A Two-Stage Adaptive Algorithm in the Frequency Domain for a Multichannel Feedforward Active Noise Control System

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The reference paths between original sources and reference sensors in multichannel feedforward active noise control (ANC) systems are often ignored by most ANC algorithms. Therefore, a two-stage adaptive algorithm in the frequency domain is proposed to deal with several of the more complicated cases, specifically addressing instances when the reference sensors must be placed far away from the noise sources. This two-stage system includes a blind pre-processing system cascaded with a traditional MFxLMS system; both systems operate in the frequency domain. The new algorithm can eliminate the effect of reference paths by performing blind pre-processing independently. The MFxLMS algorithm in the following stage can achieve faster convergence than the traditional algorithm without blind pre-processing. The computational complexity of the proposed algorithm is analysed and a numerical simulation using impulse responses measured in a real reverberant room is performed to verify the convergence performance of the proposed algorithm.

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1. INTRODUCTION

Multichannel feedforward active noise control (ANC) systems have many potential applications in aircrafts, engines, and mechanics. Many successful algorithms, such as the multichannel filtered-x LMS (MFxLMS) algorithm, have been developed; these algorithms are summarized in the work of Elliott,¹ and Haykin.² The convergence performance of the MFxLMS algorithm, however, is limited by the properties of the reference signals and the structure of the secondary paths, phenomena that have been analysed in past work.³–⁷ Most multichannel ANC algorithms operate in the time domain; however, their computational complexity appears to increase with the length of the controller. A fast and efficient MFxLMS algorithm that operates in the frequency domain is also desirable and some block filter-x LMS algorithms for single channel or multichannel systems have been proposed to improve the computational efficiency of ANC systems with fast Fourier transform (FFT).¹⁴–¹⁶

Most existing algorithms are focused on the online or offline modelling and estimation of secondary paths; however, reference paths between the original sources and the reference sensors are often ignored because the reference sensors are assumed to be located close to the original noise sources. In many practical applications, the reference sensors cannot be placed close to the original noise sources because of physical environmental limitations. Therefore, because of the lack of reference paths, the data received by the reference sensors has a high correlation each other. A simple example can be used to explain the effect of the reference paths. If all of the original sources are uncorrelated noise, the data received by the reference sensors will be the combination of the original noise sources via their respective reference paths. Thus, the correlation properties of the reference signals are completely determined by the reference paths. A detailed theoretical analysis of the effect of reference paths and secondary paths on the performance of the MFxLMS algorithm in the frequency domain was presented in our previous paper.⁹

Elliott⁸ proposed an optimal controller in the frequency domain to improve the MFxLMS convergence by including prior information about the reference signals—namely, the cross
or for non-stationary noise sources. Chen et al.\textsuperscript{9} noted that it was difficult to obtain in a time-varying environment the spectral density matrix of the reference signals—but this information was not available in the literature. Such a system is referred to as CASE [I, K, M, L]. The filter $W(z)$ of the controller is updated adaptively according to one specific algorithm, such as the MFxLMS algorithm.

Figure 1 presents a multichannel ANC system with $K$ reference sensors and $L$ error sensors that receive signals from $I$ noise sources via the reference path $B(z)$ and the primary path $H(z)$. The controller $W(z)$ receives the reference signals as inputs, to control $M$ loudspeakers and minimize noise. Such a system is referred to as CASE [I, K, M, L]. The filter $W(z)$ of the controller is updated adaptively according to one specific algorithm, such as the MFxLMS algorithm.

Elliot\textsuperscript{8} has analyzed the performance of the MFxLMS algorithm in the frequency domain and given the optimal solution for the controller, which is

$$W_{\text{opt}}(z) = -\left[C_H(z)C(z)^{-1}C_H(z)R_{xd}(z)R_{xx}^{-1}(z)\right];$$

(1)

where $R_{xx}(z)$ is the power spectral density matrix of the inputs, $R_{xd}(z)$ is the cross spectral density matrix between the inputs and the desired data received by error sensors from noise sources, and $C(z)$ is the secondary path from the microphones to the error sensors. If a causal constraint of $W(z)$ is considered and the minimum phase decomposition of $C(z)$ is

$$C(z) = C_{\text{all}}(z)C_{\text{min}}(z);$$

(2)

while the spectral factorization of $R_{xx}(z)$ is

$$R_{xx}(z) = F(z)F^H(z);$$

(3)

the optimal controller in the frequency domain can be simplified as

$$W_{\text{opt}}(z) = -\left[C_{\text{all}}^{-1}(z)C_{\text{all}}^{-1}(z)R_{xd}(z)F^{-H}(z)\right]_{+}F^{-1}(z);$$

(4)

where $[\cdot]_{+}$ defines the $z$-transform of the causal parts of the quantity in brackets. $F(z)$ is often called the shaping filter of $x(n)$; the inverse filter matrix $F^{-1}(z)$ is called the whitening filter.

In practice, the power spectral density matrix of inputs $R_{xx}(z)$ is determined by two factors: the noise sources and the reference path $B(z)$. Based on Fig. 1(a), $R_{xx}(z)$ can be written simply as

$$R_{xx}(z) = B(z)R_{nn}(z)B^H(z);$$

(5)

which includes the power spectral density matrix of noise sources $s(n)$ and the reference paths. For broadband uncorrelated noise sources, $R_{nn}(z)$ can be approximated by a diagonal matrix, while $R_{xx}(z)$ is completely dependent upon the reference path $B(z)$. According to one analysis in the frequency domain proposed by Chen and Wang et al.,\textsuperscript{9} the convergence properties of the traditional MFxLMS algorithm are completely determined by the cross spectral density matrix of the filtered reference signals, implying that the effect of the reference paths cannot be ignored. For a detailed theoretical analysis of the reference path to the ANC MFxLMS algorithm, readers are referred to Chen et al.’s work.\textsuperscript{9}

The whitening filter matrix $F^{-1}(z)$ of the optimal controller in Eq. (4) is essential to reducing the effect of the reference

\textbf{2. THE MODEL AND OPTIMAL SOLUTION FOR A MULTICHANNEL ANC SYSTEM}

In this paper, a two-stage adaptive algorithm operating in the frequency domain is proposed to address the difficulties of a complicated multichannel ANC system. Because the reference paths and primary paths will be simple for periodic noise sources, only broadband uncorrelated random noise sources are considered in this study. In our two-stage system, a new adaptive algorithm is added between the reference signals and the traditional MFxLMS algorithm, and the outputs of the first stage are expected to recover the original uncorrelated noise sources. In the second stage, the recovered noise sources become the inputs of the MFxLMS algorithm and the effect of the reference paths on the MFxLMS algorithm is eliminated. To improve the computational efficiency of our system, both filtering operation and coefficient updating are performed in the frequency domain.

The structure of this paper is as follows. In section two, our two-stage model and the optimal solution for the multichannel ANC system are introduced. Each stage of the adaptive algorithm in the frequency domain is then discussed in detail during section three, and a basic evaluation of the computational complexity of the two-stage system is presented in section four. Section five uses an example to show the convergence performance of the two-stage adaptive algorithm in the frequency domain, and conclusions are drawn in section six.

![Figure 1](image-url)
the accurate estimation of $F$ sources and reference paths cannot be obtained in advance; path may be time varying, and certain information about filter coefficients are updated in the frequency domain using be found in Cichocki and Amari’s work. structure of signals. Details about blind processing theory can be found in Cichocki and Amari’s work. In this study, we develop an adaptive blind pre-processing algorithm, in which the filter coefficients are updated in the frequency domain using FFT.

A two-stage adaptive processing system is proposed to eliminate the effects of the reference paths on the following MFxLMS algorithm, as shown in Fig. 1(b). The difference between Figs. 1(a) and 1(b) is that a new blind adaptive algorithm is added between the reference signals and the traditional ANC algorithm. The new stage assumes that all noise sources are independent broadband noises. Based on this assumption, an adaptive algorithm is proposed to pre-process the reference signals to recover the original noise sources. Thus, the effect of the reference paths can be eliminated automatically. Because noise sources and the reference paths cannot be measured a priori (and may be time varying in some practical cases), a blind pre-processing adaptive algorithm is preferred. Each stage in the two-stage adaptive processing system has a different goal. The first stage is blind pre-processing of the reference sensor data $x(n)$, which is the whitening filter $F^{-1}(z)$. Therefore, the ideal outputs of the first stage, $\tilde{x}(n)$, recover the original noise sources. The next stage includes the traditional MFxLMS algorithm with the whitened signals, $\tilde{x}(n)$, as inputs. To improve the computational efficiency of the two-stage ANC system, both adaptive algorithms operate in the frequency domain.

3. THE TWO-STAGE ADAPTIVE ALGORITHMS IN THE FREQUENCY DOMAIN

3.1. The Blind Pre-Processing Algorithm in the First Stage

As stated above, either the noise sources or the reference path may be time varying, and certain information about sources and reference paths cannot be obtained in advance; therefore, the accurate estimation of $F(\omega)$ is impossible, a situation that is called blind in ANC systems. Blind processing has been successfully applied to speech signal separation and biomedical signal processing. The basic principle of blind processing requires the statistical independence assumption for noise sources, or some other special temporal or frequency structure of signals. Details about blind processing theory can be found in Cichocki and Amari’s work. In this study, we develop an adaptive blind pre-processing algorithm, in which the filter coefficients are updated in the frequency domain using FFT.

For broadband noise sources $s(n)$, which are assumed to be independent from each other in most cases, the received signals $x(n)$ at the reference sensors can be given by

$$x(n) = [B(z)]s(n);$$

where $[B(z)]$ is defined as the filtering operation in a system, with a transfer function $B(z)$. The primary reason for using a blind pre-processing system is to design an order-Q FIR filter matrix $V(z)$ for the reference data $x(n)$ such that the outputs $\tilde{x}(n)$ approximate the original noise sources. The outputs of the blind pre-processing system in Fig. 1(b) are

$$\tilde{x}(n) = [V(z)]x(n) = \sum_{q=0}^{Q} V_q(n)x(n-q).$$

Because of the independence assumption regarding the original noise sources, the recovered outputs $\tilde{x}(n)$ can also be considered to be independent from each other. The common statistical independence measure of signals is the Kullback-Leibler divergence, which is the ratio of the joint probability density function (PDF), $p(\tilde{x}(n))$, to the product of each marginal PDF, $p_1(\tilde{x}_1(n)) \ldots p_K(\tilde{x}_K(n))$.

$$KL(\tilde{x}(n)) = \int p(\tilde{x}(n)) \ln \frac{p(\tilde{x}(n))}{p_1(\tilde{x}_1(n)) \ldots p_K(\tilde{x}_K(n))} d\tilde{x}(n);$$

and $KL(\tilde{x}(n)) \geq 0$. It is equal to zero only if all of the components of $\tilde{x}(n)$ are independent. Minimizing $KL(\tilde{x}(n))$ will yield the optimal filter $V(z)$, making the outputs $\tilde{x}(n)$ as independent as possible. Once exact minimization has been achieved, the covariance matrix of outputs $\tilde{x}(n)$

$$\text{R}_{\tilde{x}}(n) = E[\tilde{x}(n)\tilde{x}^H(n)] \approx I$$

is diagonal approximately, which means that the final outputs are also whitened and independent. Comparing Eq. (6) to Eq. (10), we can see that the blind pre-processing system $V(z)$ fills the same role as $F^{-1}(z)$, and that the effect of the reference path $B(z)$ can be eliminated completely.

Many adaptive and batch algorithms have been proposed to find the optimal filter matrix $V(z)$ by minimizing $KL$ divergence in Eq. (9), the most popular being the natural gradient algorithm by Amari,

$$V_q(n+1) = V_q(n) + \mu \left[ V_q(n) - f(\tilde{x}(n))u^T(n-q) \right];$$

$$u(n) = \sum_{r=0}^{Q} V_{q-r}(n)\tilde{x}(n-r); \quad q = 0, \ldots, Q;$$

where the nonlinear function $f(\tilde{x}) = -\partial \ln p(\tilde{x})/\partial \tilde{x}$ is called the score function of the PDF $p(\tilde{x})$, and all noise sources are assumed to have the same distribution. The updating process for each filter coefficient is very simple, only requiring about four multiplication/addition operations per adaptive filter coefficient. However, the additional computation of $u(n)$ costs the most computational time within the natural gradient algorithm in Eq. (11); therefore, a simple and efficient implementation of Eq. (11) in the frequency domain with fast Fourier transform (FFT) is desirable.
The algorithm in Eq. (11) computes the optimal filter coefficients iteratively, sample by sample, and the computational efficiency is very low. To save computational time with the help of the FFT, a block adaptive algorithm of Eq. (11) is required. Redefining the $K(Q + 1)$ input signal column vector
\[
\mathbf{x}(n) = \begin{bmatrix} \mathbf{x}^T(n) & \cdots & \mathbf{x}^T(n - Q) \end{bmatrix}^T; \tag{12}
\]
and the $K \times K(Q + 1)$ filter coefficient matrix
\[
\mathbf{V}(n) = [\mathbf{V}_0(n) \cdots \mathbf{V}_Q(n)]; \tag{13}
\]
we can rewrite the output of the blind pre-processing in Eq. (8) as
\[
\tilde{\mathbf{x}}(n) = \mathbf{V}(n)\mathbf{x}(n). \tag{14}
\]
The natural gradient algorithm in Eq. (11) can also be expressed, in a more compact form, as
\[
\mathbf{V}(n + 1) = (1 + \mu)\mathbf{V}(n) - \mu f(\tilde{\mathbf{x}}(n))\mathbf{w}^T(n); \tag{15}
\]
where the $K(Q + 1)$ temporary vector $\mathbf{u}(n)$ is defined as
\[
\tilde{\mathbf{u}}(n) = \mathbf{R}(n)\tilde{\mathbf{x}}(n). \tag{16}
\]
The $K(Q + 1) \times K(Q + 1)$ block Toeplitz symmetric matrix $\mathbf{R}(n)$ is
\[
\mathbf{R}(n) = \text{toeplitz}([\mathbf{R}_0(n) \cdots \mathbf{R}_L(n)]); \tag{17}
\]
where \text{toeplitz}[c] denotes a symmetric Toeplitz matrix containing the vector or matrix $c$. Each value of $\mathbf{R}_q(n)$, $q = 0, 1, \ldots, Q$ is related to the geometric manifold and is defined as
\[
\mathbf{R}_q(n) = \sum_{l=0}^Q \mathbf{V}_l^T(n)\mathbf{V}_{q+l}(n); \quad q = 0, 1, \ldots, Q. \tag{18}
\]
The block-based implementation of this algorithm assumes that the filter matrix $\mathbf{V}(n)$ for each block is fixed and is only updated at the end of the block based on
\[
\mathbf{V}(n + N + 1) = (1 + \mu)\mathbf{V}(n) - \mu \sum_{l=0}^{N-1} f(\tilde{\mathbf{x}}(n + l))\mathbf{w}^T(n + l); \tag{19}
\]
where $N$ is the block length, which is generally greater than or equal to the filter length $L$. It is noteworthy that the filter matrix $\mathbf{V}(n)$ is fixed for each data block, meaning the sequence $\mathbf{R}_q(n)$, $q = 0, 1, \ldots, Q$ is also updated once for each data block.

Because there is a linear convolution in Eqs. (14) and (16), and the linear correlation in Eqs. (18) and (19) can be computed efficiently using the FFT, the block-based algorithm in Eq. (19) can be implemented efficiently in the frequency domain. The $2N$-points FFT and the overlap-save method are used, but the detailed derivation and the pseudo code for fast implementation are not shown here.

It is noteworthy that the fast implementation of Eq. (19) using the FFT is different from the blind deconvolution algorithm in the frequency domain, where all inputs are first transformed into the frequency domain and then blind processing is employed in each frequency bin, whereas the fast implementation of Eq. (19) only improves the computational efficiency of linear convolution and correlation with FFT. The filter coefficients are updated in the time domain.

\section{The MFxLMS Algorithm in the Frequency Domain}

The MFxLMS algorithm has been analysed by many researchers. The updating of the controller coefficients at the $k$-th data block for $\text{CASE}[I, K, M, L]$ can be expressed in the frequency domain as
\[
\mathbf{e}(\omega, k) = \mathbf{d}(\omega, k) - \mathbf{U}(\omega, k)\mathbf{w}(\omega, k); \tag{20}
\]
where the superscript $H$ denotes the Hermitian transpose, and $\mu_1$ is the fixed step size. $\mathbf{e}(\omega, k)$ and $\mathbf{d}(\omega, k)$ are the transformed vector of the $L \times 1$ error vector $\mathbf{e}(n)$ and the desired vector $\mathbf{d}(n)$ for the $k$-th data block, respectively. $\mathbf{w}(\omega, k)$ is the transformed vector of the controller $MK \times 1$ vector with FFT
\[
\mathbf{w}(n) = [w_{11}(n) \cdots w_{M1}(n) \cdots w_{MK}(n)]^T.
\]
The $\mathbf{U}(\omega, k)$ is the $L \times MK$ filtered reference matrix for the $k$-th block, and can be written as
\[
\mathbf{U}(\omega, k) = \tilde{\mathbf{x}}^T(\omega, k) \otimes \hat{\mathbf{C}}(\omega); \tag{21}
\]
where $\otimes$ is the Kronecker product, and $\hat{\mathbf{C}}(\omega)$ is the $L \times M$ estimated secondary path matrix from loudspeakers to error sensors.

\section{Evaluation of the Computational Complexity}

The difference between our proposed algorithm and a traditional MFxLMS algorithm is that the traditional ANC controller is replaced by a new processing system, which is a cascade of two independent adaptive systems, as shown in the dashed frame in Fig. 1. Essentially, the two-stage system is more complicated than the traditional one because of the additional filtering operations required; however, the new two-stage system can improve the convergence of the entire ANC system at the cost of only a small amount of additional computational load, especially in broadband multichannel ANC systems. As stated,\(^9\) the convergence speed of the MFxLMS algorithm is determined by the eigenvalue spread of $\mathbf{R}(\omega)$, and the correlation matrix of the filtered reference signals in the frequency domain.
\[
\mathbf{R}(\omega) = [\mathbf{B}(\omega)\mathbf{B}(\omega)]^+[\hat{\mathbf{C}}^H(\omega)\hat{\mathbf{C}}(\omega)]. \tag{22}
\]
A large eigenvalue spread in Eq. (22) will result in long convergence time. The existence of the reference path $\mathbf{B}(\omega)$ will increase the eigenvalue spread of $\mathbf{R}(\omega)$. If the effect of the reference path $\mathbf{B}(\omega)$ can be eliminated by blind pre-processing, the convergence speed of the MFxLMS algorithm in the two-stage system will only be dependent upon the estimated secondary paths, and the convergence speed of the MFxLMS algorithm in the second stage will increase.

If two FFTs in the two-stage system have the same length $2N$, the outputs of the first stage in the frequency domain can be the direct inputs of the second stage; thus, the two stages can
be cascaded, which reduces the complexity. The complexity of the blind pre-processing algorithm in the frequency domain has been analysed by Douglas et al.\textsuperscript{12} This algorithm requires $4K^2 + 3K$ FFTs of length $2N$ and $1.5K^3 + 3.5K^2$ number of $2N$ point complex multiplications. If the two stages can be cascaded and the two FFTs can be reduced, there will be only $4K^2 + K$ additional FFTs in the cascaded system in Fig. 1(b). The computational complexity of the traditional MFxLMS algorithm in the frequency domain includes $K + M + 2KM + ML + L$ FFTs of length $2N$, and $KM + 2KML$ number of $2N$ point complex multiplications, which are simplified into $3K^2 + 3K$ FFTs and $2K^3 + K$ number of $2N$ point complex multiplication for a simple CASE $[K, K, K, K]$. Blind pre-processing has approximately the same complexity as the MFxLMS algorithm if an FFT with the same length is used; however, the complexity of the entire two-stage adaptive algorithm is twice that of the traditional MFxLMS algorithm.

5. NUMERICAL SIMULATIONS

A simple numerical computer simulation of CASE $[2, 2, 2, 2]$ is used to show the difference between the traditional MFxLMS algorithm and our two-stage adaptive algorithm in the frequency domain. Four measured impulse responses in a reverberant room with a sampling rate of 2 kHz are shown in Fig. 2, which are the reference path responses, and another four impulse responses shown in Fig. 3, are the primary path responses. The physical system layout for measurement of these room impulses is presented in Chen and Muto’s work.\textsuperscript{4} Because we are more concerned with reference path responses, a simple secondary path model is employed as

\[
\hat{C}(:, 1, 1) = [0.5; 0.4; 0.1]; \quad C(:, 2, 2) = [0.5; 0.4; 0.1];
\]

the estimated secondary paths are accurate when $\hat{C} = 0.95C$. This model assumes that microphones are located near error sensors and that no cross secondary paths exist.

In the traditional multichannel ANC system shown in
Fig. 1(a), the controller length is 128; an additional $2 \times 2$ filter matrix with a length of $Q = 64$ is included in the two-stage ANC system in Fig. 1(b). A 256-point FFT and $\mu_1 = 0.0003$ are used for both algorithms. In this simulation, the two noise sources are uniform white noises with unit variance, the number of samples is 409600, and both algorithms are run 100 times to compute the averaged mean square error (MSE) of $e(n)$. The nonlinear function in Eq. (11) is $f(x) = x^3$, which is suitable for sub-Gaussian random signals such as uniform white noise. The MSE of the traditional MFxLMS algorithm and the two-stage adaptive algorithm for two error sensors are plotted in Figs. 4 and 5, respectively. The convergence speed of the two-stage algorithm is higher than that of the traditional MFxLMS algorithm, and both algorithms can obtain approximately the same final MSE.

To check the ability of blind pre-processing to eliminate the reference paths, the normalized auto-correlation and cross-correlation of $\tilde{x}(n)$ after convergence are given in Fig. 6, where $\tilde{x}(n)$ is whitened and the signals are uncorrelated to each other. For comparison, the corresponding correlation results of the reference signals before blind pre-processing are also shown in Fig. 7. Because the original noise sources are assumed to be independent white noise sources, the reference signals are completely dependent upon the reference paths $B(z)$ from Eq. (5); therefore, the auto- and cross-correlation of the reference signals in Fig. 7 represent the effect of the reference paths $B(z)$. From Fig. 6, we can see that the recovered outputs of blind processing can approximate the original noise sources and the effect of $B(z)$ has been eliminated completely. This comparison can explain why the two-stage algorithm has faster convergence than the traditional MFxLMS algorithm.

An obvious advantage of using the two-stage MFxLMS algorithm in the frequency domain is that it has low computational complexity. Keeping the simulation conditions the same as those described above, but using the blind pre-processing filter and the traditional MFxLMS algorithm with the same length (which varies to 2048 from 32), the traditional MFxLMS algorithm with blind pre-processing in the time domain can be compared to our two-stage MFxLMS algorithm. The time consumed by the two algorithms over a 10-iteration average are listed in Table 1 and shown in Fig. 8, and the computational efficiency of the two-stage MFxLMS algorithm is clearly visible, especially for the long filter length.

The effect of blind pre-processing on the following MFxLMS algorithm will be more significant if the reference paths have longer response time or if there is a large eigenvalue spread of $R(\omega)$ introduced by the reference paths. Furthermore, the two-stage adaptive algorithm in the frequency domain will have better tracking ability than the traditional MFxLMS algorithm in time-varying environments or for non-stationary noise sources.

6. CONCLUSIONS

A new blind pre-processing system is added before the traditional multichannel feedforward ANC controller to eliminate

<table>
<thead>
<tr>
<th>Filter length</th>
<th>32</th>
<th>64</th>
<th>128</th>
<th>256</th>
<th>512</th>
<th>1024</th>
<th>2048</th>
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<td>Time domain (s)</td>
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<td>85</td>
<td>146</td>
<td>268</td>
<td>530</td>
<td>1068</td>
<td>2001</td>
</tr>
<tr>
<td>Frequency domain (s)</td>
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<td>14</td>
<td>17</td>
<td>22</td>
<td>31</td>
<td>48</td>
<td></td>
</tr>
</tbody>
</table>
the effect of the reference paths on the traditional MFxLMS algorithm. The new pre-processing system is combining with the traditional MFxLMS system and results in the new two-stage adaptive system. The blind pre-processing system can whiten the reference signals based on the independence assumption for the noise sources; therefore, the convergence of the two-stage adaptive algorithm is faster than that of the traditional MFxLMS algorithm at the cost of twice the computational loading.

The two-stage adaptive algorithm operating in the frequency domain is proposed to improve the computational efficiency of the entire multichannel ANC system with the help of FFT. Especially for the reference paths with large filter length, the proposed two-stage algorithm saves the more computational time apparently in comparison with the conventional algorithm in time domain, as shown in Fig. 8.

REFERENCES