Improving Tracking Performance of FxLMS Algorithm Based Active Noise Control Systems

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Abstract. Several approaches have been introduced in literature for active noise control (ANC) systems. Since FxLMS algorithm appears to be the best choice as a controller filter, researchers tend to improve performance of ANC systems by enhancing and modifying this algorithm. In this paper, the existing FxLMS algorithm is modified which provides a new structure for improving the tracking performance and convergence rate. The secondary signal y (n) is thresholded by Wavelet transform to improve tracking. The convergence rate is improved dynamically by varying the step size of the error signal.

Keywords: active noise control, FxLMS algorithm, wavelet transform, soft threshold, dynamic step size.

1 Introduction

Acoustic noise problems become more and more evident as increased numbers of industrial equipment such as engines, blowers, fans, transformers, and compressors are in use. The traditional approach to acoustic noise control uses passive techniques such as enclosures, barriers, and silencers to attenuate the undesired noise [1],[2]. These passive silencers are valued for their high attenuation over a broad frequency range; however, they are relatively large, costly, and ineffective at low frequencies. Mechanical vibration is another related type of noise that commonly creates problems in all areas of transportation and manufacturing, as well as with many household appliances. Active noise control (ANC) [3]–[4] involves an electro acoustic or electromechanical system that cancels the primary (unwanted) noise based on the principle of superposition; specifically, an anti-noise of equal amplitude and the primary (unwanted) noise based on the principle of superposition; opposite phase is generated and combined with the primary noise, thus resulting in the cancellation of both opposite phase is generated and combined with the primary noise, thus resulting in the cancellation of both noises.

The most popular adaptation algorithm used for ANC applications is the FxLMS algorithm, which is a modified version of the LMS algorithm [5]. The schematic diagram

N. Meghanathan et al. (Eds.): NeCoM, WiMoN, and WeST 2010, CCIS 90, pp. 11–20, 2010.

for a single-channel feed forward ANC system using the FxLMS algorithm is shown in figure.1.Here, P(z) is primary acoustic path between the reference noise source and the error microphone and S (z) is the secondary path following the ANC (adaptive) filter W (z). The reference signal x (n) is filtered through S (z), and appears as anti- noise signal y' (n) at the error microphone. This anti-noise signal combines with the primary noise signal d (n) 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 $\hat{S}(z)$ account for the model of the secondary path S(z) between the output of the controller and the output of the error microphone. The filtering of the reference signals x(n) through the secondary-path model $\hat{S}(z)$ is demanded by the fact that the output y(n) of the adaptive controller w(z) is filtered through the secondary path S (z). [7].

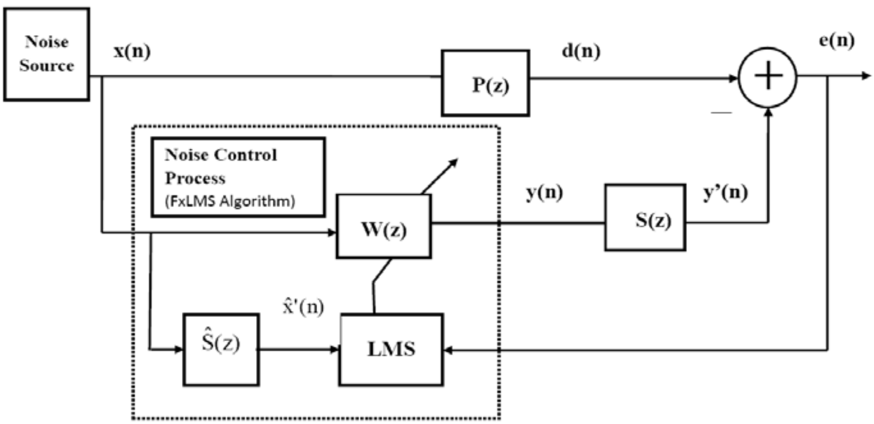


Fig. 1. Blockdiagram of FxLMS based feed forward ANC system

The main idea in this paper is to further increase the performance of FxLMS algorithm in terms of Signal to noise ratio. In modified FxLMS, secondary signal y'(n) is soft threshold by wavelet transform to improve the tracking performance. The step size is varied dynamically with respect to the error signal. Since error at the beginning is large, the step size of the algorithm is also large. This in turn increases convergence rate. As the iteration progresses, the error will simultaneously decrease. Finally, the original step size will be retained. The organization of this paper is as follows. Section 2 describes the Secondary path effects. Section 3 describes FxLMS algorithm. Section 4 introduces Wavelet transform. Section 5 describes the proposed method. Section 6 describes the simulation results and Section 7 gives the conclusion.

2 Secondary Path Effects

In ANC system, the primary noise is combined with the output of the adaptive filter. Therefore, it is necessary to compensate $\hat{S}(z)$ for the secondary-path transfer from

$y(n)$ to $e(n)$, which includes the digital-to-analog (D/A) converter, reconstruction filter, power amplifier, loudspeaker, acoustic path from loudspeaker to error microphone, error microphone, preamplifier, anti-aliasing filter, and analog-to digital (A/D) converter. The schematic diagram for a simplified ANC system is shown in figure2.

From Figure 2. , the -transform of the error signal is

$$E(z) = [P(z) - S(z)W(z)]X(z) \tag{1}$$

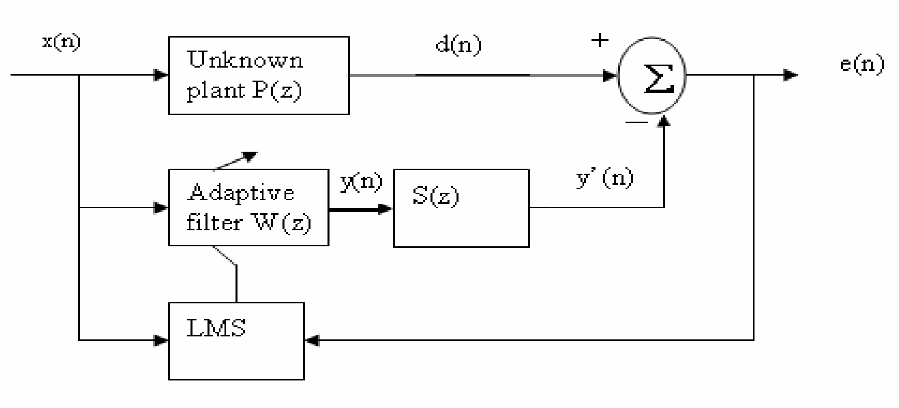


Fig. 2. Blockdiagram of simplified ANC system

We shall make the simplifying assumption here that after convergence of the adaptive filter, the residual error is ideally zero i.e., E (z) =0. This requires $W(z)$ realizing the optimal transfer function.

$$W^{o}(z) = \frac{P(z)}{S(z)} \tag{2}$$

In other words, the adaptive filter has to simultaneously Model $P(z)$ and inversely model $S(z)$. A key advantage of this approach is that with a proper model of the plant, the system can respond instantaneously to changes in the input signal caused by changes in the noise sources. However, the performance of an ANC system depends largely upon the transfer function of the secondary path. By introducing an equalizer, a more uniform secondary path frequency response is achieved. In this way, the amount of noise reduction can often be increased significantly [8]. In addition, a sufficiently high-order adaptive FIR filter is required to approximate a rational function $1/S(z)$ shown in (2). It is impossible to compensate for the inherent delay due to if the primary path does not contain a delay of at least equal length.

3 FxLMS Algorithm

The FxLMS algorithm can be applied to both feedback and feed forward structures. Block diagram of a feed forward FxLMS ANC system of Figure 1.Here P (z) accounts for primary acoustic path between reference noise source and error microphone. $\hat{S}(z)$ is obtained offline and kept fixed during the online operation of ANC. The expression for the residual error e (n) is given as

$$e(n) = d(n) - y'(n) \tag{3}$$

Where y' (n) is the controller output y(n) filtered through the secondary path S(z). y'(n) and y(n) computed as

$$y'(n) = s^T(n)y(n) \tag{4}$$

$$y(n) = w^T(n)\, x(n) \tag{5}$$

Where w (n) = [w0 (n) w_1 (n) …..w_{L-1}(n)]^T is tap weight vector, x(n)= [x(n) x(n-1)…. ….x(n-L+1)]^T is the reference signal picked by the reference microphone and s(n) is impulse response of secondary path S(z). It is assumed that there is no acoustic feedback from secondary loudspeaker to reference microphone. The FxLMS update equation for the coefficients of W (z) is given as:

$$w(n+1) = w(n) + \mu e(n)x'(n) \tag{6}$$

Where $x'(n)$ is reference signal x (n) filtered through secondary path model $\hat{S}(z)$

$$x'(n) = \hat{s}^T(n)\, x(n) \tag{7}$$

For a deep study on feed forward FxLMS algorithm the reader may refer to [7].

4 Wavelet Thresholding

The principle under which the wavelet thresholding operates is similar to the subspace concept, which relies on the fact that for many real life signals, a limited number of wavelet coefficients in the lower bands are sufficient to reconstruct a good estimate of the original signal. Usually wavelet coefficients are relatively large compared to other coefficients or to any other signal (especially noise) that has its energy spread over a large number of coefficients. Therefore, by shrinking coefficients smaller than a specific value, called threshold, we can nearly eliminate noise while preserving the important information of the original signal.

The proposed denoising algorithm is summarized as follow:

i) Compute the discrete wavelet transform for noisy signal.
ii) Based on an algorithm, called thresholding algorithm and a threshold value, shrink some detail wavelet coefficients.
iii) Compute the inverse discrete wavelet transform.

Figure.4. shows the block diagram of the basic wavelet thresholding for signal denoising. Wave shrink, which is the basic method for denoising by wavelet thresholding, shrinks the detail coefficients because these coefficients represent the high frequency components of the signal and it supposes that the most important parts of signal information reside at low frequencies. Therefore, the assumption is that in high frequencies the noise can have a bigger effect than the signal. Denoising by wavelet is performed by a thresholding algorithm, in which the wavelet coefficients smaller than a specific value, or threshold, will be shrunk or scaled [9] and [10].

The standard thresholding functions used in the wavelet based enhancement systems are hard and soft thresholding functions [11], which we review before introducing a new thresholding algorithm that offers improved performance for signal. In these algorithms, λ is the threshold value and $\delta$is the thresholding algorithm.

4.1 Hard Thresholding Algorithm

Hard thresholding is similar to setting the components of the noise subspace to zero. The hard threshold algorithm is defined as

$$\delta_{\lambda}^{H} = \begin{cases} 0 & |y| \leq \lambda \\ y & |y| > \lambda \end{cases} \tag{8}$$

In this hard thresholding algorithm, the wavelet coefficients less than the threshold λ will are replaced with zero which is represented in fig. 3-(a).

4.2 Soft Thresholding Algorithm

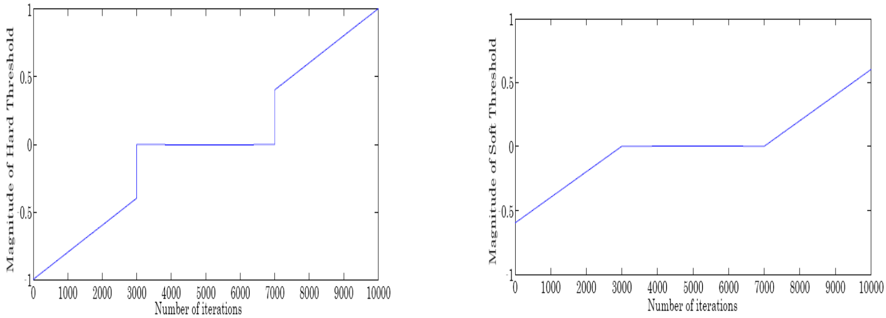
In soft thresholding, the thresholding algorithm is defined as follow: (see Figure 3-(b)).

$$\delta_{\lambda}^{S} = \begin{cases} 0 & |y| \leq \lambda \\ \mathrm{sign}(y)(|y| - \lambda) & |y| > \lambda \end{cases} \tag{9}$$

Soft thresholding goes one step further and decreases the magnitude of the remaining coefficients by the threshold value. Hard thresholding maintains the scale of the signal but introduces ringing and artifacts after reconstruction due to a discontinuity in the wavelet coefficients. Soft thresholding eliminates this discontinuity resulting in smoother signals but slightly decreases the magnitude of the reconstructed signal.

5 Proposed Method

In the proposed method $y'(n)$ is the secondary signal of FxLMS is denoising by wavelet is performed by a thresholding algorithm, in which the wavelet coefficients smaller than a specific value, or threshold, will be shrunk or scaled. The signal $y'(n)$ can be soft thresholding because of eliminates the discontinuity and resulting in smoother signal such that λ is the threshold value and δ is the thresholding algorithm in order to improving the tracking performance of FxLMS algorithm.



(a) Hard thresholding algorithm (b) Soft thresholding algorithm

Fig. 3. Thresholding algorithms (a) Hard. (b) Soft

The wavelet transform using fixed soft thresholding algorithm for signal $y'(n)$ is defined as follow:

$$\delta_{\lambda}^{S} = \begin{cases} 0 & |s^T y| \leq \lambda \\ \mathrm{sign}(s^T y)(|s^T y| - \lambda) & |s^T y| > \lambda \end{cases} \tag{10}$$

The wavelet transform using fixed soft thresholding will improve the tracking property when compared with traditional FxLMS algorithm based on active noise control systems. The threshold value used in fixed soft thresholding algorithm is $\lambda_0 = 0.45$, since the amplitude of the noise signal is small. The performance of the system can be further increased by using fixed threshold function with dynamic step size rather than the FxLMS and FxLMS with fixed soft threshold function based on the error signal $e(n)$.

In modified FxLMS, the step size is varied dynamically with respect to the error signal. Since error at the beginning is large, the step size of the algorithm is also large. This in turn increases convergence rate. As the iteration progresses, the error will simultaneously decreases. Finally, the original step size will be retained. Figure.5 shows the block diagram for purposed method. Thus the convergence rate of the FxLMS algorithm is improved by varying the step-size as well as wavelet threshold value with respect to error signal. From the Figure 5, the expression for the residual error e(n) is given as

$$e(n) = d(n) - s^T y \tag{11}$$

Initially the error in the system is very high and so very large step size is selected. Hence the convergence rate is also very high .Then the step size is varied for the instant and the previous value of the error signal e (n). Finally the error is reduced greatly by the implementation of the dynamic step size algorithm.

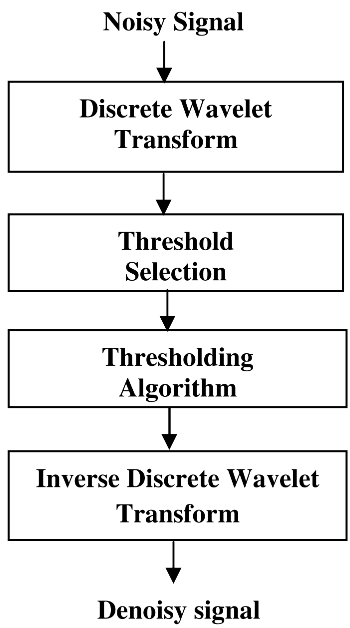


Fig. 4. Denoising by wavelet thresholding block diagram

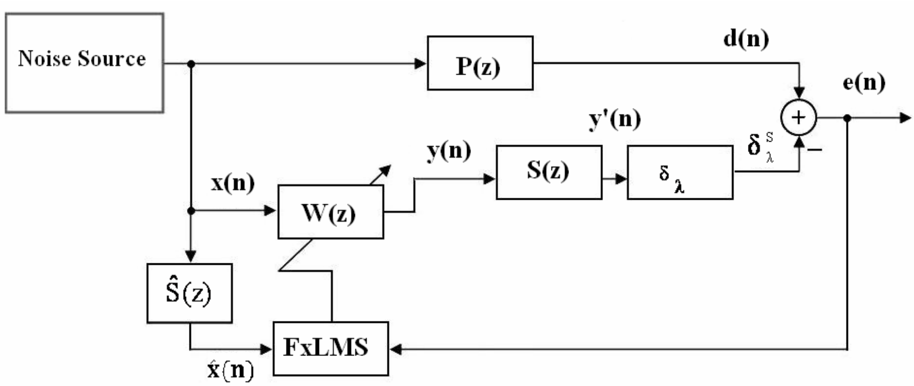


Fig. 5. Block diagram for purposed Method

This idea of dynamic step size calculation is represented in (12) and (13).

$$w(n+1) = w(n) + \mu(n)e(n)x'(n) \tag{12}$$

Where,

$$\mu(n) = \frac{\mu_0(n)}{1 - \text{abs}(e(n))} \tag{13}$$

Thus the (13) is called as modified FxLMS algorithm for improving the performance of existing algorithm.

6 Simulation Results

In this section the performance of the proposed modified FxLMS algorithm with wavelet thresholding is demonstrated using computer simulation. The performance of the fixed wavelet thresholding dynamic step size algorithm is compared with FxLMS algorithm and wavelet thresholding algorithm on the basis of noise reduction R (dB) and convergence rate is given in (14) and (15).

$$\mathrm{R(dB)} = -10\log\left(\frac{\sum e^2(n)}{\sum d^2(n)}\right) \tag{14}$$

$$\text{Convergence} \quad \text{Rate} = 20\log10\{\mathrm{abs(e)}\} \tag{15}$$

The large positive value of R indicates that more noise reduction is achieved at the error microphone. The computer simulation for modified FxLMS algorithm is illustrated in Fig.6.and Fig.7. Figure.6 shows the characteristics of Noise reduction versus number of iteration times. It has been seen that the modified FxLMS with fixed soft thresholding having dynamic step-size produce better noise reduction when compared to FxLMS and FxLMS with fixed soft thresholding.

Fig.7. shows the characteristics of convergence rate in dB with respect to number of iterations. It has been seen that the convergence rate of modified FxLMS with fixed soft thresholding having dynamic step-size increases by reducing the number of iterations when compared to FxLMS and FxLMS with fixed soft thresholding.

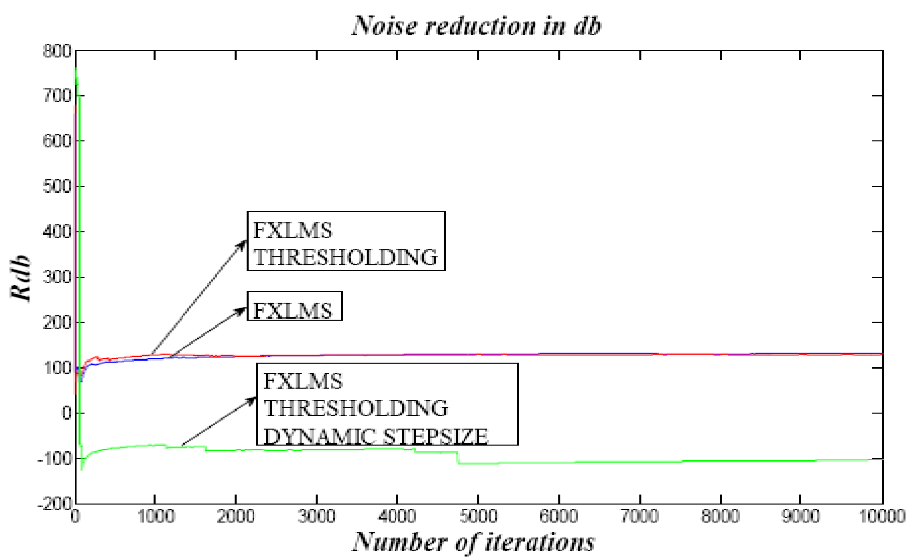


Fig. 6. Noise reduction versus iteration time *(n)*

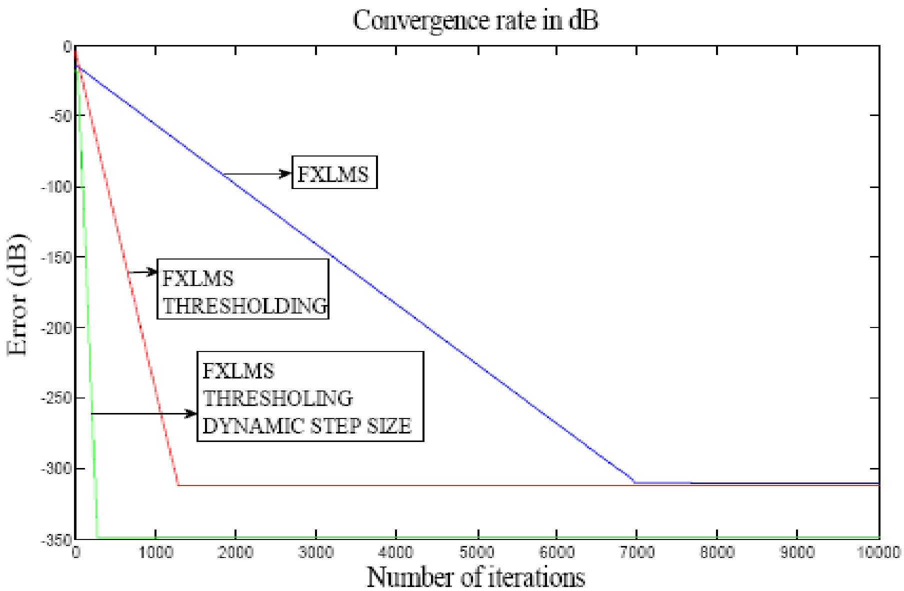


Fig. 7. Characteristics of convergence rate

7 Conclusions

Here a modified FxLMS structure for ANC system is proposed. This structure combines the concept of wavelet fixed soft thresholding with the dynamic variable step size. It shows better tracking performance and convergence rate than the conventional FxLMS algorithm and FxLMS wavelet soft threshold algorithm. Thus this method achieves an improved performance than the existing methods.

Acknowledgement

The authors would like to thank the reviewers for their many insightful comments and useful suggestions. The authors also would like to express their gratitude to our beloved chairman Lion Dr.K.S.Rangasamy and our principal Dr.K.Thagarajah for supporting this research.

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