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Nonlinear active noise control using spline adaptive filters

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ABSTRACT

A spline adaptive filter (SAF) based nonlinear active noise control (ANC) system is proposed in this paper. The SAF consists of a linear network of adaptive weights in cascade with an adaptive nonlinear network. The nonlinear network, in-turn consists of an adaptive look-up table followed by a spline interpolation network and forms an adaptive activation function. An update rule has been derived for the proposed ANC system, which not only updates the weights of the linear network, but also updates the nature of the activation function. An extensive simulation study has been conducted to evaluate the noise mitigation performance of the proposed scheme and the new method has been shown to provide improved noise cancellation efficiency with a lesser computational load in comparison with other popular ANC systems.

1. Introduction

Active noise control (ANC), which is based on the destructive superposition of sound waves has found enhanced interest amongst the research community in the recent past owing to the advancements made in control theory as well as in semiconductor technology. ANC systems can be feed-forward or feedback in nature. A basic feed-forward ANC system contains a reference microphone to measure the reference signal $x(n)$, an active loudspeaker to generate the necessary anti-noise and an error microphone to sense the level of noise mitigation obtained. The input to the active loudspeaker is governed by an adaptive controller, which is updated using an adaptive algorithm [1].

Fig. 1 shows the block diagram of a filtered-x least mean square (FxLMS) algorithm based ANC system, where $P_N(z)$ is the transfer function of the primary path (path from reference microphone to the error microphone), $S_N(z)$ is the transfer function of the secondary path (electro-acoustic path from the output of the controller to the output of the error microphone), $\widehat{S}_N(z)$ is the transfer function of the model of the secondary path, $W(z)$ is the transfer function of the adaptive controller, $d(n)$ is the output of the primary path and $y_s(n)$ is the output of the secondary path. The weights $w(n)$ of the controller are updated using FxLMS algorithm [1] as

$$w(n+1) = w(n) + 2\mu e(n)x'(n) \tag{1}$$

where μ is the learning rate, $e(n)$ is the residual noise and $x'(n)$ is the primary noise $x(n)$ filtered through $\widehat{S}_N(z)$.

It has been reported that the FxLMS algorithm based ANC schemes fail to effectively mitigate noise in the presence of nonlinearities in the ANC system. Several nonlinear ANC schemes have been developed in the recent past to improve the noise cancellation efficiency in such scenarios. An adaptive Volterra filter based ANC scheme which employs a Volterra filtered-x least mean square (VFxLMS) algorithm for weight update has been proposed in [2,3]. A nonlinear ANC system, which uses a functional link artificial neural network (FLANN) as the adaptive controller and employs a filtered-s least mean square (FsLMS) algorithm has been reported in [4]. Many attempts have been made in the recent past to improve the noise mitigation in nonlinear ANC systems [5–10].

Scarpiniti et al. has recently proposed a nonlinear spline filter [11]. The nonlinear spline filter consists of an adaptive linear network followed by an adaptive activation function and have been shown to effectively identify parameters in a nonlinear system identification problem. The authors have also shown improved performance in comparison with adaptive Volterra filters, which is a common filter used in ANC applications. An extension of the work has also been lately reported for nonlinear system identification [12]. In an endeavour to improve the noise cancellation achieved in a nonlinear ANC system, this paper proposes a spline adaptive filter based nonlinear ANC system. The adaptive nature of the activation function, makes the nonlinear spline filter a suitable candidate for effective noise cancellation in the presence of varying degrees of nonlinearities, without the need of increasing the computational load in terms of multipliers.

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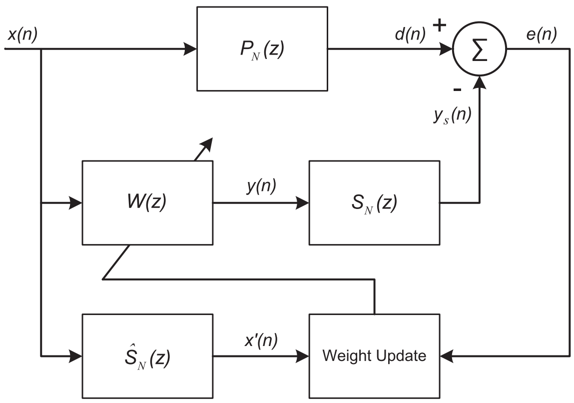

Fig. 1. Block diagram of an FxLMS algorithm based ANC system.

The rest of the paper is organized as follows. A brief introduction to a spline adaptive filter is made in Section 2. An adaptive spline filter based nonlinear ANC system is designed in Section 3. An adaptive learning algorithm for updating the weights as well as the activation functions is also derived and a convergence analysis of the update rule has also been presented in the section. A set of simulation exercises have been carried out in Section 4 to evaluate the performance of the proposed nonlinear ANC scheme. Concluding remarks are made in Section 5.

2. Spline adaptive filter

The spline adaptive filter shown in Fig. 2 is essentially a linear non-linear network, where in the linear network is a finite impulse response (FIR) filter and the nonlinear network consists of an adaptive look-up table followed by a spline interpolation network. In the figure, $x(n)$ is the input to the controller, $\alpha(n)$ is the output of the linear network and $y(n)$ is the output of the spline filter. The output of the linear network is given by

$$\alpha(n) = \boldsymbol{a}^{\mathrm{T}}(n)\boldsymbol{x}(n) \tag{2}$$

where $\boldsymbol{a}(n) = [a_0, a_1, \ldots, a_{N-1}]^{\mathrm{T}}$ is the adaptive weight vector of the linear network and $\boldsymbol{x}(n) = [x(n), x(n-1), \ldots, x(n-N+1)]^{\mathrm{T}}$ is the tap delayed input signal vector with N as the length of the tap delay line. The output of the linear network, $\alpha(n)$ and the output of the spline adaptive network, $y(n)$ are related using a nonlinear activation function ρ, which is determined using the span index i and the local parameter u. The local parameter is computed as

$$u = \frac{\alpha(n)}{\Delta x} - \left\lfloor \frac{\alpha(n)}{\Delta x} \right\rfloor \tag{3}$$

and the span index is obtained by

$$i = \left\lfloor \frac{\alpha(n)}{\Delta x} \right\rfloor + \frac{Q-1}{2} \tag{4}$$

where Q is the total number of control points in the activation function, Δx is the gap between the control points and $\lfloor \cdot \rfloor$ is the floor operator. The output of the spline adaptive filter is given by

$$y(n) = \rho_i(u) = \boldsymbol{u}^{\mathrm{T}}\boldsymbol{C}\boldsymbol{q_i} \tag{5}$$

where $\boldsymbol{u} = [u^3, u^2, u, 1]^{\mathrm{T}}$, $\boldsymbol{C}$ is the B-spline basis matrix given by

$$\boldsymbol{C} = \frac{1}{6}\begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 0 & 3 & 0 \\ 1 & 4 & 1 & 0 \end{bmatrix} \tag{6}$$

and $\boldsymbol{q_i} = [q_i, q_{i+1}, q_{i+2}, q_{i+4}]^{\mathrm{T}}$ is the control point vector.

3. Proposed nonlinear ANC system

In the proposed spline adaptive filter based ANC scheme, the adaptive controller $W(z)$ in Fig. 1 is replaced with the adaptive spline filter discussed in the previous section. The residual noise measured by the error sensor is given by

$$e(n) = d(n) - y(n) * s_N(n) \tag{7}$$

where $s_N(n)$ is the impulse response of the transfer function $S_N(z)$ and $*$ is the convolution operator. In the proposed ANC system, the weights $\boldsymbol{a}(n)$ of the linear network as well as the control parameters of the non-linear network are updated using a gradient descent update rule [1] which minimizes the cost function

$$\xi(n) = E[e^2(n)] \tag{8}$$

where $E[\cdot]$ is the expectation operator and $\xi(n)$ is dependent on both $\boldsymbol{a}(n)$ and $\boldsymbol{q_i}(n)$. Assuming $E[e^2(n)] \approx e^2(n)$, the update rule for the weight vector $\boldsymbol{a}(n)$ is given by

$$\boldsymbol{a}(n+1) = \boldsymbol{a}(n) - \frac{\mu_a}{2}\frac{\partial \xi(n)}{\partial \boldsymbol{a}(n)} \tag{9}$$

where

$$\frac{\partial \xi(n)}{\partial \boldsymbol{a}(n)} = -2e(n)\frac{\partial [y(n) * s_N(n)]}{\partial \boldsymbol{a}(n)} \tag{10}$$

$$= -2e(n)\left[\frac{\partial y}{\partial u}\frac{\partial u}{\partial \alpha}\frac{\partial \alpha}{\partial \boldsymbol{a}(n)} * s_N(n)\right] \tag{11}$$

$$= -2e(n)\left[\dot{\boldsymbol{u}}^{\mathrm{T}}\boldsymbol{C}\boldsymbol{q_i}\frac{1}{\Delta x}\boldsymbol{x}(n) * s_N(n)\right] \tag{12}$$

with $\dot{\boldsymbol{u}} = \frac{\partial \boldsymbol{u}}{\partial u}$ and μ_a as the learning rate. The weight update rule for the linear network is given by

$$\boldsymbol{a}(n+1) = \boldsymbol{a}(n) + \mu_a e(n)\boldsymbol{x}'(n) \tag{13}$$

where $\boldsymbol{x}'(n)$ is $\dot{\boldsymbol{u}}^{\mathrm{T}}\boldsymbol{C}\boldsymbol{q_i}\frac{1}{\Delta x}\boldsymbol{x}(n)$ filtered through a model of the secondary path. Similarly, the control points are updated as

$$\boldsymbol{q_i}(n+1) = \boldsymbol{q_i}(n) - \frac{\mu_q}{2}\frac{\partial \xi(n)}{\partial \boldsymbol{q_i}(n)} \tag{14}$$

where

$$\frac{\partial \xi(n)}{\partial \boldsymbol{q_i}(n)} = -2e(n)\frac{\partial [y(n) * s_N(n)]}{\partial \boldsymbol{q_i}(n)} \tag{15}$$

$$= -2e(n)\left[\boldsymbol{u}^{\mathrm{T}}\boldsymbol{C} * s_N(n)\right] \tag{16}$$

$$= -2e(n)\left[\boldsymbol{C}^{\mathrm{T}}\boldsymbol{u}'\right] \tag{17}$$

with μ_q as the learning rate for updating the control points and $\boldsymbol{u}'$ is the filtered version of $\boldsymbol{u}$. The update rule for the control points is given by

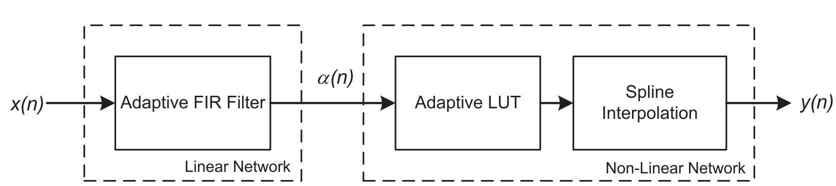

Fig. 2. Linear non-linear network.