t V \psi(k) + x_0(k-1) \tag{11}$$

Given Δt the time between iterations.

Values of Q are estimated by experiments.

The equation of observation is

$$\underline{Y} = h(\underline{X}(k), V(k)) \tag{12}$$

The function h is obtained from the equation (10).

Then we would like to get an estimation of $\underline{X}(k) = (x_0(k), C(k), \psi(k), \alpha(k), z_0(k))^t$. The measurements are a set of pixels $p_e = (xe, ye)$ on the 3 bands ($b \in (0, 1, -1)$) in the image, and the slope of the bands in the images for each pixel (Se_i). We note $m_i = (Xe_i, Ye_i, b_i, Se_i)$ the vector so formed.

A specialized image process gives an estimation $\hat{\underline{m}}(k)$ of this vector. We then suppose :

$$\hat{\underline{m}}(k) = \underline{m}(k) + \underline{V}(k) \tag{13}$$

Where $\underline{V}(k)$ is a white noise of known covariance.

Measures are linked by relations :

$$f(\underline{X}(k), \underline{m}(k)) = 0 \tag{14}$$

$$g(\underline{X}(k), \underline{m}(k)) = 0 \tag{15}$$

from (10), which yields :

$$\begin{aligned} f(\underline{X}(k), \underline{m}(k)) &= \frac{e_u e_v z_0(k)}{2(Ye(k) - e_v\alpha(k))} C(k) \\ &\quad + \frac{e_u(Ye(k) - e_v(k))}{e_v z_0(k)}(x_0(k) + b(k) \times e) \\ &\quad - e_u\psi(k) - Xe(k) \qquad (16) \\ g(\underline{X}(k), \underline{m}(k)) &= \frac{e_u}{e_v} \times \frac{x_0(k) + b(k) \times e}{z_0(k)} \\ &\quad - \frac{e_u e_v}{2} \frac{C(k) z_0(k)}{(Ye(k) - e_v\alpha(k))^2} \\ &\quad - Se(k) \qquad (17) \end{aligned}$$

It is necessary to linearize the previous equations around $(\hat{\underline{X}}(k-1), \hat{\underline{m}}(k))$ to write the measurement equation :

$$\underline{Y}(k) = H(k)\underline{X}(k) + \underline{V}(k) \tag{18}$$

We present results issues from a sequence. Figure 2 shows an image from the sequence with an overlay of the road model, while Figure 3 shows the reconstruction.

VEHICLE ASPECT

Modelling the vehicle's behaviour

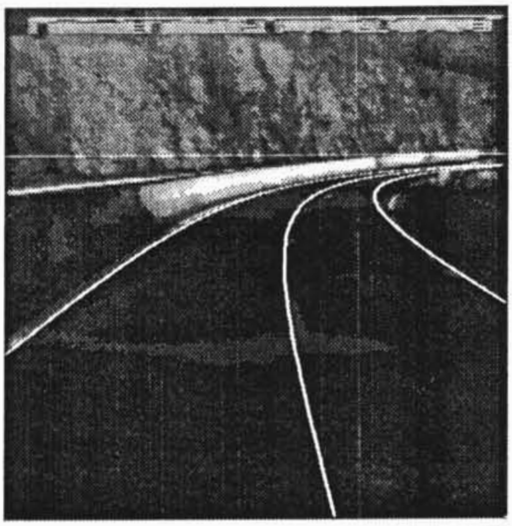

Figure 2: Road Image and Model from the on-board camera

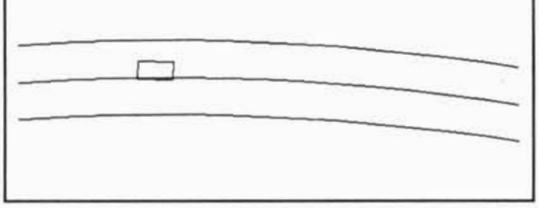

Figure 3: Reconstruction

A road vehicle is a complex dynamic system (the mathematical representation of a vehicle model currently used by the cars manufacturers involves 30 first-order nonlinear differential equations and approximatively 250 algebraic equations). Fortunately, it is not useful to take into account the whole complexity of the model for computing robust and efficient control laws. In our road following application, we have just to deal with the control of the lateral dynamics of the vehicle and a planar "bicycle" approximation model has been sufficient (Figure 4). The modelling stage can be splitted in two different parts. The first part concerns the automobile lateral dynamics which are stated as a two degree-of-freedom linear mathematical model. The second part adresses the problem of the behaviour of the steering system.

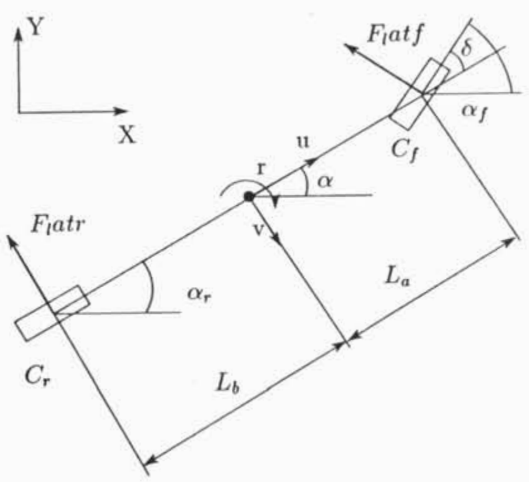

Figure 4: Vehicle model

Lateral dynamics of the vehicle: Vehicles in motion generally have a small lateral velocity component v instead of moving exactly forward [5]. The *sideslip angle* α is the resulting small angle between a vehicle's longitudinal axis and its velocity vector in the plane of the road. Likewise, each tire has a slip angle (α_f and α_r) between is free rolling direction and its velocity vector, associated with a lateral force from the road surface. The slip angles α_f and α_r may be completely determined from the longitudinal velocity u (which is assumed to be constant), the lateral velocity v (measured in the vehicle's own frame at the center of gravity), the yaw rate r, the steer angle δ_w and the geometry of the vehicle [5]. Using linear trigonometric approximations, we get :

$$\alpha = \frac{v}{u} \tag{19}$$

$$\alpha_f = \frac{v}{u} + \frac{r\,L_a}{u} - \delta_w \tag{20}$$

$$\alpha_r = \frac{v}{u} - \frac{r\,L_b}{u} \tag{21}$$

Assuming that we consider low levels of lateral acceleration, the lateral motion of the tires is only due to their deformation and not to a relative sliding at the tire-road interface. In a such condition, lateral forces can be accurately described by linear functions of the slip angles :

$$
\begin{aligned}
\vec{F_{latf}} &= -\mu C_f \alpha_f & (22)\\
\vec{F_{latr}} &= -\mu C_r \alpha_r & (23)
\end{aligned}
$$

where C_f and C_r are, respectively, the tire cornering stiffness for both front tires and both rear tires.

Finally, we assume that the sum of the lateral forces equals mass M times lateral acceleration, which comprises the time derivative of lateral velocity and centripetal acceleration and that the angular acceleration about the yaw axis depens on the yaw moment of inertia, J_z and the yawing moments due to lateral tire forces. We obtain the two fundamental equations of the dynamic :

$$
\begin{aligned}
M(\dot{v}+u\dot{\psi}) = & \quad -(C_f+C_r)\tfrac{v}{u}+(C_rL_b-C_fL_a)\tfrac{\dot{\psi}}{u}+C_f\delta_w & (24)\\
J_z\ddot{\psi} = & \quad -(C_fL_a-C_rL_b)\tfrac{v}{u}-(C_fL_a^2+C_rL_b^2)\tfrac{\dot{\psi}}{u}+C_fL_a\delta_w & (25)
\end{aligned}
$$

with $r=\dot{\psi}$ and $v=\dot{x_0}$ where ψ and x_0 are respectively the lateral deviation and the lateral position of the car with respect to the road axis (which are provided by the vision system).

The steering system The steering system of our experimental vehicle is constituted by an stepper servomotor in front of the hydraulic steering system of the vehicle. The transfert function of the whole system is modelled as an integrator (due to the stepper motor) in serie with a pure delay (due to the hydraulic part). The control input γ is a desired velocity steering wheel angle which is sampled at the video rate. It is related to the steer angle δ_w by the following equation :

$$\dot{\delta_w}(t)=\gamma(kh-\tau)\ with\ kh\le t<(k+1)h \qquad (26)$$

We have experimently identified the delay τ on our testbed vehicle as five times the sampling rate ($\tau\simeq 5.h=200ms$, see Figure 5).

State model of the complete system: From the dynamic equations of the car, we consider that $(C_rL_b-C_fL_a)\simeq 0$ and we introduce the new following parametrization :

$$
\begin{aligned}
z_1 &= x_0+\frac{M}{(C_f+C_r)}u\dot{x_0}+\frac{J_z}{(C_fL_a^2+C_rL_b^2)}u^2\psi & (27)\\
z_2 &= \psi+\frac{J_z}{(C_fL_a^2+C_rL_b^2)}u\dot{\psi} & (28)\\
z_3 &= \delta_w & (29)
\end{aligned}
$$

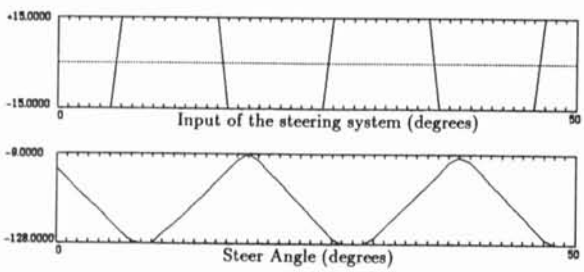

Figure 5: Steering System

Finally, by differentiating these equations and by introducing the real control input γ, we obtain the following state system :

$$
\begin{bmatrix}\dot{z_1}\\ \dot{z_2}\\ \dot{z_3}\end{bmatrix}=\begin{bmatrix}0 & u & \frac{C_f}{C_f+C_r}u\\ 0 & 0 & \frac{C_fL_a}{C_fL_a^2+C_rL_b^2}u\\ 0 & 0 & 0\end{bmatrix}\begin{bmatrix}z_1\\ z_2\\ z_3\end{bmatrix}+\begin{bmatrix}0\\ 0\\ \gamma(kh-5h)\end{bmatrix} \qquad (30)
$$

Computing the controller

The control laws which have been implemented use a technique of pole assignment using state feedback. The dynamic model of the car is defined around an equillibrium point corresponding to a constant velocity u. In order to get a dynamic response of the car independant with regard to the value of the velocity u, it seems us fruitful to implement adaptative poles linearly varying with the velocity value u. Moreover, the controller has been designed by using discrete-time approach taking into account the delays in the steering system and the sampling of the control input.

Let us consider the above continuous system $\dot{X}=AX+B\gamma(t-\tau)$ where $X=[z_1,z_2,z_3]^T$, its equivalent discrete form will be :

$$X((k+1)h)=e^{Ah}X(kh)+(\int_0^h e^{As}ds)B\gamma(kh-\tau) \qquad (31)$$

Let us denote $A'=e^{Ah}$ and $B'=(\int_0^h e^{As}ds)B$. Then, we can use as control input $\gamma(kh)=-KX(kh+\tau)$ such that :

$$X((k+1)h)=(A'-B'K)X(kh) \qquad (32)$$

where the gain matrix K will be chosen such that the poles of $(A'-B'K)$ bring to the desired dynamic response. Unfortunately, the controller currently design is not causal. To overpass this difficulty, we use the fact that, in discrete time, when the control input is piecewise constant, then, the following relation is verified :

$$X(kh+dh)=e^{Adh}X(kh)+\sum_{j=0}^{d-1}e^{Ajh}B'\gamma(kh-(j+1)h) \qquad (33)$$

Finally, we obtain the following control input :

$$\gamma(kh)=-Ke^{Adh}X(kh)-\sum_{j=0}^{d-1}Ke^{Ajh}B'\gamma(kh-(j+1)h) \qquad (34)$$

with $e^{A\Delta}=I+A\Delta+\frac{A^2\Delta^2}{2}$

From theses equations and by using a classical method of pole assignment, we can compute the gain matrix K such that the closed loop system have a real pole and two conjugated critically damped poles. After some tedious calculus, we obtain :

$$\gamma(kh)=-g_1z_1(kh)-g_2z_2(kh)-g_3z_3(kh)-\sum j=1^5k_j\gamma(kh-jh) \qquad (35)$$

with :

$$
\begin{aligned}
g_1 &= \frac{(L_a+L_b)}{u^2h^3}[1+\lambda)(1-S+P] & (36)\\
g_2 &= \frac{(L_a+L_b)}{uh^2}[7-6S+5P+\lambda(6-5S+4P)]-L_ag_1 & (37)\\
g_3 &= \frac{1}{h}[\frac{11-2S-P+\lambda(2+S+2P)}{6} & (38)\\
& \quad +5(2-S+\lambda(1-P)+\frac{25}{2}(1+\lambda)(1-S+P)] & (39)\\
k_j &= \frac{(1+\lambda)}{2}[(j+1)9j+2)-j(j-1)S+(j-1)(j)P] & (40)\\
& \quad -\lambda[(j+1)-jS+(j-1)P] & (41)\\
S &= 2e^{-\xi u\omega_1 h}\cos u\omega_1 h\sqrt{1-\xi^2} & (42)\\
P &= e^{-2\xi u\omega_1 h} & (43)\\
\lambda &= -e^{u\omega_0 h} & (44)
\end{aligned}
$$

Such a control scheme allows us to ensure a critical response to the state system $\dot{X}=AX+B\gamma(t-\tau)$ whith $X=[z_1,z_2,z_3]^T$. In practice, from the image processing, we only access to the real measurement vector $Y = [x_0, \dot{x_0}, \psi, \dot{\psi}, \delta_w]^T$ but by using the previous relations (29) it is obvious to express the control vector in function of Y.

This control scheme has been validated in simulation. The results which are presented corresponds to the response at a step in x_0. In the Figure 6, we have neglected the dynamic terms in the design of the control which is equivalent to consider the stiffness of the tires as infinitive ($C_f = C_r = \infty$). We can see that when the velocity u is increasing the system can have important overshoot (50 cm). In the second experiment, Figure 7, the control scheme above described, is fully implemented, and we obtain good results in a large rate of velocity (until 50 meters per second). These results show that the dynamic part of the model cannot be neglected when the velocity is increasing. On the other hand, we have tested the effects of the delay and we have shown that it is necessary to take into account the delay in the control scheme for insuring the stability of the vehicle.

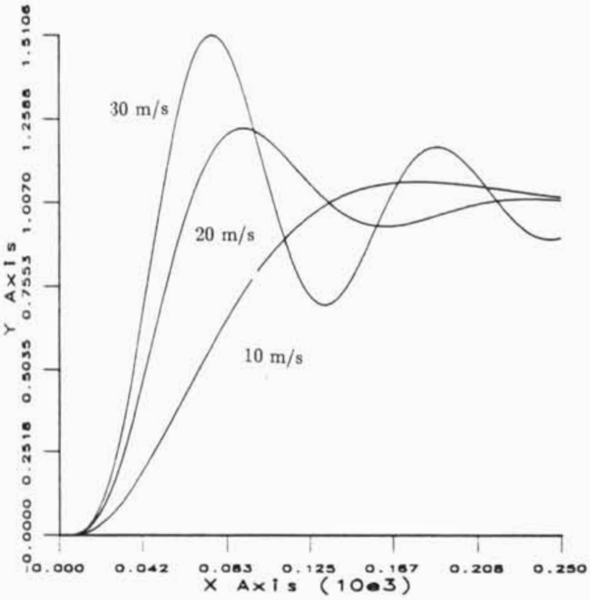

Figure 6: Discrete controller using kinematic model

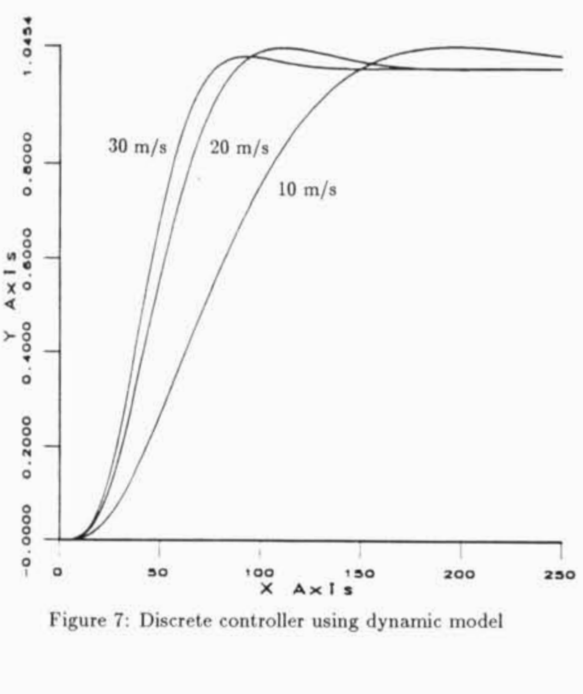

Figure 7: Discrete controller using dynamic model

RESULTS

Experimental system constituted by the vehicle, its steering system and the image processing system has been tested.

Figure 8 shows experimental results. The vehicle goes at various speeds from 0 km/h to 60 km/h. At first and during 100 iterations the driver moves the vehicle at 2 m from the middle band, then set it in the automatic driving mode. The right lateral position is the middle of the lane (1.5 m). Precision is about 10 cm.

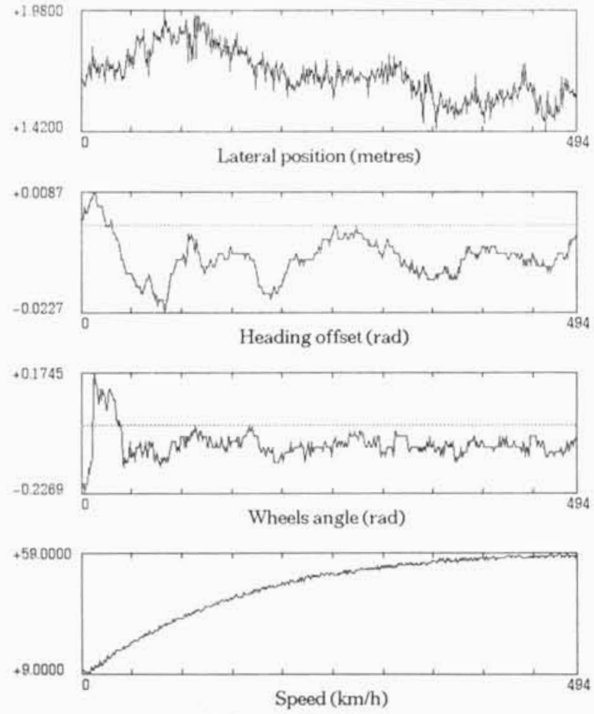

Figure 8: Results

Presently a speed range up to 80 km/h has been reached on a circuit.

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