Acoustic Echo Canceller using Adaptive IIR Filters with Prewhitening Method and Variable Step-Size LMS Algorithm

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Abstract

The future teleconferencing systems will need an appropriate system which controls properly the acoustic echo for the convenient communication. The conventional acoustic echo cancellation algorithms involve large adaptive filters identifying the impulse response of the echo path. The use of adaptive IIR filters appears to be a reasonable way to reduce computational complexity.

Effective cancellation of acoustic echo presented in teleconferencing system requires that adaptive filters have a rapid convergence speed. One of the main problems of acoustic echo cancellation techniques is that the convergence properties degrade for an highly correlated signal input such as speech signals. By the way, the introduction of linear prediction filters onto the structure of the acoustic echo cancellation represents one approach to decorrelate the speech signal. And variable step-size LMS algorithm improves the convergence speed through a little increasing of computational complexity.

In this paper, we applied these two methods to the acoustic echo canceller(AEC) and showed that these methods have better performances than the conventional AEC.

Ⅰ. Introduction

Recently, with increasing demand and interest in teleconferencing, more ideal environment, that is, the system which can communicate well with the someone in a faraway place, as if they were in same place, is to be needed. In teleconferencing system, the received speech signal of the far-end talker can be heard to near-end talker through the speaker and this signal goes back through the microphone and communication channel and can be heard to far-end talker. Furthermore, because the same frequency signal occurs repeatedly, the howling is happened and made us feel the uncomfortabality in communication. To remove these problems, the acoustic echo canceller is to be needed indispensably[6][9].

Up to now, the research on the AEC is mostly about the structure using the adaptive FIR filter, because FIR filter can be implemented easily and assure the stability of the adaptive filter. But the conference room has the very long impulse response of the acoustic path, about 100 *msec*~400 *msec*[6][9]. If the signals are sampled at 8kHz to implement this system with digital system, there are considerable problems in real-time realization because FIR filter needs thousands of taps. But the acoustic echo path can be modelled well with ARMA model. So we are able to realize the acoustic echo canceller in real-time with far less taps than those of FIR filter if we use an IIR adaptive filter[6]. LMS algorithm has been widely known due to its simplicity and robustness, leading to its implementation in many applications. And, in LMS algorithm, the value of the convergence factor, μ is known to determine the convergence characteristic of the algorithm, stability, and the error in the stationary state. Also the convergence speed and the MSE in the stationary state are proportional to μ[2]. By the way, the convergence characteristic of LMS algorithm depends on the eigenvalue spread ratio of the autocorrelation function of the input signal, stochastic characteristic of the input signal. Therefore, if the signal with large eigenvalue spread ratio, about 3000, is used for the input of adaptive filter, the convergence speed of adaptive filter is limited. The pre-whitening filter(PWF) diminishes the eigenvalue spread ratio of the autocorrelation function of input signal using adaptive filter with fewer taps. Lately, the new adaptive filtering technique was proposed. This method uses the PWF to decorrelate the input signal randomly and improves the

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convergence speed[10][11]. But seeing the power accumulation spectrum since the colored noise and the signal noise pass the PWF introduces the fact that the eigenvalue spread ratio is larger than that of the white gaussian noise as usual even if the ratio decreases significantly before passing the PWF.

To improve the convergence speed of the signal which passes through the PWF, we use the variable step-size LMS(VS-LMS) algorithm, which varies the convergence factor in time. And VS-LMS algorithm has been widely applied to communication environment, with frequently varying channel, such as equalizer for communication[3][4][7]. In this paper, we whitened the input signal by using the PWF and used the VS-LMS algorithm for IIR filter instead of the conventional VS-LMS algorithm for FIR filter and applied this system to the acoustic echo canceller. We showed that the acoustic echo canceller with the structure and algorithm used in this paper yields a superior performance to the conventional AEC when we estimate the acoustic path of room in a time-varying environment. This paper is organized as follows. Section Ⅱ introduces the structure of IIR filter used in this treatise. In section Ⅲ, the structure of PWF and the IIR VS-LMS is described. Section Ⅳ explains the simulation results of the proposed algorithm and its structure. Finally, section Ⅴ summarizes our results and suggests a future work.

Ⅱ. Adaptive IIR filtering

Adaptive IIR filter can be classified into two methods, equation error method(EEM) and output error method (OEM), according to the method by which we get the error to be minimized such as (1) and (2).

$$y_e(n) = \sum_{m=0}^{N-1} a_m(n) x(n-m) + \sum_{m=1}^{M} b_m(n) d(n-m) \tag{1}$$

$$y_o(n) = \sum_{m=0}^{N-1} a_m(n) x(n-m) + \sum_{m=1}^{M} b_m(n) y_o(n-m) \tag{2}$$

The filter output of the EEM is made up of the linear functin of the filter coefficient because the EEM doesn't include the recursive component of the filter output. On the other hand, the filter output of the OEM is comprised of the nonlinear function of the filter coefficient because it includes the recursive component. If the EEM is used, the MSE has the only one global minimum and the local minimum doesn't exist. But this method has the demerit that the estimated coefficient of the system can be biased if the estimated noise exists. On the other hand, in case of using the OEM, MSE may not be converged to the optimal value because there are many local minima. But the coefficient bias doesn't occur. Therefore, there is a trade-off between the coefficient bias and the local minimum[1].

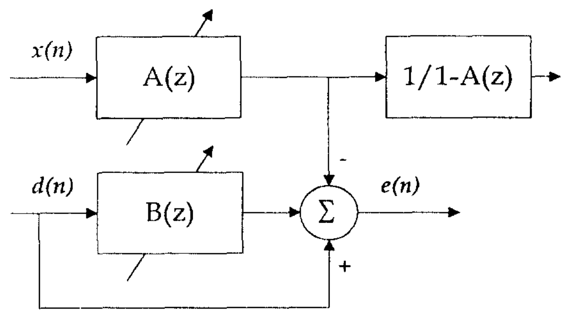


Figure 1. Adaptive IIR filter using EEM.

Adaptive IIR filter using the EEM is illustrated in Fig. 1. The EEM estimates the unknown system coefficients and has two FIR filters such as Fig. 1. Using the EEM is the same as estimating the two FIR filters. Because we resolve the stability problem, the defect of the OEM and EEM, we can assure the stability in all systems[1][8]. LMS algortihm using the EEM is as follows. In (1), input vector and tap coefficient can be given by (3) and (4) respectively. The output of the filter can be expressed as (5) and the error can be given by (6). LMS algorithm using (5), (6) and equation error method can be rewritten by (7).

$$A(n) = [a_0(n), \cdots, a_{N-1}(n)]^T$$
$$B(n) = [b_1(n), \cdots, b_M(n)]^T \tag{3}$$

$$X(n) = [x(n), \cdots, x(n-N+1)]^T$$
$$D(n) = [d(n-1), \cdots, d(n-M)]^T \tag{4}$$

$$y_e(n) = A^T(n) X(n) + B^T(n) D(n) \tag{5}$$

$$e(n) = d(n) - y_e(n) \tag{6}$$

$$A(n+1) = A(n) + \mu e(n) X(n)$$
$$B(n+1) = B(n) + \nu e(n) D(n) \tag{7}$$

Generally, the input vector and the coefficient vector are written by each vector. Because, in adaptive IIR filter, the convergence speed varies whether the convergence factor of MA part and AR part is the same value or not[9], to generalize this fact in the viewpoint of convergence factor, we can express separately the input and the coefficient vector of AR and MA part such as eq. (3)~(7). In (7), convergence factor, the function of time, becomes larger in proportion to the size of error. And if the error diminishes, the value of convergence factor is controlled to a small value.

Ⅲ. IIR VS-LMS Algorithm and PWF Structure.

2.1 IIR VS-LMS Algorithm

Research on variable step-size for adaptive filter has much diversity. The method of changing the convergence factor according to the change of estimated gradient sign and the magnitude of error using the error of filter have been studied[3][4][7]. But if these algorithms are used in an adaptive IIR filter, the performance is restricted largely by many parameters, furthermore, the algorithm has the same value when the convergence factor of AR and MA part is changed. But as explained in section Ⅱ, the convergence factor of AR and MA is to be changed differently. So we used the proposed μ-algorithm in [7] and [8] to the adaptive IIR filter.

Generally, in LMS algorithm, the coefficient of adaptive filter is adapted to minimize the MSE. Therefore convergence factor can be expressed such as in (8) and (9) if the same method as LMS algorithm is used[8]. In (8) and (9), ρ is another convergence constant, which controls the adaptive speed of varying convergence constant. If the value ρ is small enough, the μ-algorithm adapts stably. Eq. (10) shows the coefficient update equation of AR and MA part.

$$\begin{aligned}\mu(n) &= \mu(n-1) - \frac{\rho}{2}\,\frac{\partial e^2(n)}{\partial \mu(n-1)} \\ &= \mu(n-1) - \frac{\rho}{2}\,\frac{\partial^T e^2(n)}{\partial A(n)}\cdot\frac{\partial A(n)}{\partial \mu(n-1)} \\ &= \mu(n-1) + \rho e(n) e(n-1)\, X^T(n-1)\, X(n)\end{aligned} \tag{8}$$

$$\begin{aligned}\nu(n) &= \nu(n-1) - \frac{\rho}{2}\,\frac{\partial}{\partial \nu(n-1)}\,e^2(n-1) \\ &= \nu(n-1) - \frac{\rho}{2}\,\frac{\partial^T e^2(n)}{\partial B(n)}\cdot\frac{\partial B(n)}{\partial \nu(n-1)} \\ &= \nu(n-1) + \rho e(n) e(n-1)\, D^T(n-1)\, D(n)\end{aligned} \tag{9}$$

$$\begin{aligned}A(n+1) &= A(n) + \mu(n) e(n) X(n) \\ B(n+1) &= B(n) + \nu(n) e(n) D(n)\end{aligned} \tag{10}$$

Table 1. shows the comparison of the multiplication complexity between the IIR LMS algorithm with fixed convergence constant and the IIR LMS algorithm with variable step-size. The increase of a little multiplication complexity, about one and a half times, shows the improvement of convergence speed.

Table 1. The comparison of computational complexity

Algorithm	Computational complexity
Fixed step-size IIR LMS	2(N+M)
Variable step size IIR LMS	3(N+M)+4

2.2 PWF Structure.

If the input signal is white noise, this signal has the small eigenvalue spread ratio of autocorrelation matrix. So when the conventional adaptive LMS algorithm is used, it yields a comparatively rapid convergence speed. Eigenvalue spread ratio determining the convergence speed is expressed in (11).

$$X(R) = \lambda_{max}/\lambda_{min} \tag{11}$$

But, if colored noise having large correlation ratio among signals is used as an input, this algorithm is restricted by convergence speed. In this case, if the linear prediction error filter is used, we can decorrelate the input signal such as speech. So decorrelating the signal using the linear prediction filter in front part of adaptive filter and inputting the signal with decreased eigenvalue spread ratio to adaptive filter show the improvement of convergence speed[10][11]. In this paper, we proposed the equation error method adaptive IIR filter, introducing the prewhitening method, and illustrated the structure in Fig. 2.

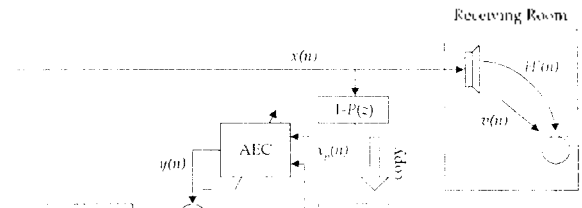


Figure 2. Acoustic echo canceller using PWF.

$1-P(z)$ is the linear prediction filter which decorrelates the input signal $x(n)$, and decreases the eigenvalue spread ratio of $x(n)$. We should make two paths, the estimation path through $(1-P(z))H^*(z)$ and the real propagation path system through $H(z)$, the same in order to estimate real impulse response $H(z)$ with adaptive IIR fiter $H^*(z)$. Therefore PWF $(1-P(z))$ has to be copied into the real propagation path. (12) shows the mathematical relationship of this method.

$$H^*(z)(1-P(z)) \equiv H(z)(1-P(z)) \tag{12}$$

To restore the error signal $e_p(n)$ distorted by PWF, the inverse filter of PWF in output part is required. Eq. (13) shows this inverse filter.

$$R(z) = \frac{1}{1 - P(z)} \tag{13}$$

Inverse filter has poles, so the inverse filter assuring the stability of system is needed. Fig. 3 and 4 illustrate the linear prediction filter and its inverse filter.

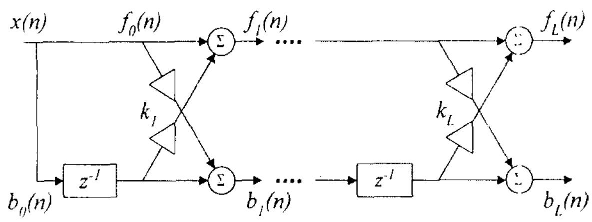


Figure 3. Lattice predictor.

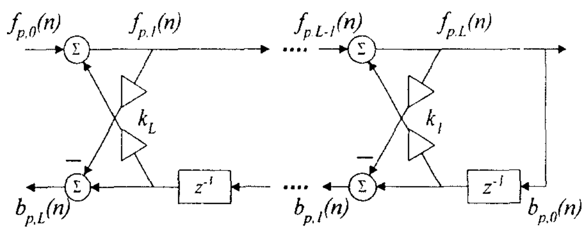


Figure 4. Inverse model of lattice predictor.

In a linear prediction filter using the lattice structure, if the reflection coefficient of the estimation filter is determined to minimize the forward estimatin error and backward estimation error concurrently, the reflection coefficient is made less than 1. From this reason, we can see that the stability of the inverse filter pole with the same reflection coefficient as the estimation filter is assurred. (14)~(18) show that the relationship of the estimation filter input and output in lattice structure and illustrate the reflection coefficient regulation method.

$$f_0(n) = b_0(n) = x(n) \tag{14}$$

$$f_i(n) = f_{i-1}(n) - k_i(n) b_{i-1}(n-1) \qquad 1 \le i \le L \tag{15}$$

$$b_i(n) = b_{i-1}(n-1) - k_i(n) f_{i-1}(n) \qquad 1 \le i \le L \tag{16}$$

$$x_p(n) = f_L(n) \tag{17}$$

$$k_i(n+1) = k_i(n) + 2\mu_i [f_i(n) b_{i-1}(n-1) + b_i(n) f_{i-1}(n)] \tag{18}$$

where $x_p(n)$ decorrelates output of the lattice structure predictor. In lattice structure predictor, used in the part which desired response signal is inputted, and the inverse lattice structure, used in the inverse filter, we used the copied reflection coefficient, which is estimated in the standard input part. Distortioned estimation error signal $e_p(n)$ of equation error method LMS algorithm is restored by the inverse lattice filter. In this case, the relationship between input and output of inverse lattice predictor is as follows,

$$f_{p,0}(n) = e_p(n) \tag{19}$$

$$f_{p,i}(n) = f_{p,i-1}(n) + k_{L-i+1}(n) b_{p,L-i+1}(n-1) \qquad 1 \le i \le L \tag{20}$$

$$b_{p,i}(n) = b_{p,i-1}(n-1) + k_i(n) f_{p,L-i+1}(n) \qquad 1 \le i \le L \tag{21}$$

$$\hat{e}(n) = f_{p,L}(n) \tag{22}$$

where $\hat{e}(n)$ is a restored estimation error.

In PWF, the recursive least squares lattice(RLSL) algorithm using posteriori estimation error for coefficient update algorithm performs better than the LMS algorithm for update algorithm. Relationship between input and output of estimation filter for lattice structure and the reflection coefficient update equation are represented in eq. (T.2-1)~(T.2-12) in [13]

Ⅳ. Simulation Results

Fig. 5 shows the teleconferencing system having acoustic echo canceller. In teleconferencing system, the transfer function of conference room acoustic path has poles which is close to the unit circle and the frequency characteristic of transfer function is flat in overall frequency bin. And the transfer function of acoustic path is modelled well by the 10th or 20th ARMA model, representing well the upper performances[6].

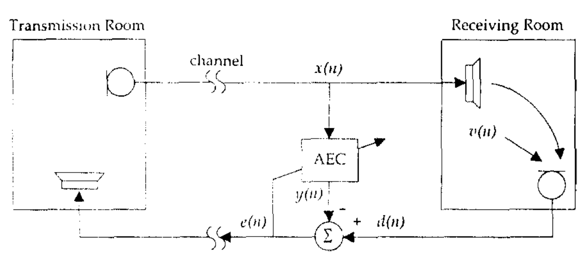


Figure 5. Teleconferencing system with AEC.

Acoustic path used in this paper is represented in eq. (23). To present the case that the environment of acoustic path changes, we assumed that the system is changed from eq. (23) to (24) in 10,000 samples among 20,000 samples used in simulation.

Colored noise and the real speech signal are used for input signal $x(n)$. And colored noise is made its variance

1 by passing white gaussian noise with zero-mean into low pass filter with different eigenvalue spread ratio.

$$H^*_1(n) = \frac{-0.8 + z^{-10}}{1 - 0.8z^{-10}} \tag{23}$$

$$H^*_2(n) = \frac{-0.85 + z^{-10}}{1 - 0.85z^{-10}} \tag{24}$$

The eigenvalue spread ratios of all-pole filter (25) and (26) are about 11, 323, respectively.

$$\frac{1}{A_1(z)} = \frac{1}{1 - 1.6z^{-1} + 0.95z^{-2}} \tag{25}$$

$$\frac{1}{A_2(z)} = \frac{0.1}{1 - 0.9z^{-1}} \tag{26}$$

Desired response signal $d(n)$ is obtained, signal-to-noise ratio(SNR) to be 30dB, by adding $v(n)$. Estimation noise, white gaussian noise with zero-mean, has no correlation with input signal. The algorithm for IIR filter uses the equation error method and simulates with optimal degree.

And the orders of IIR filter used in this paper are 50 for AR part and 50 for MA part. The comparison of convergence speed is made by using the MSE for colored noise and the ERLE for speech signal. MSE curve was obtained by ensemble averaging over 50 independent trials of simulations. To evaluate performance criterion, ERLE curve for speech signal is defined in (27).

$$ERLE(n) = 10\log 10 \left[\frac{\sum_{i=0}^{L-1} [d^2(n-i)]}{\sum_{i=0}^{L-1} [e^2(n-i)]} \right] [dB] \tag{27}$$

And the tap number of lattice filter is the order of AR part and 12 in case input is colored noise and speech signal, respectively.

When the coefficient of system function is varying and the noise is 30dB, 100dB, the result of each simulation shows that the combination method of RLS for PWF and μ-LMS for adaptive filter has the best performances. And in case of estimating the coefficient, this method shows the best coefficient estimation performance. Also this method does present the same performance when the input is speech.

Fig. 6 illustrates the impuse response used in this paper. Fig. 7 shows the speech signal, which is sampled by an woman, "대학가라는 말은 어느 시중의 거리와 차별될 수 있는 풍속도를 지니고 있어야 한다." Fig. 8 and 9 show the performances the updating of weight when the unknown time coefficient is constant and varying, respectively. Fig. 10 illustrates the comparison of MSE in three structures, VS_LMS, combination of LMS algorithm for PWF and VS_LMS, and combination of RLS algorithm for PWF and VS_LMS, when noise is 30dB and adaptive system coefficients(ASC's) are constant. As shown in fig. 10, the structure of PWF_RLS & VS_LMS has the best performance. And fig. 11 illustrates the comparison of MSE in three structures, VS_LMS, combination of LMS algorithm for PWF and VS_LMS, and combination of RLS algorithm for PWF and VS_LMS, when noise is 30dB and ASC's aren't varying. As shown in Fig. 11, the structure of PWF_RLS & VS_LMS has the best performance. Fig. 12 shows the simulation result in the same algorithms when ASCs are varying. And Fig. 13 illustrates the ERLE of three structures, TDL LMS algorithm for FIR, VS_LMS algorithm for IIR and the combination of PWF_LMS and VS_LMS for IIR filter. Also, the ERLE of TDL LMS algorithm for FIR, VS_LMS algorithm for IIR and the combination of PWF_RLS and VS_LMS for IIR filter is shown as fig. 14. The input signal used in fig. 13 and 14 is speech signal.

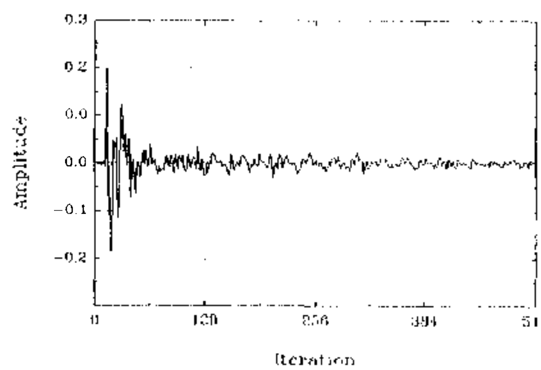


Figure 6. Impulse response of echo path in real environment.

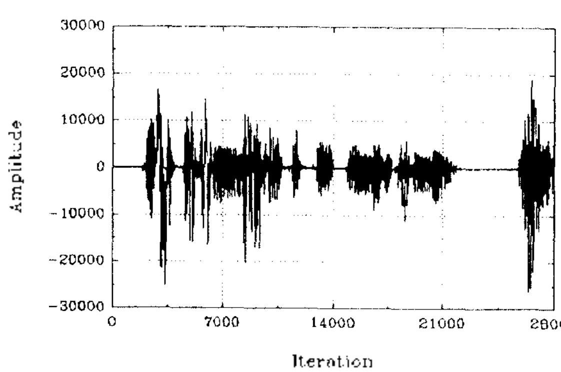


Figure 7. Speech signal.

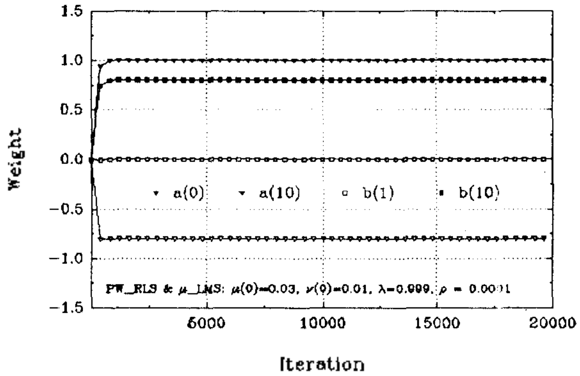


Figure 8. Trajectorise of weight when unknown system coefficients (USCs) are constant.

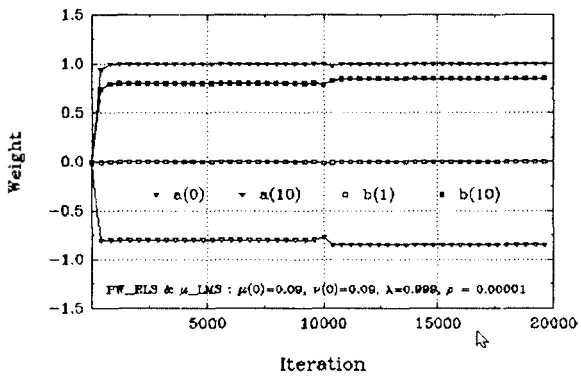


Figure 9. Trajectories of weight when USCs are varying.

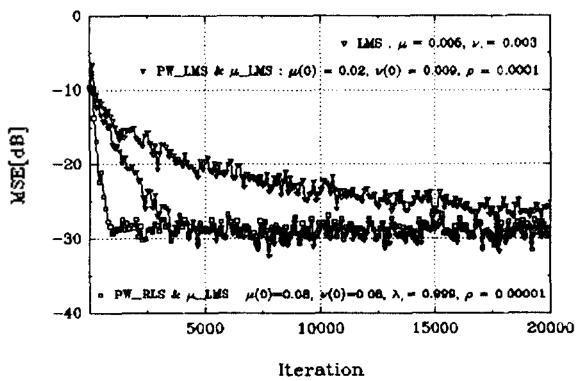


Figure 10. MSE curves according to structures when USCs are constant (SNR = 30dB).

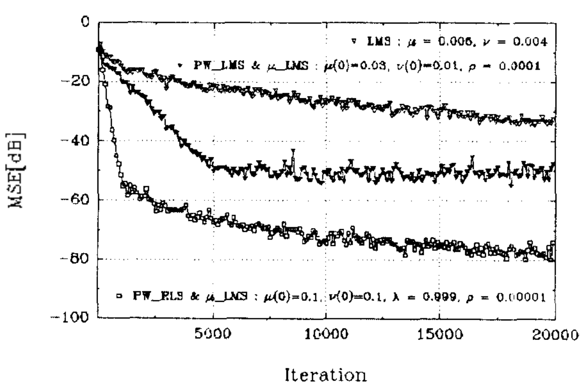


Figure 11. MSE curves according to structures when USCs are constant (SNR = 30dB).

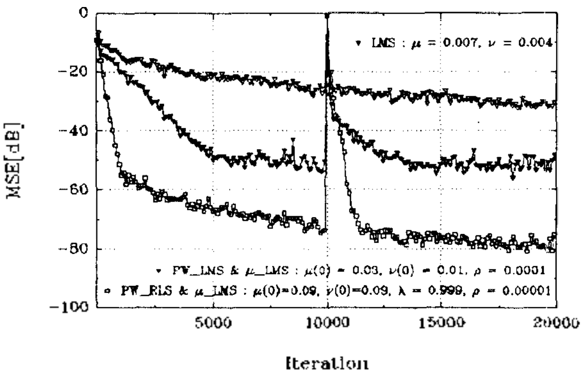


Figure 12. MSE curves accordign to structures when USCs are varying (SNR = 30dB).

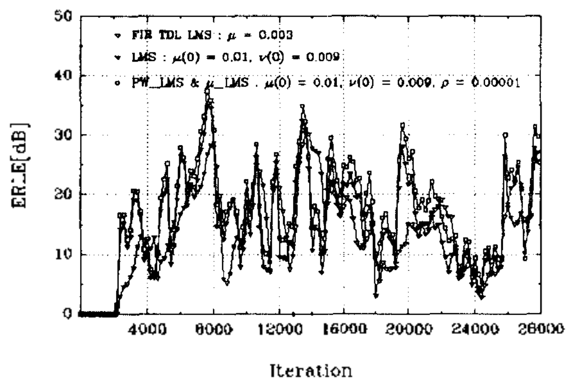
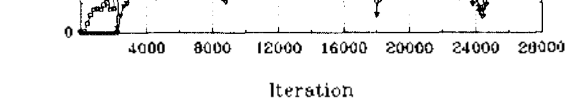


Figure 13. ERLE curves of three different structures.



V. Conclusions

In teleconferencing system, having considerably long impulse response, about 100 *msec*-400 *msec*, and varying its environment frequently, there is problem in real implementation if the adaptive FIR fiter is used for acoustic echo canceller. Therefore, in order to diminish the tap number of adaptive filter, we used the adaptive IIR filter. And we used the PWF structure to speed up the convergence speed and to decrease the degree of correlation of input signal. Also IIR VS-LMS algorithm was used for improving the convergence speed. This paper showed that the combinational structure of these two methods applied in AEC is superior to the conventional AEC. And this paper represent the best performance is shown when RLS algorithm is used for PWF and VS_LMS algorithm is utilized. In the future, the research on the combinational method of other algorithms for PWF and another VS_LMS type algorithm will be presented.

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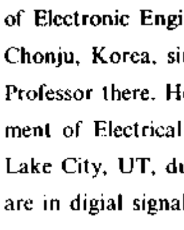

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