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Acoustic echo cancellation system based on Laguerre method and neural network

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ABSTRACT

Acoustic echo cancellation (AEC) is a fundamental requirement of signal processing to increase the quality of teleconferences. In this paper, a system that combines the Laguerre method with neural networks is proposed for AEC. In particular, the signal is processed using the Laguerre method to effectively handle nonlinear transmission line system. The results after applying the Laguerre method are then fed into a neural network for training and acoustic echo cancellation. The proposed system is tested on both linear and nonlinear transmission lines. Simulation results show that combining the Laguerre method with neural networks is highly effective for AEC in both linear and nonlinear transmission lines system. The AEC results obtained by the proposed method achieves a significant improvement in nonlinear transmission lines and it is the basis for building a practical echo cancellation system.

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1. INTRODUCTION

Acoustic echo is a factor that affects the quality of conversation in meetings as well as teleconferences meetings with multiple participants. Acoustic echo increases when two people speak simultaneously or when the microphone is placed near the speaker. Therefore, acoustic echo cancellation (AEC) is an area that has been of interest and implementation by scientists for many years [1]–[4]. Various methods have been applied to eliminate acoustic echo, such as adaptive filtering, FIR filtering, and neural networks [5]–[8]. Among them, AEC techniques based on adaptive filtering can be mentioned, such as least mean square (LMS), normalized LMS (NLMS), block LMS (BLMS) [9]–[12]. In [13], Yue Song *et al.* proposed the nonparametric variable step-size subband (NPVSS-NSAF) method for AEC. The variable step-size parameter is determined based on minimizing the sum of the square Euclidean norm of the difference between weight vectors at the current and past times. Simulation results of the proposed method show good AEC performance and fast convergence.

However, due to the nonlinear transmission line system, the use of the filters for echo cancellation still has many limitations and low performance. Therefore, more advanced techniques have been employed for AEC. One of these techniques is the use of the Laguerre method. With the application of the Laguerre method, the effectiveness of AEC has been improved [14]–[16]. In [17], Huynh combined low-pass filtering and Laguerre transformation with artificial neural networks (ANN) for AEC. The proposed system utilized a multi-layer feedforward neural network, although the exact number of hidden layers and nodes in each layer was not explicitly mentioned. In addition, music signals sampled at a frequency of 8000 Hz were used to evaluate the system's performance in this case. The AEC results of the proposed system also achieved relatively good performance.

Nowadays, with the advancement of computer science and artificial neural networks, signal processing methods using neural networks have been applied in various fields such as healthcare, industry, robotics, and education [18]–[22]. Among them, AEC using neural networks has also been employed and has achieved certain results. In practies, Seo *et al.* [23] utilized deep learning networks to eliminate acoustic echo and background noise. The proposed network architecture consisted of 6,682 nodes in the input layer, with 3 hidden layers, each hidden layer containing of 1024 nodes using sigmoid activation functions, and the output layer also utilized sigmoid activation functions with a total of 512 nodes. The training epoch was set to 50, and the initial learning rate was 10^{-5}, which decayed by 10% after epoch 20. The proposed system was evaluated based on the TIMIT database and achieved good results.

In this paper, we propose an end-to-end framework based on the Laguerre method combined with neural networks for the AEC. The signal received from the source contains echo components, which are processed using the Laguerre method. The results obtained from the Laguerre method are then fed into a neural network for training and restoring the audio signal without echo. The proposed method has the advantage of effectively canceling acoustic echo on both linear and nonlinear transmission lines system. Furthermore, the proposed method demonstrates the advantage of achieving high AEC performance with a low number of neural network inputs. The results show that the proposed method yield more excellence than other related algorithms for the AEC in the nonlinear transmission lines. The remaind of this paper is organized as follows: Section 2 describes the proposed and method for the AEC. Section 3 shows the experimental results and discussion in detail and section 4 presents some conclusions.

2. METHOD

In this section, the proposed method for the AEC is presented. In addition, the theory related to the AEC is briefly described. The detail is presented as below.

2.1. Proposed method

The AEC is a research area of great interest to scientists worldwide, in which many signal processing methods are applied and developed for the AEC. In this paper, we propose an AEC system as in Figure 1. In practice, the system consists of a preprocessing block to handle audio signals containing acoustic echo components, and the processed signals are then fed into a neural network for training and cancelling acoustic echo components to obtain the cleanest audio signal. To compare the effectiveness of the preprocessing method when combined with the adaptive filter and neural network for AEC, methods including FIR filtering and Laguerre method are utilized. The preprocessed signals are then fed into a multi-layer feedforward neural network to cancelling acoustic echo components. The AEC proposed method is also evaluated in both linear and nonlinear transmission lines system.

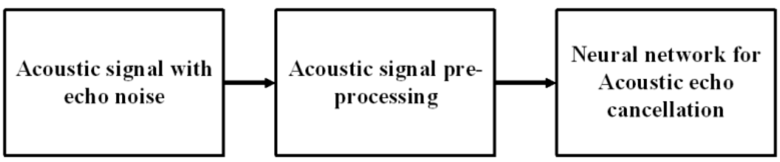

Figure 1. Proposed system for acoustic echo cancellation system

2.2. Acoustic echo cancellation principle

The block diagram of the AEC principal system is described as in Figure 2 [24]. Here, the audio signal source is denoted as $s[n]$, the impulse responses from the transmitter room to the microphone at the receiver room are $g_1[n]$ and $g_2[n]$. The impulse responses from the speaker to the microphone at the receiver room are $h_1[n]$ and $h_2[n]$. The impulse response of the adaptive filter is $\hat{h}_1[n]$ and $\hat{h}_2[n]$ (used for the AEC at the receiver room). The AEC principal system at the receiver room is described below. The output signal containing the acoustic echo $\hat{y}[n]$ is calculated as follows,

$$\hat{y}[n] = \hat{h}_1[n] * x_1[n] + \hat{h}_2[n] * x_2[n] \tag{1}$$

If $\hat{h}_1[n] = h_1[n]$ and $\hat{h}_2[n] = h_2[n]$, we have,

$$\hat{y}[n] = h_1[n] * x_1[n] + h_2[n] * x_2[n] = y[n] \quad (2)$$

In which, $y[n]$ is the output signal at the speaker without containing the acoustic echo. It is obvious that the signal transmitted from the transmitter room to the receiver room is suppressed by the subtraction filter and does not transmit back to the transmitter room. Therefore, the acoustic echo components are cancelled. The difference between the actual output signal and the output signal after processing is expressed as follows,

$$e[n] = y[n] - \hat{y}[n] = 0 \quad (3)$$

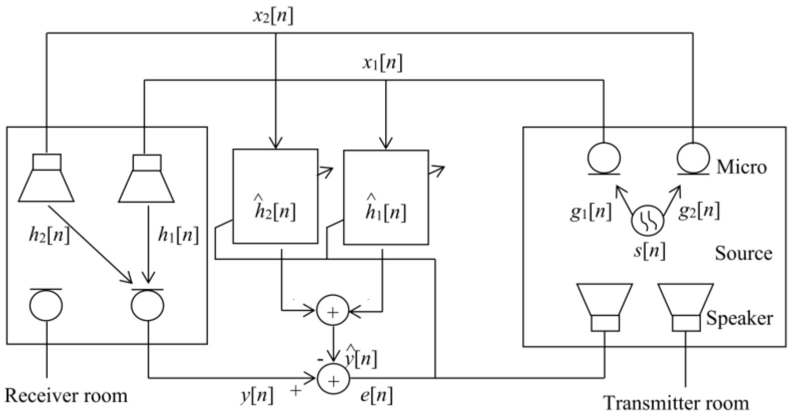

Figure 2. Principle diagram of the acoustic echo cancellation system

In practice, the impulse responses $h_1[n]$ and $h_2[n]$ may change over time. To adapt to these changes, we can utilize adaptive filtering: using a signal $e[n]$ to adjust the impulse responses $\hat{h}_1[n]$ and $\hat{h}_2[n]$ of the filter such that $e[n]$ is minimized. In addition, neural networks can be employed to train and compute the output in order to cancel the acoustic echo components.

2.3. Signal preprocessing method for AEC

To compare the performance of different processing methods for the AEC, we utilize various preprocessing techniques including the FIR filters, the Laguerre method in both time domain and frequency domain. Furthermore, adaptive filtering and neural network-based methods are employed for the AEC. In particular, when using the FIR filter method, the audio signal containing speech components is filtered using FIR filters, and the output of the FIR filters is then fed into a neural network to suppress speech components as shown in Figure 3.

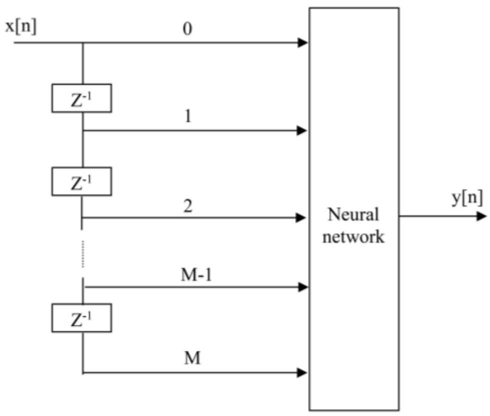

Figure 3. The AEC combines FIR filter and neural network

The main drawback of the FIR model is the need to use a neural network with a large number of parameters. To reduce the number of parameters in the neural network, we can use the Laguerre method as shown in Figure 4. The Laguerre method for the AEC is presented below [25].

$$y[n] = \sum_{k=1}^{P} g_k \, v_k[n] \tag{4}$$

In which, $v_k[n]$ is the output signal of the linear system. In addition, the impulse response of the Laguerre method shoul be calculated. Therefore, the impulse response of the Laguerre method is described as follows,

$$G[z] = \sum_{k=1}^{P} \frac{g_k}{z-\mathrm{a}} \left(\frac{1-\mathrm{a}z}{z-\mathrm{a}}\right)^{k-1} \tag{5}$$

The prominent advantage of the Laguerre method is that it addresses the drawback of the FIR model while retaining the advantages of the FIR model. We observe that $a, (-1 < a < 1)$ is a pre-selected coefficient close to the dominant pole of the impulse response of the linear system, and this effectively overcomes the drawback of the FIR model.

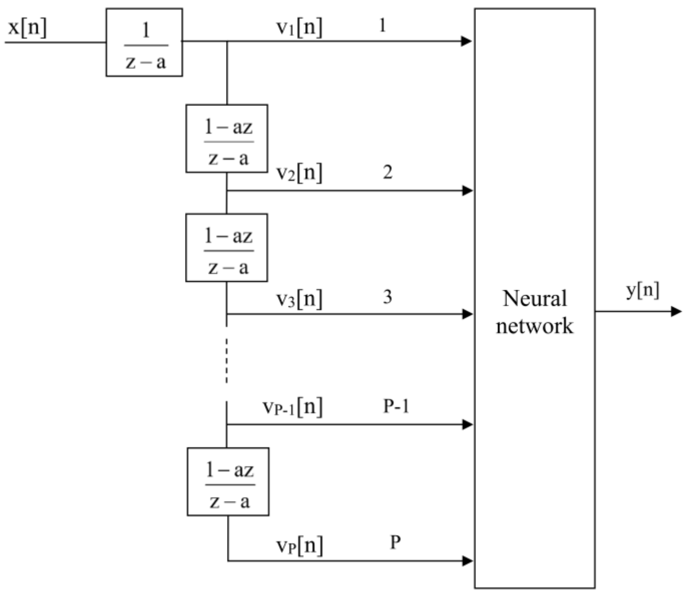

Figure 4. The AEC combines Laguerre method and neural network

The signal $X[k]$ represents the Discrete Fourier Transform (DFT) of the signal $x[n]$, where $(k = 0, 1, 2, \ldots, L-1)$. In this context, the signal $X[k]$ was passed through an FIR model to generate a signal $Y[k]$, and the signal $y[n]$ is obtained by using the inverse discrete fourier transform (IDFT) of the signal $Y[k]$. The AEC method in the frequency domain is show in Figure 5.

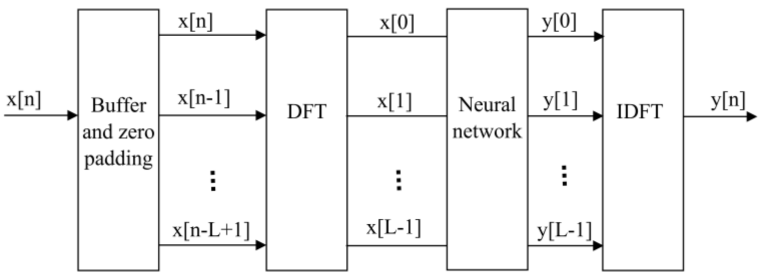

Figure 5. The AEC model in the frequency domain

2.4. Neural network for the AEC

In this paper, a multi-layer feedforward neural network method is used for the AEC as described in Figure 6. In the proposed AEC system, we employ a three-layer feedforward neural network consisting of 1 input layer, 1 hidden layer, and 1 output layer. Specifically, the input layer has the same number of nodes as the output data points of the Laguerre or FIR method, the hidden layer comprises 10 nodes, and the output layer has 1 node corresponding to the output signal $y[n]$. In addition, the activation functions for the hidden layer and output layer are "tansig" and "purelin", respectively.

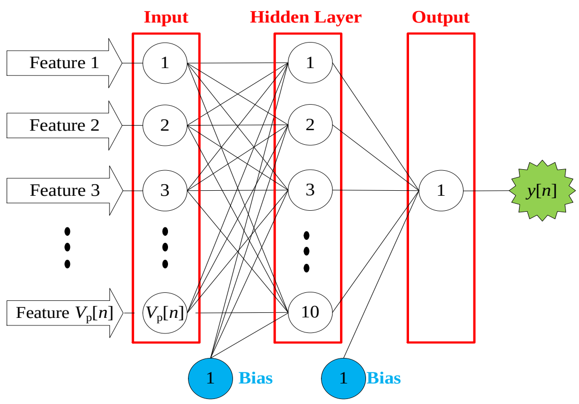

Figure 6. Multi-layer feedforward neural network for the AEC

2.5. Evaluation of the AEC performance

AEC performance evaluation methods should be used to evaluate the performance of the proposed of the AEC system. In practice, to evaluate the performance of the AEC, the error evaluates $e[n]$ is often used. The AEC performance methods based on $e[n]$ are mean square error (MSE) and echo return loss enhancement (ERLE). The increase of ERLE is determined according to the following formula [26],

$$ELRE(dB) = 10\log_{10}\frac{\sum_{i=1}^{n} y_i(k)^2}{\sum_{i=1}^{n} e_i(k)^2} \tag{6}$$

3. RESULTS AND DISCUSSION

The results of the AEC system are performed in both the time domain and frequency domain. Dealing with nonlinear transmission lines systems, we often meet more challenges in the AEC system. Therefore, we evaluate the effectiveness of the proposed AEC system for nonlinear transmission lines systems. In this paper, the proposed AEC system is tested using the recovered speech signal as presented in Figure 7.

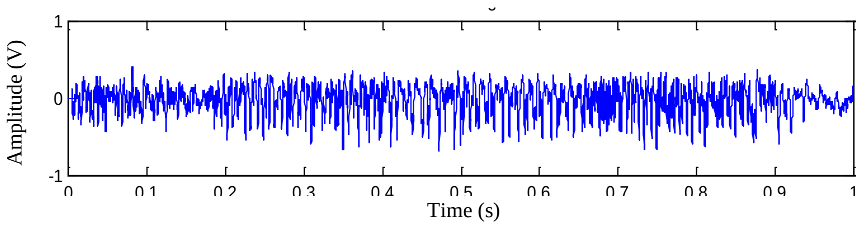

Figure 7. The returned signal is used for simulation in the system

The results of the AEC system in the time domain using adaptive filtering based on the FIR method and using the Laguerre method are presented in Figure 8. In which, Figure 8(a) shows the waveform of the error signal when using adaptive filtering based on FIR method, and Figure 8(b) shows the waveform of the error signal when using adaptive filtering based on the Laguerre method. It is evident that the performs of the AEC system based on the Laguerre method is better than that FIR method.

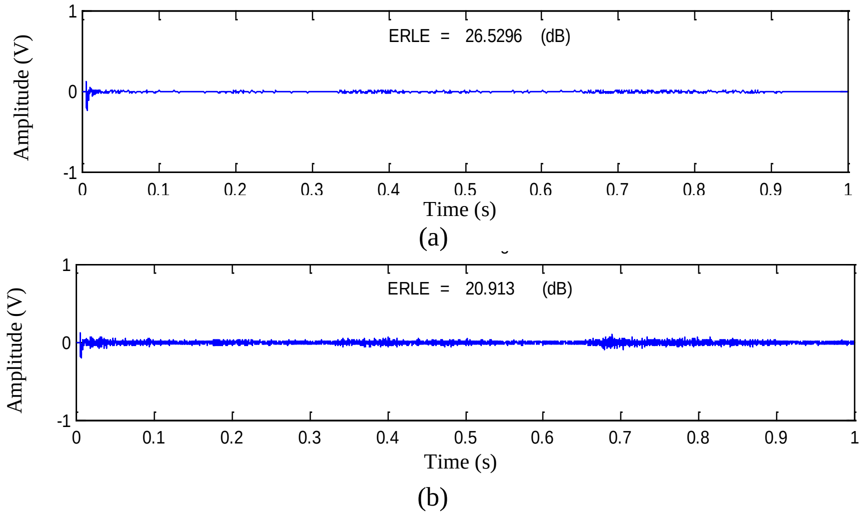

Figure 8. The AEC results are based on the adaptive filter, (a) Is the waveform of the error signal when using the FIR method and (b) Is the waveform of the error signal when using the Laguerre method

In order to improve the effectiveness of the AEC system, a multi-layer feedforward neural network is also used to eliminate acoustic echo. In this paper, the multi-layer feedforward neural network is trained with a number of epochs of 100 and the goal of neural network is set at 0.0001. The results of the AEC using the neural network are presented in Figure 9. In particular, Figure 9(a) and Figure 9(b) present the waveform of the error signal when using the FIR and Laguerre methods, respectively. Tuan Van Huynh used a artificial neural network (ANN) with activation function of *atan* for the AEC [17]. However, this research is not mention about the number of epochs and goal value.

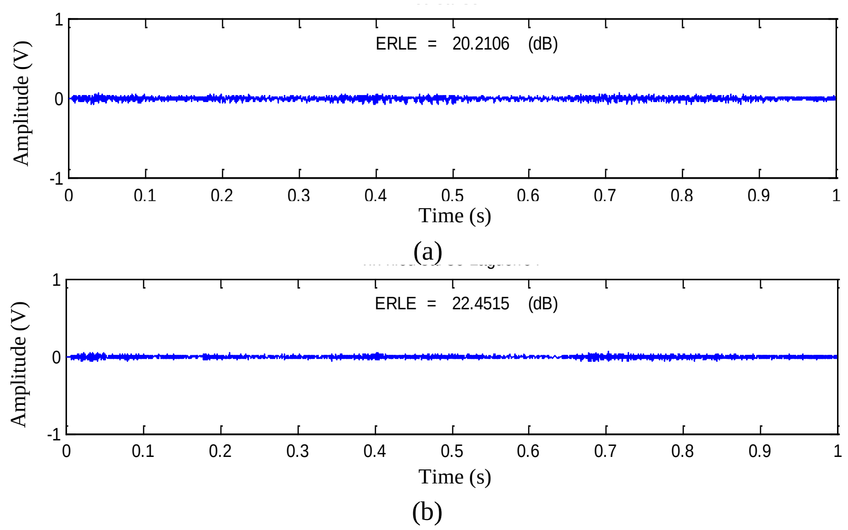

Figure 9. The AEC results based on neural network, (a) is the error signal when combined with the FIR method and (b) is the error signal when combined with the Laguerre method

The proposed AEC system is also evaluated in the frequency domain. Figure 10 presents the results of acoustic echo cancellation for a transmission lines system in the frequency domain. Figure 10(a) and Figure 10(b) display the waveform of the error signal when using the adaptive filter method and the neural network method, respectively. Based on the waveform, we observe that the neural network method outperforms the adaptive filtering method in the AEC system in the frequency domain.

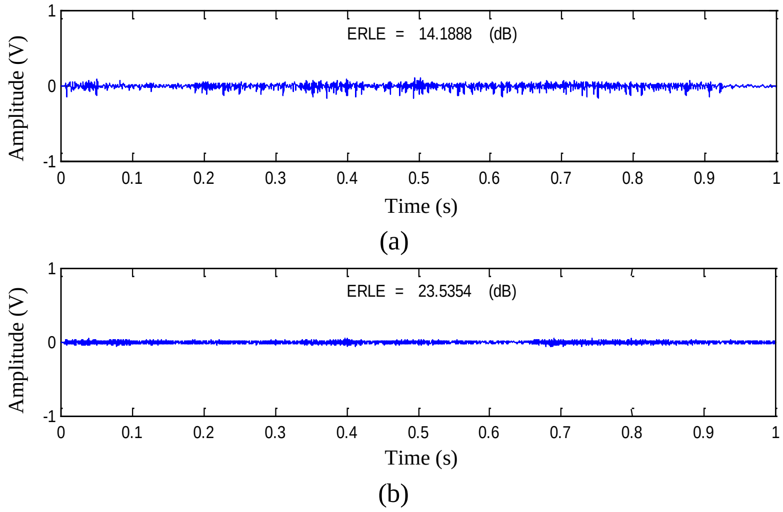

Figure 10. The AEC results based on neural network method in the frequency domain, (a) is the error signal when combined with the FIR method and (b) is the error signal when combined with the Laguerre method

To demonstrate the effectiveness of the proposed AEC method, we also evaluate the performance in the case of the nonlinear transmission lines system. Figure 11 shows the AEC results for the nonlinear transmission lines system. In particular, Figure 11(a) presents the waveform of the error signal when using the FIR method and Figure 11(b) presents the waveform of the error signal when using the Laguerre method.

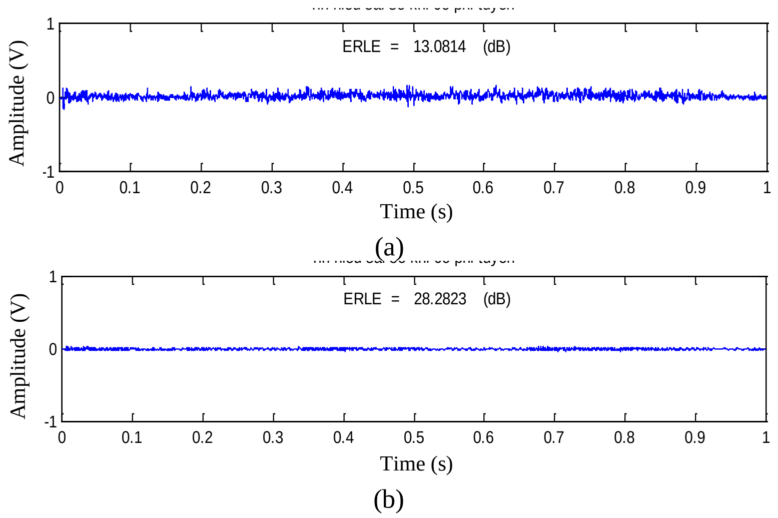

Figure 11. The AEC results based on neural network for the nonlinear transmission lines system, (a) is the error signal when combined with the FIR method and (b) is the error signal when combined with the Laguerre method

The ERLE value is also calculated to better evaluate the proposed AEC system. In practice, Table 1 and Table 2 present the ERLE value in the case of removing acoustic echo in the time domain and frequency domain. In particular, Table 1 presents the ERLE value in the case of using a combination of FIR and Laguerre methods with adaptive filtering and neural networks, respectively. It is clear that, for the linear system, using the combination of FIR method and adaptive filter gives the highest ERLE result of 26.53 dB. However, when used in combination with neural networks, the Laguerre method is better than the FIR method. Furthermore, when removing acoustic echo in the spatial domain, the neural network method is better than adaptive filter.

Table 3 presents the ERLE values for the AEC system in the nonlinear transmission lines system. For the nonlinear transmission lines system, the ERLE results indicate that using a neural network is better than using adaptive filtering.

Table 1. The comparition of ERLE value of the AEC system in time domain (unit in dB)

Method	Adaptive filter	Neural network
FIR	26.53	20.21
Laguerre	20.91	22.25

Table 2. The comparition of ERLE value of the AEC system in frequency domain (unit in dB)

Method	Adaptive filter	Neural network
Laguerre	14.19	23.54

Table 3. The comparition of ERLE value of the AEC for nonlinear transmission lines system (unit in dB)

Method	Adaptive filter	Neural network
Laguerre	13.08	28.28

From the simulation results, it is evident that the AEC system using adaptive filtering with FIR filter operates effectively in the linear transmission lines system. The AEC system using a neural network operates effectively in both linear and nonlinear transmission lines system. In addition, the AEC system using a neural network combined with the Laguerre model operates effectively even when the number of inputs to the neural network is small.

4. CONCLUSION

The methods of the acoustic echo cancellation including adaptive filter and neural networks have been investigated in this paper. Furthermore, the FIR and Laguerre methods have been applied for the AEC system. The waveform of the error signal and the ERLE value have been used to evaluate the performance of the proposed AEC methods. Based on the simulation results, it is evident that the Laguerre method outperforms the FIR method in the AEC. Moreover, the performents of the AEC system using multi-layer feedforward neural network method is better than adaptive filter. It is apparent that the Laguerre method is suitable for nonlinear transmission lines compared to FIR method. Also, the neural network is better than the adaptive filter in term of the AEC. Therefore, the system combining the Laguerre method and multi-layer feedforward neural network as proposed achieves the best AEC performent for both linear and nonlinear transmission lines system. In the future work, the deep learning methods will continue to be researched and applied for the AEC to further improve its performance. In particular, a Long short-term memory network will be utilized for the AEC.

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