Study on Satellite Vibration Control using Adaptive Control Scheme

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Abstract

Adaptive control methods are studied for the Satellite to isolate vibration in spite of the nonlinear system dynamics and parameter uncertainties of disturbance. First, a centralized control scheme is developed based on the particle swarm optimization(PSO) algorithm and feedback theory to automatically tune controller gains. A simulation study of a 3 degree-of-freedom device was conducted to evaluate the performance of the proposed control scheme. Next, since a centralized control scheme is hard to construct model dynamics and not good at performance when controller and system's environment are easily changed, a decentralized control scheme is presented to avoid these defects of the centralized control scheme from the point of view of production and maintenance. It is based on the adaptive control methodologies to find PID controller parameters. Experiment studies were conducted to apply the adaptive control scheme and evaluate the performance of the proposed control scheme with those of the conventional control schemes.

Key Word : Vibration isolation, Adaptive control, Recursive least-square algorithm, Infinite-impulse response filter

Introduction

Vibration control has been a challenging problem for both academic and industrial researchers for many years. Vibrations can be found everywhere, in vehicles, buildings, or machines. Most vibrations are undesirable because they cause unpleasant noises, unwanted stress in structures, and malfunction or failure of systems. Numerous controllers have been designed to solve vibration control problems. Most vibration control problems are nonlinear in nature, so performances of traditional control techniques may not be satisfactory. Many control theories and techniques have been employed in vibration control problems. In general, vibration controllers can be classified into four categories - passive, active, intelligent and adaptive vibration controllers.

Passive vibration absorbers have been used in many applications where vibration absorbing materials dissipate energy from vibration sources. Passive vibration control methods are easy to implement and can achieve good vibration reductions in some applications, but they are usually system dependent and frequency selective. Any change of plant dynamics may require moving vibration absorbers or replacing them with new ones that have different sizes, shapes and characteristics. Active controllers use active components whose parameters can not be adjusted on-line. The most common active controller is a PID controller of which proportional, integral, and

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derivative gains can be determined based on desired specifications and dynamics of a plant. Design of an active vibration controller requires full knowledge or an accurate model of a plant. Active vibration controllers do not deal with uncertainties and noise in plants. Any change of the plant parameters may result in redesigning the controllers. An intelligent controller is a controller that can handle various inputs, disturbances, parameter changes, and noises by using methodology from a human perspective. Research involving intelligent vibration controllers has been reported in recent years[1-3]. Mayhan and Washington [1] developed a fuzzy model reference learning vibration controller. Their results showed that the controller had the capability to improve its performance when plant uncertainties were introduced and the system properties were changed. However, disadvantages of the controller are that large amounts of code are necessary in order to develop such a controller and intensive computations in the controller may cause problem in fast real-time applications.

Adaptive controller is that its parameters are on-line adjustable. A number of algorithms have been developed in implementations of adaptive vibration controllers. A typical approach to adaptive vibration control is to feed an error signal through an appropriate filter and apply the resulting signal to a plant. Coefficients of the filter are tuned automatically by an adaptive algorithm to achieve best vibration reduction. Elliott, Stothers and Nelson[1] presented an algorithm to adapt coefficients of an array of finite impulse response (FIR) filters, whose outputs were linearly coupled to another array of error detection points to minimize mean square error signals. Eriksson, Allie, and Greiner[4] investigated the use of IIR(Infinite impulse response) adaptive filters in adaptive vibration controls. Baumann[5] studied the potential of an adaptive feedback approach to structural vibration suppression. Adaptive vibration controllers are good candidates for problems where parameters of a plant are unknown or there are uncertainties in a system. Parameters of adaptive controllers are adjusted on-line to achieve the best performance.

The principal idea of vibration isolation is to filter out the response of the system over the corner frequency. When a reaction wheels(RW) or control momentum gyros(CMG) control spacecraft attitude, vibration inevitably occurs and degrades the performance of sensitive devices. Therefore, vibration should be controlled or isolated for missions such as Earth observing, broadcasting and telecommunication between antenna and ground stations. For space applications, technicians designing controller have to consider aperiodic vibration and disturbance to ensure system performance and robustness completing various missions. In this thesis, the adaptive PID control scheme with IIR filter for system identification is used to isolate vibration under system nonlinearities and uncertainties existence.

Decentralized adaptive PID control scheme for a module-type experiment device is presented. The adaptive control theory have already been developed to solve the defects of the conventional linear control theory for uncertain systems[6, 7]. Although most control schemes for the vibration control are of centralized form, they cannot be implemented with a set of basic module-type local controllers. Thus they are unfavorable from the viewpoint of production and maintenance of the controllers. Decentralized adaptive control schemes can overcome those defects and may be effectively used for the 1 DOF vibration control device. Decentralized adaptive control schemes have been proposed by a few authors[8, 9]. Indeed, they studied and applied these schemes to reject disturbance for aperiodic systems proven in the acoustics industry against unwanted noise[10-12].Vibration isolation experiment verifies the adaptive PID control designed in this dissertation.

Next section, the 3 DOF system is introduced. For designing adaptive controller, system identification methodologies and an adaptive control scheme are continuously explained. System identification scheme with gradient algorithm and least-square algorithm is introduced and developed to recursive least-square algorithm based on IIR filter theory. Designed system identification algorithm tunes adaptively second-order system. Then, experiment results are presented after experimental device configuration and data acquisition method are explained briefly. The decentralized adaptive PID control scheme applied to 1 and 3 DOF experimental device to reject vibration are followed.

3 DOF Vibration Isolator

In general, past research isolating vibration commonly used 6 DOF isolator such as Stewart and Mallock platforms[13, 14]. The platforms arrange 6 actuators at angles and its main advantages are the compactness and equal load distribution of all 6 actuators. Although reduced coupling through orthogonal arrangement is possible, strong coupling among actuators complicates the actuator coordination and their dynamic modeling is very complex to obtain dynamic equation. Hence this dissertation proposes a 3 DOF vibration isolator as shown in Fig. 1.

The vibration isolation device has 3 DOF, one translational and two rotational motions as shown in Fig. 1. The origin of the coordinate is located at the center-of-gravity(CG) of the upper plane. w denotes z-directional translation of CG. α and β are the translational motion in the x and y-axis of the CG. w_1, w_2 and w_3 which denote z-axis translational motion of each strut are controlled by three actuators that are connected parallel to the strut.

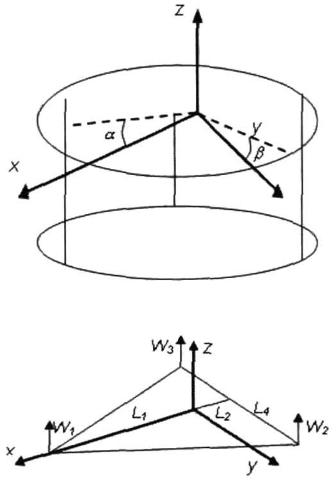
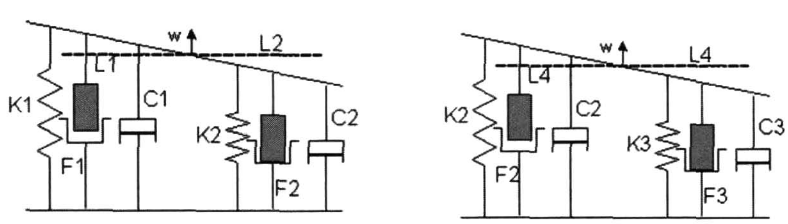


Fig. 1. Coordinate definition for the 3 DOF vibration isolator



(a) (b)

Fig. 2. Free body diagram : (a) w and α (b) w and β

A spring, a damper, and an actuator are installed in each strut as shown in Fig. 2. The K_i, C_i and $F_i\,(i = 1, 2, 3)$ are spring coefficient, damping coefficient, and actuator force, respectively.

Decentralized Adaptive Control Scheme

In the 1950s, adaptive control was motivated by the problem of designing autopilots for aircraft operating at a wide range of speeds and altitudes. Gain scheduling based on some auxiliary measurements, several rudimentary model reference adaptive control, self-adjustment of the controller parameters, and self tuning controller with explicit identification of the parameters by Kalman were attempted and verified to perform well. The 1960s was very important time in the development of control theory and adaptive control in particular. Lyapunov's stability theory was firmly established as a tool for proving convergence in adaptive control schemes. Stochastic control made giant strides with the understanding of dynamic programming due to Bellman[15]. Learning schemes proposed by Tsypkin[16] were shown to have roots in a single unified framework ofrecursive equations. In 1966, Parks found a way of redesigning the update laws proposed in the 1950s for model reference schemes so as to be able to prove convergence of his controller[17]. In the 1970s, complete proofs of stability for several adaptive schemes appeared. State space proofs stability for model reference adaptive schemes appeared in the work of Narendra, Lin, Valavani[18]. In 1982, Rohrs pointed that the assumptions under which stability of adaptive schemes had been proven were very sensitive to the presence of unmodeled dynamics, typically high-frequency parasitic modes that were neglected to limit the complexity of the controller[19]. This sparked a flood of research into the robustness of adaptive algorithms.

Most current techniques for designing control systems are based on a good understanding of the plant under study and its environment. However, the plant to be controlled is too complex and the basic physical processes in it are not fully understood. A decentralized adaptive control design techniques then need to be augmented with an identification technique aimed at obtaining a progressively better understanding of the plant. It is thus intuitive to aggregate system identification and control. Often, the two steps will be taken separately. If the system identification is recursive - that is the plant model is periodically updated on the basis of previous estimates and new data - identification and control may be performed concurrently. Abstractly, system identification could be aimed at determined if the plant is linear or nonlinear, finite of infinite dimensional, and has continuous or discrete event dynamics. Here the system is restricted to infinite dimensional, single-input single output linear plants for designing a decentralized controller. Adaptive control, then, is a technique of applying some system identification technique to obtain a model of the process and its environment from input-output experiments and using this model to design a controller. The parameters of the controller are adjusted during the operation of the plant as the amount of data available for plant identification increases. For a number of simple PID controller in process control, this is often done manually. The design techniques for adaptive systems are studied and analyzed in theory for unknown but fixed time invariant plants. In practice, they are applied to slowly time-varying and unknown plants.

1. Adaptive System Identification

In this section, some identification methods for SISO LTI systems for a decentralized adaptive control scheme are reviewed. The identification problem for a first order SISO LTI system descried by a transfer function is considered.

$$\frac{\hat{y}_p(s)}{\hat{r}(s)} = \hat{P}(s) = \frac{k_p}{(s+a_p)} \tag{1}$$

The parameters k_p and a_p are unknown and are to be determined by the identification scheme on the basis of measurements of the input and output of the plant. The plant is assumed to be stable, i.e. $a_p > 0$.

Discussing schemes based on a time-domain expression of the plant (1) is

$$\dot{y}_p(t) = -a_p y_p(t) + k_p r(t) \tag{2}$$

Measurements of y_p, $\dot{y}_p$ and r at one time instant t give us one equation with two unknown a_p and k_p. Defining nominal parameter θ^*, regressor vector $w(t)$ and $\theta(t)$, as the estimate of θ^*

and parameter error ϕ, equation (2) may be written

$$\dot{y}_p(t) = [-a_p \ k_p]\begin{bmatrix} y_p \\ r \end{bmatrix} = \theta^{*T} w(t) \tag{3}$$

$$\dot{y}_p(t) = \sum_{i=1}^{2} \theta_i^{*T} w_i(t) \tag{4}$$

based on measurement of $r(t)$ and $y_p(t)$ up to time t, $w(t)$ may be calculated, and an estimate $\theta(t)$ derived. Since each time instant gives us one equation with two unknowns, it makes sense to consider the estimate that minimizes the identification error$e_1(t)$

$$e_1(t) = \theta^T(t)w(t) - \theta^{*T}(t)w(t) = \theta^T(t)w(t) - \dot{y}_p(t) = \phi^T(t)w(t) \tag{5}$$

Note that the identification error is linear in the parameter error $\theta - \theta^*$. Equation (5) is called a linear error equation. The purpose of the identification scheme will be to calculate $\theta(t)$, on the basis of measurement of $e_1(t)$ and $w(t)$ up to time t.

2. Least-square Algorithm

The least-squares algorithm minimizes the integral-squared-error

$$ISE = \int_0^t e_1^2(\tau)d\tau = \frac{1}{2}\sum_{i=1}^{t}(y(i) - w(i)^T\theta)^2 \tag{6}$$

Owing to the linearity of the error equation the estimate may be obtained directly from the condition

$$\frac{\partial}{\partial\theta}\left[\int_0^t e_1^2(\tau)d\tau\right] = \int_0^t \frac{\partial}{\partial\theta} e_1^2(\tau)d\tau = 2\int_0^t w(t)\left[w^T(\tau)\theta(\tau) - \dot{y}_p(\tau)\right]d\tau \tag{7}$$
$$= 2\int_0^t w(\tau)\theta^T(\tau)w(\tau)d\tau - 2\int_0^t \dot{y}_p(\tau)w(t)d\tau = 0$$

so that the least-squares estimate is given by

$$\theta_{LS}(t) = \left[\int_0^t w(\tau)w(\tau)^T d\tau\right]^{-1}\left[\int_0^t \dot{y}_p(\tau)w(\tau)d\tau\right] \tag{8}$$

Plugging (3) into (8) shows that $\theta_{LS}(t) = \theta^*$, assuming that the inverse in (8) exist. For adaptive control applications, recursive formulations is interesting, where parameters are updated continuously on the basis of input-output data. Such an expression may be obtained for the least-squares algorithms by defining

$$p(t) = \left[\int_0^t w(\tau)w(\tau)^T d\tau\right]^{-1} \tag{9}$$

so that

$$\frac{d}{dt}|p^{-1}(t)| = w(t)w(t)^T \tag{10}$$

since

$$0 = \frac{d}{dt}I = \frac{d}{dt}|p(t)p^{-1}(t)| = \frac{d}{dt}|p(t)|p^{-1}(t) + p(t)\frac{d}{dt}|p^{-1}(t)| \tag{11}$$

It follows that

$$\frac{d}{dt}|p(t)|=-p(t)\frac{d}{dt}|p^{-1}(t)|p(t)=-p(t)w(t)w(t)^{T}p(t) \tag{12}$$

on the other hand, (8) may be written

$$\theta_{LS}(t)=p(t)\int_{0}^{t}w(\tau)\dot{y}_{p}(\tau)d\tau \tag{13}$$

so that, using (12)

$$\begin{aligned}\frac{d}{dt}[\theta_{LS}(t)] &= -p(t)w(t)w^{T}(t)\theta_{LS}(t)+p(t)w(t)\dot{y}_{p}(t)\\ &= -p(t)w(t)[w^{T}(t)\theta_{LS}(t)-\dot{y}_{p}(t)]=-p(t)w(t)e_{1}(t)\end{aligned} \tag{14}$$

Note that the recursive algorithm (12), (14) should be started with the correct initial conditions at some $t_0 > 0$ such that

$$p(t_0)=\left[\int_{0}^{t_0}w(\tau)w^{T}(\tau)d\tau\right]^{-1} \tag{15}$$

exists. In practice, the recursive least-squares algorithm is started with arbitrary initial conditions at $t_0 = 0$ so that

$$\dot{\theta}(t)=-p(t)w(t)[\theta^{T}w(t)-\dot{y}_{p}(t)], \qquad \theta(0)=\theta_0 \tag{16}$$

$$\dot{p}(t)=-p(t)w(t)w^{T}(t)p(t), \qquad p(0)=p_0>0 \tag{17}$$

It follows that $\theta(t)$ converges asymptotically to θ^{*} if $\int_{0}^{t}w(\tau)w^{T}(\tau)d\tau$ is unbounded as $t\to\infty$.

Another possible remedy is the covariance resetting, where p is reset to a predetermined positive definite value, whenever $\lambda_{\min}(p)$ falls under some threshold.

The normalized least-squares algorithm is defined by

$$\begin{aligned}\dot{\theta} &= -g\frac{pwe_1}{1+\mu w^{T}pw} \qquad g,\mu>0\\ \frac{dp}{dt} &= -g\frac{pww^{T}p}{1+\mu w^{T}pw}\end{aligned} \tag{18}$$

The least-squares algorithms are somewhat more complicated to implement but are found in practice to have faster convergence properties.

3. Recursive Computations of Least-squares Algorithm

In adaptive controllers the observations are obtained sequentially in real time. It is then desirable to make the computations recursively to save computation time. Computation of the least-squares estimate can be arranged in such a way that the results obtained at time $t-1$ can be used to get the estimates at time t. The function of Eq. (6) is minimal for parameters $\hat{\theta}$ such that

$$w^{T}w\hat{\theta}=w^{T}y \tag{19}$$

If the matrix $w^{T}w$ is nonsingular, the minimum is unique and given by

$$\hat{\theta} = (w^T w)^{-1} w^T y \tag{20}$$

The solution in Eq. (20) to the least-squares problem will be rewritten in a recursive form. Let $\hat{\theta}(t-1)$ denote the least-squares estimate based on $t-1$ measurements. Assume that the matrix $w^T w$ is nonsingular for all t. It follows from the definition of $P(t)$ in Eq. (15) that

$$\begin{aligned} P^{-1}(t) = w^T(t)w(t) = \sum_{i=1}^{t} w(i)w^T(i) &= \sum_{i=1}^{t-1} w(i)w^T(i) + w(t)w^{T(t)} \\ &= P^{-1}(t-1) + w(t)w^T(t) \end{aligned} \tag{21}$$

Equation (19) is called the normal equation. Equation (20) can be written as

$$\begin{aligned} \hat{\theta}(t) = \left(\sum_{i=1}^{t} w(i)w^T(i)\right)^{-1}\left(\sum_{i=1}^{t} w(i)y(i)\right) &= P(t)\left(\sum_{i=1}^{t} w(i)y(i)\right) \\ &= P(t)\left(\sum_{i=1}^{t-1} w(i)y(i) + w(t)y(t)\right) \end{aligned} \tag{22}$$

It follows from Eqs. (21) and (22) that

$$\sum_{i=1}^{t-1} w(i)y(i) = P^{-1}(t-1)\hat{\theta}(t-1) = P^{-1}(t)\hat{\theta}(t-1) - w(t)w^T(t)\hat{\theta}(t-1) \tag{23}$$

The estimate at time t can now be written as

$$\begin{aligned} \hat{\theta}(t) &= \hat{\theta}(t-1) - P(t)w(t)w^T(t)\hat{\theta}(t-1) + P(t)w(t)y(t) \\ &= \hat{\theta}(t-1) + P(t)w(t)[y(t) - w^T(t)\hat{\theta}(t-1)] \end{aligned} \tag{24}$$

Theorem 4.1 Recursive least-squares estimation(RLS)

Assume that the matrix $w(t)$ has full rank, that is, $w^T(t)w(t)$ is nonsingular, for all $t \geqq t_0$. Given $\hat{\theta}(t_0)$ and $P(t_0) = \left(\sum_{i=1}^{t} w(i)w^T(i)\right)^{-1}$, the least-squares estimate $\hat{\theta}(t)$ then satisfies the recursive equations

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - w^T(t)\hat{\theta}(t-1)) \tag{25}$$

$$K(t) = P(t)w(t) = P(t-1)w(t)(I + w^T(t)P(t-1)w(t))^{-1} \tag{26}$$

$$\begin{aligned} P(t) &= P(t-1) - P(t-1)w(t)(I + w^T(t)P(t-1)w(t))^{-1}w^T(t)P(t-1) \\ &= (I - K(t)w^T(t))P(t-1) \end{aligned} \tag{27}$$

4. RLS Algorithm Using IIR Filter

In this section, the recursive least-squares method is used to estimate parameters in models of dynamical systems for experimental application in chapter 5. Compared with previous estimation method based on transfer function, RLS algorithm using IIR model does not need differential terms such as $\dot{y}_p$ and $\dot{r}$ shown in Eq. (14) to estimate parameters although system dynamics has high order terms. It is a strong point of this estimation method. IIR filters are useful for high speed designs because they typically require a lower number of multiplies compared to FIR filters.

A linear time-invariant dynamical system is uniquely characterized by its impulse response. The impulse response is in general infinite-dimensional. The impulse response of an IIR model is of infinite duration. The general difference equation for an IIR filter is

$$A(q)y_p(t) = B(q)r(t) \tag{28}$$

where q is the forward shift operator and $A(q)$ and $B(q)$ are the polynomials

$$\begin{aligned} A(q) &= q^n + a_1 q^{n-1} + \dots + a_n \\ B(q) &= b_1 q^{m-1} + b_2 q^{m-2} + \dots + b_m \end{aligned} \tag{29}$$

n is the number of feedback taps in the IIR filter and m is the number of feedforward taps. The output of an IIR filter depends on both the previous m inputs and the previous n outputs. It is responsible for the infinite duration of the impulse response.

Equation (28) can be written as the difference equation

$$y(t) + a_1 y(t-1) + \dots + a_n y(t-n) = b_1 r(t+m-n-1) + \dots + b_m r(t-n) \tag{30}$$

Assume that the sequence of inputs has been applied to the system and the corresponding sequence of outputs has been observed. Introduce the parameter vector

$$\theta^T = [\ a_1\ \dots\ a_n\ b_1\ \dots\ b_n\ ] \tag{31}$$

and the regression vector

$$w^T(t-1) = [\ -y(t-1)\ \dots\ -y(t-n)\ r(t+m-n-1)\ \dots\ r(t-n)\ ] \tag{32}$$

Note that the output signal appears delayed in the regression vector. The way in which the elements are ordered in the matrix θ is arbitrary, provided that $w^T(t-1)$ is also similarly reordered. Later, in dealing with adaptive control, it will be natural to reorder the terms. The time index of the w vector will refer to the time when all elements in the vector are available. The model can formally be written as the regression model similar to Eq. (3)

$$y(t) = w^T(t-1)\theta \tag{33}$$

Parameter estimates can be obtained by applying the least-squares method(Theorem 4.1). Simulation example to prove this identification method is followed. Parameter estimates can be obtained by applying the least-squares method shown in Theorem 4.1. When a system has second order structure, IIR model, the regression vector and parameter vector are

$$y(t) = -a_1 y(t-1) - a_2 y(t-2) + b_1 r(t) + b_2 r(t-1) + b_3 r(t-2)$$

$$\theta^T = [\ a_1\ a_2\ b_1\ b_2\ b_3\ ]$$

$$w^T(t-1) = [\ -y(t-1)\ \ -y(t-2)\ \ r(t)\ \ r(t-1)\ \ r(t-2)\ ]$$

If some system is identifiable, there are input signals that enable the determination of the unique set of parameters by means of input-out measurements. On the other hand, the persistent excitation condition states that the input and output signals are rich enough for the coefficients to be well estimated. Therefore at least 5 different frequency domain input-output sets or square input-output set are needed for the precise system identification.

5. Model Reference Adaptive PID Control

The goal of this section is to develop parameter adaptation laws for a PID control algorithm. Consider a process with a second order transfer function

$$G(s) = \frac{Y(s)}{U(s)} = \frac{cs+d}{s^2+as+b} \tag{34}$$

where c and d are assumed to be positive.

Consider also the following PID control law, where the Laplace transform of the control signal is given by:

$$U(s) = Kp(U_c(s) - Y(s)) + \frac{K_i}{s}(U_c(s) - Y(s)) - K_d s Y(s) \tag{35}$$

Let the controller transfer function, $U(s)$ $D(s)$. Closed loop transfer function $H(s)$ can be written

$$H(s) = \frac{D(s)G(s)}{1 + D(s)G(s)} \tag{36}$$

Using Equations (25)-(27), $G(s)$ can be calculated. For experimental purpose using velocity feedback concept, controller transfer function $D(s)$ is considered as follows:

$$D(s) = \frac{K_i}{s}(u_c(s) - y(s)) \tag{37}$$

For real-time vibration isolation experiment, transfer function at a discrete time domain are needed. To find a time domain expression that will have approximately the characteristics over the frequency range, z transform is used. Assume that open-loop transfer function of reference model has 2nd order and controller has the structure as shown in Equation (37).

$$D(z) = \frac{K_i T}{2} \frac{1 + z^{-1}}{1 - z^{-1}} \tag{38}$$

$$G_m(z) = \frac{b_1 + b_2 z^{-1} + b_3 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{39}$$

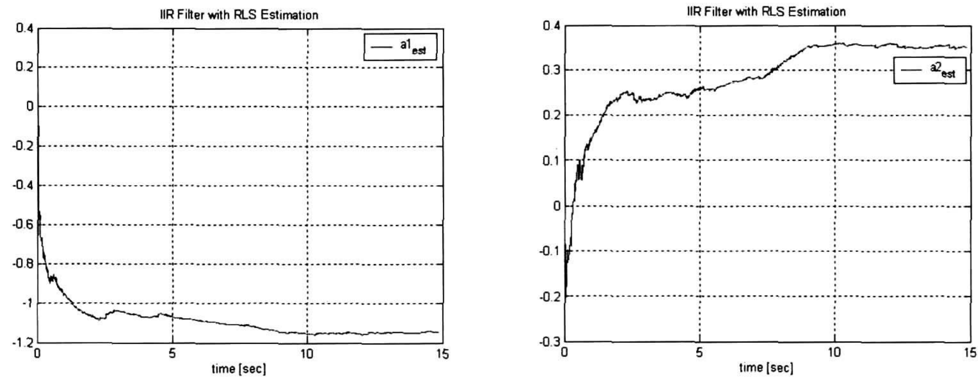
It is possible to show that applying control law (38) to system (39) gives the following closed loop transfer function at a discrete time domain:

$$H(z) = \frac{-K_i T b_1 - K_i T(b_1 + b_2)z^{-1} - K_i T(b_2 + b_3)z^{-2} - K_i T b_3 z^{-3}}{\begin{bmatrix} 2 - K_i T b_1 + (2a_1 - 2 - K_i T b_1 - K_i T b_2)z^{-1} \\ + (2a_2 - 2a_1 - K_i T b_2 - K_i T b_3)z^{-2} - (2a_2 + K_i T b_3)z^{-3} \end{bmatrix}} \tag{40}$$

which a_1, a_2, b_1, b_2, and b_3 are parameters of system transfer function by adaptive system identification algorithm. Recall that the model error, e is defined as the difference between the process output y and the reference model output y_m. It is then possible to derive adaptation rules for the controller parameters K_i of control law using MIT rule $\frac{d\theta}{dt} = -\gamma e \frac{\partial e}{\partial \theta}$ with $\theta = K_i$. The process parameters a_1, a_2, b_1, b_2, and b_3 are estimated using recursive least-square algorithm. Then, using MIT rule the approximate controller parameter adaptation laws are as follows:

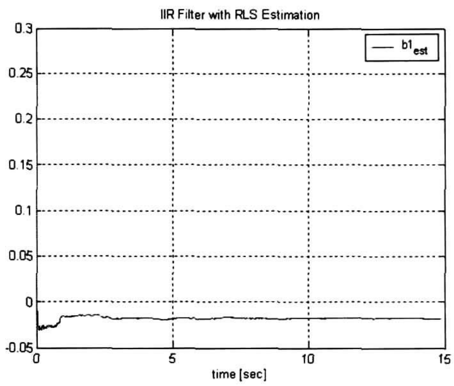
$$\begin{aligned} K_i = & \frac{-Tb_1 - T(b_1 + b_2)z^{-1} - T(b_2 + b_3)z^{-2} - Tb_3 z^{-3}}{\begin{bmatrix} 2 - K_i T b_1 + (2a_1 - 2 - K_i T b_1 - K_i T b_2)z^{-1} \\ + (2a_2 - 2a_1 - K_i T b_2 - K_i T b_3)z^{-2} - (2a_2 + K_i T b_3)z^{-3} \end{bmatrix}} \\ & - \frac{K_i T b_1 + K_i T(b_1 + b_2)z^{-1} + K_i T(b_2 + b_3)z^{-2} + K_i T b_3 z^{-3}}{\begin{bmatrix} 2 - K_i T b_1 + (2a_1 - 2 - K_i T b_1 - K_i T b_2)z^{-1} \\ + (2a_2 - 2a_1 - K_i T b_2 - K_i T b_3)z^{-2} - (2a_2 + K_i T b_3)z^{-3} \end{bmatrix}} \\ & \times (-Tb_1 - (Tb_1 + Tb_2)z^{-1} - (Tb_2 + Tb_3)z^{-2} - Tb_3 z^{-3}) \end{aligned} \tag{41}$$

Before adopting this result to experiment, a number of proper signals for adaptive system

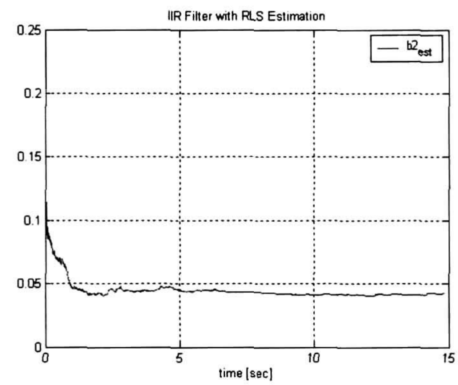


(a) (b)

Fig. 3. Parameter estimation of second order system : (a) a_1 (b) a_2



(a)



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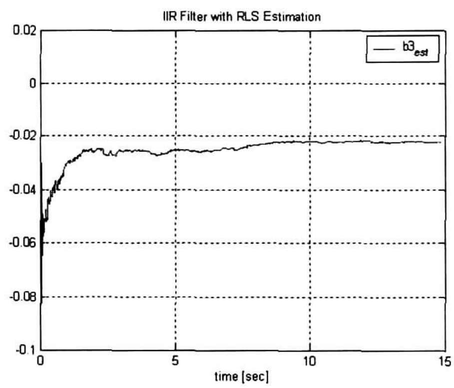


(c)

Fig. 4. Parameter estimation of second order system : (a) b_1 (b) b_2 (c) b_3

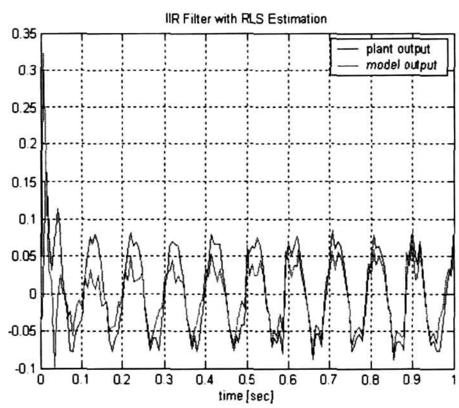


Fig. 5. Plant output and model output

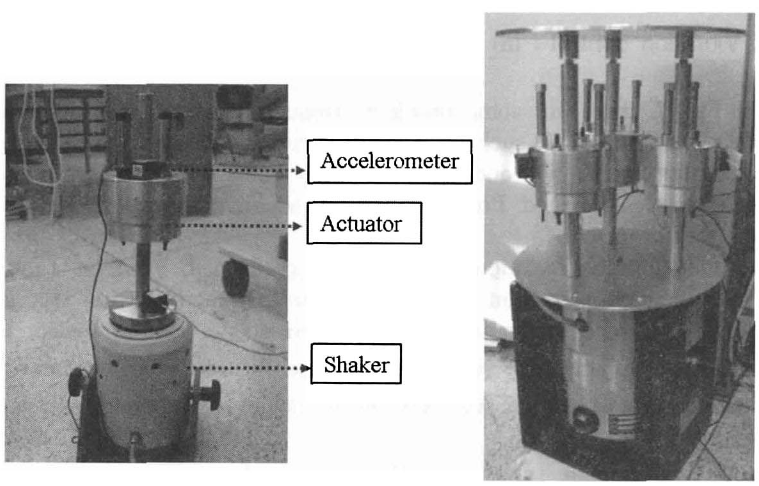
identification from the point of view of the persistent excitation condition are needed to be considered. About a number of proper signals simulation studies under disturbance are executed.

When two sinusoidal signals are used for system identification, the parameter selection error are smaller then other cases such as 5 different signals used as shown in Fig. 3-5. Next chapter uses this result, so 1Hz and 2Hz sinusoidal signals are adopted to find system parameter and then controller gain K_i are selected adaptively.

Experiment Setup and Results

The mechanical setup is a 1 DOF device and consists of active strut module, upper and lower plates, and sensors for vibration isolation experiment applying a decentralized adaptive control scheme. The lower plate is linked on electrodynamic shaker and serves as the entry point for vibration. The strut module connects the lower and the upper plate on which a payload would sit shown in Fig 6. An actuator strut is an 1 DOF modular design with sensor and actuator collocation along its axis of operation. Modularity and robustness through collocation enable standardization of the system identification and easy repair and replacement in case of a component failure. An accelerometer is located at each end of the strut module and a voice coil actuator(VCA) sits in between. The accelerometer on the upper plate measures motion of upper plate(Z) in inertial space which is caused by transmission of shaker vibration through a stiff strut module. The top accelerometer signals are used for feedback control. The bottom accelerometer measures the incoming vibration for feedforward control.

The individual components are described here. First, VCA of BEI KIMCO, LA 17-28-000a is used. The actuator can provide a maximum force of up to 71.2N with large maximum stroke of $\pm 7.6mm$. Second, data acquisition is handled with National Instrument DAQ board, PCI 6025E with 100Hz sampling rate. Third, two kinds of sensors are used in this experiment: two inertial sensors, measuring accelerometer with respect to inertial space and a length sensor, providing displacement information. For the inertial sensor, Crossbow CXL04LP1 MEMS 1 axis accelerometers are used for their compact size $0.78 \times 1.75 \times 1.07in$, low cost, and bandwidth 100 Hz. Its input range is $\pm 4g$. The accelerometer output is compensated by initial bias error. Forth, a Data Physics Electrodynamic shaker DP-V009 is used to generate or simulate vibration entering the current isolation system through the lower plate. It generates a peak force of 75N with armature travel 25.4mm, the useful frequency range DC-7000Hz. The 3 DOF vibration isolator has three of 1 DOF module as shown in Fig. 6, therefore the decentralized adaptive PID control scheme can be used for attenuate vibration.



(a) (b)

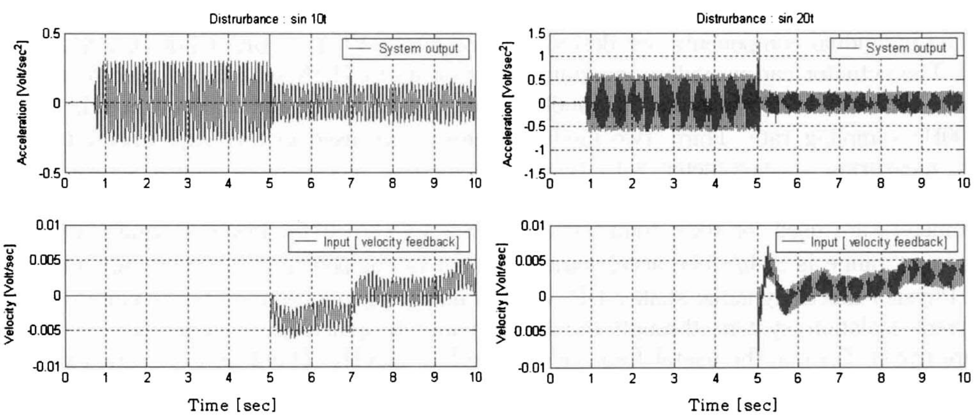
Fig. 6. 1 DOF experimental isolation stack : (a) 1 DOF (b) 3 DOF

1. Experiment Results

Vibration isolation experiment using active velocity feedback control scheme is conducted for a various frequency range. These experiment results using 1 DOF device are preliminary studies for the adaptive control. Actuator input voltage limit is ± 20 voltage. Differential controller gain is 550. Acceleration information is filtered by 50Hz low pass filter and measured by 200Hz sampling ratio. Fig. 7(a) shows vibration isolation result excited by 10Hz, 100mV sine wave from function generator. Control force is exerted 5 second after vibration excites system. The attenuation ratio is -16.3dB. Also shown in Fig. 7(b), 20Hz, 200mV sine wave vibration isolated -20.1dB. The decibel(dB) is a common unit of measurement for vibration amplitudes and rms values. The decibel was originally defined in terms of the base 10 logarithm of the power ratio of two electrical signals, or as the ration of the square of the amplitudes of two signals. Following this idea, the decibel is defined as

$$dB \equiv 10\log_{10}\left(\frac{x_1}{x_2}\right)^2 = 20\log_{10}\left(\frac{x_1}{x_2}\right) \tag{42}$$

which x_1 and x_2 are measurement data or electrical signals.



(a) (b)

Fig. 7. Vibration control : (a) 10Hz sine disturbance (b) 20Hz sine disturbance

As seen in Fig. 7, there are some problems frequently considered for conventional active control theory. Feedback data drift such as velocity is significant because velocity information is getting from acceleration integration and fixed controller gains do not secure a good performance as disturbance or dynamics changed. For these reason, adaptive algorithm needs to be considered to improve system performance.

Experiment for vibration isolation of 3 DOF is performed. First, at 1 second through 3 second system identification algorithm searches system parameters with 1Hz and 2Hz square wave actuator input and acceleration information. Then update law for selecting $K_i s$ searches proper $K_i s$ for each strut. Finally, at 5 second disturbance shakes the system and vibration control scheme with adaptively obtained gain $K_i s$ executes to isolate disturbance. Experiment results are shown in Fig. 8-10.

At a discrete time domain, 1st strut module transfer function is

$$G(z) = \frac{0.061 - 0.103z^{-1} + 0.033z^{-2}}{1 - 0.460z^{-1} + 0.158z^{-2}}$$

Using Matlab function *d2c*, system characteristics can be found. This system has poles at $s=-104 \pm 80.3i$, damping ratio 0.79, and natural frequency 131 rad/sec. The attenuation ratio is -23.35dB, -26.00dB, -29.28dB for 1st strut, 2nd strut, and 3rd strut, respectively against 10Hz, 200mV sinusoidal disturbance.

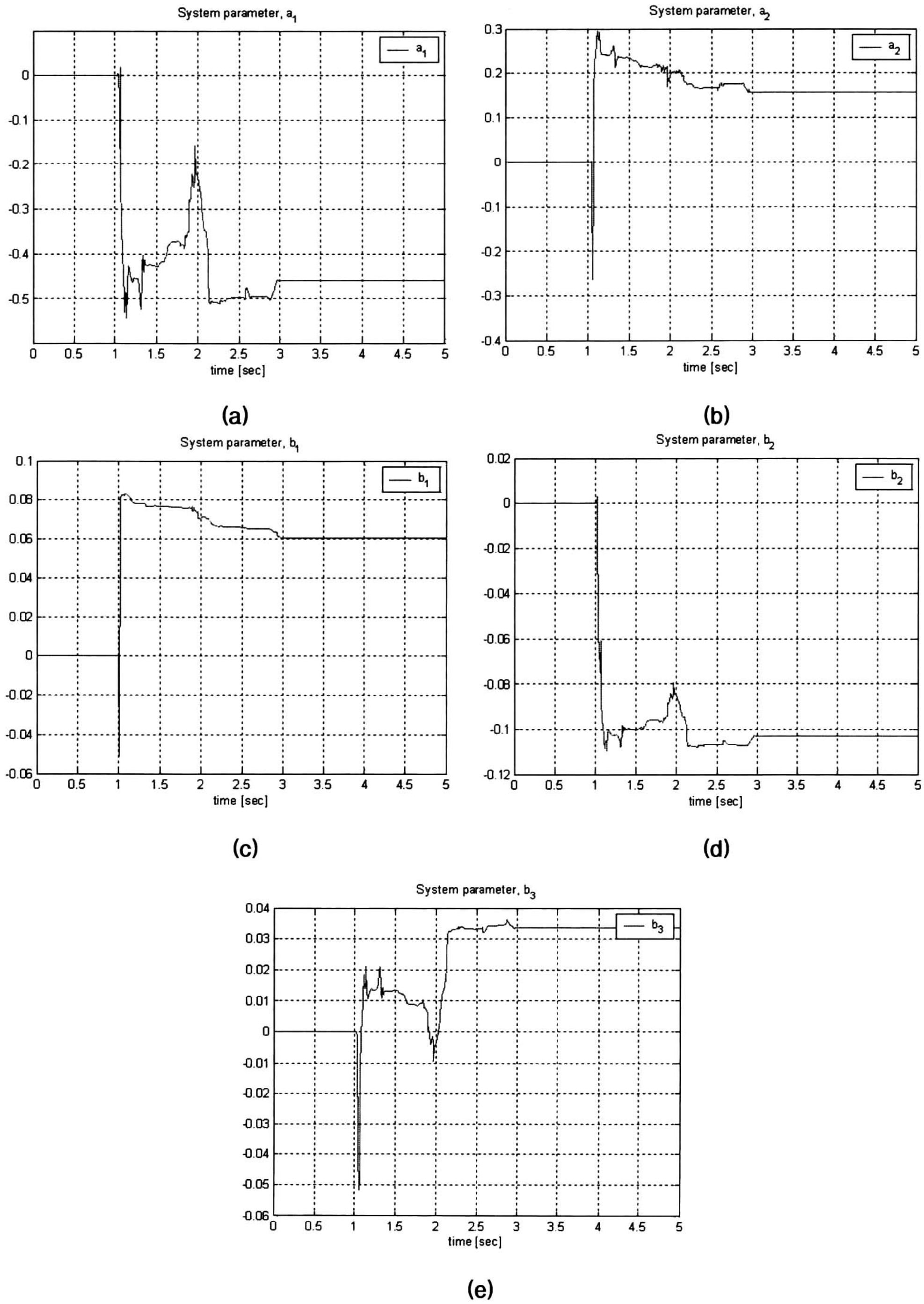
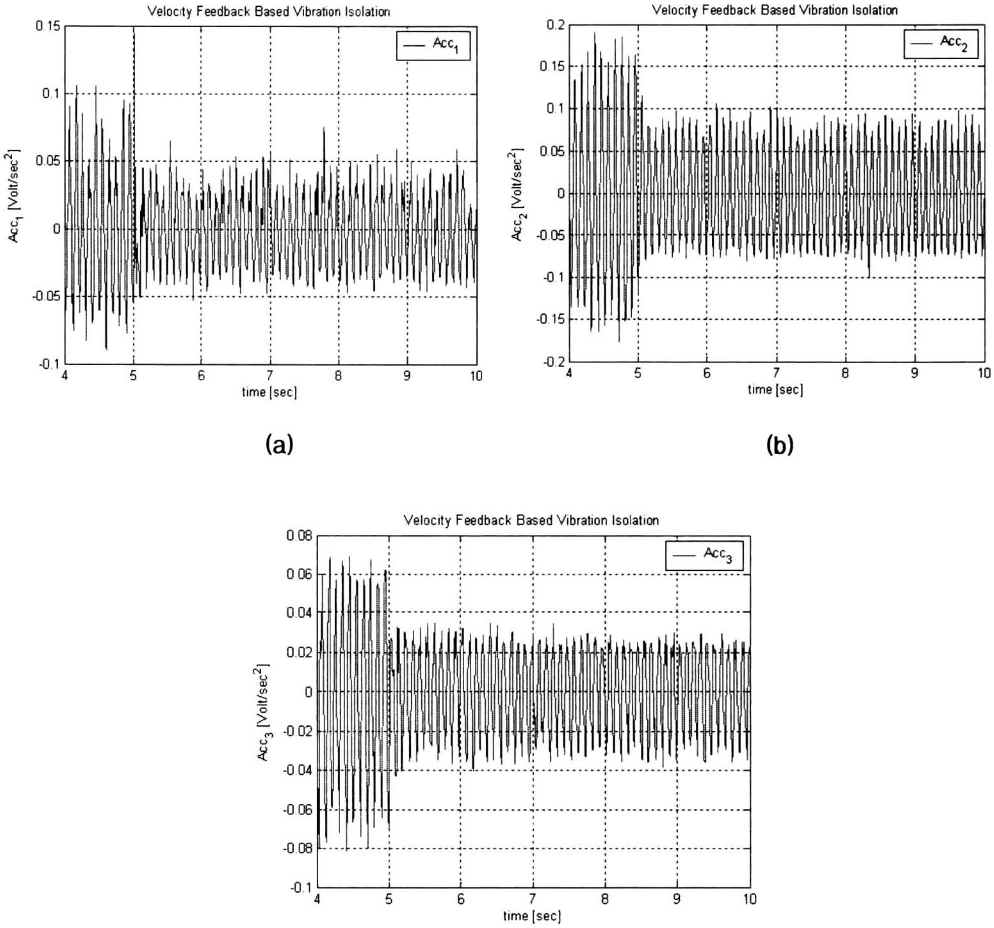


Fig. 8. System parameter for 3 DOF experiment : (a) a_1 (b) a_2 (c) b_1 (d) b_2 (e) b_3



(a) (b) (c)

(a) 1st strut acceleration (b) 2nd strut acceleration (c) 3rd strut acceleration

Fig. 9. Vibration isolation using 3 DOF stack

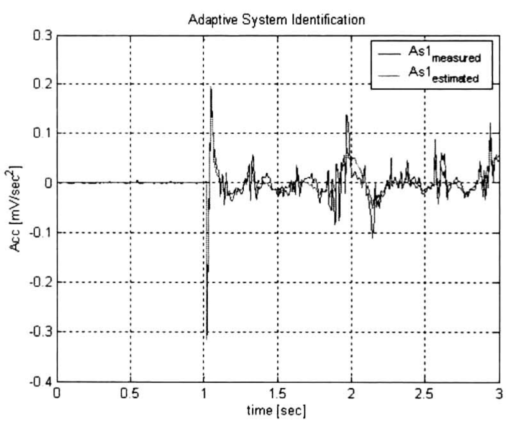


Fig. 10. System identification using RLS with IIR filter

Conclusion

In this dissertation, the centralized control scheme for a 3 DOF vibration isolation system has been built and simulation study is conducted to validate proposed control scheme. The study for applying a decentralized adaptive control scheme to module-type system is done in system identification. Recursive least-square algorithm with IIR filter is used to identify system dynamics and simulation result verifies usage of this methodology. Preliminary experiment for regular vibration isolation control using adaptive theory verifies limitation of conventional active control. These results are applied to 3 DOF experiment which is designed for this dissertation. Reliable system identification can assure better control performance. RLS with IIR filter method finds system parameter as shown in this dissertation. Simultaneously differential controller parameter is updated using this result. Developed decentralized adaptive control scheme which is composed with system identification and controller parameter updates are proved by vibration isolation experiment shown in chapter 5. Furthermore these results are expanded to 3 DOF experiment.

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