PRACTICAL IMPLEMENTATION OF SKYHOOK AND ADAPTIVE ACTIVE FORCE CONTROL TO AN AUTOMOTIVE SUSPENSION SYSTEM

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Abstract

The paper focuses on the practical implementation of a new robust control method to an automotive active suspension system using skyhook and adaptive active force control (SANAFC) strategy. The overall control system essentially comprises four feedback control loops to cater for a number of specific taks. Neural networks (NN) with modified adaptive Levenberg-Marquardt (LM) learning algorithms were used to approximate the estimated mass and inverse dynamics of the pneumatic actuator in the AFC loop. A number of experiments were carried out on a physical test rig with hardware-in-the-loop feature that fully incorporates the theoretical elements. The performance of the proposed control method was evaluated and benchmarked to examine the effectiveness of the system in suppressing the vibration effect of the suspension system. It was found that the experimental results demonstrate the superiority of the active suspension system with SANAFC scheme compared to the proportional-integhral-derivative (PID) and passive counterparts.

Keywords: Skyhook, Active Force Control, Automotive Suspension

1 Introduction

It is deemed necessary and useful to isolate disturbance elements that are prevalent in many mechanical systems. A clear example can be seen in an automotive system in which the passenger/s of a car should ideally be isolated from vibration or 'shaking' effects of the car's body when the car hits a bump or hole. In conventional passive suspension system, the mass-spring-damper elements are generally fixed, and are chosen based on the design requirements of the vehicles. Passive suspension utilizing mechanical springs and dampers is known to have the limitations of vibration isolation and lack of attitude control of the vehicle body.

In any vehicle suspension system, there are a number of performance parameters that need to be optimized. Four important parameters of considerable interest are: (i) ride comfort which is related to acceleration sensed by passengers in the vehicle when traversing a rough road surface, (ii) body motion which is associated with the pitch and roll of the sprung mass created primarily by cornering and braking maneuvers, (iii) road handling which can be related to the contact force between the tyres and road surface, and (iv) suspension deflection which refers to the relative displacement between the sprung and unsprung masses [1].

To solve the problems in suspension systems, many researchers have studied numerous active vehicle suspension strategies both theoretically and experimentally [2-6]. Many of these approaches are proposed for complicated models with non-linearity and uncertainty. Numerical and experimental results showed that such active suspension systems give relatively more satisfactory performance, but at the expense of increasing more loads to achieve active control, compared with the linear active suspension systems as reported in [7]. Intelligent control of suspension system was also proposed using fuzzy logic [8] and neural network [9]. Both methods use the intelligent mechanisms as direct or main controllers and are found to be rather time consuming to design and implement, particularly in acquiring the appropriate membership functions plus inference mechanism (for fuzzy logic control) and training parameters plus optimum network structure (for neural network control).

On the other hand, active force control (AFC) has been recognized to be simple, robust and effective compared with conventional methods in controlling dynamical systems, both in theory as well as practice [10,11]. The concept of AFC is to use some measured and estimated values of the identified system parameters namely the actuated force, acceleration of the body and estimated mass of the body. In practice, the estimated mass of the system (with the presence of disturbances that contributes to the acceleration) should be appropriately estimated using suitable methods such as the ones identified in [11]. In the proposed study, an intelligent mechanism using neural network is incorporated into the AFC loop serving not as the direct controller but merely as a means to approximate the essential parameters necessary to trigger the control action.

The objective of this paper is to design a practical hardware-in-the-loop control technique to reduce the sprung mass motion of a quarter car vehicle active suspension system with the proposed control and intelligent methods. The overall control system comprises four loops: the innermost force tracking control loop employing a classic PI controller for force tracking control of the pneumatic actuator; two intermediate control loops with skyhook and AFC to compensate for the disturbances containing the adaptive neural networks to compute on-line the estimated mass needed and the inverse dynamics of the actuator; and the outer positional control loop utilizing a PID controller to generate the target or commanded force. Performance of the vehicle suspension system is evaluated in terms of its ability to significantly reduce the sprung mass acceleration, sprung mass displacement, suspension deflection and tyre deflection in the presence of road disturbances and given operating conditions.

This paper is organized as follows. The design and underlying principles of the proposed control system is described in section 2. The experimental system is presented in section 3 while the results are analysed and discussed in section 4. Finally, the paper is concluded in section 5.

2. Design of the Control System

In this section, all the major elements constituting the design and underlying principles of the overall control system are described and presented.

2.1 Force Tracking Control Loop

The force tracking control of the actuator was first designed. The majority of the existing literatures assume that the command force can be achieved accurately and frequently done without considering the actuator dynamics which are highly nonlinear. When a less ability actuator is used, the design of the sub-loop needs to be carried out first in order to ensure force tracking ability of the actuator using a conventional PI controller [12]. The validation of the force tracking capability was done by considering sinusoidal, square wave, chirp signal and saw tooth as the input forcing functions.

In order to get appropriate values of P and I constants, *Ziegler-Nichols* formulation was used. The typical transfer function of a PID controller is given as follows:

$$G_{PID} = K_p\left(1 + \frac{1}{T_i s} + T_d s\right) \tag{1}$$

where $T_i = K_p/K_i$, $T_d = K_d/K_p$, and K_p, K_i, K_d are proportional, integral, derivative gains, respectively.

2.2 Active Force Control

AFC is first proposed by Hewit and Burdess (1981) and has been applied effectively to a number of dynamical systems [10,11,14] as a two-degree-of freedom (DOF) robust acceleration feedback controller. The compensation action of AFC involves direct measurement or estimation of a number of identified parameters. Hence, a large portion of mathematical and computational burden can be reduced significantly. AFC can be shown to complement the basic Newton's second law of motion, i.e. for a translational and rotational system. For an active vehicle suspension the equation of motion can be written as follows [14]:

$$F + Q = m_s a \tag{2}$$

where F is the applied force, Q is disturbance force, m_s is sprung mass and a is acceleration of the sprung mass, respectively. The estimated value of the disturbance force, Q', can be formulated as:

$$Q' = F' - (m_s' a') \tag{3}$$

where the superscript (′) denotes the measured or estimated values of the parameters. Specifically, F' is the measured force through the use of a force sensor (load cell), a' is the measured acceleration using accelerometer and m_s' the estimated mass that can be approximated by a number of methods described as in [11]. If the measured and estimated quantities are appropriately acquired, then a robust and stable response should be achieved.

2.3 Skyhook Control

The skyhook control introduced by Karnopp in 1995 is known as most effective in terms of the simplicity of the control algorithm. The original work uses only one inertia damper between the sprung mass and an inertial frame. The damper is connected to an inertial reference in the sky. This arrangement is fictitious, since to implement this configuration, the damper would have to be connected to a reference point which is fixed with respect to the vehicle. The fictitious force computed from the added skyhook damper is called as the actuator force (F_{sky}). The force F_{sky} of this element according to the skyhook control law is [15]:

$$F_{sky} = \begin{cases} -B_{sky}\dot{z}_s & ,\text{if } \dot{z}_s(\dot{z}_s - \dot{z}_u) \geq 0 \\ 0 & ,\text{if } \dot{z}_s(\dot{z}_s - \dot{z}_u) < 0 \end{cases} \quad (4)$$

where B_{sky} is a constant value determined to be approximately 3000 N/m/s in the experimental system.

2.4 Outermost PID Control Loop

The description of the PID controller is similar to that described in section 2.1, and the resulting controller gains were computed as K_p = 35, K_i = 1.9 and K_d = 360.

2.5 Incorporation of Neural Network

NN has been potentially used in intelligent control system because it can learn, adapt, and approximate nonlinear functions very well. The feed-forward NN structure in this study employed a single hidden layer network with three hidden neurons that resemble the one described in [16]. Sigmoid bipolar function is chosen for the hidden layer and linear function for the output layer. All parameters of the model were normalized in the range (-1,1) representing the minimum and maximum range of the parameter values. Error between the outputs of the plant and network is used as the learning signal for NN to obtain the appropriate weights and biases. The learning algorithm which is based on minimizing the error (mean square error) can be given as follows:

$$e^2(k) = (y_d(k) - y_a(k))^T (y_d(k) - y_a(k)) \quad (5)$$

where e is current error, y_d is desired output, y_a is current output at iteration-k.

To minimize the error with respect to the weights, the equations governing the updating of the weights of each layer using LM method can be represented as follows [17]:

$$w_{ij}(k+1) = w_{ij}(k) + \Delta w_{ij}(k) \quad (6)$$

$$\Delta w_{ij}(k) = \left[J^T(w_{ij}(k))J(w_{ij}(k)) + \mu I\right]^{-1} J(w_{ij}(k))e(w_{ij}(k)) \quad (7)$$

where $w_{i,j}$ is weight, J is Jacobian matrix, μ is learning rate and I is identity matrix.

There are two identical neural networks (in terms of structure and topology) with LM algorithms used in the AFC loop. Each neural network has one hidden layer with three associative neurons and each neuron uses sigmoid bipolar function. The first network, NN1 computes the estimated mass, while the second one, NN2 calculates the inverse dynamics of the pneumatic actuator. Both the estimated mass and inverse dynamics of the actuator have to be ascertained to effect the compensation of disturbances in the AFC loop. The input of NN1 is the sprung mass acceleration while the output of the network is the estimated mass. For NN2, its input is the force signal from the pneumatic actuator while its corresponding the output is the command signal prior to the summing junction of the AFC loop. Minimizing both NN1 and NN2 errors is applied for updating the weights and biases using the adaptive LM learning algorithms.

2.6 Proposed SANAFC scheme

Having shown all the individual elements of the control and intelligent techniques, the complete SANAFC scheme can be seen in Figure 1. Although the system looks complex, the actual implementation can be easily realized through simulation and experimental study with the aid of MATLAB and its related components through Simulink, Control System Toolbox, Neural Network Toolbox and Real-Time Workshop (RTW).

3. Experimental System

This section presents the practical aspect of the suspension system that employs the proposed control technique. A schematic of the experimental set-up and a photograph of the actual rig are given in Figure 2. The relevant parameters of the vehicle active suspension system are presented in Table 1.

4. Results and Discussion

4.1 Force tracking control

The experimental results of the force tracking control are shown in Figure 3 which clearly shows that the actual trajectories are capable in tracking the desired ones. This signifies that the appropriate controller setting enables the pneumatic actuator to operate satisfactorily.

4.2 Experimental results

In this section, the benefits of active suspension using skyhook adaptive neuro AFC (SANAFC) over passive suspension and active suspension using PID controller for a sinusoidal road input frequency 1.5 Hz, amplitude 3.5 cm are investigated both through simulation as well as experimental studies. The results can be seen in Figure 4.

From Figure 4, the amplitudes of sprung mass acceleration, sprung mass displacement and suspension deflection for active suspension based on SANAFC scheme show much better results compared with the PID controller and passive suspension counterparts.

5. Conclusion

A novel controller employing the skyhook adaptive neuro active force control (SANAFC) has been designed and practically implemented for the control of a vehicle quarter car active suspension. From the experimental results, it can be deduced that the active suspension based on SANAFC controller outperforms the PID controller and passive suspension in all selected performance criteria. Future works may include more effort in improving the tyre deflection performance and considering other operating and loading conditions.

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7. References

[1] Miller, L.R. “Tuning passive, semi active, and fully active suspension”, *Proceedings of the 27th Conference on Decision and Control*, Austin, Texas, 7-9 December, vol. 3, 1988, pp. 2047-2053.

[2] Alleyne, A. and Hedrick, J.K., “'Nonlinear adaptive control of active suspension”, *IEEE Trans. on Control System Technology*, vol. 3(1), 1995, pp. 94-101.

[3] Lin, J.S. and Kenellakopoulos, I., “Nonlinear design of active suspensions”, *Control Systems Magazine*, vol. 17(3), 1997, pp. 45-59.

[4] Ikenaga, S.A., Lewis, F.L., Davis, L., Kampos, J., Evans, M. and Scully, S., “Active suspension control using a novel strut and active filtered feedback: design and implementation”, *Procs. of IEEE International Conference on Control Applications*, Hawaii, USA, 1999, pp. 1502-1508.

[5] Yoshimura, T., Kume, A., Kurimoto, M. and Hino, J., “Construction of an active suspension system of a quarter car model using the concept of sliding mode control”, *Journal of Sound and Vibration*, 239(2), 2001, pp. 187-199.

[6] Huang, S.J. and Lin, W.C., “A self organizing fuzzy controller for an active suspension system’, *Journal of Vibration and Control*, vol. 9(9), 2003, pp. 1023-1040.

[7] Yoshimura T. and Takagi A., “Pneumatic active suspension system for a one-wheel car model using fuzzy reasoning and a disturbance observer”, *Journal of Zhejiang University SCIENCE*, vol. 5(9), 2004, pp. 1060-1068.

[8] D’Amato, F.J. and Viassolo, D.E., “Fuzzy Control for Active Suspensions”, *Mechatronics*, vol. 10, 2000, pp. 897-920.

[9] Fu, L.J., Cao, J.G., Liao, C.R. and Chen, B., “Study on Neural Networks Control Algorithms for Automotive Adaptive Suspension Systems”, *Procs. of International Conference on Neural Networks and Brain 2005*, vol. 3, 2005, pp. 1795-1799.

[10] Hewit, J.R. and Burdess, J.R., “An active method for the control of mechanical systems in the presence of unmeasurable forcing”, *Trans. on Mechanisms and Machines Theory*, 21(3), 1986, pp. 393-400.

[11] Mailah, M., “Intelligent active force control of a rigid robot arm using neural network and iterative learning algorithms”, University of Dundee, *Ph.D. Thesis*, 1998.

[12] Chantranuwathana, S. and Peng, H., “Force tracking control for active suspensions - theory and experiments”, *Proceedings of the IEEE International*

Conference on Control Applications, 22-27 August, Hawaii, USA, vol. 1, 1999, pp. 442–447.

[13] Astrom, K.J. and Hagglund, T., "Automatic tuning of simple regulators with specification on phase and amplitude margin", *Automatica*, vol. 20, 1984, pp. 645–651.

[14] Hewit, J.R. and Marouf, K.B., "Practical control enhancement via mechatronics design", *IEEE Transactions on Industrial Electronics*, vol. 43(1), 1996, pp. 16-22.

[15] Valásek, M. and Kortüm, W., *Mechanical Systems Design Handbook: Modeling, Measurement, and Control*, Taylor and Francis Group, LLC, 2006.

[16] Wilamowski, B.M., Chen, Y. and Malinowski, A., "Efficient algorithm for training neural networks with one hidden layer", *Proceedings of International Joint Conference on Neural Networks*, vol. 3, 1999, pp. 1725-1728.

[17] Hagan, M.T. and Menhaj, M.B., "Training feedforward networks with the Marquardt algorithm", *IEEE Transactions on Neural Network*, vol. 5(6), 1994, pp. 989-993.

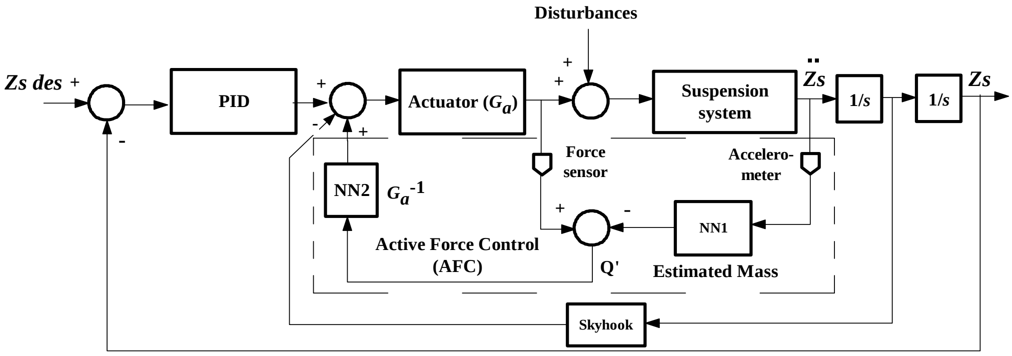
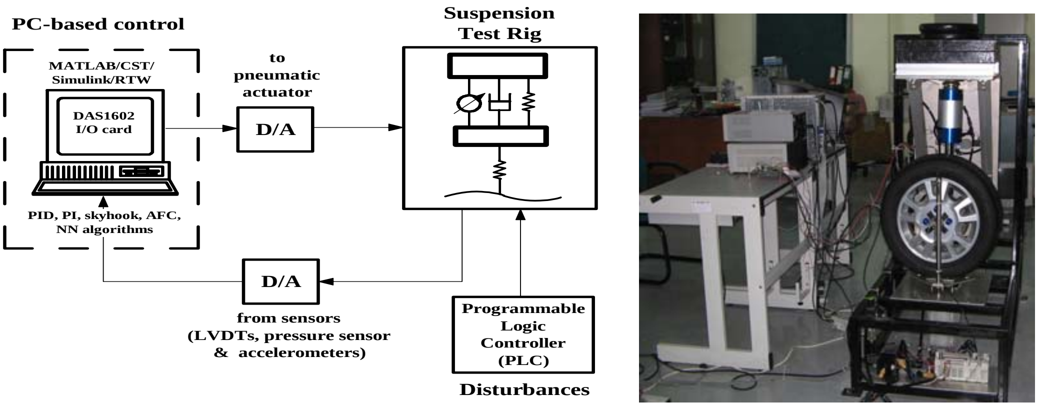


Figure 1. Proposed SANAFC control scheme



(a) (b)

Figure 2. (a) A schematic of the experimental set-up and (b) A photograph of the actual suspension system

Table 1. Vehicle suspension and pneumatic parameters

Description	Passive Suspension	Description	Pneumatic parameter
Sprung mass	180 kg	Supply pressure	$6x10^5$ N/m^2
Unsprung mass	25 kg	Atmosphere pressure	$1x10^5$ N/m^2
Suspension damping	1,000 N/msec^{-1}	Stroke length	116 mm
Suspension spring stiffness	16,000 N/m	Diameter bore	40 mm
Tyre stiffness	190,000 N/m	Ram area	0.0076 mm^2
		Gas constant	287 J/KgK
		Discharge coefficient	0.8
		Specific heat constant	1.4

		Supply temperature	$293^{o}K$

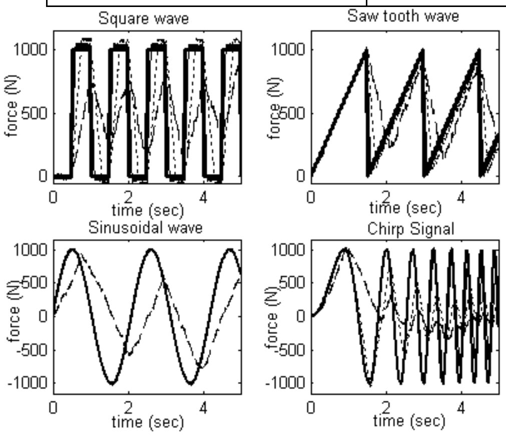


Figure 3. Force tracking control of the actuator

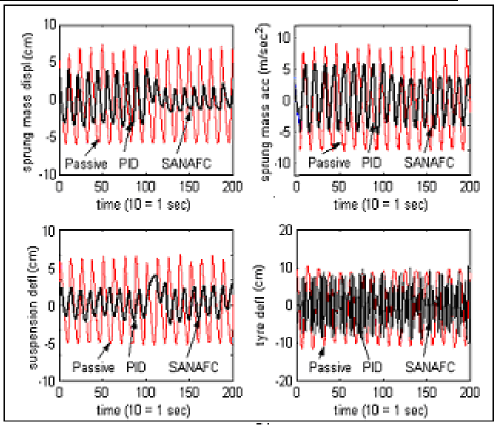


Figure 4. Active suspensions with sinusoidal excitation, 3.5 cm height, frequency = 1.5 Hz