

Interval Fuzzy Modeling Applied to Model Based Fault Detection of an Active Suspension System

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Abstract: This paper presented an investigation on fault detection of an active suspension system using interval fuzzy modeling. A well known nonlinear classical controller called back-stepping method is used to simulate dynamic response of a half-car suspension system. Confidence bands for the system input-outputs data is approximated using an interval fuzzy model. Then Fault detection has been done by the use of these confidence bands. Simulation results depict that the proposed fault detection is highly effective in evaluating the performance of an active suspension system.

Keywords: Active Suspension System; Fault Detection; Interval Fuzzy modeling.

I. INTRODUCTION

The interval fuzzy model identification is a methodology for approximating the functions of a finite set of input and output measurements. This approach can also be used to compress information in the case of a nonlinear function family approximation to obtain the interval of parameters that results in a band containing the whole set of measurements [4-6]. Interval fuzzy model also has been used for detecting faults of nonlinear input-output systems with unstructured uncertainties or interval type parameters [7-9].

The residual signal formation and evaluating of it, is a very important part of a fault detection procedure. The major advantage of using interval fuzzy model is, easier generation of residual signal than other methods.

This study tries to use Interval fuzzy model for evaluating the performance of active suspension system. A suspension system is one of the important components of a vehicle which plays a crucial role in handling ride convenience and safety of a vehicle. There are three types of suspension: passive suspension, active suspension and semi-active suspension. An active suspension system is specified by employing some types of suspension force generation such as pneumatic, electromagnetic or hydraulic actuators. Interests are significantly growing on designing and controlling of active suspension systems for automobiles in the past three decades. Most of the researches have been done till now, focused on designing a controller for a passive system to improve the driving characteristics of an automobile or simply changing

passive systems to active ones. Just a few amounts of recent published papers have also chosen more complex models in order to more precise results, Such as the half-car model with four degree of freedom using various types of controllers as linear and fuzzy logic controllers and also the classical back stepping scheme. Complete modeling of active suspension systems using simulation tools and software has also been done. Identification of active suspension systems have been performed in many cases for specific purposes by the use of various approaches as a basis for controller design and for model based fault detection on a quarter-car model [2,6].

The paper is organized as follows. Firstly, the model of a half-car suspension system is introduced. Then a nonlinear back-stepping controller applied on it. Furthermore the interval fuzzy model of a half-car suspension system is presented after derivation of an interval fuzzy model. Finally residual formation with a fault-diagnostic scenario is described with some concluding remarks.

II. SUSPENSION MODEL, DYNAMICS AND SIMULATION

The model of a half-car suspension system is shown in Figure 1[6]. The model is excited by road surface bump.

The displacements of the sprung mass (car body) for front and rear bodies are given by

Front Body

$$Z_{sf} = Z - a \sin \theta \approx Z - a\theta \quad (1)$$

Rear Body

$$Z_{sr} = Z + b \sin \theta \approx Z + b\theta \quad (2)$$

where Z_{sf} is the front body displacement, Z_{sr} is the rear body displacement, a is the longitudinal distance between front axle and centre of gravity, b is the longitudinal distance between rear axle and centre of gravity, θ is the stroke angel and Z is the displacement of centre of gravity.

$$y = \beta^T(x_p)\Theta x \quad (14)$$

where

$$\alpha = \frac{1}{m_s} + \frac{a^2}{J_y}, \beta = \frac{1}{m_s} - \frac{ab}{J_y}, \gamma = \frac{1}{m_s} + \frac{b^2}{J_y}$$

$z_1, z_2, z_3, z_4, \mu_2, \mu_4$ are nonlinear parameters and functions which are obtained through controller procedure design and certainly affect our simulations; But their equations have not been represented here again. Figure 2 illustrates the effect of controller on the front body mass displacement.

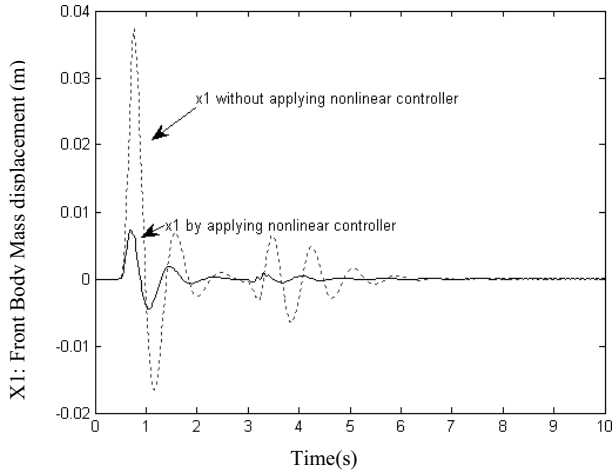


Figure 2: the effect of controller on the front body mass displacement

Z_{rf} And Z_{rr} are the road excitations that have been chosen as

$$z_{rf}(t) = \mu_r(1 - rand(1)) \quad , \quad 0.5 \leq t \leq 0.75 \quad (11)$$

$$z_{rr}(t) = \mu_r(1 - rand(1)) \quad , \quad 3 \leq t \leq 3.25 \quad (12)$$

where μ_r is amplitude defining the bump height here set to $\mu_r = 0.025$ for a bump height of 5cm. The parameters of the half-car model selected for this study are taken from [1].

III. MODELING AND FAULT DETECTION OF THE HALF-CAR MODEL WITH INTERVAL FUZZY MODEL

In this section after derivation of an interval fuzzy model interval fuzzy model of a half-car suspension system has been presented.

A. Derivation of an interval fuzzy model

A typical fuzzy TS-type model in affine form can be supposed as a set of rules.

$$R_j: \text{If } x_p = A_j, \text{ then } y = \theta_j^T x, \quad j=1 \dots n \quad (13)$$

The variable $x_p = u$ is the model input and y is the model output and θ_j is a vector of fuzzy parameters, respectively. The consequent vector is denoted $x^T = [u, 1]$. Unity is added to the vector for describing the output functions in affine form. Equation (13) can be rewritten as following.

$\beta^T(x_p) = [\beta_1(x_p), \beta_2(x_p), \dots, \beta_m(x_p)]$ is a vector of normalized membership functions. Matrix of the coefficients for the whole set of rules is $\Theta^T = [\theta_1, \theta_2, \dots, \theta_m]$.

Now, we want to find upper and lower boundary functions that satisfy following conditions for any arbitrary $\varepsilon > 0$ and for each $z = [x_p \ x^T]^T$.

$$\bar{g}(Z) \geq \text{Max } g(z), \exists g \in \mathcal{G} : \bar{g}(z) < g(z) + \varepsilon \quad (15)$$

$$\underline{g}(Z) \geq \text{Min } g(z), \exists g \in \mathcal{G} : \underline{g}(z) > g(z) + \varepsilon \quad (16)$$

In the above equations, it has been let that $C \subset R^{n+2}$ is a compact set and $\mathcal{G} = \{g: C \rightarrow R\}$ is a class of nonlinear functions. Finding bounds in (15) and (16) requires masses data; therefore it is impossible to find exact bounds because only finite amount of data is available.

For solving this problem Stone-Weierstrass theorem has been used. This theorem says that, for any real continuous function g , on a compact set $C \subset R^d$ and arbitrary $\varepsilon > 0$, there exist a fuzzy system f , such that [7-9]

$$\sup |f(z_i) - g(z_i)|_{z_i \in Z} < \varepsilon \quad \forall i \quad (17)$$

By Stone-Weierstrass extension theorem the following equations will be obtained.

$$0 < \bar{f}(z_i) - g(z_i) < \varepsilon \quad \forall i \quad (18)$$

$$-\varepsilon < \underline{f}(z_i) - g(z_i) < 0 \quad \forall i \quad (19)$$

The defined band should be as narrow as possible. The upper and the lower fuzzy functions can be found by solving the following optimization problems, respectively. Both problems can be known as linear programming problems.

$$\min_{\Theta} \max_{z_i \in Z} |y_i - \underline{f}(z_i)| \quad \text{s.t.} \quad y_i - \underline{f}(z_i) \geq 0 \quad (20)$$

$$\min_{\Theta} \max_{z_i \in Z} |y_i - \bar{f}(z_i)| \quad \text{s.t.} \quad y_i - \bar{f}(z_i) \geq 0 \quad (21)$$

$\underline{f}(z_i) = \beta^T(x_p)\underline{\Theta}x$ and $\bar{f}(z_i) = \beta^T(x_p)\bar{\Theta}x$ in (20), (21). Required data are obtained by sampling different functions from $\mathcal{G}$ with arbitrary values of z_i .

B. Interval fuzzy model of half-car suspension system

In this section interval fuzzy model has been used for identification and modeling of half car suspension system. As mentioned before, this method is used for functions of a finite set of input and output measurements or systems with interval parameters on the other hand there is a class of functions for description of one system.

It is assumed that parameters' uncertainty of the half-car suspension is 1%. On the other word it is assumed 1% perturbation of nominal value of parameters is acceptable. It's the key idea for using interval fuzzy model for identification of the purposed system. Therefore new model for active suspension system with uncertain parameter will be obtained.

This new model is used to produce the data set for identification of the interval fuzzy model. Responses of the system were studied by 80 different simulations. In each iteration the input signal remained fixed where as uncertain parameters' value changed. The input vector includes Z_{rf} and Z_{rr} . Training of the model has achieved by first 60 simulations and 20 iteration used for validation.

All of the eight state variables of the half-car suspension system have been identified with 8 multi input-Single output interval fuzzy models (INFUMO). Main system and its nonlinear controller consider as a single system. Thus the resultant system is nonlinear. The results of these identifications for two state variables are presented in figures 4 and 5.

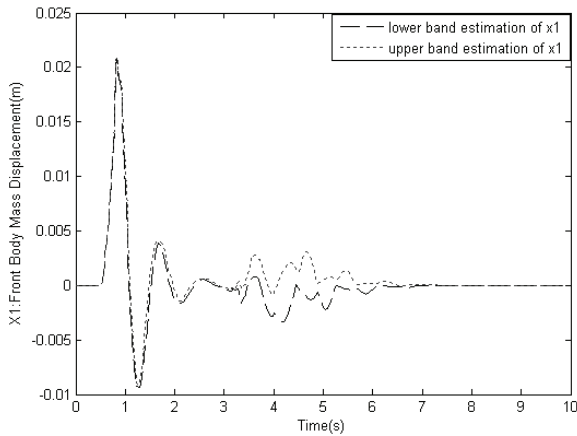


Figure 3: identification of the front body mass displacement with interval fuzzy model

Identified bounds have been used for fault detection of purposed system. Using resultant Interval fuzzy models residual signal could be obtained.

The benefit of this method is that confidence bands for output signals could be obtained easily, and these bands could be used for generating residual signal. The residual signal could be defined in the following way [7-9]:

$$\text{if } y_{out} < \hat{y}, re(y_{out}) = \frac{y_{out} - \hat{y}}{\hat{y} - \hat{y}} \quad (22)$$

$$\text{if } y_{out} > \hat{y}, re(y_{out}) = \frac{y_{out} - \hat{y}}{\hat{y} - \hat{y}} \quad (23)$$

$$\hat{y} = \frac{\bar{\hat{y}} + \hat{y}}{2} \quad (24)$$

The residual signal in (22), (23) is zero when the output is equal to $\hat{y}$ and approaches the value 1 if the measurement output is close to one of the interval bounds.

C. Fault detection

Different fault detection methods have been applied to passive, semi-active, and active suspension systems till now. Fault detection of front and rear damper and springs were not possible in Karami et.al [6] model at all whereas it has been done in this research. As mentioned in the previous section, in

this case study, it has been supposed that 1% perturbation of nominal parameters' values is acceptable.

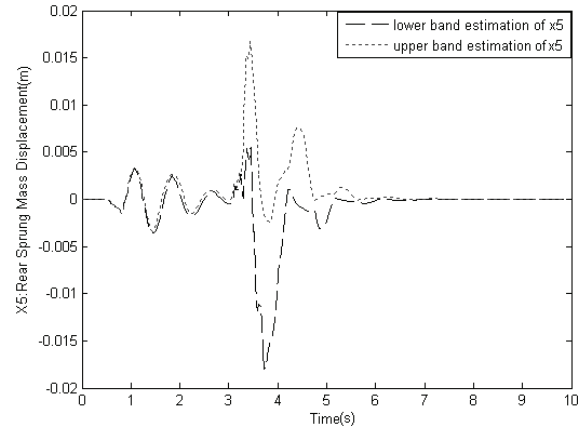


Figure 4: identification of the rear sprung mass displacement with interval fuzzy model

Figure 6 shows the fault detection scheme that has been used in this paper. Each of the state variables of the half-car suspension system assumed to be an output of the system.

In the previous section for each of the state variables an INFUMO has been found. Interval fuzzy models have been put in the parallel position with the main system.

It is possible to use only one INFUMO however eight INFUMOs are used for more accurate fault detection. Residual signals enter the alarm signal blocks, if the value of residual signals are more than unity output of the alarm signal blocks become one otherwise it will be zero.

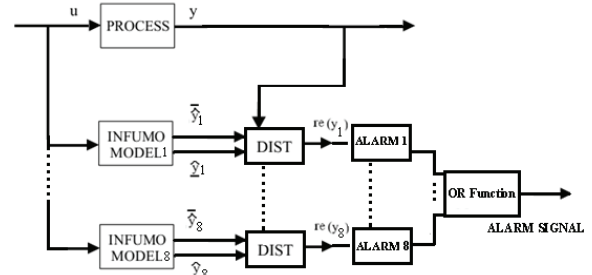


Figure 5: Fault detection using INFUMO model

The last alarm signal is logical OR of eight outputs of the alarm signal blocks. Therefore, if all outputs of system belong to the corresponding identified bounds the performance of the system is correct; otherwise a fault occurred in the system.

10% and 20% fault have been applied on different rear and front component of half-car suspension system. The time of simulation is ten seconds. Since faults have been applied on the system before starting simulation, the alarm signal value expected to be unity during whole time of simulation.

Results are shown in figs 6 to 11. Figure 6 shows an instance of residual signal and its corresponding alarm signal these signals are obtained when 20% fault occurred on the rear damper. Figs 7 to 11 are the main alarm signals that show the occurrence of fault in the different component of the half-car suspension system. Totally these figures reveal that

particularly for up to 20% applied fault, there is a good agreement with the expected result of the problem. Although for 20% fault better results have been obtained, this method can be used for detecting 10% fault that occurred on system's rear and front dampers and springs. The results have been briefly presented in the table 1.

Finally, 30% abrupt fault has been applied on sensor1 at $t=4s$. The result has been shown in fig11. This figure shows that by this method it is possible to detect the time of occurrence of fault.

TABLE I. RESULT OF FAULT DETECTION FOR DIFFERENT COMPONENT OF HALF-CAR SUSPENSION SYSTEM

Fault	B_r	B_f	K_r	K_f
20% fault	Well	Well	Well	Well
10% fault	Well	Well	Not bad	Not bad

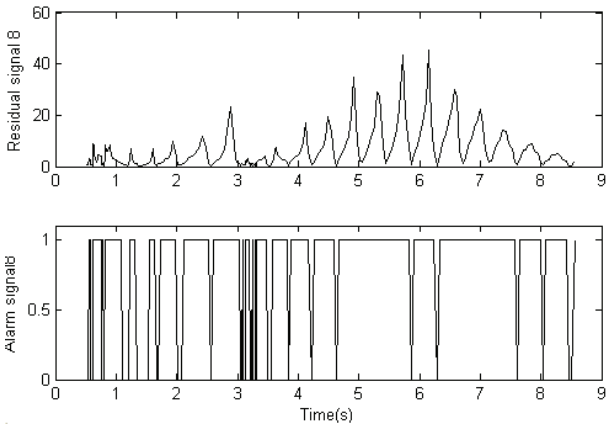


Figure 6: a. shows residual signal when 20% fault occurred on Br. b. shows alarm signal when 20% fault occurred on Br

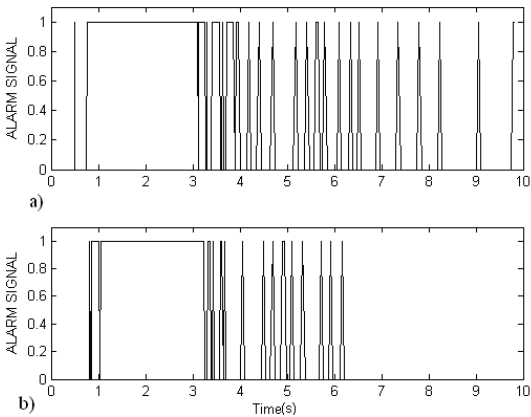


Figure 7: a. shows alarm signal when 20% fault occurred on Kf. b. shows alarm signal when 10% fault occurred on Kf

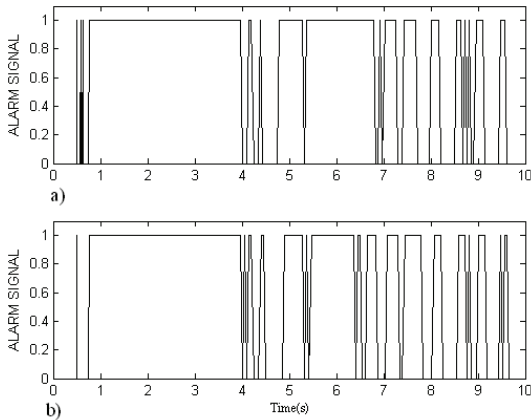


Figure 8: a. shows alarm signal when 20% fault occurred on Bf. b. shows alarm signal when 10% fault occurred on Bf

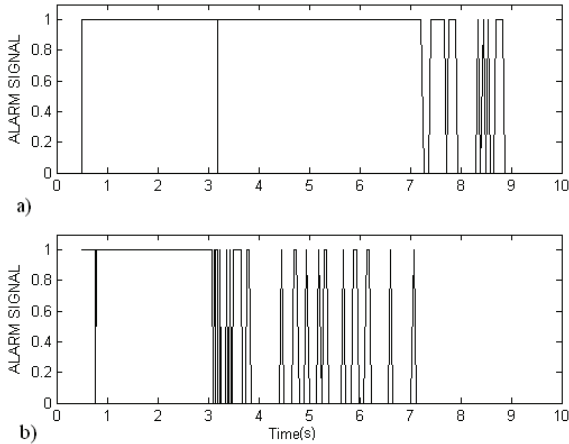


Figure 9: a. shows alarm signal when 20% fault occurred on Kr. b. shows alarm signal when 10% fault occurred on Kr

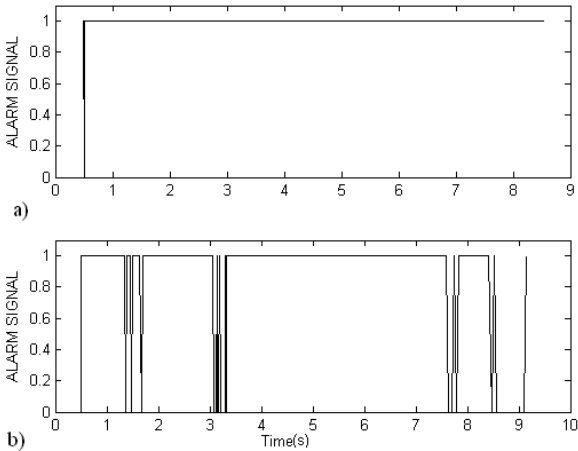


Figure 10: a. shows alarm signal when 20% fault occurred on Br. b. shows alarm signal when 10% fault occurred on Br

IV. CONCLUSION

An application of interval fuzzy model for fault detection of an active suspension system is introduced in this paper. Interval fuzzy model was applied for residual signal generation. Introduced approach has been employed in fault detection for a class of the processes with interval-type parameters or for a nonlinear system with uncertain parameters. In this paper uncertainty was added to the active suspension system. Therefore, the novelty of this paper is applying interval fuzzy model for fault detection of half-car suspension system that hasn't uncertain parameters.

Simulation results have shown that proposed method could be an effective tool for fault detection of active sustention system. This method was able to detect 20% fault very well and also it has good result for 10% fault. Furthermore this method can be used for on-line application too.

For more accurate fault detection, finding more narrow confidence bands for state variables is suggested. In this work it is assumed 1% uncertainty exists in the parameters value. If less uncertainty to be assumed for parameters value, more narrow bands can be obtained.

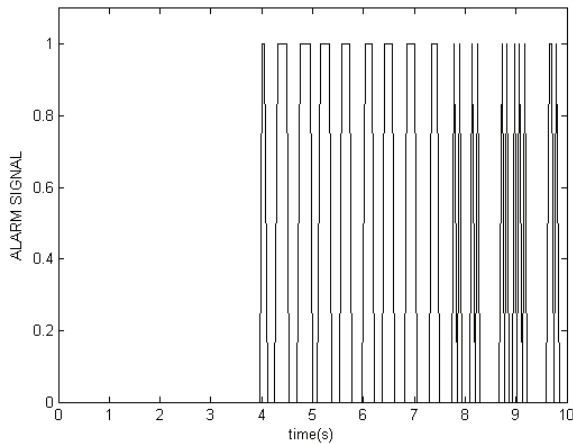


Figure 11: alarm signal when 30% fault occurred on sensor1 (output1) at t=4s

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