Control Engineering Practice 49 (2016) 173–186

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

Modeling, diagnosis and estimation of actuator faults in vehicle suspensions

Diana Hernández-Alcántara [a], Juan C. Tudón-Martínez [a,*], Luis Amézquita-Brooks [b], Carlos A. Vivas-López [a], Rubén Morales-Menéndez [a]

[a] Tecnológico de Monterrey, School of Engineering and Sciences, Av. Garza Sada # 2501 64,849 Monterrey, N.L., Mexico
[b] Universidad Autónoma de Nuevo León, Av. Universidad s/n. San Nicolás de los Garza, N.L., Mexico

ARTICLE INFO

Article history:
Received 30 June 2015
Received in revised form
24 October 2015
Accepted 9 December 2015
Available online 31 December 2015

Keywords:
Fault diagnosis
Fault identification
Semi-active dampers

ABSTRACT

This paper deals with the modeling, diagnosis and estimation of faults in automotive *Semi-Active* (*SA*) dampers, particularly oil leakages in the actuator. An experimental multiplicative fault model is proposed and statistically validated with an index error of 15% for damper leakage. The fault model is used as design basis for two *Fault Detection and Isolation* (*FDI*) frameworks. The *Frequency-based Fault Estimator* (*FFE*) is based on the effect of the damper fault in the frequency domain and the *Robust Parity Space* (*RPS*) consists in a residual generator sensitive to the fault in the time domain. The model-based *FDI* systems were experimentally validated in a 1:5 scaled vehicle, fully instrumented and equipped with *SA* dampers. The experimental results show that, while both approaches represent suitable options for commercial applications, the *RPS* estimator has the fastest detection time and proportionality to the fault level. In addition, the *RPS* approach has better robustness to vehicle mass uncertainties. On the other hand, the *FFE* presents lower sensitivity to road profile and semi-active damper input variations. Additionally, this estimator requires a lower number of sensors and has a lower computational overhead.

1. Introduction

In recent years vehicle manufacturers have been gradually increasing the number of control systems to improve the vehicle performance and meet stricter security requirements. Many advanced vehicle control systems have been developed, for instance in Bououden, Chadli, and Karimi (2015) a robust nonlinear predictive control for an active suspension system is proposed; in Wang, Jing, Karimi, and Chen (2015) a fault-tolerant H_∞ control with finite-frequency constraint is designed for an active suspension system; in Dahmani, Chadli, Rabhi, and Hajjaji (2015) an unknown-input fuzzy observer is used to estimate the road and the vehicle curvatures in a lane departure detection algorithm, in Du, Zhang, and Dong (2010) a yaw-moment controller is proposed for improving vehicle handling and stability; and in Poussot-Vassal et al. (2011) a joint control of the suspension and braking systems, based on LPV/H_∞, is used to improve the vehicle comfort in normal driving conditions and the stability when critical situations are detected. The implementation of these control systems demands the incorporation of a greater number of sensors on board. The increased complexity of the systems and the availability of sensors introduce the necessity of fault detection modules and fault tolerant control systems.

The suspension system is one of the main subsystems in a vehicle, its key objectives are to isolate the vehicle body from the road disturbances (comfort) and to maintain tire-road contact in order to provide an adequate handling (road-holding). Automotive suspension systems can be classified as passive, active or semi-active. Passive suspensions consist of a spring and a damper with time-invariant characteristics. *Semi-Active* (*SA*) and active suspensions include actuators whose properties can vary according to an external control signal. The main difference between active and *SA* suspensions is that the first ones are able to store, dissipate and generate energy whereas *SA* suspensions are only able to store and dissipate energy. Typically, better performance can be achieved with active suspensions at the cost of increased energy consumption and complexity in comparison with *SA* systems.

Since any system is subject to faults, the development of *Fault Detection and Isolation* (*FDI*) techniques for automotive suspensions is necessary to maintain the reliability of the vehicle. This is more relevant when using *SA* dampers, which are more prone to fault than passive dampers. Depending on the magnitude and location of a fault, the severity of its effect could vary from the loss of

---

* Corresponding author.
E-mail addresses: d.hernandez.phd.mty@itesm.mx (D. Hernández-Alcántara), jc.tudon.phd.mty@itesm.mx (J.C. Tudón-Martínez), amezquita-brooks@ieee.org (L. Amézquita-Brooks), ca.vivas.phd.mty@itesm.mx (C.A. Vivas-López), rmm@itesm.mx (R. Morales-Menéndez).

http://dx.doi.org/10.1016/j.conengprac.2015.12.002
0967-0661/

comfort to the loss of vehicle stability including rollover. It has been found that weak shock absorbers can induce longer braking distances of up to 20% and deteriorate the vehicle handling, Börner, Isermann, and Schmitt (2002).

Although there are several theoretical methods for *FDI* design, a crucial step is the adequate characterization of realistic fault events. Some *FDI* methods for *SA* suspensions consider additive fault modeling (Odendaal & Jones, 2014; Varrier, Koenig, & Martinez, 2014); however, before applying such approaches it is necessary to verify if the malfunctions can be modeled as additive faults. The most common fault in *SA* dampers is oil leakage, Dixon (2007); several causes for damper leakage are reported in Sachs (2008). The use of an experimental damper fault model not only validates the importance of knowing its effect into the vehicle, but it can also be used as design basis for an *FDI* system or even for a *Fault-Tolerant Controller* (*FTC*).

Different nonlinear *FDI* methods have been proposed in the literature. For instance, in Chadli, Abdo, and Ding (2013) a fault detection observer is designed for a Takagi–Sugeno fuzzy model subject to sensor faults. The fault detection observer design problem is formulated as an H_{-}/H_{∞} problem to minimize the effect of the disturbances and maximize the sensitivity to faults. Nonetheless there are few reports dealing with *FDI* schemes for automotive suspension systems. A fault estimation scheme based on parity relations for *SA* dampers is presented in Weispfenning (1997) and Fischer and Isermann (2004). In these papers, the parameters of a faulty *Quarter of Vehicle* (*QoV*) suspension model are estimated using a recursive identification algorithm; these parameters are then used to generate parity relations and fault signatures. In Fischer, Börner, Schmitt, and Isermann (2007) and Börner et al. (2002) the residuals and the deviation of the damper parameters are used to generate the fault diagnosis using *Artificial Intelligence* (*AI*) methods. Although the results of these papers are commendable, most online estimation methods such as *Recursive-Least-Squares* (*RLS*) need excitation and other operating requirements which may be restrictive when the road profile is unknown. In addition, *AI* methods have a high computational load and normally require a high degree of manual fine tuning.

Other forms of residual generation based on observers have been proposed for damper faults. In Yetendje, Seron, and De Dona (2007) a bank of *unknown input observers* is used to detect and isolate actuator faults in active suspensions. Since each residue is sensitive to a predetermined faulty mode specified in the observer design, a new faulty behavior could not be well diagnosed. A Lyapunov-based observer for damper faults (parametric fault) is proposed in Vidal, Acho, Pozo, and Rodellar (2010); based on a bank of observers, the nominal robust observer is used as a benchmark to create the residue of the damping force.

Alternatively, Ferreira et al. (2009) proposed a methodology to diagnose the condition of an automotive passive damper by using the transmissibility function of motion between the unsprung and sprung masses. This approach has the advantage of not depending on a model; however, it is applicable only to passive dampers and it is only suitable for fault detection purposes. An extension of the transmissibility approach for *SA* dampers is presented in Lozoya-Santos, Tudón-Martínez, Morales-Menendez, Ramírez-Mendoza, and Garza-Castañón (2012). The application of wavelet analysis represents another data-driven approach. For instance, in Azadi and Soltani (2007), a wavelet analysis is used to detect and isolate a damper with a faulty bushing in one corner of the vehicle.

The literature review reveals that reports (theoretical or application-oriented) dealing with passive and semi-active damper fault detection are not widespread. While several reports can be found for active suspension systems and other fault-tolerant applications for automotive subsystems, in the case of semi-active dampers there are very few reports with experimental results. With the intention of demonstrating that semi-active damper fault detection systems are viable in practice, in this paper two *FDI* schemes are presented and validated experimentally. The proposed *FDI* schemes are inspired in the preliminary results presented in Tudón-Martínez et al. (2013) and Hernandez-Alcantara, Amezquita-Brooks, Vivas-Lopez, Morales-Menendez, and Ramirez-Mendoza (2013). In Tudón-Martínez et al. (2013) the authors proposed a robust fault estimator based on the parity space method by creating residues insensitive to uncertainties, but sensitive to faults in *SA* shock absorbers. In Hernandez-Alcantara et al. (2013) a *FDI* method based on the analysis of the faulty system in the frequency domain is introduced. Under simulation, both schemes are able to detect multiplicative damper faults under a wide range of road-profile conditions and considering the nonlinear damper behavior. This paper presents an experimental validation of both *FDI* methods using damper leakage as a fault case of study. A comparative analysis allows us to identify complementary features which can be exploited in different scenarios. Both schemes are tested in an experimental 1:5 scale vehicle prototype.

The *QoV* (*Quarter of Vehicle*) model has several parameters which are not subject to significant perturbation; for instance the unsprung mass and main suspension spring which can be both accurately measured and do not change much over time. On the other hand, the sprung mass is subject to parametric uncertainty due to vehicle payload changes. In addition, another smaller source of parametric uncertainty is the tire which can also be subject to parametric uncertainty due to inflation pressure. In this sense, the effects of sprung mass and tire stiffness coefficient uncertainties for both *FDI* strategies are also studied revealing that the proposed algorithms are fairly robust to these uncertainties. Nonetheless, a limitation of the proposed algorithms is that it is only possible to assess the level of robustness to parametric uncertainty a posteriori; that is, the estimators are designed using a nominal model and the effect of the uncertainty is evaluated numerically afterwards. If further robustness to parametric

Table 1
Definition of variables.

Variable	Description	Units
α	Ratio of the faulty force and the nominal force	–
ρ_1	Nonlinear part of the damper model	–
υ	Control effort of the *ER* damper (duty cycle)	–
ω_f	Band-pass center-frequency of the filter	rad/s
ω_s	Sprung mass resonance frequency	rad/s
a_1, a_2	Pre-yield viscous damping coefficients of *Guo* model	s/m, 1/m
b_1	Viscous damping coefficient of *Guo* model	N s/m
b_2	Stiffness coefficient of *Guo* model	N/m
c_p	Linear approximation of the viscous damping	N s/m
f_c	Dynamic yield force of *Guo* model	N
F_δ	Loss of force	N
F_p	Force of a passive damper	N
F_{SA}	Force of a semi-active (healthy) damper	N
$\overline{F}_{SA}$	Force of a faulty damper	N
G_f	Band pass filter transfer function	-
G_s	Transfer function from z_s to z_r	–
G_{us}	Transfer function from z_{us} to z_r	–
k_s	Suspension stiffness	N/m
k_t	Tire stiffness	N/m
m_s	Sprung mass	Kg
m_{us}	Unsprung mass	Kg
T_s	Fault index of the frequency based *FDI* method	–
z_{def}, $\dot{z}_{def}$	Displacement and velocity of the damper piston	m, m/s
z_r	Road profile	N
z_s, $\dot{z}_s$, $\ddot{z}_s$	Sprung mass displacement, velocity, acceleration	m, m/s, m/s^2
z_{us}, $\dot{z}_{us}$, $\ddot{z}_{us}$	Unsprung mass displacement, velocity, acceleration	m, m/s, m/s^2