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Letter to the Editor

A model predictive algorithm for active noise control with online secondary path modelling

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1. Introduction

Active noise control (ANC) using feedforward control techniques has been the topic of much research in recent years. Active attenuation is a more attractive mean to achieve large amount of noise reduction in a small package or in a duct, particularly at low frequencies (below 500 Hz). A popular adaptive filtering algorithm is the filter-x LMS (FXLMS) algorithm for finite impulse response (FIR) filter [1], because of its simplicity, robustness and relatively low computational load. The block diagram of an ANC system-based FXLMS algorithm is shown in Fig. 1. The FXLMS algorithm is an extension of LMS algorithm for ANC systems, which takes into account of the influence of secondary path transfer function $\mathbf{H}(z)$ [2]. The secondary path $\mathbf{H}(z)$ comprises the D/A converter, smoothing filter, power amplifier, secondary loudspeaker, acoustic path from the loudspeaker to error microphone, error microphone, anti-aliasing filter, and A/D converter [3]. Compare the updating equations of FXLMS algorithm with LMS algorithm, it can be found that even if the $x(n)$ is a white noise, generally, the filter-x signal $x'(n)$ should not be a white noise. When an ANC system is designed, two important problems must be considered. Firstly, a flat frequency response of the secondary path should be constructed, so the FXLMS algorithm can take a good performance like LMS algorithm. Secondly, the model of the secondary path must be estimated before the operation of the ANC system. If the phase difference for a particular frequency between the true and the estimated model is more than 90°, the ANC system can become unstable. It is therefore very important for an ANC system that the model of the secondary path is estimated fast and precisely [2–4].

The secondary path, $\mathbf{H}(z)$, may be estimated off-line prior to the operation of the ANC system when the primary noise, $x(k)$, does not exist. However, in some practical cases, $x(k)$, always exists and $\mathbf{H}(z)$ can be time varying or non-linear [5,6]. For these cases, online modelling of $\mathbf{H}(z)$ is

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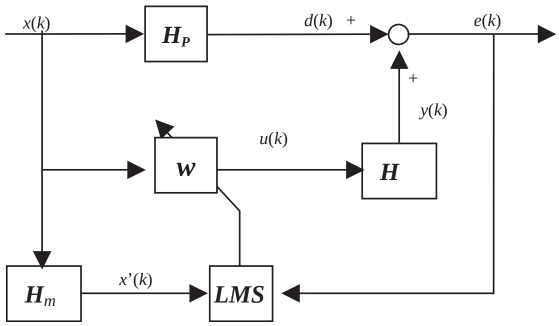


Fig. 1. Block diagram of a ANC system using FXLMS algorithm.

required to ensure the convergence of the FXLMS algorithm for the ANC system. A number of methods for online modelling of the secondary path $\mathbf{H}(z)$ have been proposed [7,8]. These methods can be divided into two types [2,3]. The first approach involves the injection of additional zero-mean white random noise into the ANC system, utilizes a system identification method to estimate $\mathbf{H}(z)$. The auxiliary noise is uncorrelated with primary noise $x(k)$. The second approach, called the overall modelling algorithm, using control signal $u(k)$ to excite the secondary path model $\mathbf{H}_m(z)$, employs an extended least-squares technique to model $\mathbf{H}(z)$. A detailed comparison of these two online modelling approaches has been done in Ref. [7]. For a multi-channel control system, the controller converges within the first 100 iterations if off-line modelling technique is used. It needs thousands of iterations to achieve the same performance with online modelling approaches. Some new online secondary path modelling methods have been presented to improve the convergent performance of the FXLMS algorithms [2,3]. In Ref. [2], two short additional adaptive filters are introduced to improve the convergent performance of the secondary path modelling. The approach is designed to deal with the active control of periodic noise. In Ref. [3], three cross-updated LMS adaptive filters are used to reduce mutual disturbances between the operation of the ANC controller and the modelling of the secondary path. Computer simulating results show that this method can produce superior performance compared to other methods.

In this paper, a new ANC system with online secondary path modelling is proposed. A model predictive control (MPC) technique, dynamic matrix control (DMC), is modified to design the ANC system. An optimal technology is utilized to design the controller, and two filters are used to estimate the primary path $\mathbf{H}_p(z)$ and the secondary path $\mathbf{H}(z)$. An overall online modelling algorithm is adopted, and the two filters are adaptively updated online by the extended LMS algorithm. This paper is organized as follows: Section 2 describes the proposed DMC method for the ANC system. Section 3 describes the online modelling approach for the primary path $\mathbf{H}_p(z)$ and secondary path $\mathbf{H}(z)$. The FXLMS algorithm and the proposed algorithm are compared using computer simulations in Section 4. Finally, the conclusions are given in Section 5.

2. DMC approach for ANC system

The time delay is a fundamental difficulty of process control. Consideration of this problem led to the development of model predictive control strategy [9]. The model predictive control is introduced in Refs. [10,11]. In the model predictive control algorithm, a dynamic model of plant is used to predict the effect of future actions of the control variables on the output. The future moves of the control variables are determined by optimization with the objective of minimizing the predicted error. Using the updated information (measurements) from the plant, the optimization is repeated at each sampling time [10].

The truncated step response model is used in the DMC. It can be transformed from impulse response model, which can be easily obtained. For the single-in, single-out case, the truncated step response model looks like

$$y(k) = \sum_{i=1}^{N} a_i \Delta u(k-i) + a_N u(k-N-1), \tag{1}$$

where $\Delta u(k) = u(k) - u(k-1)$ and a_i is the step response coefficients. Depending on the time delay of the system, the leading step response coefficients may be zero. At the present time k, the behavior of the plant over a horizon P is considered. Using the truncated step response model, the plant response to changes in the control variable is predicted. The moves of the control variable are selected, such that the predicted response has certain desirable characteristics. Only the first computed change in the control variable is implemented. At time $k+1$, the computation is repeated with the horizon moved by one time interval [10].

For the ANC system (Fig. 1), at time k, the primary noise signal is picked up by a reference microphone. After time $k+q$, the noise will begin to influence the error signal measured by the error microphone, where, q is the time delay of the primary path. The delay can be estimated by the time traveled of the acoustic wave. In an ANC system, the secondary path corresponds to the plant of classical control systems. The control variable should be selected so as to make the output of secondary path of opposite value to the output of primary path at time $k+P$. The performance objective is selected as follows:

$$J(k) = \mathbf{e}^{\mathrm{T}}\mathbf{e} + \Delta\mathbf{u}_2^{\mathrm{T}}\mathbf{R}\Delta\mathbf{u}_2 = (\mathbf{d}(k) + \hat{\mathbf{y}}(k))^{\mathrm{T}}(\mathbf{d}(k) + \hat{\mathbf{y}}(k)) + \Delta\mathbf{u}_2^{\mathrm{T}}\mathbf{R}\Delta\mathbf{u}_2, \tag{2}$$

$$d(k+j|k) = \sum_{i=1}^{n} \mathbf{H}_p(i) x(k-i+j-q), \quad j = 1, 2, \ldots P. \tag{3}$$

$$\hat{\mathbf{y}}(k) = \mathbf{A}\Delta\mathbf{u}_1(k) + \mathbf{B}\Delta\mathbf{u}_2(k) + a_s\mathbf{u}(k), \tag{4}$$

$$\hat{\mathbf{y}}(k) = [\hat{y}(k+1|k), \hat{y}(k+2|k), \ldots, \hat{y}(k+P|k)]^{\mathrm{T}}_{P\times 1}, \tag{5}$$

$$\Delta\mathbf{u}_1(k) = [\Delta u(k-N+1), \Delta u(k-N+2), \ldots, \Delta u(k-1)]^{\mathrm{T}}_{(N-1)\times 1}, \tag{6}$$

$$\Delta\mathbf{u}_2(k) = [\Delta u(k), \Delta u(k+1), \ldots, \Delta u(k+M-1)]^{\mathrm{T}}_{M\times 1}, \tag{7}$$

$$\mathbf{u}(k) = [u(k-N), u(k-N+1), \ldots, u(k-N+P-1)]^{\mathrm{T}}_{P\times 1}, \tag{8}$$

$$\mathbf{A} = \begin{bmatrix} a_N & a_{N-1} & & \cdots & \cdots & a_2 \\ & a_N & & \cdots & \cdots & a_3 \\ & & \ddots & \vdots & \vdots & \vdots \\ & & & a_N & \cdots & a_{P+1} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} a_1 & & & \\ a_2 & a_1 & & \\ & & \ddots & \\ & & & a_1 \\ \vdots & \vdots & \vdots & \vdots \\ a_P & a_{P-1} & \cdots & a_{P-M+1} \end{bmatrix}, \tag{9}$$

$$\mathbf{d}(k) = [d(k+1|k), d(k+2|k), \ldots, d(k+P|k)]^{\mathrm{T}}_{P\times 1} \tag{10}$$

where $d(k+j|k)$ is the predicted value of d at time $k+j$ based on information available at time k, $\hat{y}(k+j|k)$ is the modelling predicted value of y at time $k+j$ based on information available at time k, $\mathbf{H}_p(i)$ is the model impulse response coefficient of primary path, a_i is the model step response coefficient of secondary path, N is the truncation order of secondary path, n is the truncation order of primary path, P is the horizon length, M is the number of control variable moves in the future ($\Delta u(k+j) = 0$, when $j > M$; $M < P$), R is the weighting matrix and $\mathbf{A}, \mathbf{B}$ are the dynamic matrices.

At time k, $\mathbf{u}(k)$ and $\Delta\mathbf{u}_1(k)$ are available information. The M-step ahead incremental control variable moves vector, $\Delta\mathbf{u}_2(k)$, are selected to minimize the quadratic objective

$$\Delta\mathbf{u}_2(k) = -[\mathbf{B}^{\mathrm{T}}\mathbf{B} + \mathbf{R}]^{-1}\mathbf{B}^{\mathrm{T}}[\mathbf{d}(k) + \mathbf{A}\Delta\mathbf{u}_1(k) + a_s\mathbf{u}(k)] \tag{11}$$

at time k. Only the first coefficient of $\Delta\mathbf{u}_2(k)$ is required to be computed, and the control variable $u(k) = u(k-1) + \Delta u(k)$ is implemented. At time $k+1$, the computation is repeated with an increment of one time interval. From Eq. (3), one can find that the horizon length must be chosen as $P \leqslant q$, else at time k, the predicted value of d at time $k+P$ will not be obtained. In addition, the horizon length should be $d_1 < P$, where d_1 is the time delay of the secondary path.

If the models are accurate, and there are not additive disturbances in the ANC system, the error $e(k)$ can be manipulated to zero. However, modelling error and additive disturbances always exist in the practical control systems. The predicted values must be corrected by measured error feedback

$$\hat{\mathbf{y}}_1(k+1) = \hat{\mathbf{y}}(k+1) + \mathbf{h}e(k+1), \tag{12}$$

where $\mathbf{h}$ is a correcting vector. After error feedback correction, the M-step ahead incremental control variable moves vector, $\Delta\mathbf{u}_2(k)$, becomes

$$\Delta\mathbf{u}_2(k) = -[\mathbf{B}^{\mathrm{T}}\mathbf{B} + \mathbf{R}]^{-1}\mathbf{B}^{\mathrm{T}}[\mathbf{d}(k) + \mathbf{A}\Delta\mathbf{u}_1(k) + a_s\mathbf{u}(k) + \mathbf{h}e(k)]. \tag{13}$$

3. Adaptive DMC approach for ANC system

In the last section, the DMC algorithm for ANC system is presented. The primary path and the secondary path are estimated off-line prior to the operation of the ANC system. For the secondary path off-line modelling, a zero-mean white random noise excitation signal can be generated by a computer. But the same excitation signal is difficult to obtain for the primary path modelling, because the reference signal sampled by the computer has passed the reference microphone, anti-aliasing filter, and A/D converter.

Fig. 2 gives the block diagram of the adaptive ANC system with online primary path modelling, and the secondary path model has been estimated off-line. In Fig. 2, the $\mathbf{H}_m$ and $\mathbf{H}_{pm}$ are the estimated impulse responses of the secondary path and primary path, respectively. The coefficient vector can be updated as follows:

$$\mathbf{H}_{pm}(k+1) = \mathbf{H}_{pm}(k) + \mu e_p(k)\mathbf{x}(k-q), \tag{14}$$

where μ is the learning rate. From Eq. (14), one can find that the reference signal $x(k)$, but not the filter reference signal $x'(k)$, is used to update the coefficient vector. The secondary path does not degrade the convergence performance of the primary path modelling. The adaptive control ANC system runs as follows:

1. At time k, the first coefficient of incremental control variable moves vector, $\Delta\mathbf{u}_2(k)$, is computed, and the instantaneous control variable $u(k) = u(k-1) + \Delta u(k)$ is implemented. From Eqs. (1) to (13), the impulse responses of the secondary path and primary path, $\mathbf{H}(z)$ and $\mathbf{H}_p(z)$, are replaced by the estimated impulse responses of the secondary path and primary path, $\mathbf{H}_{pm}(z)$ and $\mathbf{H}_m(z)$, respectively.
2. The impulse responses coefficient vector of primary path is updated by Eq. (14).
3. At time $k+1$, the computation is repeated with an increased of one time interval.

In the adaptive control algorithm, the dynamic matrices $\mathbf{A}, \mathbf{B}$ and the matrix inverse in Eq. (13) can be computed off-line before the operation of the ANC system, since they are invariable when the adaptive ANC system is running. The computing load of the adaptive algorithm is similar to that of the FXLMS algorithm when the ANC system is running.

When $\mathbf{H}(z)$ is time varying or $x(k)$ exists, the online modelling algorithm must be selected to ensure the convergence of the adaptive ANC system. A model predictive algorithm for ANC system with online secondary path modelling is proposed. The block diagram of proposed

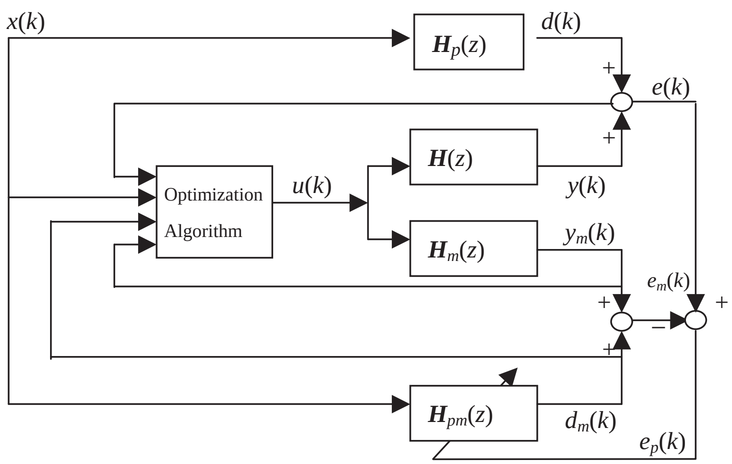


Fig. 2. Block diagram of adaptive ANC system with online primary path.

algorithm is shown in Fig. 3. This online modelling algorithm is similar to overall modelling algorithm. The two impulse response coefficient vectors can be updated as follows:

$$\mathbf{H}_{pm}(k+1) = \mathbf{H}_{pm}(k) + \mu e_p(k)\mathbf{x}(k-q),$$
$$\mathbf{H}_m(k+1) = \mathbf{H}_m(k) + \eta e_p(k)\mathbf{u}_n(k), \tag{15}$$

where μ and η is the learning rates. $\mathbf{u}_n(k) = [u(k-N+1)\ \ u(k-N+1), \ldots, u(k)]^{\mathrm{T}}$ is the vector of the past control variables. At first glance, the model predictive algorithm for ANC system with online secondary path modelling is similar to the previous adaptive algorithm. But they are different in essence. The later algorithm is more complex than the other algorithm when the adaptive ANC system is running. The adaptive control ANC system with online secondary path modelling runs as follows:

(1) At time k, the dynamic matrices $\mathbf{A}, \mathbf{B}$ and the matrix inverse in Eq. (13) is computed, and the first coefficient of incremental control variable moves vector, $\Delta\mathbf{u}_2(k)$, is computed. After that, the instantaneous control variable $u(k) = u(k-1) + \Delta u(k)$ is implemented. In Eqs. (1)–(13), the impulse responses of the secondary path and primary path, $\mathbf{H}$ and $\mathbf{H}_p$, is replaced by the estimated impulse responses of the secondary path and primary path, $\mathbf{H}_{pm}$ and $\mathbf{H}_m$, respectively.
(2) The impulse response coefficient vectors of primary path and secondary path are updated by Eqs. (14) and (15).
(3) At time $k+1$ the computation is repeated with the horizon moved by one time interval.

Unlike former algorithm, in this adaptive control algorithm, the dynamic matrices $\mathbf{A}, \mathbf{B}$ and the matrix inverse in Eq. (13) are computed online with the operation of the ANC system. Because they are changed at every time, when the adaptive ANC system is running. The computing load of the adaptive algorithm is heavier than that of previous algorithm. This is the cost of having online secondary path modelling.

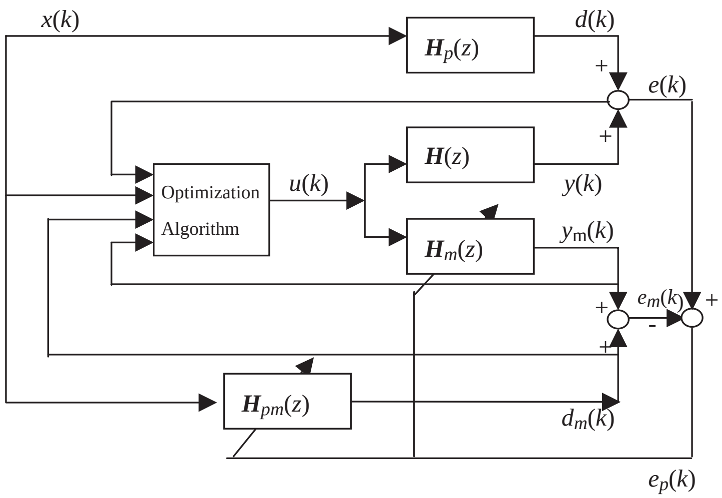


Fig. 3. Block diagram of adaptive ANC system with online secondary path.

4. Computer simulations

In this section, some computer simulations have been conducted to evaluate the performances of the proposed methods. The sampling frequency used for simulation is set at 1000 Hz, and the simulating time is 1.5 s. Both the adaptive filter $\mathbf{W}(z)$ and the secondary path model are 16-taps FIR filters in the FXLMS algorithm. A linear active noise control example is selected, and the acoustic paths are chosen as follows:

The primary acoustic path from noise source to error microphone is

$$\mathbf{H}_p(z) = 0.8z^{-9} + 0.6z^{-10} - 0.2z^{-11} - 0.5z^{-12} - 0.1z^{-13} + 0.4z^{-14} - 0.05z^{-15}. \tag{16}$$

The secondary acoustic path from secondary source to error microphone is

$$\mathbf{H}(z) = z^{-5} + 2.5z^{-6} + 1.76z^{-7} + 0.15z^{-8} - 0.4825z^{-9} - 0.18625z^{-10} - 0.005z^{-11} - 0.001875z^{-12}. \tag{17}$$

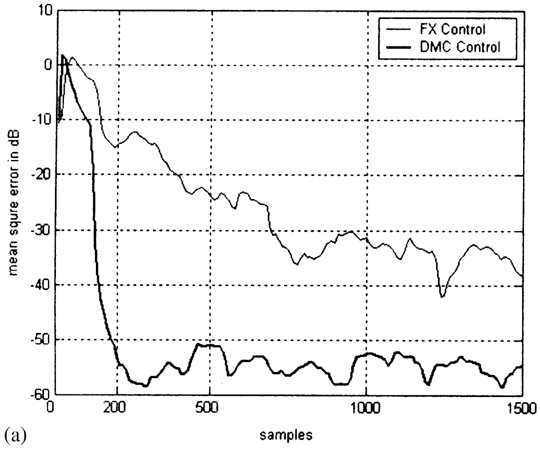
There is a zero $z = 1.5$ outside the unit circle and five samples delay in the secondary path, which is a non-minimum-phase system. It contains the main characteristics of the real secondary path. Computer simulations are carried out to compare the performance of proposed method with that of FXLMS algorithm. Two categories of simulations are presented in this section for all case, one for the narrowband ANC system and another for the broadband ANC system. In the simulations of the narrowband ANC system, the primary noise, $x(k)$, is assumed to be two unitary amplitude of sinusoid waves with frequencies 100 and 250 Hz, respectively. In the simulations of the broadband ANC system, the primary noise, $x(k)$, is assumed to be a unitary amplitude of white noise with zero mean. The simulations using the proposed method are tested for three cases, and the results are compared with the results using FXLMS algorithm.

Case 1: Both primary path and secondary path are time invariable. The secondary model, $\mathbf{H}_m(z)$, is estimated using off-line modelling technique

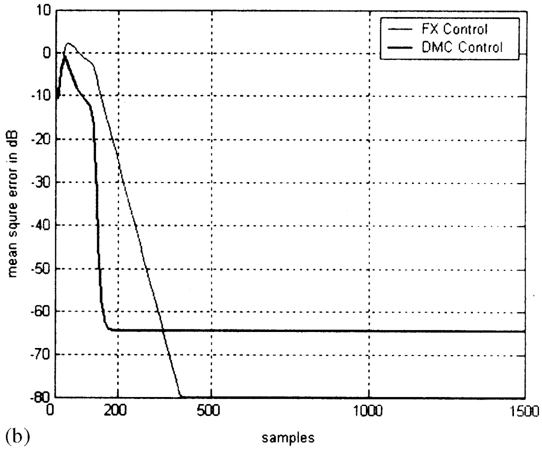
$$\mathbf{H}_m(z) = z^{-5} + 2.3z^{-6} + 1.56z^{-7} + 0.15z^{-8} - 0.4825z^{-9} - 0.18625z^{-10} - 0.005z^{-11} - 0.001875z^{-12}.$$

The classical FXLMS algorithm for ANC system is tried first. The initial value of adaptive filter $\mathbf{W}(z)$ is zero. The step size for updating $\mathbf{W}(z)$ is 0.01/16. After that the DMC algorithm for ANC system with online primary path is tried. The parameters used in this algorithm are selected as follows:

The truncation order of the secondary path is $N = 13$, the truncation order of primary path is $n = 7$, the horizon length is $P = 9$, the number of control variable moves in the future is $M = 4$, and weighting matrix is $R = 0.01*\mathbf{I}$, where $\mathbf{I}$ is identical matrix. The initial value of primary path model, $\mathbf{H}_{pm}(z)$, is zero. The step size for updating $\mathbf{H}_{pm}(z)$ is 0.6/13. Fig. 4(a) and (b) show the mean-square error curves versus the iterations (samples). The result of dynamic matrix control for ANC system with online primary path is shown in solid thick threads, and the result of FXLMS is shown in solid thin lines. From the results shown in Fig. 4, it can be seen that after 200 iterations, the mean-square errors of proposed method settle on about −55 dB for broadband ANC system and about −65 dB for narrowband ANC system. The convergence rates of proposed method are much faster than that of the FXLMS algorithm. It is much obvious for the broadband ANC system.



(a)



(b)

Fig. 4. (a) The error curves of proposed algorithm and FXLMS algorithm for broadband ANC system with off-line secondary path modelling. (b) The error curves of proposed algorithm and FXLMS algorithm for narrowband ANC system with off-line secondary path modelling.

Case 2: The secondary path is obtained using off-line modelling technology like case 1, but the primary path has a sudden change at the 700th iteration. The first coefficient of impulse response of the primary path changes from 0.8 to -0.2. The parameters are chosen similar to case 1.

Fig. 5(a) and (b) show the mean-square error curves. The solid thick lines indicate results of proposed algorithm, and the solid thin lines indicate result of FXLMS algorithm. From the results shown in Fig. 5, it can be seen that after 300 iterations, for broadband ANC system, the mean-square errors of proposed method settle on about same level as the errors before the sudden change of primary path. For narrowband ANC system, about 100 iterations are required to settle on the level as the errors before the sudden change of primary path. The proposed method can track the change of the primary path very fast, regardless of whether it is a broadband ANC system or a narrowband ANC system.

Case 3: The secondary path is obtained using overall online modelling technology. For the broadband ANC system, the secondary path experiences sudden change after 1000 iteration, and the same change take place after 700 iteration in the narrowband ANC system. The second coefficient of impulse response of the secondary path changes from 2.5 to 3.8. The parameters are chosen similar to case 1. The initial values of secondary model, $\mathbf{H}_m(z)$, is chosen as follows:

$$\mathbf{H}_m(z) = 0.1z^{-5} + 0.3z^{-6} + 0.2z^{-7} + 0.05z^{-8} - 0.0825z^{-9} - 0.18625z^{-10} - 0.05z^{-11} - 0.01875z^{-12}.$$

Fig. 6(a) and (b) show the mean-square error curves. Comparing Fig. 6 with Figs. 3 and 4, it can be found that the secondary path is very important to the convergence speed of the ANC system. The convergence rate of the adaptive ANC system with online modelling technique is slightly lower. From the results shown in Fig. 6, it can be seen that the proposed method can rapidly track the change of the secondary path, no matter it is a broadband ANC system or a narrowband ANC system.

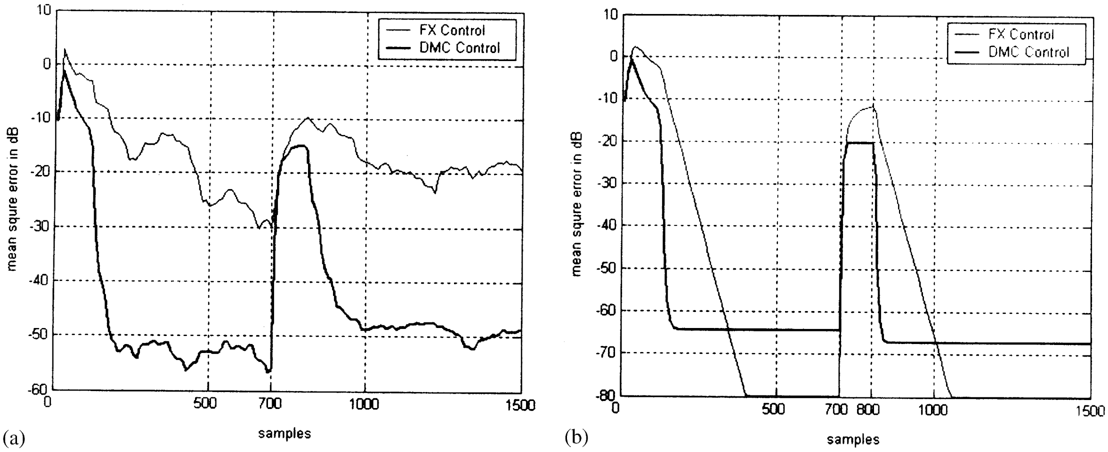


Fig. 5. (a) The error curves of proposed algorithm and FXLMS algorithm for broadband ANC system with off-line secondary path modelling. (b) The error curves of proposed algorithm and FXLMS algorithm for narrowband ANC system with off-line secondary path modelling. At iterations number 700, the primary path has a sudden change in both (a) and (b).

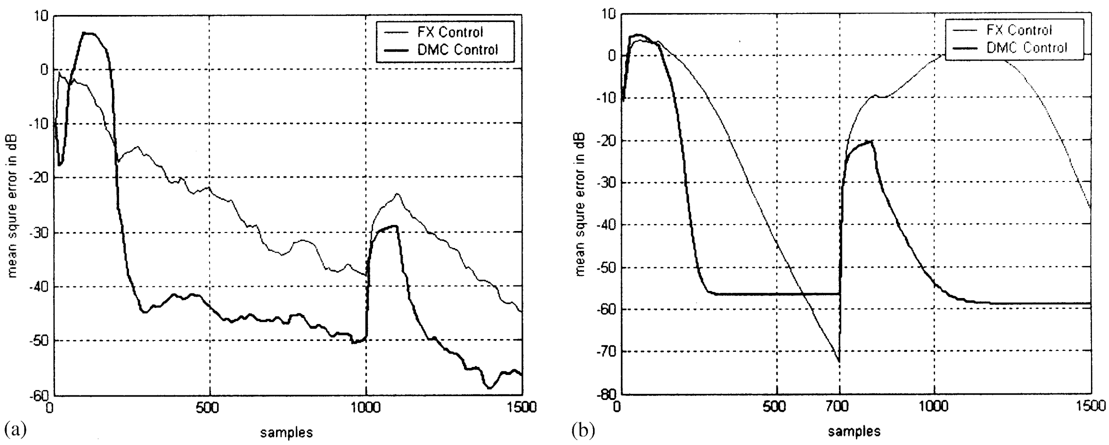


Fig. 6. (a) The error curves of proposed algorithm and FXLMS algorithm for broadband ANC system with online secondary path modelling. (b) The error curves of proposed algorithm and FXLMS algorithm for narrowband ANC system with online secondary path modelling. The secondary path has a sudden change in (a) at iterations number 1000, and in (b) at iterations number 700.

Another simulation is carried out to compare the overall online modelling with injection additional random noise online modelling. The additional random noise injected for the secondary path modelling is assumed to be zero-mean white noise with amplitude of 0.01.

Fig. 7(a) and (b) show the mean-square error curves. The result of FXLMS algorithm for ANC system with injection additional noise online secondary path modelling is shown in solid thick threads, and the result of overall online modelling is shown in solid thin lines. From the results shown in Fig. 7, it can be seen that for broadband ANC system, the convergence rates of the difference online modelling method are similar. Before the sudden change of the secondary path,

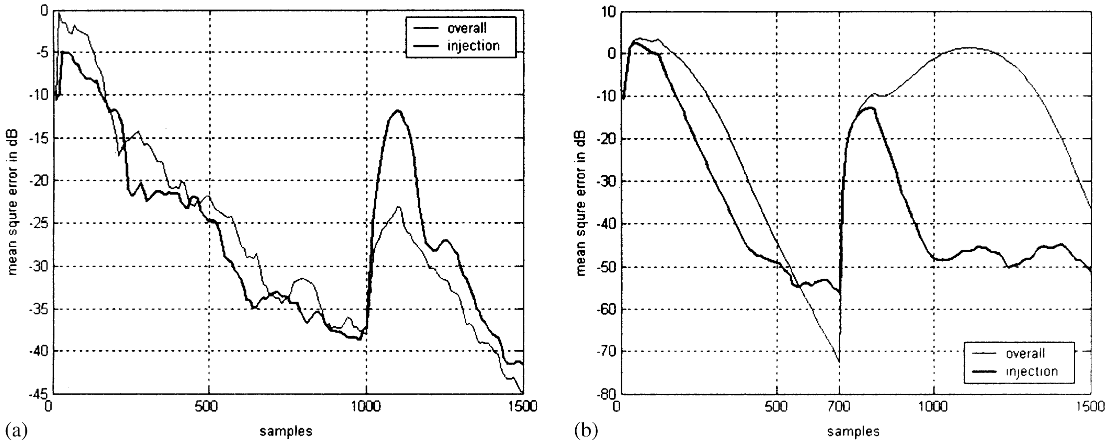


Fig. 7. (a) The error curves of FXLMS algorithm for broadband ANC system with difference online secondary path modelling. (b) The error curves of FXLMS algorithm for narrowband ANC system with difference online secondary path modelling. The secondary path has a sudden change in (a) at iterations number 1000, and in (b) at iterations number 700.

the convergence speed of the injected noise modelling method is faster, but the overall modelling method is better for tracking the sudden change of secondary path. For narrowband ANC system, the injected noise modelling method is better than the overall modelling method. It can track the sudden change of secondary path faster than the overall modelling method.

5. Conclusions

The designing of the secondary path is the key step for constructing an active noise control (ANC) system. The time delay and time variable are the inherent characteristics of the secondary path. The model predictive control utilizes explicit identifiable model to predict the responses of the plant, so that the increment of the control can be computed by the predictive errors. The dynamic matrix control (DMC) uses the step responses of the plant, which are easy obtained in practices. A modified DMC algorithm for the ANC system is proposed. It can deal with the time delay and time variable of the secondary path. Because the two adaptive filters for modelling the primary path and the secondary path are collaterally arranged, the mutual disturbances between the operation of the ANC controller and modelling of the secondary can be reduced greatly. Some simulations have been presented, the results showed that the proposed method is very effective to deal with the time delay and time variable in the secondary path of the ANC system. It can rapidly track the sudden changes in the secondary path and the primary path of the ANC system.

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