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Technical note

A bilinear functional link artificial neural network filter for nonlinear active noise control and its stability condition

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ABSTRACT

Since the functional link artificial neural network (FLANN) filter using trigonometric expansions do not exploit cross-terms (products of input samples and /or past output samples with different time shifts), its performance for nonlinear active noise control (ANC) can be considerably degraded, especially in strong nonlinearity environment. In order to overcome this drawback, a novel bilinear FLANN (BFLANN) filter for the nonlinear ANC is proposed in this paper. In addition, a sufficient condition that guarantees the stability of the BFLANN filter is also presented. Simulation results demonstrate that the proposed BFLANN filter based nonlinear ANC can achieve better performance than the FLANN and generalized FLANN (GFLANN) filters based nonlinear ANC in the presence of strong nonlinearity.

1. Introduction

In order to solve acoustic noise problems (such as noises from engines, fans and compressors…), the active noise control (ANC) systems have become a potential solution and attracted attention of many researchers [1,2]. It is well known that conventional ANC system using the linear filter as a linear controller has been widely and popularly applied [3,4]. However, since the linear ANC system does not take account of nonlinearity that is contained in the components of the actual ANC systems, its performance may be seriously degraded [5–7].

To deal with this problem, various types of nonlinear filters based on the polynomial filter (PF) and neural networks (NNs) such as radial basic function (RBF) [6], multilayer neural network (MLNN) [8–10], recurrent neural network (RNN) [11] and Volterra filters (VFs) [12,13] have been used in the nonlinear ANC systems with good result. These nonlinear filters, however, exhibit numerous disadvantages such as the complicated architecture and the heavy computational burden of its implementation.

In addition, an effective alternative to nonlinear filter in nonlinear ANC systems is the well-known FLANN filter using trigonometric expansions[14–20], and its several modifications (such as recursive FLANN [21,22], reduced feedback FLANN [23] and hybrid active noise control system-based FLANN [24–27]) have also been presented in recent years.

However, as pointed out in [28], the performance of nonlinear ANC systems using the FLANN can be negatively affected because of the lack of cross-terms. This becomes more serious as the strong nonlinearity is present in the components of the actual ANC systems. In [28], Sicuranza and Carini have proposed a GFLANN filter with the use of trigonometric expansions including suitable cross-terms for nonlinear ANC system. Research results indicate that GFLANN controller has better performance than FLANN and high-order Volterra controllers in the presence of strong nonlinearity in the primary or secondary paths. With the aim of further exploiting the advantage of the cross product terms, a bilinear FLANN (BFLANN) filter for nonlinear ANC system is presented in this paper. Unlike the GFLANN, thanks for employing both feedback and feedforward polynomials, the proposed filter can accurately model nonlinear systems with shorter filter length.

The rest of this paper is organized as follows: Section 2 proposes new BFLANN filter for nonlinear ANC system; Section 3 and 4 present the analysis of stability condition and computational complexity, respectively; Section 5 provides computer simulation studies of the proposed controller; finally, the conclusion is drawn in Section 6.

2. BFLANN filter for nonlinear ANC system

The block diagram of the NANC system using BFLANN filter is illustrated in Fig. 1. Here, the transfer functions P(z), S(z) represent the primary path from the reference microphone to the error microphone and the secondary path from the output of the filter to the output of the error microphone, respectively.

The $P(z)$, $S(z)$ and input signal $x(n)$ may contain nonlinearities.

In order to avoid the confusion and complication, in this section we just introduce the BFLANN of order $P = 1$. The approach can be easily

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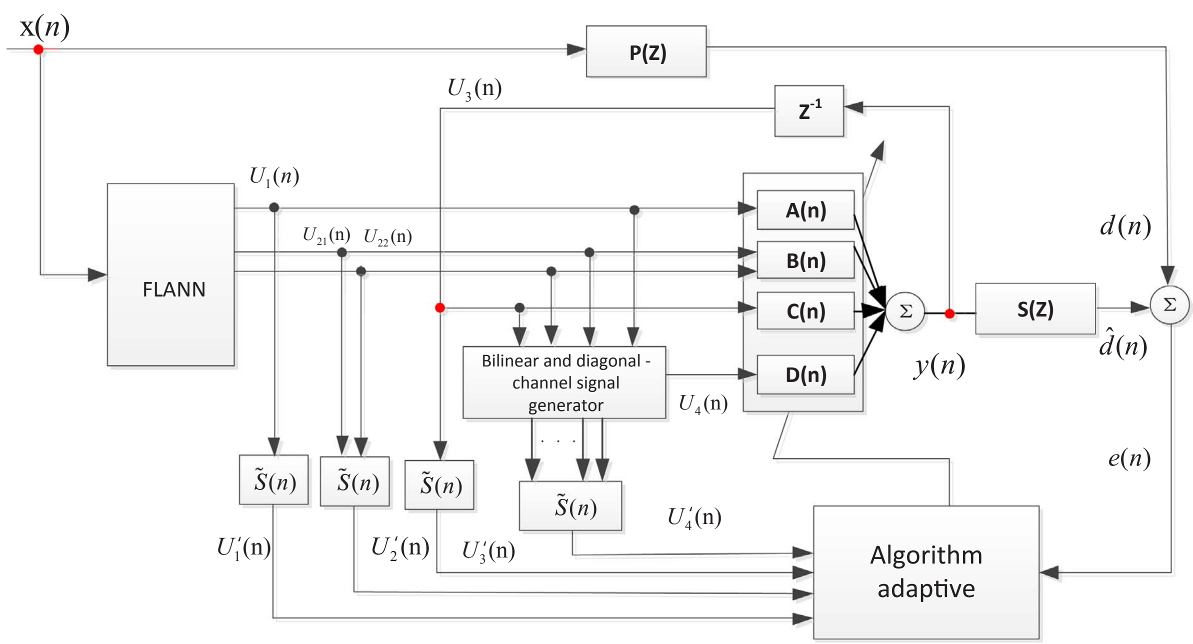

Fig. 1. The nonlinear ANC system based on the BFLANN filter.

extended to a BFLANN filter of any order P.

Therefore, similar to [29], the relationship between input $x(n)$ and output $y(n)$ of the BFLANN filter with a memory length of L expressed as

$$\begin{aligned} y(n) = & \sum_{j=0}^{L-1} a_j(n)x(n-j) + \sum_{j=0}^{L-1} b1_j(n)\sin(\pi x(n-j)) \\ & + \sum_{j=0}^{L-1} b2_j(n)\cos(\pi x(n-j)) + \sum_{j=1}^{L-1} c_j(n)y(n-j) \\ & + \sum_{i=0}^{L-1}\sum_{j=1}^{L-1} d1_{i,j}(n)x(n-i)y(n-j) + \sum_{i=0}^{L-1}\sum_{j=1}^{L-1} d2_{i,j}(n)\sin(\pi x(n \\ & -i))y(n-j) + \sum_{i=0}^{L-1}\sum_{j=1}^{L-1} d3_{i,j}(n)\cos(\pi x(n-i))y(n-j) \end{aligned} \quad (1)$$

where $a_j(n)$, $b1_j(n)$ and $b2_j(n)$ are feedforward coefficients extended by FLANN with the order $P = 1$; $c_j(n)$ are feedback coefficients; $d1_{i,j}(n)$, $d2_{i,j}(n)$ and $d3_{i,j}(n)$ are the coefficients of cross-terms.

Similar to [30–33], in order to achieve an efficient implementation based on a filter bank formed with FIR filters, (1) can be equivalently written as follows

$$\begin{aligned} y(n) = & \sum_{j=0}^{L-1} a_j(n)x(n-j) + \sum_{j=0}^{L-1} b1_j(n)\sin(\pi x(n-j)) \\ & + \sum_{j=0}^{L-1} b2_j(n)\cos(\pi x(n-j)) + \sum_{j=1}^{L-1} c_j(n)y(n-j) \\ & + \sum_{i=1}^{L-1}\sum_{j=0}^{L-i-1} g1_{i,j}(n)x(n-j)y(n-j-i) + \sum_{i=1}^{L-1}\sum_{j=0}^{L-i-1} h1_{i,j}(n)x(n-i \\ & -j)y(n-1-j) + \sum_{i=1}^{L-1}\sum_{j=0}^{L-i-1} g2_{i,j}(n)sin(\pi x(n-j))y(n-j-i) \\ & + \sum_{i=1}^{L-1}\sum_{j=0}^{L-i-1} h2_{i,j}(n)sin(\pi x(n-i-j))y(n-1-j) \\ & + \sum_{i=1}^{L-1}\sum_{j=0}^{L-i-1} g3_{i,j}(n)cos(\pi x(n-j))y(n-j-i) \\ & + \sum_{i=1}^{L-1}\sum_{j=0}^{L-i-1} h3_{i,j}(n)cos(\pi x(n-i-j))y(n-1-j) \end{aligned} \quad (2)$$

where i denotes the bilinear filter channel number and j designates the time index; $g1_{i,j}(n)$, $h1_{i,j}(n)$, $g2_{i,j}(n)$, $h2_{i,j}(n)$ and $g3_{i,j}(n)$, $h3_{i,j}(n)$ are the coefficients of the cross-terms.

To derive the adaptive algorithm for BFLANN filter, the model in (2) is rewritten under the vector form as follows

$$\begin{aligned} y(n) = & A^T(n)U_1(n) + B_1^T(n)U_{21}(n) + B_2^T(n)U_{22}(n) + C^T(n)U_3(n) \\ & + \sum_{i=1}^{L-1} G1_i^T(n)V1_i(n) + \sum_{i=1}^{L-1} H1_i^T(n)Q1_i(n) + \sum_{i=1}^{L-1} G2_i^T(n)V2_i(n) \\ & + \sum_{i=1}^{L-1} H2_i^T(n)Q2_i(n) + \sum_{i=1}^{L-1} G3_i^T(n)V3_i(n) + \sum_{i=1}^{L-1} H3_i^T(n)Q3_i(n) \end{aligned} \quad (3)$$

where signal vectors and their corresponding coefficient vectors are listed below

$$A(n) = [a_0(n)a_1(n)\cdots a_{L-1}(n)]^T \quad (4)$$

$$U_1(n) = [x(n)x(n-1)\cdots x(n-L+1)]^T \quad (5)$$

$$B_1(n) = [b1_0(n)b1_1(n)\cdots b1_{L-1}(n)]^T \quad (6)$$

$$U_{21}(n) = [\sin(\pi x(n))\sin(\pi x(n-1))\cdots\sin(\pi x(n-L+2))\sin(\pi x(n-L+1))]^T \quad (7)$$

$$B_2(n) = [b2_0(n)b2_1(n)\cdots b2_{L-1}(n)]^T \quad (8)$$

$$U_{22}(n) = [cos(\pi x(n))cos(\pi x(n-1))\cdots\cos(\pi x(n-L+2))cos(\pi x(n-L+1))]^T \quad (9)$$

$$C(n) = [c_1(n)c_2(n)\cdots c_{L-1}(n)]^T \quad (10)$$

$$U_3(n) = [y(n-1)y(n-2)\cdots y(n-L+1)]^T \quad (11)$$

For $i = 1,2,\ldots,L-1$

$$G1_i^T(n) = [g1_{i,0}(n)g1_{i,1}(n)\cdots g1_{i,L-i-1}(n)]^T \quad (12)$$

$$V1_i^T(n) = [x(n)y(n-i)x(n-1)y(n-i-1)\ldots x(n-L+1+i)y(n-L+1)]^T \quad (13)$$