**International Journal of Electrical and Computer Engineering (IJECE)**
Vol. 14, No. 4, August 2024, pp. 3922~3930
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i4.pp3922-3930


# Efficient implementation of the functional links artificial neural networks with cross-terms for nonlinear active noise control

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**Article Info**

***Article history:***

Received Jan 5, 2024
Revised Mar 19, 2024
Accepted Apr 2, 2024

***Keywords:***

Active noise control
Functional links artificial neural networks
Generalized functional links artificial neural networks
Nonlinear filter
Partial update

**ABSTRACT**

This paper proposes an efficient extension of functional links artificial neural networks (EE-FLANN) for the active noise control (ANC) application. The developed EE-FLANN controller can upgrade the model accuracy with the actual system thanks to adding the cross-terms to the trigonometric function. Unlike the method in the generalized FLANN (GFLANN) controller, the EE-FLANN exploits include cross-term symmetry. However, this causes the computational burden to increase remarkably. To reduce this disadvantage, we truncate the cross-terms appropriately based on the simplified strategy. Furthermore, the adaptive algorithm is designed to partially update the filter coefficients appropriately. Specifically, the cross-terms that do not satisfy certain magnitude conditions will be omitted during the update process to reduce costs. Experiments have shown that the proposed EE-FLANN controller can achieve comparable performance to the GFLANN controller but the complexity is reduced by up to 20%.



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## 1. INTRODUCTION

Research on noise-canceling has been receiving special attention from many scholars around the world [1]–[5]. There are two basic methods for this problem. The passive noise control (PNC) method uses soundproofing or sound-absorbing materials to reduce high-frequency noise sources [3]. Whereas, the active noise control (ANC) exploits the interference properties of two sound waves to suppress low-frequency noise. Linear controllers (e.g., finite impulse response (FIR)) have been widely used in traditional ANC applications [2], [3]. However, to compensate for nonlinear distortions arising in the system, nonlinear controllers have been adopted to replace the FIR controller [5]. Prominent among these systems are controllers based on artificial neural networks (ANN), multilayer perceptron networks (MLPs), Volterra, functional links artificial neural networks (FLANN) [5].

Many studies in [6]–[8] have shown that the FLANN is an effective alternative to the MLPs. Its structure includes trigonometric extension functions, has no hidden layers and thus computational complexity is lower than that of the MLPs. The FLANN has been applied for nonlinear identification, signal prediction, and acoustic echo cancellation [6]–[12]. The FLANN-based ANC system was first developed by Das and Panda in 2004 [13] and pointed out to be effective in reducing noise for systems containing nonlinearity. After the work [13], many improved FLANN controllers were developed [14]–[19]. In study [14], a recursive FLANN filter with a stability condition was introduced. Two structures based on feedback FLANN (FFLANN) have been presented in [15]. The FLANN filters with exponentially varying sinusoidal nonlinearity have been developed in [16], [17]. Several schemes based on the convex combination FLANN have also been proposed in literatures

[18], [19]. However, because the nature of FLANN is a point-wise expansion function [14], [20], its performance is degraded when the system contains the memory nonlinearity. Additionally, the influence of memory nonlinearity in ANC systems is remarkable. To mitigate this disadvantage, the authors in [20] developed the GFLANN structure based on exploiting cross-terms. Thanks to this idea, many improved structures of the GFLANN have been given in [21]–[25].

This paper develops an EE-FLANN structure for nonlinear ANC based on efficient exploitation of the cross-terms. The cross-terms are formed based on the comprehensive model and the suitable selection technique. In addition, to mitigate the computational costs for the EE-FLANN controller, the M-max partial update strategy has been adopted. Many computational simulations have been performed to evaluate the proposed EE-FLANN controller for the ANC system. The rest of this study includes: section 2 proposes EE-FLANN structure for the ANC system, section 3 analyzes the computational cost, section 4 presents simulation experiments; and section 5 is the conclusion.

## 2. PROPOSED CONTROLLER

Figure 1 illustrates the GFLANN filter-based ANC system that was developed in [20]. Here, the GFLANN is the nonlinear controller; the $P(z)$ denotes transmission line between input signal $X(n)$ and primary noise $d(n)$; the $S(z)$ denotes transmission line between the output of the controller $y(n)$ and the estimate of $d(n)$; $e(n)$ illustrates the residual noise. This paper presents another implementation for exploiting the cross-terms, which differs from the approach taken in [20]. Furthermore, the study adopts a simplified strategy described in [26] to truncate the cross-terms and employs the partial update algorithm to reduce computational complexity.

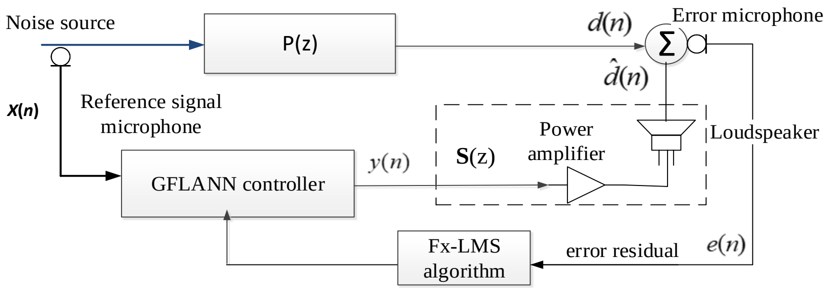


Figure 1. Illustrates the GFLANN filter-based ANC system

### 2.1. EE-FLANN structure

As reported in [20], the FLANN structure can improve the capabilities of nonlinear signal processing when adding the cross-terms into its extension function. However, the strategy uses cross-terms that will affect the performance and complexity. Assuming $X(n) = [x(n)x(n-1), \dots, x(n-N+2)x(n-N+1)]T$ denotes $N$ external input signal, the expansion of FLANN is described by (1).

$$y_{FLANN}(n) = \sum_{i=0}^{N-1} \varphi_i(n)\, x(n-i) + \sum_{b=1}^{B} \sum_{i=0}^{N-1} \psi 1_{bi}\,(n)\, sin(\, b\pi x(n-i)) + \sum_{b=1}^{B} \sum_{i=0}^{N-1} \psi 2_{bi}\,(n)\, cos(\, b\pi x(n-i)) \quad (1)$$

where $\varphi_i(n), \psi 1_{bi}(n), \psi 2_{bi}(n)$ denote the coefficients corresponding to the expanded input samples including the linear and the $sin()$, $cos()$ parts; $B$ denotes order of the FLANN. This paper adds the cross-terms to the first-order FLANN structure according to the following manning:

$$y(n) = \sum_{i=0}^{N-1} \varphi_i(n)\, x(n-i) + \sum_{i=0}^{N-1} \psi 1_i\,(n)\, sin(\,\pi x(n-i)) + \sum_{i=0}^{N-1} \psi 2_i\,(n)\, cos(\,\pi x(n-i)) + \sum_{t=0}^{N-1} \sum_{v=1}^{N-1} \tau 1_{i,j}\,(n) x(n-t)\, sin(\,\pi x(n-v)) + \sum_{t=0}^{N-1} \sum_{v=1}^{N-1} \tau 2_{i,j}\,(n) x(n-t)\, cos(\,\pi x(n-v)) \quad (2)$$

where $\tau 1_{i,j}$, $\tau 2_{i,j}$ denote the weights of the cross-terms.

As mentioned above, adding cross-terms to the FLANN expansion function can increase the computational cost. Sicuranza and Carini [20] used a method similar to that implemented in the Volterra filter to reduce computational cost. By adopting the strategy of the bilinear filter [26], the cross-terms in this study are truncated to,

$$y(n)=\sum_{i=0}^{N-1}\varphi_i(n)\,x(n-i)+\sum_{i=0}^{N-1}\psi1_i\,(n)\,sin(\pi x(n-i))+\sum_{i=0}^{N-1}\psi2_i\,(n)\,cos(\pi x(n-i))+\sum_{t=R_1}^{R_2}\sum_{v=0}^{N-1}\tau1_{i,j}\,(n)x(n-t)\,sin(\pi x(n-v))+\sum_{t=R_1}^{R_2}\sum_{v=0}^{N-1}\tau2_{i,j}\,(n)x(n-t)\,cos(\pi x(n-v)) \quad (3)$$

where $R_1=\lfloor N/2\rfloor-\Lambda$; $R_2=\lfloor N/2\rfloor+\Lambda$; $\Lambda<\lfloor N/2\rfloor$ represents the choice parameter of the cross terms, $\lfloor\bullet\rfloor$ is truncation operation [26]. Equation (3) represents the model of the proposed EE-FLANN structure.

Refer to the method in [22], we represent (3) in vector form as (4):

$$y(n)=\Phi^T(n)X(n)+\Psi1^T(n)X1(n)+\Psi2^T(n)X2(n)+T1^T(n)X3(n)+T2^T(n)X4(n) \quad (4)$$

where the coefficient and signal vectors are expressed as (5)-(10).

$$\Phi(n)=[\varphi_0(n)\quad\varphi_1(n),\ldots.,\varphi_{N-1}(n)]^T \quad (5)$$

$$X(n)=[x(n)\quad x(n-1),\ldots.,x(n-N+1)]^T \quad (6)$$

$$\Psi1(n)=[\psi1_0(n)\quad\psi1_1(n),\ldots..,\psi1_{N-1}(n)]^T \quad (7)$$

$$X1(n)=[sin(\pi x(n))\quad sin(\pi x(n-1)),\ldots.,sin(\pi x(n-N+1))]^T \quad (8)$$

$$\Psi2(n)=[\psi2_0(n)\quad\psi2_1(n),\ldots.,\psi2_{N-1}(n)]^T \quad (9)$$

$$X2(n)=[cos(\pi x(n))\quad cos(\pi x(n-1)),\ldots\ldots,cos(\pi x(n-N+1))]^T \quad (10)$$

Notice that the coefficients vector T1($n$) consists of the following vectors:

$$T1(n)=[T1_{R1}(n)^T T1_{R1+1}(n)^T,\ldots..,T1_{R2}(n)^T]^T \quad (11)$$

where

$$T1_{R1}(n)=[\tau1_{R1,1}(n)\quad\tau1_{R1,2}(n)\quad\cdots\quad\tau1_{R1,N}(n)\quad]^T \quad (12)$$

$$T1_{R1+1}(n)=[\tau1_{R1+1,1}(n)\quad\tau1_{R1+1,2}(n)\quad\cdots\quad\tau1_{R1+1,N}(n)\quad]^T \quad (13)$$

$$M\ =\ M$$
$$T1_{R2}(n)=[\tau1_{R2,1}(n)\quad\tau1_{R2,2}(n)\quad\cdots\quad\tau1_{R2,N}(n)\quad]^T \quad (14)$$

Corresponding to the vector T1($n$), the input samples $X_3(n)$ include the following vectors:

$$X3(n)=[X3_{R1}(n)^T X3_{R1+1}(n)^T\cdots X3_{R2}(n)^T]^T \quad (15)$$

where

$$X3_{R1}(n)=\left[x(n-R_1)\,sin(\pi x(n-1))\quad x(n-R_1)\,sin(\pi x(n-2)\right)\cdots x\,(n-R_1)\,sin(\pi x(n-N+1))]^T \quad (16)$$

$$X3_{R1+1}(n)=\left[x(n-R_1-1)\,sin(\pi x(n-1))\quad x(n-R_1-1)\,sin(\pi x(n-2)\right)\cdots x\,(n-R_1-1)\,sin(\pi x(n-N+1))]^T \quad (17)$$

$$M\ =\ M$$
$$X3_{R2}(n)=\left[x(n-R_2)\,sin(\pi x(n-1))\quad x(n-R_2)\,sin(\pi x(n-2)\right)\cdots x\,(n-R_2)\,sin(\pi x(n-N+1))]^T \quad (18)$$

The weight vector $T2(n)$ and input sample vectors $X4(n)$ for the cross-terms of the $cos()$ function are derived in the same way as $T1(n)$ and $X3(n)$. Figure 2 shows a structure of the proposed EE-FLANN expansion function.

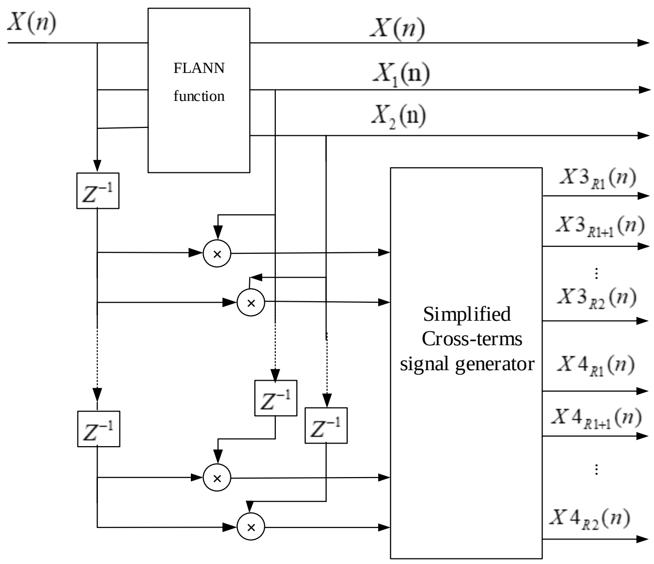


Figure 2. The proposed EE-FLANN structure

### 2.2. Adaptive algorithm

Based on the adaptive filtering principle, we adopt the following cost function $\xi(n) = E[e^2(n)]$. The goal of the algorithm is to reach optimal weights through the function $\xi(n)$. Figure 3 shows the ANC using the proposed EE-FLANN controller with adaptive algorithm.

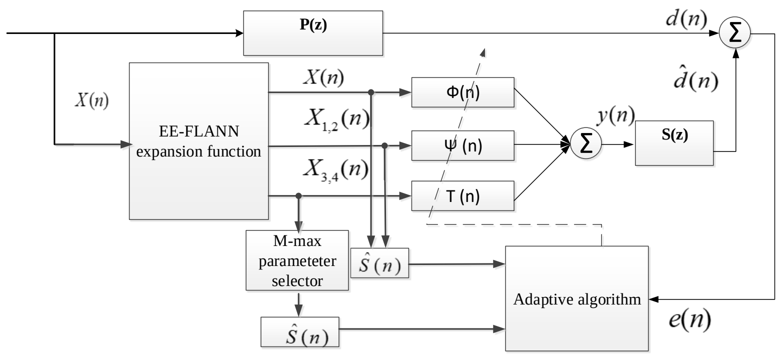


Figure 3. The ANC using the proposed EE-FLANN controller

For calculation convenience, we represent the coefficient vectors as (19).

$$H(n) = [\Phi^T(n) \;\; \Psi 1^T(n) \;\; \Psi 2^T(n) \;\; T1^T(n) \;\; T2^T(n)]^T \tag{19}$$

Correspondingly, we represent the input sample vector as (20).

$$U(n) = [X^T(n) \;\; X1^T(n) \;\; X2^T(n) \;\; X3^T(n) \;\; X4^T(n)]^T \tag{20}$$

Therefore, the output of the EEFLANN can be expressed as (21).

$$y(n) = H^T(n)U(n) \tag{21}$$

Based on adaptive filtering theory, the vector $H(n)$ is adaptively adjusted by (22).

$$H(n+1) = H(n) - \frac{1}{2}\mu\frac{\partial E(e^2(n))}{\partial H(n)} = H(n) + \mu e(n)\frac{\partial \hat{d}(n)}{\partial H(n)} \tag{22}$$

Assuming the memory-size of $S(z)$ equal to $K_S$, the partial derivatives $\frac{\partial \hat{d}(n)}{\partial H(n)}$ in (22) is transformed into $\frac{\partial \hat{d}(n)}{\partial H(n)} = \sum_{l=0}^{Ks} \frac{\partial \hat{d}(n)}{\partial y(n-l)} \frac{\partial y(n-l)}{\partial H(n)}$. Setting the parameter $\mu$ so that the vector $H(n)$ adapts slowly, the term $\frac{\partial y(n-l)}{\partial H(n)}$ is calculated by (23).

$$\frac{\partial y(n-l)}{\partial H(n)} \approx \frac{\partial y(n-l)}{\partial H(n-l)} = \left[\left[\frac{\partial y(n-l)}{\partial \Phi(n-l)}\right]^T \left[\frac{\partial y(n-l)}{\partial \Psi 1(n-l)}\right]^T \left[\frac{\partial y(n-l)}{\partial \Psi 2(n-l)}\right]^T \left[\frac{\partial y(n-l)}{\partial T1(n-l)}\right]^T \left[\frac{\partial y(n-l)}{\partial T2(n-l)}\right]^T\right]^T$$
$$= \left[X^T(n-l) \;\; X1^T(n-l) \;\; X2^T(n-l) \;\; X3^T(n-l) \;\; X4^T(n-l)\right]^T = U(n-l) \quad (23)$$

Substituting the result in (23) into the partial derivative above, we obtain (24).

$$\frac{\partial \hat{d}(n)}{\partial H(n)} = \sum_{l=0}^{Ks} \frac{\partial \hat{d}(n)}{\partial y(n-l)} U(n-l) \quad (24)$$

Referring to [27], we adopt a virtual secondary path having the following coefficients,

$$\tilde{\Xi}(n) = \left[\tilde{\vartheta}(n,0), \tilde{\vartheta}(n,1), \ldots, \tilde{\vartheta}(n,l), \ldots., \tilde{\vartheta}(n,Ks)\right]^T = \left[\frac{\partial \hat{d}(n)}{\partial y(n)}, \frac{\partial \hat{d}(n)}{\partial y(n-1)}, \ldots., \frac{\partial \hat{d}(n)}{\partial y(n-Ks)}\right]^T \quad (25)$$

Substituting the coefficients (25) into (24), we have (26).

$$\frac{\partial \hat{d}(n)}{\partial H(n)} = \sum_{l=0}^{K_s} \tilde{\vartheta}(n,l)\, U(n-l) \quad (26)$$

Note that the term $\sum_{l=0}^{K_s} \tilde{\vartheta}(n,l)\, U(n-l)$ in (26) is the convolution of $U(n)$ and $\tilde{\Xi}(n)$. Set $U_f(n) = U(n) * \tilde{\Xi}(n)$, with $U_f(n)$ is the filtered input samples by the $S(z)$, * represents the convolution. Combining (26) and (22), we have the equation for updating the weights.

$$H(n+1) = H(n) + \mu U_f(n) e(n) \quad (27)$$

For flexibility, (27) can be expressed in groups of weights with the same characteristics. Namely, the group of the external input sample coefficients $\Phi(n)$; the group of $sin(.)$ $cos(.)$ signal coeficients $\Psi(n) = [\,\Psi1^T(n), \Psi2^T(n)]^T$; the group of the cross-terms coefficients $T(n) = [T1^T(n) \;\; T2^T(n)]^T$. Furthermore, the algorithm can apply the M-max partial update strategy to optimize the selection of the cross-terms [28]–[31]. Therefore, (27) can be rewritten by (28)-(30).

$$\Phi(n+1) = \Phi(n) + \mu_1 e(n) Xf(n) \quad (28)$$

$$\Psi(n+1) = \Psi(n) + \mu_2 e(n) Xf_{12}(n) \quad (29)$$

$$T(n+1) = T(n) + \mu_3 \Gamma(n) e(n) Xf_{3,4}(n) \quad (30)$$

with $Xf(n) = \tilde{\Xi}(n) * X(n)$; $Xf_{1,2}(n) = \tilde{\Xi}(n) * [X1(n)^T X2(n)^T]^T$; $Xf_{3,4}(n) = \tilde{\Xi}(n) * [X3(n)^T X4(n)^T]^T$; and $\Gamma(n)$ denotes matrix of set of $M$ largest input signal values, refer to [24] we can be defined as (31).

$$\Gamma(n) = \begin{bmatrix} \gamma_1(n) & 0 & \cdots & 0 \\ 0 & \gamma_2(n) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \gamma_{L_c}(n) \end{bmatrix} \quad (31)$$

where, $$\gamma_j(n) = \begin{cases} 1 & if \;\; |xf34_j(n)| \in \max_{1 \le m \le Lc}(|xf34_k(n)|, M) \\ 0 & otherwise \end{cases} \quad (32)$$

where $xf34_j(n)$ is the $j^{th}$ term of vector $xf34(n)$; $L_c = (R_2 - R_1 + 1)N$ denotes the number of the cross-terms; $M$ is the M-max parameter ($1 \le M \le L_C$).

## 3. COMPLEXITY ANALYSIS

In this section, the computational cost of the EE-FLANN and that of the works in [13] and [20] have been analyzed. The complexity of the ANC system includes the following basic operations: i) The operations for calculating the output of the controller; ii) The operations for calculating the filtered reference signal; and iii) The operations for calculating the weights update. Assuming that $N$, $N_g$, and $N_f$ denote the external signal length for EE-FLANN, GFLANN, and FLANN respectively; $\Lambda$ the parameter of the EE-FLANN; $M$ denotes the M-max parameter; $N_d$ is parameter of the GFLANN; $Ks$ is the size of the secondary path. Table 1 illustrates a complexity comparison for all systems.

Table 1. Comparison of the complexity of controllers

| Controllers | Multiplications | Additions |
|---|---|---|
| FLANN | $2(2B+1)N_f+(2B+1)Ks$ | $2(2B+1)N_f+(2B+1)(Ks-1)$ |
| GFLANN | $6N_g+2N_d(N_d+1)+(3+2N_d)Ks$ | $6N_g+2N_d(N_d+1)+(3+2N_d)(Ks-1)$ |
| EE-FLANN | $6N+2(\Lambda+1)N+M+(3+M)K_s$ | $6N+2(\Lambda+1)N+M+(3+M)(K_s-1)$ |

## 4. RESULTS AND DISCUSSION

To evaluate the effectiveness, many simulations comparing the noise reduction of the EE-FLANN controller and that of GFLANN [20] and FLANN [13] controllers have been presented. In all experiments, the NMSE performance [21] of controllers is calculated by (33).

$$NMSE = 10\,log\,1\,0\left(\frac{E(e^2(n))}{\delta_d^2}\right) \tag{33}$$

where $\delta_d^2$ denotes variance of the $d(n)$. The parameters are set: FLANN (memory length $N_f = 10$, extension order $B$=3); GFLANN (memory length $N_g$=10; cross-term selection parameter $N_d$=9); EE-FLANN (memory length $N$=10; cross-term selection parameter $\Lambda$ =3, the M-max parameter selection $M$=20).

### 4.1. Experiment 1

To compare the performance, we adopt the nonlinear model as investigated in [17]. Noise source model: $x(n)=\sqrt{2}\times\sin(2\pi 500n/8000)$. The secondary path model: $S(z) = z^{-2} + 1.5z^{-3} - z^{-4}$. Primary path model: $d(n) = t(n-2) + 0.8t^2(n-2) - 0.4t^3(n-2)$, where $t(n)=x(n)*k(n)$ and $k(n)$ is the impulsive response of the transfer function $k(z) = z^{-3} - 0.3z^{-4} + 0.2z^{-5}$.

Figure 4 illustrates the NMSE performance of the FLANN, GFLANN, proposed EE-FLANN controllers. It is easy to see that the proposed EE-FLANN controller outperforms the FLANN controller, and is equivalent to the GFLANN controller. Besides, Table 2 reveals the complexity of EE-FLANN controller reducing by 20% multiplication and 23% addition in comparison with that of GFLANN.

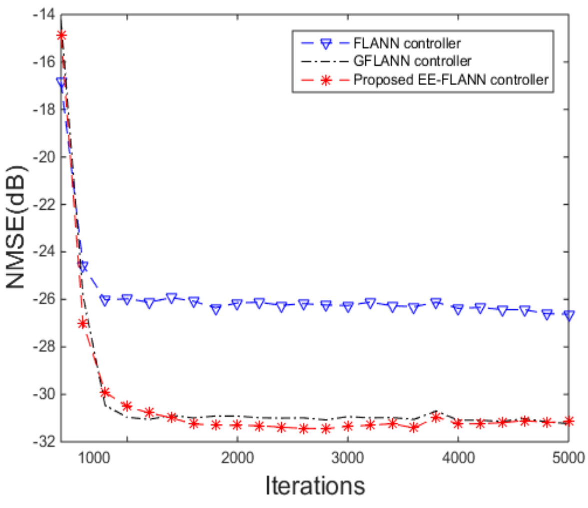


Figure 4. Comparison of the noise-canceling performance of the controllers in experiment 1

Table 2. Illustrate the computational cost of controllers per iteration

| Controllers | | Multiplications | Additions |
|---|---|---|---|
| FLANN | ($N_f$=10, $B$=3, $Ks$=5) | 185 | 168 |
| GFLANN | $N_g$=10, $N_d$=9, $Ks$=5) | 345 | 324 |
| EE-FLANN | ($N$=10, $\Lambda$ =3, $Ks$=5, $M$=20) | 275 | 252 |

### 4.2. Experiment 2

In this experiment, we adopt a secondary path model similar to experiment 3 of the study [20], as (34):

$$\alpha(n) = tanh(y(n))$$
$$\hat{d}(n) = \alpha(n) + 0.2\alpha(n-1) + 0.05\alpha(n-2) \quad (34)$$

The primary path model is referred from [21],

$$d(n) = x(n) + 0.8x(n-1) - 0.8x(n)x(n-1) + 0.3x(n-2) + 0.9x(n)x(n-2) + 0.4x(n-3) + 0.7x(n-3)x(n-3) - 3.9x^2(n-1)x(n-2) - 2.6x^2(n-1)x(n-3) + 2.1x^2(n-2)x(n-3) \quad (35)$$

Two input data scenarios are selected: case 1: The noise source model is a chaotic process $x(n+1) = \lambda x(n-1)[1 - x(n-1)]$, where λ=4 and x(0)=0.9 [13].
Case 2: The noise source model is a colored noise

$$x(n) = 0.04x(n-1) - 0.034x(n-2) + 0.0396x(n-3) - 0.07565x(n-4) + 0.06984\beta(n-4) + 0.0353\beta(n-3) - 0.137\beta(n-2) - 0.1\beta(n) - 0.01\beta(n-1) \quad (36)$$

where $\beta(n)$ denotes Gaussian white noise [17].

The NMSE performance and complexity of all three FLANN, GFLANN, and EE-FLANN controllers are shown in Figures 5, 6, and Table 3, respectively. For more clarity, we give a comparison of the noise attenuation [20] of the systems in Table 3. Note that we calculate the noise attenuation of the algorithms after 30,000 samples. Based on the simulation results, we see the EE-FLANN-based system reaches better noise reduction and lower complexity than the GFLANN-based system.

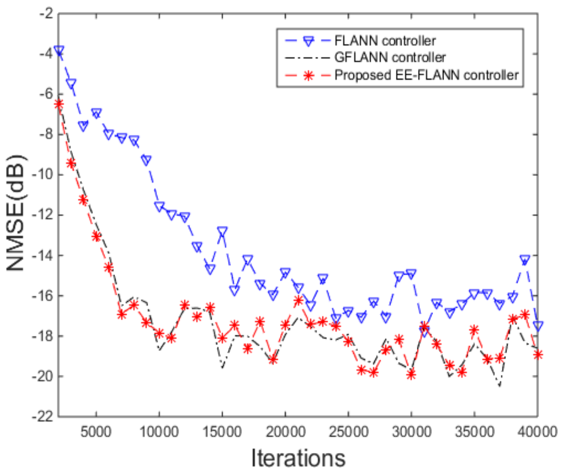


Figure 5. Comparison of the performance of the controllers for the chaotic noise source

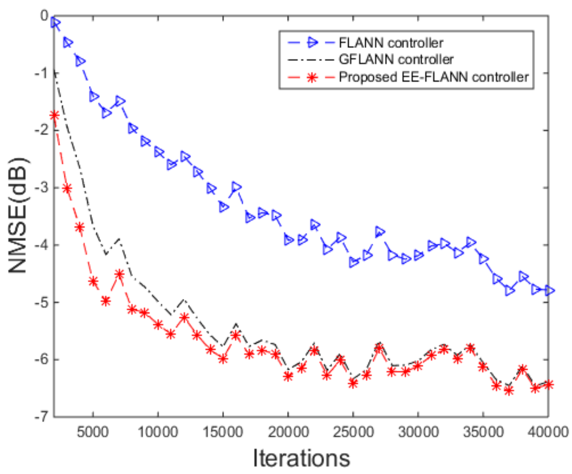


Figure 6. Comparison of performance of the controllers for the colored noise source

Table 3. The noise attenuation (NA) and the computational complexity per iteration

| Controllers | NA for chaotic noise (dB) | NA for colored noise (dB) | Mul | Add |
|---|---|---|---|---|
| FLANN ($N_f$=10, $B$=3, $Ks$=3) | 6.7254 | 4.0963 | 161 | 154 |
| GFLANN ($N_g$=10, $N_d$=9, $Ks$=3) | 9.1059 | 5.8566 | 303 | 312 |
| EE-FLANN ($N$=10, $\Lambda$ =3, $Ks$=3, $M$=20) | 9.1760 | 5.9543 | 229 | 206 |

### 4.3. Experiment 3

To illustrate the strong nonlinear distortion arising in the ANC system, this experiment uses the secondary path model in study [27], $\hat{d}(n) = y(n) + 0.35y(n-1) - 0.5y(n)y(n-1) + 0.09y(n-2) + 0.4y(n)y(n-2)$. The model of the nonlinear primary path is used similar to experiment 2. The reference noise source is assumed to be a Gaussian process.

Figure 7 exhibits the NMSE performance of the FLANN, GFLANN, proposed EE-FLANN controllers for experiment 3. The EE-FLANN controller is superior to FLANN and slightly better than GFLANN in terms of noise reduction. This is suitable because the structure of the proposed EE-FLANN exploits the symmetric cross-terms, thus the obtained performance may be better than GFLANN.

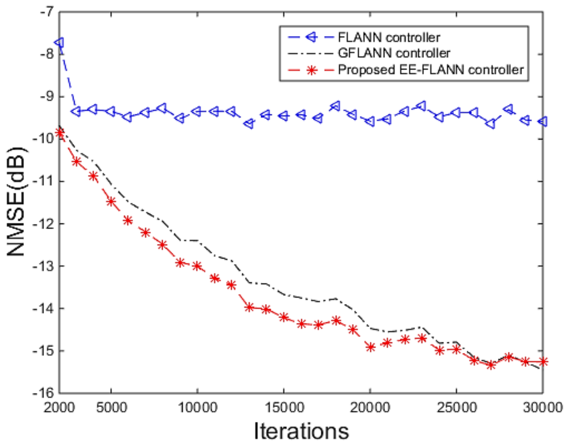


Figure 7. Comparison of performance of the controllers for experiment 3

## 5. CONCLUSION

This paper proposes the EE-FLANN controller for nonlinear ANC applications. The EE-FLANN exploits symmetric cross-terms to improve performance and uses a simplified technique to choose appropriate cross-terms. In addition, the adaptive algorithm is developed based on the data-dependent partial update strategy, thus, the EE-FLANN controller can decrease complexity at the weight update stage. The simulation results as well as the complexity analysis of the EE-FLANN controller proved the effectiveness of the developed solution.

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