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Adaptive Filters for Real-Time System Identification and Control

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An adaptive filter or a neural network concept has been used to develop an algorithm for real-time system identification and control. The algorithm permits not only identification of transfer functions of linear structural systems but also extraction of modal parameters such as natural frequencies, damping ratios, and mode shape coefficients in real time. Because the algorithm is capable of identifying a single mode at a time, bandpass filters are employed to make it work properly for systems with multiple modes. The algorithm has been implemented in a digital signal processor-based data acquisition and control system for the system identification and control experiments with the U.S. Naval Research Laboratory space truss. It was experimentally demonstrated that the algorithm was capable of identifying modal parameters of the truss accurately by using a truss tip-mounted accelerometer as a sensor and a piezoceramic active strut as a disturbance source. The algorithm was also successfully employed to conduct active vibration suppression and performance monitoring of the feedback controller by using the active strut and a collocated force transducer.

Introduction

SPACECRAFT designed to support envisioned U.S. Navy space missions such as a space-based interferometer are expected to be large and lightweight to meet the mission objectives while achieving the necessary launch economy. These large, lightweight spacecraft will be more flexible than their predecessors and conventional rigid-body attitude and maneuvering controllers will not be satisfactory in meeting more stringent attitude control, jitter, and pointing requirements. These spacecraft are also expected to have articulating bodies on board such as solar arrays and large antennae. Dynamic characteristics of the structure may vary as the orientation of these articulating bodies changes. Accurate knowledge of the structural motion of the flexible spacecraft under loadings induced by dynamic maneuvers, articulating bodies, and thermal gradients will be critical in meeting the performance requirements. Engineers at the Naval Center for Space Technology (NCST) at the U.S. Naval Research Laboratory (NRL) have been examining technologies that enable accurate measurement of structural motion and methods of utilizing the measurement information to enhance performance of the spacecraft by suppressing unwanted structural vibration.

To examine these technologies effectively, a space truss simulator facility has been developed at NCST. The facility includes a 3.7-m, 12-bay, T-shaped aluminum truss structure referred to as the NRL space truss; control actuators including active struts and precision reaction mass actuators; Bragg-grating fiber optic sensors; a digital signal processor (DSP)-based data acquisition and control system; and other supporting hardware and software capable of conducting modal testing, finite element analysis, and dynamic simulations. The NRL space truss represents a flexible space structure that carries various payloads and instruments. Control actuators along with the DSP system provide a real-time system identification and closed-loop control capability.

This paper describes efforts that have been made at NCST from the perspective of system identification and active vibration suppression. To suppress vibration effectively for a flexible structure whose structural dynamic properties are changing, a procedure is needed to estimate the change as it occurs, and the controller should be adaptive to the identified change to maintain performance and stability. As a step toward developing an adaptive vibration suppression controller, a real-time modal parameter identification algorithm with an adaptive filter concept is developed and its application to active vibration suppression is investigated here.

In the past decade, there has been extensive research on modal parameter identification of linear, time-invariant systems primarily for off-line applications such as the eigensystem realization algorithm (ERA),[1,2] the polyreference technique,[3] and the observer-Kalman filter identification algorithm[4] to name just a few. To extend some of the time-domain algorithms for the identification of time-varying dynamic systems, several recursive or on-line versions have also been investigated.[5,6] The on-line system identification algorithms derived from system realization theory such as the recursive versions of the ERA[5] are capable of extracting the minimum order realization of the system matrices in real time. However, modal parameter extraction has not been conducted in real time, because modal parameter extraction typically requires an eigensolution of the system matrices, and the eigensolution process is numerically intensive for on-line implementation.

It has been recognized by researchers that neural networks or adaptive filters are useful for system identification and control.[7–9] In these studies, neural networks are employed successfully to help develop a model that can duplicate a given input–output time history through either on- or off-line training. For on-line implementation, the adaptive filters can be very efficient computationally, especially when the LMS (least mean square) algorithm[10] is used to update the filter coefficients. However, it is difficult to relate the parameters in the model directly to physically meaningful quantities such as natural frequencies, damping ratios, and mode shapes of a structure.

In this paper, a real-time system identification algorithm is presented based on an adaptive filter or a neural network concept. The structure of the adaptive filter is designed to allow direct correlation between the filter coefficients and modal parameters. Because the adaptive filter coefficients are identified with the LMS algorithm,

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on-line implementation of the algorithm is computationally efficient. The implementation and performance of the algorithm in a DSP-based data acquisition system are described in this paper. The application of the algorithm for active vibration suppression and closed-loop control performance monitoring of the NRL space truss is also presented.

Real-Time System Identification Algorithm

The basic concepts and theoretical development of the real-time system identification algorithm are presented here including 1) the design of adaptive filters and transfer function identification, 2) filter coefficients update procedure, and 3) modal parameter identification.

Design of Adaptive Filters and Transfer Function Identification

Adaptive filters have been used extensively for signal processing[10] and engineering applications such as noise and vibration control.[11] An adaptive filter with linear elements is shown in Fig. 1. The nth input signal at time step k is denoted as $x_{n,k}$, and the corresponding coefficient or weight is denoted as $w_{n,k}$. The weighted sum of the inputs produces the filter output at time step $k(\hat{y}_k)$. The difference between the desired output (y_k) and the filter output becomes the error signal (e_k). The adaptation algorithm is then used to update the coefficients in the direction that minimizes the error signal. By updating the coefficients in real time, the filters are capable of tracking time-varying plant dynamics. For given input–output time histories, there would exist many possible filter designs as a combination of the number of coefficients employed and input–output arrangements. All of them could produce satisfactory identification results. The objective of this investigation is to find the filter design that allows direct identification of physically meaningful quantities such as natural frequencies, damping ratios, and mode shapes.

To design the desired filter, consider the transfer function of a single-input, single-output system in the s domain as

$$\frac{Y_q(s)}{U_p(s)} = \sum_{i=1}^{N} \frac{\phi_{p_i}\phi_{q_i}}{s^2 + 2\zeta_i\omega_i s + \omega_i^2} \tag{1}$$

where $Y_q(s)$ and $U_p(s)$ represent the displacement at degree-of-freedom (DOF) q and force input at DOF p, respectively; N is the number of modes used to represent the structural response; ω_i and ζ_i are the ith natural frequency in radian per second and damping ratio, respectively; and ϕ_{p_i} and ϕ_{q_i} are the ith mode shape coefficients at DOF p and q, respectively. The structural response is represented as a superposition of responses from individual modes. Consider the ith mode only and then the transfer function in Eq. (1) is converted into the z domain by using the bilinear (TUSTIN) transformation[12] of

$$s = 2f_s[(z-1)/(z+1)] \tag{2}$$

where f_s is the sampling frequency in hertz. The resulting transfer function becomes

$$\frac{Y_q(z)}{U_p(z)} = \frac{\left(b_k/4f_s^2\right)(1 + 2z^{-1} + z^{-2})}{1 + a_{1k}z^{-1} + a_{2k}z^{-2}} \tag{3}$$

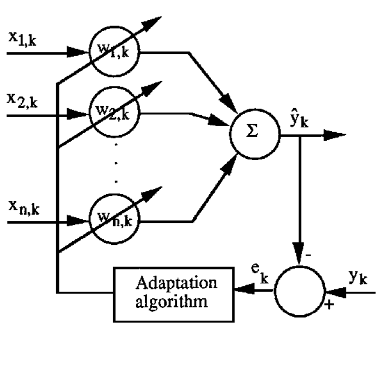


Fig. 1 Block diagram of an adaptive filter.

where the subscript k indicates the values at time step k and the coefficients b_k, a_{1k}, and a_{2k} are written as

$$b_k = \frac{\phi_{p_i}\phi_{q_i}}{1 + (\zeta_i\omega_i/f_s) + (\omega_i/2f_s)^2} \tag{4}$$

$$a_{1k} = \frac{-2 + \left(\omega_i^2/2f_s^2\right)}{1 + (\zeta_i\omega_i/f_s) + (\omega_i/2f_s)^2} \tag{5}$$

$$a_{2k} = \frac{1 - (\zeta_i\omega_i/f_s) + (\omega_i/2f_s)^2}{1 + (\zeta_i\omega_i/f_s) + (\omega_i/2f_s)^2} \tag{6}$$

The transfer function in Eq. (3) is referred to as an infinite impulse response filter in the signal processing literature.[10] Define

$$x_{1,k} = u_k + 2u_{k-1} + u_{k-2} \qquad x_{2,k} = y_{k-1} \qquad x_{3,k} = y_{k-2} \tag{7}$$

and

$$w_{1,k} = b_k\big/4f_s^2 \qquad w_{2,k} = -a_{1k} \qquad w_{3,k} = -a_{2k} \tag{8}$$

where u_k and y_k correspond to $U_p(z)$ and $Y_q(z)$, respectively. Then the transfer function in Eq. (3) can be cast into the form of an adaptive filter in Fig. 1 with three inputs, i.e., $n = 3$. If the filter coefficients in Eq. (8) are identified, the transfer function in Eq. (3) will be readily identified.

It has been shown above that the filter coefficients can be used to identify the transfer function based on displacement response measurement. The same coefficients can also be used to identify transfer functions for velocity and acceleration responses. Consider the transfer function for the ith mode in the s domain for velocity and acceleration responses due to force input as

$$\frac{V_q(s)}{U_p(s)} \equiv \frac{sY_q(s)}{U_p(s)} = \frac{\phi_{p_i}\phi_{q_i}s}{s^2 + 2\zeta_i\omega_i s + \omega_i^2} \tag{9}$$

$$\frac{A_q(s)}{U_p(s)} \equiv \frac{s^2Y_q(s)}{U_p(s)} = \frac{\phi_{p_i}\phi_{q_i}s^2}{s^2 + 2\zeta_i\omega_i s + \omega_i^2} \tag{10}$$

respectively. By going through the bilinear transformation in Eq. (2), the transfer functions in the z domain are identified as

$$\frac{V_q(z)}{U_p(z)} = \frac{(b_k/2f_s)(1 - z^{-2})}{1 + a_{1k}z^{-1} + a_{2k}z^{-2}} \tag{11}$$

$$\frac{A_q(z)}{U_p(z)} = \frac{b_k(1 - 2z^{-1} + z^{-2})}{1 + a_{1k}z^{-1} + a_{2k}z^{-2}} \tag{12}$$

for velocity and acceleration responses, respectively. The coefficients b_k, a_{1k}, and a_{2k} in Eqs. (11) and (12) are defined in Eqs. (4–6). Examination of Eqs. (11) and (12) in comparison to Eq. (3) reveals that the transfer functions have identical denominators and similar numerators. Because the sampling frequency is known, once the transfer function is identified for one type of response, the transfer functions corresponding to the other two responses will be easily identified. This attribute of the transfer functions provides the capability of either differentiating or integrating the response signals without using integrators or differentiators. This capability is used later to integrate a force transducer signal for feedback control with an active strut.

Filter Coefficients Update Procedure

The adaptation algorithm block in Fig. 1 is described here. The objective of the filter coefficients update is to find the values that minimize

$$J = \sum_{k=1}^{m} e_k^2 = \sum_{k=1}^{m} (y_k - \hat{y}_k)^2 \tag{13}$$

where m is the number of samples and

$$\hat{y}_k = \sum_{j=1}^{3} w_{j,k} x_{j,k} \tag{14}$$

Filter coefficients are updated by using the adaptive LMS algorithm[10] as

$$w_{j,k+1} = w_{j,k} - \alpha_j \frac{\partial J}{\partial w_{j,k}} \tag{15}$$

By substituting Eq. (13) into Eq. (15) and rearranging, we obtain

$$w_{j,k+1} = w_{j,k} + 2\alpha_j e_k x_{j,k} \tag{16}$$

where the positive constant α_j is the learning rate corresponding to the jth coefficient, and it determines how fast or slow the coefficients are being updated. If α_j is zero, the coefficients will not be changed. If α_j is too large, the coefficients may not converge.

Because the magnitudes of the input signals to the filter ($x_{1,k}$, $x_{2,k}$, and $x_{3,k}$) and the converged values of the coefficients can be different, possibly by an order of magnitude, proper scaling of the signals is needed to allow the coefficients to converge at about the same rate. This scaling is conducted by defining a modified learning rate $\hat{\alpha}_j$ as

$$\hat{\alpha}_j = \alpha_j \frac{w_{j,\infty}}{\|\boldsymbol{x}_j\|_{\mathrm{rms}}} \tag{17}$$

where $\|\boldsymbol{x}_j\|_{\mathrm{rms}}$ means the rms value of the jth input signal and $w_{j,\infty}$ is an estimated value of the jth weight.

The estimates of the coefficients or weights can be made available by conducting an off-line identification. Assume that a set of input and output time histories has been measured for either a time-varying or a time-invariant system. Then, to minimize the error signal (e_k), a system of linear equations can be developed using Eqs. (13) and (14) as

$$\begin{bmatrix} x_{1,1} & x_{2,1} & x_{3,1} \\ x_{1,2} & x_{2,2} & x_{3,2} \\ \vdots & \vdots & \vdots \\ x_{1,m} & x_{2,m} & x_{3,m} \end{bmatrix} \begin{Bmatrix} w_{1,\infty} \\ w_{2,\infty} \\ w_{3,\infty} \end{Bmatrix} = \begin{Bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{Bmatrix} \quad \text{or} \quad \boldsymbol{X}\boldsymbol{w}_\infty = \boldsymbol{y} \tag{18}$$

Using a least-squares solution, the coefficients can be estimated as

$$\boldsymbol{w}_\infty = \boldsymbol{X}^+ \boldsymbol{y} \tag{19}$$

where the superscript + represents a pseudoinverse. If the plant dynamics is time invariant, the estimated coefficients will correspond to the converged values obtained from the real-time identification. Otherwise, because the real-time estimates track the changing parameters for a time-varying plant, the least-squares estimates will give averaged values of the coefficients for the duration of the measured time histories.

Modal Parameter Identification

The transfer functions identified in the z domain can be utilized to extract modal parameters. For instance, the transfer function in Eq. (12) can be transformed back into the s domain using the inverse bilinear transformation of

$$z = \frac{2f_s + s}{2f_s - s} \tag{20}$$

The transformed transfer function is then written as

$$\frac{A_q(s)}{U_p(s)} = \frac{[4b_k/(1 - a_{1k} + a_{2k})]s^2}{s^2 + [4f_s(1 - a_{2k})/(1 - a_{1k} + a_{2k})]s + \left[4f_s^2(1 + a_{1k} + a_{2k})/(1 - a_{1k} + a_{2k})\right]} \tag{21}$$

By examining the transfer function in the preceding equation in comparison to the transfer function in Eq. (10), it can be easily seen that natural frequency (ω_i, radian per second), damping ratio (ζ_i),

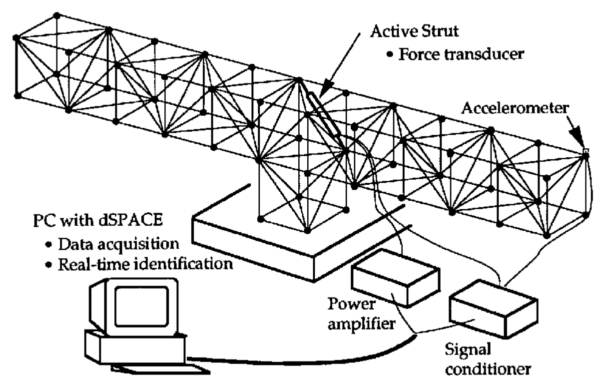


Fig. 2 NRL truss.

and mode shape amplitude ($\phi_{p_i}\phi_{q_i}$) for the ith mode are related to transfer function coefficients as follows:

$$\omega_i = 2f_s \sqrt{\frac{1 + a_{1k} + a_{2k}}{1 - a_{1k} + a_{2k}}} \tag{22}$$

$$\zeta_i = \frac{2f_s(1 - a_{2k})}{\omega_i(1 - a_{1k} + a_{2k})} \tag{23}$$

$$\phi_{p_i}\phi_{q_i} = \frac{4b_k}{1 - a_{1k} + a_{2k}} \tag{24}$$

where f_s is the sampling frequency in hertz. The modal parameters in Eqs. (22–24) can be identified in real time as the transfer function coefficients (b_k, a_{1k}, and a_{2k}) are updated in real time by the adaptive filter.

Real-Time System Identification and Control Experiments Using the NRL Truss

The real-time system identification algorithm described previously was employed for the system identification and control experiments with the NRL space truss used as a test structure. This section details the experiments and the results.

Description of the Experimental Apparatus

The NRL space truss depicted in Fig. 2 represents a flexible spacecraft structure that may support solar arrays, scientific instrumentation, or sensor platforms. The truss is an assembly of batten/longeron and diagonal struts interconnected by node balls. Each strut consists of an aluminum tube member of 0.79 cm (outer diameter) and 0.89 mm (wall thickness). The struts are 26.5 cm long for longerons/battens and 40.6 cm long for diagonals. The T-shaped truss is clamped at its base and is extended two bays vertically and 11 bays horizontally. Each bay is a cube with a side dimension of 34 cm.

A piezoceramic active strut is substituted for a diagonal truss member in the center bay of the truss as indicated in Fig. 2. The active strut provides an excitation source to the structure and is located where the second mode of the truss can be easily excited. The second mode exhibits a seesaw motion of the transverse boom in the vertical plane. For the second mode, the struts in the two vertical bays and the three horizontal bays at the center of the transverse boom experience most of the deformation, whereas the remaining horizontal bays move without significant deformation of individual struts. As indicated in Fig. 2, the active strut includes a force transducer that measures the axial force in the strut. The active strut used in this study is designed and fabricated at the California Institute of Technology, Jet Propulsion Laboratory (JPL), and is on loan to

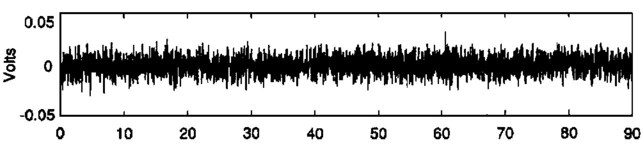
the NRL. Its construction and characteristics are similar to those described in Ref. 13. The active strut consists of a preloaded stack of piezoceramic disks in a cylindrical housing.

Data acquisition and real-time modal parameter identification are conducted with a high-speed DSP-based system called dSPACE. The dSPACE system consists of a Texas Instrument TMS320C40 DSP chip and the software interfaces including Real-Time Interface (RTI), TRACE, and COCKPIT. A C-code is written for implementation of the identification algorithm and controllers in the DSP system. RTI serves as an interface between the C-code written by a user and the DSP system by facilitating the process of downloading and running the C-coded algorithm. TRACE is used for real-time display of time histories and data recording. COCKPIT is employed to make real-time changes of the identification algorithm parameters such as the learning rate and control gains while the DSP is running.

Modal Parameter Identification Experiment

For the real-time identification experiment, band-limited Gaussian noise (0–50 Hz) was generated by a signal generator. The signal was then used to drive the JPL active strut located in the center bay of the truss. As shown in Fig. 2, an accelerometer was mounted at a free end of the truss in the vertical direction to measure the response of the truss. Typical time histories of the disturbance and response signals are shown in Fig. 3. These signals were used to update the filter coefficients and to conduct system identification. As described previously, the real-time system identification algorithm was developed based on the assumption that a single mode is identified at a time. Because the disturbance is of a random nature and the acceleration response has multiple frequency contents in it, the signals need to be filtered to extract a single frequency. In this experiment, the signal corresponding to the second mode of the truss was extracted by using a fourth-order Butterworth filter. The filter has a high-pass break frequency of 10 Hz and a low-pass break frequency of 25 Hz. Sampling frequency was set at 256 Hz. This filtering process was also implemented in the DSP system.

Filtered disturbance and response signals were then fed into the adaptive filter for filter coefficients update and modal parameter and transfer function identification. This process is schematically shown in Fig. 4. The results of the filter coefficient updates and the corresponding modal parameters of the second mode of the truss are shown in Figs. 5 and 6, respectively. In the figures, the left-hand column is used to show the overall trend of the values and the right-hand column is used to show the converged values. Initially, the filter coefficients were set to zero. Figures 5 and 6 indicate



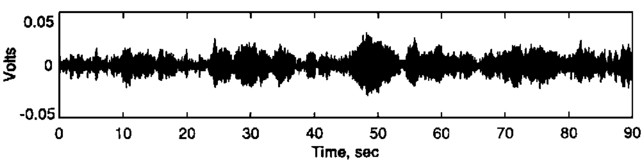


Fig. 3 Typical time histories of disturbance and response signals.

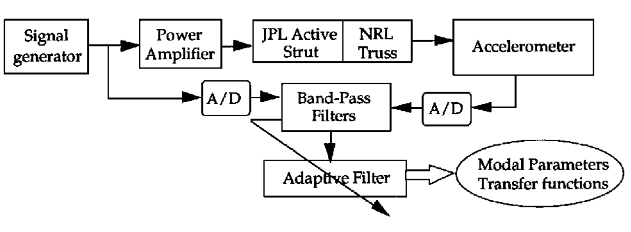


Fig. 4 System identification process.

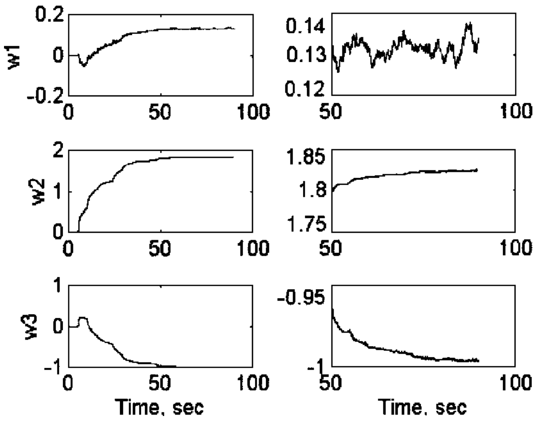


Fig. 5 Time history of updated filter coefficients.

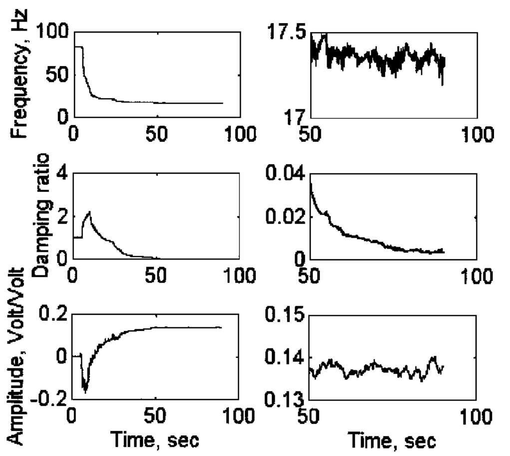


Fig. 6 Time history of updated modal parameters.

convergence to the correct values as the coefficient updating process begins at about 5 s. The natural frequency converged to about 17.4 Hz, and the damping ratio converged to about 0.002 (0.2% of the critical damping). These values agree well with those obtained from independent modal tests, i.e., 17.2–17.4 Hz for natural frequency and 0.0015–0.004 for the modal damping ratio.

Active Vibration Suppression Experiment

To investigate the feasibility of using the real-time system identification algorithm for active vibration suppression, a feedback control experiment was conducted using the JPL active strut and a collocated force transducer. The block diagram of the controller used for this study is depicted in Fig. 7. As demonstrated by other vibration-suppression studies with active struts,[14,15] damping can be augmented effectively by a feedback controller with an integrated force transducer signal. By integrating the force measurement, the signal needed for active damping is produced, which is 90 deg out of phase with respect to the force measurement.

In this investigation, instead of using an integrator $(1/s)$, the identified filter coefficients were employed to conduct the integration. Similar to the system identification process, as depicted in Fig. 7, the input signal to the power amplifier for the active strut and the force measurement signal were filtered by using the same bandpass filters used previously. By treating the force measurement as acceleration, coefficients of an adaptive filter and the corresponding modal parameters were updated. Then the identified filter coefficients were substituted into the velocity transfer function in Eq. (11) and, using the filtered input signal, the integrated force signal was produced. The signal was then multiplied by a gain and used to close the loop for feedback control as shown in Fig. 7. The signal generator produces a sinusoidal disturbance signal of 17.5 Hz, which drives the second natural frequency of the truss.

Figure 8 shows various time histories measured in real time during the system identification and active control experiments. Included

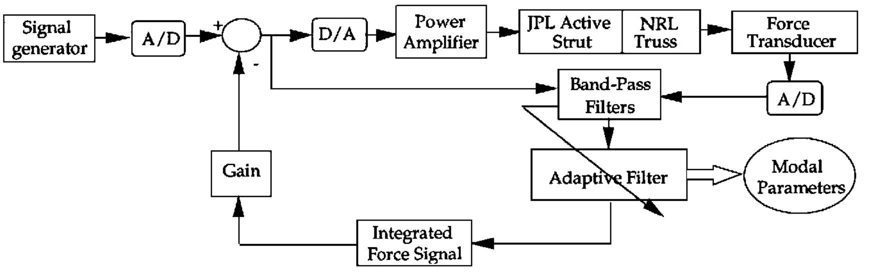


Fig. 7 Block diagram for active vibration suppression.

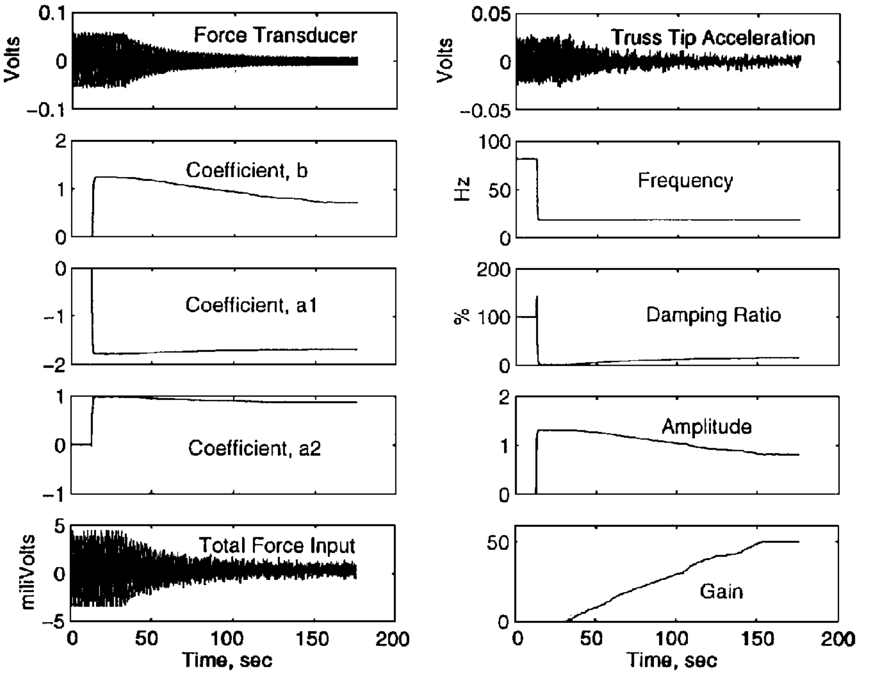


Fig. 8 Results of real-time system identification and control experiment.

are the filter coefficients and corresponding modal parameters, the force transducer and truss tip accelerometer responses, the total voltage command to the power amplifier for the active strut, and the closed-loop gain. Initially, the signal generator was turned on with zero feedback gain and zero learning rates for the adaptive filter. The filter coefficients update process was initiated at about 15 s. The weights and modal parameters converged to the values corresponding to the open-loop system. Then, the feedback gain adjustment was started from about 35 s until the maximum gain of 50 was reached at about 150 s while the system is still running. During the process, the increase in damping ratio and reduction in mode shape amplitude were monitored in real time as shown. The truss tip acceleration response also shows that the truss vibration is being suppressed because of the active control. Although this real-time system identification and control experiment was intended to show an adaptive feedback control capability, the results clearly show that the identification algorithm is capable of monitoring the performance of the feedback controller. It appears that this monitoring capability will be useful in conducting overall health monitoring of actively controlled systems including structures[16] as well as sensors and actuators.

Concluding Remarks

A real-time system identification algorithm using adaptive filters has been developed and its capability has been demonstrated experimentally with the NRL truss and the active strut in a DSP-based data acquisition and control environment. Because the algorithm is currently capable of identifying a single mode at a time, bandpass filters were employed to extract the signal corresponding to the second mode of the truss. The identified modal parameters of the second mode of the truss were accurate in comparison to independent modal test results. Although the algorithm can be tailored to identify one mode at a time by using bandpass filters for multiple mode identification, it is desirable to develop the capability of identifying multiple modes simultaneously.

For the control experiment with the active strut and a collocated force transducer, a significant increase in damping was achieved by using the integrated force feedback. Instead of an integrator, the identified filter coefficients were used to successfully produce an integrated force signal. The system identification algorithm was used to monitor the closed-loop performance of the controller in real time as the feedback gain was adjusted. The algorithm may also be useful in monitoring the health of an active control system including structures, sensors, and actuators. The results of this experiment indicate that an adaptive control for a time-varying plant would be feasible with the real-time system identification algorithm described in this paper.

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