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ACTIVE VIBRATION ATTENUATION OF SMART MATERIAL SYSTEMS WITH MODEL-BASED AND NONLINEAR MULTISPECTRAL CONTROLLERS

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ABSTRACT

Many efforts have been concentrated on the active noise and vibration control with smart material systems. However, previous studies are limited to the reduction of a single frequency. Thus, more investigations are needed on multispectral control, which deals with multiple frequency components simultaneously. The main objective of this research is to establish a model-based and nonlinear multispectral controller by integrating the least mean squares (LMS) algorithm with model-based controllers. It is expected that multispectral signals are managed appropriately by model-based controls and nonlinear control covers the nonlinearity, model uncertainty, and other unexpected conditions. Performances of the proposed algorithms are validated with simulations and experiments in various cases. Novel methodologies developed in this research are expected to be employed for numerous applications in active vibration and noise control studies such as structural vibration attenuation, vehicle vibration and noise reduction, and active struts for aircrafts, helicopters, and other vibrating platforms.

INTRODUCTION

Recently, many research works have been concentrated on the active noise and vibration control with smart material systems. Among several applications in this field, active struts with smart materials attached on them are utilized for attenuating vibrations transmitted from the gearbox, which cause very annoying noise in the cabin. There have been many research works on the active vibration control, especially related to the active struts of various vehicles. Loewy [1] proposed several different designs of passive struts made of springs and dampers to mitigate the vibration and noise. Kawaguchi [2] developed an active vibration reduction system using hydraulic actuators inside gearbox struts. Sutton [3] tested a helicopter gearbox strut containing three magnetostrictive actuators to indicate the ability of actively reducing vibration of the gearbox. Millott [4] proposed an active noise control system for canceling gear mesh noise of the S-76 helicopter using proof-mass actuators. Baz, and Asiri [5-7] investigated periodic structures and their use in active controls. Gembler, Maier, and Hoffmann [8-10] established an active vibration isolation technique by using active gearbox struts with multilayer piezoelectric stacks and applied filtered-x LMS algorithm to achieve reduction at the primary gear mesh frequency. However, while one principal gear-meshing frequency can be considerably mitigated, it is difficult to manage broadband frequencies. Since previous studies are limited to the reduction of a single frequency, more investigations are needed on multispectral control methods dealing with multiple frequency components such as sidebands and higher harmonics simultaneously.

The main objective of this research is to establish a model-based and nonlinear multispectral controller for the active noise and vibration control with smart material systems by integrating the least mean squares (LMS) algorithm with model-based controllers. With the assistance of nonlinear techniques and a process model for designing a novel controller, it is expected that multispectral frequency components are managed appropriately by model-based controls and nonlinear control covers the nonlinearity, model uncertainty, and other unexpected conditions. LMS, one of the most widespread feedforward control algorithm due to its simplicity, is a recursive algorithm that updates the coefficients of adaptive digital filters with error signals and a given reference input, which has frequency components to be controlled. This algorithm is utilized to change the coefficients of the adaptive filter and generate the filter output as close as possible to the desired signal from the system by minimizing the mean squared error. A novel model-based control technique called model predictive sliding mode control (MPSMC) is developed from the motivation of enhancing the conventional sliding mode control over a couple of drawbacks with the assistance of the model predictive control. The key feature of MPSMC is driving system states to reach the sliding surface with an optimized way as compared to the discontinuous action of the sliding mode control. Modified LMS algorithms are developed with supports of the conventional sliding mode control and MPSMC. Performances of the proposed algorithms are validated with simulations and experiments in several situations.

NOMENCLATURE

$\boldsymbol{A}$ = state matrix in discrete time
A_C = state matrix in continuous time
$A^{\wedge}$ = augmented state matrix
$\boldsymbol{B}$ = input matrix in discrete time
B_C = input matrix in continuous time
$B^{\wedge}$ = augmented input matrix
D_C = disturbance matrix in continuous time
$D^{\wedge}$ = augmented disturbance matrix
E = error vector between the state and the reference
E_k = error vector in discrete time
F = time varying disturbance vector
$\boldsymbol{G}$ = matrix determining the sliding surface
J = cost function of the MPSMC
M = magnitude of discontinuous inputs
N = receding horizon
$\boldsymbol{P}$ = cross correlation vector
$\boldsymbol{P}^{\wedge}$ = direct estimation of cross correlation vector
P_c = control path dynamics
P_c^* = model of control path dynamics
P_d = disturbance plant
$\boldsymbol{R}$ = auto correlation matrix
$\boldsymbol{R}^{\wedge}$ = direct estimation of auto correlation matrix
R = reference inputs
S_k = sliding surface of the MPSMC
$S_{\rightarrow}$ = future values of the sliding mode
U = input vector
U_k = input vector in discrete time
$\Delta U_{\rightarrow}$ = future values of the input vector
X = state vector
Z_k = augmented state vector
$\boldsymbol{d}$ = total disturbance
$\boldsymbol{d_k}$ = total disturbance in discrete time
d_k = unwanted signal
$d_{\rightarrow}$ = future values of the disturbance vector
e_k = error signal
s_k = sliding surface of modified LMS algorithms
u_k = reference signal
u_k^* = filtered reference signal
w_k = filter coefficient vector
$w_k^{\wedge}$ = filter coefficient vector in LMS algorithm
y_k = adaptive filter output
y_k^* = output of the control path dynamics
$y_{C,k}$ = output of sliding mode controller
$y_{F,k}$ = original filter output
α = constant determining the sliding surface
ε = thickness of boundary layer
λ = weighting factor for the change of control input
μ = weighting factor in the LMS algorithm
ξ = cost function of the steepest descent method
$\xi^{\wedge}$ = direct estimation of cost function
$\nabla\xi$ = gradient of cost function

ADAPTIVE FILTERING SYSTEM WITH LMS

Adaptive filtering systems carry out numerical tasks to achieve an expected form of signals in the area of engineering such as electronics and computer science. With recent growth of digital computer technologies, digital filters in the discrete time domain are utilized for these systems. Normally, adaptive digital filtering system generates second-path signals against the output signals of acoustic or structural systems in order to reduce or cancel out the original output signals. Especially, FIR (finite impulse response) filter is widely being used among several types of filters since it is very simple, stable inherently, and easy to implement. The coefficients of digital filters are automatically updated by utilizing recursive algorithms at every sampling instant. This methodology can be applied to active noise and vibration reduction, inverse modeling, and system identification.

LMS (least mean squares) algorithm is a well-known and widely utilized algorithm in the company of several adaptive and recursive algorithms implemented in adaptive digital filtering systems. This algorithm is originated from the stochastic gradient of a signal's squared error and the formulation is relatively simple [11]. The LMS algorithm adjusts coefficients of a transversal filter output to generate the output of the adaptive filter as close as possible to the unwanted signal that we are interested in. There are two signals required for this algorithm; a reference signal u_k with frequency components to be treated, and the error signal e_k at the current time step which is obtained by subtracting the adaptive filter output y_k from the unwanted signal d_k. Updating equation for the digital filter coefficients can be derived from the minimization of the mean squared error with the steepest descent algorithm. One of the most appealing properties in the LMS algorithm is that there is no need of matrix inversions which makes the algorithm complicated and average correlation functions from the gradient estimate [12].

In disregard of several advantages, the LMS algorithm is inappropriate in the situation that there is a control path dynamics. In actual experimental environments, there are always some influences from actuators, sensors, amplifiers, data acquisition systems, filters, and so on. From the existence of a transport delay or a phase shift introduced from this additional dynamics, the whole system can be destabilized or converged to a fallacious state, since the filter output y_k and the signal y_k^* subtracted from the unwanted response d_k is different as shown in figure 1. FX-LMS (filtered-X least mean squares) algorithm is developed based on the conventional LMS algorithm with compensation in the reference signal. The control path dynamics is identified first and it is located after the reference signal working as a filter. This filtered signal is applied to the LMS algorithm instead of the original reference signal. Figure 1 shows the schematic of an adaptive filtering system with the filtered-X LMS algorithm.

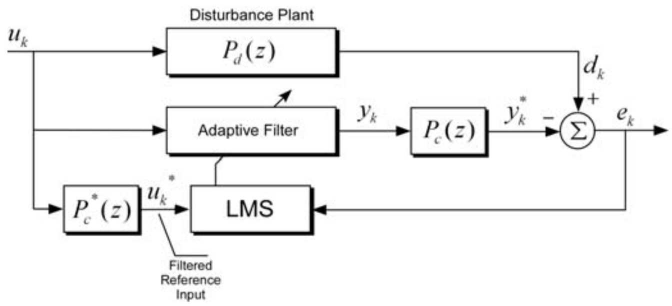

Figure 1. Adaptive filtering system with FX-LMS

The FIR filter output y_k is obtained by multiplying a vector of the reference signal u_{k-j} and a vector of the filter coefficients $w_{j,k}$, which is the j^{th} filter coefficient at the instant k.

$$y_k = \sum_{j=0}^{N} w_{j,k} \cdot u_{k-j} \tag{1}$$

The response of the disturbance plant defined as an unwanted signal d_k and the error e_k is obtained by subtracting the filter output y_k from the unwanted signal d_k.

$$e_k = d_k - y_k \tag{2}$$

At first, a cost function is defined as a mean square of the error signal e_k since a unique minimum is guaranteed from this quadratic function.

$$\xi = E[{e_k}^2] \tag{3}$$

This cost function can also be written as follows by substituting equations 1, 2 into equation 3.

$$\xi = E[{d_k}^2] - 2{w_k}^T P + {w_k}^T R w_k \tag{4}$$

$$\text{where} \quad P = E[u_k \cdot d_k], \quad R = E[u_k \cdot {u_k}^T] \tag{5}$$

Equation 5 defines a vector P, which is the expected value of the cross correlation between the reference and the unwanted signal. Also, it defines a matrix R, which is the expected value of the auto correlation of the reference. The basis of the filtered-X least mean squares algorithm is the steepest descent method as shown in equation 6. It has been widely employed because of its simplicity and the algorithm of updating filter coefficients can be derived by utilizing this method.

$$w_{k+1} = w_k - \frac{\mu}{2} \nabla \xi \tag{6}$$

By differentiating equation 4, the gradient of the cost function is obtained as equation 7. When equation 7 is substituted into equation 6, the steepest descent algorithm is obtained finally as equation 8. μ is a parameter that determines the stability and the time of the algorithm.

$$\nabla \xi = 2Rw_k - 2P \tag{7}$$

$$w_{k+1} = w_k + \mu[P - Rw_k] \tag{8}$$

In this algorithm, the gradient of the cost function should be calculated at every sampling time, which is not a trivial process. Especially, it is very difficult to obtain the expected values of the averaged error, the cross correlation P, and the auto correlation R. Thus, in order to simplify this process, direct estimates at a certain instant for these three are assumed to be the expected values and they are utilized for the LMS algorithm [13]. The squared error, the cross correlation vector, and the auto correlation matrix is redefined.

$$\hat{\xi} = {e_k}^2, \quad \hat{P} = u_k \cdot d_k, \quad \hat{R} = u_k \cdot {u_k}^T \tag{9}$$

Following a similar procedure as the steepest descent algorithm is defined, equation 7 and 9 is substituted into equation 6 and 9 and the LMS algorithm is derived as equation 11.

$$\hat{\nabla}\xi = 2u_k \cdot {u_k}^T \cdot \hat{w}_k - 2u_k \cdot d_k = -2u_k[d_k - y_k] = -2u_k \cdot e_k \tag{10}$$

$$\hat{w}_{k+1} = \hat{w}_k + \mu u_k \cdot e_k \tag{11}$$

In the FX-LMS algorithm, a filtered reference input u_k^* is employed in the updating equation of the filter coefficients and the rest of the formulation is the same as the LMS algorithm. Equation 12 defines the FX-LMS algorithm.

$$\hat{w}_{k+1} = \hat{w}_k + \mu {u_k}^* \cdot e_k \tag{12}$$

The largest contribution of the filter $P_c^*(z)$ in front of the reference input is that it has the same amount of transport delay as the control path dynamics $P_c(z)$. In this aspect, a remarkable drawback of the FX-LMS is found that a system identification process should be done for obtaining $P_c^*(z)$ in advance. Online system identification can solve this issue. However, it makes the whole system complicated to implement. There are some defects in the LMS algorithm as well. Since the original steepest descent algorithm is simplified with the assumptions in equation 9, the filter coefficients would not be on the exact steepest descent surface and this usually causes imperfect and noisy tracking. In addition, it tends to attenuate the mean squared error, which lead to residual spectrum with dominant side-bands and degrade sound quality.

MODEL PREDICTIVE SLIDING MODE CONTROL

A state-of-the-art model-based control technique entitled to the model predictive sliding mode control (MPSMC) is introduced in this section. It is introduced by Washington [14] and the motivation of this novel controller is originated from overcoming various drawbacks of the sliding mode control (SMC), which is one of the most prevalent nonlinear control methodologies recently. SMC is very attractive because of its various strong points. It is robust, insensitive to original system dynamics such as uncertainty and nonlinearity, and able to decouple higher order systems [15]. However, discontinuous inputs give rise to the well-known chattering phenomenon which causes the whole system unstable, since most common actuators cannot switch their direction at an infinite frequency. Moreover, in case of the SMC in the discrete time domain (DSMC), the sliding mode is enforced at the very next time step causing the saturation of the control system [16].

Thus, an enhanced controller is required to manage these problems with a model-based control technique that moves the state trajectory to the sliding mode optimally, rather than the discontinuous inputs, and does not saturate the control system. Model predictive control (MPC) is integrated with the SMC to form the MPSMC. In the concept of MPC, a process model is required and it is utilized to envision responses of the given system in the future up to a certain time step from the receding horizon concept [17]. With a cost function and various constraints, an optimized control input vector in the future is derived at every time step using present and past values of the input and output. The key feature of the MPC is that it carries the system states as close as possible to the reference trajectory. MPC is relatively easy to use for multivariable systems and it can deal with difficult situations such as constraints, inverse responses, and time delays. Since formulations of the MPSMC are similar to those of the MPC, these two are compared for better understandings. Figure 2 shows the concept of the MPC.

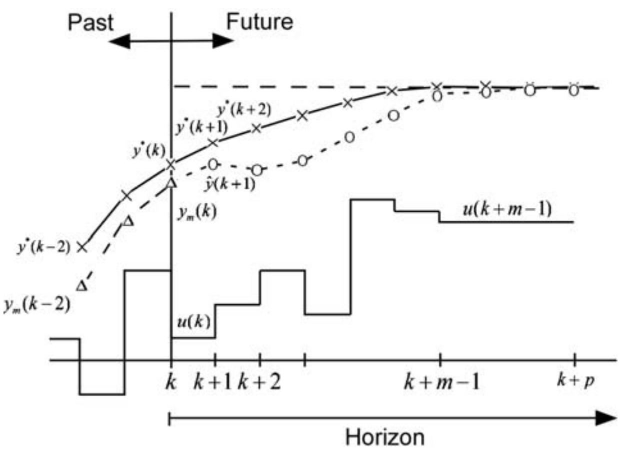

Figure 2. Model predictive control concept

At first, a continuous dynamic system is defined in the state space form as equation 13. X is a state vector, U is an input vector, and F is a time varying disturbance vector.

$$\dot{X} = A_C X + B_C U + D_C F \tag{13}$$

An error vector E, difference between the states X the reference R, is introduced for tracking problems and equation 13 is rewritten as equation 14. The term d encompasses model uncertainties, nonlinearities, disturbances, and reference input effects.

$$\dot{E} = A_C E + B_C U + d \tag{14}$$

Where $$d = A_C R + D_C F - \dot{R} \tag{15}$$

Since the formulations of the MPSMC are described in the discrete time domain, equation 14 is converted to a difference equation.

$$E_{k+1} = AE_k + BU_k + d_k \tag{16}$$

Then, an augmented system equation with a newly defined state Z_k is introduced in equation 18. This state is the combination of the error state vector E_k and the input vector U_{k-1}.

$$\begin{bmatrix} E_{k+1} \\ U_k \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} E_k \\ U_{k-1} \end{bmatrix} + \begin{bmatrix} B \\ I \end{bmatrix} \Delta U_k + \begin{bmatrix} I \\ 0 \end{bmatrix} d_k \tag{17}$$

$$\Rightarrow \quad Z_{k+1} = \hat{A} Z_k + \hat{B} \Delta U_k + \hat{D} d_k \tag{18}$$

Based on this new state vector, a sliding surface is defined in the Z plane.

$$S_k = G Z_k \tag{19}$$

In the concept of MPC, a prediction equation of the system states is derived by combining the system equation from $k+1^{th}$ to $k+N^{th}$ time step. N represents a receding horizon. On the contrary, in the concept of MPSMC, a prediction equation of the sliding mode described in equation 19 is obtained as shown in equation 20. $S_{\rightarrow k}$, $\Delta U_{\rightarrow k-1}$, and $d_{\rightarrow k-1}$ are the future predictions of the sliding mode, input, and disturbance up to N step in the future, as described in equation 21.

$$\underset{\rightarrow k}{S} = PZ_k + H\Delta \underset{\rightarrow k-1}{U} + L\hat{D} \underset{\rightarrow k-1}{d} \tag{20}$$

Where $$\underset{\rightarrow k}{S} = [S_{k+1} \ \cdots \ S_{k+N}]^T, \ \Delta \underset{\rightarrow k-1}{U} = [\Delta U_k \ \cdots \ \Delta U_{k+N-1}]^T, \ \underset{\rightarrow k-1}{d} = [d_k \ \cdots \ d_{k+N-1}]^T \tag{21}$$

$$P = \begin{bmatrix} G\hat{A} \\ G\hat{A}^2 \\ \vdots \\ G\hat{A}^N \end{bmatrix}, H = \begin{bmatrix} G\hat{B} & 0 & \cdots & 0 \\ G\hat{A}\hat{B} & G\hat{B} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ G\hat{A}^{N-1}\hat{B} & G\hat{A}^{N-2}\hat{B} & \cdots & G\hat{B} \end{bmatrix}, L = \begin{bmatrix} G & 0 & \cdots & 0 \\ G\hat{A} & G & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ G\hat{A}^{N-1} & G\hat{A}^{N-2} & \cdots & G \end{bmatrix} \tag{22}$$

Next, a cost function J in equation 23 is selected by summing the square of sliding mode predictions and the square of control input changes in the future, with a weighting factor λ . This cost function is minimized to obtain the optimized control input change ΔU_k at the k^{th} instant.

$$\min_{\underset{\rightarrow}{\Delta U}} J = \left\| \underset{\rightarrow}{S} \right\|^2 + \lambda \left\| \underset{\rightarrow}{\Delta U} \right\|^2 \tag{23}$$

where $$\Delta U_k = -e_1^T (H^T H + \lambda I)^{-1} H^T (PZ_k + L\hat{D} \underset{\rightarrow}{d}) \tag{24}$$

and $$e_1^T = [1 \quad 0 \quad 0 \quad \cdots \quad 0]^T \tag{25}$$

In equation 24, the last term $d_{\rightarrow}$ is the only unknown term at this point. It is the future predictions of the disturbance and commonly the system dynamics of the disturbance is now known in real cases. Accordingly, a simple assumption is made for the estimation of this vector. An estimation of the disturbance at $k\text{-}1^{th}$ time step is possible with available information in the present, as described in equation 27 which is reorganized with the disturbance term d_{k-1} on the left hand. Then, d_{k-1} is replicated N times to make an estimated disturbances in the future as shown in equation 26.

$$\underset{\rightarrow est}{d} = [d_{k-1} \quad d_{k-1} \quad \cdots \quad d_{k-1}]^T \tag{26}$$

where $$d_{k-1} = E_k - AE_{k-1} - BU_{k-1} \tag{27}$$

Figure 3 shows the schematic of the model predictive sliding mode control system.

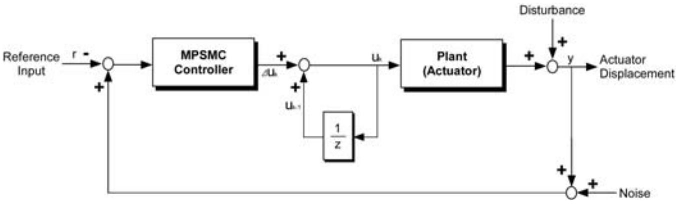

Figure 3. MPSMC system

The competence of the MPSMC has been investigated and verified with various kinds of systems such as the two-stage actuation system of a clutch [18], unimorph bending type piezoelectric actuators [19], an active cantilevered beam [20], and a piezoelectric stack actuator [21]. Note that the tracking performance of this control technique is remarkable even if an inaccurate process model of the given dynamic system is utilized to design the MPSMC.

MODIFICATION OF LMS ALGORITHM

In chapter 2 and 3, the LMS algorithm for adaptive filtering systems and the model predictive sliding mode control are represented. Integrating these two methodologies together, a state-of-the-art adaptive filtering algorithm is developed, which has more superior performance for nonlinear systems and multispectral signals. This chapter deals with the development of three improved LMS algorithms with the assistance of nonlinear and model-based control methods. Nonlinear controllers contribute to managing uncertainties, disturbances, and nonlinearities, while model-based controllers contribute to the multispectral control effectively with the assistance of the known system model. In this research, two modified LMS algorithms with the sliding mode control are proposed first and lastly, another modified LMS algorithm with the MPSMC is proposed, which the MPSMC is utilized to enhance the conventional LMS.

Sliding Mode LMS (SM-LMS) Method 1

Since the cost function defined in the conventional LMS algorithm is quadratic, the minimum value of the function always exists and it is the most attractive property of this algorithm. On the other hand, as the magnitude of the unwanted signal increases linearly, problems on the LMS algorithm become serious such as immoderate mean squared errors and misadjustment [22]. Thus, sliding mode control is employed for developing a modified LMS algorithm for a smoother and quick convergence in order to overcome these defects. While the squared error between the unwanted signal and the filter output is utilized as a cost function in the LMS algorithm, a squared sliding mode in equation 28, defined in the error plane, is employed as a cost function.

$$\xi = E[s_k{}^2] \quad \text{where} \quad s_k = \alpha e_k + e_{k-1} \qquad (28)$$

After error signals ek and ek-1 are rewritten with equation 1 and 2, the cost function ξ in equation 28 is expanded as shown in equation 29.

$$\xi = \alpha^2 \left\{ E[d_k{}^2] - 2w_k{}^T P_k + w_k{}^T R_k w_k \right\} + \left\{ E[d_{k-1}{}^2] - 2w_{k-1}{}^T P_{1,k} + w_{k-1}{}^T R_{1,k} w_{k-1} \right\}$$
$$+ 2\alpha \left\{ E[d_k \cdot d_{k-1}] - w_{k-1}{}^T P_{2,k} - w_k{}^T P_{3,k} + w_k{}^T R_{2,k} w_{k-1} \right\} \qquad (29)$$

Next, by differentiating the cost function with respect to w_k, the gradient $\nabla\xi$ is obtained as equation 30. The auto correlation matrices R and the cross correlation vectors P are defined in equation 31.

$$\nabla\xi = -2\alpha^2 P_k + 2\alpha^2 R_k w_k - 2\alpha P_{3,k} + 2\alpha R_{2,k} w_{k-1} \qquad (30)$$

$$\text{where} \quad P_k = E[u_k \cdot d_k], \ P_{3,k} = E[u_k \cdot d_{k-1}]$$
$$R_k = E[u_k \cdot u_k{}^T], \ R_{2,k} = E[u_k \cdot u_{k-1}{}^T] \qquad (31)$$

Following a similar procedure in case of the LMS, the squared sliding mode, the cross correlation vector, and the auto correlation matrix is redefined with direct estimates at a certain instant for these three.

$$\hat{\xi} = s_k{}^2 \qquad (32)$$

$$\hat{P}_k = u_k \cdot d_k, \ \hat{P}_{3,k} = u_k \cdot d_{k-1}$$
$$\hat{R}_k = u_k \cdot u_k{}^T, \ \hat{R}_{2,k} = u_k \cdot u_{k-1}{}^T \qquad (33)$$

Substituting for P and R from equation 30, the gradient of the cost function can be expressed in equation 34.

$$\nabla\hat{\xi} = -2\alpha^2 \cdot u_k \cdot e_k - 2\alpha \cdot u_k \cdot e_{k-1} \qquad (34)$$

Finally, a new sliding mode LMS algorithm, named as the SM-LMS method 1, is derived by integrating equation 6 with equation 34.

$$\hat{w}_{k+1} = \hat{w}_k + \mu \cdot u_k \cdot \left\{ \alpha^2 \cdot e_k + \alpha \cdot e_{k-1} \right\} \qquad (35)$$

Sliding Mode LMS (SM-LMS) Method 2

Although many efforts have been devoted to develop enhanced LMS algorithms, the adaptive digital filtering system itself is still a feedforward control system. There are some limitations to manage various conditions such as sensor noise, unwanted disturbance, time varying secondary path dynamics, and controller uncertainty. Thus, a novel structure of adaptive digital filtering system is introduced with a sliding mode controller in the feedback loop, named as the sliding mode LMS method 2. The sliding mode controller functions as a feedback control which compensates the error from the original LMS algorithm. Figure 4 shows the system with the SM-LMS method 2.

The sliding mode is defined as the case of SM-LMS method 1 and the control input $y_{C,k}$ in the feedback loop is obtained from equation 37. The error signal e_k in equation 38 is the difference between the output of the control path dynamics $y_k{}^*$ and the unwanted signal d_k.

$$y_{C,k} = -M sign(s_k) \quad \text{where} \quad s_k = \alpha e_k + e_{k-1} \qquad (37)$$

$$e_k = d_k - y_k^*$$ (38)

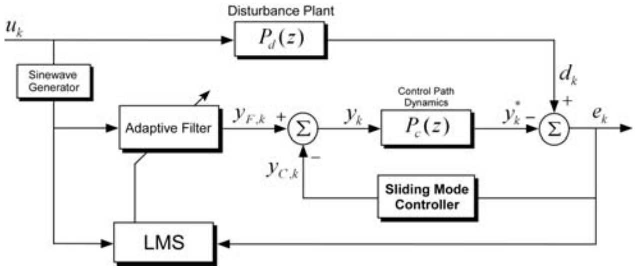

Figure 4. Sliding mode LMS method 2

Then, a modified filter output y_k is introduced by subtracting the output of the sliding mode controller $y_{C,k}$ from the original filter output $y_{F,k}$ as equation 39 and it is utilized as an input to the control path dynamics.

$$y_k = y_{F,k} - y_{C,k}$$ (39)

Since the chattering phenomenon can make the system noisy and unstable, a boundary layer method is applied to this situation as shown in equation 40 and 41. However, it degrades the overall performance of the control system.

$$y_{C,k} = -M sign(s_k) \quad \text{if} \quad s > \varepsilon$$ (40)

$$y_{C,k} = -\frac{M}{\varepsilon} \cdot s_k \quad \text{if} \quad s \le \varepsilon$$ (41)

Model Predictive Sliding Mode LMS (MPSM-LMS)

This section proposes another and the last modified LMS algorithm, named model predictive sliding mode LMS (MPSM-LMS). The schematic of the control system is exactly the same as the case of the sliding mode LMS method 2 shown in figure 4, except that the controller in the feedback loop is the model predictive sliding mode control (MPSMC) instead of the sliding mode controller. If the disturbance plant $P_d(z)$ is known or identified, even if it is done very crudely, the MPSMC can be designed. In the same way, a modified filter output is introduced by subtracting the output of the MPSMC from the original filter output and it is utilized as an input to the control path dynamics. This novel method is more robust and has better convergence performance with multispectral signals since it has a model-based controller in the system structure. Figure 5 shows the MPSM-LMS system.

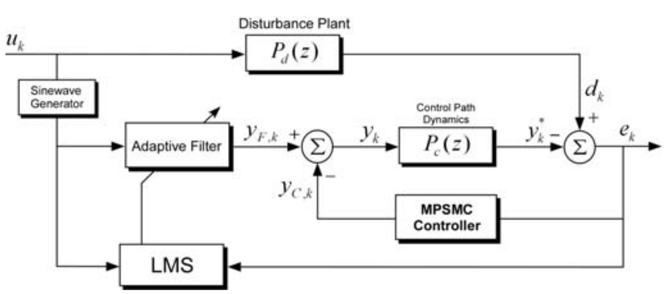

Figure 5. Model predictive sliding mode LMS

RESULTS

Modifications of the conventional LMS algorithm are proposed in the previous section. In this section, their performances are validated in simulations with three different kinds of multispectral signals; a combination of three sine waves having different frequencies each other, amplitude modulated signal, and frequency modulated signal. Tracking performances in time domain and estimation errors are compared and their characteristics are discussed.

Signal with three frequency components

First, among three multispectral signals, a combination of three sine waves with different frequencies each other is utilized to compare the performance of the conventional LMS algorithm and three proposed algorithms. The FIR filter in the adaptive digital filtering system contains two coefficients and the disturbance plant is set to be a second order system with its natural frequency ω_n*=800Hz* and the damping ratio ξ*=0.1*. A signal with three frequency components at 850*Hz*, 1000*Hz*, and 1150*Hz* is generated and applied as the disturbance plant input to make the desired signal. A sine wave with 1000*Hz* frequency is utilized as the reference input. Figure 6 compares the desired signal and the filter output in time domain with the LMS algorithm and the MPSM-LMS algorithm. Also, figure 7 compares the desired signal and the filter output in time domain with the SM-LMS method 1 and the SM-LMS method 2. Figure 8 shows estimation errors using four different algorithms.

In case of the LMS algorithm, the filter output shows overshoots when the desired signal undergoes a sudden change in direction. SM-LMS method 1 shows better tracking performance than the conventional LMS algorithm, while it cannot track well in the transient portion of the signal. When the trajectory of the filter coefficients is observed, the change of the filter coefficients is more effective than in the case of the LMS.

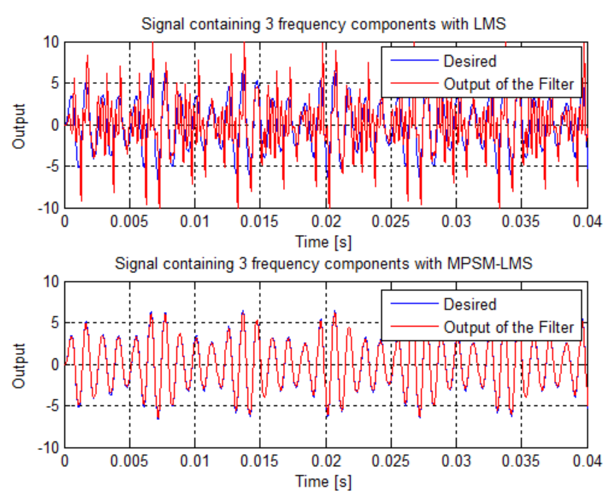

Figure 6. Time response with LMS and MPSM-LMS

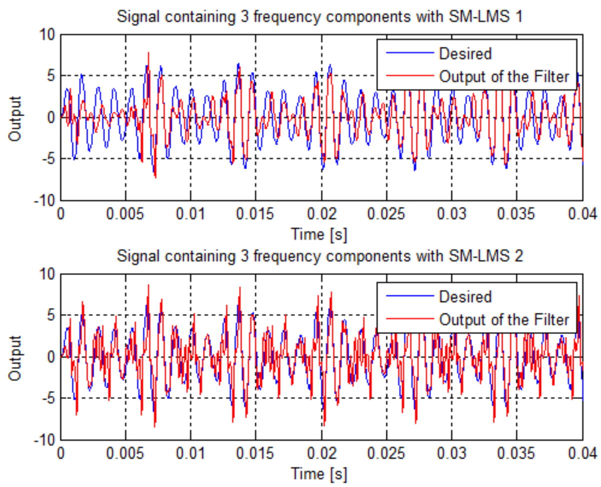

Figure 7. Time response with SM-LMS method 1 / 2

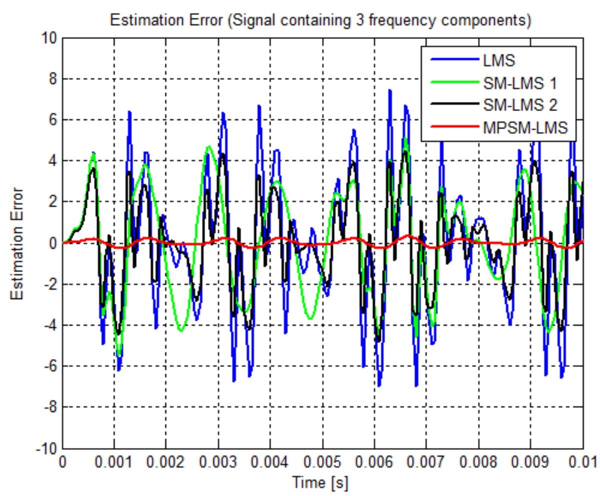

Figure 8. Estimation error (3 frequencies)

However, although the updating algorithm of the adaptive filtering system is enhanced by integrating with the sliding mode control, the whole digital filtering system is yet a feedforward control. This indicates that the SM-LMS method 1 is not sufficient to manage unexpected disturbances, and uncertainties. SM-LMS method 2 shows better performance over the LMS algorithm. However, since it is using a boundary layer method in order to reduce the effect of the chattering phenomenon, the tracking performance is somewhat degraded. MPSM-LMS reduces the estimation error much better than other three methods and shows good performances in the transient portion and the steady-state portion of signals.

Amplitude Modulated (AM) Signal

Similar condition is applied to this case as well. The FIR filter in the adaptive digital filtering system contains two coefficients and the disturbance plant is set to be a second order system with its natural frequency $\omega_n=800Hz$ and the damping ratio $\xi=0.1$. An original signal is assumed to be a sine wave with 120Hz frequency and a carrier signal is assumed to be a sine wave with 1500Hz frequency.

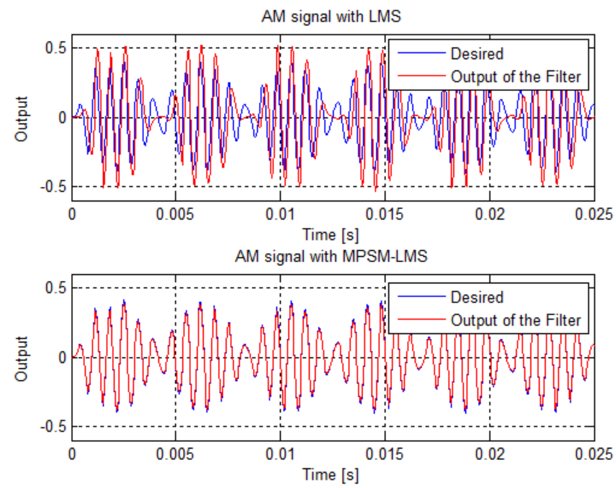

Figure 9. Time response with LMS and MPSM-LMS

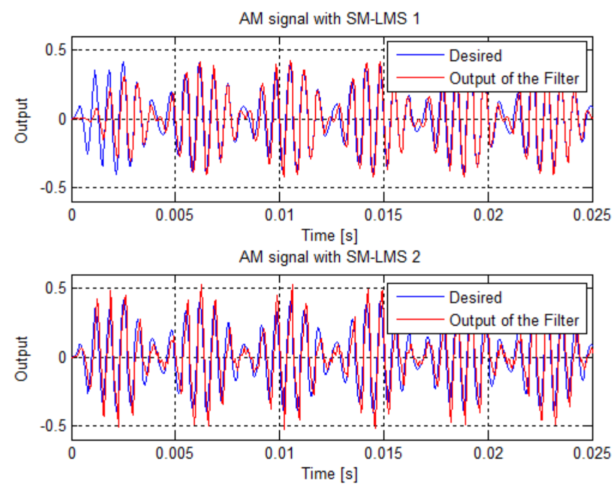

Figure 10. Time response with SM-LMS method 1 / 2

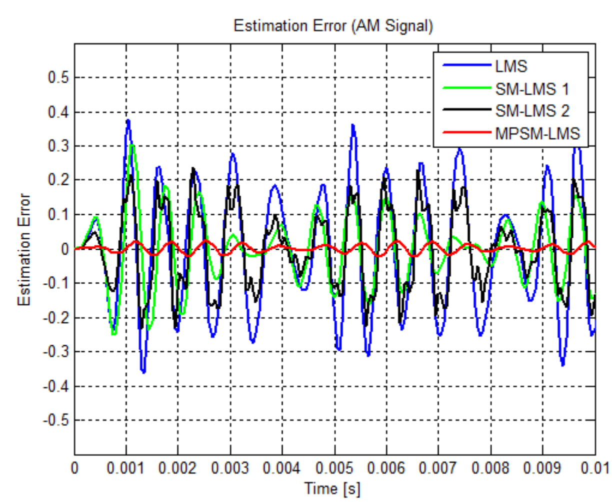

Figure 11. Estimation error (AM)

This AM signal is generated and applied as the disturbance plant input to make the desired signal. A sine wave with 120*Hz* frequency is utilized as the reference input. Figure 9 compares the desired signal and the filter output in time domain with the LMS algorithm and the MPSM-LMS algorithm. Also, figure 10 compares the desired signal and the filter output in time domain with the SM-LMS method 1 and the SM-LMS method 2. Figure 11 shows estimation errors using four different algorithms.

Results are similar to the case of the signal with three frequency components. In case of the LMS algorithm, the filter output shows overshoots when the desired signal undergoes a sudden change in direction. SM-LMS method 1 shows better tracking performance than the conventional LMS algorithm, while it cannot track well in the transient portion of the signal. SM-LMS method 2 shows better performance over the LMS algorithm. However, the chattering phenomenon makes the tracking performance degraded. MPSM-LMS reduces the estimation error much better than other three methods and shows good performances in the transient portion and the steady-state portion of signals.

<u>Frequency Modulated (FM) Signal</u>

Similar condition is applied to this case as well. The FIR filter in the adaptive digital filtering system contains two coefficients and the disturbance plant is set to be a second order system with its natural frequency $\omega_n=800Hz$ and the damping ratio $\xi=0.1$. An original signal is assumed to be a sine wave with 120*Hz* frequency and a carrier signal is assumed to be a sine wave with 1500*Hz* frequency.

This FM signal is generated and applied as the disturbance plant input to make the desired signal. A sine wave with 120*Hz* frequency is utilized as the reference input. Figure 12 compares the desired signal and the filter output in time domain with the LMS algorithm and the MPSM-LMS algorithm. Also, figure 13 compares the SM-LMS method 1 and the SM-LMS method 2. Figure 14 shows estimation errors of four different algorithms.

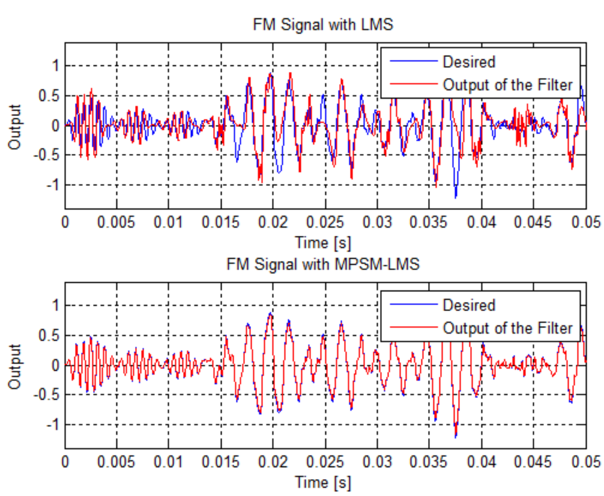

Figure 12. Time response with LMS and MPSM-LMS

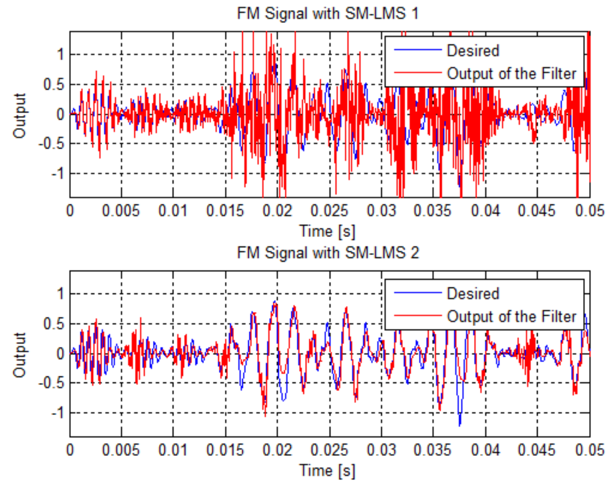

Figure 13. Time response with SM-LMS method 1 / 2

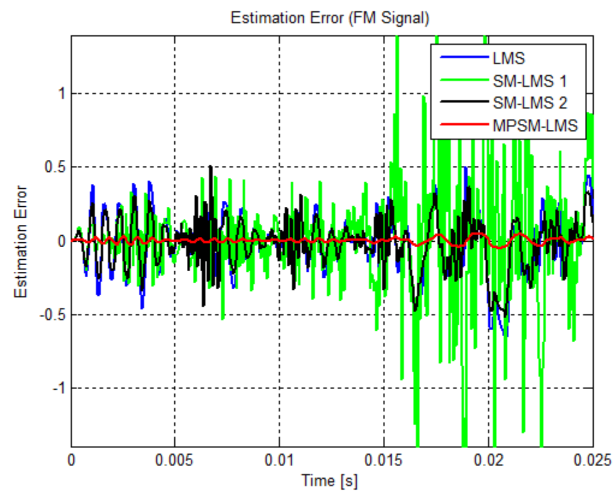

Figure 14. Estimation error (AM)

Results are similar to the case of the signal with three frequency components except the SM-LMS method 1. In case of the LMS algorithm, the filter output shows overshoots when the desired signal undergoes a sudden change in direction. SM-LMS method 1 tends to have worse tracking performance than the other techniques. SM-LMS method 2 shows better performance over the LMS algorithm. However, the chattering phenomenon makes the tracking performance degraded. MPSM-LMS reduces the estimation error much better than other three methods and shows good performances in the transient portion and the steady-state portion of signals.

Moreover, assuming a case which the disturbance plant has uncertainties in it, the MPSM-LMS is checked with two different disturbance plants from the one utilized for designing the MPSMC and it shows similar performance with those plants for the controller design. Thus, MPSM-LMS has better converging performance and it is more robust than the other algorithms. Note that the SM-LMS method 2 and the MPSM-LMS do not require a filter after the reference signal for its stability even though there exist a control path dynamics which makes the system unstable without a filter.

CONCLUSION AND FUTURE WORK

Three enhanced LMS algorithms are proposed in this paper. In the adaptive filtering system, the sliding mode control and the model predictive sliding mode control are integrated to get both advantages of nonlinear and model-based control techniques. Performances of the proposed algorithms are validated with multispectral and modulated signals. Novel methodologies developed in this research are expected to be employed for numerous applications in active vibration and noise control studies such as structural vibration attenuation, vehicle vibration and noise reduction, and active struts for aircrafts, helicopters, and other vibrating platforms. Thus, this work will enhance vibration and noise control systems applied to vehicles and engineering structures by dealing with a broad extent of multispectral signals effectively.

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