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Adaptive variable step-size neural controller for nonlinear feedback active noise control systems ☆

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ABSTRACT

Adaptive filter techniques and the filtered-x least mean square (FxLMS) algorithm have been used in Active Noise Control (ANC) systems. However, their effectiveness may degrade due to the nonlinearities and modeling errors in the system. In this paper, a new feedback ANC system with an adaptive neural controller and variable step-size learning parameters (VSSP) is proposed to improve the performance. A nonlinear adaptive controller with the FxLMS algorithm is first designed to replace the traditional adaptive FIR filter; then, a variable step-size learning method is developed for online updating the controller parameters. The proposed control is implemented without any offline learning phase, while faster convergence and better noise elimination can be achieved. The main contribution is that we show how to analyze the stability of the proposed closed-loop ANC systems, and prove the convergence of the presented adaptations. Moreover, the computational complexities of different methods are compared. Comparative simulation results demonstrate the validity of the proposed methods for attenuating different noise sources transferred via nonlinear paths, and show the improved performance over classical methods.

1. Introduction

Noise and vibration in the environment have drawn increasing attentions due to the use of various equipments that also serve as noise sources, such as motors, fans and transformers. As reported by the World Health Organization [1,2], noise and vibration cause a sensation of discomfort and harm to human health. Thus, the issue of noise control has been the focus of many researchers in the past decades. In general, there are two methods of noise control schemes, e.g. passive noise control (PNC) [3] and active noise control (ANC) [4]. The passive methods are effective for controlling the broadband noise and have been successfully used in the high-frequency noise circumstances. However, for narrowband noise and low-frequency noise, PNC is inefficient because of its bulky structure. Hence, ANC technology [5] was developed to handle more complex noise.

In general, ANC systems are designed based on the principle that a secondary noise source is generated to cancel the aggregate noise in the noise control area, which has a same amplitude but opposite phase compared to the primary noise. Recently, with advanced digital signal processing techniques, it is possible to obtain better acoustic performance by employing appropriate control approaches [6]. For this purpose, various ANC methods have been used in practical applications [5–9], e.g. vehicle transportation, aircraft engineers, heating, air conditioning duct systems, etc. These available control methods are briefly classified into two categories: feedforward control [10] and feedback control [11]. Feedforward ANC systems must anticipate the reference signal input (noise source). Therefore, feedforward ANC approaches may not be feasible for the cases, where the noise source cannot be measured in the specific environments (e.g. high temperature, corrosive chemicals). To solve this problem, feedback ANC system (FANC) was developed, which uses only an error signal in the summing junction. Thus, feedback ANC strategies can address the unforeseen noise sources [12,13]. Some available results show that feedback ANC systems based on adaptive finite impulse response (FIR) filter and filtered-x least-mean-square (FxLMS) algorithm work well for the cases with linear paths [14,15]. However, in

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practical applications, the nonlinearities in the primary path and secondary path may degrade the control performance [16]. Thus, the development of nonlinear controllers/filters is necessary. In this respect, functional link neural networks (FLNN) were used in [13,17] as feedback adaptive filters to cope with nonlinear systems. Adaptive bilinear filter [18,35] and adaptive recursive second-order Volterra (RSOV) filter [19] have been introduced for active control of nonlinear noise processes. Moreover, multilayer neural networks [20] were also used to control nonlinear plants. One notable issue in the neural network (NN) based ANC is the lack of appropriate fast learning algorithm and the rigorous proof of closed-loop stability.

Historically, the least mean square (LMS) algorithm has been used for ANC systems [21–24] due to their simplicity in the design and implementation. However, the convergence rate of conventional FxLMS algorithms may be unsatisfactory because the adopted constant learning gains (or step-size) may not be able to handle the wider operation regimes. To improve the convergence speed, several modifications have been introduced in [25–28]. The adjustment of the step-size parameter in [25] is implemented by minimizing the square of the control error. The simplicity of this algorithm allows us to implement it in practical ANC systems. However, the convergence of the time-varying step-size (VSS) parameter was not studied, and specific bounds of those learning gains should be selected in a priori manner to avoid the windup of the step-size, in particular when there are measurement noise. Thus, an extra time average of the error variables was further incorporated in [26] to retain its performance in the presence of measurement noise. In the recent work [27,28], novel leakage terms have been imposed on the gradient-based algorithms to update the step-size parameters [27] and to adjust the tap length [28]. Although better performance can be obtained in comparison to [25], the increased computational costs and more stringent assumptions (e.g. independence condition) are required. Nevertheless, only linear feedforward ANC systems are studied via the FxLMS algorithm.

Based on the above observations, this paper presents a nonlinear neural network NN filter for ANC feedback systems, where an improved LMS algorithm with time-varying learning gains (or step-size parameter) is proposed to eliminate noise passing through the nonlinear path. This scheme can ensure the reliability and reduce the complexity of nonlinear feedback ANC systems. To online determine the NN weights with fast convergence, we suggest a new variable step-size least mean square (VSS-LMS) algorithm for online tuning the step-size, where the idea initially proposed in [25] is modified to update the NN weights. The convergence of these step-size parameters are proved, where the Lyapunov function is used. In this sense, this paper introduces a new theoretical framework to prove the closed-loop stability and the convergence of the suggested adaptive laws without using the maximum and minimum bounds [26]. Finally, extensive comparisons and simulations are investigated to validate the suggested algorithms in terms of the computational complexity and the control performance.

This paper is organized as follows. Section 2 introduces the basis of FANC system, and the design of nonlinear FANC using a new VSS-LMS algorithm. In Section 3, appropriate comparisons to available results are studied to address the computational complexities. Simulations are shown in Section 4 and conclusions are summarized in Section 5.

2. Adaptive neural network feedback ANC system

2.1. Basis of feedback ANC system

The schematic of a feedback ANC system with adaptive control is presented in Fig. 1 [29,30], where $d(n)$ is the noise generated by the noise source $s(n)$ and propagated through the primary path $P(z)$, which should be eliminated. The filter $W(z)$ is used as the controller that generates the driving signal for the secondary noise source $y(n)$ propagating through the secondary path $S(z)$ to provide the canceling signal $v(n)$ in the control noise area. A microphone is placed in this region to measure the residual noise $e(n)$. The control $W(z)$ is online updated adaptively such that the residual noise $e(n)$ can be minimized. To address this problem, the control parameters should be updated adaptively based on the reference $\widehat{d}(n)$ and the error $e(n)$ because the exact noise $d(n)$ cannot be measured.

In this system, the secondary path $S(z)$ includes the dynamics of the digital-analog converter, analog-digital converter, reconstruction filter, power amplifier, loudspeaker, error microphone, preamplifier, acoustic path from the loudspeaker to the summing junction and the acoustic path from the summing junction to the error microphone, etc. In this paper, we assume that the secondary path $S(z)$ is known. In fact, $S(z)$ can be modeled by using a FIR filter (or NN) $\widehat{S}(z)$, where its coefficients can be obtained in terms of off-line system identification methods. In particular, the modeling uncertainties will be addressed via the suggested nonlinear neural control.

For the purpose of control design, various control schemes can be adopted as $W(z)$, e.g. FIR filter. However, in those linear controls (e.g. FIR filter), the model uncertainties of $S(z)$ and the induced nonlinearities cannot be handled effectively. In this paper, a nonlinear control scheme with neural network will be introduced.

2.2. Feedback ANC system design with LMS algorithm

This subsection will first present the idea for incorporating neural network into the ANC synthesis, and specifically, the closed-loop stability will be proved. The idea for using neural network is mainly motivated by the fact that neural network can be used to approximate unknown nonlinear smooth functions [31,32]. The block diagram of the proposed nonlinear ANC system is shown in Fig. 2.

The major difference between Figs. 1 and 2 lies in that a neural network is used as the nonlinear control $W(z)$. From Fig. 2, the residual noise is given by

$$e(n) = d(n) - v(n) \tag{1}$$

with

$$v(n) = \sum_{j=0}^{J} s_j y(n-j) \tag{2}$$

$$\widehat{d}(n) = e(n) + \sum_{j=0}^{J} \widehat{s}_j y(n-j) \tag{3}$$

where s_j are the coefficients of the FIR filter $S(z)$, which define the dynamics of the secondary path dynamics, $\widehat{d}(n)$ is the reference signal serving as the input of ANC control, and $\widehat{s}_j$ is the estimation of s_j. Here, we assume $\widehat{s}_j = s_j$ because the model of the secondary path

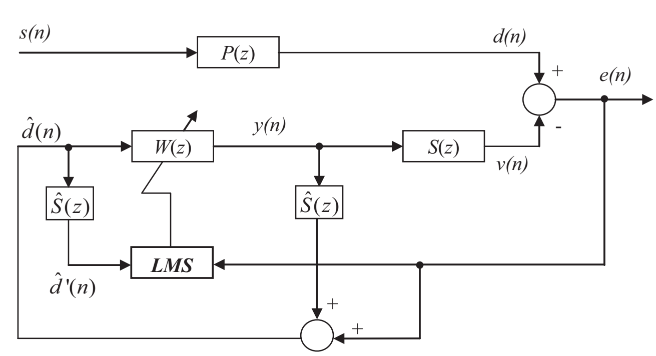

Fig. 1. Schematic of feedback ANC system.