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A new method for a nonlinear acoustic echo cancellation system

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Abstract - Acoustic echo cancellation (AEC) is a fundamental requirement of signal processing to increase the quality of teleconferences. AEC has been concerned since the 1950s in telecommunications and efficient solutions for linear echo cancellation had been devised. Teleconferencing systems employ FIR adaptive filter to echo cancellation. However, in this case the problem is difficult to solve because of nonlinear echo path. In this paper, we propose a new method for acoustic echo cancellation system which uses neural network combined with Laguerre filter model to reduce echo signal in nonlinear system. The results of simulations on Simulink will demonstrate the efficiency of the solution.

Key Words: *acoustic echo cancellation, AEC, neural network.*

1. INTRODUCTION

Sound is the object enriched, beautifully added to our lives. But people are harassed, etc., such as echoes. Echo cancellation is a matter of practical research today. There are two echo cancellation methods: echo cancellation using adaptive filtering and echo cancellation using neural networks. Within this paper, the author will introduce the advantages of echo cancellation using the neural network combined with the Laguerre model.

The rapid development of technology has changed the whole way in which people communicate. Today, people like to talk to each other over the phone without having to hold the phone in their hands. In those situations, you need to use a speaker and a microphone in place to receive calls. This will allow more people to be able to join the conversation at the same time as at a telephone conference [2, 5, 8, 15]. However, the sound coming from the speaker will reflect on the surface of the room, echoed and picked up by the microphone. As a result, the other line will hear its own sound, which is called echo.

An acoustic echo is a repetition of the same waveform or by reflection at perfect impedance coordinates. The echoes are born in places where the transmission medium is suddenly changed or because of the sound feedback between the loudspeaker and the microphone of a telecommunication system [4, 7, 10 12]. Elimination of sound echoes is a matter of practical importance, such as echo cancellation in conference rooms or handheld users, live video meetings, etc. There are two types of echoes in telecommunication networks: electromagnetic echoes and acoustic echoes. Electromagnetic echoes are caused by impedance mismatch at different points along the transmission channel. Echoes are generated at two-wire to four-wire connections in telecommunications systems [1, 3, 4, 7, 14]. Acoustic echoes are caused by reflections of sound waves (between speakers and microphones) in telephones and telecommunications systems [4, 6, 13, 18]. There are two groups of solutions to this problem, Echo Suppression and Echo Cancellation. This paper will focus on the study of adaptive filtering algorithms, Laguerre filter and neural network for echo cancellation to improve the quality of the conversation.

This paper presents an AEC system by using neural network structure. A new method for a nonlinear acoustic echo cancellation system using artificial neural network combined with Laguerre filter model is proposed, where the model of neural network is simplified to meet the characteristic of an AEC system. The remainder of the paper is organized as follows. Section 2 describes the AEC system and proposes a new method for AEC system. In section 3, the results of the proposed AEC system are presented. The conclusions of the work as well as suggestions for further research are given in section 4.

2. METHODOLOGY

Adaptive filter

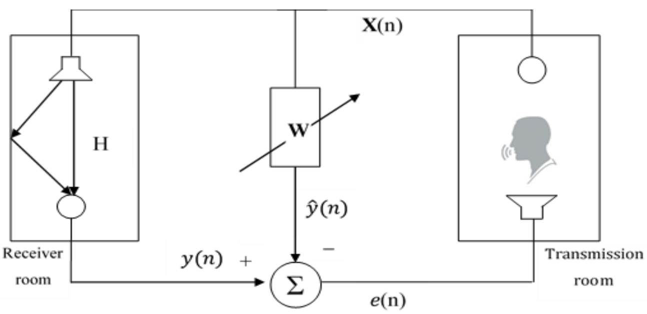

Figure 1. Diagram of AEC system

The common method for echo cancellation is using an adaptive filter. The adaptive filter algorithm adjusts the parameters of the filter to minimize the error between *y(n)* and $\hat{y}(n)$ echo signals. Figure 1 shows a block diagram of a single channel echo cancellation system. In that, *H(n)* is the impulse response of the sound environment, *W(n)* are coefficients of FIR filter. The goal is to make the estimated echo signal $\hat{y}(n)$ equal to the primary echo *y(n)*. At each loop, the error signal *e(n)* is feedback on the filter so that the filter has the information and adjusts the output [6, 7, 11].

As shown in figure 1, the estimated echo signal is

$$\hat{y}(n) = \sum_{m=0}^{L-1} w_m(n)x(n-m) = \boldsymbol{W}^T(n)\boldsymbol{X}(n) \quad (1)$$

and error signal

$$e(n) = y(n) - \boldsymbol{W}^T(n)\boldsymbol{X}(n) \quad (2)$$

where

$$\boldsymbol{W}(n) = [w_0(n)\ w_1(n) \ldots\ w_{L-1}(n)]^T \quad (3)$$

$$\boldsymbol{X}(n) = [x(n)\ x(n-1) \ldots\ x(n-L+1)]^T \quad (4)$$

where L is order filter.

Laguerre filter

The Laguerre filter algorithm can be created by replacing the delay time in the FIR filter with phase filters (figure 2) with the $H_{AP}(a, z)$ transfer function and add the low pass filter $H_{LPF}(a, z)$ at the input [16, 18, 19].

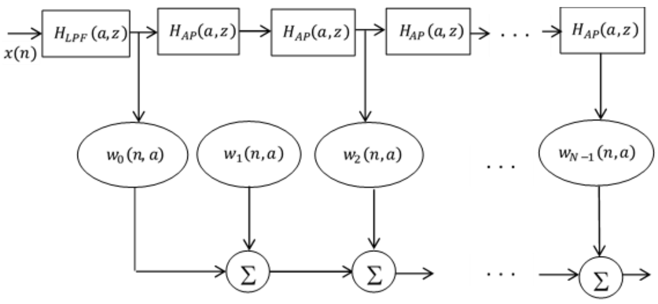

Figure 2. Diagram of Laguerre filter model

$$H_{AP}(a, z) = \frac{z^{-1}-a}{1-az^{-1}} \quad (5)$$

$$H_{LPF}(a, z) = \frac{\sqrt{1-a^2}}{1-az^{-1}} \quad (6)$$

For each value of a, the coefficient of the filter is calculated so that $\hat{y}(n)$ is the best. The Laguerre filter is stable when and only when $|a| < 1$. If $a = 0$, the Laguerre filter degenerates into a familiar horizontal filter. Based on the steepest-descent method, to minimize the output instantaneous error of a filter, we have a retrieval equation for calculating the filter coefficients:

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + 2\mu e(n)\boldsymbol{X}(n) \quad (7)$$

The output signal of the filter is calculated using the coefficient vector from the previous loop and the current input vector

$$\hat{y}_n(n, a) = \boldsymbol{W}^T(n, a)\boldsymbol{X}(n, a) \quad (8)$$

The estimated error value e (n) is the difference between the echo value y (n) and the estimate echo y (n):

$$e(n) = y(n) - \hat{y}(n) \quad (9)$$

This method has some complex drawbacks and it is difficult to perform with a nonlinear environment.

Artificial Neural Network (ANN)

Artificial neural network is the simplest reproduction of biological neurons. Each artificial neuron is created that will synthesize the input information and convert it to output. The general structure of an ANN consists of three components: the input layer, the hidden layer, and the output layer. Each artificial neuron produces an output value, and the output value depends on the transfer function. The hidden layer consists of neurons that receive input data from neurons in the previous layer. In an ANN there can be many hidden classes.

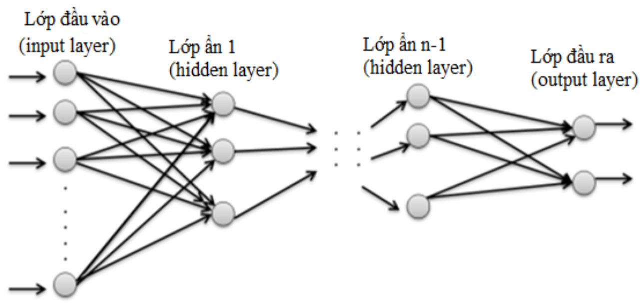

Figure 3. Multi-layered neural network model

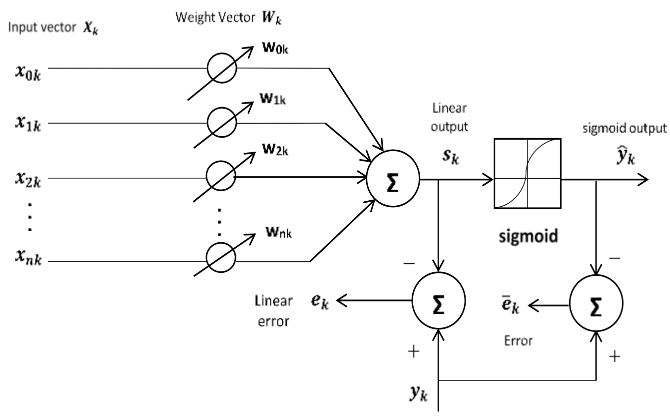

Figure 4. The ANN with sigmoid nonlinear function

The most common methods for reducing mean square error (MSE) is based on the steepest descent approach. The adaptation of an ANN using the fastest descent method starts with an arbitrary value W (weighted system vector). The slope of the MSE function is calculated and the weight vector is adjusted for the value of the gradient function.

This procedure is repeated which causes the MSE to continuously decrease and the weight vector approaches an optimal value.

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + \mu(-\nabla_K) \quad (10)$$

where μ is the control parameter for stability and convergence rate, and ∇ is the value of the gradient at a point on the MSE surface corresponding to $\boldsymbol{W} = \boldsymbol{W}_k$. These rules are then generalized to apply to neural networks.

Figure 4 shows the ANN associated with the sigmoid nonlinear function. The input and output relations of the sigmoid function are represented by $\hat{y}_k = sgm(s_k)$. The sigmoid function is hyperbolic tangent:

$$\hat{y}_k = \tanh(s_k) = \frac{1-e^{-2s_k}}{1+e^{-2s_k}} \quad (11)$$

The weights of ANN are adjusted to minimize the mean error $\bar{e}_k$, which is defined as:

$$\bar{e}_k = y_k - \hat{y}_k = y_k - sgm(s_k) \quad (12)$$

This goal is achieved by selecting the appropriate weight vector. Then we will set up the back propagation algorithm for ANN. Instantaneous gradients are obtained with each input vector, and use the steepest descent method to minimize error.

In figure 4, the estimated instantaneous gradient value obtained from the input vector $\boldsymbol{X}_k$ is given by:

$$\nabla_k = \frac{\partial(\bar{e}_k)^2}{\partial \boldsymbol{W}_k} = 2\bar{e}_k \frac{\partial \bar{e}_k}{\partial \boldsymbol{W}_k} \quad (13)$$

where

$$\frac{\partial \bar{e}_k}{\partial \boldsymbol{W}_k} = -\frac{\partial sgm(s_k)}{\partial \boldsymbol{W}_k} = -sgm'(s_k)\frac{\partial s_k}{\partial \boldsymbol{W}_k} \quad (14)$$

and $s_k = \boldsymbol{X}_k^T . \boldsymbol{W}_k$

From (13) and (14), we obtain

$$\nabla_k = -2\bar{e}_k . sgm(s_k)\boldsymbol{X}_k$$

Based on the steepest descent method to minimize error after the sum of s_k through the nonlinear sigmoid function. The algorithm is as follows:

$$W_{k+1} = \boldsymbol{W}_k + \mu(-\nabla_k) = \boldsymbol{W}_k + 2\mu\bar{e}_k . sgm'(s_k). \boldsymbol{X}_k \quad (15)$$

If the sigmoid function is chosen as a hyperbolic tangent function (11), the derivative $sgm'(s_k)$ is given by:

$$sgm'(s_k) = \frac{\partial(\tanh(s_k))}{\partial s_k} = 1 - (\tanh(s_k))^2 = 1 - y_k^2 \quad (16)$$

Accordingly, equation (15) becomes:

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + 2\mu\bar{e}_k(1-y_k^2)\boldsymbol{X}_k \quad (17)$$

Artificial Neural Network using nonlinear function

In this section, we propose an acoustic echo cancellation system using ANN combined with Laguerre filter for echo cancellation in nonlinear acoustic environment. To simulate a nonlinear acoustic environment, we use the function: $atan(10^*\mu)/5$ and it is designed as figure 5.

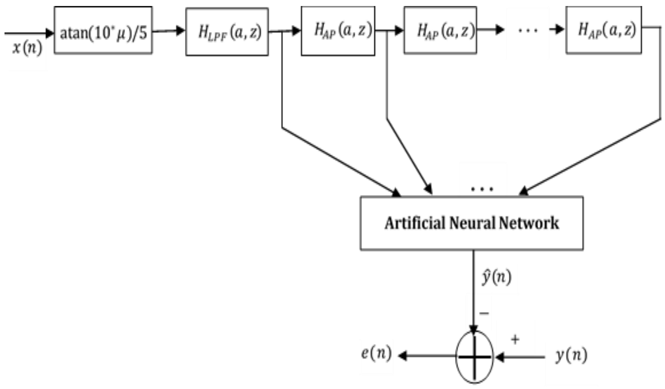

Figure 5. The proposed AEC system using ANN combined with Laguerre filter

3. EXPERIMENTAL RESULTS

In this section, we present the results of AEC systems in a linear and nonlinear acoustic environment. Based on RLS (Recursive least squares) algorithm to update the coefficients or weights of adaptive filter, Laguerre filter and neural network combined with Laguerre filter algorithms. In this experiment, noise sources include music signals (eg any song) were applied to excite the receiver room. Sampling frequency of 8000 Hz was used throughout the experiment, the learning rate for W is chosen as $\eta = 1$. Results of AEC systems are implemented on Simulink.

To evaluate the effectiveness of the AEC systems we use mean square error (MSE) and echo return loss enhancement (ERLE) which respectively are defined as follows

$$MSE = \frac{1}{N}\sum[e(n)]^2 \quad (18)$$

$$ERLE = \frac{\sum[y(n)]^2}{\sum[e(n)]^2} \quad (19)$$

where *y(n)* is acoustic echo signal, *e(n)* is error signal, *N* is number of steps interaction.

Linear acoustic environment

The error signal corresponding to the AEC systems using the adaptive filter (RLS-F), Laguerre filter (RLS-L) and the three-layer ANN combined with the Laguerre filter (ALN-3) filters is shown in figure 6 and figure 7. When the AEC system is activated, mean square error of the residual echoes (error signal) is attenuated very fast respectively. This demonstrates that the AEC systems work effectively.

The results of figures 6 and 7 demonstrate that the ALN-3 algorithm has an MSE amplitude less than RLS-L and RLS-F algorithms, which suggests that the ALN-3 algorithm works very well in linear acoustic environment.

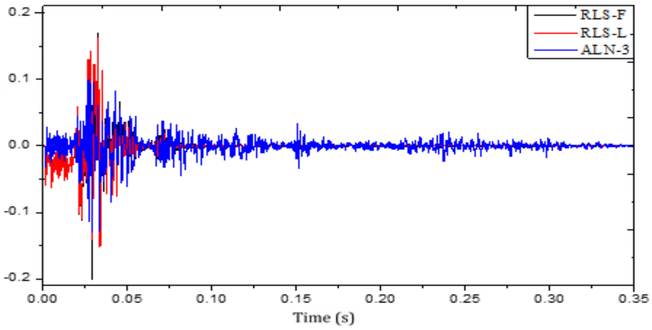

Figure 6. The error signal of the linear AEC systems

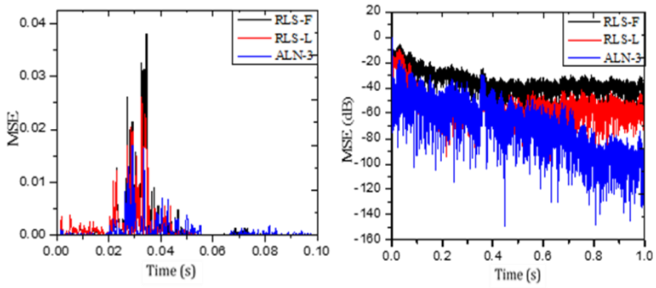

Figure 7. The MSE value of the linear AEC systems

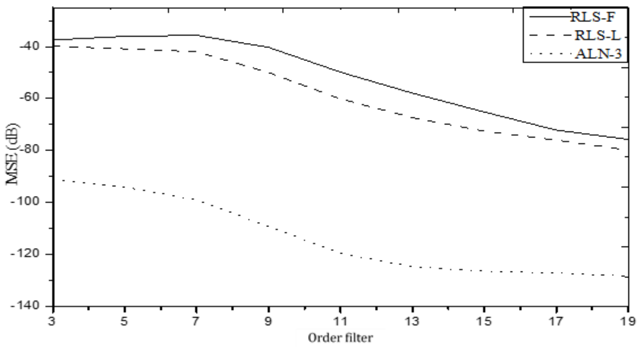

Figure 8. The MSE value varies with order filter of the linear AEC systems

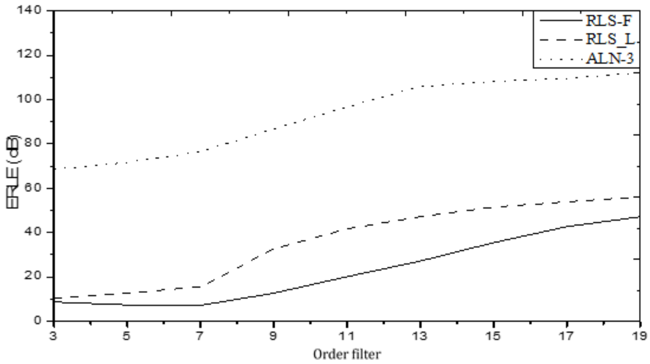

Figure 9. The ERLE value varies with order filter of the linear AEC systems

Based on the results of figure 8, we find that the MSE value decreases with order filter and the *ALN-3* algorithm has a smaller MSE value than the *RLS-L* and the *RLS-F* algorithm. And figure 9 shows that the ERLE value increases corresponding with order filter and the *ALN-3* algorithm has a larger ERLE value than the *RLS-F* and the *RLS-L* algorithm. The results show that the proposed AEC system using neural network combined with Laguerre filter worked effectively and stability in linear acoustic environment.

Nonlinear acoustic environment

To evaluate the proposed AEC system, we also implemented it in a nonlinear acoustic environment (figure 5). We make a comparison of the results of the adaptive filter, the Laguerre filter and the neural network combined with Laguerre filter algorithms. The results of figures 10 and 11 show that the proposed AEC system (ALN-3) algorithm also works very well in nonlinear acoustic environment.

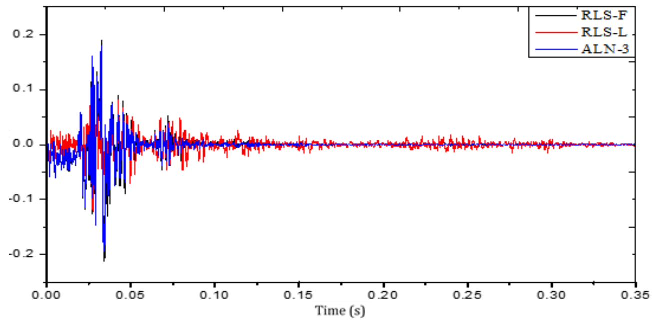

Figure 10. The error signal of the nonlinear AEC systems

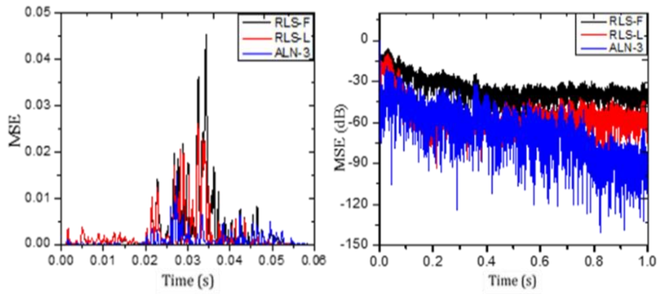

Figure 11. The MSE value of the nonlinear AEC systems

The curves of figure 12 and figure 13 also show, that the proposed AEC system using neural network combined with Laguerre filter worked effectively and stability in nonlinear acoustic environment. The results also show that in the nonlinear acoustic environment adaptive filtering and Laguerre filtering algorithms perform less efficiently in a linear acoustic environment. However, in the nonlinear acoustic environment the neural network combined with Laguerre filter algorithm performed better than itself in a linear acoustic environment. Therefore, the proposed AEC system will perform better in real situations.

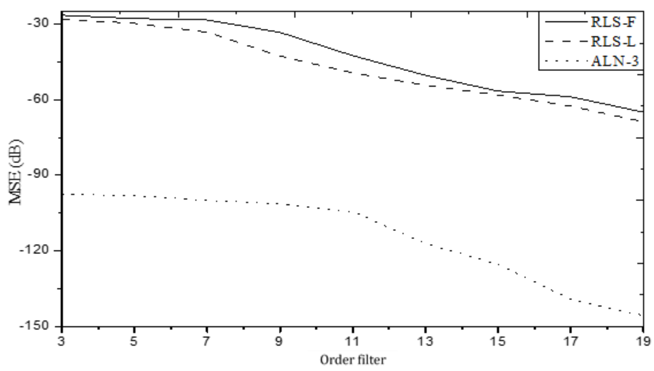

Figure 12. The MSE value varies with order filter of the nonlinear AEC systems

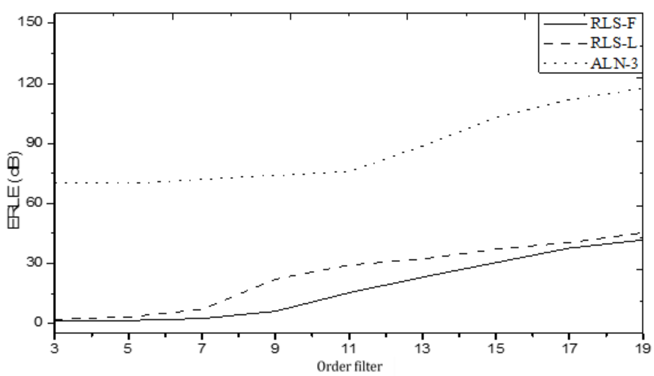

Figure 13. The ERLE value varies with order filter of the nonlinear AEC systems

Table 1. Comparing the complexity of algorithms

Methods	Order filter / Operation	3	11	19	General formula (N: order filter)
RLS-F	Add/ sub	27	363	1083	$3N^2$
	Multiplication	36	484	1444	$4N^2$
RLS-L	Add/ sub	32	384	1120	$3N^2 + 2N - 1$
	Multiplication	50	538	1538	$4N^2 + 5N - 1$
ALN-3	Add/ sub	53	189	325	$17N + 2$
	Multiplication	131	483	835	$44N - 1$

4. CONCLUSIONS

Based on the neural network technique and Laguerre filter algorithm, we develop a new ANC system with saturation compensation. The learning algorithm is carried out using the gradient steepest descent method.

The results are provided to illustrate the performance of the proposed AEC system in both the linear acoustic environment and the nonlinear acoustic environment cases.

The simulation results system show that the proposed AEC system operated effectively. We will continue to study other algorithms more optimally to improve the efficiency of acoustic echo cancellation algorithms.

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