Performance Analysis of Feedforward Adaptive Noise Canceller Using Nfxlms Algorithm

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Abstract: The adaptive filter operates by estimating the statistics of the incoming signal and adjusting its own response in such a way as to minimize some cost-function. The Active Noise Control (ANC) uses a primary input containing the corrupted signal and a reference input containing noise correlated in some unknown way with primary noise. The reference input is adaptively filtered and subtracted from the primary input to obtain the signal estimate. Adaptive filtering before subtraction allows the treatment of inputs that are deterministic or stochastic, stationary or time variable. A useful approach to this filter optimization problem is to minimize the mean square value of the error signal. In this paper, we have implemented the Adaptive Noise Cancellation using Filtered-x Least Mean Square (FxLMS) algorithm. Experimental results with MATLAB Simulation are presented that illustrate the usefulness of adaptive noise cancellation technique using FxLMS algorithm and Normalized FxLMS algorithm in a variety of practical situations.

Keywords: Noise Control (ANC), Filtered-x LMS (FxLMS), Normalized FxLMS.

I. INTRODUCTION

Active Noise Control (ANC) is based on the simple principle of destructive interference of propagating acoustic waves. The basic idea was proposed by Lueg, in 1936. Many successful applications of ANC have been reported, The most popular adaptive algorithm used for ANC applications is the filtered-x least mean square (FxLMS) algorithm which is a modified version of the LMS algorithm. The FxLMS algorithm is computationally simple, but its convergence speed is slow. Different ANC algorithms, with improved convergence properties, have been proposed, viz.,1) lattice-ANC systems; 2) infinite impulse response (IIR) filter-based LMS algorithms called filtered-u recursive LMS (FuRLMS), and filtered-v algorithms;3) recursive least squares (RLS) based algorithms called filtered-x RLS (FxRLS) and filtered-x fast-transversal-filter (FxFTF); and 4) frequency-domain-ANC systems . There are the following problems with these approaches: 1) IIR-based structures have inherent stability problems; 2) other approaches mentioned above increase the computational burden substantially; and 3) RLS-based ANC systems have numerical instability problems. These reasons make FxLMS still a good choice for ANC applications. Hence in this we describe FxLMS algorithm in the application of Active Noise Control (ANC). Here we can also discuss about the variants of FxLMS algorithm with improved convergence. The performance analysis of different FxLMS algorithms is compared. The experimental results can be obtained from the Mat Lab Simulation.

II. ACTIVE NOISE CONTROL

The purpose of active noise control is to generate an anti-noise signal from a loudspeaker to minimize the noise level of the original signal. Traditional noise control

techniques use passive treatments to minimize the noise level. The traditional noise control techniques can minimize noise that has a medium or high frequencies. However, these techniques cannot minimize noise that has a low frequency. With active noise control, you can produce an anti-noise signal with the same low frequency as the low-frequency noise signal. The phases of the anti-noise signal are opposite to those of the low-frequency noise signal. When the two signals reach the same point, they satisfy the superposition principle and negate each other.
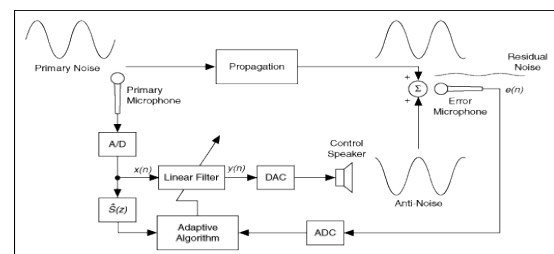

Fig-1: Active Noise Control System

In this active noise control system, we need two microphones and one speaker. Place one microphone close to the noise source and place the other microphone in the sound field where you want to minimize the noise. The microphone close to the noise source is known as the primary microphone. The microphone in the sound field is known as the error microphone. Use the loudspeaker, known as the control speaker, to transmit the anti-noise signal that the adaptive filter generates. During the noise control process, the adaptive filter adjusts the filter coefficients and transmits the output signal to the control speaker.

III.   FXLMS ALGORITHM

The block diagram for a single-channel feedforward ANC system using the FxLMS algorithm is shown in Fig. 2. Where $P(z)$ is the primary acoustic path between the reference noise source and the error microphone. The reference noise signal $x(n)$ is filtered through $P(z)$ and appears as a primary noise signal at the error microphone. The objective of the adaptive filter $W(z)$ is to generate an appropriate anti-noise signal $y(n)$ propagated by the secondary loudspeaker. This anti-noise signal combines with the primary noise signal to create a zone of silence in the vicinity of the error microphone. The error microphone measures the residual noise $e(n)$, which is used by $W(z)$ for its adaptation to minimize the sound pressure at error microphone. Here $\hat{S}(z)$ accounts for the model of the secondary path $S(z)$ between the output $y(n)$ of the controller and the output $e(n)$ of the error microphone. The filtering of the reference signal $x(n)$ through $\hat{S}(z)$ is demanded by the fact that the output $y(n)$ of the adaptive filter is filtered through $S(z)$.
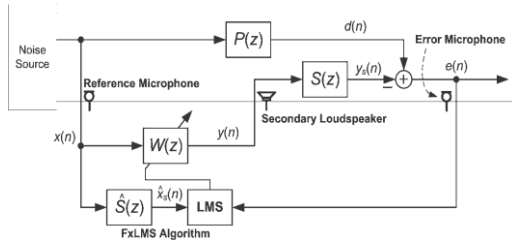

Fig-2:Block diagram of FxLMS algorithm-based single-channel feedforward ANC system.

Assuming that $W(z)$ is an FIR filter of tap-weight length Lw, the secondary signal $y(n)$ isexpressed as

$$y = \boldsymbol{w}^T(n)\boldsymbol{x}(n) \tag{1}$$

where

$$\boldsymbol{w}(n) = \left[w_0(n), w_1(n), \ldots, w_{L_w-1}(n),\right]^T \tag{2}$$

is the tap-weight vector, and

$$\boldsymbol{x}(n) = [x(n), x(n-1), \ldots, x(n-L_w+1)]^T \tag{3}$$

is an Lw–sample vector the reference signal $x(n)$.
The residual error signal $e(n)$ is given as

$$e(n) = d(n) - y_s(n) \tag{4}$$

Where $d(n) = p(n) * x(n)$ is the primary disturbance signal, $y_s(n) = s(n) * y(n)$ is the secondary cancelling signal, *denotes linear convolution, and $p(n)$ and $s(n)$ are impulse responses of the primary path $P(z)$ and secondary path $S(z)$, respectively.

Minimizing the mean squared error (MSE) cost function;

$$J(n) = E\{e^2(n)\} \approx e^2(n),$$

Where $E\{\cdot\}$ is the expectation of quantity inside; the FxLMS update equation for the coefficients of $W(z)$ is given as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu_w e(n)\hat{\boldsymbol{x}}_s(n) \tag{5}$$

Where μ_w is the step size parameter,

$$\hat{\boldsymbol{x}}_s(n) = [\hat{\boldsymbol{x}}_s(n), \hat{\boldsymbol{x}}_s(n-1), \ldots, \hat{\boldsymbol{x}}_s(n-L_w+1)]^T \tag{6}$$

is filtered-reference signal vector being generated as

$$\hat{\boldsymbol{x}}_s(n) = \hat{s}(n) * \boldsymbol{x}(n) \tag{7}$$

Where $\hat{S}(n)$ is impulse response of the secondary path modelling filter $\hat{S}(z)$.

IV.   VARIENTS OF FXLMS ALGORITHM

A. Sun's Algorithm

Consider feedforward ANC system of Fig. 1, where we assume that noise source is impulsive and follows SαS distribution as explained earlier. The reference signal vector; used in the update equation of the FxLMS algorithm and in generating the cancelling signal $y(n)$; is given in Eq. (3) which shows that the samples of the reference signal $x(n)$ at different time are treated "equally". It may cause the FxLMS algorithm to become unstable in the presence of impulsive noise. To overcome this problem, a simple modification to FxLMS algorithm is proposed. In this algorithm, hereafter referred as Sun's algorithm, the samples of the reference signal $x(n)$ are ignored, if their magnitude is above a certain threshold set by statistics of the signal.Thus the reference signal is modified as

$$x'(n) = \begin{cases} x(n), & if\ x(n) \in [c_1, c_2] \\ 0, & otherwise \end{cases} \tag{8}$$

Here, the thresholding parameters $c1$ and $c2$ can be obtained offline for ANC systems. A few comments on choosing these parameters are given later. Thus Sun's algorithm for ANC of impulsive noise is given as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu_w e(n)\hat{\boldsymbol{x}}'_s(n) \tag{9}$$

Where$\hat{\boldsymbol{x}}'_s(n) = [\hat{\boldsymbol{x}}'_s(n), \hat{\boldsymbol{x}}'_s(n-1), \ldots, \hat{\boldsymbol{x}}'_s(n-L_w+1)]^T$ is generated as

$$\hat{\boldsymbol{x}}'_s(n) = \hat{s}(n) * \boldsymbol{x}'(n) \tag{10}$$

Where

$$\boldsymbol{x}'(n) = [x'(n), x'(n-1), \ldots, x'(n-L_w+1)]^T \tag{11}$$

is a modified reference signal vector with $x'(n)$ being obtained using Eq. (8). The main advantage is that the computational complexity of this algorithm is same as that of the FxLMS algorithm.

B. Modified Sun's Algorithm

The Sun's algorithm becomes unstable for $\alpha < 1.5$, then the PDF is peaky and the reference noise is highly impulsive. Furthermore, the convergence speed of this algorithm is very slow. The main problem is that ignoring the peaky samples in the update of FxLMS algorithm does not mean that these samples will not appear in the residual error $e(n)$. The residual error may still be peaky, and in the worst case the algorithm may become unstable. In order to improve the stability of the Sun's algorithmthe idea of Eq. (8)is extended to the error signal $e(n)$ as well, and a new error signal is obtained

$$e'(n) = \begin{cases} e(n), & if\ e(n) \in [c_1, c_2] \\ 0, & otherwise \end{cases} \tag{12}$$

Effectively, the idea is to freeze the adaptation of $W(z)$ when a large amplitude is detected in the error signal $e(n)$. Thus modified-Sun's algorithm for ANC of impulse noise is proposed as

$$w(n + 1) = w(n) + \mu_w e'(n)\hat{x}'_s(n) \qquad (13)$$

C. Modified FxLMS (MFxLMS) Algorithm

In order to further improve the robustness of the Sun's algorithm; instead of ignoring the large amplitude sample; we may clip the sample by a threshold value, and thus the reference signal is modified as

$$x''(n) = \begin{cases} c_1, & x(n) \le c_1 \\ c_2, & x(n) \ge c_2 \\ x(n), & otherwise \end{cases} \qquad (14)$$

As stated earlier, ignoring (or even clipping) the peaky samples in the update of FxLMS algorithm does not mean that peaky samples will not appear in the residual error $e(n)$. The residual error may still be so peaky, that in the worst case might cause ANC to become unstable. We extend the idea of Eq. (14) to the error signal $e(n)$ as well, and a new error signal is obtained as

$$e''(n) = \begin{cases} c_1, & e(n) \le c_1 \\ c_2, & e(n) \ge c_2 \\ e(n), & otherwise \end{cases} \qquad (15)$$

and the modified FxLMS (MFxLMS) algorithm for ANC of impulsive noise sources is as given below

$$w(n + 1) = w(n) + \mu_w e''(n)\hat{x}''_s(n) \qquad (16)$$

Where
$$\hat{x}''_s(n) = [\hat{x}''_s(n), \hat{x}''_s(n - 1), ..., \hat{x}''_s(n - L_w + 1)]^T$$
is generated as

$$\hat{x}''_s(n) = \hat{s}(n) * x''(n) \qquad (17)$$

Where

$$x''(n) = [x''(n), x''(n - 1), ..., x''(n - L_w + 1)]^T \qquad (18)$$
is a modified reference signal vector.

D. Normalized FxLMS (NFxLMS) Algorithm

All algorithms discussed so far; Sun's algorithm and its variants; require an appropriate selection of the thresholding parameters $[c_1, c_2]$. The probability of the sample less than c_1 or larger than c_2 are assumed to be 0, which is consistent with the fact that the tail of PDF for practical noise always tends to 0 when the noise value is approaching $\pm\infty$. Effectively, Sun's algorithm assumes the same PDF for $x'(n)$ with in $[c_1, c_2]$ as that of $x(n)$, and neglects the tail beyond $[c_1, c_2]$. The stability of Sun's algorithms depends heavily on appropriate choice of $[c_1, c_2]$.Thus, the performance of this algorithm also depends on the parameters c_1 and c_2.

In order to overcome this difficulty of choosing appropriate thresholding parameters, we propose an FxLMS algorithm that does not use modified reference and/or error signals, and hence does not require selection of the thresholding parameters $[c_1, c_2]$. Following the

concept of normalized LMS (NLMS) algorithm (Douglas, 1994), the normalized FxLMS (NFxLMS) can be given as

$$w(n + 1) = w(n) + \mu(n)e(n)\hat{x}_s(n) \qquad (19)$$

where normalized time-varying step size parameter $\mu(n)$ is computed as

$$\mu(n) = \frac{\tilde{\mu}}{\|\hat{x}_s(n)\|_2^2 + \delta} \qquad (20)$$

Where $\tilde{\mu}$ is fixed step size parameter, $\hat{x}_s(n)2$ is $l2$-norm of the filtered-reference signal vector that can be computed from current available data, and δ is small positive number added to avoid division by zero.

E. Modified Normalized FxLMS (MNFxLMS) Algorithm

When the reference signal has a large peak, its energy would increase, and this would in turn decrease the effective step size of NFxLMS algorithm.As stated earlier, the error signal is also peaky in nature and its effect must also be taken into account. Wepropose following modified normalized step size for FxLMS algorithm.

$$\mu(n) = \frac{\tilde{\mu}}{\|\hat{x}_s(n)\|_2^2 + E_e(n) + \delta} \qquad (21)$$

Where $Ee(n)$ is energy of the residual error signal $e(n)$ that can be estimated online using a low pass estimator as

$$E_e(n) = \lambda E_e(n - 1) + (1 - \lambda)e^2(n) \qquad (22)$$

Where λ is the forgetting factor $(0.9 <\_ < 1)$.

V.   SIMULATION RESULTS

The secondary propagation path is the path the anti-noise takes from the output loudspeaker to the error microphone within the quiet zone. The following commands generate a loudspeaker-to-error microphone impulse response that is band limited to the range 160 - 2000 Hz and with a filter length of 0.1 seconds. For this active noise control task, we shall use a sampling frequency of 5000 Hz.
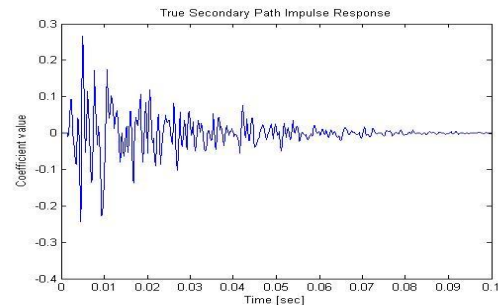

Fig-3: True secondary path impulse response

The first task in active noise control is to estimate the impulse response of the secondary propagation path. Typically, the length of the secondary path filter estimate is not as long as the actual secondary path and need not be for adequate control in most cases. We shall use a secondary path filter length of 250 taps, corresponding to an impulse response length of 31 msec. While any adaptive FIR filtering algorithm could be used for this purpose, the normalized LMS algorithm is often used due to its simplicity and robustness. Plots of the output and

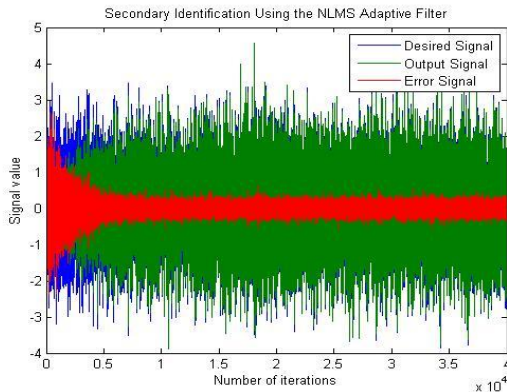error signals show that the algorithm converges after about 10000 iterations.

Fig-4: Secondary identification using NLMS algorithm

How accurate is the secondary path impulse response estimate? This plot shows the coefficients of both the true and estimated path. Only the tail of the true impulse response is not estimated accurately. This residual error does not significantly harm the performance of the active noise control system during its operation in the chosen task.
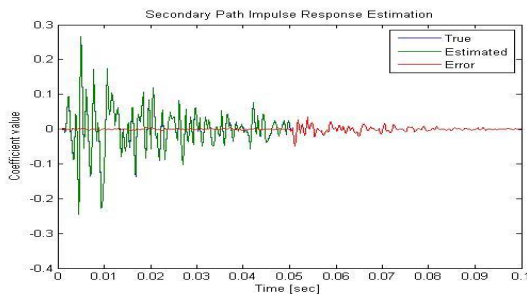

Fig-5: Estimation of secondary path impulse response

The propagation path of the noise to be cancelled can also be characterized by a linear filter. The following shows an input-to-error microphone impulse response that is band limited to the range 200 - 800 Hz and has a filter length of 0.1 seconds.
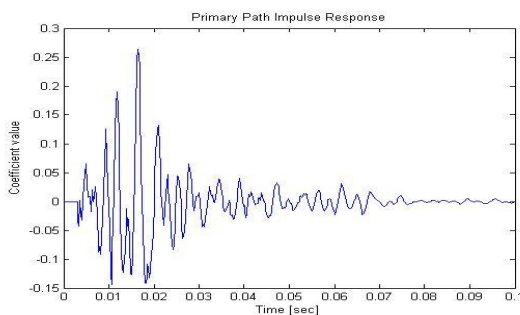

Fig-6: Primary path impulse response

Typical active noise control applications involve the sounds of rotating machinery due to their annoying characteristics. Here, we have synthetically generated 7.5 seconds of a noise that might come from a typical electric motor. Listening to its sound at the error microphone before cancellation, it has the characteristic industrial "whine" of such motors. The spectrum of the sound is also plotted.
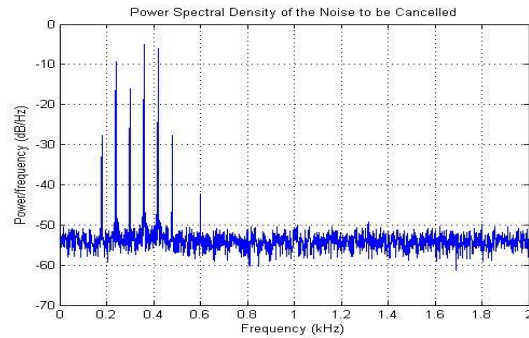

Fig-7: Power spectral density of noise to be cancelled

The most popular adaptive algorithm for active noise control is the filtered-X LMS algorithm. This algorithm uses the secondary path estimate to calculate an output signal whose contribution at the error sensor destructively interferes with the undesired noise. The reference signal is a noisy version of the undesired sound measured near its source. We shall use a controller filter length of about 44 msec and a step size of 0.0001 for these signal statistics
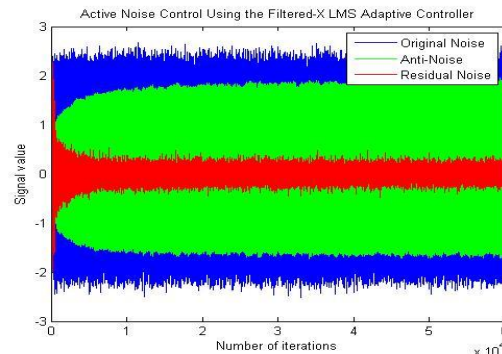

Fig-8: Active noise control using Fx-LMS algorithm

Comparing the spectrum of the residual error signal with that of the original noise signal, we see that most of the periodic components have been attenuated considerably. The steady-state cancellation performance may not be uniform across all frequencies, however. Such is often the case for real-world systems applied to active noise control tasks.
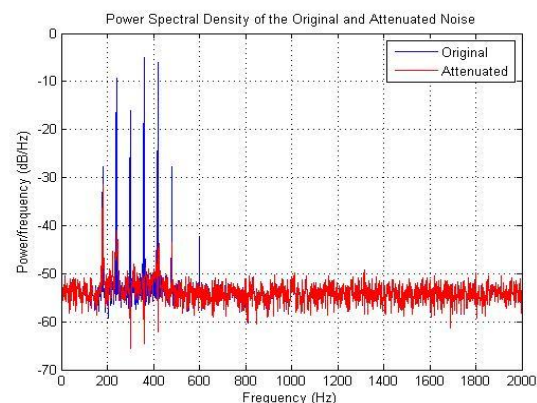

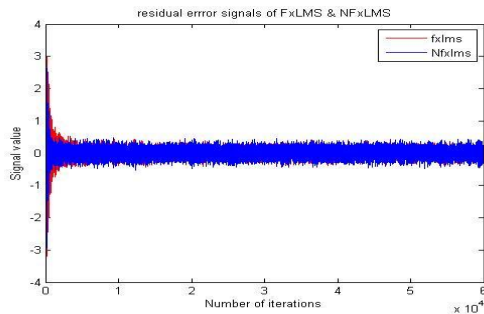Fig-9: Power spectral density of original and Attenuated noise

Fig-10: Residual error signals of FxLMS & NFxLMS

VI. CONCLUSION

From the above Mat Lab simulation results, we can observed that the Active Noise Control using Normalized Filtered-x LMS (NFxLMS) algorithm gives more performance compared to the conventional Filtered-x LMS (FxLMS) algorithm .

REFERENCES

[1] Akhtar, M. T. &Mitsuhashi, W. (2009b). Robust adaptive algorithms for active noise control of impulse noise. Proceedings of IEEE International Conference Acoustic Speech Signal Processing (ICASSP), pp. 261–264, April 19-24, 2009.

[2] Akhtar, M. T. & Abe, M. &Kawamata, M. (2006). A new variable step size LMS algorithm-based method for improved online secondary path modelling in active noise control systems. IEEE Transactions Audio Speech Language Processing, Vol. 14, No. 2, 2006, pp. 720–726.

[3] Xiao, Y. & Ma, L. &Khorasani, K. & Ikuta, A. (2006). A new robust narrowband active noise control systemin the presence of frequencymismatch. IEEE Transactions Audio Speech Language Processing, Vol. 14, No. 6, Nov. 2006, pp. 2189–2200.

[4] Kuo, S.M. &Kuo, K. &Gan,W. S. (2010). Active noise control: Open problems and challenges. Proceedings of International Conference on Green Circuits and Systems (ICGCS), pp. 164–169, Shanghai, 21-23 June 2010.

[5] Kuo, S.M. &Chakravarthy, S. R. &Gireddy, R. & Gupta, A. (2008). Experiment of active snore noise control systems. Noise Control Engineering Journal, Vol. 56, No. 1, Jan-Feb., 2008, pp. 16–24.

[6] Akhtar, M. T. &Abe,M. &Kawamata, M. (2005). A new structure for feedforward active noise control systems with improved online secondary path modeling. IEEE Transactions Speech Audio Processing, Vol. 13, No. 5, 2005, pp. 1082–1088.

[7] Aydin, G. &Arikan, O. &Centin, E. (1999). Robust adaptive fintering algorithms for α-stable random process, IEEE Transactions Circuits Systems–II: Analog Digital Signal Processing, Vol. 46, No. 2, pp. 198–202, 1999.

[8] Douglas, S. C. (1994). A family of normalized LMS algorithms. IEEE Signal Processing Letters, Vol. 1, No. 3, 1994, pp. 49–51.