Performance Improvement of Acoustic Echo Cancellers Using Delayless Subband Adaptive Filters And Fast Affine Projection Algorithm

*Kyung-Seung Ahn, and *Heung-Ki Baik

Abstract

Since the introduction of hands-free phone set and teleconferencing system, acoustic echo cancellation has been a challenge for engineers. Recently many researches have shown that the best solution for the acoustic echo compensation problem is represented by an adaptive filter which iteratively tries to identify the unknown impulse response of the system from loudspeaker to microphone. In this paper, we apply the delayless subband adaptive filters and fast affine projection algorithm for the identification of room impulse response. Simulation results show 3~8 dB more enhanced performance than conventional fullband adaptive filters or subband adaptive filters. In addition, fast affine projection algorithm shows better convergence speed at the expense of the low computational complexity than conventional LMS algorithm.

I. Introduction

Echo is the phenomenon in which a delayed and distorted version of an original source or signal is reflected back to the source. It's generated in long-distance telecommunication system or digital mobile phone system because of transmission distance and speech data processing. And the acoustic coupling between loudspeaker and microphone is a severe problem for modern audio terminal such as teleconferencing system and hands-free phone set. Acoustic echo path is a time varying system, so adaptive filtering is the indispensable condition for the natural communication[1][2]. Unfortunately, such signal processing applications involve adaptive filters with hundreds of taps because of the long reverberation time. The computational burden associated with these long adaptive filters precludes their use for many low-cost applications. In addition, adaptive filters with may taps may also suffer from slow convergence, especially if the input signal spectrum has a large dynamic range, ill-conditioned. To overcome this problem, adaptive filtering in subband is a new technique for the real-time identification of large impulse response like the ones encountered in applications of acoustic echo cancellation(AEC) and affine projection(AFP) algorithm is new algorithm for the fast convergence speed. But conventional subband adaptive filtering is ruled out for such AEC because delay is introduced into the signal processing path and AFP algorithm introduces other difficulty such as an increasement in computational load in hardware.

* Chonbuk National University

Manuscript Received : February 23, 1998.

This paper presents delayless subband adaptive filters which is proposed by Morgan and fast affine projection (FAP) algorithm, so we apply the AEC problems. FAP's important features include LMS like computational complexity and RLS like convergence speed where the adaptive filter input signal is ill-conditioned signal or speech signal[8]. So above facts make good solution for the application such as AEC problems.

II. Basic principles of AEC

The acoustic echo appears when one or both ends in a communication use audio terminals with acoustic feedback from the loudspeaker to the microphone, like teleconferencing systems which is presented in figure 1.

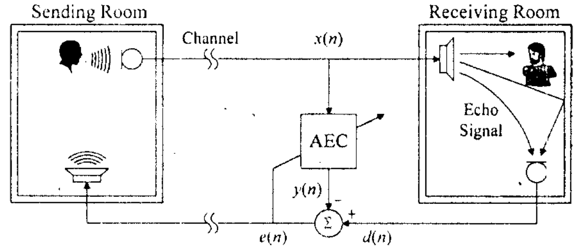

Figure 1. Teleconferencing system.

The speech signal from the sending room is sent into the receiving room by a loudspeaker, the speech is picked up by a microphone and sent to the remote user. Because of the acoustic echo path from the loudspeaker to the microphone, including the reflections on wall and people inside the room, some sent speech in sending speech is fed back to the remote user in sending room. This phenomenon may arise the howling and it cut natural communication. AEC is indispensable problem for the natural communication.

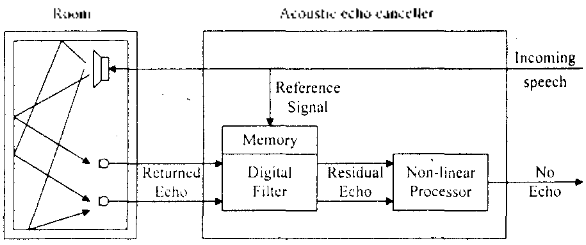

Figure 2. Basic principle of an acoustic echo canceller.

Figure 2 shows the basic principle of AEC. Basically, an AEC is an adaptive filter fed by the incoming speech signal, AEC modelizes the acoustic echo path and yields at its output a echo replica signal which is subtracted from real acoustic echo signal.

Ⅲ. Delayless Subband Adaptive Filters

The disadvantages of conventional subband adaptive filters techniques are that delay is produced into the signal path by due to the filter bank used to devide the signal in each frequency band[4][5]. And nonideal filter bank characteristics introduce the aliasing problems which degrade the quality of signal. But delayless subband adaptive filters which is proposed by Morgan are new type of subband adaptive filter architecture. Figure 3 shows the delayless subband adaptive filters architecture. This new subband adaptive filter architecture in which the adaptive weights are computed in subband, but collectively transformed into an equivalent set of wideband filter weights. In this manners, signal processing path delay and increasement of aliasing effect are avoided while retaining the computational and convergence speed advantages of classical subband processing.

We divide input signal and desired signal in each band and update the adaptive filter weights using adaptive algorithm in each band. This coefficients are values of the time domain in each frequency band, so we transform these values into the frequency domain and we use frequency stacking each operating band. If we have real value input signal then wideband filter coefficients are real value. Therefore we stack complex weights in frequency domain using half of total subbands and the other half values are made by complex conjugate. And using IFFT we transform wideband filter weights into the time domain. After making wideband filter weights, we develope the convolution. We made the estimated echo signal and subtracted it from real echo signal and we have error signal. In this manner we have operation to update filter weights in each subband and error signal is generated in wideband, time-domain. So we avoid signal processing delay and diminish the aliasing effects as classical subband adaptive filter problems. But we must have filter bank for generating each band signal such as classical subband filtering. One way to implement the delayless subband adaptive filter is to employ the polyphase FFT technique. This method hold in common output of prototype low pass filter in each band[5][9]. Polyphase implementation method is that signal pass through the prototype low pass filter and we have divided signal in each band using DFT filter bank. That implementation lessen only one low pass filtering comparative with classical subband adaptive filtering which use the band pass filtering. And we can calculate effectively when using FFT. Figure 4 shows the process of decimation after dividing in each band.

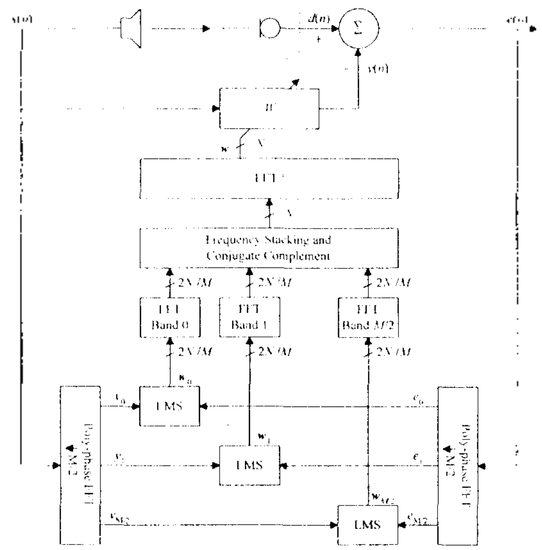

Figure 3. Delayless subband adaptive filter structure.

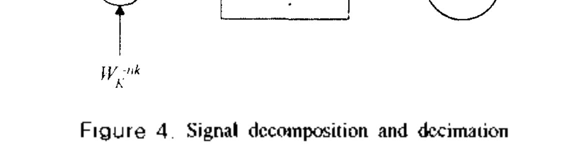

Figure 4. Signal decomposition and decimation

Now, we see real implementation of polyphase FFT filter bank. In figure 4, $x_k(n)$ is represented as follows:

$$x_k(m) = \sum_{n=-\infty}^{\infty} h(mM-n)x(n)\, W_K^{-nk} = \sum_{n=-\infty}^{\infty} h(n)x(mM-n)\, W_K^{(mM-n)k} \quad (1)$$

$$k = 0, 1, \cdots, K-1$$

From eq. (1), let $n = rK+\rho$, $\rho = 0, 1, \cdots, K-1$ and using $K = 2M$, we find as follows:

$$x_k(m) = W_K^{-mMk} \sum_{\rho=0}^{K-1} \Big\{ \sum_{r=-\infty}^{\infty} h(rK+\rho) \cdot x((m-2r)M-\rho) \Big\}\, W_K^{k\rho} \quad (2)$$

In eq. (2) we replace another variables as follows:

$$\overline{P_\rho}(m) = h(mK+\rho) \quad (3)$$

$$x_\rho(m) = x(mM-\rho) \quad (4)$$

And we can write as follows:

$$x_k(m) = W_K^{mMk} \sum_{\rho=0}^{K-1} \Big\{ \sum_{r=-\infty}^{\infty} \overline{P_\rho}(r)\, x_\rho(m-2r) \Big\} W_K^{k\rho} \quad (5)$$

From eq. (5), let other variables:

$$y_\rho(m) = \sum_{r=-\infty}^{\infty} \overline{P_\rho}(r)\, x_\rho(m-2r) \quad (6)$$

and we can see as follows:

$$x_k(m) = \mathrm{DFT}^*[y_\rho(m)]\, W_K^{-mMk} = \mathrm{DFT}^*[y_{\rho+mM}(m)] \quad (7)$$

Above the eq. DFT* is represented by DFT kernal using $W_k = e^{j2\pi/K}$ replaced by general DFT kernal $W_k = e^{-j2\pi/K}$. So we can find the other expression of eq. (1) as follows eq. (8).

$$x_k(m) = \begin{cases} \mathrm{DFT}^*[y_\rho(m)], & \text{for } k = 0, 2, 4, \cdots \\ \mathrm{DFT}^*[y_{\rho+M}(m)], & \text{for } k = 1, 3, 5, \cdots \end{cases} \quad (8)$$

In eq. (3), $\overline{P_\rho}(m)$ is sampled data by factor K of prototype low pass filter $h(n)$, i.e. ρth band filter co-efficients decimated by factor M. In eq. (4), $x_\rho(m)$ is a ρth band input signal sampled by M. In eq. (6) $y_\rho(m)$ is the value of convolution between input signal, $x_\rho(m)$ and filter coefficients, $\overline{P_\rho}(m)$. From eq. (8), we can find kth band output $x_k(m)$ using DFT* of $y_\rho(m)$. And we can find also each band input signal which divided by in each band shifted by M samples when $m = 1, 3, 5, \cdots$ using periodic property of DFT.

Now, we consider a concrete example. Impulse response of unknown system has 512 samples and we consider a system identification using 32-band subband adaptive filtering technique.

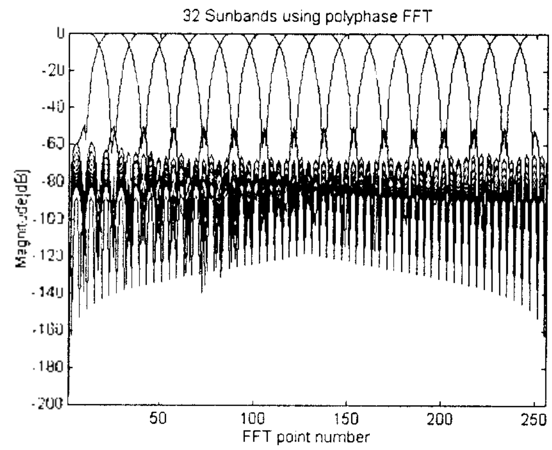

Figure 5. Frequency response of polyphase FFT filter band in M=32.

Figure 5 shows the resulting frequency response of the 17 filters. After decimation by a factor D=16, each sub-band spans the 512-tap wideband filter using 32 taps per subband. The subband adaptive weights are transformed by 32-point FFT to obtain 32 frequencies per subband, which are then stacked as showed in figure 6 to form points 0~255 of a 512-point array, frequency sampling method.

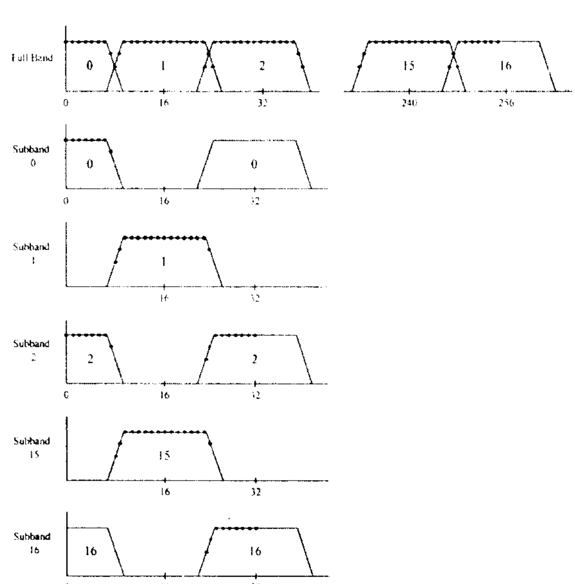

Figure 6. Frequency stacking for 32-subband polyphase FFT.

The array is then completed by setting point 256 equal to zero and using complex conjugates of points 1~255 in reverse order. Finally, the 512-point array is transformed by a 512-point IFFT to obtain the wideband filter weights.

Ⅳ. Fast Affine Projection Algorithm

In many adaptive filtering algorithms, the LMS algorithm is generally used in practice because of its simplicity and robustness. The computational complexity of the LMS algorithm is low, however, convergence speed is very slow and tracking performance is poor for a colored input signal. On the other hand, the RLS algorithm has the fast convergence speed, but its large computational complexity is a drawback. In recent years, an algorithm called affine projection(AFP) algorithm has been studied. This algorithm has properties that lie between those of the LMS and RLS algorithm, less complexity than RLS algorithm, but much faster convergence than LMS algorithm for an colored input signal such as speech which can be modeled as a low-order AR process[8].

We consider *priori* error vector and *posteriori* error vector as follows:

$$\boldsymbol{E}(n) = \boldsymbol{D}(n) - \boldsymbol{X}^T(n)\,\boldsymbol{w}(n-1) \tag{9}$$

$$\boldsymbol{E}_a(n) = \boldsymbol{D}(n) - \boldsymbol{X}^T(n)\,\boldsymbol{w}(n) \tag{10}$$

where

$$\begin{aligned} \boldsymbol{D}(n) &= [d(n),\, d(n-1),\, \cdots,\, d(n-p+1)]^T \\ \boldsymbol{X}(n) &= [\ \boldsymbol{x}_L(n),\ \boldsymbol{x}_L(n-1), \cdots,\ \boldsymbol{x}_L(n-p+1)] \\ \boldsymbol{x}_L(n) &= [x(n),\, x(n-1),\, \cdots,\, x(n-L+1)]^T \end{aligned} \tag{11}$$

and p and L are represented the projection order and adaptive filter length.

If we substitute $\boldsymbol{D}(n)$ in (9) into (10) and let posteriori error vector to zero vector, then we have

$$\boldsymbol{E}(n) = \boldsymbol{X}^T(n)\,[\,\boldsymbol{w}(n) - \boldsymbol{w}(n-1)] \tag{12}$$

where $\boldsymbol{E}(n) = [\,e_0(n),\, \cdots,\, e_{p-1}(n)]^T$, $L\times 1$ weight vector under condition that $p < L$ is the solution of underdetermined linear equation of Eucleadian minimum vector norm as follows:

$$\Delta\boldsymbol{w}(n) = \boldsymbol{X}(n)\,[\,\boldsymbol{X}^T(n)\,\boldsymbol{X}(n)]^{-1}\,\boldsymbol{E}(n) \tag{13}$$

From (13), we have weight update equation of AFP algorithm as follows:

$$\boldsymbol{w}(n) = \boldsymbol{w}(n-1) + \mu\,\boldsymbol{X}(n)\,\boldsymbol{K}(n) \tag{14}$$

where $\boldsymbol{K}(n) = [\,\boldsymbol{X}^T(n)\,\boldsymbol{X}(n) + \delta\boldsymbol{I}\,]^{-1}\boldsymbol{E}(n) = \boldsymbol{R}^{-1}(n)\,\boldsymbol{E}(n)$ is a decorrelation filter.

Updating the filter weights vector requires $(p-1)L$ computational complexity for decorrelation, $O(p^3)$ for calculation of the decorrelation filter, and $2L$ for filter adjustment and convolution.

AFP algorithm still has a computational burden because of matrix inverse of decorrelation filter. Using the fast transversal filter(FTF) method we can solve that problem. We omit the detailed deviation of the FAP algorithm but only list its process in table 1. The reduction of computational complexity is achieved by the recursive update of the decorrelation vector $\boldsymbol{K}(n)$ proposed by reference [8].

Table 1. Fast affine projection algorithm.

Initialization

$F(0) = B(0) = \delta$

$\boldsymbol{f}(0) = [\,1\ \boldsymbol{0}^T\,],\quad \boldsymbol{b}(0) = [\,\boldsymbol{0}^T\ 1\,]$

Iteration

Do (T.1) - (T.9), for $n = 1, 2, 3, \cdots$

using sliding windowed FRLS to update

$$F(n),\ B(n),\ \boldsymbol{f}(n),\ \boldsymbol{b}(n) \tag{T.1}$$

$$\boldsymbol{r}_{xx}(n) = \boldsymbol{r}_{xx}(n-1) + x(n)\,\boldsymbol{x}'_L(n) - x(n-L)\,\boldsymbol{x}'(n-L) \tag{T.2}$$

$$e(n) = d(n) - \boldsymbol{x}_L^T(n)\,\hat{\boldsymbol{w}}(n-1) - \mu\,\boldsymbol{r}_{xx}^T(n)\,\bar{\boldsymbol{K}}(n-1) \tag{T.3}$$

$$\boldsymbol{E}(n) = \begin{vmatrix} e(n) \\ (1-\mu)\,\bar{\boldsymbol{E}}(n-1) \end{vmatrix} \tag{T.4}$$

$$\boldsymbol{K}(n) = \begin{bmatrix} 0 \\ \tilde{\boldsymbol{K}}(n) \end{bmatrix} + \frac{1}{F(n)}\,\boldsymbol{f}(n)\,\boldsymbol{f}^T(n)\,\boldsymbol{E}(n) \tag{T.5}$$

$$\begin{bmatrix} \tilde{\boldsymbol{K}}(n) \\ 0 \end{bmatrix} = \boldsymbol{K}(n) - \frac{1}{B(n)}\,\boldsymbol{b}(n)\,\boldsymbol{b}^T(n)\,\boldsymbol{E}(n) \tag{T.6}$$

Ⅴ. Simulation Results

In this section, we describe simulations performed to shown the better performance described in the previous sections and to compare experimentally the performance of the delayless subband adaptive filters and FAP algorithm to that of the fullband adaptive filters and classical LMS algorithm. These simulations are system identification experiment. In each case, an adaptive filter is placed in parallel with the system to be modelled. This experimental setup is shown in figure 7.

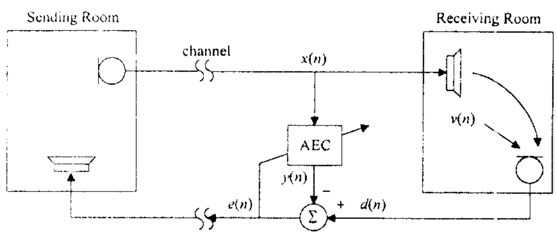

Figure 7. Teleconferecing system with AEC.

For the real simulation, the unknown system was generally simulated by a truncated impulse response measured in a real seminar room has about 2m × 8m × 8m volume and microphone was placed 1.5m from loudspeaker. White gaussian noise with zero-mean is used for this measurement as source signal of loudspeaker. After getting data from loudspeaker, we used the DT-2821 which is a specific-purpose DSP board for the A/D conversion. In addition this measurement was achieved at simultaneously. Figure 8 shows a measured impulse response of the room with 512 samples.

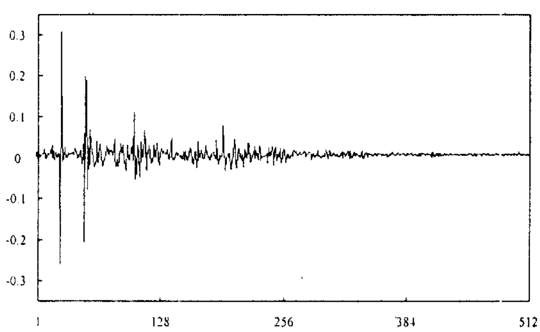

Figure 8. Measured impulse response of room.

The input signal is a colored noise which is obtained as the output of the all-pole filter with transfer function eq. (15). Obtained colored noise has a eigenvalue spread ratio with about 10000. And real speech signal also used for adaptive filter input signal.

$$A(z) = \frac{1}{1-0.95z^{-1}+0.19z^{-2}-0.09z^{-3}+0.5z^{-4}} \quad (15)$$

To evaluate performance index, we use the MSE curve for colored signal and ERLE curve for speech signal as eq. (16).

$$\mathrm{ERLE}(n) = 10\log_{10}\left[\frac{\sum_{i=0}^{L-1} d^2(n-i)}{\sum_{i=0}^{L-1} e^2(n-i)}\right] \quad (16)$$

And we use the prototype low pass filter with 64-tap which is used for filter bank in delayless subband adaptive filter. We experiments this simulation with 512-tap fullband adaptive filter, 2-band, 4-band, and 8-band delayless subband adaptive filter.

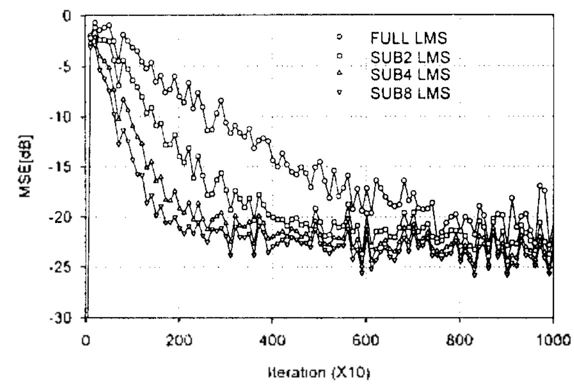

Figure 9. Comparative MSE curves of LMS algorithm in each structure.

Figure 9 shows the behavior of the LMS algorithm in fullband and 2-band, 4-band, 8-band delayless subband adaptive filtering. Convergence speed can be improved by increasing the subband number.

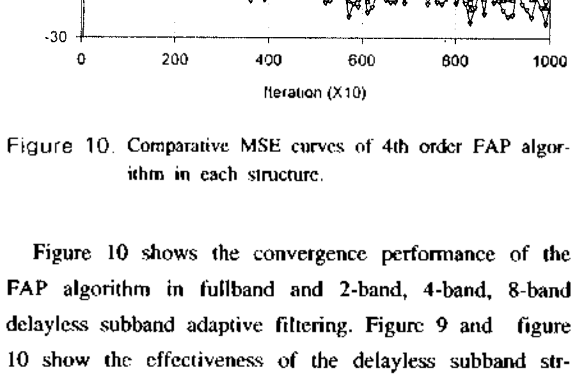

Figure 10. Comparative MSE curves of 4th order FAP algorithm in each structure.

Figure 10 shows the convergence performance of the FAP algorithm in fullband and 2-band, 4-band, 8-band delayless subband adaptive filtering. Figure 9 and figure 10 show the effectiveness of the delayless subband structure. Instead of using fullband with projection order of $p=8$, which has high computational load, we can use 8-band delayless subband adaptive filtering with LMS algorithm and yields low computational load.

In figure 11 and figure 12, the ERLE obtained with fullband and 2-band, 4-band, 8-band delayless subband adaptive filtering real speech signal input for LMS and

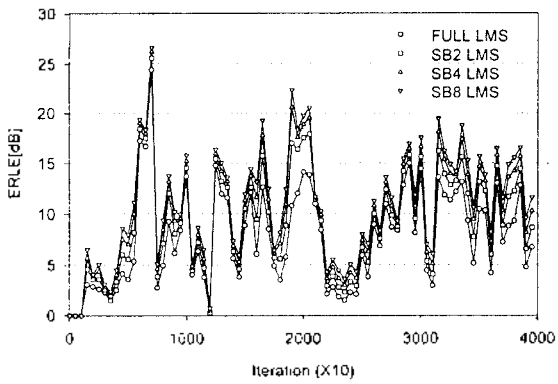

Figure 11. Comparative ERLE curves of LMS algorithm in each structure.

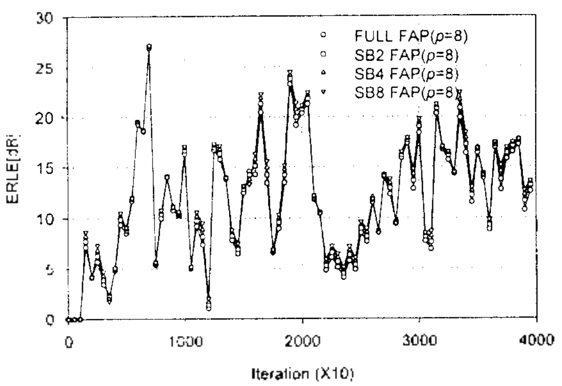

Figure 12. Comparative ERLE curves of 8th order FAP algorithm in each structure.

FAP algorithm. We can see that the performance for delayless subband adaptive filter in each band is better than fullband adaptive filter by 3 dB~8 dB. But we can see that almost same performance because of the FAP algorithm in nature which has RLS like convergence speed. From figure 9 to figure 12, we can see fact that delayless subband adaptive filter and FAP algorithm have better performance over fullband adaptive filter and LMS algorithm.

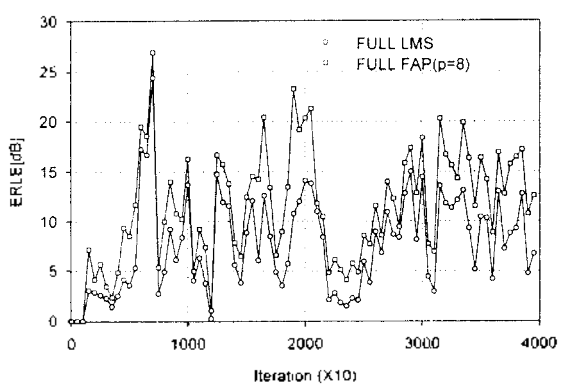

Figure 13. ERLE curves of LMS and 8th order FAP algorithm in fullband adaptive filters

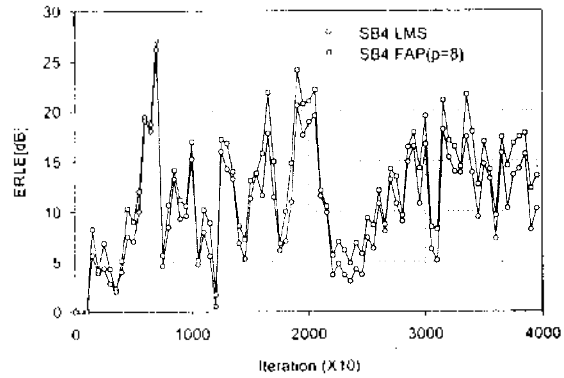

Figure 14. ERLE curves of LMS and 8th order FAP algorithm in 4-band delayless subband adaptive filters

Figure 13 and figure 14 show that FAP algorithm has superior performance rather than LMS algorithm. By inspection, we can observe that ERLE values are increased more or less by 3~5 dB on both figures.

For real time implementation of AEC, we can use LMS algorithm in delayless subband adaptive filter which has merit with computational load. And we see the convergence speed can be improved by increasing the projection oder or band number in FAP algorithm or delayless subband adaptive filter.

VI. Conclusions

In teleconferencing system, having considerably long reverberation time and time varying system, there is problem for real time implementation if we use classical method. We used the delayless subband adaptive filter architecture to improve the convergence speed, diminish the computation load and use the FAP algorithm for more convergence speed. And we analyzed the comparative performance of LMS algorithm and FAP algorithm with fullband and delayless subband adaptive filter. Simulation results showed the fact that more band number in delayless subband adaptive filter had better performance and FAP algorithm had better convergence speed than LMS algorithm. For real time implementation, we used the delayless subband adaptive filter which was avoided the signal path delay problem in classical subband adaptive filters. And we see the LMS algorithm can be used for real time processing in delayless subband adaptive filter. Furthermore we can use other method, such as discrete cosine transform(DCT), for making real adaptive weights in delayless subband adaptive filter which was used by FFT which method reduces computational complexity.

Reference

1. R. H. Moffett, "Echo and delay problems in some digital communication systems," *IEEE Commun. Mag.*, vol. 25, no. 8, pp. 41-47, Aug. 1987.
2. K. Murano, S. Unagami, and F. Amano, "Echo cancellation and applications," *IEEE Commun. Mag.*, vol. 28, no. 1, pp. 49-55, Jan. 1990.
3. P. P. Vaidyanathan, Multirate Systems and Filter Banks. Englewood Cliffs, NJ: Prentice-Hall, 1993.
4. A. Gilloire and M. Vetterli, "Adaptive filtering in subbands with critical sampling: analysis, experiments, and application to acoustic echo cancellation," *IEEE Trans. Signal Processing*, vol. 40, no. 8, pp. 1862-1875, Aug. 1992.
5. D. R. Morgan and C. Thi, "A delayless subband adaptive filter architecture," *IEEE Trans. Signal Processing*. vol. 43, no. 8. pp. 1819-1830, Aug. 1995.
6. S. Haykin, *Adaptive Filter Theory*. Englewood Cliffs, NJ: Prentice-Hall, 1996.
7. A. Gilloire and M. Vetterli, "Adaptive filtering in subbands," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Processing*, 1988, pp. 1572-1575.
8. Steven L. Gay and Sanjeev Tavathia, "The fast affine projection algorithm," in Proc. *IEEE Int. Conf. Acoust, Speech, Signal Processing*, 1995, pp. 3023-3026.
9. E. R. Ferrara, Jr. *et al, Adaptive Filters*. Englewood Cliffs, NJ: Prentice-Hall, 1985.

▲Kyung-seung Ahn

Kyung-seung Ahn was born in Namwon, Chonbuk, Korea, in 1973. He received the B.S, M.S. degrees in electronic engineering from the Chonbuk National University, Chonju, Korea, in 1996 and 1998, respectively. His research areas of interest are signal processing and its implementation.

▲Heung-ki Baik

Heung-ki Baik was born in Chonju, Chonbuk, Korea, on Jan. 5, 1955. He received the B.S, M.S., and Ph.Dr. degrees in 1977, 1979, and 1987, respectively. He has been with the department of electronic engineering, Chonbuk National University, Chonju, Korea, since 1981 and is currently a professor there. He was a visiting scholar in the department of electrical engineering University of Utah, Salt Lake city, UT, during 1990~1991. His research interests are in digital signal processing with emphasis on adaptive and nonlinear signal processing.