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MODEL-BASED SENSOR FAULT DIAGNOSIS OF VEHICLE SUSPENSIONS WITH A SUPPORT VECTOR MACHINE

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ABSTRACT−In this paper, a means of generating residuals based on a quarter-car model and evaluating them using a support vector machine (SVM) is proposed. The proposed model-based residual generator shows very robust performance regardless of unknown road surface conditions. In addition, an SVM classifier without empirically set thresholds is used to evaluate the residuals. The proposed method is expected to reduce the effort required to design fault diagnosis algorithms. While an unknown input observer is used to generate the residual, the relative velocity of the vehicle suspension is obtained additionally. The proposed algorithm is verified using commercial vehicle simulator Carsim with Matlab & Simulink. As a result, the fault diagnosis algorithm proposed in this paper can detect sensor faults that cannot be detected by a limit checking method and can reduce the effort required when designing algorithms.

KEY WORDS : Fault diagnosis, Support vector machine, Vehicle suspension, Unknown input observer

NOMENCLATURE

m_s, m_u : sprung/unsprung mass, kg
k_s, k_t : spring/tire stiffness, N/m
c_n : nominal damping coefficient, Ns/m
c_{sky} : sky-hook damping coefficient, Ns/m
β : damper bandwidth, -
z_s, z_u : sprung/unsprung mass position, m
z_r : unknown road input, m
v_s, v_u : sprung/unsprung mass vertical velocity, m/s
$f(x)$: hyperplane of support vector machine, -
$\mathbf{w}$: normal vector of hyperplane, -
r : geometrical distance, -
α : Lagrangian multiplier, -
$K(x_i, x_j)$: kernel function, -

1. INTRODUCTION

Suspension systems are an essential component in determining the ride quality and handling performance of vehicles. Due to an existing trade-off relationship, an uncontrolled passive suspension system cannot improve both the ride quality and handing performance at the same time (Rajamani, 2011). To address this issue, various studies have attempted to improve ride quality and handling performance of vehicles simultaneously using a controlled suspension system (Roh and Park, 1998; Savaresi and Spelta, 2009). Especially in practical areas, semi-active suspensions (Butsuen, 1989) are adopted owing to energy savings, packaging and cost issues. For this reasons, semi-active suspension is used more extensively than active suspension. Thus far, various algorithms have been developed which control the damping characteristics of semi-active suspensions effectively. To apply a control algorithm, most vehicles currently produced are equipped with a body-vertical accelerometer and wheel-vertical accelerometers (Kim *et al*., 2005). Control algorithms use these sensors to improve ride comfort and handling performance. However, if the sensor constituting the suspension control system fails, such a failure can affect the control performance seriously and even causes a collapse of the vehicle stability. Especially with regard to vehicle suspension control systems, the possibility of a system collapse due to a sensor failure is fairly high because various sensors are integrated into the system. Therefore, in order to guarantee the performance of a semi-active suspension system, the control algorithm and the algorithm used to diagnose faults in sensors are essential.

In accordance with these demands, sensor fault diagnosis algorithms for vehicle suspensions have been widely developed and applied for many years. For example, a limit-checking method (Gertler, 2013) that diagnoses a sensor fault when the measurement exceeds a predetermined threshold value is widely used in practical areas. However, the limit-checking method cannot sensitively diagnose certain sensor faults, such as gain faults and offset faults. Therefore, a model-based fault diagnosis method (Ding, 2008) using a dynamic model of a suspension system was recently proposed and studied in an

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effort to implement a more robust and sensitive diagnosis algorithm. Addas (Chamseddine and Noura, 2008) used a sliding-mode observer to diagnose sensor failures in vehicle suspension systems. Although their study demonstrated robustness against disturbances, additional sensors were needed to implement fault diagnosis algorithms. Börner *et al*. (2002) used parity equations to detect sensor faults. Sebastien (Varrier *et al*., 2013) used parity space analysis to diagnose sensor faults. However, the parity relationship method of filtering system inputs and outputs using parity vectors incurs a disadvantage since the residual responds to unknown system uncertainties. In order to overcome these drawbacks, this paper proposes a vehicle suspension sensor fault diagnosis algorithm based on an unknown input observer using a quarter-car model. The proposed fault diagnosis algorithm is designed for two vertical accelerometer type systems commonly used in practical applications and to ensure robustness against unknown road input factors. Since the quarter-car model is described as a bilinear system with bilinear measurements, this paper proposes a bilinear system fault diagnosis algorithm (Kinnaert, 1999; Zasadzinski *et al*., 2003). In addition, the suspension-relative velocity required to control the vehicle suspension is also derived from the diagnostic algorithm. Furthermore, the support vector machine (SVM) is used to evaluate the residuals generated by the unknown input observer. This machine-learning application method can reduce the effort required when designing fault diagnosis algorithms and achieve excellent performance at the same time. Fault diagnosis with machine learning (Widodo and Yang, 2007) is rarely used in relation to vehicle suspension systems. In particular, hybrid methods (Gao *et al*., 2015) which combine model-based fault diagnosis and machine learning (Liang and Du, 2007) have rarely been studied.

This paper is organized as follows. First, a quarter-car model is introduced in Section 2. In Section 3, a residual generator based on an unknown input observer is designed. Using this residual, Section 4 introduces the SVM-based decision-making process. Next, the simulation for verification is performed. In the end, this paper shows that the proposed diagnosis algorithm provides robust performance under various road conditions.

2. SEMI-ACTIVE VEHICLE SUSPENSION SYSTEM

In this section, the quarter-car model using two vertical accelerometers is described in terms of dynamic equations. Owing to its simplicity and accuracy, the quarter-car model has long been used in suspension control research.

Figure 1 shows that the quarter-car model consists of a sprung mass and an unsprung mass. The dynamic equation for this model is given below.

$$m_s \ddot{z}_s = -k_s(z_s - z_u) - (c_{sky} + c_n)(\dot{z}_s - \dot{z}_u) \tag{1}$$

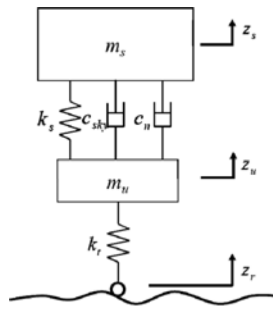

Figure 1. Quarter-car model of the semi-active suspension system.

$$m_u \ddot{z}_u = -k_s(z_u - z_r) - (c_{sky} + c_n)(\dot{z}_u - \dot{z}_s) - k_t(\dot{z}_u - \dot{z}_r) \tag{2}$$

In actual situations, the damping force of a vehicle suspension system has highly nonlinear characteristics. Due to its complexity, however, linearized suspension damping force is used in many articles (Joo *et al*., 2000; Szászi *et al*., 2002). Therefore, as in other studies, this paper designs a fault diagnosis algorithm using a linearized suspension damping model. Figure 2 shows the actual damping force and linearized damping force. In this paper, the least square approximation is used to linearize the actual damping force. In addition, the sky-hook damping control algorithm, widely used in practical applications, is used to control the semi-active damper in this paper. The sky-hook control (Savaresi *et al*., 2005) law is expressed as follows:

$$\begin{cases} c_{sky}(t) = c_{max}, & if \quad v_s(t)(v_s(t) - v_u(t)) \geq 0 \\ c_{sky}(t) = c_{min}, & if \quad v_s(t)(v_s(t) - v_u(t)) < 0 \end{cases} \tag{3}$$

$$\dot{c}(t) = -\beta c(t) + \beta c_{sky}(t) + c_n \tag{4}$$

The parameters used in this paper are described in Table 1.

Based on Equations (1) and (2), the state-space sensor

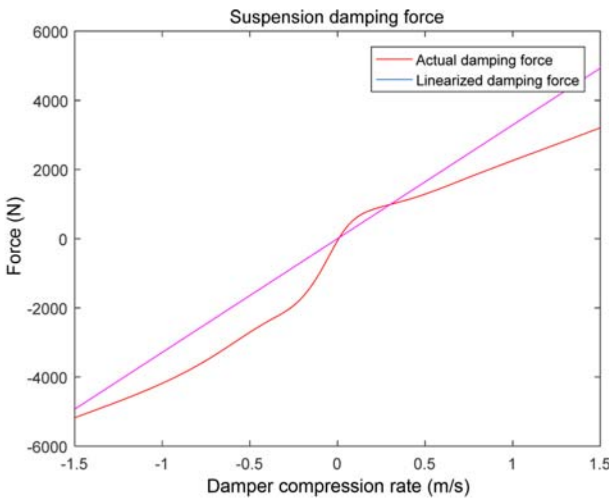

Figure 2. Linear and nonlinear damping characteristics.

Table 1. Vehicle parameters.

Parameter	Variable
Sprung mass	441.5 kg
Unsprung mass	40 kg
Spring stiffness	99670 N/m
Nominal damping (Linear)	214.12 Ns/m
Tire vertical stiffness	268000 N/m
U_{max}	5285.3 Ns/m
U_{min}	– 1033.7 Ns/m

fault model, which uses sprung and unsprung mass accelerometers, is expressed as shown below.

$$\underbrace{\begin{pmatrix}\dot z_s-\dot z_u\\ \ddot z_s\\ \dot z_u-\dot z_r\\ \ddot z_u\end{pmatrix}}_{\dot x}=\underbrace{\begin{pmatrix}0&1&0&-1\\ k_s/m_s&-c_s/m_s&0&c_s/m_s\\ 0&0&0&1\\ k_s/m_u&c_s/m_u&-k_t/m_u&-c_s/m_u\end{pmatrix}}_{A^0}\underbrace{\begin{pmatrix}z_s-z_u\\ \dot z_s\\ z_u-z_r\\ \dot z_u\end{pmatrix}}_{x}$$
$$+\underbrace{c_{sky}}_{u}\underbrace{\begin{pmatrix}0&0&0&0\\ 0&-1/m_s&0&1/m_s\\ 0&0&0&0\\ 0&1/m_u&0&-1/m_u\end{pmatrix}}_{A^1}\underbrace{\begin{pmatrix}z_s-z_u\\ \dot z_s\\ z_u-z_r\\ \dot z_u\end{pmatrix}}_{x}+\underbrace{\begin{pmatrix}0\\0\\-1\\0\end{pmatrix}}_{D}\underbrace{\dot z_r}_{w} \tag{5}$$

$$\underbrace{\begin{pmatrix}\ddot z_s\\ \ddot z_u\end{pmatrix}}_{y}=\underbrace{\begin{pmatrix}k_s/m_s&-c_n/m_s&0&c_n/m_s\\ k_s/m_u&c_n/m_u&-k_t/m_u&-c_n/m_u\end{pmatrix}}_{C^0}\underbrace{\begin{pmatrix}z_s-z_u\\ \dot z_s\\ z_u-z_r\\ \dot z_u\end{pmatrix}}_{x}$$
$$+\underbrace{c_{sky}}_{u}\underbrace{\begin{pmatrix}0&-1/m_s&0&1/m_s\\ 0&1/m_u&0&-1/m_u\end{pmatrix}}_{C^1}\underbrace{\begin{pmatrix}z_s-z_u\\ \dot z_s\\ z_u-z_r\\ \dot z_u\end{pmatrix}}_{x}+\underbrace{\begin{pmatrix}1\\0\end{pmatrix}}_{F}\underbrace{f}_{f} \tag{6}$$

In accordance with Equations (5) and (6), the sensor fault of the suspension system is described as an additive fault. Before designing a model-based fault diagnosis algorithm, fault detectability should be contemplated with regard to feasibility testing. Additive fault detectability can be assessed using the following theorem (Ding, 2008):

Theorem 1: Given system Equations (5) and (6), an additive fault f is detectable if and only if the following equation holds:

$$C(sI-A)^{-1}E+F\neq 0 \tag{7}$$

From Equation (7), E means the model fault of the system. Since this paper mainly focuses on the suspension sensor fault, the E matrix is assumed zero. It is noteworthy that Equation (7) is applicable only to linear system. Assuming that the bounded input c_{sky} is an arbitrary constant in the control region, Equations (6) and (7) can be represented as a linear system. Then, it is confirmed that Equation (7) always holds within the control region $\Omega\in\left[U_{min}\quad U_{max}\right]$. In conclusion, sensor faults in the vehicle suspension systems can be detected using a model-based diagnosis method.

3. DESIGN UNKNOWN INPUT RESIDUAL GENERATOR

In this section, the residual generator based on an unknown input observer for a quarter-car semi-active suspension system is proposed. According to Section 2, since the quarter-car model is not a linear system but is instead a bilinear system, the residual generator proposed in this paper has a different form to implement a bilinear residual generator. Over the last few years, various methods have been proposed to generate residuals for fault diagnoses of bilinear systems. According to previous findings (Zasadzinski *et al*., 2003), an unknown input residual generator for a bilinear system expressed by Equations (5) and (6) can be expressed in the following form:

$$T\dot{\hat x}=N^0T\hat x+uN^1T\hat x+Ly \tag{8}$$

$$\theta=M^0T\hat x+uM^1T\hat x+Jy \tag{9}$$

where $\hat x$ is the estimated states, T is the transformation matrix and θ is the residual.

According to Equation (8), the unknown input observer is also expressed as the bilinear system. In addition, from Equation (9), it can be seen that the residual is generated by the combination of the estimated states and the system measurements. The residual generator with the form defined by Equations (8) and (9) should meet several conditions. First, the estimation error should be robust to unknown inputs and states. In addition, the generated residual should also be robust to unknown states. Finally, if the system is healthy, the estimation error and residual must converge. To design a residual generator satisfying these conditions, the error dynamics is considered. The error state is defined as follows:

$$e=T\hat x-Tx \tag{10}$$

Then the error dynamics can then be described by the equations below.

$$\begin{aligned}\dot e&=N^0e+uN^1e+(N^0T-TA^0+LC^0)x\\ &\quad+u(N^1T-TA^1+LC^1)x-TDw\end{aligned} \tag{11}$$

In addition, the residual is described as

$$\theta=M^0e+uM^1e+(M^0T+JC^0)x+u(M^1T+JC^1)x \tag{12}$$

Using the developed error dynamics, the matrices that make up the unknown input residual generator are obtained by the following theorem (Zasadzinski *et al*., 2003).

Theorem 2: System Equations (8) and (9) represent an unknown input residual generator if N, L, M, J, T and Q > 0 and a real $\mu > 0$ satisfying the following constraints:

$$N^{i}T - TA^{i} + LC^{i} = 0 \quad (13)$$

$$TD = 0 \quad (14)$$

$$M^{i}T + JC^{i} = 0 \quad (15)$$

$$N^{T}(u)Q + QN(u) + \mu I < 0 \quad (16)$$

where $N(u) = N^{0} + uN^{1}$ (17)

According to Equations (13) and (14), it can be seen that the estimation error is robust to the unknown input and the system states. Similarly, Equation (15) indicates that the residual is robust to the unknown input and the system states. In addition, satisfying Equation (16) ensures the stability of the unknown input observer.

Using the vehicle parameters and theorem 2, the unknown input residual generator matrices are obtained as follows:

$$N^{0} = \begin{bmatrix} -1.4359 & 0.9692 & 0.0144 & -0.9692 \\ -1.3374 & -0.0287 & 0.0054 & 0.0287 \\ -0.0146 & -0.0003 & -1.0009 & 0.0003 \\ 1.3372 & 0.0287 & -0.0054 & -0.0287 \end{bmatrix} \quad (18)$$

$$N^{1} = \begin{bmatrix} 0 & -0.1441 & 0 & 0.1441 \\ 0 & -0.1342 & 0 & 0.1342 \\ 0 & -0.0015 & 0 & 0.0015 \\ 0 & 0.1342 & 0 & 0.1342 \end{bmatrix} \times 10^{-4} \quad (19)$$

$$L = \begin{bmatrix} -0.0059 & 0 \\ 0.9945 & 0 \\ -0.0001 & 0 \\ 0.0055 & 1 \end{bmatrix} \quad (20)$$

$$M^{0} = \begin{bmatrix} 1.0032 & 0.0216 & 1.0000 & -0.0216 \end{bmatrix} \quad (21)$$

$$M^{1} = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix} \quad (22)$$

$$J = \begin{bmatrix} 0.0041 & 0 \end{bmatrix} \quad (23)$$

4. SVM-BASED RESIDUAL EVALUATION

In the real world, residuals generated by a model-based fault-diagnosis method are contaminated by unknown model uncertainties and disturbances. Therefore, it is also important to evaluate the ability of each generated residual to perform robustly in the event of a fault diagnosis. This residual evaluation is mainly performed using a predetermined threshold. However, setting a threshold that satisfies both robustness and sensitivity of the diagnostic algorithm requires a great deal of effort. Therefore, a SVM-based residual evaluation method is proposed in this paper. SVM is a machine-learning technique optimized for binary classification and requiring a small data set. Therefore, it is an appropriate way to evaluate residuals under healthy and faulty conditions.

4.1. SVM Classifier Design for Evaluating Residual

The SVM classifier used in this paper is designed based on SVM theory as developed by Vapnik (2013). The basic concept of SVM is to set the decision boundary that classifies class to the maximum classification margin. For N datasets x_j with positive and negative states, the linear decision boundary that separates this dataset can be described as a hyperplane, as follows:

$$f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} + b = 0 \quad (24)$$

Note that **w** is the normal vector of the hyperplane and *b* is the bias factor.

Figure 3 describes the concept of SVM. In this figure, it is assumed that blue-o represents a positive case, red-x represents a negative case and D.B (opt) means the optimal decision boundary (hyper plane) which obtained by solving optimization problem. Similarly, D.B (b=/bopt) means the decision boundary which has bias factor *b* deviated from the optimal bias factor and D.B (w=/wopt) means the decision boundary which has normal vector **w** deviated from the optimal normal vector. The classifier with the decision boundary represented by the dotted line becomes more likely to discriminate that data between the red solid line and the blue solid line as negative. This can degrade the performance of the classification algorithm. Likewise, in the case of a decision boundary depicted with a solid black line, performance degrades compared to the optimized decision boundary. Therefore, it is necessary to solve optimization problem in order to find optimal **w** and *b*.

To classify the dataset, it is assumed that the labels are assigned as $y_j = 1$ for a positive class and $y_j = -1$ for a

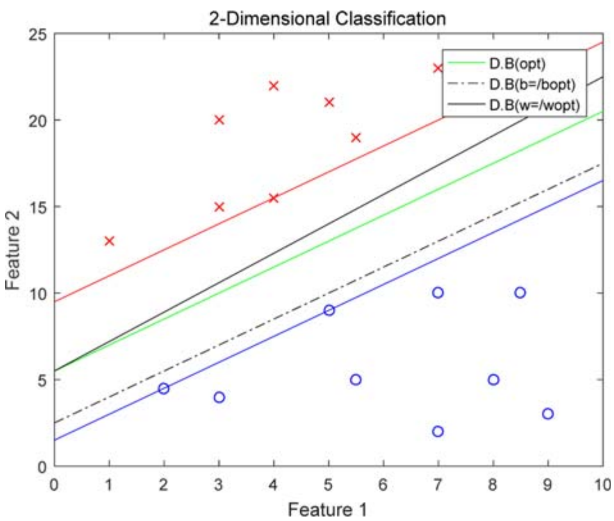

Figure 3. 2-Dimensional classification using SVM.

negative class, and the hyperplane is set to have the following properties:

$$f(x_j) = 1 \quad if \quad y_j = 1$$
$$f(x_j) = -1 \quad if \quad y_j = -1 \tag{25}$$

According to Equation (25), it can be seen that the positive and negative class are divided depending on the sign of $f(x_j)$. In general, the classification margin is described as the distance from the nearest dataset to the hyperplane. According to SVM theory, the nearest dataset is referred to as a support vector. The distance r between support vector $\mathbf{x}$ and data on hyperplane $\mathbf{x}_p$ is expressed as shown below.

$$\mathbf{x} = \mathbf{x}_p + r\frac{\mathbf{w}}{\|\mathbf{w}\|},\ f(\mathbf{x}_p) = 0 \tag{26}$$

By substituting the Equation (26) into the Equation (24), the following equation can be obtained.

$$f(\mathbf{x}) = \mathbf{w}\cdot\mathbf{x} + b = \mathbf{w}\cdot\left(\mathbf{x}_p + r\frac{\mathbf{w}}{\|\mathbf{w}\|}\right) + b = r\|\mathbf{w}\| \tag{27}$$

Therefore,

$$r = \frac{f(\mathbf{x})}{\|\mathbf{w}\|} \tag{28}$$

As a result, the problem of maximizing the distance r without including data between the hyperplanes passing through the support vector can be expressed as follows.

$$\min_{w,b} \frac{1}{2}\|\mathbf{w}\|^2 \text{ subject to } (\mathbf{w}\cdot\mathbf{x} + b)y \geq 1 \tag{29}$$

To apply this theory to actual data, the noise and reliability of the dataset should be considered. Therefore, in most SVM studies, a slack variable is specified to cope with errors in the data. When applying a slack variable, the problem of obtaining the optimal hyperplane is expressed as follows.

$$\min_{w,b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_j \xi_j$$

$$\text{subject to } (\mathbf{w}\cdot\mathbf{x} + b)y \geq 1 - \xi_j,\ \xi_j \geq 0 \tag{30}$$

From Equation (30), a slack variable serves to penalize object functions for errors that exceed a given decision boundary. By using the Karush-Kuhn-Tucker condition (Cristianini and Shawe-Taylor, 2000) and the Lagrangian multiplier, Equations (29) and (30) can be presented as:

$$\max_\alpha \sum_j \alpha_j - \frac{1}{2}\sum_i\sum_j \alpha_i\alpha_j y_i y_j x_i x_j$$

$$\text{subject to } \alpha_j \geq 0 \tag{31}$$

Additionally, a technique for generating nonlinear decision boundaries using kernel functions is commonly used. A kernel function is used to map the input space into a higher dimensional feature space. In this paper, the residual is evaluated using various kernel functions which are mainly used in SVM applications, especially with regard to fault diagnosis. According to earlier work, the design of the SVM classifier used here can be expressed in the form of the following optimization problem.

$$\max_{\alpha\geq 0} \sum_j \alpha_j - \frac{1}{2}\sum_i\sum_j \alpha_i\alpha_j y_i y_j K(x_i, x_j)$$

$$\text{Subject to } \alpha_j \geq 0 \tag{32}$$

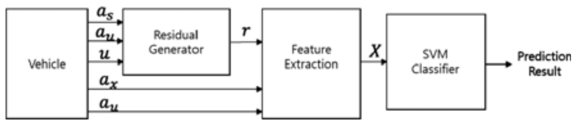

Figure 4. Sensor fault diagnosis scheme.

4.2. Residual Evaluation

Using the designed SVM classifier, a residual evaluation is conducted. The scaled residual, vehicle longitudinal acceleration and lateral acceleration are considered as the inputs and the prediction result is considered as the output. The longitudinal and lateral acceleration values of the vehicle, as determined by sensors built into the vehicle, are used to account for the effects of uncertainty and disturbances in the model. In addition, the mean and variance of data commonly used in previous learning applications are used as features to configure the data set of the SVM classifier. The residual evaluation using the SVM is shown in the following figure.

5. SIMULATION VERIFICATION

In this section, the simulation verification is performed using the vehicle simulator Carsim and Matlab & Simulink. This section is structured as follows. First, the performance of the unknown input residual generator is verified on various road surfaces. Next, SVM classifiers composed of various kernel functions are derived using residual signals obtained from various simulation scenarios. Finally, the performance of the SVM classifier is verified using well-known performance measures for machine learning.

5.1. Simulation Set-up

In this paper, several road surface driving simulations are conducted to verify the performance of the residual generator. First, a low-frequency wavy road with a range of 0.02 m to 0.10 m is selected to verify the performance of the residual generator when the motion of the sprung mass is dominant. Next, a 3.6 m × 0.1 m speed-bump crossing simulation is performed to verify the performance of the residual generator when the motion of the unsprung mass is dominant. Finally, to evaluate the effect of gravity on the residual generator, a wavy uphill road simulation is

Table 2. Simulation scenarios.

Case	Maneuver	Variable
1	Wavy road	35 km/h
2	Speed bump	30 km/h
3	Wavy uphill road	30 km/h

performed. In this section, the upper limit of the sprung mass acceleration is assumed to be 2.5 g and the lower limit is assumed to be – 0.2 g. Furthermore, the types of the sensor fault are a gain fault of 0.8 and a bias fault of + 2 m/s^2. The simulation scenarios are specified in the following table.

5.2. Simulation Results

5.2.1. Wavy road simulation

Figure 5 shows the residual generated by the unknown input residual generator. According to the figure, a gain fault of 0.8, which is difficult to detect by the limit checking method, occurred at one second. In order to be used in the SVM classifier, a preprocessing method such as low-pass filtering must be performed on the residual signal. As a result of the simulation, it is confirmed that the residual does not change significantly when there is no fault, whereas the residual changes greatly if a fault occurs. In another case, Figure 6 verifies that proposed residual generator has also robust performance for sensor bias fault. According to the simulation results, the limit checking method with the aforementioned limit cannot detect the sensor fault. In addition, the figure shows that the performance of the unknown input observer is confirmed. To verify the stability of the observer, an initial condition error is added, but the estimated state converges to the actual state.

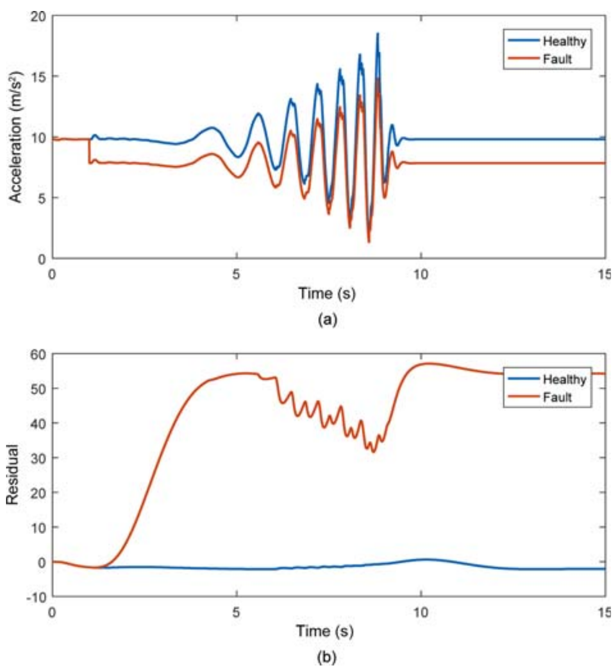

Figure 5. Wavy road simulation results for residual generation (gain fault): (a) Front left sprung mass acceleration; (b) Residual generated by the unknown input residual generator.

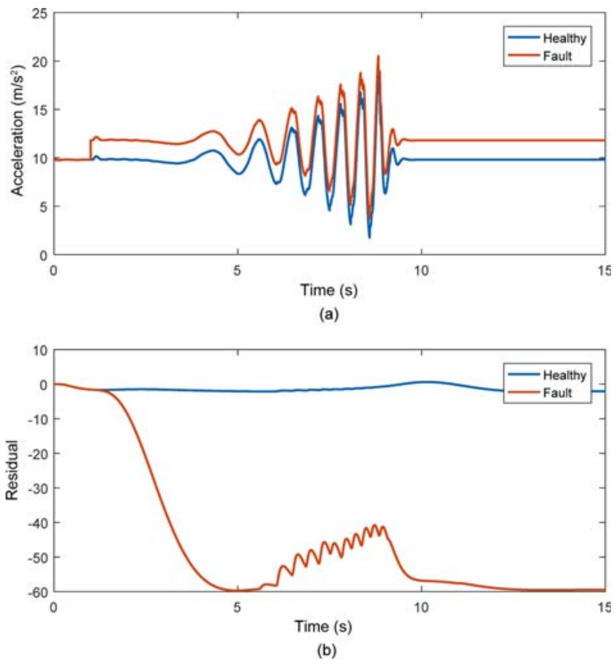

Figure 6. Wavy road simulation results for residual generation (bias fault): (a) Front left sprung mass acceleration; (b) Residual generated by the unknown input residual generator.

5.2.2. Speed-bump simulation

Figures 8 and 9 show the result of the speed-bump

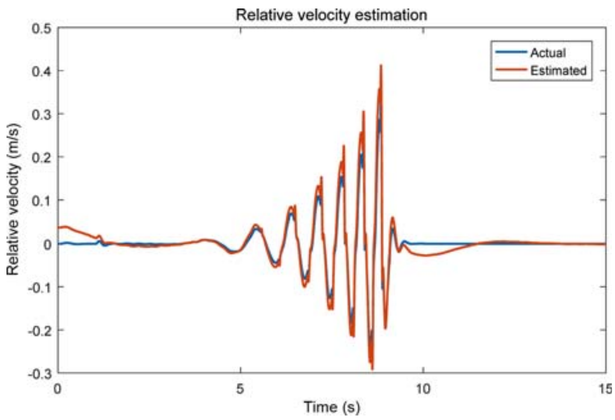

Figure 7. Wavy road simulation results for the relative velocity estimation: Front left suspension relative velocity.

scenario. Since the motion of the sprung mass is more dominant, the effects of the damping nonlinearity have a greater impact on the unknown input observer. Despite this condition, the residual generator based on an unknown input observer generated a robust residual in a healthy condition. However, if a fault occurs, the residual changes significantly. Given that preprocessing is performed on the residual signal, the response of the residual is delayed. The effects of this delay are covered in the following section. As with previous scenarios, the proposed residual generator exhibits robust performance against sensor gain and bias fault. However, it has been determined that the limit checking method cannot detect this fault scenarios.

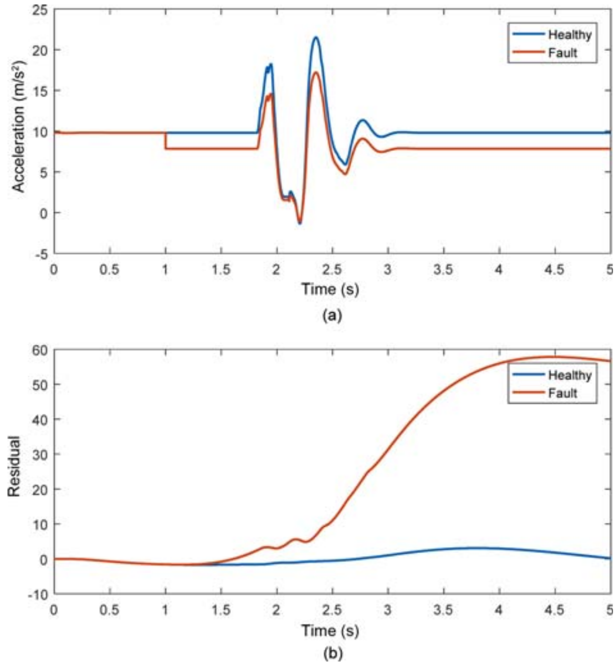

Figure 8. Speed-bump simulation results for residual generation (gain fault): (a) Front left sprung mass acceleration; (b) Residual generated by the unknown input residual generator.

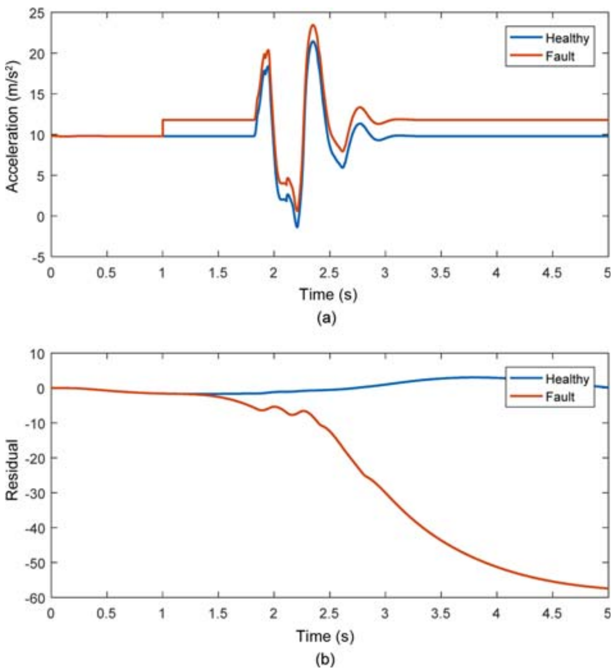

Figure 9. Speed-bump simulation results for residual generation (bias fault): (a) Front left sprung mass acceleration; (b) Residual generated by the unknown input residual generator.

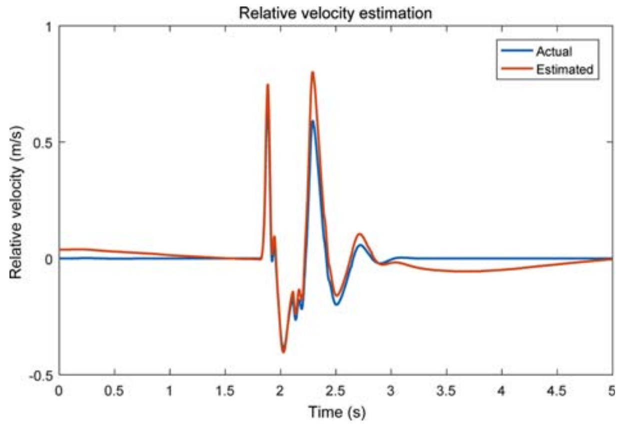

Figure 10. Speed-bump simulation results for the relative velocity estimation: Front left suspension relative velocity.

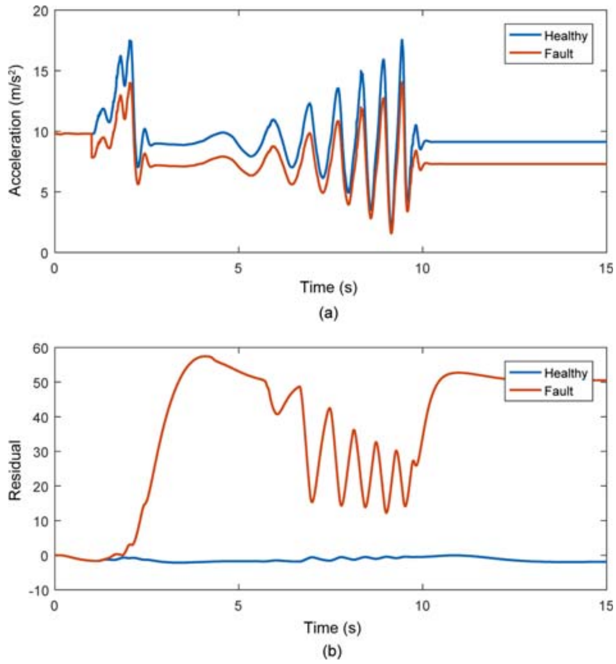

Figure 11. Wavy uphill road simulation results for residual generation (gain fault): (a) Front left sprung mass acceleration; (b) Residual generated by the unknown input residual generator.

5.2.3. Wavy uphill road simulation

The quarter-car model used in this paper does not take into account the gravity read by the vertical accelerometer. However, since the sensor attached to the vehicle measures vertical acceleration while accounting for gravity, when the road surface is inclined, the sensor signal has bias due to gravity. Therefore, when designing a fault diagnosis algorithm using an accelerometer, it is necessary to consider the diagnostic performance on the inclined road surface where bias of the sensor signal due to gravity arises. According to the Figures 11 and 12, it can be confirmed that the unknown-input-observer-based residual generator shows robust performance even when not considering gravity in the quarter-car model.

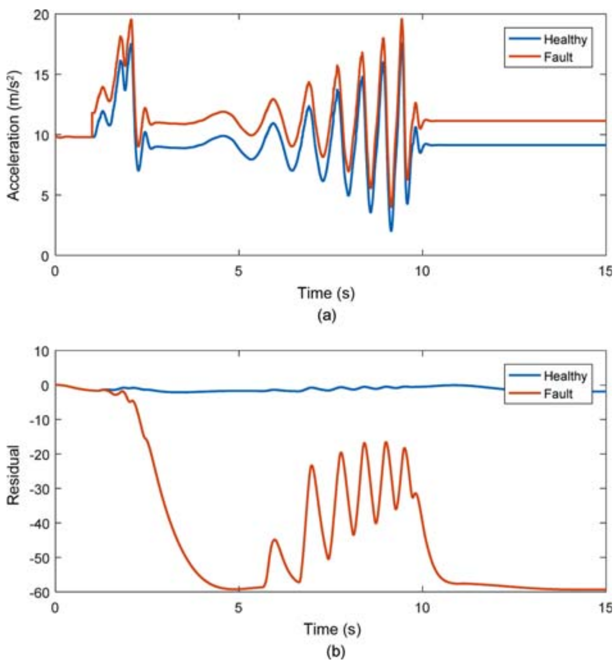

Figure 12. Wavy uphill road simulation results for residual generation (bias fault): (a) Front left sprung mass acceleration; (b) Residual generated by the unknown input residual generator.

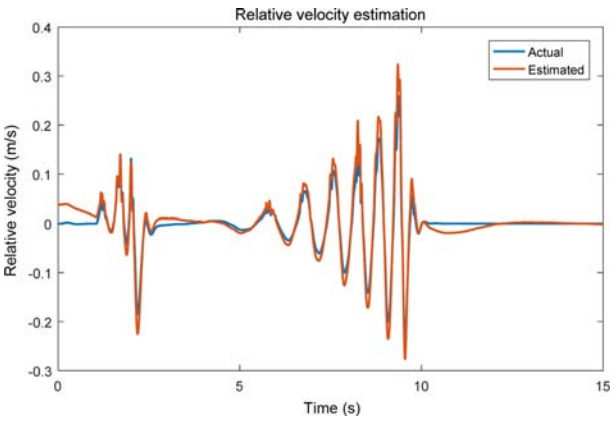

Figure 13. Wavy uphill road simulation results for the relative velocity estimation: Front left suspension relative velocity.

5.3. Residual Evaluation Results

In this paper, it is proposed to evaluate residual generated by model-based fault diagnosis algorithm by statistical method using SVM. Therefore, this section presents and discusses the residual evaluation results using the SVM classifier. To construct the SVM classifier, sensor signals and residual are collected using various simulations that describe the driving environment of the vehicle. Table specifies various scenarios for collecting data to be used for SVM classifier learning.

In order to verify the performance of the residual evaluation method using the SVM, five-cross validation and the $F_{0.5}$-Measure are used. In general, a fault diagnosis algorithm should be designed to minimize the number of false-positive errors, i.e., the detection of a fault in the absence of an actual fault. In other words, the $F_{0.5}$-Measure can be used more effectively in performance evaluations of fault diagnosis algorithms since it emphasizes precision in the representation of the ratio of the false-positive error. In this paper, various types of SVM classifiers are constructed and tested using the Matlab quadratic programming solver.

Table 3. Simulations for data collection.

Simulation	Driving environment	Number of data
1	Speed bump	30
2	Half bump	30
3	Hill, bank and curve	294
4	Wavy road	110
5	Hill and wavy road	110
6	Cross sign road	110
7	Hill and cross sign road	110
8	Sinusoidal road #1	390
9	Sinusoidal road #2	390
10	Sinusoidal road #3	390
11	Long straight road	2134

Table 4. SVM classifier performance outcomes.

Kernel function	Kernel scale	$F_{0.5}$-Measure
Linear	-	0.9958
Quadratic	-	0.9969
Gaussian RBF	9.8	0.9937
Gaussian RBF	2.4	0.9940
Gaussian RBF	0.61	0.9768

Table 4 shows the classification results using the SVM classifier with various kernel functions. According to the table, the SVM classifier using the residuals achieves high accuracy. However, the classification performance deteriorates as the kernel scale of the Gaussian RBF function is reduced and the complexity of the SVM model is increased. This occurs since data over-fitting arises as the complexity of the model increases. As a result of checking the error cases, it is confirmed that most of the errors are false-negative errors. In addition, it is confirmed that a false-negative error is caused by the residual response delay due to the residual preprocessing. Hence, the decision boundary generated using the SVM classifier acts as a threshold of the residuals. In addition, according to the principle of Occam's razor, it can be concluded that the SVM classifier with a simple structure such as a linear or quadratic SVM is better suited for decision making using a residual than other SVM classifiers.

6. CONCLUSION

In this paper, a model-based residual generation method and a support-vector-machine-based decision making process are proposed for vehicle suspension sensor fault diagnoses. First, an unknown input residual generator is designed for a vehicle suspension system, which is described as a bilinear system. Next, the SVM classifier is used to evaluate the generated residuals. This paper also validates the performance of the unknown input residual generator and SVM classifier using the commercial vehicle simulator Carsim. As a result, it is confirmed that a robust residual signal can be obtained by the unknown input residual generator regardless of the road surface or the model uncertainty. Consequently, the fault sensitivity and robustness of diagnostic algorithms can be improved relative to existing algorithm such as the limit checking method. In addition, the SVM classifier is used to evaluate a residual generated by a model-based method. With the use of a performance measure, it could be confirmed that the SVM classifier with an uncomplicated structure achieves excellent performance. As a result of using the performance measure, in this case the F-measure, it could be confirmed that the SVM classifier with an uncomplicated structure achieves excellent performance. Since the SVM classifier replaces the heuristically tuned residual threshold, it becomes possible to reduce the effort required to design fault diagnosis algorithms. In conclusion, the proposed fault diagnosis algorithm can be used to detect sensor faults robustly in vehicle suspension systems. The proposed fault diagnosis algorithm has a limitation that there is a performance deviation depending on the configuration of the residual data set used for learning. In this paper, the data set is collected based on simulations. However, if the proposed fault diagnosis method is applied to an actual vehicle, actual vehicle test data have to be collected in various scenarios.

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