ADAPTIVE SEMI-ACTIVE CONTROL OF SUSPENSION SYSTEM WITH MR DAMPER

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Abstract: The paper is concerned with a fully adaptive semiactive control which can deal with uncertainties in both models of MR damper and suspension mechanism. The proposed approach consists of two adaptive control: One is an adaptive inverse control for compensating the nonlinear hysteresis dynamics of the MR damper, which can be realized by identifying a forward model of MR damper and then calculating the input voltage to MR damper to generate a reference damping force. It can also be realized directly by updating the inverse model of MR damper without identification of forward model, which works as an adaptive inverse controller. The other is an adaptive reference control which gives the desired damping force to match the seat dynamics to a specified reference dynamics even in the presence of uncertainties in the suspension system. Validity of the proposed algorithm is discussed in simulation studies.

Keywords: Suspension control. Adaptive control. Semi-active control. MR damper. Vibration isolation.

1. INTRODUCTION

Magnetorheological (MR) damper is a promising semi-active device in areas of vibration isolation for suspension systems and civil structures. The viscosity of MR fluid is controllable depending on input voltage or current. The MR damper inherently has hysteresis characteristics in nonlinear friction mechanism, and many efforts have been devoted to the modeling of nonlinear behavior from static and dynamic points of view (Yang, 2001)(Spencer Jr. and Carlson, 1997). Static or quasi-static models include no dynamics but can express a nonlinear mapping from velocity to damping force (Yang, 2001)(Pan and Honda, 2000)(Choi and Lee, 1998). It is not easy to identify the hysteresis curve by using a small number of model parameters from actual road suface excitation data. To model the hysteresis dynamics explicitly, the Bouc-Wen model and its variations have also been investigated, in which the input-output relation is expressed by a set of nonlinear differential equations (Yang, 2001)(Spencer Jr. and Carlson, 1997). Hammerstein class of nonlinear model was also investigated (Song and Miller, 2005). These models can simulate the nonlinear behavior of the MR damper, however it includes too many nonlinear model parameters to be identified in a real-time manner. Alternative modeling is based on the LuGre friction model (René and Alvarez, 2002) which was originally developed to describe nonlinear friction phenomena (Canudas and Lischinsky, 1995). It has rather simple structure and the number of model parameters can also be reduced, however, it is not adequate for real-time design of an inverse controller. We have given an MR damper model based on the LuGre model and an analytical method for adaptive inverse controller (Sakai and Sano, 2003)(Terasawa and Sano, 2004).

It is desired that the input to MR damper is determined so that the specified damping force is produced to attenuate vibrations of suspension. The necessary damping force can be calculated to minimize the LQ or LQG performance when the linear dynamic equation is given for the controlled structure. A clipped-optimal control algorithm has also been applied (Dyke and Carlson, 1996), in which a linear optimal controller combined with a force feedback loop was designed to adjust the input voltage. Its modification was also considered (Lai and Liao, 2002)(Zhang and

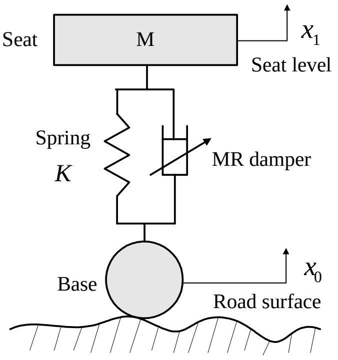


Fig. 1. Suspension system with MR damper

Zhang, 2006). These approaches did not use any inversion dynamics of MR damper. By regarding the total system including the MR damper and structure as a nonlinear controlled system, nonlinear control design methods can also be applied, such as sliding mode control (Lai and Liao, 2002), adaptive skyhook control (Zuo and Nayfeh, 2004), gain scheduled control and others.

The purpose of the paper is to give a new fully adaptive control approach which can deal with uncertainties in both models of MR damper and suspension mechanism. The proposed approach consists of two adaptive controllers: One is an adaptive inverse control for compensating the nonlinear hysteresis dynamics of the MR damper, which can be realized by identifying a forward model of the MR damper and then calculating the input voltage to MR damper to generate a reference damping force. It can also be realized directly by updating the inverse model of MR damper without identification of forward model, which works as an adaptive inverse controller. The other is an adaptive reference control which gives the desired damping force to match the seat dynamics to a specified reference dynamics even in the presence of uncertainties in the suspension system. Validity of the proposed algorithm is discussed in simulation studies.

2. FULLY ADAPTIVE APPROACH

Fig.1 illustrates a suspension system installed with MR damper between the seat and base (road surface). The dynamic equation is expressed by

$$M\ddot{x}_1(t) + f_{MR}(\dot{x}, v) + K(x_1 - x_0) = 0 \quad (1)$$

$$x(t) \equiv x_1(t) - x_0(t) \quad (2)$$

where $x(t)$ is the relative displacement, M is the mass, K is the spring constant, and $f_{MR}(\dot{x}, v)$ is the damping force supplied by the MR damper.

Fig.2 and Fig.3 show schematic diagrams of the proposed fully adaptive semiactive control for the suspension system. The adaptive algorithm consists of two controllers: One is an adaptive inverse controller which can give required input voltage v to MR damper so that the damping force f_{MR}

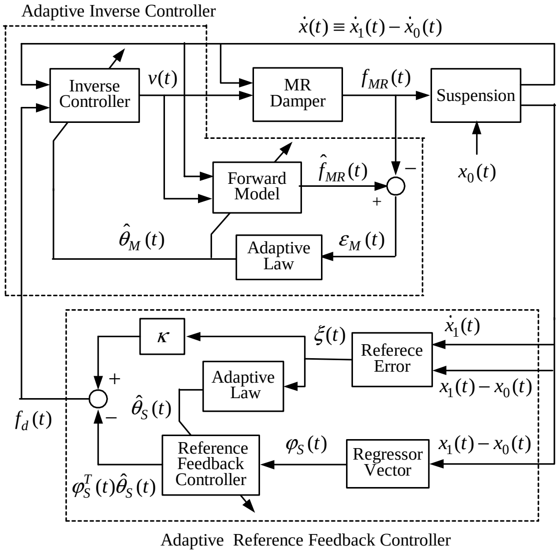


Fig. 2. Proposed fully adaptive semiactive control scheme based on forward modeling

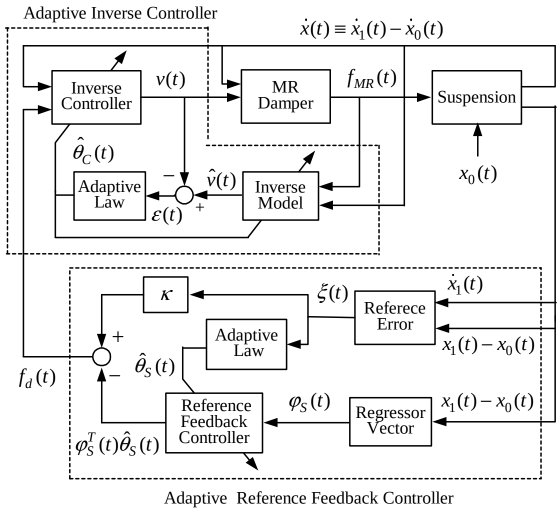


Fig. 3. Proposed fully adaptive semiactive control scheme based on inverse modeling

be equal to specified command damping force f_d. If the adaptive inverse controller is designed so that the linearization from $f_d(t)$ to $f_{MR}(t)$ can be attained, that is, $f_d(t) = f_{MR}(t)$, we can realize almost active control. For construction of the inverse controller, the forward model of MR damper is identified and then the input voltage to MR damper is calculated as shown in Fig.2. Fig.3 gives an alternative scheme in which the inverse controller is directly updated without identification of MR damper. The adaptive reference feedback control which can match the seat dynamic response to a desired reference dynamics even when the suspension system involves parametric uncertainty in M and K. Since the MR damper is actually a nonlinear semi-active device, it is difficult to make it work as an active device, and it needs very fine and complicated tuning of both the adaptive inverse controller and adaptive reference controller.

3. ADAPTIVE INVERSE CONTROL

3.1 Forward Modeling of MR Damper

MR damper is a semi-active device in which the viscosity of the fluid is controllable by the input voltage or current. A variety of approaches have been taken to modeling of the nonlinear hysteresis behavior of the MR damper. Compared to the Bouc-Wen model (Yang, 2001)(Spencer Jr. and Carlson, 1997), the LuGre model has simpler structure and smaller number of parameters needed for expression of its behavior (René and Alvarez, 2002). We have also modified the LuGre model so that a necessary input voltage can be analytically calculated to produce the specified command damping force f_d (Sakai and Sano, 2003).

The damping force f_{MR} is expressed by

$$f_{MR} = \sigma_a z + \sigma_0 z v + \sigma_1 \dot{z} + \sigma_2 \dot{x} + \sigma_b \dot{x} v, \qquad (3)$$

$$\dot{z} = \dot{x} - a_0 |\dot{x}| z \qquad (4)$$

where $z(t)$ is an internal state variable (m), $\dot{x}(t)$ velocity of structure attached with MR damper (m/s), σ_0 stiffness of $z(t)$ influenced by $v(t)$ (N/(m·V)), σ_1 damping coefficient of $z(t)$ (N·s/m), σ_2 viscous damping coefficient (N·s/m), σ_a stiffness of $z(t)$ (N/m), σ_b viscous damping coefficient influenced by $v(t)$ (N·s/(m·V)), and a_0 constant value (V/N). Substituting (4) into (3), we obtain the nonlinear input-output relation as

$$\begin{aligned} f_{MR} &= \sigma_a z + \sigma_0 z v - \sigma_1 a_0 |\dot{x}| z \\ &\quad + (\sigma_1 + \sigma_2)\,\dot{x} + \sigma_b \dot{x} v = \boldsymbol{\theta}_M^T \boldsymbol{\varphi}_M \end{aligned} \qquad (5)$$

where $\boldsymbol{\theta}_M = (\sigma_a,\ \sigma_0,\ \sigma_1 a_0,\ \sigma_1 + \sigma_2,\ \sigma_b)^T = (\theta_1,\ \theta_2,\ \theta_3,\ \theta_4,\ \theta_5)^T$, and $\boldsymbol{\varphi}_M = (z,\ zv,\ -|\dot{x}|z,\ \dot{x},\ \dot{x}v)^T$.

Let the identified parameter vector $\hat{\boldsymbol{\theta}}_M$ be denoted by $\hat{\boldsymbol{\theta}}_M = (\hat{\theta}_1,\ \hat{\theta}_2,\ \hat{\theta}_3,\ \hat{\theta}_4,\ \hat{\theta}_5)^T$. Since the internal state z of the MR damper model cannot be measured, the regressor vector $\boldsymbol{\varphi}_M$ should be replaced with its estimate $\hat{\boldsymbol{\varphi}}_M$ as

$$\hat{\boldsymbol{\varphi}}_M = (\ \hat{z},\ \hat{z}v,\ -|\dot{x}|\hat{z},\ \dot{x},\ \dot{x}v\ )^T \qquad (6)$$

where the estimate $\hat{z}$ is given later by using the updated model parameters. The output of the identification model is now described as

$$\hat{f}_{MR} = \hat{\boldsymbol{\theta}}_M^T \hat{\boldsymbol{\varphi}}_M. \qquad (7)$$

By using the damping force estimation error defined by $\varepsilon_M \equiv \hat{f}_{MR} - f_{MR}$, and the identified parameter $\hat{a}_0$, the estimate $\hat{z}$ of the internal state can be calculated as

$$\dot{\hat{z}} = \dot{x} - \hat{a}_0 |\dot{x}| \hat{z} - L\varepsilon_M, \qquad (8)$$

where L is an observer gain such that $0 \le L \le 1/\hat{\sigma}_{1\max}$, and the upper bound is decided by the stability of the adaptive observer.

To assure the stability of the adaptive identification algorithm, we introduce the normalizing signal as $N_M = \left(\rho + \hat{\boldsymbol{\varphi}}_M^T \hat{\boldsymbol{\varphi}}_M\right)^{1/2},\quad \rho > 0$. By dividing the signals and errors by N_M as $\boldsymbol{\varphi}_{MN} = \boldsymbol{\varphi}_M / N_M$, $\hat{\boldsymbol{\varphi}}_{MN} = \hat{\boldsymbol{\varphi}}_M / N_M$ and $\varepsilon_{N_M} = \hat{f}_{MRN} - f_{MRN}$, where $f_{MRN} = f_{MR}/N_M$ and $\hat{f}_{MRN} = \hat{\boldsymbol{\theta}}^T \hat{\boldsymbol{\varphi}}_{MN}$, we can give the adaptive law with a variable gain for updating the model parameters as

$$\dot{\hat{\boldsymbol{\theta}}}_M = -\boldsymbol{\Gamma} \hat{\boldsymbol{\varphi}}_{MN} \varepsilon_N \qquad (9)$$

$$\dot{\boldsymbol{\Gamma}}_M = \lambda_1 \boldsymbol{\Gamma}_M - \lambda_2 \boldsymbol{\Gamma}_M \hat{\boldsymbol{\varphi}}_{MN} \hat{\boldsymbol{\varphi}}_{MN}^T \boldsymbol{\Gamma}_M \qquad (10)$$

where λ_1, λ_2 and $\boldsymbol{\Gamma}_M(0)$ have to satisfy the following constraints: $\lambda_1 \ge 0$, $0 \le \lambda_2 < 2$, $\boldsymbol{\Gamma}_M(0) = \boldsymbol{\Gamma}_M^T(0) > 0$. For practical implementation, $\boldsymbol{\Gamma}_M(t)$ is chosen constant. Thus, the physical model parameters can be calculated from the relation (5).

3.2 Analytic Form of Inverse Controller

The role of the adaptive inverse controller shown in Fig.3 is to decide the control input voltage v to the MR damper so that the actual damping force f_{MR} may coincide with the specified command damping force f_d, even in the presence of uncertainty in the MR damper model. The input voltage giving f_d can be analytically calculated by taking an inverse model of the proposed mathematical model of MR damper (5). Actually using the identified model parameters, the input voltage v is given from (3) and (4) as

$$\begin{aligned} \rho &= \hat{\sigma}_0 \hat{z} + \hat{\sigma}_b \dot{x} \\ d_\rho &= \begin{cases} \rho & \text{for } \ \rho < -\delta,\ \ \delta < \rho \\ \delta\ \mathrm{sgn}(\rho) & \text{for } \ -\delta \le \rho \le \delta \end{cases} \\ v_c &= \frac{f_d - \{\hat{\sigma}_a \hat{z} - \sigma_1 \hat{a}_0 |\dot{x}_1| \hat{z} + (\sigma_1 + \hat{\sigma}_2)\dot{x}_1 - L\varepsilon\}}{d_\rho} \\ v &= \begin{cases} 0 & \text{for } \ v_c \le 0 \\ v_c & \text{for } \ 0 < v_c \le V_{\max} \\ V_{\max} & \text{for } \ V_{\max} < v_c \end{cases} \end{aligned} \qquad (11)$$

where f_d is the specified command damping force, which will be given in the next section. v is assumed to be fixed near $\rho = 0$.

3.3 Inverse Modeling of MR Damper

In the above, the inverse controller is obtained analytically from the estimated parameters of the forward model of MR damper. However, as expressed in (11), some adjustable parameters appear in the denominator of the inverse controller and so zero-division should be avoided. Furthermore, it becomes rather complicated to analyze the stability of the total system given in Fig.5. Therefore, as an alternative approach, *i.e.*, we will give an inverse model of the MR damper directly adjusted adaptively. Since the damper force $F_{MR}(t)$ is given as a function of the velocity $\dot{x}(t)$, input voltage $v(t)$ and internal state $z(t)$ as shown in (4), its inverse model for the input voltage $v(t)$ can be expressed as a function of $\dot{x}(t)$, $z(t)$ and $f_{MR}(t)$. Hence, we consider an inverse model which is expressed by a linearly parameterized polynomial model as:

$$v(t) = \sum_{j=0}^{n} \sum_{i=0}^{m} h_{i+(m+1)k+1} \left|\dot{x}\right|^{i} \left|z\right|^{j} f_{MR}\mathrm{sgn}(\dot{x}) \tag{12}$$

where the inverse model has two inputs of $\dot{x}$ and f_{MR}, and one output of $v(t)$. z is an internal state of the MR damper, which can be calculated as given previously by

$$\dot{z}(t) = \dot{x}(t) - a_0|\dot{x}(t)|z(t)$$

where a nominal value of a_0 is assumed to be known via the forward modeling. In simulation, an inverse model with $m = 4$ and $n = 1$ will be adopted.

The inverse model is also expressed in a vector form as

$$v(t) = \boldsymbol{\theta}_C \boldsymbol{\varphi}_C(t) \tag{13}$$

where

$$\begin{aligned}
\boldsymbol{\theta}_C &= (h_1,\ h_2,\ \cdots,\ h_{(n+1)(m+1)})^T \\
&= (\theta_1,\ \theta_2,\ \cdots,\ \theta_{(n+1)(m+1)})^T \\
\boldsymbol{\varphi}_C(t) &= (F_{MR}\ \mathrm{sgn}(\dot{x}),\ |\dot{x}|F_{MR}\ \mathrm{sgn}(\dot{x}),\ \cdots, \\
&\qquad |z|F_{MR}\ \mathrm{sgn}(\dot{x}),\ |\dot{x}||z|F_{MR}\ \mathrm{sgn}(\dot{x}),\ \cdots, \\
&\qquad |\dot{x}|^m|z|^n F_{MR}\ \mathrm{sgn}(\dot{x}))^T
\end{aligned}$$

The identified model is now expressed as

$$\hat{v}(t) = \hat{\boldsymbol{\theta}}_C^T(t)\boldsymbol{\varphi}_C(t) \tag{14}$$

where $\hat{\boldsymbol{\theta}}_C(t) = (\hat{\theta}_1(t),\ \hat{\theta}_2(t),\ \cdots\ ,\hat{\theta}_{(m+1)(n+1)})^T$. $\hat{\boldsymbol{\theta}}_C(t)$ is adjusted in an on-line manner so as to minimize the identification error $\varepsilon_C(t)$ defined as

$$\varepsilon_C(t) = \hat{v}(t) - v(t) \tag{15}$$

Similarly the normalizing signal defined by $N_C = \left(\rho + \boldsymbol{\varphi}_C^T\boldsymbol{\varphi}_C\right)^{1/2}$, $\rho > 0$ is employed to assure the stability of the adaptive identification algorithm. By dividing the signals and errors by N_C as $\boldsymbol{\varphi}_{CN} = \boldsymbol{\varphi}_C/N_C$ and $\varepsilon_{N_C} = \hat{v}_{N_C} - v_{N_C}$, where $v_{N_C} = v/N_C$ and $\hat{v}_{N_C} = \hat{\boldsymbol{\theta}}_C^T\boldsymbol{\varphi}_{CN}$, we can give the adaptive law with a variable gain for updating the model parameters as

$$\dot{\hat{\boldsymbol{\theta}}}_C = -\boldsymbol{\Gamma}_C\boldsymbol{\varphi}_{CN}\varepsilon_{CN} \tag{16}$$

$$\dot{\boldsymbol{\Gamma}}_C = \lambda_1\boldsymbol{\Gamma}_C - \lambda_2\boldsymbol{\Gamma}_C\boldsymbol{\varphi}_{CN}\boldsymbol{\varphi}_{CN}^T\boldsymbol{\Gamma}_C \tag{17}$$

where λ_1, λ_2 and $\boldsymbol{\Gamma}_C(0)$ have to satisfy the following constraints: $\lambda_1 \geq 0$, $0 \leq \lambda_2 < 2$, $\boldsymbol{\Gamma}_C(0) = \boldsymbol{\Gamma}_C^T(0) > 0$. For practical implementation, $\boldsymbol{\Gamma}_C(t)$ is chosen constant.

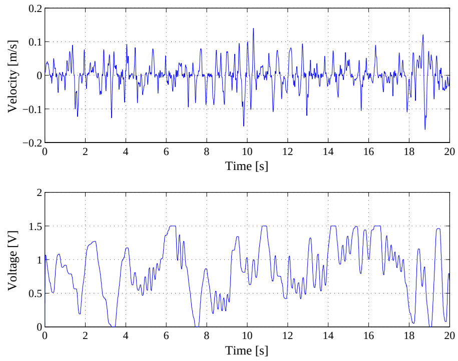


Fig. 4. Two inputs: voltage and velocity in experiment

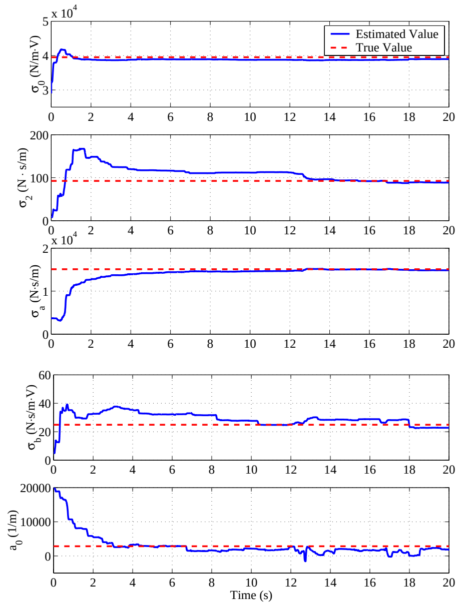


Fig. 5. Identified forward model parameters

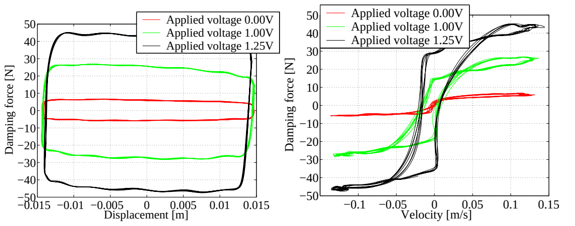
4. MODEL VERIFICATION BY EXPERIMENTS

Experiments for the adaptive identification was made using a small type of MR damper (RD-1097-01) provided by Lord Corp. A laser sensor was placed to measure the displacement x of the piston rod of the MR damper, and a strain sensor was installed in series with the damper to measure the output force f_{MR}. The signals x, v and f_{MR} were sampled at the rate 1 kHz. The identified forward model has two inputs of velocity $\dot{x}$ and voltage v and one output f_{MR}. The time profiles of the inputs $\dot{x}$ and v applied to the MR damper are illustrated in Fig.4. The convergence behavior of the forward model parameters $\hat{\boldsymbol{\theta}}_M$ of the MR damper is plotted in Fig.5. The dotted line shows the least squares parameter estimates obtained by batch processing, which are listed in Table 1.

To observe the hysteresis characteristics of the MR damper, a sinusoid displacement with amplitude of 1.5cm is applied for three constant voltages 0, 1 and 1.25 V. The measurement results show that the MR damper has the hysteresis behavior between the velocity $\dot{x}$ and damper force f as shown in Fig.6(a), and the hysteresis property

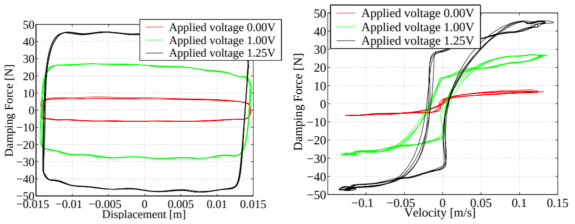
Table 1. Identified model parameters

Parameters	LS estimate	Initial values
σ_0 [N/m· V]	3.95×10^4	2.90×10^4
σ_1 [N·s/m]	0.131	-
σ_2 [N·s/m]	92.5	8.00
σ_a [N/m]	1.51×10^4	3.50×10^3
σ_b [N·s/(m·V)]	24.9	5.00
a_0 [m^{-1}]	2.85×10^3	2.00×10^4



(a) Measured force-displacement (b) Measured force-velocity hysteresis loop

Fig. 6. Measured hysteresis characteristics of MR damper



(a) Measured force-displacement (b) Measured force-velocity hysteresis loop

Fig. 7. Estimated hysteresis characteristics of MR damper with always updated parameters obtained by the proposed adaptive identification method

between f and x shown in Fig.6(b). Fig.7(a)(b) gives the estimated hysteresis behavior obtained by the recursive forward modeling with the adaptive observer. The forward model is very precisely identified by the proposed adaptive scheme.

The inverse model with ten adjustable parameters ($m = 4$ and $n = 1$) were also identified using the data set of the two inputs f_{MR} and $\dot{x}$, and one output v. The convergence behavior of the ten inverse model parameters are summarized in Fig.8. Almost all estimated parameters converge to those obtained by the batch-processing of the LS method.

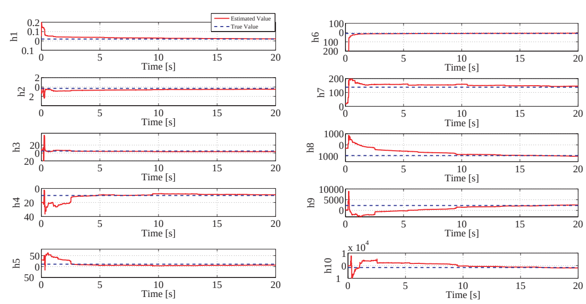


Fig. 8. Convergence behavior of adaptive inverse controller parameters to those obtained by the batch-processing of the LS method (blue broken lines).

5. ADAPTIVE REFERENCE FEEDBACK CONTROL

The role of the adaptive reference feedback controller is to provide a desired damper force to the adaptive inverse controller so that the seat dynamics can match the reference dynamics. The desired damper force is decided by the skyhook approach in a case when the mass and spring constants are both unknown. Following the adaptive scheme (Zuo and Nayfeh, 2004), the desired reference dynamics is specified by

$$\ddot{x}_1 + 2\zeta\omega\dot{x}_1 + \omega^2(x_1 - x_0) = 0 \qquad (18)$$

where ω is natural frequency, and ζ is a damping constant. Then, the control error ξ_1 is given by

$$\xi = \dot{x}_1 + (s + 2\zeta\omega)^{-1}\omega^2(x_1 - x_0) \qquad (19)$$

The adaptive control law is given as

$$f = \kappa\xi(t) - \boldsymbol{\varphi}_S(t)^T\hat{\boldsymbol{\theta}}_S(t) \qquad (20)$$

where

$$\boldsymbol{\theta}_S = (K, M)^T$$

$$\boldsymbol{\varphi}_S(t) = (x_1 - x_0,\ -\frac{\omega^2 s}{s + 2\zeta\omega}(x_1 - x_0)^T$$

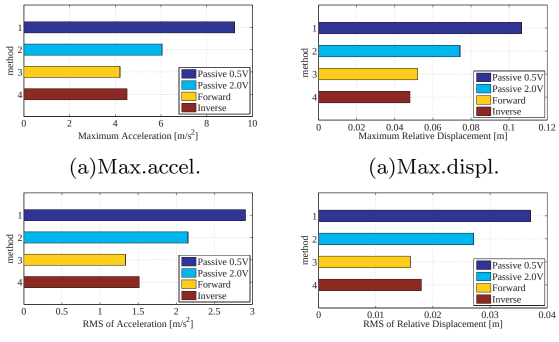
The adjustable parameters $\hat{\boldsymbol{\theta}}_S$ are updated by

$$\dot{\hat{\boldsymbol{\theta}}}_S(t) = \dot{\tilde{\boldsymbol{\theta}}}_S(t) = -\boldsymbol{P}\boldsymbol{\varphi}_S(t)\xi(t) \qquad (21)$$

It was shown that the gain κ in (20) can take an any positive constant (Zuo and Nayfeh, 2004), if the MR damper model is precisely known a priori. However, as in the previous section, when the forward model is updated in an on-line manner and two adaptive algorithms work together, the gain κ should take a positive constant larger than 3/2, on the assumption that the model parameters σ_0, σ_1 and a_0 are known. Furthermore, if the inverse modeling is adopted for the adaptive inverse controller, the gain should satisfy that $\kappa > h(z, \dot{x})$, where $h(z, \dot{x})$ is accessible in on-line manner. The proof is omitted here.

6. SIMULATION RESULTS

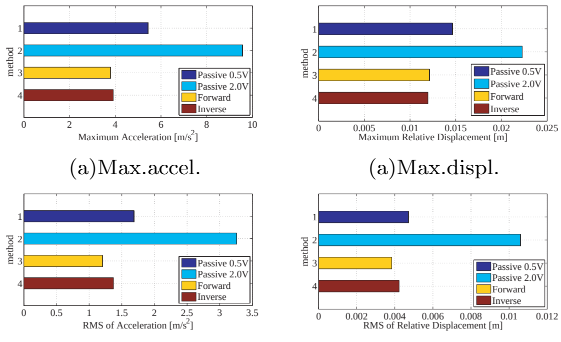
We consider a suspension system shown in Fig.1, where the parameters are set as $M = 86.4$ [kg] and $K = 7004$ [N/m], which are the same as in (Song and Miller, 2005). The parameters of the MR damper are specified as: $\sigma_0 = 4.0 \times 10^4$ [N/mV], $\sigma_1 = 2.0 \times 10^2$ [Ns/m], $\sigma_2 = 1.0 \times 10^2$ [Ns/m], $\sigma_a = 1.5 \times 10^4$ [N/m], $\sigma_b = 2.5 \times 10^3$ [Ns/(mV)], $a_0 = 1.9 \times 10^2$, which are all unknown. An upper limit of input voltage to the MR damper is set at 2.5[V], so $v(t)$ takes 0 to 2.5[V]. The base of the dynamic system in Fig.1 is excited by the road surface, which is given by three random signal sequences with different power spectra:



(a)Max.accel. (a)Max.displ.

(a)RMS of accel.. (a)RMS of displ.

Fig. 9. Comparison of maximum and rms of acceleration and relative displacement for base ecitation with power in *middle low* frequency range (b)



(a)Max.accel. (a)Max.displ.

(a)RMS of accel.. (a)RMS of displ.

Fig. 10. Comparison of maximum and rms of acceleration and relative displacement for base ecitation with power in *high* frequency range (d)

Excitation signals (a) with power from 1.0 $\sim$ 2.0 [Hz] (in low frequency) and (b) with power from 2.0 $\sim$ 5.0 [Hz] (in high frequency). We compared four schemes: (1) Passive low damping with 0.5 [V], (2) Passive high damping with 2.0 [V], (3) Forward modeling based scheme, and (4) Inverse modeling based scheme. Fig.9 and Fig.10 summarize the comparison of the maximum and rms values of seat acceleration and displacement for various schemes in various power spectrum of excitations. The proposed adaptive schemes based on the forward modeling and inverse modeling performs very well in acceleration and displacement responses, compared to the passive damper with fixed input voltage.

7. CONCLUSION

We have presented the fully adaptive semiactive control algorithm which consists of the adaptive inverse controller compensating for nonlinear hysteresis dynamics of MR damper, and the adaptive reference controller matching the seat response to a reference dynamics even if the mass and spring constants are unknown. The forward and inverse modeling schemes were introduced for the adaptive inverse controllers. Conditions for assuring stability of the total control system have been considered, and the effectiveness of the proposed scheme has been validated in numerical simulation.

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