Active Noise Control Using Functional Link Artificial Neural Network (FLANN)

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Abstract: The exponential increase of noise pollution and ineffectiveness of passive techniques for noise mitigation have led to the development of active noise control system .The conventional active noise control (ANC) system is essentially linear in nature and has been successfully applied in controlling both broadband and narrowband noise sources. The application areas are heating, ventilating and air conditioning (HVAC) systems, exhaust and motor noise, headset and airplanes. In many practical applications the acoustic noise generated from dynamical systems is nonlinear and deterministic or stochastic, colour, and non-Gaussian. It has been reported that the linear techniques used to control such noise exhibit degradation in performance. In addition, the actuators of an active noise control (ANC) system very often have nonminium-phase response. A linear controller under such situations can not model the inverse of the actuator, and hence yields poor performance. A novel filtered-s least mean square (FSLMS) algorithm based ANC structure, which functions as a nonlinear controller, is proposed in this thesis and the performance analysis of FSLMS algorithm is compared with that of filtered-x least mean square(FXLMS) algorithm to show the residual noise power and convergence speed of proposed algorithm has a better performance.

Keywords: ANC, FSLMS, FXLMS, FLANN, Acoustic Noise.

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1 Introduction

Hybrid Electric Vehicles (HEV) vehicles require an energy management strategy to control the power split between the engine and the electric motors. Energy management can also be applied to the electric power system of a vehicle with a conventional drive train. The idea of controlling the vehicle power is initiated by the fact that energy losses in the internal combustion engine, alternator, and battery change according to their operating point. Minimizing these energy losses will result in an energy management strategy achieving higher fuel economy. Strategies that are based on heuristics can easily be implemented in a real vehicle by using a rule-based strategy [1] or by using fuzzy logic [2]. Although these strategies can offer a significant improvement in energy efficiency, they do not guarantee an optimal result in all situations. Hence, there is a requirement to develop strategies based on optimization techniques.To find the optimal solution, techniques as linear programming [3], optimal control [4], and especially Dynamic

Programming [5, 6] have been studied. In general, these techniques do not offer an online solution, because they assume that the future driving cycle is entirely known. Nevertheless, their result can be used as a bench-mark for the performance of other strategies, or to derive rules for a rule-based strategy. If only the present state of the vehicle is considered, optimization at each time instant can be beneficial, but profits will be limited [7].A different approach is taken by Kolmanovsky et.al [8] and Lin et.al in [9]. Instead of focusing on one particular driving cycle, a certain set of driving cycles is considered, resulting in a stochastic optimization approach. The difficulty is to cover a real-world driving situation with a set of individual driving cycles.The present investigation is an attempt to develop a novel method consisting of three steps. These steps are (1) Reduction of the model of the vehicle, (2) Energy management using modified dynamic programming (MDP) and (3) Use of better materials e.g. lighter materials for weight reduction.

2 Previous Research

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]–[6] 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 opposite phase is generated and combined with the primary noise, thus resulting in the cancellation of both noises as shown in figure 1

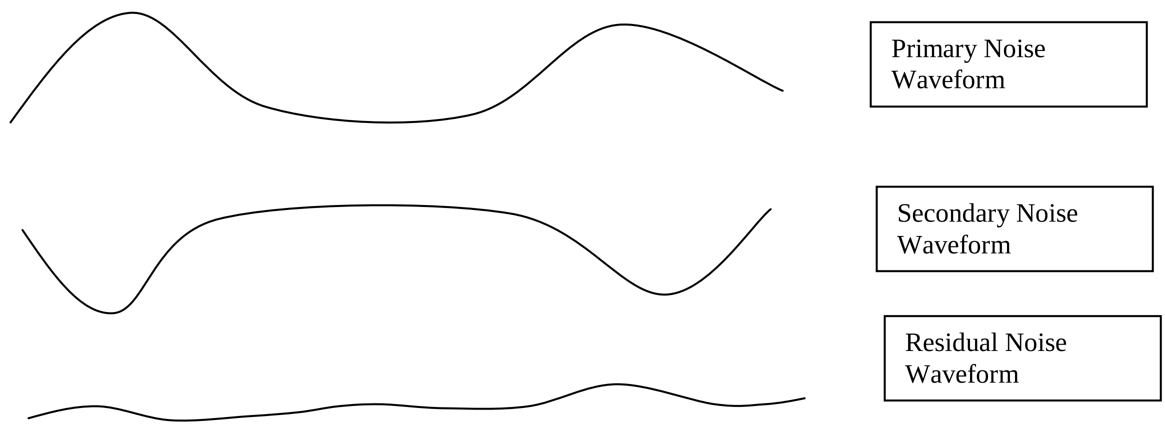

Figure1. Physical concept of Active Noise Control*.*

The ANC system efficiently attenuates low-frequency noise where passive methods are either ineffective or tend to be very expensive or bulky. ANC is developing rapidly because it permits improvements in noise control, often with potential benefits in size, weight, volume, and cost. The design of acoustic ANC utilizing a microphone and an electronically driven loudspeaker to generate a cancelling sound was first proposed in a 1936 patent by Lug [7]. Since the characteristics of the acoustic noise source and the environment are time varying, the frequency content, amplitude, phase, and sound velocity of the undesired noise are non stationary . An ANC system must therefore be adaptive in order to cope with these variations. Adaptive filters [8]–[16] adjust their coefficients to minimize an error signal and can be realized as (transversal) finite impulse response (FIR), (recursive) infinite impulse response (IIR), lattice, and transform- domain filters. The most common form of adaptive filter is the transversal filter using the Least mean- square (LMS) algorithm. It is desirable for the noise canceller to be digital [19], where signals from electro acoustic or electromechanical transducers are sampled and processed in real time using digital signal processing (DSP) systems. In the 1980’s, development of DSP chips enabled low-cost implementation of powerful adaptive algorithms [21] and encouraged widespread development and application of ANC systems. The continuous progress of ANC involves the development of improved adaptive signal processing algorithms, transducers, and DSP hardware. More sophisticated algorithms allow faster convergence and greater noise attenuation and are more robust to interference. The development of improved DSP hardware allows these more sophisticated algorithms to be implemented in real time to improve system performance. Noise is defined as any kind of undesirable disturbance, whether it is borne by electrical, acoustic, vibration, or any other kind of media. Therefore, ANC algorithms introduced can be applied to different types of noise using appropriate sensors and secondary sources. For electrical engineers involved in the development of ANC systems, [3], [5], and [6] provide excellent introduction to acoustics and vibration.

3 Basic Principle

The basic broad-band ANC system is described as an adaptive system identification framework in figure 2. in which an adaptive filter is used to estimate an unknown plant .The primary path consists of the acoustic response from the reference sensor to the error sensor where the noise attenuation is to be realized. If the plant is dynamic, the adaptive algorithm then has the task of continuously tracking time variations of the plant dynamics. The most important difference between Figure 2. and the traditional system identification scheme is the use of an acoustic summing junction instead of the subtraction of electrical signals.

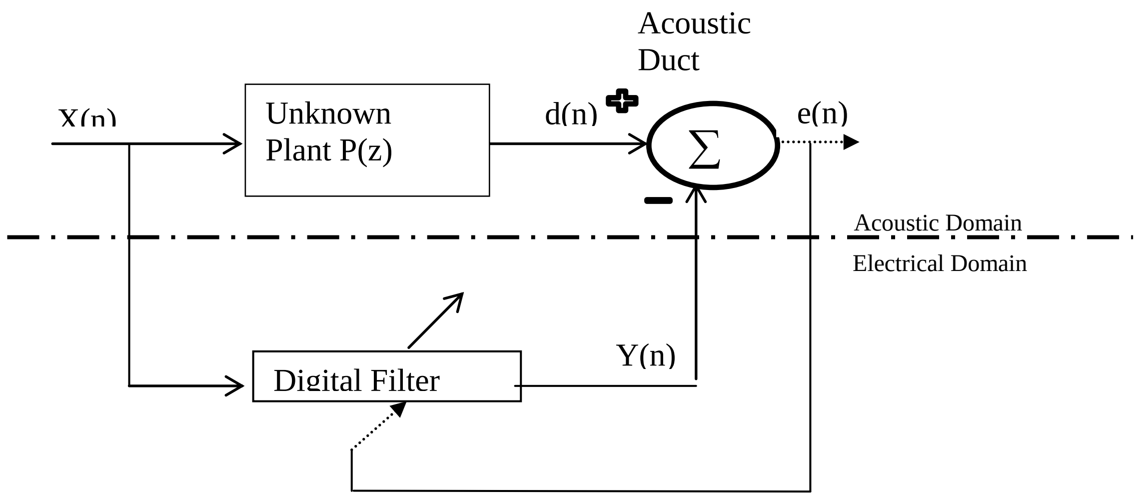

Figure 2. System identification of ANC

The objective of the adaptive filter is to minimize the residual error signal. From figure 2. $E(z) = 0$, after the adaptive filter $W(z)$ converges. We have $W(z) = P(z)$ for $X(z) \neq 0$ which implies that $y(n) = d(n)$. Therefore, the adaptive filter output $y(n)$ is identical to the primary disturbance $d(n)$. When $d(n)$ and $y(n)$ are acoustically combined, the residual error is $e(n) = d(n) - y(n) = 0$, which results in perfect cancellation of both sounds based on the principle of superposition. The performance of ANC can be determined by frequency-domain analysis of the residual error signal $e(n)$ .The auto power spectrum of $e(n)$ is given by [4]

$$S_{ee}(w) = [1 - C_{dx}(w)]S_{dd}(w) \tag{1}$$

where $C_{dx}(w)$ is the magnitude-squared coherence function [28] between two wide- sense stationary random processes $d(n)$ and $x(n)$ and $S_{dd}(w)$ is the auto power spectrum of $d(n)$. The equation indicates that the performance of the ANC system is dependent on the coherence, which is a measure of noise and the relative linearity of the two processes $d(n)$ and $x(n)$. In order to realize a small residual error, it is necessary to have very high coherence $[C_{dx}(w) \approx 1]$ at frequencies for which there is significant disturbance energy. The maximum noise reduction of an ANC system at frequency w in decibels is given by $-10\log_{10}[1 - C_{dx}(w)]$.

As illustrated in Figure 2. after the reference signal is picked up by the reference sensor, the controller will have some time to calculate the right output to the cancelling loudspeaker. If this electrical delay becomes longer than the acoustic delay from the reference microphone to the cancelling loudspeaker, the performance of the system will be substantially degraded. That is because the controller response is non causal when the electrical delay is longer than the acoustic delay. When the causality condition is met, the ANC system is capable of cancelling broad-band random noise. If causality is not possible, the system can effectively control only narrow-band or periodic noise.

3.1. *Secondary- Path Effect*

The use of the adaptive filter for ANC application is complicated by the fact that the summing junction in Figure. 2 represents acoustic superposition in the space from the cancelling loudspeaker to the error microphone, where the primary noise is combined with the output of the adaptive filter. Therefore, it is necessary to compensate for the secondary-path transfer function S(z) from y(n) to e(n) which includes the digital-to-analogue (D/A) converter, reconstruction filter, power amplifier, loudspeaker, acoustic path from loudspeaker to error microphone, error microphone, preamplifier, ant aliasing filter, and analogue-to-digital(A/D) converter. For analysis purpose, we represent actual system in figure. 2 by block diagram of Figure.3 as shown below

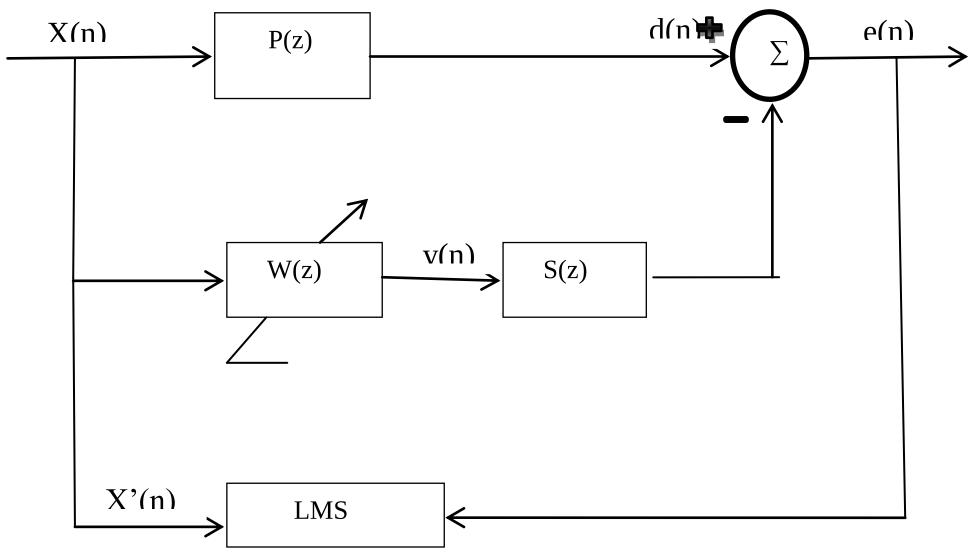

Figure.3. Simplified block diagram of ANC system

From Figure.3 , the z -transform of the error signal is given by

$$E(z) = [P(z) - S(z)W(z)]X(z) \quad (2)$$

According to equation (1), the residual error is limited by the coherence of the reference signal. Taking assumption that after convergence of the adaptive filter, the residual error is ideally zero [i.e. E(z)=0].This requires W(z) to realize the optimal transfer function

$$W(z) = \frac{P(z)}{S(z)} \quad (3)$$

The adaptive filter has to simultaneously model $P(z)$ and inversely model (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. 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. So the amount of noise reduction can be increased significantly [16]. In addition, a sufficiently high- order adaptive FIR filter is required to approximate a rational function $\frac{1}{S(z)}$ as in equation (3). It is impossible to compensate for the inherent delay due to $S(z)$ if the primary path $P(z)$ does not contain a delay of at least equal length.

3.2. Wave Form Synthesis Method

Structures and Algorithms*:* The waveform synthesizer stores cancelling noise waveform samples $\{W_l(n)l = 0,1, \dots\dots. L - 1\}$ in unique contiguous memory addresses, L where the number of samples is over one cycle of the waveform and n is the current time index. TheType equation here.se samples represent the required waveform to be generated and are sequentially sent to a D/A converter to produce the actual cancelling noise waveform for the secondary loudspeaker. Thus

$$y(n) = W_{j(n)}(n) \qquad (4)$$

represents the j(n) the element of wave form samples, where $j(n) = n$ mod L and can be implemented mod and can be implemented as a pointer incremented in a circular fashion between zero and L-1 for each sampling period, controlled by interrupts generated from the synchronization signal. The residual noise picked up by the error microphone is synchronously sampled with the reference signal timing pulses. In a practical system, there is a delay between the time the signal $[y(n) = W_{j(n)}(n)]$ is fed to the loudspeaker and the time it is received at the error microphone. This delay can be accommodated by subtracting a time offset from the circular pointer j(n). Thus, the adaptation unit adjusts the values of the waveform samples using a variant of the LMS algorithm

$$W_\ell(n + 1) = \{W_\ell(n) + \mu e(n), \ell = j(n - \triangle)\} \qquad (5)$$

W(n), otherwise

Where $\triangle$=[ζ / T] and $\triangle$ is the time delay, which is constant for a given loudspeaker-microphone arrangement, T is the sampling period, and $[x]$ greatest integer less than or equal to x. This offset number must be updated as the sampling rate varies, since it is synchronized with the noise source.

4. Principle and Analysis

The waveform synthesis method is equivalent to an adaptive FIR filter of order L=N excited by a Kronecker impulse train of period N=T_0/T samples

$$x(n) = \sum_{k-\infty}^{\infty} \delta(n - kN) \qquad (6)$$

where $\delta(.)$ the discrete Kronecker delta function and $T_0 = 2\pi/\omega_0$ is the period of the noise with fundamental angular frequency ω_0 Temporarily neglecting secondary path effects, Figure 4 shows how the periodic noise is cancelled by the output of an adaptive filter using the periodic impulse train as the reference input $x(n)$

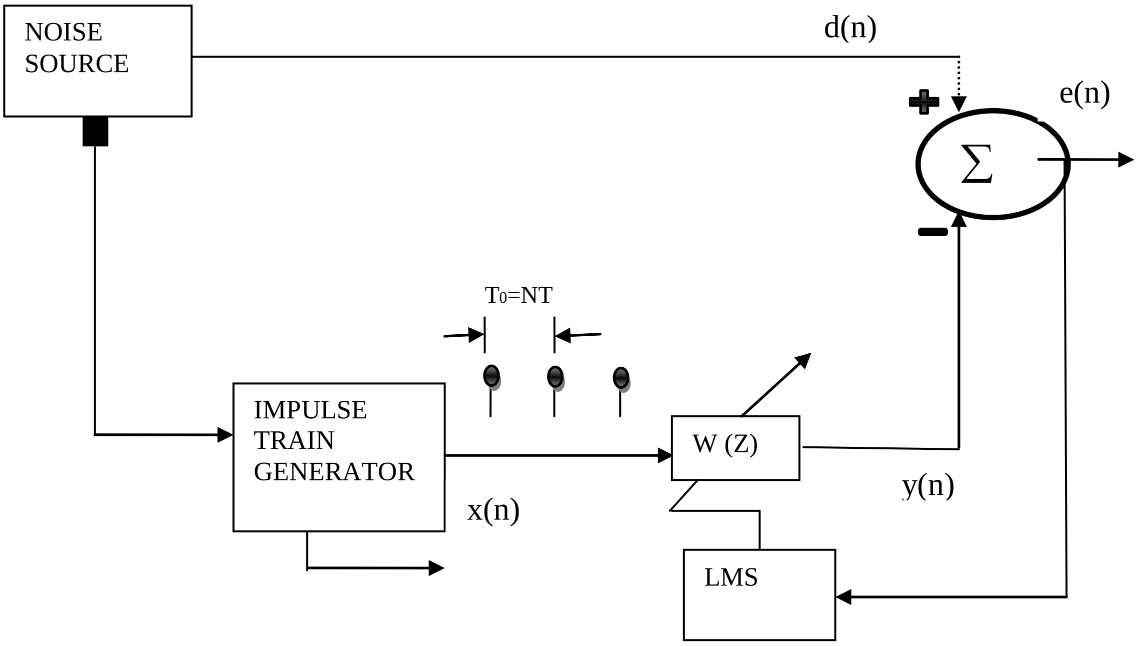

Figure.4. Equivalent diagram of waveform synthesis method using impulse train input and neglecting secondary path effect.

For reference signal and an adaptive filter with order L-N the transfer function $H(z)$ between the primary input $D(z)$ and the error output $E(z)$ is derived as

$$H(z) = \frac{E(z)}{D(z)} = \frac{1-z^{-l}}{1-(1-\mu)z^{-l}} \tag{7}$$

The zeros have constant amplitude $|z| = 1$ and are equally spaced $2\pi/L$ the unit circle of the z plane to create nulls in the frequency response at harmonic frequencies $kw_{0\beta}$. Therefore, the tonal components of the periodic noise at the fundamental and harmonic frequencies are attenuated by this multiple-notch filter. The poles have the same frequency as the zeros but are equally spaced on a circle at distance $1 - \mu$ from the origin. The effect of the poles is to introduce a resonance in the vicinity of the null, thus reducing the bandwidth of the notch. It gives a practical limitation on the value of μ from stability considerations; that is, $0 < \mu < 1$ for an impulse train of unit amplitude. The 3-dB bandwidth of each notch for $\mu \ll 1$ is approximated as $\beta \approx \mu/\pi T$. This shows that the bandwidth of the notch filter is proportional to the step size μ. In general case, the time constant of the response envelope decay is approximately $T \approx T/\mu$ (second). Therefore, there is trade off between the notch bandwidth and the duration of the transient response, which is determined by the step size and the sampling rate of the narrow-band ANC system.

5. Performance Of FSLMS Algorithm

To demonstrate the effectiveness an robustness of the proposed algorithm, computer simulations are performed on nonlinear situation in an ANC system. In these simulations, the secondary path transfer function $A(z)$ and its estimate$A^{\blacksquare}(z)$ are taken to be identical.
The primary noise signal is chosen to be a logistic chaotic type which is generated using the recursive equation

$$x(n+1) = \lambda x(n)[1 - x(n)] \tag{8}$$

Where $\lambda = 4$ and x(1) = 0.9 are chosen. This nonlinear noise process is then normalized to have unity signal power. In this experiment the primary path transfer function is considered to be

$$B(z) = z^{-5} - 0.3z^{-6} + 0.2z^{-7} \quad (9)$$

and the secondary path transfer function is taken as the minimum-phase model $A(z) = A^{\Delta}(z) = z^{-2} + 0.5z^{-3}$. The FSLMS algorithm with memory size 10 is chosen. The functional expansion of the input signal is of first-order type (p=1) . For the purpose of comparison, both FXLMS and FSLMS [7] are also simulated and . For the proposed FSLMS algorithm, the selected step-size is $\mu = 0.004$.

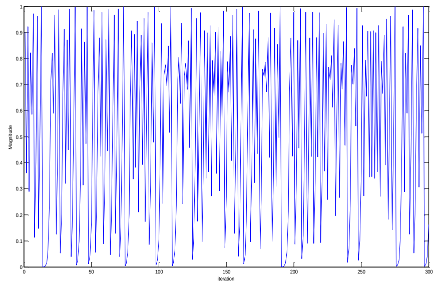

Figure.5. Chaotic input for FSLMS algorithm $(\boldsymbol{x(n+1) = \lambda x(n)[1 - x(n)]})$

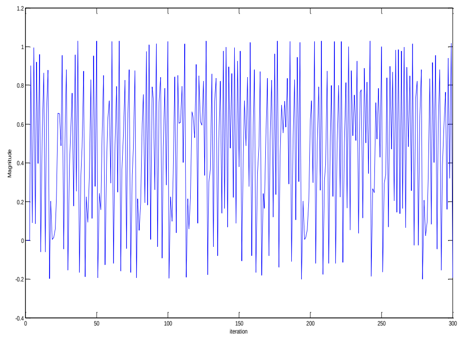

Figure.6. Desired output for FSLMS algorithm

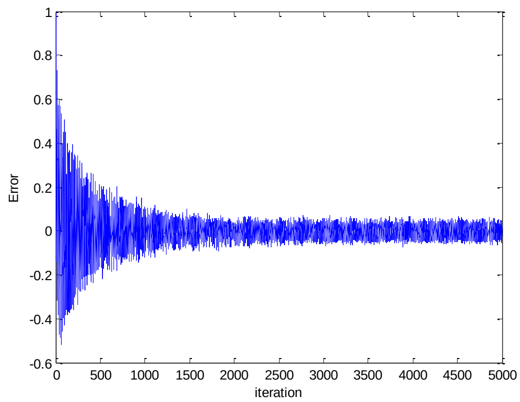

Figure.7. Plot of Error

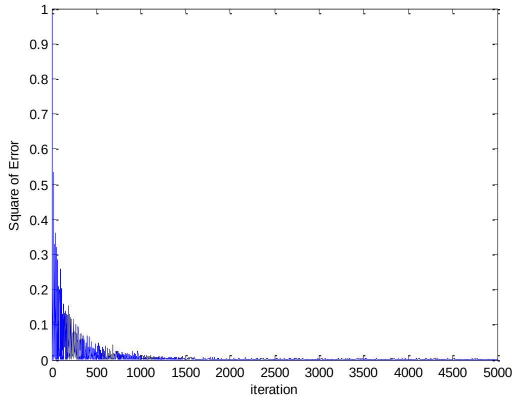

Figure.8. Plot of Error square

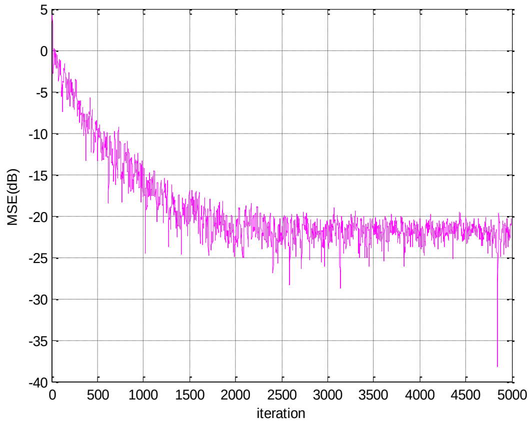

Figure.9. For chaotic input FSLMS algorithm

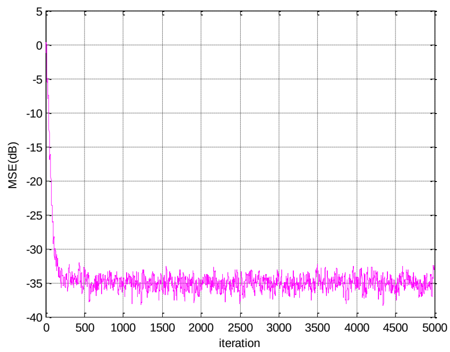

Figure.10. For sinusoidal input of 500Hz at sampling frequency 8000Hz FSLMS algorithm

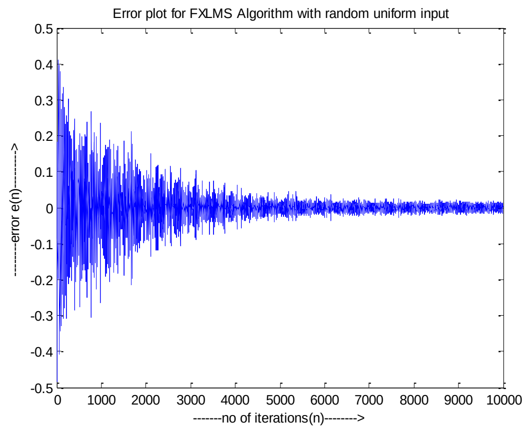

Figure.11. Error plot for FXLMS algorithm (μ=0.02)

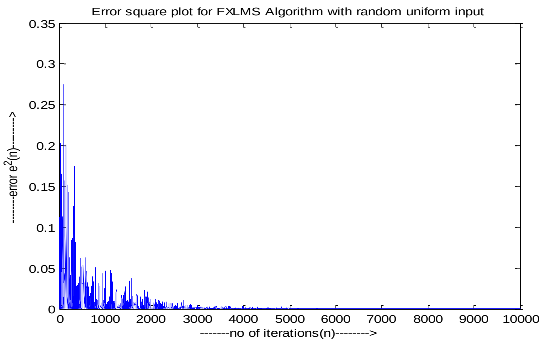

Figure.12. Error square plot for FXLMS Algorithm with random uniform input

6. Conclusion

A filtered –s LMS algorithm is simulated for use in a feed forward ANC system to mitigate nonlinear noise process. The FSLMS algorithm is derived using functional link artificial neural network(FLANN) as the basic structure. From performance analysis we conclude that the FSLMS algorithm perform better in terms of residual noise power and convergence speed in comparison to FXLMS algorithm when ANC is nonlinear. This work can be extended to reduce computational complexity.

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