Intelligent Estimation of System Parameters for Active Vehicle Suspension Control

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Abstract

Active control of vehicle suspension systems typically relies on linear, time-invariant, lumped-parameter dynamic models. While these models are convenient, nominally accurate, and tractable due to the abundance of linear control techniques, they neglect potentially significant nonlinearities and time-varying dynamics present in real suspension systems. One approach to improving the effectiveness of such linear control applications is to introduce time and spatially-dependent coefficients, making the model adaptable to parameter variations and unmodeled dynamics. In this paper, the authors demonstrate an intelligent parameter estimation approach, using structured artificial neural networks, to continually adapt the lumped parameters of a linear, quarter-car suspension model. Results are presented for simulated and experimental quarter-vehicle suspension system data, and clearly demonstrate the viability of this approach.

Introduction and Background

In the last 15 years there has been a great deal of literature published on applications of various control techniques for active suspensions [1]. The majority of these research contributions are theoretical in nature, and assume a linear quarter, half, or full car suspension model during the controller design process. However, the dynamics of a real suspension are inherently nonlinear and will lead to a degradation of the suspension performance in certain ranges. This is especially true of off-road vehicles, which are subject to much larger terrain disturbances and consequently greater amounts of wheel travel. In addition, the dynamic properties of a suspension system are likely to change during the vehicle's life cycle. In light of these facts, it is natural to consider the use of adaptive, nonlinear system identification techniques to provide accurate system models that can lead to improved suspension performance.

While there are many techniques available for estimating the dynamic response characteristics of linear systems using input and output data, there are considerably fewer techniques available for estimating the response of nonlinear systems [2,3]. A common approach is to assume a model form that is nonlinear, but is linear in the parameters (e.g. $\dot{x} = a_1x + a_2x^2 + a_3x^3 + \dots$). A model of this form allows for the use of least squares (or recursive least squares in the case of dynamic estimation) techniques to determine the unknown model parameters from system data [2,4,5]. A major drawback of this approach is that the structure of the nonlinearity must be assumed

before proceeding through the estimation process. This structure could be deduced from physical knowledge or experience, or it could be a “black box” architecture, such as polynomial regression or artificial neural network [6]. In the first case, an accurate physical model may be difficult to derive for complex or time-varying systems. In the second case, the system identification structure provides little or no physical insight to the system dynamics. Therefore, it may be worthwhile to consider a technique that combines the physical insight of linear, lumped-parameter modeling with the flexibility of the nonlinear “black box” approach.

This paper describes a Radial Basis Function (RBF) neural network based approach for identifying the sprung mass dynamics of a nonlinear, quarter vehicle system. The nonlinear dynamics are assumed to be caused by parameter variations that can be modeled as nonlinear functions of measurable system states. Since there may be multiple nonlinear parameters that must be estimated, separate networks are used to identify each one. This gives rise to a modular [7] or structured [8] network, where all of the subnetworks are trained simultaneously using measured input/output data that describes the dynamics of the system. The technique will first be demonstrated using data from a simulated quarter vehicle model traversing rough terrain. Next, the real world applicability of the technique is demonstrated using laboratory data from an experimental quarter vehicle test rig. Background information pertaining to the quarter-vehicle dynamic model and the experimental test rig are given below.

Quarter-Vehicle Dynamic Model

A basic system model representing one quarter of a vehicle is shown in Figure 1. The suspension model is composed of a nonlinear spring (k_s) to support the vehicle static weight, nonlinear damping (b_s), a tire model (k_t, b_t , and m_w), and sprung mass (m_b).

The state equations for this model are:

$$\begin{aligned} m_b \ddot{y}_b + b_s(\dot{\Delta}) \dot{y}_b + k_s(\Delta) y_b &= b_s(\dot{\Delta}) \dot{y}_w + k_s(\Delta) y_w \\ m_w \ddot{y}_w + (b_s(\dot{\Delta}) + b_t) \dot{y}_w + (k_s(\Delta) + k_t) y_w &= k_t y_g + b_t \dot{y}_g + b_s(\dot{\Delta}) \dot{y}_b + k_s(\Delta) y_b \end{aligned} \quad (1)$$

Equation 1.0 is a standard, fourth-order, linear dynamic system with time- and spatially-dependent parameters on the suspension stiffness and damping terms, $k_s(\Delta)$ and $b_s(\dot{\Delta})$. For system identification on actual vehicles (and the experimental test platform), no assumptions were made regarding the nonlinear variations of these parameters. However, it was anticipated that suspension stiffness would be relatively constant in the center of the range of suspension travel, and increase on the outer limits of this range due to kinematic restrictions on the wheel and linkage motions. It was also anticipated that the viscous damping coefficient would be sharply higher at near-zero velocities, due the existence of stiction and dry friction in the suspension. Such characteristics are typical of many realistic suspension dampers [9].

UT-CEM Quarter Vehicle Test Rig

This research work was conducted as part of the University of Texas Center for Electromechanics (UT-CEM) Electromechanical Suspension (EMS) program, which is developing high-bandwidth electromechanical actuators to actively control suspension forces at each wheel for high speed travel over off-road terrains [10,11,12]. Currently, UT-CEM has a single-wheel test rig in operation to test advanced EMS control algorithms. The test rig was designed to have properties comparable to a military off-road High Mobility Multi-purpose Wheeled Vehicle (HMMWV), and is shown in Figure 2. For the experimental portions of this research, data was collected from this test rig and was used to verify the utility of the intelligent system identification procedure.

Intelligent System Identification

Earlier research [2] has shown that it is possible to define a linear controller consisting of three constant gains applied to relative displacement, relative velocity, and absolute sprung mass velocity that completely specifies the sprung mass dynamics for a linear plant model. Unfortunately, most real systems do not have linear dynamics over their entire operating range. In an effort to achieve the desired dynamics, the linear controller will be implemented as part of an indirect self tuning regulator (STR) design [4,13]. As portrayed in the block diagram of Figure 3, online system identification is a key component in the design of the STR.

Structured RBF Network Architecture

Previously, a fourth-order dynamic model was presented for the suspension system shown in Figure 1. The first equation represents the sprung mass dynamics while the second equation represents the wheel dynamics. The differential equation for the wheel dynamics is not required during the controller design process [2]. Clearly, the two equations are linked by relative motion and it is not possible to change the dynamics of one without affecting the dynamics of the other. If only one of the equations is used in the design of the controller it is necessary to check the stability of the other equation at the end of the process. In general, previous simulation results have shown that it is possible to design suitable controllers that do not result in unstable wheel dynamics. Therefore, only the dynamics associated with the sprung mass will be considered in the identification process.

For estimation purposes, the differential equation for the passive sprung mass dynamics is assumed to be as follows:

$$m_b \ddot{y}_b + b_s(\dot{\Delta}) \dot{y}_b + k_s(\Delta) y_b = b_s(\dot{\Delta}) \dot{y}_w + k_s(\Delta) y_w \quad (2)$$

where $b_s(\dot{\Delta})$ and $k_s(\Delta)$ are assumed to be arbitrary nonlinear functions of measurable system data. Rearranging Equation 2 and substituting $\Delta = y_w - y_b$ leads to the following relationship:

$$\ddot{y}_b = \frac{1}{m_b} (k_s(\Delta) \cdot \Delta + b_s(\dot{\Delta}) \cdot \dot{\Delta}) \quad (3)$$

This equation denotes a straightforward input to output relationship derived using basic physics. The relative displacement, relative velocity, and sprung mass acceleration are easily measured using inexpensive sensing

equipment. The equation has an intuitive appeal because it represents a linear model for the system at each point in the operating space provided that $k_s(\Delta)$, $b_s(\dot{\Delta})$ and m_b are estimated accurately. Before using this equation for the estimation process, it is important to understand the limits of its use. In the strictest sense, it is not possible to uniquely identify all three parameters in this equation. This is due to the fact that there are actually an infinite number of sets of parameters that will yield the same input to output mapping (essentially there are three unknowns in one equation). However, the results presented in this paper will demonstrate that the backpropagation training process of the RBF networks converges to an accurate approximation of the “true” solutions, due to differences in error gradients associated with each unknown parameter, provided that reasonable judgment is used in picking the initial network weights.

As stated earlier, the parameters $k_s(\Delta)$ and $b_s(\dot{\Delta})$ are assumed to be arbitrary nonlinear functions of the selected system states. In general, the structure of these nonlinearities is not known. Artificial neural networks are used to model these functions because of their well-established capabilities as “universal function approximators” [7]. A separate network is used for each nonlinear parameter, leading to a naturally modular or structured neural network [14,15]. A network of this type combines the intuitive appeal of the physics based model with the “universal function approximating” capability of neural networks. It should be noted that while the neural networks alleviate the problem of determining the exact nature of each nonlinearity, it is still up to the engineer to determine:

- the number and location of nonlinear parameters in the system
- the system states upon which these nonlinearities depend
- the number of hidden layer neurons in each RBF model
- the activation function characteristics for each neuron in each RBF model

Figure 4 illustrates the structured network configuration used for estimating the nonlinear parameters $\hat{k}_s(i)$ and $\hat{b}_s(i)$ as functions of the discrete-time suspension displacement $\Delta(i)$ and suspension velocity $\dot{\Delta}(i)$, respectively, where the “^” notation denotes an estimated value. Instantaneous spring force estimates $\hat{F}_k(i)$ and damping force estimates $\hat{F}_b(i)$, used to compute the instantaneous sprung mass acceleration estimate $\hat{y}_b(i)$, are shown in the figure. The output weights w_1 , w_2 , and w_3 are associated with the $\hat{k}_s(i)$, $\hat{b}_s(i)$ and $\hat{m}_b(i)$ networks, respectively. It should be noted that the $\hat{m}_b(i)$ network is nothing more than a single scalar weight, as sprung mass is assumed to be unknown but not a function of the system states. The activation functions associated with the $\hat{k}_s(i)$ and $\hat{b}_s(i)$ networks are uniformly distributed across the input range for the approximated function. The details of the RBF training process, and system identification simulations, are presented in the following sections.

Derivation of Training Equations (Backpropagation of Error)

Because there are three distinct networks in the structured model of Figure 4, three distinct weight update equations are implemented for training. In each case, the update equations are formulated so that training proceeds in the negative gradient of the error cost function $J(e)$, which is defined based on the error between the actual sprung mass accelerations $\ddot{y}_b(i)$ and the predicted sprung mass accelerations $\hat{\ddot{y}}_b(i)$:

$$e(i) = \ddot{y}_b(i) - \hat{\ddot{y}}_b(i)$$

$$J(e) = \frac{1}{2N} \sum_{i=1}^N e(i)^2$$

For each discrete-time sample $(\Delta(i), \dot{\Delta}(i))$, the structured network's outputs are:

$$\hat{k}_s = f_{rbf1}(\Delta(i)) \cdot \mathbf{w}_1$$

$$\hat{b}_s = f_{rbf2}(\dot{\Delta}(i)) \cdot \mathbf{w}_2$$

$$\hat{m}_b = \frac{1}{\mathbf{w}_3}$$

$$\hat{\ddot{y}}_b(i+1) = \mathbf{w}_3 (\hat{k}_s \cdot \Delta(i) + \hat{b}_s \cdot \dot{\Delta}(i))$$

Errors are backpropagated to obtain the weight update equations:

$$\begin{aligned} \mathbf{w}_1(i+1) &= \mathbf{w}_1(i) - \eta_1 \frac{\partial J(e)}{\partial \mathbf{w}_1} = \mathbf{w}_1(i) + \eta_1 \mathbf{w}_3 \Delta(i) f_{rbf1}'(\Delta(i)) \\ \mathbf{w}_2(i+1) &= \mathbf{w}_2(i) - \eta_2 \frac{\partial J(e)}{\partial \mathbf{w}_2} = \mathbf{w}_2(i) + \eta_2 \mathbf{w}_3 \dot{\Delta}(i) f_{rbf2}'(\dot{\Delta}(i)) \\ \mathbf{w}_3(i+1) &= \mathbf{w}_3(i) - \eta_3 \frac{\partial J(e)}{\partial \mathbf{w}_3} = \mathbf{w}_3(i) + \eta_3 (\hat{k}_s \cdot \Delta(i) + \hat{b}_s \cdot \dot{\Delta}(i)) \end{aligned} \quad (4)$$

Intelligent System Identification: Simulation Results

To quantify the effectiveness of the RBF network in predicting the nonlinear parameter variations of the quarter vehicle model, a series of Matlab training simulations was conducted. First, the equations of motion for the quarter vehicle model (Equation 1) were combined with standard HMMWV vehicle parameters and synthesized terrain inputs to obtain “typical” off-road vehicle response profiles.

The nonlinear characteristics of variations in suspension stiffness and damping were assumed for these preliminary simulations. The spring force was structured to be linear about static equilibrium (constant $k_s(\Delta)$), but increase nonlinearly near the limits of suspension travel. Such stiffness characteristics might occur in a real suspension system due to kinematics of the wheel and linkage motions. A plot of the spring force function normalized with respect to k_0 is shown in Figure 5a. The damping force was structured to increase most rapidly in the center of the operating range (a high peak in $b_s(\dot{\Delta})$) and increase more gradually in the outer portions of the range (constant $b_s(\dot{\Delta})$). The steep slope in the center of the damping force plot (Figure 5b) is indicative of a suspension system with dry friction. Such characteristics are typical of many realistic suspension dampers [9].

Next, the simulated vehicle response data was sub-sampled to obtain input/output training data for the RBF network. Finally, the RBF training equations (Eqn 4), were implemented into a network training algorithm using the simulated vehicle response data. The initial weights of the RBF networks were set to identical values so that the initial parameter estimates were within 50% of their nominal values, and the adaptation parameters η_1 , η_2 , and η_3 were tuned to ensure rapid, yet stable, convergence during training. The initial value of the error cost function $J(e)$ was 0.2698. Training continued until the error cost function leveled off at 0.0003 (1000 training epochs). At this point, the network's predictions of sprung mass acceleration $\hat{y}_b(i)$ were indistinguishable from the "actual" accelerations $\ddot{y}_b(i)$, as presented in Figure 6. Additionally, the RBF network did an excellent job of predicting the nonlinear variations of suspension stiffness and damping as functions of the selected input space (Figures 7 and 8).

Intelligent System Identification: Experimental Results

Based on the successes of intelligent system identification using simulated data, experimental tests were conducted to obtain actual dynamic data for training. Specifically, the quarter-car testbed (Figure 2) was excited using a hydraulically-actuated terrain input $y_g(t)$, and the resulting suspension displacement $\Delta(t)$ and sprung-mass acceleration $\ddot{y}_b(t)$ were acquired at a sampling rate of 200 Hz. A swept sinusoid input profile, with a frequency range of $0.1 \text{ Hz} \leq f_g \leq 25.0 \text{ Hz}$ and an amplitude of 0.025 m , was selected for the terrain input to ensure adequate excitation of the system's vertical dynamics. The collected data clearly revealed a resonant frequency for the sprung mass at 1.4 Hz, and a resonant frequency for the unsprung mass at approximately 5.0 Hz (Figure 9).

Next, the experimental vehicle response data was sub-sampled to obtain input/output training data for the RBF network. Finally, the RBF training equations (Eqn 4), were implemented into a network training algorithm using the experimental response data. The RBF weights and the adaptation parameters η_1 , η_2 , and η_3 were initialized as before to ensure rapid, yet stable, convergence during training. The initial value of the error cost function $J(e)$ was 0.030. Training continued until the error cost function leveled off at 0.007 (1000 training epochs). At this point, the network's predictions of sprung mass acceleration $\hat{y}_b(i)$ were very reasonable approximations to the "actual" measured accelerations $\ddot{y}_b(i)$, as shown in Figure 10. Figure 11 compares the RBF's approximation of suspension stiffness variation with "actual" measurements taken from the quarter-vehicle test rig. Because the range of suspension travel was relatively small ($\pm 0.03 \text{ m}$), the spring rate was relatively constant, as confirmed by the measurements. The wide spread in measured stiffness is partially due to hysteresis in the suspension, as different stiffnesses were measured depending on the direction of suspension travel (which was not an input to the RBF network). Figure 12 shows the network's approximation of damping as a function of relative suspension velocity. No suitable technique could be devised to experimentally measure this variation, but the trend is in agreement with characteristics reported in the literature [9].

Conclusions

The intelligent system identification approach presented in this paper represents an important step forward in the application of linear control techniques to active vehicle suspension control. The simulated results of Figures 6 – 8 clearly demonstrate the “universal function approximation” capabilities of the structured RBF neural networks. More importantly, the experimental results of Figures 10 – 12 validate this approach on actual suspensions within unknown characteristics. Although the simulations presented here were performed off-line, these techniques can and will be modified for real-time, on-line identification and control applications. Specifically, research here at UT-CEM will focus on the application of these techniques to an off-road HMMWV application and a city bus application. Obviously, the collection and presentation of training data must be extensively modified for real-time implementation, and the selection of training rates will be much different.

The results presented in this paper were obtained from a passive suspension system, but the inclusion of actuator force to the quarter vehicle dynamics (Eqn 1) and network structure (Figure 4), is expected to improve the network’s capabilities to estimate certain vehicle parameters, particularly sprung mass. Tests are currently underway using UT-CEM’s quarter vehicle test rig to completely cancel the sprung mass dynamics using this intelligent estimation technique.

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References

- [1] Hrovat, D., Survey of Advanced Suspension Developments and Related Optimal Control Applications, *Automatica*, Vol. 33, No. 10, 1997.
- [2] K.T. Schuetze, J.H. Beno, Wm.F. Weldon and S.V. Sreenivasan, *A Comparison of Controller Designs for an Active, Electromagnetic, Offroad Vehicle Suspension System Traveling at High Speed*, presented at the SAE International Congress and Exposition, Detroit, MI, February 23-26, 1998.
- [3] L. Ljung, T. Glad, *Modeling of Dynamic Systems*, Prentice Hall, 1994.
- [4] M. Sunwoo, K.C. Cheok, *Investigation of Adaptive Control Approaches for Vehicle Active Suspension Systems*, Proceedings of 1991 American Control Conference, Vol. 2, pp. 1542-1547, 1991.
- [5] E.S. Kim, *Nonlinear Indirect Adaptive Control of a Quarter Car Active Suspension*, Proceedings of the 1996 IEEE International Conference on Control Applications, pp.61-66, 1996.
- [6] L. Ljung, *Issues in System Identification*, IEEE Control Systems, pp. 25-29, January 1991.
- [7] S. Haykin, *Neural Networks, A Comprehensive Foundation*, Prentice Hall, 1994.

- [8] L. Bruzzone, F. Roli, S.B. Serpico, *Structured Neural Networks for Signal Classification*, Signal Processing, Vol. 64, no. 3, pp. 271-290, 1998.
- [9] D. Bastow, G.P. Howard, *Car Suspension and Handling*, 3rd Ed., Society of Automotive Engineers, Inc., 1993.
- [10] J.H. Beno, D.A. Bresie, S.K. Ingram, D.A. Weeks, Wm.F. Weldon, *Electromechanical Suspension System*, Final Report to U.S. Army Tank and Automotive Command, Warren, MI, June 1995.
- [11] D.A. Weeks, J.H. Beno, D.A. Bresie, A.M. Guenin, *Control System for Single Wheel Station Tracked Vehicle Active Electromagnetic Suspension*, presented SAE International Congress and Exposition, Detroit, MI, February 24-27, 1997.
- [12] D.A. Weeks, J.H. Beno, D.A. Bresie, A.M. Guenin, *Laboratory Testing of Active Electromagnetic Near Constant Force Suspension (NCFS) Concept on Subscale Four Corner, Full Vehicle Test-Rig*, presented SAE International Congress and Exposition, Detroit, MI, February 24-27, 1997.
- [13] K.J. Åström, B. Wittenmark, *Adaptive Control*, 2nd Ed., Addison Wesley, 1995.
- [14] Fernandez, B., Parlos, A.G., and Tsai, W.K., *Non-linear Dynamic System Identification using Artificial Neural Networks*, Proceedings of the 1990 International Joint Conference on Neural Networks, Vol. 2, pp. 133-141, June 1990.
- [15] Murty, V.V., Sreedhar, R., Fernandez, B., Masada, G.Y., Hill, A.S., *Boiler System Identification using Sparse Neural Networks*, DSC Advances in Robust and Nonlinear Control Systems, Proceedings of the 1993 ASME Winter Annual Meeting, November 1993.

Figure 1: Basic System Model and Definition of Terms

Figure 2: UT-CEM Quarter HMMWV Test Rig

Figure 3: General Configuration for an Indirect Self Tuning Regulator

Figure 4: Structured Neural Network for Estimating Functions $b_s(\Delta)$ and $k_s(\Delta)$.

Figure 5a: Nonlinear Spring Force Structure

Figure 5b: Nonlinear Damping Force Structure

Figure 6: Predicted vs Actual Sprung Mass Accelerations ($\hat{y}_b(i)$, $\ddot{y}_b(i)$) During Training Simulations.

Figure 7: Predicted vs Actual Suspension Stiffness, as Functions of Suspension Displacement ($k_s(\Delta)$, $\hat{k}_s(\Delta)$) During Training Simulations.

Figure 8: Predicted vs Actual Suspension Damping, as Functions of Suspension Velocity ($b_s(\dot{\Delta})$, $\hat{b}_s(\dot{\Delta})$)
During Training Simulations.

Figure 9: Magnitude Spectrum of Sprung Mass During Experimental Quarter Car Sweep Tests.

Figure 10: Predicted vs. Actual Sprung Mass Acceleration ($\ddot{y}_b(t)$): Experimental Quarter Car Sweep Tests.

Figure 11: Predicted vs. Measured Suspension Stiffness, as Functions of Suspension Displacement ($\hat{k}_s(\Delta(i)), k_s(\Delta(i))$): Experimental Quarter Car Sweep Tests.

Figure 12: Predicted Suspension Damping, as a Function of Suspension Velocity ($\hat{b}_s(\dot{\Delta}(i))$) During Experimental Quarter Car Sweep Tests.