A MODIFIED STRUCTURE FOR FEED FORWARD ACTIVE NOISE CONTROL SYSTEMS WITH IMPROVED PERFORMANCE

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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 noise reduction and convergence rate. Here the proposed method uses two variable step sizes, one for control filter and another for modelling filter. The control filter step size is varied based on the secondary path threshold signal $\hat{\delta}_\lambda$. *The modelling filter step size is varied based on error signal* $f(n)$. *It is shown that in the proposed method ANC system noise reduction rate and convergence rate are improved dynamically than the FxLMS variable step size methods. The computer simulations results indicate effectiveness of the proposed method.*

KEYWORDS

Active noise control, FxLMS algorithm, Wavelet transform, Soft threshold, Variable Step Size (VSS).

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 for a single-channel feed forward ANC system using the FxLMS algorithm is shown in figure.1.Here $P(z)$

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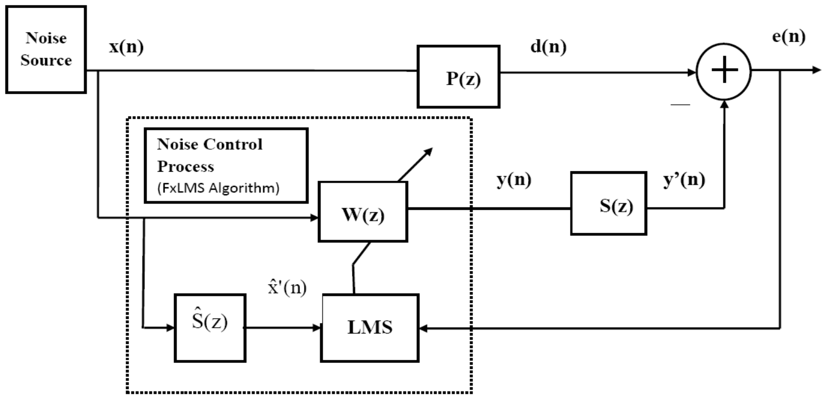


Figure 1. Block diagram of FxLMS based feed forward ANC system.

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].

The main idea in this paper is to improve the performance of the FxLMS algorithm in terms of noise reduction and convergence rate. In modified FxLMS, secondary signal $y'(n)$ is threshold by wavelet transform; the control filter step size is varied dynamically with respect to the threshold secondary signal $\hat{\delta}_\lambda$. Since error $e(n)$ at the beginning is large, the threshold secondary signals are also large $\hat{\delta}_\lambda$. For the large value of $\hat{\delta}_\lambda$, the method uses small step size μ_p and vice-versa. In addition to that the method uses a variable step size μ_s for modelling filter. The modelling filter step size is varied based on the error signal $f(n)$. 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.

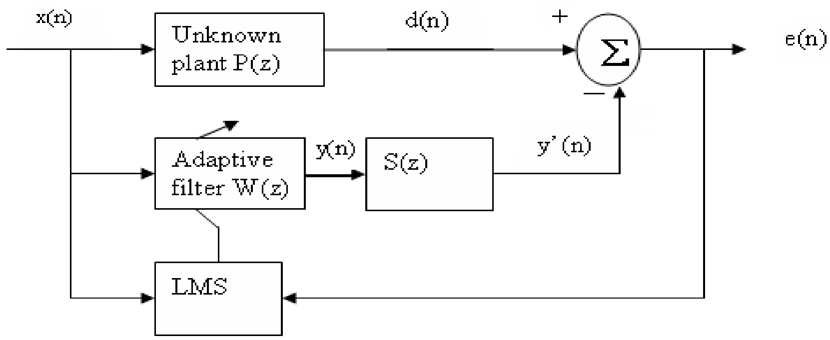


Figure 2. Block diagram of simplified ANC system

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

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

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 $\mathrm{W(z)}$ 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 $\mathrm{P(z)}$ and inversely model $\mathrm{S(z)}$. 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 $1/\mathrm{S(z)}$ 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. $\hat{\mathrm{S}}(\mathrm{z})$ 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.

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

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

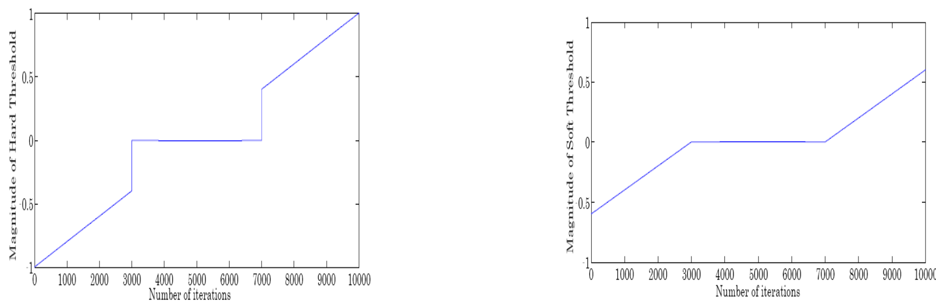
In this hard thresholding algorithm, the wavelet coefficients less than the threshold λ will are replaced with zero which is represented in fig. 3-(a).

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.



a) Hard thresholding algorithm (b) Soft thresholding algorithm

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

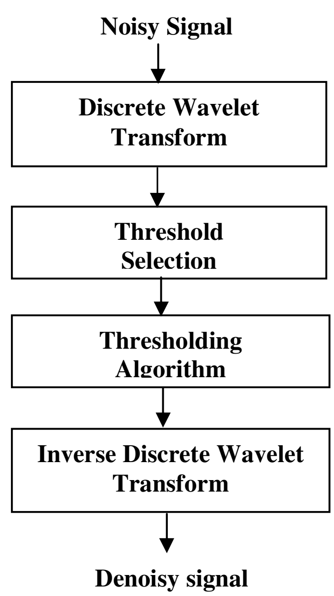


Figure 4. Denoising by wavelet thresholding block diagram

5. PROPOSED METHOD

In modified FxLMS, the secondary signal $y'(n)$ is thresholded by wavelet transform δ_λ; the control filter step size is varied dynamically with respect to the threshold secondary signal $\hat{\delta}_\lambda$. Since error $e(n)$ at the beginning is large, the threshold secondary signal $\hat{\delta}_\lambda$ is also large. For the large value of $\hat{\delta}_\lambda$, the method uses small step size μ_p and vice-versa. The method also introduces a new variable step size μ_s for modelling filter. The modelling filter step size μ_s adaptively changes based on the error signal $f(n)$.Here the step size μ_s is inversely proportional to the error signal $f(n)$. If the error signal $f(n)$ is large, then the step size μ_s is small and vice versa. This in turn increases the performance of the proposed method shown in figure 5.

Consider Figure 5 which shows the block diagram of the proposed method. Assuming that $W(z)$ is an FIR filter of tap-weight length L, the output signal $y(n)$ is computed as

$$y(n) = w^T(n)x_L(n) \tag{10}$$

Here $w(n) = [w_0(n)\, w_1(n) \ldots\ldots w_{L-1}(n)]^T$ is tap weight vector, $x(n) = [x(n)\, x(n-1) \ldots\ldots x(n-L+1)]^T$ is the L sample reference signal vector. An internally generated zero means white Gaussian noise signal, $v(n)$ uncorrelated with the reference signal $x(n)$ is injected at the output $y(n)$ of the control filter. Thus the residual error signal e (n) is given as

$$e(n) = [d(n) - \hat{\delta}_\lambda(n)] \tag{11}$$

Here $d(n) = p(n) * x(n)$ is the primary disturbance signal, $y'(n) = s(n) * y(n)$ is the cancelling signal, $v'(n) = s(n) * v(n)$ is the modeling signal, $p(n)$ and $s(n)$ are the impulse responses of the $P(z)$ and $S(z)$ respectively. The secondary signal $y'(n)$ is denoised using wavelet transform, because wavelet transform is capable of providing the time and frequency information simultaneously. The time- domain signal is passed through various high pass and low pass filters, which filter out either high frequency or low frequency portions of the signal. This operation is called decomposition. Higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency. This means that, a certain high frequency component can be located better in time (with less relative error) than a low frequency component. On contrary, a low frequency component can be located better in frequency compared to high frequency component.

In our proposed error de-noise method is performed in the following steps.

1. Decomposing of the noisy-signal $y'(n)$ using wavelet transform to obtain the denoise coefficient $\hat{\delta}_\lambda$.
2. Thresholding, to obtain the estimated wavelet coefficient $\hat{\delta}_\lambda$. For each level a threshold value is found, and it is applied for the denoise coefficient δ_λ. The method uses soft-threshold wavelet transform, to find estimated wavelet transform and estimated wavelet co-efficient $\hat{\delta}_\lambda$

$$\hat{\delta}_\lambda = \begin{cases} \operatorname{sgn}(\delta_\lambda)(|\delta_\lambda| - \lambda_j), & |\delta_\lambda| \geq \lambda_j \\ 0 & |\delta_\lambda| < \lambda_j \end{cases} \tag{12}$$

3. Reconstructing the denoised signal $y'(n)$ from $\hat{\delta}_\lambda$ by inverse discrete wavelet transform.

Assuming that the modeling filter $\hat{S}(z)$ is an FIR filter of tap-weight length M ,its output $\hat{v}'(n)$ is given as

$$\hat{v}'(n) = \hat{s}^T(n) v_M(n) \tag{13}$$

Here $\hat{s}(n) = [\hat{s}_0(n), \hat{s}_1(n) ......\hat{s}_{M-1}(n)]^T$ is the impulse response of $\hat{S}(z)$, $v_M(n) = [v(n), v(n-1)......v(n-M+1)]^T$.

The control filter step size varied as

$$\mu_p = \frac{\mu_0}{1 + \hat{\delta}_\lambda} \tag{14}$$

Here μ_0 is the initial step size, whose value is 0.025.

The error in secondary path $f(n)$ can be obtained as,

$$f(n) = e(n) - \hat{v}'(n) \tag{15}$$

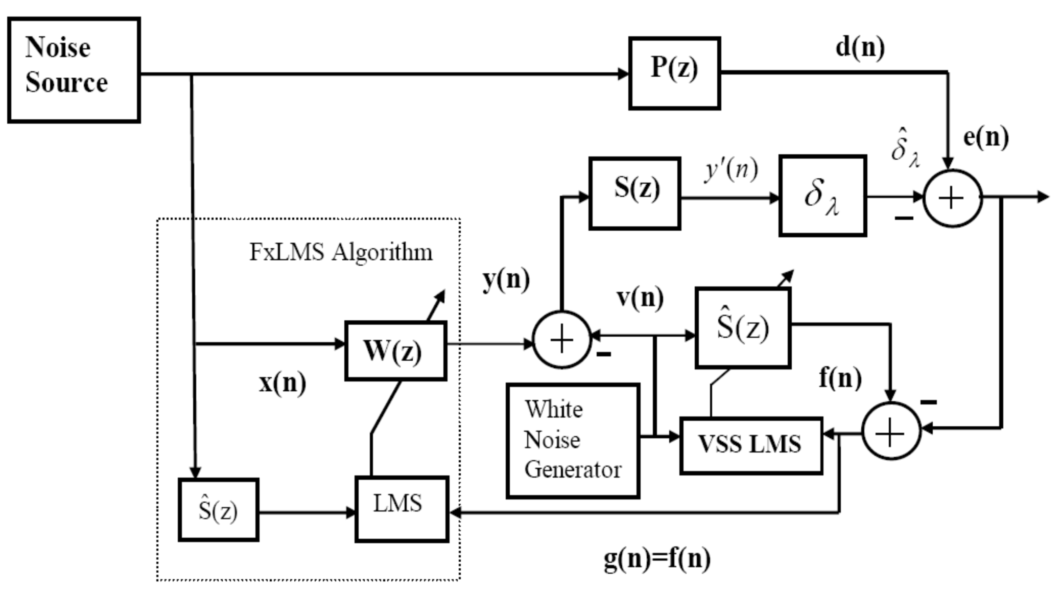


Figure 5. Block diagram for purposed Method

Finally the weights of the control filter can be updated by using steepest descent FxLMS algorithm as

$$w(n+1) = w(n) + \mu_p f(n) x'(n) \tag{16}$$

The modelling filter uses VSS –LMS algorithm to update filter coefficients. The step size μ_s of the modelling filter is varied based on $f(n)$,which is

$$\mu_s = \frac{\mu_0}{1 + f(n)} \tag{17}$$

Finally the weights of the modeling filter can be updated as

$$\hat{s}(n+1) = \hat{s}(n) + \mu_s(n) f(n) \hat{v}'(n) \tag{18}$$

Since $\hat{v}'(n)$ is the estimation of the generated white noise $v(n)$.

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 variable wavelet thresholding dynamic step size algorithm is compared with FxLMS variable step size algorithm on the basis of noise reduction R (dB) and convergence rate is given in (19) and (20).

$$\mathrm{R(dB)} = -10\log\left(\frac{\sum \mathrm{e}^2(n)}{\sum \mathrm{d}^2(n)}\right) \tag{19}$$

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

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 variable soft thresholding having dynamic step-size produces better noise reduction when compared to FxLMS with variable step size.

Figure 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 variable soft thresholding having dynamic step-size increases by reducing the number of iterations when compared to FxLMS with variable step size.

Figure.8. shows the characteristics of relative modeling error in dB with respect to number of iterations. It has been seen that the relative modeling error of modified FxLMS provides better performance compared with FxLMS with variable step size.

Figure.9 shows the characteristic of error versus number of iterations. It has been seen that error of the modified FxLMS provides better performance than that of the FxLMS variable step size method.

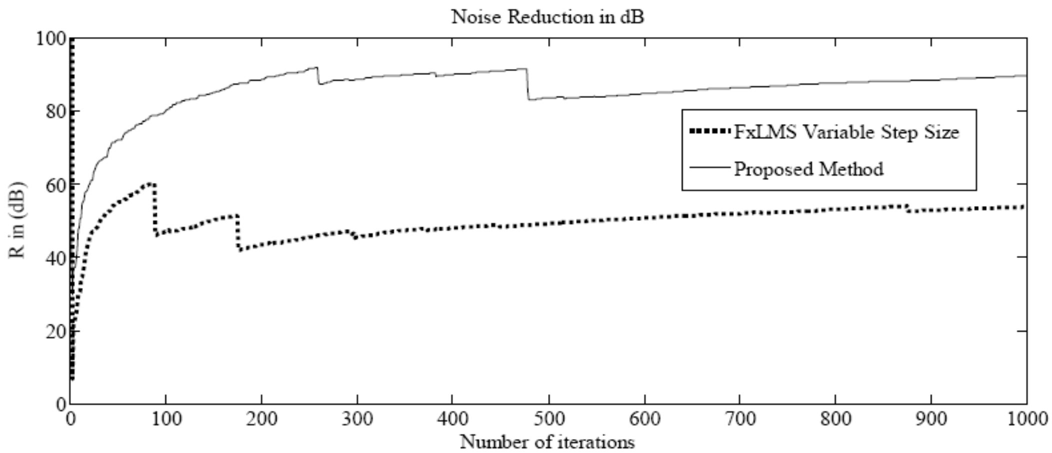


Figure 6. Noise reduction versus iteration time *(n)*

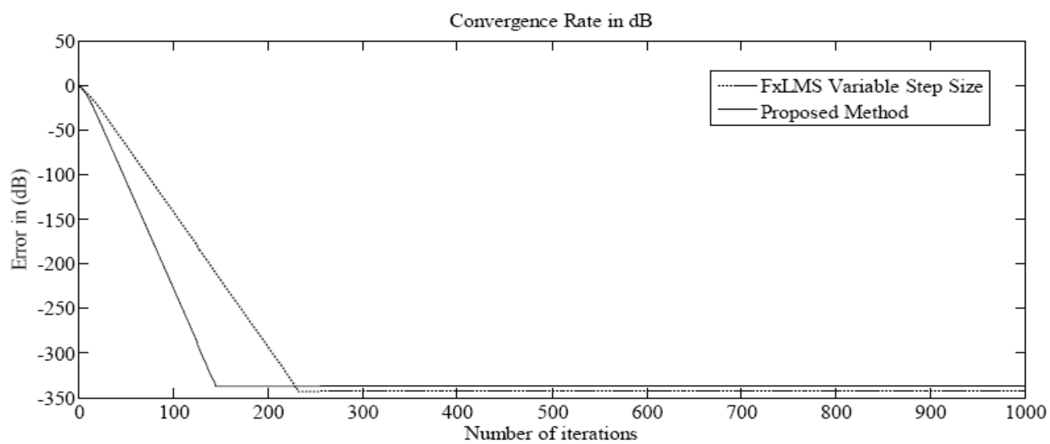


Figure 7. Characteristics of convergence rate

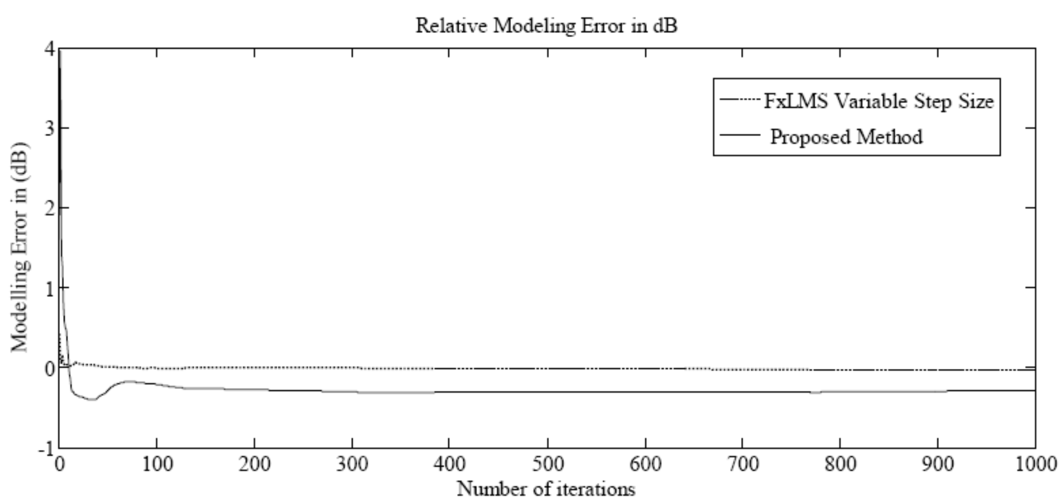


Figure.8. Characteristics of relative modeling error.

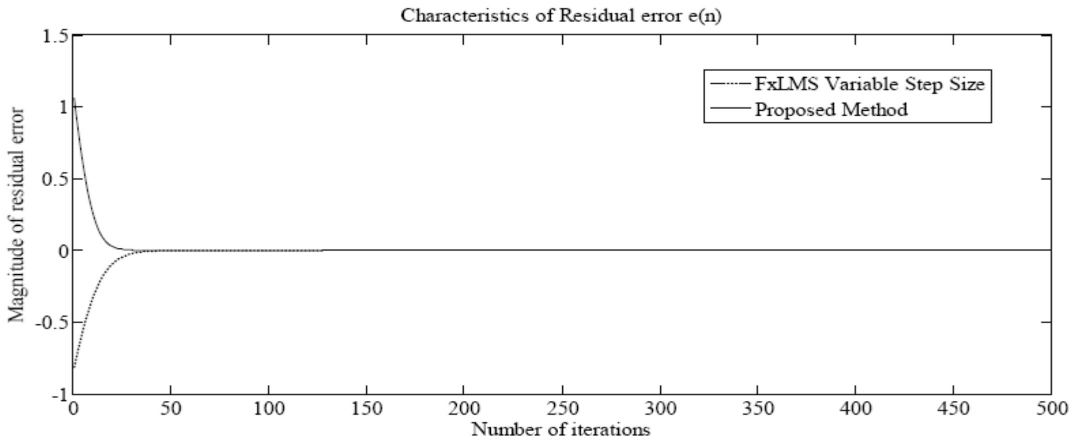


Figure.9. Characteristics of residual error $e(n)$

6. CONCLUSIONS

This paper has proposed an ANC system with on- line secondary path modelling and modified FxLMS structure. This method combines the concept of variable wavelet soft thresholding and dynamic variable step size. Computer simulations have been conducted for a single-channel feed forward ANC system. Comparative result shown in this paper demonstrates the effectiveness of the proposed method. It shows better performance and convergence rate than the FxLMS variable step size method.

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