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Robust fault tolerant tracking controller design for vehicle dynamics: A descriptor approach

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ABSTRACT

In this paper, an active Fault Tolerant Tracking Controller (FTTC) scheme dedicated to vehicle dynamics system is proposed. To address the challenging problem, an uncertain dynamic model of the vehicle is firstly developed, by considering the lateral forces nonlinearities as a Takagi–Sugeno (TS) representation, the sideslip angle as unmeasurable premise variables and the road bank angle as an unknown input. Subsequently, the vehicle dynamic states with the sensor faults are jointly estimated by a descriptor observer on the basis of the roll rate and the steering angle measures. Then a fault tolerant tracking controller is synthesized and solutions are proposed in terms of Linear Matrix Inequalities (LMIs). Simulation results show that the proposed FT control approach can effectively improve tracking performance of the vehicle motion.

1. Introduction

In recent years, driver assistance and safety systems have attracted increasing research efforts in automotive industry. Indeed, the number of road deaths decreases since the introduction of safety systems with significant improvements taken into account driven conditions (tire/road adhesion variation, speed variation, steering abrupt change of driver, load transfer, wind, etc.). Moreover, considerable work has been carried out on collision warning, collision avoidance, adaptive cruise control and automated lane-keeping systems. Nowadays, more and more cars are equipped with Traction Control System (TCS), anti-lock brake system (ABS) or many variants of the Electronic Stability Program (ESP) [1–3].

As such systems increasingly depend on accurate information about vehicle states which are obtained by direct measurement; the appropriate sensors may be unreliable, inaccurate, or even faulty. More practically, breaking control, lane departure avoidance and rollover detection generally make use of the lateral vehicle dynamics which are impossible or hard to measure accurately with cost sensors [1–3].

These challenges have been addressed in some previous works based on estimation and/or observation techniques of these dynamic parameters using available measurement [2,4,5]. In this context, several research works involving various methods have been conducted for vehicle dynamics, road bank angle and unknown inputs estimation [6–8,41–45]. In [6], lateral vehicle dynamics are estimated based on a descriptor approach for a proportional-integral (PI) observer. In [7], the authors proposed a road bank angle estimation algorithm based on a proportional-integral H_∞ filter for a modified bicycle model to improve robustness against modeling errors and uncertainties. Furthermore, the lateral control system must have fault tolerant ability such that the system maintains stability and acceptable performance despite of the failure situation [4]. Many work dealing with FTC design has been developed where significant results have been proposed in [10,11] and references therein. Recently, FTC strategies allow the adaptation of the control law on the basis of the estimation of faults affecting the system components (as sensors or actuators) [9,20,30–38]. The success of these methods mainly depends on the model complexity [12–14]. Accordingly, numerous FTC approaches for nonlinear systems approximated by Takagi–Sugeno representation have been developed [39,40], and some useful results for the trajectory tracking problem are proposed in [17–20,25,26,31].

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In this paper, an active FTT controller strategy is proposed for a vehicle system to preserve the closed-loop stability in spite of sensor faults. The main contributions of this paper lie in the following aspects.

(1) A T-S representation is proposed to describe the vehicle dynamics in large domains [15,16], and changes in road friction have been taken into account by introducing parameter uncertainties.
(2) A model-based descriptor observer with unknown input is designed in order to estimate both vehicle dynamics and road geometry (road curvature and road bank angle). Hence, a vision system (camera) is used to measure the lateral displacement at a look-ahead distance of the vehicle.
(3) To improve stability and performances of the vehicle dynamic system, an FTC strategy is proposed to deal with the sensor faults, and to ensure the trajectory tracking performance of a desired reference vehicle model by means of a control scheme with a T-S descriptor observer and unknown inputs attenuation based on an H_∞ optimization criterion.
(4) Whereas previous works considers a fixed slip angle, our work takes into account the variation of tire slip angles. For that purpose, a descriptor observer is used to estimate jointly states and time-varying faults.
(5) The case of membership functions depending on unmeasurable premise variables is also considered for observer and controller design and the proposed solutions are formulated in terms of LMIs conditions.

The remainder of the paper is organized as follows: Section 2 introduces the vehicle lateral and roll dynamics model and its representation by an uncertain T-S fuzzy model. Section 3 focuses on the proposed active FTTC methodology based on the descriptor observer, which is designed by considering the road angle as an unknown input. Section 4 gives simulation results to show the effectiveness of the design procedures and confirm the trajectory tracking of the reference vehicle model in presence of sensor faults. Finally, Section 5 concludes this paper. In the sequel, for the sake of simplicity, the time variable will be omitted for space convenience.

Notation. Throughout this paper, $\mathcal{H}(A)$ denotes the Hermitian of the matrix A, i.e. $\mathcal{H}(A) = A + A^T$. The symbol * indicates the transposed element in the symmetric positions of a matrix and $diag(\partial_1, \ldots, \partial_r)$ is a block diagonal matrix which diagonal entries are defined by $\partial_1, \ldots, \partial_r$.

2. Vehicle model for trajectory tracking control

The proposed model in this study describes vehicle lateral and roll dynamics (see Fig. 1). This later is obtained by considering the well known single-track (bicycle) model with a roll degree of freedom [4]. With the sideslip angle β, the vehicle yaw rate ψ and the roll angle Φ being the differential variables, the lateral and roll dynamics of the vehicle can be described as follows [2,12,21,22]:

$$\begin{cases} m\left(v\dot{\beta} + v\dot{\psi} + \ddot{\Phi}h\right) = 2F_{yf} + 2F_{yr} - m_s g\Phi_r \\ I_z\ddot{\psi} = 2F_{yf}l_f - 2F_{yr}l_r \\ I_x\ddot{\Phi} = m_s gh(\Phi + \Phi_r) + m_s a_y h - K_\Phi\Phi - C_\Phi\dot{\Phi} \end{cases} \tag{1}$$

where Φ_r is the road bank angle, m and J are the mass and the yaw moment of inertia respectively. For further description of the parameters appearing in the dynamics model refer to Table 1. In the following, F_f and F_r are the lumped lateral tire force of the front and rear tires, respectively. These forces are given as functions of tire slip angles by the non-linear expressions [23,24]:

$$\begin{aligned} F_f &= D_f(\sigma)sin\left[L_f(\sigma)tan^{-1}\left\{G_f(\sigma)(1 - V_f(\sigma))\alpha_f + V_f(\sigma)tan^{-1}(G_f(\sigma)\alpha_f)\right\}\right] \\ F_r &= D_r(\sigma)sin\left[L_r(\sigma)tan^{-1}\left\{G_r(\sigma)(1 - V_r(\sigma))\alpha_r + V_r(\sigma)tan^{-1}(G_r(\sigma)\alpha_r)\right\}\right] \end{aligned} \tag{2}$$

with

$$\alpha_f = \delta_f - \beta - \frac{l_f\dot{\psi}}{v}, \quad \alpha_r = \frac{l_f\dot{\psi}}{v} - \beta \tag{3}$$

where α_f and α_r are the slip angle of the front and rear tires, respectively (see Fig. 1). δ_f is the front steering angle. Coefficients D_i, L_i, G_i and V_i $(i = f,\ r)$ depend on the tire characteristics, road adhesion coefficient σ and the vehicle operational conditions. As the complexity of the vehicle model given in (1) depends on the nonlinear cornering forces model, a linear representation can be obtained, when the slip angles are very small. Next, a T-S model approximation is adopted to cope with the nonlinearities of the cornering forces.

2.1. TS model for the cornering forces

To derive the vehicle T-S fuzzy representation, the nonlinear behavior of forces in (2) is approximated by two slip regions M_1 and M_2 as follows:

$$\text{If}|\alpha_f| \text{ is } M_1 \text{ then } \begin{cases} F_f = S_{f1}(\sigma)\alpha_f \\ F_r = S_{r1}(\sigma)\alpha_r \end{cases} \tag{4}$$

$$\text{If}|\alpha_f| \text{ is } M_2 \text{ then } \begin{cases} F_f = S_{f2}(\sigma)\alpha_f \\ F_r = S_{r2}(\sigma)\alpha_r \end{cases} \tag{5}$$

where S_{fi}, and S_{ri} represent the front and rear tire stiffness coefficient respectively, which depend on the road adhesion and the vehicle mass. The overall forces are then approximated by:

$$\begin{cases} F_f = \mu_1(|\alpha_f|)S_{f1}(\sigma)\alpha_f + \mu_2(|\alpha_f|)S_{f2}(\sigma)\alpha_f \\ F_r = \mu_1(|\alpha_f|)S_{r1}(\sigma)\alpha_r + \mu_2(|\alpha_f|)S_{r2}(\sigma)\alpha_r \end{cases} \tag{6}$$

where $\mu_i(|\alpha_f|)$ are the weighting functions depending on the vector of the unmeasurable scheduling variable $|\alpha_f|$. These nonlinear functions satisfy the convex sum property:

$$\begin{cases} 0 \leqslant \mu_i(|\alpha_f|) \leqslant 1 \\ \sum_{i=1}^{2}\mu_i(|\alpha_f|) = 1 \ \forall i \in \{1,2\} \end{cases} \tag{7}$$

with

$$\mu_i(|\alpha_f|) = \frac{\xi_i(|\alpha_f|)}{\sum_{i=1}^{2}\xi_i(|\alpha_f|)}, \quad \xi_i(|\alpha_f|) = \frac{1}{\left[1 + \left|\left(\frac{|\alpha_f| - c_i}{a_i}\right)\right|\right]^{2b_i}} \tag{8}$$

The membership functions parameters (a_i, b_i and c_i) and the stiffness coefficients values are identified using the Levenberg–Marquardt algorithm, combined with the least square method [23]. According to Table 1, the following parameter values of a vehicle are obtained for a dry road, [15]: $a_1 = 0.085$, $a_2 = 3.872$, $b_1 = 0.674$, $b_2 = 22.817$, $c_1 = 0.022$, $c_2 = 3.853$, $S_{f1} = 96{,}240$, $S_{f2} = 829.15$, $S_{r1} = 107{,}180$, $S_{r2} = 650.44$.

2.2. T-S model representation with vision system measurement

By considering that the lateral displacement of the vehicle at a look-ahead distance is measured using a vision system (Fig. 2), the equation describing the evolution of the measurement extracted from image, caused by the motion of the car and changes in road geometry can be written as follows [15]: