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Vehicle Roll and Road Bank Angles Estimation

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Abstract: Driving safety can be enhanced by better understanding of risk situation, which can be achieved by the knowledge of vehicle dynamic states as well as the road geometry. Among the parameters of the road that have an influence on vehicle dynamics, one can find the bank angle, which can not however be measured by low cost onboard sensors. In this paper, a new method of road bank angle and vehicle roll estimation using an unknown input proportional integral (PI) observer is proposed. To reach this goal, first a bicycle vehicle model is chosen. This model is quite simple but well appropriate for the considered application. Thereafter, an Extended Kalman Filter (EKF) is developed in order to estimate the sideslip angle which is also difficult to measure with low cost sensors. This estimate is then used as an input of the PI observer in order to estimate vehicle roll angle and the road bank angle (road attribute). Testing on measurements obtained with a prototype vehicle shows the good behavior the proposed estimation scheme.

1. INTRODUCTION

Over the last ten years, research on driving assistance systems increased and aims to avoid accidents by giving help to the driver in critical situations. A common used assumption related to the road geometry consider that the is an horizontal plan. Most of the time, this assumption consists in a safety margin, as road is generally designed in order to report a part of the lateral acceleration in curves due to its non zero bank angle. However, it is also well known that some black spots sections exist on rural roads and badly shaped curves, with inadequate bank angle decrease vehicle stability. For example the maximum driving velocity in a curve is constrained by the bank angle of the road. Thus, driving assistance systems can take advantage of such road attributes knowledge. These attributes are unfortunately difficult to measure with commonly low cost technology sensors used in automotive industry. In this case, the development of virtual sensors are of primary importance. Software system make use of available sensor to provide an estimation of the non directly available variable. In this paper an observer based estimation of the vehicle state and the road bank angle is proposed. It uses the concept of unknown input Proportional-Integral (PI) observer. The PI observer is a generalized version of the Luenberger observer [2, 5]. It was introduced by Wojciechowski in 1978 for nonsingular monovariable systems and then generalized for multivariable systems by Shafai and Caroll in 1985. Thereafter and according to [6], Koeing and Mammar generalize the application of the PI observer while proposing to apply it to singular systems. Marx in [1] provides certain necessary assumptions for the synthesis of the PI observer and applies it in the field of robust diagnosis and singular systems.

Several research works have been conducted for road bank angle and unknown input estimation using unknown input PI observers [4, 7, 11, 14]. In [14] an unknown input PI observer was developed for the reconstruction of vehicle lateral dynamics state while the road bank angle and the wind lateral force are considered as signal faults acting as unknown inputs. In [4], the study has been extended to vehicle roll movement, but the roll angle is assumed to be measured. This consideration is not so real, because its measure is still not easy.

The goal of this paper is to overcome this limitation by proposing a new design methodology for road bank angle and vehicle roll angle estimation.
The used structure is similar to that developed in [1]. We show how to determine the parameters of the observer as solutions of optimization problem under Linear Matrix Inequalities (LMI) constraints. The improvement of the observer performances in particular regarding the convergence speed of the estimation error towards zero is examined.

The remainder of the paper is organized as follows: In section 2, the vehicle model used to develop the unknown inputs PI observer is presented. Model equations, road kinematics and sensors used are described. Section 3 describes the sideslip angle estimation method using Extended Kalman Filter (EKF). The synthesis of the unknown input PI observer is presented in section 4, where the structure and the associated LMI constraints are detailed. Parameters adaptation for the observer gain computation are presented in section 5. In section 6, some experimental validation results are discussed, while section 7 wraps with some conclusions.

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2. VEHICLE MODEL

2.1 Model equations

Several models of road vehicles have been developed in the literature [4, 9], The vehicle lateral dynamics are modeled by considering a three degree-of-freedom bicycle vehicle model including slip, yaw and roll motions [10]. This model uses the assumption of symmetry of the vehicle and is sufficiently accurate to approximate lateral dynamics (see Fig. 1).

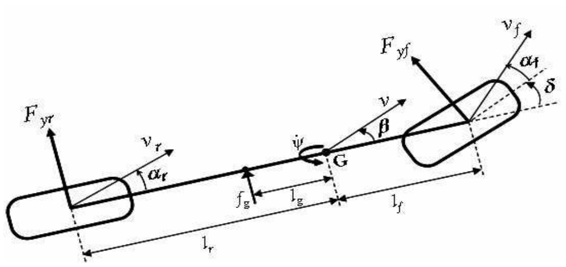

Fig. 1. bicycle vehicle model

In normal driving situation, lateral tire forces can be modeled as proportional to slip angles of each axle. The front and rear tire forces (F_{yf}, F_{yr}) and tire slip angles (α_f, α_r) are defined as follow:

$$\begin{cases} F_{yf} = C_{sf}\alpha_f = C_{sf}\left(\delta - \beta - \dfrac{l_f\dot{\psi}}{v}\right) \\ F_{yr} = C_{sr}\alpha_r = -C_{sr}\left(\beta - \dfrac{l_r\dot{\psi}}{v}\right) \end{cases} \tag{1}$$

C_{sf} and C_{sr} are the cornering stiffness of the front and rear tires respectively, l_f and l_r are the distances between center of gravity and the front and rear axles respectively, and the control input δ represents the front wheels steering angle.

The state-space form of the four-state linear model can be written as follow:

$$\dot{\overline{x}} = \overline{\overline{A}}\overline{x} + \overline{\overline{B}}\delta + \overline{\overline{B}}_{w_1}\phi_r + \overline{\overline{B}}_{w_2}f_g \tag{2}$$

where :

$$\overline{\overline{A}} = \begin{bmatrix} -\dfrac{I_eC_0}{I_xmv} & -1 - \dfrac{I_eC_1}{I_xmv^2} & \dfrac{h_r\left(mgh_r - k_r\right)}{I_xv} & -\dfrac{h_rl_r}{I_xv} \\ -\dfrac{C_1}{I_z} & -\dfrac{C_2}{I_zv} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ -\dfrac{C_0h_r}{I_x} & -\dfrac{C_1h_r}{I_xv} & \dfrac{mgh_r - k_r}{I_x} & -\dfrac{b_r}{I_x} \end{bmatrix}$$

$$\overline{\overline{B}} = \begin{bmatrix} \dfrac{I_eC_{sf}}{I_xmv} \\ \dfrac{l_fC_{sf}}{I_z} \\ 0 \\ \dfrac{C_{sf}}{I_x} \end{bmatrix}, \overline{\overline{B}}_{w_1} = \begin{bmatrix} -\dfrac{g}{v} \\ 0 \\ 0 \\ 0 \end{bmatrix}, \overline{\overline{B}}_{w_2} = \begin{bmatrix} \dfrac{1}{mv} \\ \dfrac{l_g}{I_z} \\ 0 \\ 0 \end{bmatrix}$$

where l_g is the distance between the centre of gravity and the dot of application of the lateral wind force. The coefficients C_0, C_1 and C_2 are given by:

$$\begin{cases} C_0 = C_{sf} + C_{sr} \\ C_1 = l_fC_{sf} - l_rC_{sr} \\ C_2 = l_f^2C_{sf} + l_r^2C_{sr} \\ I_e = I_x + mh_r^2 \end{cases}$$

The state vector of the linear model is :

$$\overline{x} = \left[\, \beta \;\; \dot{\psi} \;\; \phi_v \;\; \dot{\phi}_v \,\right]^T$$

where ϕ_v is the vehicle roll angle and $\dot{\phi}_v$ is the vehicle roll rate. Derivation of the model equations can be found in [11]

Table 1 shows the nomenclature of the used vehicle model.

Table 1. Nomenclature of the vehicle model

v	vehicle speed	$m.s^{-1}$	[3 30]
m	vehicle mass	kg	1560
I_z	moment of inertia about the yaw axis	$kg.m^2$	2200
I_x	moment of inertia about the roll axis	$kg.m^2$	380
k_r	roll stiffness coefficient	$N.m.rad^{-1}$	75545
b_r	roll damping coefficient	$N.m.s.rad^{-1}$	4475
β	sideslip angle	rad	-
$\dot{\psi}$	yaw rate	$rad.s^{-1}$	-
g	gravity acceleration	$m.s^{-2}$	9.81

2.2 Road kinematics

In this subsection, we will model the banked road on which the vehicle is drived. Fig. 2 shows a rolling movement of the vehicle in the presence of the road bank angle. The vehicle body rotates around the roll center of the vehicle. The distance h_r represents the height of the center of gravity G from the roll center. ϕ_r is the road bank angle.

3. VEHICLE STATE ESTIMATION USING EKF

The implementation of an unknown input PI observer for the estimation of the road bank angle which is considered as a potential fault in presence of disturbance input requires the observability of the system which is only

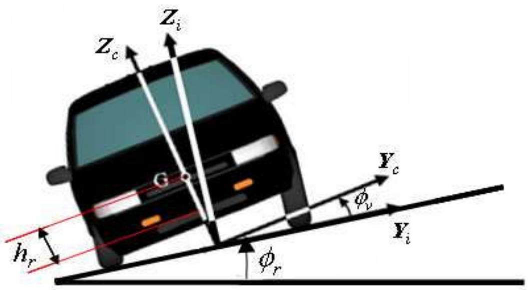

Fig. 2. vehicle roll angle and road bank angle.

obtained under the assumption of the availability of the sideslip angle β. As the variable is not directly available as measurement, a preliminary estimation procedure for the lateral and longitudinal speed of the vehicle center of gravity is developed using a discrete time version of the Extended Kalman Filter (EKF) [12].

The nonlinear discrete time model used in this case has for state vector x_{ek} constituted by the longitudinal and lateral speed and the yaw rate. The vehicle roll motion is neglected.

$$x_{ek} = [V_x \ V_y \ \dot{\psi}]$$

Model input is constituted by the front wheels steering angle and the four tires rotational velocities w_i, $(i = 1, ..., 4)$.

$$u_{ek} = [\delta \ \omega_1 \ \omega_2 \ \omega_3 \ \omega_4]$$

$$\begin{cases} V_x(k+1) = V_x(k) + \dfrac{\Delta T}{m}\left(\displaystyle\sum_{i=1}^{4} F_{xi}(k) + m\dot{\psi}(k)V_y(k) - C_x V_x^2(k)\right) \\ V_y(k+1) = V_y(k) + \dfrac{\Delta T}{m}\left(\displaystyle\sum_{i=1}^{4} F_{yi}(k) - m\dot{\psi}(k)V_x(k) - C_y V_y^2(k)\right) \\ \dot{\psi}(k+1) = \dot{\psi}(k) + \dfrac{\Delta T}{I_z}\left(\displaystyle\sum_{i=1}^{4} M_{z\,i}(k)\right) \end{cases} \quad (3)$$

For the extended Kalman filter, we use the linear model of the forces to reduce the complexity of the filter. The Longitudinal and lateral forces are then calculated using Dugoff forces model [8] represented below:

$$\begin{cases} F_{xi} = C_{xxi}\dfrac{\lambda_i}{1-\lambda_i}k_i \\ F_{yi} = C_{yyi}\dfrac{\tan\alpha_i}{1-\lambda_i}k_i \end{cases} \quad (4)$$

with

$$k_i = \begin{cases} (2-\sigma_i)\sigma_i & \text{if } \sigma_i < 1 \\ 1 & \text{if } \sigma_i \geq 1 \end{cases} \quad (5)$$

and

$$\sigma_i = \frac{(1-\lambda_i)\mu_i F_{ni}}{2\sqrt{C_{x0}^2\lambda_i^2 + C_{y0}^2\tan^2\alpha_i}} \quad (6)$$

C_{x_0} and C_{y_0} are respectively longitudinal and lateral stiffness Coefficient, and μ_i is the friction coefficient for each tire considered equal to 1.

F_{ni}, λ_i and α_i are respectively normal force, longitudinal slip and lateral slip of each tire:

$$\begin{cases} \lambda_i = \dfrac{R\omega_i - V_{xi}}{max(R\omega_i, V_{xi})} \\ \hat{\alpha}_i = \delta_i - \arctan(\dfrac{\hat{V}_{yi}}{V_{xi}}) \end{cases} \quad (7)$$

where R is the wheel radius. The yaw rate is measured using a gyrometer. The vehicle longitudinal speed is computed as the mean of two rear wheels speeds which are less subject to slip. From where the formulation of the equations the discrete time nonlinear model used for the Extended Kalman Filter design is given by:

$$\begin{cases} x_{ek}(k+1) = f(x_{ek}(k), u_{ek}(k)) \\ y = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} x_{ek}(k) \end{cases} \quad (8)$$

Figure 3 shows the results obtained with the use of measurements collected using a vehicle prototype running on the Satory test track located near Versailles (France). All state variable are well estimated. Particularly, Fig. 3-d demonstrates that the estimated sideslip angle is sufficiently close to the measure provided by the high cost Correvit sensor mounted of the prototype vehicle.

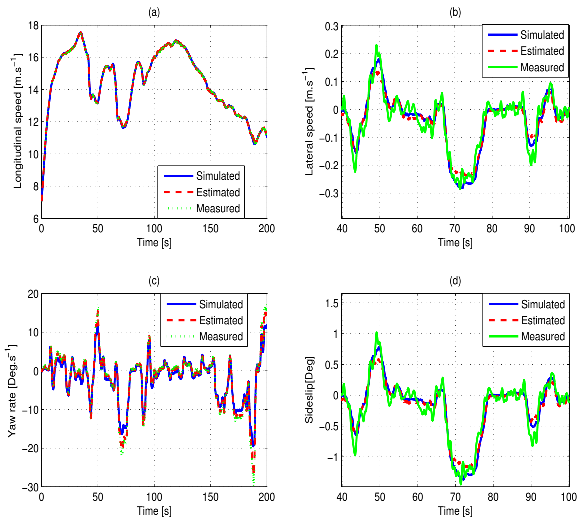

Fig. 3. Longitudinal speed, lateral speed, yaw rate and sideslip angle estimation.

4. SYNTHESIS OF UNKNOWN INPUT PROPORTIONAL INTEGRAL OBSERVER

4.1 Structure and existence conditions of the PI observer

The synthesis of the proportional integral observer, is made in the framework of the H_∞ control. It aims to minimize and limit *a priori* the influence of the unknown

inputs on the estimation error [1].
Let the linear system defined by:

$$\begin{cases} \underline{E}\dot{x}(t) = \underline{A}x(t) + \underline{B}u(t) + \underline{E}_1 w(t) + \underline{R}_1 f(t) \\ \underline{y}(t) = \underline{C}x(t) + \underline{D}u(t) + \underline{R}_2 f(t) \end{cases} \tag{9}$$

Where $x(t) \in \Re^n$ is the state vector, $f(t) \in \Re^{n_f}$ is the fault vector, $w(t) \in \Re^{n_w}$ is the unknown inputs vector, $u(t) \in \Re^{n_u}$ is the input vector and $y(t) \in \Re^m$ represents the output vector of the system.
The matrices $\underline{E}$ and $\underline{A} \in \Re^{l*n}$ are not necessarily square, the other matrices and vectors defined above are of compatible size with $\underline{E}$. The rank of $\underline{E}$ is noted n_r.
The unknown inputs PI observer given by equation 10, was proposed to estimate the dynamic states of the model as well as the faults which affect it.

$$\begin{cases} \dot{z} = Fz + (L_1 + L_2)\,y + Ju + H\hat{f} \\ \dot{\hat{f}} = L_3\,(y - \hat{y}) \\ \hat{x} = M_1 z + M_2 y + M_3 u \\ \hat{y} = C\hat{x} + Du + K\hat{f} \end{cases} \tag{10}$$

The existence conditions of this observer are given by three assumptions [1]:

- rank $[\underline{E}\ \underline{E}_1] = \text{rank}(\underline{E})$.
- $(\underline{E}, \underline{A}, \underline{C})$ is imp-observable.
- $\dot{f}(t) = 0$.

The diagram of the unknown input PI observer structure is represented in Fig. 4.

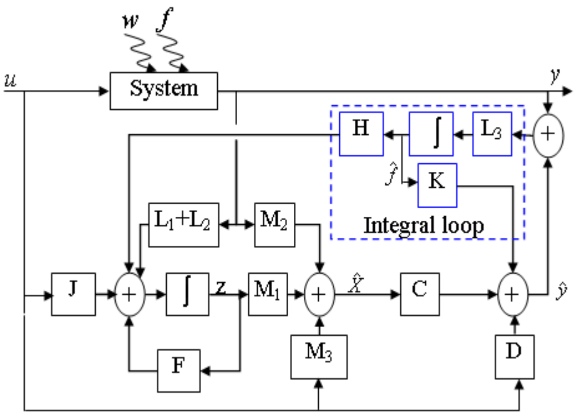

Fig. 4. PI observer structure diagram

To be able to express the estimation errors in the form of a usual dynamic system, a matrix $P \in \Re^{l \times l}$ is introduced. This matrix ensures the compression of the lines of $\underline{E}$ in order to obtain a matrix $\left[\, E^T \ \ C^T \,\right]^T$ of full row column. The following new system is then obtained :

$$\begin{cases} E\dot{x}(t) = Ax(t) + Bu(t) + E_1 w(t) + R_1 f(t) \\ y(t) = Cx(t) + Du(t) + R_2 f(t) \end{cases} \tag{11}$$

where $E \in \Re^{n_r \times n}$ is full row. Dimensions of the other matrices are defined as follows :

$$\begin{array}{c} P\underline{E} = \begin{bmatrix} E \\ 0 \end{bmatrix} \quad P\underline{A} = \begin{bmatrix} A \\ A_b \end{bmatrix} \quad P\underline{B} = \begin{bmatrix} B \\ B_b \end{bmatrix} \\ P\underline{R}_1 = \begin{bmatrix} R_1 \\ R_{1b} \end{bmatrix} \quad P\underline{E}_1 = \begin{bmatrix} E_1 \\ 0 \end{bmatrix} \end{array} \tag{12}$$

$$\begin{array}{c} y(t) = \begin{bmatrix} -B_b\,u(t) \\ \underline{y}(t) \end{bmatrix} \quad C = \begin{bmatrix} A_b \\ \underline{C} \end{bmatrix} \\ D = \begin{bmatrix} 0 \\ \underline{D} \end{bmatrix} \quad R_2 = \begin{bmatrix} R_{1b} \\ \underline{R}_2 \end{bmatrix} \end{array} \tag{13}$$

Once the existence conditions of the PI observer checked, it remains now to determine the various parameters which constitute it. They are defined according to the vector :

$$\bar{L} = \begin{bmatrix} L_2 \\ L_3 \end{bmatrix}$$

4.2 Observer gain calculation using LMI

The dynamics of the errors are written in the following matrix form :

$$\begin{array}{c} \begin{bmatrix} \dot{e_x} \\ \dot{e_f} \end{bmatrix} = \left[\overline{A} - \overline{L}\,\overline{C}\right] \begin{bmatrix} e_x \\ e_f \end{bmatrix} + \overline{B}w \\ \begin{bmatrix} e_x \\ e_f \end{bmatrix} = \overline{D} \begin{bmatrix} e_x \\ e_f \end{bmatrix} \end{array} \tag{14}$$

where $\overline{A}$, $\overline{B}$, $\overline{C}$, *and* $\overline{D}$ are defined by :

$$\begin{array}{c} \overline{A} = \begin{bmatrix} T_1 A & T_1 R_1 \\ 0 & 0 \end{bmatrix} \quad \overline{B} = \begin{bmatrix} T_1 E_1 \\ 0 \end{bmatrix} \\ \overline{C} = [\, C \ \ R_2 \,] \quad \overline{D} = \begin{bmatrix} I_n & 0 \\ 0 & I_{nf} \end{bmatrix} \end{array} \tag{15}$$

T_1 and T_2 are given by :

$$\begin{cases} T_1 = \left(E^T E + C^T C\right)^{-1} E^T \\ T_2 = \left(E^T E + C^T C\right)^{-1} C^T \end{cases} \tag{16}$$

Theorem 1 is used to determine the vector $\bar{L}$ in order to minimize the H_∞ norm of the disturbances transfer w on the states and faults estimation errors $e_x = x - \hat{x}$ and $e_f = f - \hat{f}$ respectively. The PI observer exists if and only if the matrix $\left[\overline{A} - \overline{LC}\right]$ is a matrix of Hurwitz. It is then necessary to find a vector $\bar{L}$ which ensures the following condition [1]:

$$\left\| \overline{D}\left(sI - \left(\overline{A} - \overline{LC}\right)\right)^{-1} \overline{B} \right\|_\infty < \gamma \tag{17}$$

where γ is the smallest possible positive real.

Theorem 1 *The robust PI observer defined by (10) for the system (9) is obtained by minimization of γ under the following LMI constraints : $\gamma > 0 \in \Re$, $X \in \Re^{(n+n_f)\times(n+n_f)}$* and $Y \in \Re^{(n+n_f)\times(m+n-n_r)}$.

$$\begin{cases} \begin{bmatrix} \overline{A}^T X + X\overline{A} - Y\overline{C} - \overline{C}^T Y^T & X\overline{B} & \overline{D}^T \\ \overline{B}^T X & -\gamma I_{n_d} & 0 \\ \overline{D} & 0 & -\gamma I_{n_d+n_f} \end{bmatrix} \prec 0 \\ X \succ 0 \end{cases} \tag{18}$$

In order to avoid a possible low convergence rate of the observer towards the actual values, it is possible to add an LMI constraint given by(19), which forces the speed of convergence while imposing that the poles of $\overline{A} - \overline{LC}$ are in the complex left half-plane defined by $\{z \,|R_e(z) < -\lambda\}$, and $\lambda > 0$.

$$X\left(\overline{A} + \lambda I\right) + \left(\overline{A} + \lambda I\right)^T X - Y\overline{C} - \overline{C}^T Y^T \prec 0 \qquad (19)$$

The matrix $\overline{L}$ is then defined by :

$$\overline{L} = \begin{bmatrix} L_2 \\ L_3 \end{bmatrix} = X^{-1}Y \qquad (20)$$

and

$$\begin{array}{l} F = T_1A - L_2C,\ L_1 = FT_2,\ J = T_1B - (L_1 + L_2)\,D, \\ H = T_1R_1 - L_2R_2,\ M_1 = I_n,\ M_2 = T_2,\ M_3 = -T_2D, \\ \quad K = R_2 \end{array} \qquad (21)$$

The representation in the state space form of PI observer having for inputs, the control signal u and the output y of the equivalent system, and for output, the estimated state $\hat{x}$ and faults $\hat{f}$, is given by :

$$\begin{bmatrix} \dot{z} \\ \dot{\hat{f}} \end{bmatrix} = \begin{bmatrix} F & H \\ -L_3C & -L_3R_2 \end{bmatrix} \begin{bmatrix} z \\ \hat{f} \end{bmatrix} +$$

$$\begin{bmatrix} L_1 + L_2 & J \\ L_3\left(I_m - CT_2\right) & L_3\left(CT_2 - I_m\right)D \end{bmatrix} \begin{bmatrix} y \\ u \end{bmatrix}$$

and

$$\begin{bmatrix} \hat{x} \\ \hat{f} \end{bmatrix} = \begin{bmatrix} I_n & 0 \\ 0 & I_{n_f} \end{bmatrix} \begin{bmatrix} z \\ f \end{bmatrix} + \begin{bmatrix} T_2 & -T_2D \\ 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ u \end{bmatrix}$$

5. STATE AND ROAD BANK ANGLE ESTIMATION

5.1 System adaptation for the observer design

In this section, we present the necessary matrices adaptation for the application of the PI Observer to the vehicle model given by equation 2.

One can establish that by choosing: $\underline{A} = \overline{\overline{A}}$, $\underline{B} = \overline{\overline{B}}$, $\underline{E} = I_4$, $\underline{R}_1 = \overline{\overline{B}}_{w1}$, $\underline{E}_1 = \overline{\overline{B}}_{w2}$ and the other matrices equal to zero, the vehicle model fits to the PI observer design framework developed above. The measurement vector y and the matrix C are given by:

$$y = \left[\,\beta\ \dot{\psi}\ \dot{\phi}_v\,\right]^T,\ C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

5.2 Simulation results

This part presents the simulation results obtained for the vehicle state and the road bank angle.

The steering angle applied to the vehicle model, the considered road bank angle are provided respectively in Fig. 5 and Fig. 8-a. The vehicle forward speed is maintained

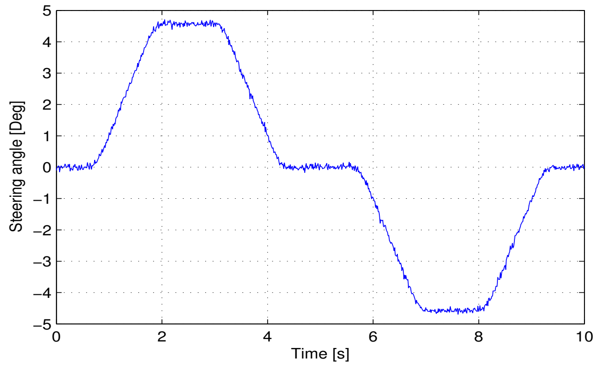

Fig. 5. Steering angle

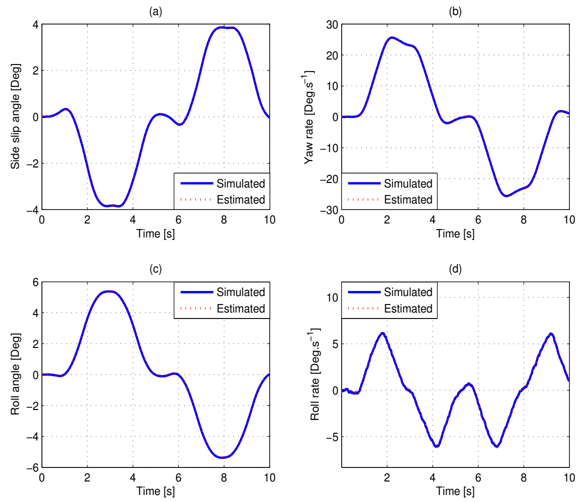

Fig. 6. Estimated and simulated states: Sideslip angle (a), Yaw rate (b), Roll angle (c) and Roll rate (d). (estimated (dashed) and simulated (solid))

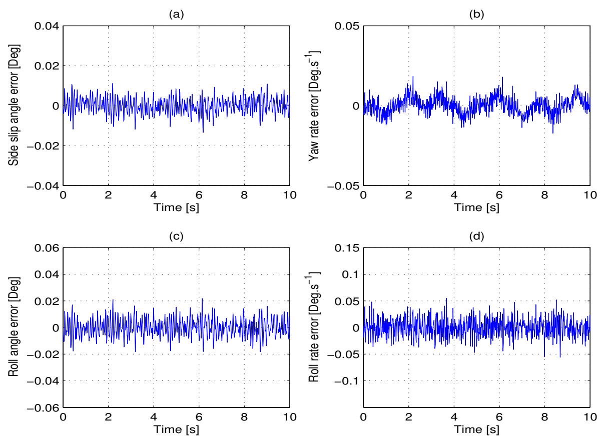

Fig. 7. States estimation errors

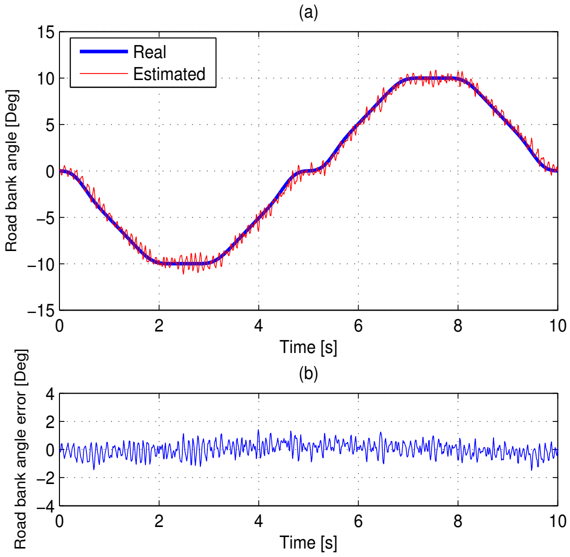

Fig. 8. Road bank angle

constant and approximately equal to $20m/s$ ($72km/h$).

Figure 6 represents respectively the sideslip angle (a), the yaw rate (b), the vehicle roll angle (c) and the roll rate (d). The estimation errors are represented in Fig. 7, we can see clearly that these errors are very small. The estimate of the road attribute (bank angle) is given in Fig. 8-a and the estimation errors are in Fig. 8-b. All the figure confirm the adequate behavior of the model and the observers.

6. EXPERIMENTAL RESULTS

In this part, the vehicle velocity is considered as the mean of the two translational velocity of the two rear wheels which are the less subjected to the slips. As the speed is a varying paramter, the system (2) can be considered as a Linear Parameter Varying (LPV) system. However, in order to reduce the computing time and to avoid the calculation of the LMI each time, velocity intervals for which the PI observer gain can be considered as constant are defined under the condition that the matrix $\left[\overline{A} - \overline{LC}\right]$ remains an Hurwitz matrix. The γ parameter which minimizes the influence of the unknown inputs on estimates is also fixed for each interval. And with an aim of accelerating the convergence of PI observer, we have fixed the λ parameter at 10.
The experimental vehicle is equipped with a optical steering angle sensor, inertial sensor (INS), wheel angular velocity sensors (ABS) and lateral speed sensor (Correvit). The steering angle of the front wheels is shown in Fig. 9-a, while the estimation result for the state vector is provided in Fig. 9-b, 9-c and 9-d, for the sideslip angle, the yaw rate and the roll angle respectively. Finally, estimation results for the roll angle and road bank angle are shown in Fig. 10.

All the figures confirm that the PI observer is able to estimate state-space vector components and road bank angle accurately.

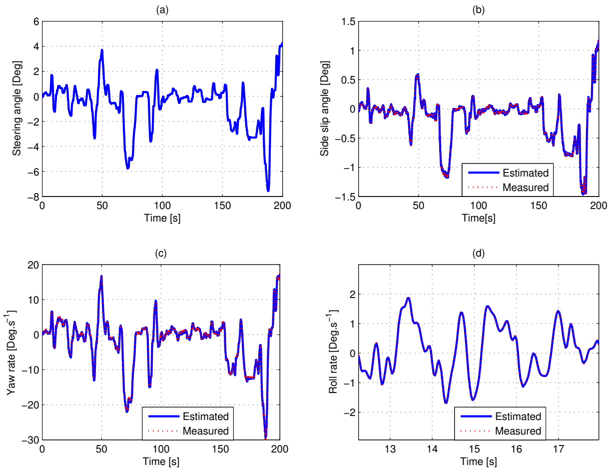

Fig. 9. Steering angle(a) and estimated states: Sideslip angle (b), Yaw rate (c) and Roll rate (d), (estimated (solid) and measured (dashed))

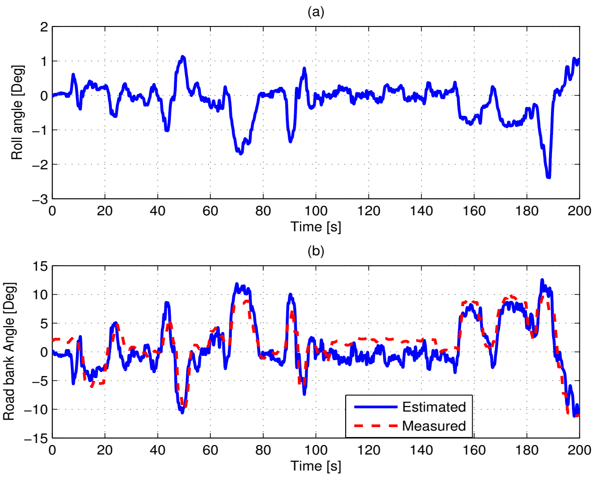

Fig. 10. Roll angle and Road bank angle estimation

7. CONCLUSIONS

In this paper an estimation method for the roll angle as well as for the reconstruction of the bank angle which is one of most relevant curved road attribute. This attribute is estimated by considering it as an input fault applied to vehicle bicycle model. An unknown input PI observer is thus able to achieve a sufficiently accurate estimation. LMI constraints used for the synthesis of the observer matrices offer flexibility for controlling observer convergence speed and the attenuation of the effect of the unknown input on the estimates. Results obtained when the observer is applied to measurements collected with a prototype vehicle show that the estimation procedure performs well. Vehicle roll angle and road bank angle are accurately estimated. This work is designed to improve, at low cost, the controllability vehicle roll, optimize the speed limits around a curve and avoid critical situations.

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