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Fault Detection and Diagnosis of Automotive Suspension Systems

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Abstract

An automobile consists of complex electrical systems, mechanical systems and control parts, all of them interacting among the steering, brake, suspension systems, and so on. Also, the objectives of an automobile control are to achieve the high driving performance, comfort, and safety and to satisfy common requirements. However, the suspension systems are often faced safety-critical situations due to their passive characters. Hence, the aims of this paper are to investigate the fault detection and diagnosis process of automotive suspension systems, especially the full-car model, via a filter bank approach and to detect the occurrence of any change, for instance, to keep maintaining the reliability and safety of automotive components. For our investigation, the Kalman filter, one of the most effective filters, was designed to track the automotive suspension system. Additionally, in order to evaluate the performance of the fault detection and diagnosis, the process is validated through our simulation to illustrate that the fault detection and diagnosis process capable of detecting effectively any faults in actuators.

Key words: Fault detection and diagnosis, Kalman filter, Automotive suspension systems.

1. Introduction

The active suspension systems have played an important role in the modern vehicles. Also it is an interesting of control areas and fault detection and diagnosis process (FDA). The concepts and background of using FDA using model based-techniques to detect and diagnose the fault in the engineering system are provided many reports such as Gertler [1] and Isermann [2]. The FDA process to detect and diagnosis the fault in active suspension system was used in the previous works by Boner et al [3] and Yetendje et al. [4].

In this work, we focused on the area of fault detection and diagnosis process (FDA) to detect and diagnose faults in the active suspension systems. The model-base technique using an observer bank approach was used to detect fault and isolate the fault element of the active suspension system under the road disturbance and noises. The output signal from the fault observers were compared with those from the normal observer.

The remainder in this paper is organized as follows: The vehicle model is presented in Section 2, The LQR and Kalman filter we employ for the active suspension are briefly described in section 3. In section 4 the FDA using an observer bank is presented. The simulation results are shown in section 5. In section 6, the conclusion is stated.

2. Vehicle Modeling

The vehicle model we consider in this paper consists of five parts, namely, the chassis (sprung mass) and four wheel-axle assemblies (unsprung masses) as shown in Park and Kim [5]. Assumming that the sprung mass is rigid and has freedom of motion in the vertical, pitch, and roll directions. Each of the unsprung masses has freedom of motion in the vertical direction. Thus, the full-car model has 7 degrees of freedom. Each suspension comprises a linear spring, a damper, and an actuator to generate pushing-force between the chassis and each axle. For convenience, suppose that the dynamics of the actuators are negligible, compared to the response of suspensions.

The equations of motion of the full-car model are as follows:

$$M_s\ddot{p} = GB_s\,(\dot{z}_u - \dot{z}_s)\; + GK_{sr}(z_u - z_s) + Gu \tag{1}$$

$$M_u\ddot{z}_u = B_s(\dot{z}_s - \dot{z}_u) + K_{ss}(z_s - z_u) + K_t(z_r - z_u) - u \tag{2}$$

where

$$p = [z_c\ \theta\ \emptyset]^T \in \mathbb{R}^3\,,$$
$$z_j = [z_{j1}\ \ z_{j2}\ \ \ z_{j3}\ \ z_{j4}]^T \in \mathbb{R}^4\,,\quad j = u, s, r$$
$$u = [u_1\ \ u_2\ \ u_3\ \ u_4]^T \in \mathbb{R}^4,$$

where z_c , $\theta,$ and $\emptyset$ stand for the vertical displacement at the center of gravity, the roll angle, and the pitch angle of the sprung mass, respectively, and z_{ui}, z_{si}, z_{ri}, and u_i represent the vertical displacement of the unspung mass, the vertical displacement of the road, and the pushing force generated by the actuator at suspension i, respectively.

The matrices that appear in Eq. (1) and (2) are expressed as

$$M_s = \mathrm{diag}(m_s,\ I_\theta,\ I_\emptyset),$$
$$M_u = \mathrm{diag}(m_f,\ m_f,\ m_r,\ m_r),$$
$$B_s = \mathrm{diag}(b_f,\ b_f,\ b_r,\ b_r),$$
$$K_{ss} = \mathrm{diag}\big(k_f,\ k_f,\ k_r,\ k_r\big),$$

$$K_t = \begin{bmatrix} k_{tf} & 0 & 0 & 0 \\ 0 & k_{tf} & 0 & 0 \\ 0 & 0 & k_{tf} & 0 \\ 0 & 0 & 0 & k_{tf} \end{bmatrix},$$

$$K_t \begin{bmatrix} k_f + r_f/2 & -r_f/2 & 0 & 0 \\ -r_f/2 & k_f + r_f/2 & 0 & 0 \\ 0 & 0 & k_f + r_f/2 & -r_f/2 \\ 0 & 0 & 0 & k_f + r_f/2 \end{bmatrix},$$

$$G = \begin{bmatrix} 1 & 1 & 1 & 1 \\ -t_f & t_f & -t_f & t_f \\ -l_f & -l_f & l_f & l_f \end{bmatrix}$$

where all the parameters employed are shown in Table 1 as well as their numerical values used in the later simulations.

Additionally, let us define z_s and p have a kinematic relationship of

$$z_s = G^T\,p. \tag{3}$$

Substituting Eq. (3) into Eq. (1) and (2), we have

$$M\ddot{z} + B_z\dot{z} + K_a z - K_b z_r = G_a u \tag{4}$$

where

$$z = [p^T\ \ z_u^T]^T \in \mathbb{R}^7$$

All the matrices are also of appropriate dimensions:

$$M=\begin{bmatrix}M_s & 0\\ 0 & M_s\end{bmatrix},\quad B_z=\begin{bmatrix}GB_sG^T & 0\\ -B_sG^T & B_s\end{bmatrix}$$

$$K_a=\begin{bmatrix}GB_{sT}G^T & -GB_{sT}\\ -K_{ss}G^T & K_t+K_{ss}\end{bmatrix},$$

$$K_b=\begin{bmatrix}0\\ K_t\end{bmatrix},\ \text{and}\ G_a=\begin{bmatrix}G\\ -I\end{bmatrix},$$

Equation (4) can be represented as a state-space form of

$$\dot{x}=Ax+Bu+Fz_r \tag{5}$$

where $x=[z^T\ \ \dot{z}^T]^T\ \in\ \mathbb{R}^{14}$

$$A=\begin{bmatrix}0 & 1\\ -M^{-1}K_a & -M^{-1}B_z\end{bmatrix},$$

$$B=\begin{bmatrix}0\\ M^{-1}G_a\end{bmatrix},\ \text{and}\ F=\begin{bmatrix}0\\ M^{-1}K_b\end{bmatrix}$$

3. LQR and Kalman Filter Design

It is well known that the road/terrain irregularities can be easily modeled as the output of a linear shaping filter with an input of white noise. Here, the filter is modeled as a first-order system [6] as

$$\dot{z}_r+\alpha z_r=w \tag{6}$$

where w is the white noise and α is the product of the road type coefficient and the vehicle speed. If the state vector is defined as $x_s=[x^T\ \ z_r^T]^T$, from Eq. (5) and (6), it is easy to have the augmented state-space representation of the plant as follows,

$$\dot{x}_s=A_sx_s+B_su+F_sw \tag{7}$$

where

$$A=\begin{bmatrix}A & F\\ 0 & -\alpha I\end{bmatrix},\ B_s=\begin{bmatrix}B\\ 0\end{bmatrix},\ F_s=\begin{bmatrix}0\\ I\end{bmatrix}$$

Here, the LQR controller is designed to minimize a cost function of chassis acceleration, suspension deflections and tire deflections, respectively, represented by

$$J=\lim_{t\to\infty}\frac{1}{t}E\left\{\int_0^t(p_1\ddot{z}^2+p_1\ddot{\theta}^2+p_3\ddot{\phi}^2\right.$$

$$+\left\{\ +p_4\sum_{i=1}^{4}(z_{si}-z_{ui})^2+\right.$$

$$+p_5\sum_{i=1}^{4}(z_{ui}\ -z_{ri})^2$$

$$\left.+p_6\sum_{i=1}^{4}u_i^2)dt\right\}$$

where the values of weighting factors (p_i) are shown on Table 1.

Table 1: Weighting factors of the cost function.

p_1	p_2	p_3	p_4	p_5	p_6
1x10^6	3x10^5	3x10^5	1x10^8	1x10^8	1

Such a cost function above is equivalent to the minimization in the deterministic cost in eq. (8) as follows:

$$J=\int_0^\infty(x(t)^TQx(t)+u(t)^TRu(t))dt$$

Therefore, the optimal solution, for any initial state, is $u(t)=-K_rx(t)$ where $K_r=R^{-1}B^TX$ and $X=X^T\geq 0$ is the unique positive semi-definite solution of the algebraic Riccati equation

$$A^TX+XA-XBR^{-1}B^TX+Q=0$$

Since it is well-known that all states of vehicle model cannot measureable, it is easy to employ Kalman filters, one of the most powerful ones, to estimate such unmeasureable states. In addition, the Kalman filter has the structure of an ordinary state estimator or observer with

$$\dot{\hat{x}}=A\hat{x}+Bu+K_f(y-C\hat{x})$$

The optimal choice of K_f, that minimizes $E\{[x-\hat{x}]^T[x-\hat{x}]\}$, is given by $K_f=YC^TV^{-1}$ where $Y=Y^T\geq 0$ is the unique positive semi-definite solution of the algebraic Riccati equation

$$YA^T+AY-YC^TBV^{-1}CY+W=0$$

For further LQR and Kalman filter details, the reader is referred to as Lewis [7].

4. Fault Detection and Diagnosis Process Using an Observer Bank [8]

The FDA process using an observer bank is utilized in the mechanical system such as works by Park [9] and Isermann [2]. The concept is also used in this paper as the previous works by Borner et al. [3] and Yetendje et. al. [4]. However, in this paper, the model of car is a full model given by Park and Kim [5] and the noises are included in the process. The vehicle suspension is controlled by the LQR algorithm and in the normal situation the 4 actuators works together in order to stabilize the car. Assume that fault occurs at one actuator at each a time, the input matrix is manipulated as the work by Borner et. at. [3],

$$B_i = BL_i \;, L_i = diag[l_1, l_2, l_3, l_4],$$
$$l_i \in \{1,0\}$$

Therefore, B_1 $, B_2,$ B_3 and B_4 are corresponding to each fault observer whereas B_5 is corresponding to normal observer.

All observers are driven by the same input $u(t)$ while the following measurement or output signals easily chosen

$$y(t) = [z \;\; \theta \;\; \emptyset \;\; z_{u1} \;\; z_{u2} \;\; z_{u3} \;\; z_{u4}]^T,$$

are measured from real system, based on $u(t)$ and $y(t)$.

Assume that fault occurs at one actuator at each a time. Therefore, the observer banks, as shown in Figure 1, are constructed from fault observer (observer#1, 2, 3, 4) and a normal observer (observer #5). Each of observers is the Kalman filter and attempts to track the behavior of the real system. Observer Bank generator the residual vector $\vec{r}(t)$ corresponds to each observer. Normal observers would generate $\vec{r}_5(t)$ while fault observers (#1, 2, 3, 4) generate the $\vec{r}_1, \vec{r}_2, \vec{r}_3$ and $\vec{r}_4$ corresponding to a fault actuator occurring on left front, right front of the vehicle left rear, and sight rear, respectively. Then, all residuals will be analyzed in order to detect and isolate the location of the fault actuator. The idea of the FDA can be concluded as the following diagram.

5. Simulation Results

The simulation results with fault occurring at the front right wheel can be shown in figure2. The component of residual $\overrightarrow{r_2}(t)$ referred to the error corresponding to each output signal $z\,, \theta\,, \emptyset\,, z_{u1}\,, z_{u2}\,, z_{u3}$ and z_{u4}. The non zero value of each component represents the detection of the suspension system. However, in order to locate the position of the fault actuator.

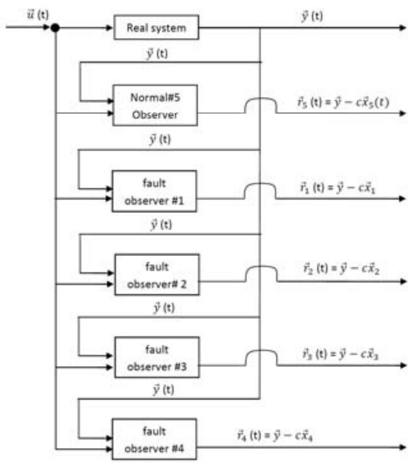

Figure 1: Observer bank

The some components of residuals from each fault observer are needed to be analyzed. Our simulation focuses on situation when fault occur one at a time on each position of actuator of each wheel. The criteria used in this paper are norm of error signal, Mean of error signal and the mean square error (MSE). All criteria can be shown in Table 2 Table 3 and

Table 4 respectively. When the actuator of the suspension is damage one at each wheel. It can be discussed as followings. As considering the value of norm of error of each measurement signal corresponding each of fault mode (positions of the fault actuator), It is clear that the maximum value of norm, mean, and mean square error of error of each signal occur at the fault position at each mode. For example when, a fault occurs at actuator of front right wheel (mode 2). The error of measurement signal z_{u2} of mode2 relative to that of mode 5 is highest as represented in term of norm of absolute error, mean of error and mean square error as colored in green. Also, types of errors are agreed in every mode.

Table 2. : The Norm value of selected component of residual vector of location of fault.

Measurement	Norm of Error signal			
	Mode1 Front Left	Mode2 Front Right	Mode3 Rear Left	Mode4 Rear Right
Zu1	0.14511 *1.0e-3	0.03547 *1.0e-3	0.01177 *1.0e-3	0.01047 *1.0e-3
Zu2	0.02278 *1.0e-3	0.15035 *1.0e-3	0.01178 *1.0e-3	0.01047 *1.0e-3
Zu3	0.01124 *1.0e-3	0.01273 *1.0e-3	0.05859 *1.0e-3	0.05948 *1.0e-3
Zu4	0.011254023605 *1.0e-3	0.012719741676579 *1.0e-3	0.058591225951445 *1.0e-3	0.0594866174633 *1.0e-3

Table 3. : The mean value of selected component of residual vector of location of fault.

Measurement Signal	Mean of Error signal			
	Mode1 Front Left	Mode2 Front Right	Mode3 Rear Left	Mode4 Rear Right
Zu1	0.37192 *1.0e-5	0.08794 *1.0e-5	0.02863 *1.0e-5	0.02644 *1.0e-5
Zu2	0.05445 *1.0e-5	0.37788 *1.0e-5	0.02865 *1.0e-5	0.02642 *1.0e-5
Zu3	0.02709*1.0e-5	0.03246 *1.0e-5	0.14734 *1.0e-5	0.15228 *1.0e-5
Zu4	0.027110587119325 *1.0e-005	0.032413404787704 *1.0e-005	0.147343646200949 *1.0e-005	0.152294903687689 *1.0e-005

Table 4. : The MSE value of selected component of residual vector of location of fault.

Measurement Signal	Mean Square of Error signal			
	Mode1 Front Left	Mode2 Front Right	Mode3 Rear Left	Mode4 Rear Right
Zu1	0.210384524943782 *1.0e-10	0.005184256320313 *1.0e-10	0.001262763457116 *1.0e-10	0.001265265207979 *1.0e-10
Zu2	0.012571581462547 *1.0e-10	0.225843549752908 *1.0e-10	0.001620604068006 *1.0e-10	0.001616301981208 *1.0e-10
Zu3	0.001385912480942 *1.0e-10	0.001388031925451 *1.0e-10	0.034295182186124 *1.0e-10	0.034295022562370 *1.0e-10
Zu4	0.001097053061423 *1.0e-10	0.001095578935375 *1.0e-10	0.035348594751770 *1.0e-10	0.035351225346988 *1.0e-10

Next, we consider the situation when damage or faults occur at two position of suspension system. First we consider norm of error of measurement signal corresponding to each fault mode. Based on the values of norm, mean and mean square error as shown in Table 5.,Table 6. and Table 7. The most of maximum values of all type of error occur at the pair of measurement signals corresponding to the fault positions which are colored in green. Even though such as mode 2 , mode 4 and mode 5 the maximum value of those criteria do not occur at measurement signal corresponding to the mode as the value colored in pink. However, algorithm predicts the correct one position from two fault positions of suspension system.

Table 5. : The Norm value of selected component of residual vector of location of fault of two fault position.

Signal	Norm of Error signal					
	Mode1 Front Left Front Right	Mode2 Front Left Rear Right	Mode3 Front Left Rear Left	Mode4 Front Right Rear Right	Mode5 Front Right Rear Left	Mode 6 Rear Right Rear Left
Zu1	0.148946996047516 *1.0e-003	0.147226896087832 *1.0e-003	0.146999227283393 *1.0e-003	0.022548498780351 *1.0e-003	0.023148082849871 *1.0e-003	0.0148614635465 *1.0e-003

Zu2	0.125625868588601*1.0e-003	0.028156859417679*1.0e-003	0.028865131652422*1.0e-003	0.122682788344530*1.0e-003	0.122805186367448*1.0e-003	0.0148617188567*1.0e-003
Zu3	0.012745514074370*1.0e-003	0.065892671131767*1.0e-003	0.066478259671411*1.0e-003	0.065481844777933*1.0e-003	0.065365771715934*1.0e-003	0.0946481190965*1.0e-003
Zu4	0.012751357212449*1.0e-003	0.065893740648154*1.0e-003	0.066490722605823*1.0e-003	0.065486749622458*1.0e-003	0.065362737615120*1.0e-003	0.0946512958555*1.0e-003

Table 6. : The mean value of selected component of residual vector of location of fault of two fault position.

Signal	Mean of Error signal					
	Mode1 Front Left Front Right	Mode2 Front Left Rear Right	Mode3 Front Left Rear Left	Mode4 Front Right Rear Right	Mode5 Front Right Rear Left	Mode6 Rear Right Rear Left
Zu1	0.369141465571268*1.0e-005	0.364969908340097*1.0e-005	0.366140471733839*1.0e-005	0.022548498780351*1.0e-005	0.058729388422433*1.0e-005	0.038055303641689*1.0e-005
Zu2	0.31889775327*1.0e-0005	0.0728541887*1.0e-005	0.0745690161*1.0e-005	0.3063577683*1.0e-005	0.3084602667*1.0e-005	0.03806191303*1.0e-005
Zu3	0.03146920617*1.0e-005	0.1652243401*1.0e-005	0.1672492424*1.0e-005	0.1646756328*1.0e-005	0.1657475603*1.0e-005	0.24016235650*1.0e-005
Zu4	0.03150650656*1.0e-005	0.1652081676*1.0e-005	0.1673001544*1.0e-005	0.1647005354*1.0e-005	0.1657402189*1.0e-005	0.24017122974*1.0e-005

Table 7.: The MSE value of selected component of residual vector of location of fault of two fault position.

Signal	Mean Square of Error signal					
	Mode1 Front Left Front Right	Mode2 Front Left Rear Right	Mode3 Front Left Rear Left	Mode4 Front Right Rear Right	Mode5 Front Right Rear Left	Mode6 Rear Right Rear Left
Zu1	0.2216304458*1.0e-10	0.21654104826*1.0e-10	0.2158718563*1.0e-10	0.005079268703*1.0e-10	0.0053529844*1.0e-10	0.0022064249*1.0e-10
Zu2	0.1576609275*1.0e-10	0.00792016715*1.0e-10	0.0083236346*1.0e-10	0.150360305254*1.0e-10	0.1506604775*1.0e-10	0.0022065000*1.0e-10
Zu3	0.00162285843176*1.0e-10	0.043375066022769*1.0e-10	0.044149440648746*1.0e-10	0.042835884071142*1.0e-10	0.042684156963233 1.0e-10	0.08949317131377*1.0e-10
Zu4	0.001624346*1.0e-10	0.04337647409*1.0e-10	0.0441659959*1.0e-10	0.042842301459 1.0e-10	0.0426801944*1.0e-10	0.089499178*1.0e-10

Conclusions

This paper is dealt with investigation in the fault detection and diagnosis process of automotive suspension systems, particularly the full car model, using a Kalman filter bank and LQR approach to keep maintaining the reliability and safety of automotive suspension systems. Our simulation results have shown to evaluate the performance of the fault detection and diagnosis capable of detecting effectively any faults in actuators. It is clear that the algorithm can locate the fault positions in the suspension system correctly when a single fault occurs at each position. In order to locate the multiple faults in the suspension system, it is necessary to use other or criteria which can be considered as a future work.

Reference:

[1] J. Gertler, Fault Detection and Diagnosis in Engineering Systems, 1998.

[2] R. Isermann, "Model-Based Fault Detection and Diagnosis-Status and Applications", DarmStadt University of Technology, 2004.

[3] M. Borner, et al., "Comparison of Different Fault Detection Algorithms for Active Body Control Components Automotive Suspension" ACC, 2001.

[4] A. Yetendje, et al. "Diagnosis and actuator fault tolerant control vehicle active suspension," 2007.

[5] J. H. Park and Y. S. Kim. "Decentralized variable structure control for active suspensions based on a full-car model", 1998.

[6] A. Hac, "Adaptive control of vehicle suspensions", Vehicle system dynamics, vol. 16, pp. 57-74, 1987.

[7] F. Lewis, Optimal Estimation with an Introduction to Stochastic Control Theory, 1986.

[8] R. Patton, et al., Fault Diagnosis in Dynamic Systems Theory and Applications, Prentice Hall. 1989.

[9] R.-W. Park, "Crack Detection, Localization and Estimation and The intensity in a Turbo Rotor, " ASME, Jakarta, Indonesia, Paper No.96-TA-031, pp.1-7., 1996