Applied Acoustics 139 (2018) 174–181

Contents lists available at ScienceDirect

Applied Acoustics

journal homepage: www.elsevier.com/locate/apacoust

A generalized exponential functional link artificial neural networks filter with channel-reduced diagonal structure for nonlinear active noise control

Dinh Cong Le[a,b], Jiashu Zhang[a,*], Defang Li[a], Sheng Zhang[a]

[a] Sichuan Province Key Lab of Signal and Information Processing, Southwest Jiaotong University, Chengdu 610031, PR China
[b] Institute of Engineering and Technology, Vinh University, Viet Nam

ARTICLE INFO

Keywords:
Functional link artificial neural networks
Active noise control
Diagonal-channel structure
Cross-term

ABSTRACT

The nonlinear adaptive exponential functional link artificial neural networks (E-FLANN) filter has been introduced to improve the noise reduction capability of the functional link artificial neural networks (FLANN) in nonlinear active noise control (NANC) system. It, however, suffers from a heavy computational burden at the nonlinear secondary path (NSP) and poor convergence performance in strong nonlinearity systems. To surmount these shortcomings, a computationally efficient generalized E-FLANN filter with the channel-reduced diagonal structure (GE-FLANN-CRD) for NANC system is developed in this paper. Based on introducing the suitable cross-terms and adaptive exponential factor into the trigonometric functional expansions, the nonlinear processing capability of the filter is enhanced in NANC. Also, by applying the filtered-error least mean square (FELMS) algorithm to the GE-FLANN-CRD, it substantially decreases the computational cost to update the exponential factor. Computer simulations demonstrate that the proposed filter-based the NANC system performs better than the FLANN, E-FLANN and Generalized FLANN (GFLANN) filters-based NANC system in the presence of strong nonlinearity.

1. Introduction

To compensate the nonlinear distortions that exist in the actual NANC systems, many researchers have successfully used various nonlinear adaptive filters as the controller. Based on the Volterra filter, bilinear filter, and spline filter, adaptive controllers for NANC system have been proposed in [1–3]. One another method using neural networks (NNs) has also been reported in the literature on NANC, such as multi-layer perceptron (MLP) [4], radial basis function (RBF) [5], the fuzzy neural network [6] and the recurrent neural network (RNN) [7]. Beside, many wavelet frames (such as POLYnominal WindOwed Gaussian (POLYWOG), superposed LOGistic functions (SLOG) and superposed LOGistic functions (SLOG)) have been applied to NANC systems by M Akraminia et al., [8–10]. Apart from those approaches, an efficient alternative based on FLANN using trigonometric functional expansions has received much attention due to its single layer architecture [11–14]. In consequence, various modifiers of FLANN structure for NANC systems have been proposed. Emerging among them can be listed as recursive FLANN (RFLANN) [15], generalized FLANN (GFLANN) [16], bilinear FLANN (BFLANN) [17], convex/cascade combinations of the nonlinear adaptive FLANN filter and other adaptive filters such as the adaptive infinite impulse response (IIR) [18], Volterra [19], FLANN [20] and Legendre polynomial [21].

Recently, in order to further improve the nonlinear modeling capability of the pure sinusoids-based FLANN filter, an adaptive exponential FLANN (E-FLANN) filter has been presented and successfully applied for NANC [22]. In this study, trigonometric functional expansions with the magnitude of the sinusoid are adjusted along with an adaptive exponential factor. However, because of the extra computational cost of filtering the signal through the secondary path to update the exponential factor, its computational complexity increases significantly, especially in the case of NSP. Moreover, in the presence of strong nonlinearity in the secondary or/and primary paths, the performance of the E-FLANN filter may be reduced. This may be caused by the mixed terms with different time delays that exist in the primary and secondary paths under such circumstances (as indicated in [23]). In order to address the aforementioned problems, two improvements are proposed in this paper. Firstly, a generalized E-FLANN with channel-reduced diagonal structure (GE-FLANN -CRD) is presented. It is designed by exploiting suitable cross-terms (the products of input samples at different time delays with trigonometric functions with exponentially varying amplitude) with an implementation based on a diagonal-channel structure. Secondly, a filter-error LMS (FELMS) algorithm is proposed to the GE-FLANN-CRD -based NANC system.

* Corresponding author.
E-mail address: jszhang@home.swjtu.edu.cn (J. Zhang).

https://doi.org/10.1016/j.apacoust.2018.04.020
Received 14 December 2017; Received in revised form 15 March 2018; Accepted 16 April 2018
0003-682X/

The rest of this paper is organized as follows. Section 2 proposes GE-FLANN-CRD filter for NANC system. Sections 3 and 4 presents the analysis of computational complexity and stability, respectively. Section 5 provides computer simulation studies of the proposed controller. Finally, the conclusion is drawn in Section 6.

2. Proposed GE-FLANN-CRD filter for NANC system

2.1. The GE-FLANN-CRD filter and its multichannel implementation

An E-FLANN filter of order P, memory length N, using the trigonometric expansion with exponentially varying amplitudes [22] can be described by the input-output relationship as follows

$$y_E(n) = W_E^T(n)X_{EF}(n) \tag{1}$$

where $W_E(n) = [w_{1E}, w_{2E}, \ldots, w_{ME}]^T$ denotes the adaptive weight vector; $[\bullet]^T$ is transpose of a vector; $M = N(2P+1)$ and $X_{EF}(n)$ is the expanded input signal vector

$$\begin{aligned}X_{EF}(n) = [&x(n), e^{-\beta(n)|x(n)|}\sin(\pi x(n)), e^{-\beta(n)|x(n)|}\cos(\pi x(n)), \ldots\\ &, e^{-\beta(n)|x(n)|}\sin(P\pi x(n)), e^{-\beta(n)|x(n)|}\cos(P\pi x(n)), x(n\\ &-1), e^{-\beta(n)|x(n-1)|}\sin(\pi x(n-1)), e^{-\beta(n)|x(n-1)|}\cos(\pi x(n-1)), \ldots\\ &, e^{-\beta(n)|x(n-1)|}\sin(P\pi x(n-1)), e^{-\beta(n)|x(n-1)|}\cos(P\pi x(n-1))\ldots\\ &, x(n-N+1), e^{-\beta(n)|x(n-N+1)|}\sin(\pi x(n-N\\ &+1)), e^{-\beta(n)|x(n-N+1)|}\cos(\pi x(n-N+1)), \ldots, e^{-\beta(n)|x(n-N+1)|}\\ &\times \sin(P\pi x(n-N+1)), e^{-\beta(n)|x(n-N+1)|}\cos(P\pi x(n-N+1))]^T\end{aligned} \tag{2}$$

where $\beta(n)$ is an adaptive exponential parameter and $X(n) = [x(n)\ x(n-1) \ldots x(n-N+1)]^T$ is the vector of input samples to the E-FLANN filter.

The output of the E-FLANN filter is easily implemented based on a filter bank structure as

$$\begin{aligned}y_E(n) = &\sum_{i=0}^{N-1} a_i(n)x(n-i) + \sum_{i=0}^{N-1} b1_i(n)e^{-\beta(n)|x(n-i)|}\sin(\pi x(n-i))\\ &+ \sum_{i=0}^{N-1} b2_i(n)e^{-\beta(n)|x(n-i)|}\cos(\pi x(n-i))\\ &+ \ldots + \sum_{i=0}^{N-1} b(P+1)_i(n)e^{-\beta(n)|x(n-i)|}\sin(P\pi x(n-i))\\ &+ \sum_{i=0}^{N-1} b(P+2)_i(n)e^{-\beta(n)|x(n-i)|}\cos(P\pi x(n-i))\end{aligned} \tag{3}$$

where $a_i(n)$, $b1_i(n)$, $b2_i(n)$, $b(P+1)_i(n)$, $b(P+2)_i(n)$ are the corresponding adaptive coefficients.

As discussed above, the performance of the E-FLANN may be degraded in the existence of strong nonlinearity. The main reason may be that its nonlinear extension function lacks cross-terms. To surmount this shortcoming, the cross-terms involving the products of input samples at different time delays with trigonometric functions with exponentially varying amplitudes are introduced into functional expansion. Theoretically, this method can be easily extended to any order $P > 1$. However, to avoid confusion in analysis, in this section we only consider introducing cross-terms into the E-FLANN filter with the order $P = 1$. Hence, a generalized E-FLANN (GE-FLANN) is defined as

$$\begin{aligned}y(n) = &\sum_{i=0}^{N-1} a_i(n)x(n-i) + \sum_{i=0}^{N-1} b1_i(n)e^{-\beta(n)|x(n-i)|}\sin(\pi x(n-i))\\ &+ \sum_{i=0}^{N-1} b2_i(n)e^{-\beta(n)|x(n-i)|}\cos(\pi x(n-i)) + \sum_{i=0}^{N-1}\sum_{j=1}^{N-1} C1_{i,j}(n)x(n\\ &-i)e^{-\beta(n)|x(n-j)|}\sin(\pi x(n-j)) + \sum_{i=0}^{N-1}\sum_{j=1}^{N-1} C2_{i,j}(n)x(n\\ &-i)e^{-\beta(n)|x(n-j)|}\cos(\pi x(n-j))\end{aligned} \tag{4}$$

where $C1_{i,j}(n)$ and $C2_{i,j}(n)$ are the coefficients of cross-terms.

Note that the first three components on the right-hand side of the equation above satisfy a time-shift property while the last two components including the cross-terms do not satisfy this property. This results in increasing computational burden when applied to NANC systems. Therefore, we need to consider the diagonal structure feature for the cross-terms, as pointed out in [24–26].

Similar to [26], a GE-FLANN with channel-reduced diagonal structure (GE-FLANN-CRD) is presented as

$$\begin{aligned}y(n) = &\sum_{i=0}^{N-1} a_i(n)x(n-i) + \sum_{i=0}^{N-1} b1_i(n)e^{-\beta(n)|x(n-i)|}\sin(\pi x(n-i))\\ &+ \sum_{i=0}^{N-1} b2_i(n)e^{-\beta(n)|x(n-i)|}\cos(\pi x(n-i))\\ &+ sum_{m=1}^{P_r}\sum_{k=0}^{N-m-1} C11_{m,k}(n)x(n-k)e^{-\beta(n)|x(n-m-k)|}\sin(\pi x(n-m\\ &-k)) + \sum_{m=1}^{P_r}\sum_{k=0}^{N-m-1} C12_{m,k}(n)x(n-m-k)e^{-\beta(n)|x(n-k-1)|}\sin(\pi x(n\\ &-k-1)) + \sum_{m=1}^{P_r}\sum_{k=0}^{N-m-1} C21_{m,k}(n)x(n-k)e^{-\beta(n)|x(n-m-k)|}\cos(\pi x(n\\ &-m-k)) + \sum_{m=1}^{P_r}\sum_{k=0}^{N-m-1} C22_{m,k}(n)x(n-m\\ &-k)e^{-\beta(n)|x(n-k-1)|}\cos(\pi x(n-k-1))\end{aligned} \tag{5}$$

where m denotes the diagonal channel number, k designates the time index, $C11_{m,k}(n)$, $C12_{m,k}(n)$, $C21_{m,k}(n)$ and $C22_{m,k}(n)$ are the coefficients of the cross-terms. Pr is a positive integer and $1 \le P_r \le N-1$. Note that the channels of the cross-terms are defined so that the channel signal sequence satisfies a time-shift property and the diagonal channel number depend on the parameter P_r

To derive the adaptive algorithm for the GE-FLANN-CRD filter, we can rewrite (5) using the vector form as

$$\begin{aligned}y(n) = &A^T(n)U_1(n) + B_1^T(n)U_{21}(n) + B_2^T(n)U_{22}(n)\\ &+ \sum_{m=1}^{P_r} C11_m^T(n)V11_m(n) + \sum_{m=1}^{P_r} C12_m^T(n)V12_m(n)\\ &+ \sum_{m=1}^{P_r} C21_m^T(n)V21_m(n) + \sum_{m=1}^{P_r} C22_m^T(n)V22_m(n)\end{aligned} \tag{6}$$

where the coefficient vector and the corresponding input signal vector are defined by

$$A(n) = [a_0(n)a_1(n)\ldots a_{N-1}(n)]^T \tag{7}$$

$$U_1(n) = [x(n)x(n-1)\ldots x(n-N+1)]^T \tag{8}$$

$$B_1(n) = [b1_0(n)b1_1(n)\ldots b1_{N-1}(n)]^T \tag{9}$$

$$U_{21}(n) = [e^{-\beta(n)|x(n)|}\sin(\pi x(n))\ldots e^{-\beta(n)|x(n-N+1)|}\sin(\pi x(n-N+1))]^T \tag{10}$$

$$B_2(n) = [b2_0(n)b2_1(n)\ldots b2_{N-1}(n)]^T \tag{11}$$

$$U_{22}(n) = [e^{-\beta(n)|x(n)|}\cos(\pi x(n))\ldots e^{-\beta(n)|x(n-N+1)|}\cos(\pi x(n-N+1))]^T \tag{12}$$