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Nonlinear feedback active noise control for broadband chaotic noise

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ABSTRACT

Feedback active noise control has been used for tonal noise only and it is impractical for broadband noise. In this paper, it has been proposed that the feedback ANC algorithm can be applied to a broadband noise if the noise characteristic is chaotic in nature. Chaotic noise is neither tonal nor random; it is broadband and nonlinearly predictable. It is generated from dynamic sources such as fans, airfoils, etc. Therefore, a nonlinear controller using a functional link artificial neural network is proposed in a feedback configuration to control chaotic noise. A series of synthetic chaotic noise is generated for performance evaluation of the algorithm. It is shown that the proposed nonlinear controller is capable to control the broadband chaotic noise using feedback ANC which uses only one microphone whereas the conventional filtered-X least mean square (FXLMS) algorithm is incapable for controlling this type of noise.

1. Introduction

Active noise control (ANC) [1–3] is becoming an interesting research topic for the past few decades due to the concern on the adverse effect of acoustic noise due to the rapid growth of population and machineries. Passive noise control techniques work well at high frequencies, but are ineffective or impractical at low frequencies. The ANC is an alternative, wherein an anti-noise is generated to kill the undesired noise by using the principle of destructive interference. The controller of the ANC systems can be either non-adaptive or adaptive depending on the properties of the noise field. The amplitude and frequency of the unwanted noise does not remain constant in practical situations. The noise may distort with the change in the environmental conditions like pressure, temperature and component aging, etc. Therefore, for the effectiveness of the ANC system to these changed conditions, the controller needs to be adaptive. The ANC system is further classified as feedforward and feedback depending upon the availability of the coherent reference input. In feedforward ANC systems, the reference input is provided by a reference microphone. But in feedback ANC, there is no reference microphone and the reference input is estimated from the error microphone signal. The drawback of the feedforward ANC system is that because of the presence of the reference microphone, the secondary source (loudspeaker) output may get feedback to the reference microphone signal and it may degrade the performance of the ANC system. But since there is no reference microphone in feedback ANC, there is no such feedback of the secondary source output. Another drawback of the feedforward ANC system is that, if there are multiple noise sources, then multiple reference microphones are required to provide multiple reference inputs and multiple adaptive filters are required for the adaptation purpose of each input. So in such cases, the system becomes complicated and also costly. But in feedback ANC system, there is no reference microphone, and hence only one adaptive filter is required. Therefore, it is computationally efficient and economical for multiple references.

Feedback ANC is mainly used for predictable noise which is tonal [4–6] and it cannot be used for random broadband noise. However, another type of noise which is called chaotic noise has gained importance these days. No work has been reported as yet where feedback ANC is used for controlling chaotic noise which is broadband in nature. The chaotic noise is a nonlinear deterministic noise and is generated from dynamic systems such as fans, blowers, grinders and airfoils, etc. [7–14]. Furthermore, the secondary path, which is the path from the output of the controller till the error microphone input, shows non-minimum phase response. This imposes the ANC to act as a predictor. This is because, the secondary path is placed after ANC block and hence ANC ultimately has to model the inverse of the secondary path. If the secondary path is non-minimum phase, whose inverse does not exist, but a causal inverse exists, forces the ANC to be predictable. Therefore, a chaotic noise which is nonlinearly predictable noise can be controlled by a nonlinear controller. Conventional ANC systems with linear controller using filtered-x least mean square (FXLMS) algorithm provides poor performance, and sometimes even fail to control such type of noise. Therefore, for the mitigation of chaotic noise, nonlinear controllers are employed which provide better

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result than that obtained with linear controllers. Researchers have proposed various nonlinear controllers such as radial basis function neural network [7], artificial neural networks (ANN) [8–11], functional link artificial neural networks (FLANN) based on trigonometric [13,16–18] or piecewise linear functional expansions [15], functional link neural networks (FLNN) [20] and adaptive Volterra filters [12], bilinear filter [21], etc. ANC systems with the FLANN using filtered-s least mean square (FSLMS) algorithms are more advantageous than the ANC systems using Volterra filtered-x least mean square (VFXLMS) algorithms because of their better performance and less computational complexity. However, the ANC systems developed with these nonlinear controllers are feedforward systems with logistic chaotic noise as the input signal.

Behavior of acoustic noise as chaotic has been studied in many papers. Few of them are cited here. Sound generated aerodynamically has chaotic property which has been shown in [22]. Frequency spectra of acoustic ambient noise in ocean and their sources are shown in [23]. Acoustic chaos and nonlinear dynamics have been investigated in [24–26]. Results of experimental investigation of chaotic sound waves are shown in [27]. Control of chaotic motion of a airfoil is presented in [28]. In [29], numerical study of sound emission by 2D regular and chaotic vortex configurations has been made. Study of wave chaos in acoustics and elasticity is presented in [30].

It is apparent from the literature survey that the acoustic/sound waves can be chaotic which means these may be nonlinearly deterministic. Therefore, there is a need of actively controlling these noise and hence in this paper, a feedback ANC system is proposed based on the FSLMS algorithm for controlling nonlinear noise process i.e. logistic chaotic noise. In addition, a series of modified logistic chaotic noises are generated for the simulation study with the proposed algorithm. For every type of noise, the response of the proposed algorithm is compared to the FXLMS based one.

Organization of the paper is as follows. Section 2 presents the mathematical formulation of a series of modified logistic chaotic noises and their characterization. The proposed nonlinear control algorithms are presented in Section 3. Section 4 deals with the exhaustive computer simulation. Section 5 concludes the paper.

2. Chaotic noise

Chaotic signal has been an important topic of research these days in communication engineering. As chaotic signals are typically broadband, random-like and difficult to predict, they are utilized for masking information-bearing waveforms such as modulating waveforms in spread spectrums systems. However, the acoustic noise generated from dynamic systems can also be chaotic in nature. It has been shown in [7,11–13,19] that noise generating from fans, airfoils, etc. are chaotic in nature. In all these papers, the logistic chaotic noise has been used for evaluating the performance of their nonlinear controllers. The equation representing the logistic chaotic noise [13] is as follows

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

with $\lambda = 4$ and $x(0) = 0.9$, $n = 1, 2, 3, \ldots$

In this noise, the next state depends only on its present state. The sequence generated from Eq. (1) is named as logistic chaotic noise 1. Therefore, a one step predictor can predict the noise. However, there may be cases where the next state depends on the past states. Accordingly, Eq. (1) is modified to generate various other types of noise series.

For example:

The equation representing the modified logistic chaotic noise 2 is

$$x(n) = \lambda\, x(n-2)[1 - x(n-2)], \quad n = 2, 3, 4, \ldots \tag{2}$$

with $\lambda = 4$, and $x(n) = 0.9$, *if* $0 \le n \le 1$.

The equation representing the modified logistic chaotic noise 3 is

$$x(n) = \lambda\, x(n-3)[1 - x(n-3)], \quad n = 3, 4, 5, \ldots \tag{3}$$

with $\lambda = 4$, and $x(n) = 0.9$, *if* $0 \le n \le 2$.

The equation representing the modified logistic chaotic noise 4 is

$$x(n) = \lambda\, x(n-4)[1 - x(n-4)], \quad n = 4, 5, 6, \ldots \tag{4}$$

with $\lambda = 4$, and $x(n) = 0.9$, *if* $0 \le n \le 3$.

The equation representing the modified logistic chaotic noise 5 is

$$x(n) = \lambda\, x(n-5)[1 - x(n-5)], \quad n = 5, 6, 7, \ldots \tag{5}$$

with $\lambda = 4$, and $x(n) = 0.9$, *if* $0 \le n \le 4$.

The equation representing the modified logistic chaotic noise 6 is

$$x(n) = \lambda\, x(n-6)[1 - x(n-6)], \quad n = 6, 7, 8, \ldots \tag{6}$$

with $\lambda = 4$, and $x(n) = 0.9$, *if* $0 \le n \le 5$.

For comparison purpose, the tonal noise is generated by the equation

$$x(n) = \sin\left(\frac{2\pi f n}{f_s}\right) \tag{7}$$

where $f = 500$ Hz and the sampling frequency $f_s = 10,000$ Hz.

And the uniform random noise is generated between −0.5 and 0.5 using Matlab function

$$x(n) = (rand - 0.5) \tag{8}$$

2.1. Properties

Phase plots: To analyze the chaoticness of the signals, the phase plots of the logistic chaotic noise 1 and its modified versions are plotted in Fig. 1 where the sample $x(n)$ is plotted against the delayed sample $x(n-1)$. Fig. 2(a) and (b) represents the phase plots of tonal and random noise respectively for comparison purpose.

From Fig. 1, it is seen that the phase plot of the logistic chaotic noise 1 has dense periodic orbits which means the points on the orbit are approached randomly. This also indicates that, a chaotic noise has a set of stable states, but these states are not periodically repeated as is seen in tonal noise case. But random signal doesn't display any such periodic orbits in the phase plot as shown in Fig. 2(b) where the points on the phase plot are scattered and don't form any particular pattern. The phase plot of tonal noise has an orbit. But the points on the phase plot of tonal noise are approached sequentially on the same orbit, which means they are neither random nor chaotic. Therefore, from the above discussion, it is clear that for a signal to be chaotic, the points on the phase space should lie within a particular pattern, i.e. they are neither randomly nor sequentially approached. The phase plots of the modified versions of the logistic chaotic noise 1 contain square, rectangular and parabolic patterns and are thus chaotic.

Time domain: In time domain all these noises are plotted for 10 samples in Fig. 3 to see their stable states. It is found that in case of original logistic chaotic noise 1, there is no repetition in consecutive samples, where as the dependence with the delayed sample increases as the consecutive samples are repeated in the chaotic noises 2–6. This may be treated as sampling the same steady state at a higher sampling rate. However, better chaotic noise can be derived which would not have these repetitions. This is kept for the scope of the future research.

Frequency content: All these above chaotic noises are plotted in frequency domain using Welch power spectral density

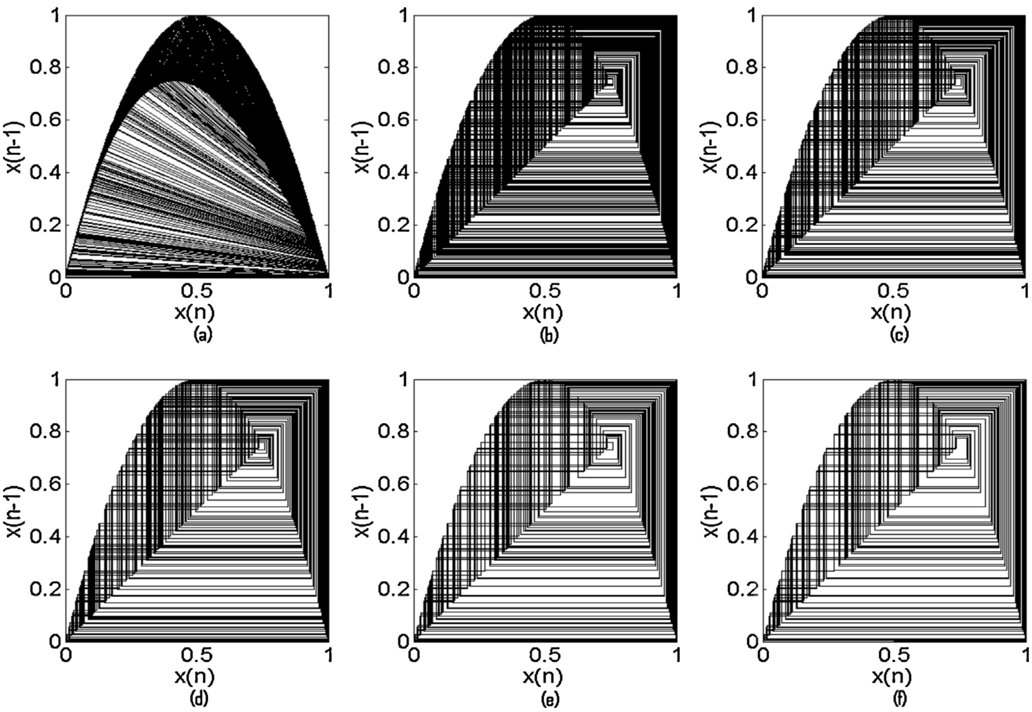

Fig. 1. Phase plots of (a) logistic chaotic noise 1, (b) modified logistic chaotic noise 2, (c) modified logistic chaotic noise 3, (d) modified logistic chaotic noise 4, (e) modified logistic chaotic noise 5 and (f) modified logistic chaotic noise 6.

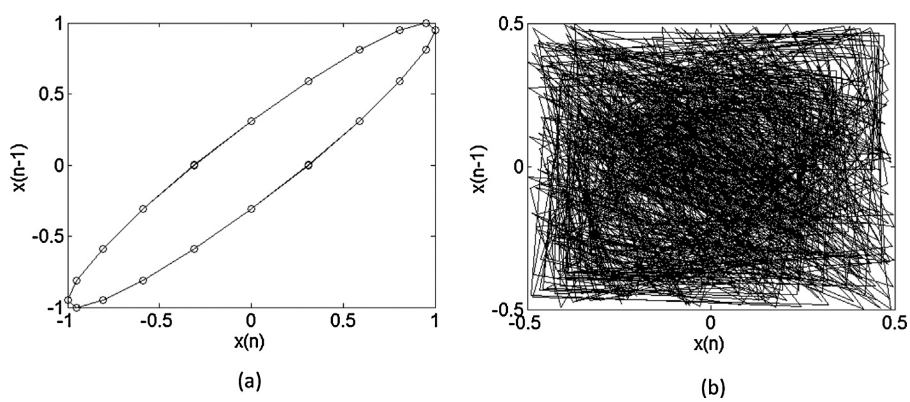

Fig. 2. Phase plots of (a) tonal noise and (b) random noise.

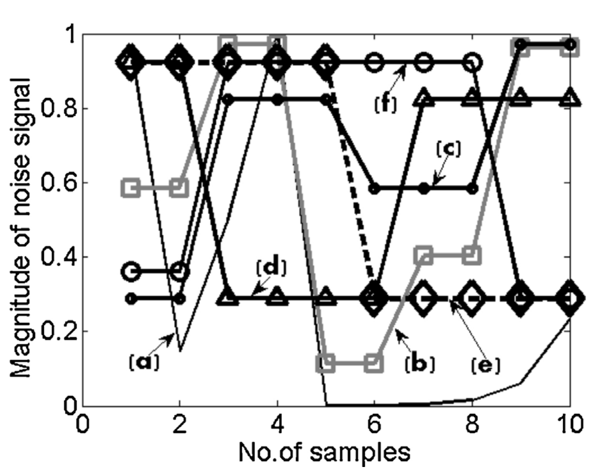

Fig. 3. Time domain plots of (a) logistic chaotic noise 1, (b) modified logistic chaotic noise 2, (c) modified logistic chaotic noise 3, (d) modified logistic chaotic noise 4, (e) modified logistic chaotic noise 5 and (f) modified logistic chaotic noise 6.

estimate. It was found that the logistic chaotic noise 1 is highly broadband. The modified logistic chaotic noises 2–6 are mostly broadband with some frequency notches as shown in Fig. 4.

Practical noise: It is very important to know whether a predictable noise is chaotic or not. To know this the simplest test is the phase plot. It is shown in [19], through phase plot that the airfoil noise shows chaotic property. Other recorded noise can be tested with different sampling frequencies. This is kept for our future work.

3. Proposed FLANN based feedback ANC

The FLANN has been previously applied to feedforward ANC [13,17,19]. In this section, the FLANN algorithm is suitably modified to be used in a feedback ANC configuration. The block diagram of the proposed feedback ANC is shown in Fig. 5 where $x_c(n)$ represents the chaotic noise at the canceling point. The ANC output $f(n)$ is acoustically mixed with the undesired noise $x_c(n)$ and the residual

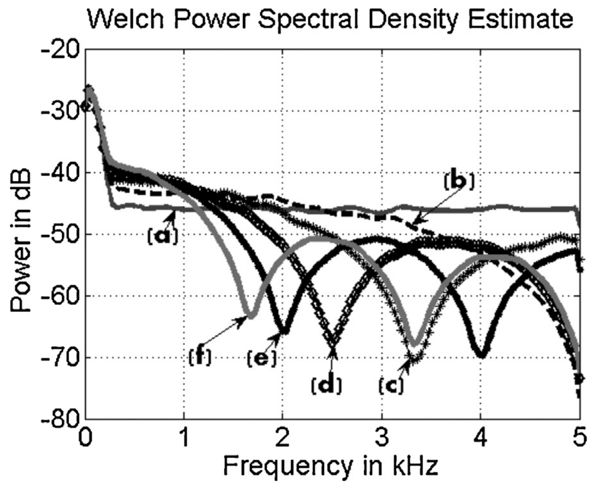

Fig. 4. Power spectral density plots of (a) logistic chaotic noise 1, (b) modified logistic chaotic noise 2, (c) modified logistic chaotic noise 3, (d) modified logistic chaotic noise 4, (e) modified logistic chaotic noise 5 and (f) modified logistic chaotic noise 6.

noise is sensed by the error microphone $e(n)$ which is represented as

$$e(n) = x_c(n) + f(n) \tag{9}$$

where

$$f(n) = f_c(n) * s(n) \tag{10}$$

"*" denotes convolution operation, $s(n)$ is the impulse response of the secondary path [1].

$f_c(n)$ is the output of the FLANN based ANC which is computed as follows

$$f_c(n) = \sum_{m=1}^{2M+1} f_m(n) \tag{11}$$

where

$$f_m(n) = \mathbf{s}_\mathbf{m}^T(n)\mathbf{w}_\mathbf{m}(n), \quad n = 1, 2, 3, \ldots, 2M+1 \tag{12}$$

and M is the order of the functional expansion. $\mathbf{s}_\mathbf{m}(n)$ is the input signal vector of mth subfilter of the FLANN based adaptive controller and $\mathbf{w}_\mathbf{m}(n)$ is the corresponding time varying weight vector and are expressed as

$$\mathbf{w}_\mathbf{m}(n) = [w_{m,0}(n) \quad w_{m,1}(n) \ldots w_{m,N-1}(n)]^T \tag{13}$$

and

$$\mathbf{s}_\mathbf{m}(n) = [s_m(n) s_m(n-1) \quad \ldots \quad s_m(n-N+1)]^T \tag{14}$$

where N represents the memory size of each sub-filter. Here for $1 \le p \le M$, each element of $S_m(n)$ can be computed as

$$s_m(n) = \begin{cases} \hat{x}_c(n), & m = 1 \\ \sin[p\pi\hat{x}_c(n)], & m \ \text{ is even} \\ \cos[p\pi\hat{x}_c(n)], & m \ \text{ is odd} \end{cases} \tag{15}$$

where $1 \le p \le M$ and $1 \le m \le 2M+1$. The estimated reference input $\hat{x}_c(n)$ is computed as

$$\hat{x}_c(n) = e(n) - \hat{f}(n) \tag{16}$$

$\hat{f}(n)$ is obtained by filtering $f_c(n)$ through the secondary path estimate transfer function $\hat{S}(z)$ ($\hat{s}(n)$ being its impulse response) as follows

$$\hat{f}(n) = f_c(n) * \hat{s}(n) \tag{17}$$

The weights of the FLANN based adaptive filter are updated as follows

$$\mathbf{w}_\mathbf{m}(n+1) = \mathbf{w}_\mathbf{m}(n) - \mu_m \mathbf{s}'_\mathbf{m}(n) e(n) \tag{18}$$

where μ_m represents the step size of the mth adaptive filter and $\mathbf{s}'_\mathbf{m}(n)$ represents the filtered output of the functionally expanded estimated reference signal through the secondary path estimate transfer function $\hat{S}(z)$ and the input signal vector $\mathbf{s}_\mathbf{m}(n)$ and is expressed as

$$\mathbf{s}'_\mathbf{m}(n) = \mathbf{s}_\mathbf{m}(n)\hat{S}(z) \tag{19}$$

In the previously proposed algorithm [13], the reference signal was available. Therefore, there was no need to estimate it. But in this proposed model, the reference signal is estimated from the error microphone signal. This algorithm can be approximately modified

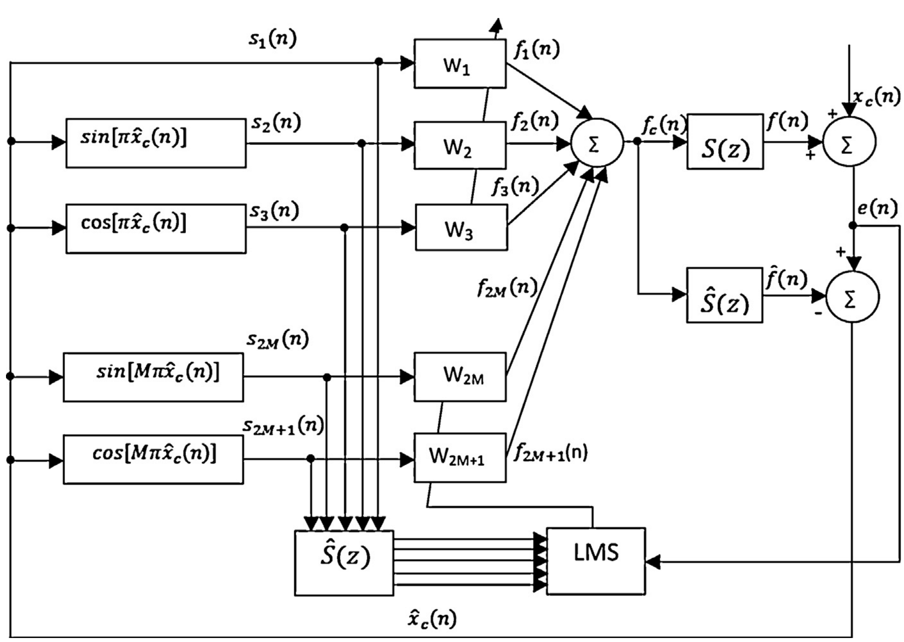

Fig. 5. Block diagram of proposed feedback ANC for chaotic noise control.

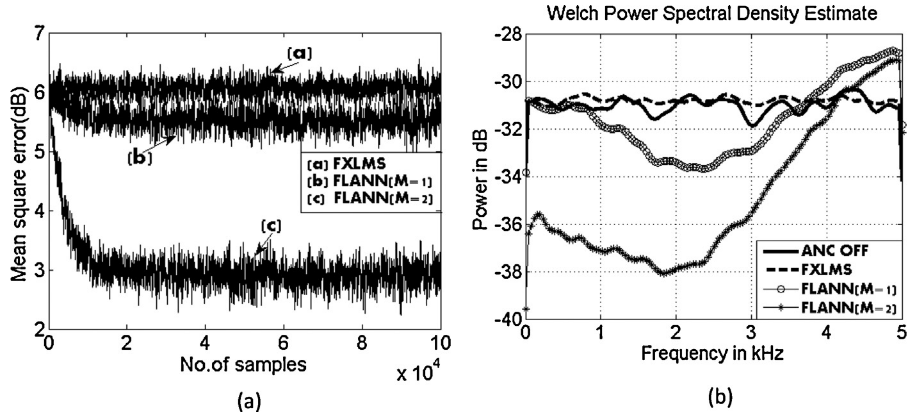

Fig. 6. (a) Mean square error in dB plot and (b) power spectral density (PSD) plot of the logistic chaotic noise 1.

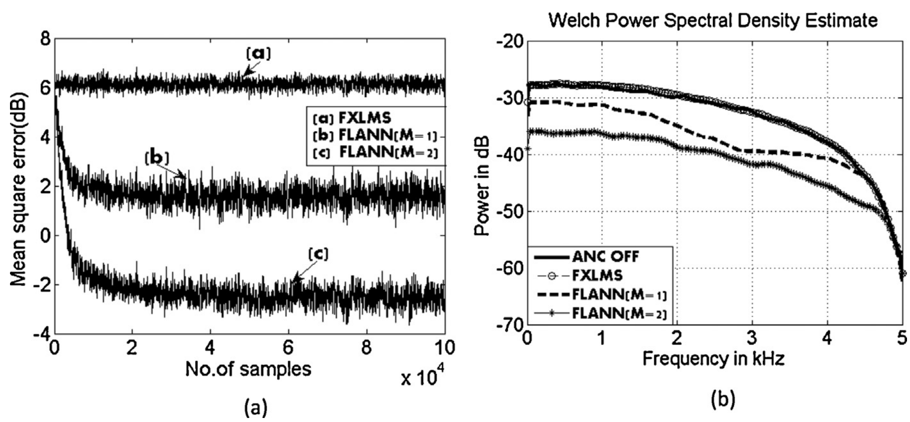

Fig. 7. (a) Mean square error in dB plot and (b) power spectral density (PSD) plot of the modified logistic chaotic noise 2.

to incorporate other nonlinear control structures such as artificial neural network (ANN) [8–11], Volterra series [12] and piecewise linear expansions [15].

4. Simulations and results

In this section, the simulation experiments are conducted to evaluate the effectiveness of the proposed algorithm with the logistic chaotic noise 1 and its modified versions. In all these experiments, the secondary path transfer function is considered to be $S(z) = z^{-2} + 1.5z^{-3} - z^{-4}$. The order of the functional expansion is considered as either $M = 1$ or $M = 2$ and the memory size is assumed to be $N = 50$. The result is then compared with the conventional FXLMS algorithm. The step size for the FXLMS algorithm is chosen to be $\mu = 0.0001$ and for both the first and second order of the functional expansion, the step size is taken to be $\mu_m = 0.0001$ for $m \geq 1$.

Experiment 1: In this experiment, the performance of the FXLMS, first order FLANN and second order FLANN algorithms are compared. The noise to be controlled is chosen as a logistic chaotic noise 1 generated using (1), being normalized to have zero mean and signal power to 2, where $x(0) = 0.9$, and $\lambda = 4$. The power spectral density plot of the noise when ANC is OFF and when ANC (using FXLMS, FSLMS ($M = 1$) or FSLMS ($M = 2$)) is ON is plotted. Fig. 6(a) shows the comparative mean square error in dB plot and Fig. 6(b) shows the comparative power spectral density plot when logistic chaotic noise 1 is used in the simulation.

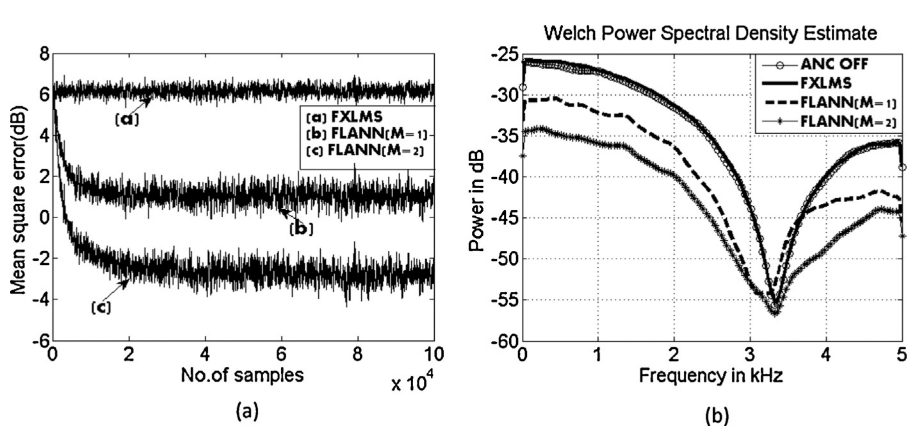

Fig. 8. (a) Mean square error in dB plot and (b) power spectral density (PSD) plot of the modified logistic chaotic noise 3.

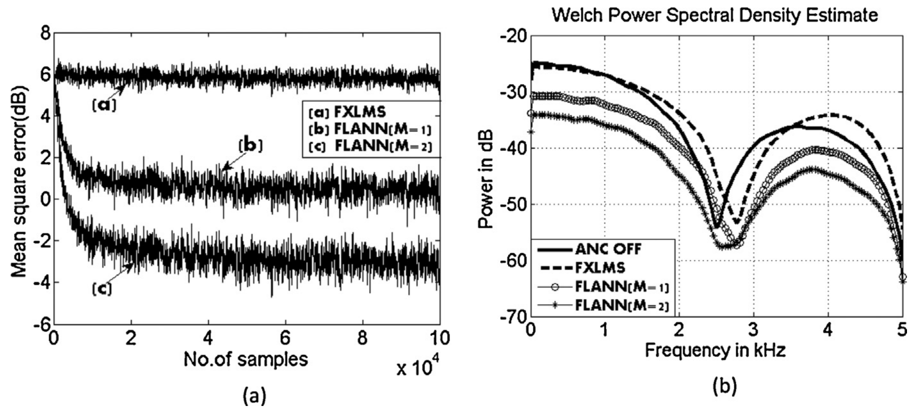

Fig. 9. (a) Mean square error in dB plot and (b) power spectral density (PSD) plot of the modified logistic chaotic noise 4.

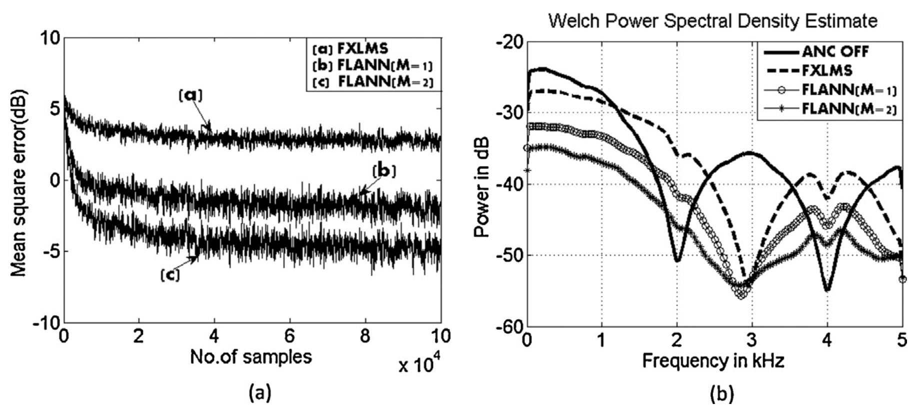

Fig. 10. (a) Mean square error in dB plot and (b) power spectral density (PSD) plot of the modified logistic chaotic noise 5.

It is found that, the FLANN ($M=2$) outperforms the FLANN ($M=1$) and FXLMS algorithm. FXLMS being a linear controller is incapable of predicting the nonlinear noise process such as chaotic noise, whereas the FLANN ($M=1$) and FLANN ($M=2$) are nonlinear controllers, with later being more nonlinear performs better than the other two algorithms.

Experiment 2: In this experiment, the desired noise is modified logistic chaotic noise 2 with the relation (2) being normalized to have zero mean and signal power 2. Fig. 7(a) shows the comparative mean square error in dB plot and Fig. 7(b) shows the power spectral density (PSD) plot of the noise before and after cancelation when the modified logistic chaotic noise 2 was used in the simulation.

From this experiment, it was found that for a type of noise like modified logistic chaotic noise 2, the FXLMS doesn't converge at all. However, both FLANN ($M=1$) and FLANN ($M=2$) are converged. This shows that the nonlinear control algorithm is capable of predicting this type of chaotic noise better than the chaotic noise used in the Experiment 1. The PSD plot in Fig. 7(b) also shows the efficiency of the FLANN based controller to control the broadband noise.

Experiment 3: In this experiment, the desired noise is modified logistic chaotic noise 3, generated using (3) being normalized to have zero mean and signal power to 2. Fig. 8(a) shows the mean square error in dB plot and Fig. 8(b) shows the power spectral density (PSD) plot of the modified logistic chaotic noise 3.

Like experiment 2, this noise is also quite predictable by nonlinear function and unpredictable by linear function. This is evident from Fig. 8(a) and (b) that the FLANN controllers are capable of

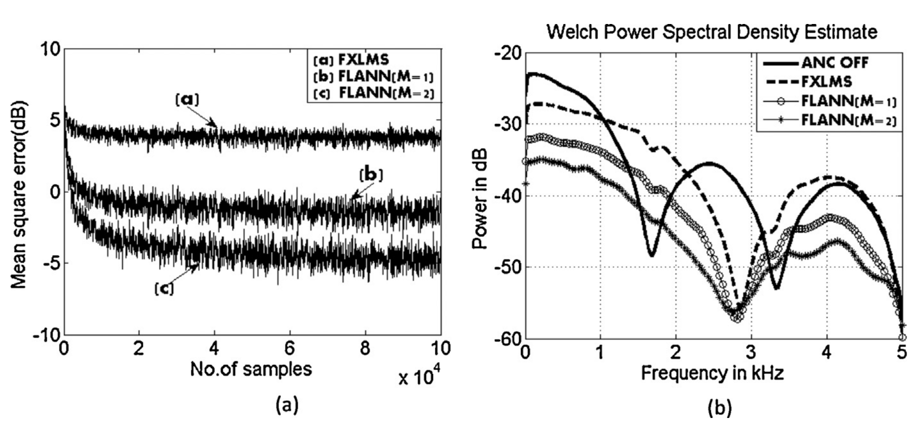

Fig. 11. (a) Mean square error in dB plot and (b) power spectral density (PSD) plot of the modified logistic chaotic noise 6.

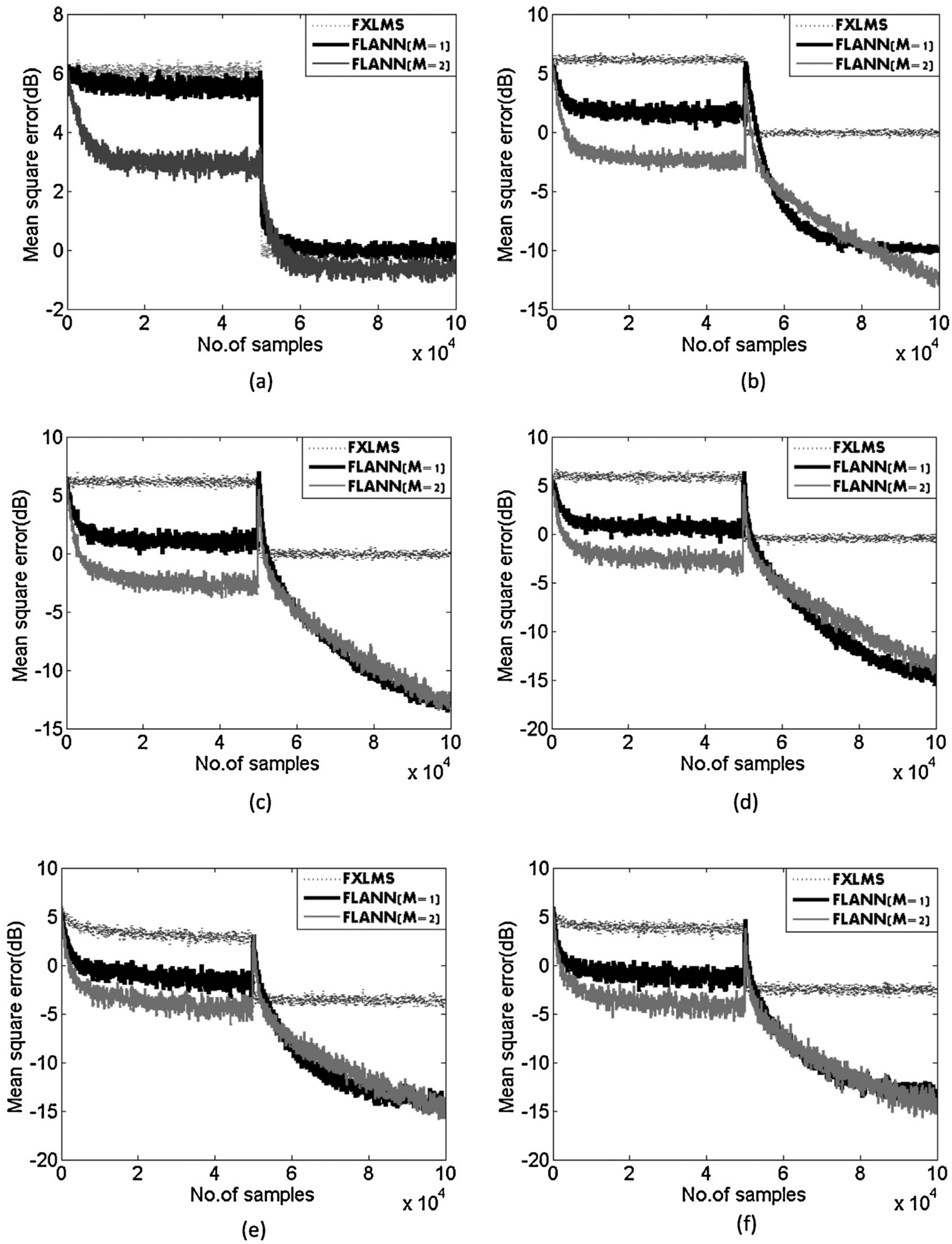

Fig. 12. Mean square error in dB plot for the change in the signal power after 50,000 iterations of (a) logistic chaotic noise 1, (b) modified logistic chaotic noise 2, (c) modified logistic chaotic noise 3, (d) modified logistic chaotic noise 4, (e) modified logistic chaotic noise 5, and (f) modified logistic chaotic noise 6.

controlling the noise over a wideband whereas the conventional FXLMS doesn't show any evidence of noise reduction.

Experiment 4: In this experiment, the noise to be controlled is chosen as the modified logistic chaotic noise 4, generated using (4) being normalized to have zero mean and signal power to 2. Fig. 9(a) shows the mean square error in dB plot and Fig. 9(b) shows the power spectral density (PSD) plot under modified logistic chaotic noise 4 case.

It was shown in Fig. 9(a) that the noise controlling capacity of FLANN controller for modified logistic chaotic noise 4 is better than modified logistic chaotic noise 3 which shows that the noise control is highly dependent on the noise characteristic. This also shows that the linear controller is incapable of controlling such noise.

The PSD plot in Fig. 9(b) shows the effectiveness of the proposed algorithm to control this type of noise.

Experiment 5: In this experiment, the desired noise is modified logistic chaotic noise 5, generated using Eq. (5) with zero mean and signal power normalized to 2. Fig. 10(a) shows the mean square error in dB plot and Fig. 10(b) shows the power spectral density (PSD) plot while controlling modified logistic chaotic noise 5.

Like the previous experiments, the FLANN controller also showed improve performance compared to the FXLMS based controller both in terms of mean square error and PSD plots.

Experiment 6: In this experiment, the desired noise is modified logistic chaotic noise 6, generated using Eq. (6) with zero mean and signal power normalized to 2. Fig. 11(a) shows the mean square

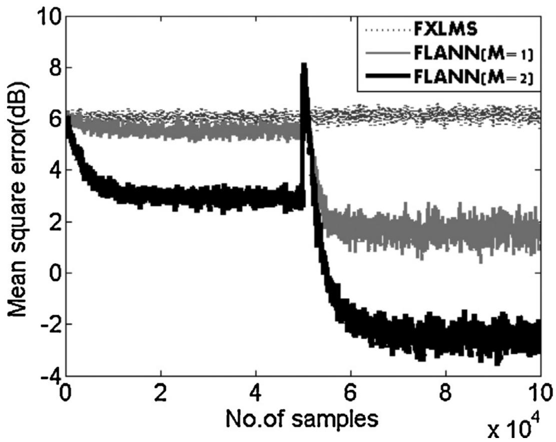

Fig. 13. Mean square error in dB plot for change in the primary noise from logistic chaotic noise 1 to modified logistic chaotic noise 2 after 50,000 iterations.

error in dB plot and Fig. 11(b) shows the power spectral density (PSD) plot of the modified logistic chaotic noise 6.

Both these plots showed improved noise reduction capability for FLANN based controllers, but not for FXLMS controller.

Experiment 7: In this experiment, the adaptation capability of the proposed model to the change in power of noise to be controlled is studied. The logistic chaotic noise 1 with zero mean and signal power normalized to 2 was used up to 50,000 samples and after that the power of the signal is changed to half of its initial power. The same experiment is conducted for all rest 5 modified logistic chaotic noise sequences to check the adaptation capability of the proposed model. Fig. 12 shows how the proposed model is able to adapt to the change in the signal power after 50,000 iterations.

Experiment 8: In this experiment, the adaptation capability of the proposed model is checked by changing the noise type after 50,000 iterations. The desired noise was logistic chaotic noise 1 generated using Eq. (1), with zero mean and signal power normalized to 2. After 50,000 iterations, the signal is changed to modified logistic chaotic noise 2 of Eq. (2) with zero mean and signal power is normalized to 2. Fig. 13 shows how the proposed model is able to adapt to the change in noise type after 50,000 iterations.

5. Conclusions

This paper focused on the development of a nonlinear feedback ANC system based on the FLANN based algorithm for controlling the nonlinear noise like chaotic noise and a series of modified chaotic noise sequences. Simulation experiments were conducted to evaluate the performance of the proposed algorithm. It was found that the proposed algorithm obtains better result and in most cases outperforms the conventional FXLMS algorithm for all the 6 chaotic noise sequences. This algorithm may be tested with some recorded noise to check the effectiveness of the algorithm to the practical noises.

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