Artificial Neural Network Algorithm for Acoustic Echo Cancellation Applications

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Abstract - The problem of an acoustic echo cancellation (AEC) has attracted a considerable amount of research attention over the past several decades. An AEC system is a fundamental requirement of signal processing to increase the quality of teleconferences. The AEC system is typically intended for use in high quality teleconferencing systems and multi-participant desktop conferencing that implement sound transmission through two channels. Among the numerous techniques that were developed, the optimal adaptive filter can be considered as one of the most fundamental echo reduction approaches, which has been de-lineated in different forms and adopted in various applications. However, in this case the problem is difficult to solve because of nonlinear echo path. In this paper, we focus on an artificial neural network (ANN) algorithm for acoustic echo cancellation system which reduce echo signal in nonlinear system. The results of simulations on Simulink with acoustic echo sources will demonstrate the efficiency of the AEC systems.

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

1. INTRODUCTION

AEC has been an active research topic for more than four decades [1, 3, 4]. With the advent of digital computing and signal processing, the problem of AEC was clearly posed and thoroughly studied. Echo cancellation is a topic of practical research today. There are many algorithms for echo cancellation such as an adaptive filter, a Laguerre filter, and an artificial neural networks. Within this paper, the author will introduce the advantages of echo cancellation using an adaptive filter (with algorithms as least mean square - LMS, normalised least mean square - NLMS and recursive least square – RLS) and an artificial neural network techniques.

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, 6, 8]. 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. The echoes are born in places

where the transmission environment is suddenly changed or because of the sound feedback between the loudspeaker and the microphone of a telecommunication system [4, 7]. 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, 4]. Acoustic echoes are caused by reflections of sound waves (between speakers and microphones) in telephones and telecommunications systems [5, 8].

There are two groups of solutions to this problem, Echo Suppression and Echo Cancellation. Because of the high correlation between the two channel signals, rapidly converging ANN algorithms are required. In this work, we propose focus on the study of adaptive filtering and neural network algorithms 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 an artificial neural network combined with an adaptive 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 algorithms of AEC systems and proposes a method for an AEC using ANN. In section 3, the results of the AEC systems are presented. The conclusions of the work as well as suggestions for further research are given in section 4.

2. AEC SYSTEM ALGORITHMS

Normally, an adaptive filter is used in AEC systems. Stereophonic AEC can be viewed as a straightforward generalization of the single-channel acoustic echo cancellation principle. Schematic diagram of a two-channel echo cancellation system is described in figure 1. It shows this technique for one microphone in the receiving room (which is represented by the two echo paths, H_{11} and H_{12}, between the two loudspeakers and the microphone). The adaptive filter algorithm adjusts the parameters of the filter to minimize the error between $y_1(n)$ and $\hat{y}_1(n)$ echo signals (and $y_2(n)$ and $\hat{y}_2(n)$). In that, $H_{11}, H_{12}, H_{21}, H_{22}$ are

the impulse response of the sound environment; W_{11}, W_{12}, W_{21}, W_{22} are coefficients of the adaptive filter. The goal is to make the estimated echo signal $\hat{y}_1(n)$ and $\hat{y}_2(n)$ equal to the primary echo $y_1(n)$ and $y_2(n)$. At each loop, the error signal $e_1(n)$ and $e_2(n)$ are feedback on the adaptive filter so that the adaptive filter has an information and adjusts the output [6, 7]. The two reference signals, $X_1(n)$ and $X_2(n)$, from the transmission room are obtained by two microphones in the case of teleconferencing.
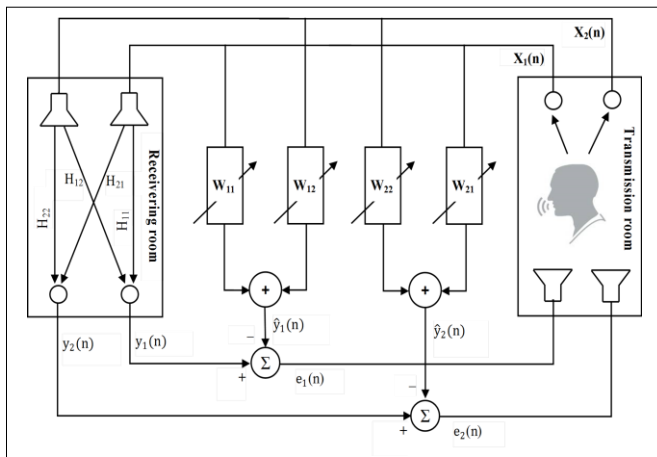
Figure 1. Schematic diagram of two-channel AEC system

In figure 1, the estimated echo signals are

$$\hat{y}_1(n) = \boldsymbol{W}_{11}^T(n)\boldsymbol{X}_1(n) + \boldsymbol{W}_{12}^T(n)\boldsymbol{X}_2(n) \qquad (1)$$

$$\hat{y}_2(n) = \boldsymbol{W}_{21}^T(n)\boldsymbol{X}_1(n) + \boldsymbol{W}_{22}^T(n)\boldsymbol{X}_2(n) \qquad (2)$$

and error signals as (3) and (4)

$$e_1(n) = y_1(n) - \hat{y}_1(n) \qquad (3)$$

$$e_2(n) = y_2(n) - \hat{y}_2(n) \qquad (4)$$

where

$$\boldsymbol{W}_{11}(n) = [w_{110}(n)w_{111}(n) \dots w_{11L-1}(n)]^T \qquad (5)$$

$$\boldsymbol{W}_{12}(n) = [w_{120}(n)w_{121}(n) \dots w_{12L-1}(n)]^T \qquad (6)$$

$$\boldsymbol{X}_1(n) = [x_1(n)x_1(n-1) \dots x_1(n-L+1)]^T \qquad (7)$$

$$\boldsymbol{X}_2(n) = [x_2(n)x_2(n-1) \dots x_2(n-L+1)]^T \qquad (8)$$

where L is order filter.

Error signals of filters are minimized by steepest-descent algorithms, general equation for calculating the adaptive filter coefficients as (9):

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + 2\mu e(n)\boldsymbol{X}(n) \qquad (9)$$

The output signal (estimated echo signals) of the adaptive filter is calculated using the coefficient vector from the previous loop and the current input vector,

$$\hat{y}_n(n,a) = \boldsymbol{W}^T(n,a)\boldsymbol{X}(n,a) \qquad (10)$$

The residual error signal $e(n)$ is the difference between the echo signal $y(n)$ and the estimate echo signal $\hat{y}(n)$:

$$e(n) = y(n) - \hat{y}(n) \qquad (11)$$

This method has some complex drawbacks and it is difficult to perform in case an AEC system with a nonlinear environment.

Artificial Neural Network (ANN)

In the past few years, neural networks have been widely accepted and applied successfully in a variety of fields, such as finance, health, geology, physics and information technology. Indeed, wherever there is a problem of prediction, classification and control, neural networks can be applied. Each artificial neuron is created that will synthesize the input information and transfer to output. The structure of an ANN (as figure 2) consists of three layers: input layer, hidden layers, and 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 layers.
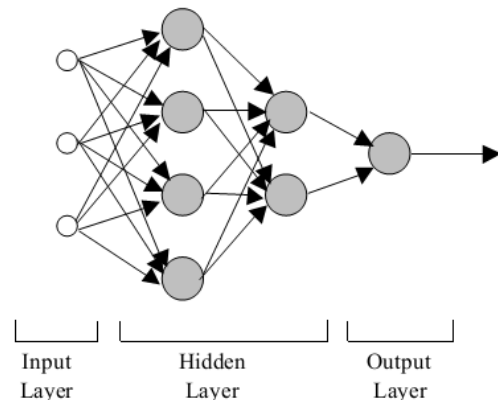

Figure 2. Multi-layered neural network model

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.

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + \mu(-\nabla_K) \qquad (12)$$

where μ is the parameter for stability and convergence rate, and ∇_K is the value of the gradient at a point on the MSE surface corresponding to $\boldsymbol{W} = \boldsymbol{W}_k$.
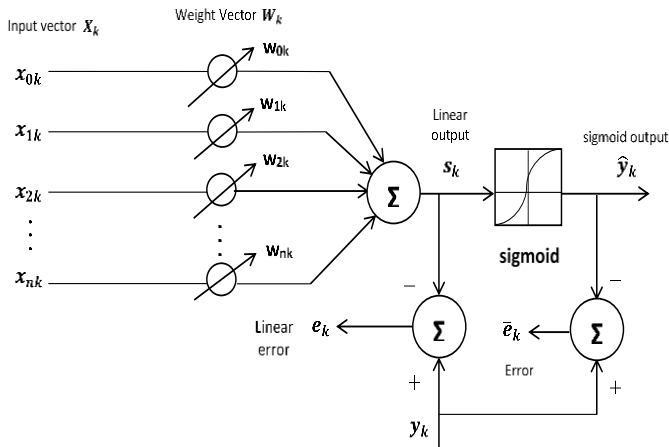
Figure 3. The ANN with sigmoid nonlinear function

Figure 3 shows the ANN using the sigmoid nonlinear function at output. The input and output relations of the sigmoid function are represented by $\hat{y}_k = sgm(s_k)$. The sigmoid function is hyperbolic tangent:

$$\hat{y}_k = \tanh(s_k) = \frac{1 - e^{-2s_k}}{1 + e^{-2s_k}} \qquad (13)$$

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

$$\bar{e}_k = y_k - \hat{y}_k = y_k - sgm(s_k) \qquad (14)$$

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 3, the estimated instantaneous gradient value obtained from the input vector X_k is given by:

$$\nabla_k = \frac{\partial (\bar{e}_k)^2}{\partial W_k} = 2\bar{e}_k \frac{\partial \bar{e}_k}{\partial W_k} \qquad (15)$$

where

$$\frac{\partial \bar{e}_k}{\partial W_k} = -\frac{\partial sgm(s_k)}{\partial W_k} = -sgm'(s_k)\frac{\partial s_k}{\partial W_k} \qquad (16)$$

and $\qquad\qquad s_k = X_k^T . W_k$

From (15) and (16), we obtain

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

Based on the steepest descent method to minimize error after the sum of s_k through the nonlinear sigmoid function.

$$W_{k+1} = W_k + \mu(-\nabla_k) = W_k + 2\mu\bar{e}_k . sgm'(s_k).X_k$$
$$(17)$$

If the sigmoid function is chosen as a hyperbolic tangent function (13), the derivative $sgm'(s_k)$ is given by:

$$sgm'(s_k) = \frac{\partial(\tanh(s_k))}{\partial s_k} = 1 - (\tanh(s_k))^2 = 1 - y_k^2 \quad (18)$$

Accordingly, equation (17) becomes:

$$W_{k+1} = W_k + 2\mu\bar{e}_k(1 - y_k^2)X_k \qquad (19)$$

Artificial Neural Network using nonlinear function

In this section, we propose an acoustic echo cancellation system using an ANN combined with the adaptive filters 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 4.
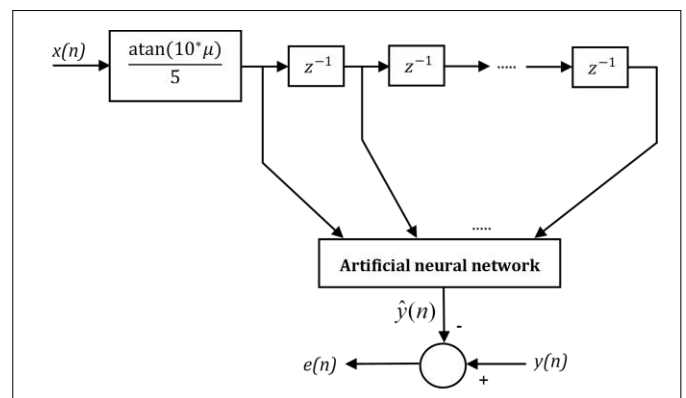

Figure 4. The proposed AEC system using an ANN

3. SIMULATION RESULTS

In simulation, we present the results of AEC systems in a linear and a nonlinear acoustic environment. Based on LMS, NLMS, RLS algorithms to update the coefficients or weights of the neural network combined with an adaptive filter and a Laguerre filter algorithms. In the experiment, echo acoustic sources include music signals are applied to excite the receivering room. Sampling frequency of 44100 Hz was used throughout the simulation. Results of AEC systems are implemented on simulink/matlab.

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

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

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

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

Linear acoustic environment

In figure 5 show the error signal corresponding to the AEC systems using the adaptive filter algorithms (LMS,

NLMS, RLS). And the error signal corresponding to the AEC systems using the three-layer ANN (AAN-3) combined with the adaptive filter (AFN) and AAN-3 combined with the Laguerre filter (ALN) are shown figure 6. When the AEC system is activated, mean square error of the residual echoes (error signal) is attenuated very fast respectively.

Based on the results of figure 5 and figure 6, the results demonstrate that the ALN algorithm has a MSE amplitude less than LMS, NLMS RLS and AFN algorithms, which suggests that the ALN algorithm works very well in linear acoustic environment. When order filter increase, we find that a MSE value of ALN algorithm decreases extremly fastly.
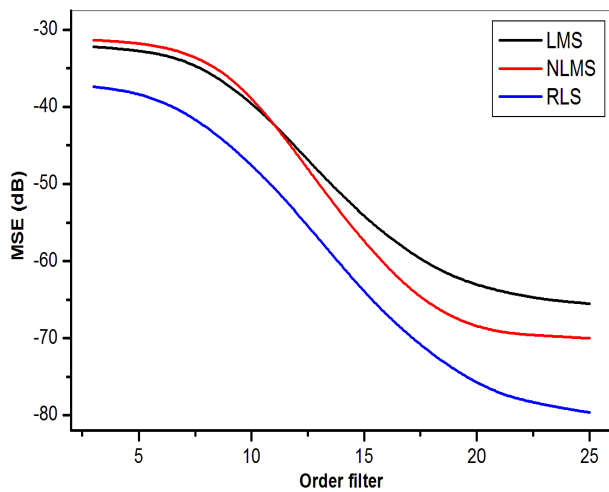
Figure 5. The MSE value varies with order filter of the linear AEC systems using adaptive filter algorithms
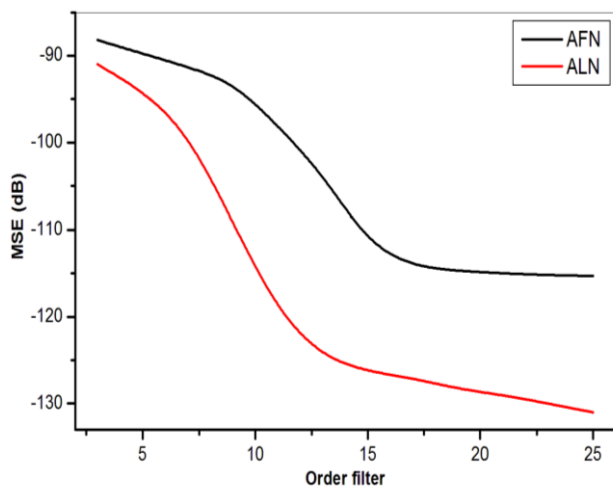

Figure 6. The MSE value varies with order filter of the linear AEC systems using AFN and ALN algorithms
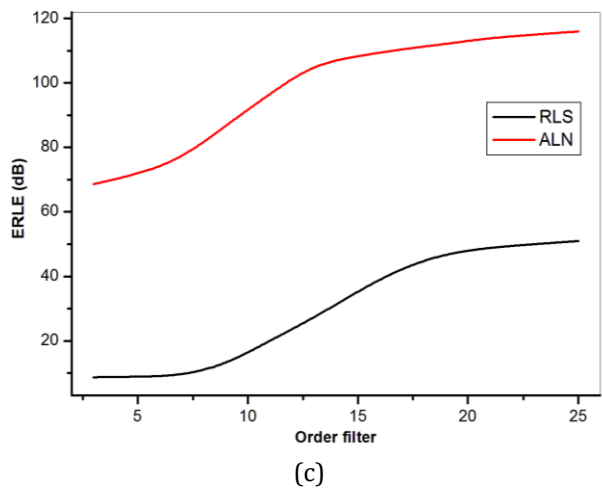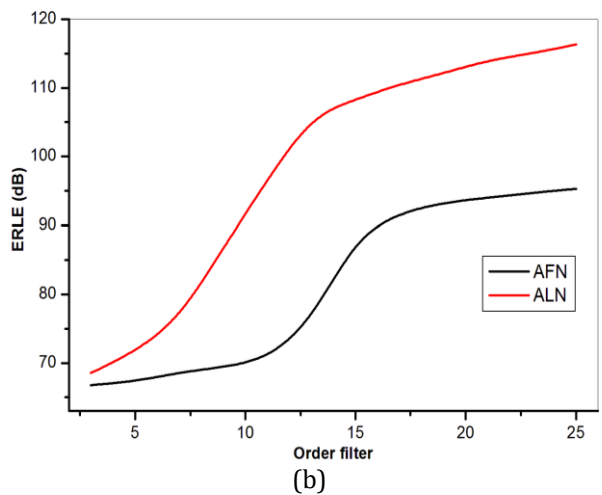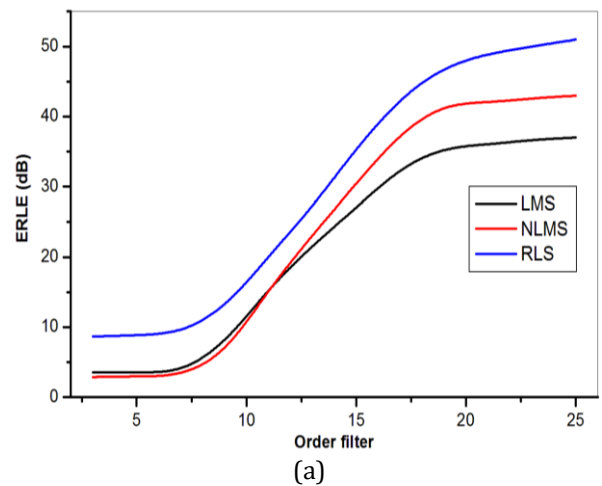

(a)

(b)

(c)

Figure 7. The ERLE value varies with order filter of the linear AEC systems: (a) AEC using LSM, NLSM, RLS algorithms; (b) AEC using AFN and ALN algorithms; (c) selected the best algorithm in (a) to compare with the best algorithm in (b).

And figure 7 shows that the ERLE value increases corresponding with order filter and the *ALN* algorithm has a larger ERLE value than the LMS, NLMS, *RLS* and the *AFN* algorithms. The results show that the proposed AEC
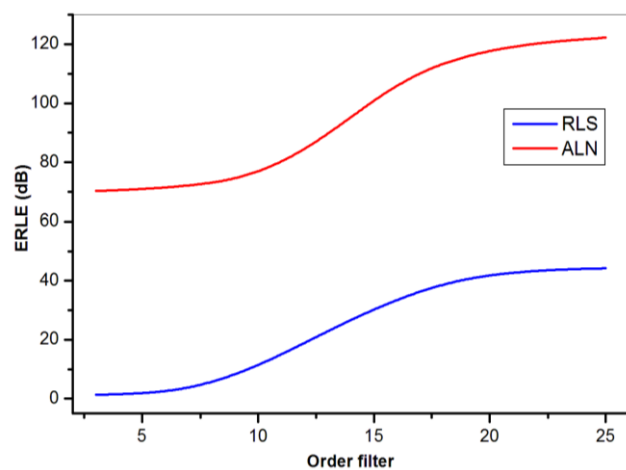
system using the neural network combined with the Laguerre filter (ALN) worked effectively and stability in linear acoustic environment.

Nonlinear acoustic environment

To evaluate the proposed AEC system, we also implemented it in a nonlinear acoustic environment (figure 4). We make a comparison of the results of the adaptive filter (RLS algorithm) and the neural network combined with a Laguerre filter (ALN) algorithms . The results of figure 8 shows that the proposed AEC system (ALN) algorithm also works very well in nonlinear acoustic environment.
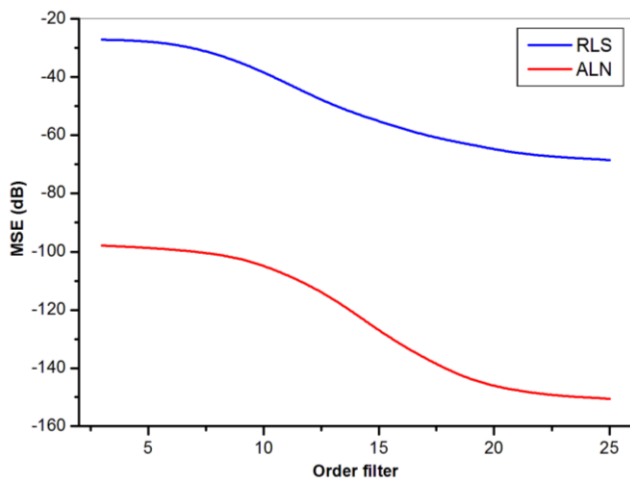
Figure 8. The MSE value varies with order filter of the nonlinear AEC systems

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

The curves of figure 9 shows that the proposed AEC system using the neural network combined with the Laguerre filter worked effectively in nonlinear acoustic environment. The results find that the adaptive filtering algorithm perform less efficiently in a linear acoustic environment. However, in the nonlinear acoustic environment the ALN algorithm performed better than

itself in a linear acoustic environment. Comparing the complexity of algorithms as table 1.

Table 1. Comparing the complexity of algorithms

Methods	Order filter / Operation	3	15	25	General formula (N: order filter)
RLS	Add/ sub	27	675	1875	$3N^2$
	Multiplication	36	900	2500	$4N^2$
ALN	Add/ sub	53	257	427	$17N + 2$
	Multiplication	131	659	1099	$44N - 1$

4. CONCLUSIONS

We have researched the AEC systems using the adaptive filter, the Laguerre filter and the artificial neural network techniques. The learning algorithms are carried out using the gradient steepest descent method. The results are provided to illustrate the performance of the proposed AEC systems in both the linear acoustic environment and the nonlinear acoustic environment cases.

The simulation results system show that the proposed AEC system operated effectively. Especially, the ALN algorithm is worked very well in the nonlinear acoustic environment. We will continue to study other algorithms more optimally to improve the efficiency of acoustic echo cancellation algorithms.

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