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Fuzzy uncertain observer with unknown inputs for Lane departure detection

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***Abstract*— This paper presents a lane departure detection method. The road curvature is estimated and compared to the vehicle trajectory curvature. The proposed algorithm reduces false alarms and integrates the driver corrections by taking account of the steering dynamics. The used nonlinear model deduced from the vehicle lateral dynamics and a vision system is represented by a T-S fuzzy uncertain model with unknown inputs. Stability conditions of such observers are expressed in terms of linear matrix inequalities (LMI). Simulation results obtained in two various driving scenarios show the efficiency of the proposed method.**

I. INTRODUCTION

Lane departure represents a large part of car accidents. Accident analysis published in [1], studied by the French road administration (CEESAR, France) shows that a large part of road fatalities (approximately 30%) is a result of this kind of accident. Moreover, the mortality of these fatalities is two time higher than other ones.

The development of lane keeping devices is a widespread research area since the last years. Different driver assistances were proposed [2] [3], they vary from simple warning systems to active limiting and correcting driver trajectory systems. The goal is the avoidance of large lateral excursions. Often, these systems seem, from a driver's point of view, intrusive (they warn him excessively). The main problem is to find a driving risk indicator which can be used to engage the assistances. This indicator has to approach the driver behavior and shall, integrating his correction, not to warn him when he is already correcting his maneuver. For example the TLC (time to line crossing) and the DLC (distance to line crossing) are two driving risk indicators who have received considerable attention during the two last decades [3] [4]. In this paper the estimated road curvature is compared to the vehicle trajectory curvature in order to define a lane departure indicator.

Estimating vehicle dynamics and road attributes are of primary importance for the implementation of warning and active safety systems. More particularly, lane departure avoidance and excessive yaw motion limitation systems generally make use of the lateral vehicle dynamics which are impossible or hard to measure accurately with cost effective sensors [5] [18]. In this work, we use a vision system (camera) to measure the lateral displacement at a lookahead distance of the vehicle. A representation of the nonlinear model of lateral vehicle dynamics by an uncertain Takagi-Sugeno (TS) fuzzy model will be considered [6] [7] [8] . This representation is largely used and studied these lasts years (see for example [9] [10] [11] [12]).

This paper is organized as follows: section II introduces the used car model and its representation by an uncertain fuzzy model. A T-S observer obtained by the interpolation of classical luenberger observers involving additive terms used to overcome the uncertainties is designed in section III. Section IV presents the methodology considered to define the driving risk and detect the lane departure. Finally, simulation results are presented in section V.

II. VEHICLE MODEL DESCRIPTION

The model used in this work describe vehicle lateral dynamics in a turn lane [13], which is obtained from the bicycle model “Fig. 1” and a vision system with lateral displacement measure.

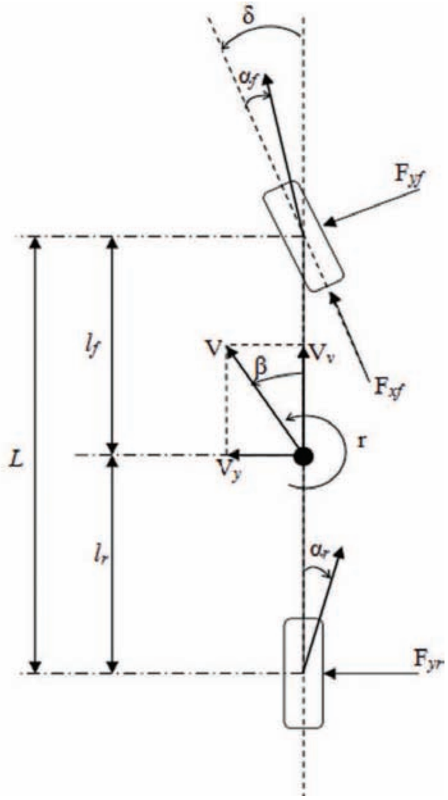

Fig. 1. bicycle model

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A. Lateral model

The two-dimensional model with nonlinear tire characteristics of the four wheels vehicle behavior can be described by the following differential equations [12]:

$$\begin{cases} mv(\dot{\beta}+\dot{\psi}) = 2F_{yf}+2F_{yr} \\ J_{zz}\ddot{\psi} = 2F_{yf}l_f - 2F_{yr}l_r \end{cases} \quad (1)$$

Where β denotes the sideslip angle, ψ is the yaw angle, F_f is the cornering force of the two front tires, F_r is the corning force of the two rear tires. v is the vehicle velocity, Iz is the yaw moment of inertia, m is the vehicle mass.

Using the so-called magic formula [14], the cornering forces F_f and F_r are given as functions of tire slip angles by the following expressions:

$$\begin{cases} F_{yf} = D_f sin[C_f tan^{-1} B_f(1-E_f)\alpha_f + E_f tan^{-1}(B_f\alpha_f)] \\ \\ F_{yr} = D_r sin[C_r tan^{-1} B_r(1-E_r)\alpha_r + E_r tan^{-1}(B_r\alpha_r)] \end{cases} \quad (2)$$

with

$$\begin{cases} \alpha_f = \delta_f - \frac{l_f\dot{\psi}}{v} - \beta \\ \alpha_r = \delta_r + \frac{l_r\dot{\psi}}{v} - \beta \end{cases} \quad (3)$$

Where δ_f is the front steer angle, δ_r is the rear steer angle, α_f is the slip angle of the front tires and α_r is the slip angle of the rear tires "Fig. 1".

Coefficients $D_i, C_i, B_i \, and \, E_i (i = f, r)$ depend on the tire characteristics, road adhesion coefficient and the vehicle operational conditions.

To obtain the TS fuzzy model, we have modeled the front and rear lateral forces (2) by the following rules:

If $|\alpha_f|$ is M_1 then $\begin{cases} F_{yf} = C_{f1}\alpha_f \\ F_{yr} = C_{r1}\alpha_r \end{cases}$

If $|\alpha_f|$ is M_2 then $\begin{cases} F_{yf} = C_{f2}\alpha_f \\ F_{yr} = C_{r2}\alpha_r \end{cases}$

The overall forces are obtained by :

$$\begin{cases} F_{yf} = \mu_1(|\alpha_f|)C_{f1}\alpha_f + \mu_2(|\alpha_f|)C_{f2}\alpha_f \\ \\ F_{yr} = \mu_1(|\alpha_f|)C_{r1}\alpha_r + \mu_2(|\alpha_f|)C_{r2}\alpha_r \end{cases} \quad (4)$$

Where $\mu_j(j = 1,2)$ is the j^{th} bell curve membership function of fuzzy set M_j. They satisfy the following properties:

$$\begin{cases} \sum_{i=1}^{2} \mu_i(|\alpha_f|) = 1 \\ 0 \le \mu_i(|\alpha_f|) \; \le 1 \; \forall i = 1,2 \end{cases} \quad (5)$$

The expressions of the membership functions used are:

$$\mu_i(|\alpha_f|) = \frac{\beta_i(|\alpha_f|)}{\sum_{i=1}^{2} \beta_i(|\alpha_f|)}, i = 1,2$$

$$\beta_i(|\alpha_f|) = \frac{1}{\left(1+\left|\left(\frac{|\alpha_f - c_i|}{a_i}\right)\right)\right|^{2b_i}}$$

Using an identification method based on the Levenbenrg-marquadt algorithm [15] combined with the least square method, allows to determine parameters of membership functions $(a_i, b_i \, and \, c_i)$ and stiffness coefficients values.

For a road friction coefficient $\mu = 0.7$ the following values are obtained:

$a_1 = 0.0978$, $b_1 = 0.7079$, $c_1 = 0.0137$
$a_2 = 0.1924$, $b_2 = 0.7445$, $c_2 = -1.1388$
$C_{f1} = 69120$, $C_{f2} = -796.64$
$C_{r1} = 56458$, $C_{r2} = -876.24$

Using the above approximation idea of nonlinear lateral forces by TS rules, nonlinear model (1) can be represented by the following TS fuzzy model:

$$\begin{bmatrix} \dot{\beta}(t) \\ \ddot{\psi}(t) \end{bmatrix} = \sum_{i=1}^{2} \mu_i(|\alpha_f|) \begin{bmatrix} a_{11i} & a_{12i} \\ a_{21i} & a_{22i} \end{bmatrix} \times \begin{bmatrix} \beta(t) \\ \dot{\psi}(t) \end{bmatrix} + \begin{bmatrix} b_{1i} \\ b_{2i} \end{bmatrix} \delta(t) \quad (6)$$

with:

$a_{11i} = -2\frac{C_{ri}+C_{fi}}{mv}$, $a_{12i} = -1-2\frac{l_f C_{fi} - l_r C_{ri}}{mv^2}$

$a_{21i} = -2\frac{l_f C_{fi} - l_r C_{ri}}{J_{zz}}$, $a_{22i} = -2\frac{l_f^2 C_{fi} + l_r^2 C_{ri}}{J_{zz} v}$

$b_{1i} = 2\frac{C_{fi}}{mv}$, $b_{2i} = 2\frac{l_f C_{fi}}{J_{zz}}$

The nominal values of the vehicle parameters are given in the following table:

TABLE I
NOMINAL VALUES OF THE VEHICLE PARAMETERS

$m(Kg)$	$J_{zz}(Kg.m^2)$	$l_f(m)$	$l_r(m)$	$v(m.s^{-1})$
1500	2454	1.0065	1.4625	20

B. T-S model with Vision system measurement

Using a vision system measuring the lateral displacement of the vehicle at a look-ahead distance "Fig. 2", the equations describing the evolution of the measurement extracted from image, caused by the motion of the car and changes in the road geometry can be written as follows [18]:

$$\dot{y_s} = v(\beta + \Delta\psi) + l_s\Delta\dot{\psi} \quad (7)$$

The angular displacement $\Delta\psi$ is obtained as follows:

$$\Delta\dot{\psi} = \dot{\psi} - \frac{v}{R_c} = \dot{\psi} - vw \quad (8)$$

y_s is the offset from the centerline at the look-ahead distance, $\Delta\psi$ the angle between the tangent to the road and the orientation of the vehicle with respect to the road, l_s the look-ahead distance at which the measurement is taken and w the road curvature.

Combining the vehicle lateral dynamics (6) and the vision dynamics (7) and (8) leads to a single dynamical system with the following form:

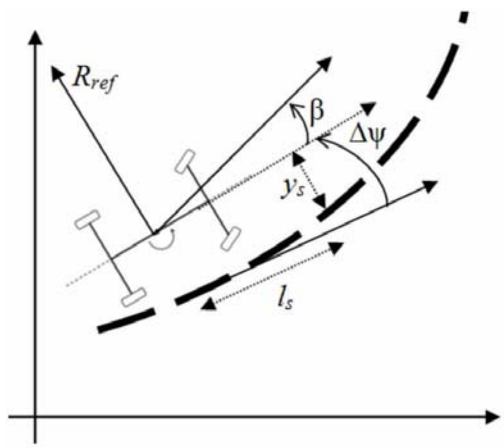

Fig. 2. Vision System measurement

$$\begin{bmatrix} \dot{\beta}(t) \\ \ddot{\psi}(t) \\ \dot{y}_s(t) \\ \Delta\dot{\psi}(t) \end{bmatrix} = \sum_{i=1}^{2} \mu_i(|\alpha_f|) \begin{bmatrix} a_{11i} & a_{12i} & 0 & 0 \\ a_{21i} & a_{22i} & 0 & 0 \\ v & l_s & 0 & v \\ 0 & 1 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} \beta(t) \\ \dot{\psi}(t) \\ y_s(t) \\ \Delta\psi(t) \end{bmatrix} + \begin{bmatrix} b_{1i} \\ b_{2i} \\ 0 \\ 0 \end{bmatrix} \delta(t) + \begin{bmatrix} 0 \\ 0 \\ -l_s v \\ -v \end{bmatrix} w(t) \quad (9)$$

By considering δ as the known input, w the unknown input of the system, we obtain the following TS fuzzy model:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{2} \mu_i(|\alpha_f|)\big(A_i x(t) + B_i u(t)\big) + B_w w(t) \\ y(t) = Cx(t) \end{cases} \quad (10)$$

with

$$A_i = \begin{bmatrix} a_{11i} & a_{12i} & 0 & 0 \\ a_{21i} & a_{22i} & 0 & 0 \\ v & l_s & 0 & v \\ 0 & 1 & 0 & 0 \end{bmatrix}, B_i = \begin{bmatrix} b_{1i} \\ b_{2i} \\ 0 \\ 0 \end{bmatrix}$$

$$B_w = \begin{bmatrix} 0 \\ 0 \\ -l_s v \\ -v \end{bmatrix}, C = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}$$

To take into account the variation of the stiffness coefficients, vehicle mass variation and modelisation/approximation errors, we introduce uncertainties in the system. The model described in (10) becomes:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{2} \mu_i(|\alpha_f|)\big((A_i + \Delta A_i)x + (B_i + \Delta B_i)u\big) + B_w w \\ y(t) = Cx(t) \end{cases} \quad (11)$$

The variable matrices $\Delta A_i(t)$ and $\Delta B_i(t)$ are assumed to be bounded, such that $\|\Delta A_i\| < \gamma_i$ and $\|\Delta B_i\| < \tau_i$ where γ_i and τ_i are positive scalars. The unknown input w is also bounded, i.e., $\|w\| < \rho$.

III. Unknown input T-S observer design

In this paper, we consider the state estimation of an uncertain multiple model perturbed by unknown inputs "Fig. 3". The proposed multiple observer is based on a linear combination of local observers involving sliding terms allowing to compensate the uncertainties and the unknown inputs $w(t)$.

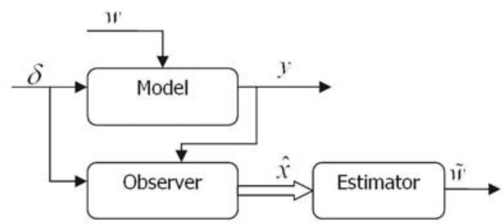

Fig. 3. Observer structure

A. T-S observer design conditions

The proposed multiple observer of the multiple model (11) has the following form:

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{2} \mu_i(|\alpha_f|)\big(A_i\hat{x}(t) + B_i u(t) + L_i(y(t) - C\hat{x}(t)) + B_w \mu(t) + \alpha_i(t)\big) \\ \hat{y}(t) = C\hat{x}(t) \end{cases} \quad (12)$$

The aim of the design is to determine gain matrices L_i and variables $\mu(t) \in \Re^q$ and $\alpha_i(t) \in \Re^n$, that guarantee the asymptotic convergence of $\hat{x}(t)$ towards $x(t)$. Let us note that the variables $\mu(t)$ and $\alpha_i(t)$ compensate respectively the errors due to the unknown inputs and the model uncertainties. Let us define the state estimation error:

$$e(t) = x(t) - \hat{x}(t) \quad (13)$$

The output estimation error is defined as follows:

$$r(t) = y(t) - \hat{y}(t) = C(x(t) - \hat{x}(t)) = Ce(t) \quad (14)$$

The dynamic of the state estimation error is governed by:

$$\dot{e}(t) = \sum_{i=1}^{2} \mu_i(|\alpha_f|)\big(\overline{A}_i e(t) + \Delta A_i x(t) + \overline{B}_w \overline{w}(t) + \overline{B}_w \mu(t) - \alpha_i(t)\big) \quad (15)$$

Where

$$\overline{w}(t) = [w(t)\ b(t)]^T \quad , \quad b(t) = \sum_{i=1}^{2} \mu_i \Delta B_i^T u(t)$$

Thorme 1 [16]: The state estimation of the robust state T-S observer (12) converges globally asymptotically to the state of the T-S model (11) if there exists a matrix $P > 0$, some matrice F and positive scalars β_1 and β_2 satisfying the following constraints:

$$\begin{cases} \overline{A}_i^T P + P\overline{A}_i + \beta_1^{-1}P^2 + \beta_1(1+\beta_2^{-1})\gamma_i^2 I < 0 \\ C^T F^T = P\overline{B}_w, \qquad i = 1,2 \end{cases} \quad (16)$$

with

$$\overline{A}_i = A_i - L_i C \tag{17}$$

and $\mu(t)$ and $\alpha_i(t)$ are defined as :

$$\begin{cases} \mu(t) = -\frac{Fr(t)}{\|Fr(t)\|}\rho \\ \\ \alpha_i(t) = \beta_1(1+\beta_2)\gamma_i^2 \frac{\widehat{x}(t)^T \widehat{x}(t)}{2r(t)^T r(t)} P^{-1} C^T r(t) \end{cases}, \quad if \quad r \neq 0$$

$$\begin{cases} \mu(t) = 0 \\ \alpha_i(t) = 0 \end{cases}, \quad otherwise \tag{18}$$

Remark 1.:To improve the observer proposed in [15], we replace ρ in expression (18) with $m(t)$ by considering the following update law

$$\dot{m}(t) = Gr^T r,\ m(0) > 0 \tag{19}$$

Where G is a design constant that can be used to regulate the increasing rate of $m(t)$.large G means that the state estimation error converges to zero faster [17].

B. Resolution method

By considering the following change of variable:

$$W_i = PL_i \tag{20}$$

The inequalities (16) can be written as:

$$\begin{cases} A_i^T P + PA_i - C^T W_i^T - W_i C + \beta_1^{-1} P^2 + \beta_3 \gamma_i^2 I < 0 \\ C^T F^T = P\overline{B}_w, \qquad i = 1,2 \end{cases} \tag{21}$$

where

$$\beta_3 = \beta_1(1+\beta_2^{-1}) \tag{22}$$

Applying the Schur complement, we obtain from (22) the following LMI formulation:

$$\begin{cases} \begin{bmatrix} A_i^T P + PA_i - C^T W_i^T - W_i C + \beta_3 \gamma_i^2 I & P \\ P & -\beta_1 I \end{bmatrix} < 0 \\ \\ C^T F^T = P\overline{B}_w, \qquad i = 1,2 \end{cases} \tag{23}$$

The solution of this LMI in P and W_i allows one to compute the observer gains $L_i = P^{-1} W_i$ and $F, \beta 1, \beta 2$ and then $\alpha(t)$ and $\mu(t)$ which define completely the observer (12).

It is important to note that a potential problem arises in the implementation of this multiple observer: when the output estimation error r(t) tends towards zero, the magnitude of $\alpha(t)$ and $\mu(t)$ may increase without bound. This problem is overcome as follows. The terms $\alpha(t)$ and $\mu(t)$ are fixed to zero when the output estimation error is such that $\|r(t)\| < \zeta$ a small positive number chosen by the user. In this case, the estimation error cannot converge to zero but to a small neighborhood of zero depending on the choice of ζ

C. Road curvature estimation

Once the states of the system rebuilt, they will be used to estimate the road curvature. From equation (8), the road curvature w can be computed as follows:

$$\tilde{w} = \frac{1}{v}\dot{\hat{\psi}} - \frac{1}{v}\Delta\dot{\hat{\psi}} \tag{24}$$

where v is the vehicle velocity, $\dot{\hat{\psi}}$ and $\Delta\dot{\hat{\psi}}$ are the estimate results of the observer.

IV. Lane departure detection

Now that the road curvature is estimated, it can be compared with the vehicle trajectory curvature w_v in order to detect any lane departure.

Computing the steady state of equation (6), leads to the steady state yaw rate described by:

$$\frac{\dot{\psi}}{\delta} = \frac{v}{l - \frac{mv^2(l_f C_f - l_r C_r)}{l C_f C_r}} \tag{25}$$

where $l = l_f + l_r$

The vehicle trajectory radius R_v is given by

$$R_v = v/\dot{\psi} \tag{26}$$

Then the vehicle trajectory curvature can be computed from (25) and (26) as follows

$$w_v = \frac{1}{R_v} = \frac{\delta}{l - \frac{mv^2(l_f C_f - l_r C_r)}{l C_f C_r}} \tag{27}$$

A. Lane departure detection algorithm

Risk indicators studied in the last decade for the lane departure problem like the TLC present several limitations, they are time consuming and require accurate road information [3], moreover they are approximated geometrically without vehicle dynamics and don't integrate driver corrections.

The risk indicator r_1 used here is given by the difference between the estimated road curvature $\widehat{w}$ obtained from the vision system equation (24) and the vehicle trajectory curvature w_v obtained from (27) [19] [20].

To reduce false alarms and no detection of a possible lane departure we have to take into account of the steering dynamics $\dot{\delta}$, we will be able to avoid false alarms when the driver is already correcting his maneuver.

We define a second indicator r_2, when r_1 exceeds a threshold value r_{Thres1}, the driver must begin correcting his maneuver ($\frac{\dot{\delta}}{r_1} > \varepsilon$) and then we compute the second indicator r_2 given by:

$$r_2 = \frac{\widetilde{w} - w_v}{\dot{w}_v} \tag{28}$$

The indicator r_2 is defined as the time remaining for the vehicle to have the same trajectory that the road, it must be always lower than the minimal value r_{Thres2}. All these steps are summarized in The following algorithm:

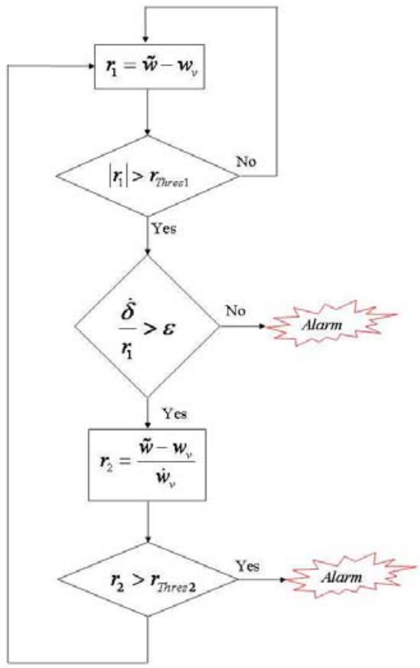

Fig. 4. Lane departure detection algorithm

B. Simulation results

In this section, we illustrate the above presented methods and present the different scenarios used to demonstrate the effectiveness of the used techniques.

Consider the double turn example shown in “Fig. 5”, the following assumptions are made:

Assumption A1: The road curvature in a turn is considered to be constant.

Assumption A2: A straight lane has a zero road curvature.

Assumption A3: The vehicle moves with a constance velocity. Under assumption $A1 \sim A3$, the double turn

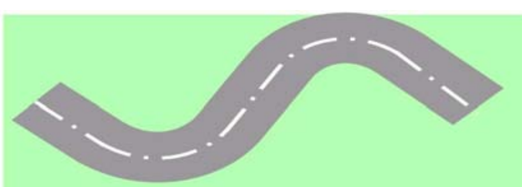

Fig. 5. Double turn example

considered can be represented as a signal (first curve of“Fig. 6”) and used as unknown input to be estimated using the observer results.

Uncertainties of the model are such that $\Delta A_i(t) = \pm 10\% A_i(t) = 0.1 A_i \eta(t)$ and $\Delta B_i(t) = \pm 10\% B_i(t) = 0.1 B_i \eta(t)$ the function $\eta(t)$ is a Gaussian random function with zero mean and a unity variance.

The resolution of equation (23) using LMI tools leads to the following matrices $P, F\ and\ L_i$:

$$P = \begin{bmatrix} 206.3010 & 344.7786 & -0.1545 & 0.0165 \\ 344.7786 & 860.3926 & -0.0758 & 0.0082 \\ -0.1545 & -0.0758 & 4.0191 & -0.2166 \\ 0.0165 & 0.0082 & -0.2166 & 0.0166 \end{bmatrix},$$

$$L_1 = \begin{bmatrix} -0.300 & 0.100 & 511.6 & 4733.5 \end{bmatrix}$$

$$L_2 = \begin{bmatrix} -0.400 & 0.100 & 506.1 & 4543.4 \end{bmatrix}$$

$$F = \begin{bmatrix} 4.3319 & -0.1545 & -0.0758 & 4.0191 & -0.2166 \end{bmatrix}^T$$
$$\beta_1 = 623.25, \quad \beta_3 = 2007.6.$$

The system (11) is simulated using the known input $\delta(t)$ and unknown input $w(t)$ depicted in “Fig. 6”.

The vehicle estimated state using the above observer are shown in “Fig. 7” and the road curvature estimation is illustrated in “Fig. 8”. Risque indicators r_1 and r_2 are

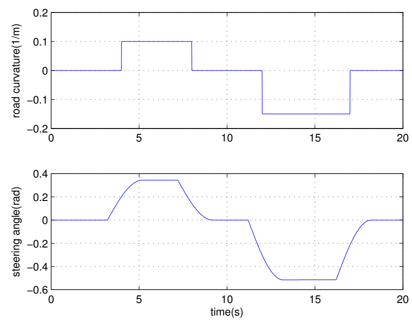

Fig. 6. Steering angle and road curvature

computed in two scenarios (“Fig. 9” and “Fig. 10”). In the first scenario the vehicle follows the lane considered. In the second, we simulate a lane departure at $t = 12s$. In “Fig. 10” the driver risks reach great values starting from the moment when the lane departure is simulated.

V. CONCLUSIONS AND FUTURE WORKS

A technique of lane departure detection based on road curvature estimation is proposed. The aim here is that only one sensor is used and no knowledge on the path road is needed. The used nonlinear model deduced from the vehicle lateral dynamics and a vision system is represented by a T-S fuzzy uncertain model affected by unknown inputs. A T-S observer using the principle of interpolation of local observers with uncertainties has been used to estimate system states and then the road curvature. Design conditions are given in LMI terms easy to solve using numerical tools. The proposed algorithm to detect lane departures is very efficient and practical, it uses two risk indicators and takes into account of the steering dynamics. We have also shown the efficiency of the risk indicators proposed by considering two driving scenarios in a double turn . further works will extend the different approaches by considering more complex vehicle model and implement the proposed algorithm in experimental validation.

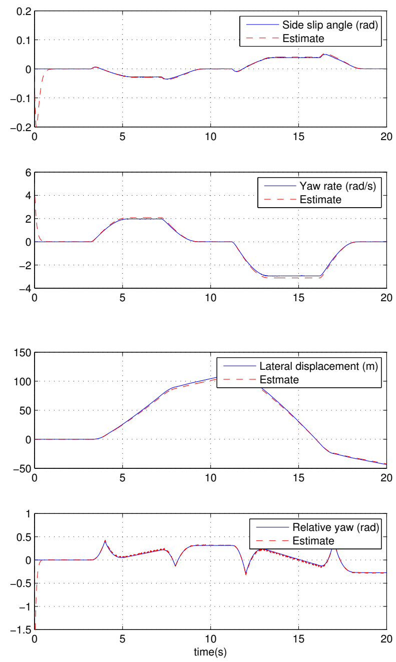

Fig. 7. Vehicle states estimation

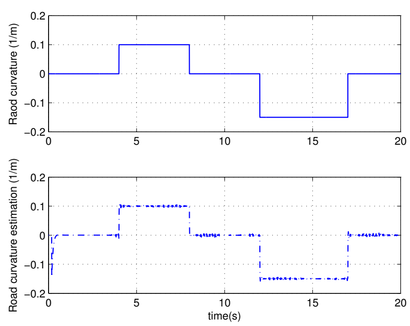

Fig. 8. road curvature estimation

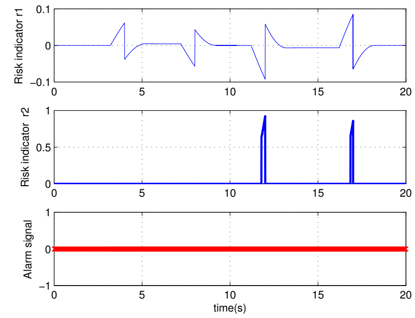

Fig. 9. Risk indicators in Scenario 1

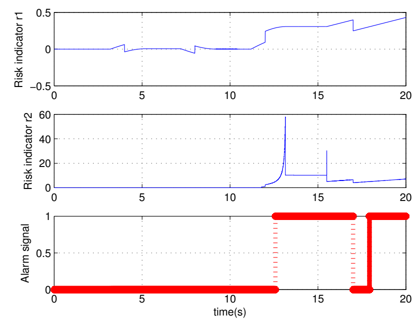

Fig. 10. Risk indicators in Scenario 2

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