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## 분할등화기를 이용한 개선된 비적응필터

### (Improved Multiplication Free Adaptive Digital Filter with the Fractionally-Spaced Equalizer)

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#### 요 약

데이터 전송채널에서 부호간섭(ISI)을 제거하기 위해 개선된 비적응 디지털필터(IMADF)의 구조와 수렴해석이 이루어진다. 0 평균, 백색잡음하에서 분할등화기(FSE)를 이용한 IMADF의 수렴특성을 해석한다. 실험결과 IMADF 알고리즘의 수렴특성이 Sign 알고리즘과는 같으나, MADF 알고리즘 보다 우수하다. 특히 입력신호의 상관관계가 높을 때 유용한 특성을 갖는다.

#### Abstract

In order to remove the intersymbol interference(ISI) phenomenon in data transmission channel, the structure and convergence analysis of the improved multiplication free adaptive digital filter(IMADF) is presented. Under conditions of zero-mean, wide-sense stationary and white Gaussian noise, it is shown that this paper analyze the convergence characteristics of the IMADF with a fractionally-spaced equalizer(FSE). In the experimental results, the convergence characteristics of the IMADF algorithm is almost same as the sign algorithm, but is better than the MADF algorithm. Here, this algorithm has useful characteristics when the correlation of the input signal is highly.

**Key Word** : ISI, IMADF, MADF, Sign algorithm, convergence

#### I. INTRODUCTION

In many areas of digital communication, control and signal processing, it is often desired to extract useful information from a set of noisy data by designing an optimum filter. On way of solving this filter-optimization problem, a Wiener filter<sup>[1]</sup> was used first. But, the design of the wiener filter

assumes that the signals being processed are stationary and require a set of linear matrix equations to find optimum filter coefficients.

An efficient adaptive filtering method<sup>[2-6]</sup> gradually learns the required correlations of the input signals and adjusts its coefficients recursively according to some suitably chosen static criterion. Now, by starting with some sets of initial conditions, the adaptive filter makes it possible to perform satisfactorily in such environments where complete of the signal statistics is unavailable. One of the most widely used adaptive filter is the least-mean square (LMS) algorithm<sup>[7,8]</sup>. This approach is a stochastic

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gradient algorithm in which the adaptive filter updates each tap weight of the FIR transversal filter. However, the convergence analysis of the LMS algorithm is complicated in the sense that the adaptive filter coefficients are recursively updated by a quadratic function of input sequence. Also, since the convergence of the LMS algorithm is controlled mostly by the constant convergence parameter, the filter coefficients can only approach a neighborhood of the optimum value<sup>[9]</sup>.

One of the simplified modifications of the LMS algorithm is the sign algorithm in which only the plus or negative sign of the estimation error is used to update filter coefficients. In fact, the sign algorithm is a stochastic gradient algorithm that attempts to minimize a mean-error cost function, whilst the LMS algorithm tries to minimize a mean-squared estimation error cost function. An implementation of adaptive filters with various LMS is realized to the TMS320C25 or the TMS320C30<sup>[10, 11]</sup>. But, we need to reduce the multiplication operation in any application areas such as an adaptive equalizer, adaptive echo canceller and adaptive predictor.

In order to realize their implementation, the multiplication-free adaptive filter using delta modulation was first proposed by Peled and Liu<sup>[12]</sup>. W.Lee, Un and C.Lee<sup>[13]</sup> has introduced the multiplication-free adaptive digital filter [MADF] that processes the differential pulse code modulation (DPCM) using the popular LMS algorithm.

Mathews<sup>[14]</sup> have presented the MADF algorithm including DPCM and the sign algorithm. Park, Youn and Cha<sup>[15]</sup> have showed another forms of the MADF. Especially, Cho<sup>[16]</sup> analyzed the convergence characteristics of an efficient adaptive digital filtering algorithm and structures, and showed that the convergence properties strongly depend upon the eigenvalue of the input data autocovariance matrix. Also, Mathews and Cho<sup>[17]</sup> have presented a convergence analysis of the sign algorithm operating in stationary environments by successfully relaxing

the write signal assumption.

Meanwhile, the intersymbol interference (ISI) phenomenon takes place in fast data transmission<sup>[18]</sup>. One of methods reducing the ISI uses the equalizer<sup>[4, 5]</sup>. Until recently, such a equalizer have used the synchronous transversal equalizer (STE). But, the STE has the disadvantage that can't cancel the noisy completely and can't control the amplitude and phase of the signal in outer of Nyquist frequency domain. In order to solve those problems, the fractionally spaced equalizer (FSE) was proposed by Gitlin and Weinstein<sup>[19]</sup>. They have showed that the FSE could compensate for serious delay distortion in data transmission channel. But, the increased arithmetic operation due to oversampling is deteriorated more and less the performance of the filter.

Besides the training FSE using intersymbol interpolation was proposed by Ling<sup>[20]</sup>. Leung, Chan and Lau<sup>[21]</sup> have proposed an efficient FSE with low computation for data transmission. Song and Yoon<sup>[22]</sup> have presented the convergence characteristics of modified MADF algorithm reducing the ISI in data transmission.

In this paper, the improved multiplication-free adaptive digital filter (IMADF) using the FSE to remove the ISI is proposed. In order to estimate the convergence characteristics of an IMADF algorithm, under conditions of zero-mean, wide-sense stationary and white Gaussian noise, we analyze the mean-square error and its behavior. The characteristics parameters for estimating the performance of the algorithm are selected in the experiments. By comparing with the existed algorithms, it is shown that the convergence characteristics of the IMADF algorithm is almost same as the sign algorithm, but is faster than the MADF algorithm. Also, it is shown that the IMADF algorithm has useful characteristics when the correlation of the input signal is highly.

## II. The IMADF algorithm

The multiplication-free adaptive digital filter (MADF) structure requiring zero-multiplication was introduced<sup>[14, 16]</sup>. In particular, the MADF structure employs a DPCM system for the reference input signal, and the reference input vectors are used in the update equation for the adaptive filter coefficients<sup>[14]</sup>. The vector consisting of the reconstructed signals is used as the input vector in the coefficient update equation<sup>[16-17]</sup>.

Fig. 1 shows an improved MADF structure. In comparison with the MADF, the IMADF algorithm uses  $\beta \tilde{X}(n)$  for update filter coefficient, and the one-step predicted filter. Let  $d(n)$  and  $x(n)$  be the primary and the reference input signals to the adaptive filter, respectively. From the structure,  $\tilde{X}(n)$  and  $\tilde{g}(n)$  denote the predicted and the reconstructed input signal vectors of the DPCM, respectively<sup>[17, 21]</sup>. Also, let  $B(n)$  define the vectors consisting of the quantizer outputs of DPCM as

$$B(n) = [b(n), b(n-1), \dots, b(n-(N+1))] \quad (1)$$

$$= Q(\epsilon(n))$$

where  $Q\{\epsilon(n)\}$  corresponds to the vector obtained by quantizing each element of  $\epsilon(n)$

So, the following set of equations describes the IMADF algorithm.

$$\hat{X}(n) = \beta \tilde{X}(n-1) \quad (2)$$

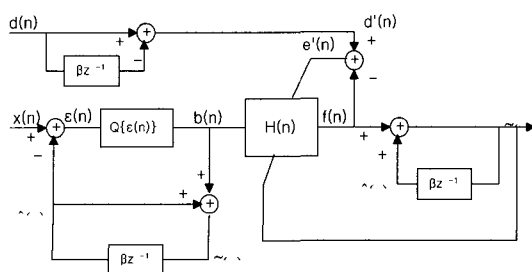


그림 1. IMADF의 블록도  
Fig. 1. Block diagram of IMADF.

$$\tilde{X}(n) = \hat{X}(n) + B(n) \quad (3)$$

$$f(n) = B^T(n)H(n) \quad (4)$$

$$\hat{g}(n) = \beta \tilde{g}(n-1) \quad (5)$$

$$\tilde{g}(n) = \hat{g}(n) + f(n) \quad (6)$$

$$d'(n) = d(n) - \beta d(n-1) \quad (7)$$

$$e'(n) = d'(n) - f(n) \quad (8)$$

Where  $\beta$  ( $0 < |\beta| < 1$ ) denotes the one-step prediction coefficient used in the DPCM system. The final transfer equation is written as

$$H(n+1) = H(n) + \mu \tilde{X}(n) \text{sign}\{e'(n)\} \quad (9)$$

Substituting equations (2) in (3) gives

$$B(n) = \tilde{X}(n) - \beta \tilde{X}(n-1) \quad (10)$$

From equations (4) ~ (6) and (10), it follows that

$$\tilde{g}(n) = \beta \tilde{g}(n-1) + [\tilde{X}^T(n) - \beta \tilde{X}^T(n-1)]H(n) \quad (11)$$

Substituting the equation (9) in (11), under zero initial conditions, the equation (11) can be rewritten as

$$\tilde{g}(n) = \tilde{X}^T(n)H(n) - \mu \sum_{k=1}^{n-1} \beta^{n-k} \tilde{X}^T(k) \tilde{X}(k) \text{sign}\{e'(k)\} \quad (12)$$

where for small values of  $\mu$  and small reconstruction error of the DPCM system,  $\tilde{g}(n)$  represents a good approximation of the sequence generated by a conventional adaptive filter. In order to reduce the computational complexity of the equation (12) during the hardware implementation,  $\mu$  will be selected to be a negative power of two;  $\beta$  to be (possibly one minus) a negative integer power of two; and  $\Delta$  the quantization step size of the DPCM system to be again an (possibly negative) integer power of two. Selecting  $\mu$  and  $\beta$  in equations (6), (12) and (13), it is observed that the multiplications with  $\mu$  can be replaced by bit-shift operation and one addition

operation each<sup>[13, 15-16]</sup>. Furthermore, since each element of  $B(n)$  is an integer multiple of quantization step  $\Delta$ , each multiplication in equation(4) can be replaced by a bit-shift operation as long as the number of quantization levels in the DPCM system.

Here we use 13 quantization levels with a range of  $-6\Delta$  and  $6\Delta$  in the DPCM system. Each multiplication can be processed by two bit-shift operations and one addition operation. Therefore the filter structure introduced to Fig. 1 requires no multipliers in its implementation.

In order to analyze of the convergence characteristics, three of assumptions will be used<sup>[14, 16-17]</sup>. Then, notations of  $R_{xx}$  and  $R_{\tilde{x}\tilde{x}}$  denoting the autocorrelation matrices of respective  $X(n)$  and  $\tilde{X}(n)$  will be used. Similarly, notations of  $R_{dx}$  and  $R_{d\tilde{x}}$  presenting crosscorrelation vectors of  $d(n)$ ,  $X(n)$  and  $\tilde{X}(n)$  will be used. By utilizing upper equations, we can obtain the reconstruction error vector  $\eta(n)$  of the DPCM system at a time  $n$  defined as

$$\eta(n) = X(n) - \tilde{X}(n) \quad (13)$$

and the covariance matrix that each element of  $\eta(n)$  is uniformly distributed in  $(-\Delta/2, \Delta/2)$  yields

$$R_{\eta\eta} = E\{\eta(n)\eta^T(n)\} = \sigma_\eta^2 I \quad (14)$$

By using equations (13) and (14), equations  $R_{d\tilde{x}}$  and  $R_{\tilde{x}\tilde{x}}$  represent

$$R_{d\tilde{x}} = E\{d(n)[X(n) - \eta(n)]\} = R_{dx} \quad (15)$$

$$\begin{aligned} R_{\tilde{x}\tilde{x}} &= E\{(X(n) - \eta(n))[X^T(n) - \eta^T(n)]\} \\ &= R_{xx} + \sigma_\eta^2 I \end{aligned} \quad (16)$$

When  $d(n)$  is estimated as linear combination of the elements of  $\tilde{X}(n)$ , the optimal filter coefficient vector  $H_{opt}$  and the optimal error  $e_{min}(n)$ <sup>[14, 16-17]</sup> are given

$$H_{opt} = R_{\tilde{x}\tilde{x}}^{-1} R_{d\tilde{x}} \quad (17)$$

$$e_{min}(n) = d'(n) - \tilde{X}^T(n)H_{opt} \quad (18)$$

Note that  $H_{opt}$  given by equation (17) is not the same as that for the LMS or the sign algorithm and the MADF algorithm.

By an orthogonal principle,  $E\{e_{min}(n)\tilde{X}(n)\}$  is zero<sup>[16, 24]</sup>. From the difference  $H(n)$  and  $H_{opt}$ , we can define the coefficient misalignment vector as

$$V(n) = H(n) - H_{opt} \quad (19)$$

and its autocorrelation matrix as

$$K(n) = E\{V(n)V^T(n)\} \quad (20)$$

By using equation (19) in (9), the update equation for the coefficient misalignment vector be written

$$V(n+1) = V(n) + \mu\tilde{X}(n)\text{sign}\{e'(n)\} \quad (21)$$

and substituting equation (10) in (21) yields its filter coefficient vector<sup>[4]</sup> as

$$\begin{aligned} H(n+1) &= H(n) + \mu\tilde{X}(n)\text{sign}\{e(n) - \beta e(n-1)\} \\ &\quad - \mu\beta\tilde{X}(n-1)\text{sign}\{e(n) - \beta e(n-1)\} \end{aligned} \quad (22)$$

The optimal coefficient  $H_{opt}$  of the convergence condition by equation (15) and (16) gives

$$H_{opt} = R_{\tilde{x}\tilde{x}}^{-1} R_{d\tilde{x}} = R_{xx}^{-1} R_{dx} \quad (23)$$

An update equation for  $K(n)$  from the equation (20) yields the following expression for the mean-squared behavior of the coefficient misalignment vector<sup>[17]</sup>.

$$\begin{aligned} K(n+1) &= K(n) + \mu^2 R_{\tilde{x}\tilde{x}} \\ &\quad - \sqrt{\frac{2}{\pi}} \frac{\mu}{\sigma_e'(n)} [K(n)R_{\tilde{x}\tilde{x}} + R_{\tilde{x}\tilde{x}}K(n)] \end{aligned} \quad (24)$$

In order to evaluate the steady-state response of

the mean-squared estimation error<sup>[8, 16-17]</sup>, define the following limiting value :

$$\sigma_e^2(\infty) \approx \xi'_{\min} + \frac{\mu}{2} \sqrt{\frac{2}{\pi}} \sqrt{\xi'_{\min}} \text{tr}\{R_{\bar{x}\bar{x}}\} \quad (25)$$

$$K(\infty) = K'(\infty) = \frac{\mu}{2} \sqrt{\frac{2}{\pi}} \sigma_e'(\infty) I \quad (26)$$

where

$$\begin{aligned} \xi'_{\min} &= E\{e'^2_{\min}(n)\} \\ &= E\{d'^2(n)\} - H_{opt}^T R_{d\bar{x}} \end{aligned} \quad (27)$$

Using equation(8) and steady-state assumption<sup>[8, 16, 22]</sup>, it follows that

$$\sigma_e^2(\infty) = (1 + \beta^2) \sigma_e^2(\infty) \quad (28)$$

$$\xi'_{\min} = (1 + \beta^2) \xi_{\min} \quad (29)$$

where  $\xi_{\min}$  is  $E\{e^2_{\min}(n)\}$ . By using  $\text{tr}(R)$  in terms of the autocorrelation function  $R_{xx}$ , equations (25) and (26) give

$$\text{tr}\{R_{BB}\} = (1 - \beta^2) \text{tr}\{R_{\bar{x}\bar{x}}\} \quad (30)$$

Therefore, expressing the equation (25)

$$\begin{aligned} \sigma_e^2 &= (1 + \beta^2) \xi_{\min} + \frac{\mu}{2} \sqrt{\frac{\pi}{2}} \sqrt{1 + \beta^2} \\ &\quad \sqrt{\xi_{\min}} (1 - \beta^2) \text{tr}\{R_{\bar{x}\bar{x}}\} \end{aligned} \quad (31)$$

As a Results, it follows that

$$\begin{aligned} \sigma_e^2(\infty) &= \xi_{\min} \\ &+ \frac{1 - \beta^2}{\sqrt{1 + \beta^2}} \frac{\mu}{2} \sqrt{\frac{\pi \xi_{\min}}{2}} [\text{tr}\{R_{xx}\} + N \sigma_e^2] \end{aligned} \quad (32)$$

where  $\sigma_e^2$  denote the quantization error in DPCM system. The mean-squared estimation error for the MADF algorithm<sup>[17]</sup> gives

$$\sigma_e^2(\infty) = \xi_{\min} + \frac{\mu}{2} \sqrt{\frac{\pi \xi_{\min}}{2}} [\text{tr}\{R_{xx}\} + N \sigma_e^2] \quad (33)$$

On comparing equation (32) and (33), there is a modification of  $(1 - \beta^2) / \sqrt{1 + \beta^2}$ . It is shown that the equation(32) of the IMADF algorithm converges faster than the equation (33) of the MADF algorithm in identical steady-state. But, the performance due to the one-step predicted coefficient can be deteriorated. To obtain the benefits of the IMADF algorithm, therefore, the correlation of the input signal must be highly.

### III. The FSE

The effect of an equalization is to compensate for transmission-channel impairment such as frequency-dependent phase and amplitude distortion<sup>[18]</sup>. On considering an arbitrary impulse response for the transmission-channel, the received signal  $r(nT)$  sampled at a time  $nT$  yields

$$r(nT) = \sum_{k=-\infty}^{\infty} a_k h(nT - kT) \quad (34)$$

where  $T$  is the symbol period,  $a_k$  is the transmit information and  $h()$  is the impulse response.

Note that the peaks of  $r(nT)$  roughly relate to the sense of the corresponding transmit pulse. However, the value of  $r(nT)$  can be quite different from those transmitted because of intersymbol interference effects<sup>[18, 19]</sup>. In some instances, it can be advantages to sample at a multiple of the symbol rate to implement a fractionally spaced signal processing<sup>[19, 20]</sup>. To explain the ISI phenomenon, the transmitted signal replaced by  $nT + t_0$  can be written as

$$\begin{aligned} r(nT + t_0) &= a_n + \sum_{\substack{j=0 \\ j \neq n}}^{N-1} a_j h(nT + t_0 - jT) \\ &+ N(nT + t_0) \end{aligned} \quad (35)$$

where  $t_0$  is the delay time,  $a_n$  is the source signal, is the transmitted information signal,  $h(t)$  is the channel impulse response and  $N(t)$  is the white

Gaussian noise. The second term of equation (35) presents the ISI phenomenon. Fig. 2 shows the block diagram of the FSE(fractionally-spaced equalizer).

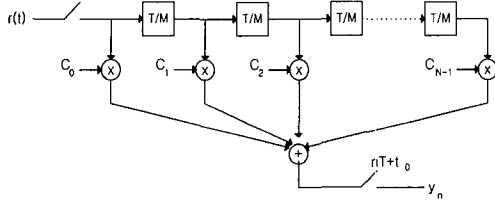


그림 2. FSE의 블록도

Fig. 2. The block diagram of the FSE.

The output of the FSE replaced by delay tap  $kT/M$  ( $k$  and  $M$  are integers,  $M > k$ ) yields

$$y_n = \sum_{k=0}^{N-1} C_k r(nT + t_0 - \frac{kT}{M}) \quad (36)$$

where  $C_n$  is the filter coefficient, and  $N$  is the order of delay tap. The Fourier transform of  $C_n$  with delay tap ( $L < T(1 + \alpha)$ , ( $\alpha$  is the prime number) gives

$$C_L(\omega) = \sum_{k=0}^{N-1} C_k e^{-j\omega kL} \quad (37)$$

If  $\pi/L$  is greater than  $(1 + \alpha)\pi/T$ , the spectrum of  $C_L(\omega)$  have an over-state component. Now, let the input signal of the FSE is sampled at a time rate  $T$ . Then the spectrum of the equalizer with  $2\pi/L$  period be written as

$$F_L(\omega) = C_L(\omega) \sum_{k=0}^{N-1} H(\omega + k \frac{2\pi}{L}) e^{j(\omega + 2k\pi/L)\tau} \quad (38)$$

where  $\tau$  is a delay time. The spectrum in case of  $\pi/L > (1 + \alpha)\pi/T$  exists only at  $k=0$ , and then yields

$$F_L(\omega) = C_L(\omega) H(\omega) e^{j\omega\tau} \quad (39)$$

Therefore, the phase and amplitude distortion due to the term  $e^{j\omega\tau}$  of the equation (39) is compensated. Now let it consider the output error. The

coefficient of T/M quantization update every input signals based on the mean-squared error of each symbol. Then the filter coefficient is rewritten as

$$C_k(n+1) = C_k(n) - \mu \cdot \text{sign} \{e'(n)\} r(nT + t_0 - \frac{kT}{M}) \quad (40)$$

where  $C_k(n+1)$ ,  $0 \leq k \leq N-1$ , presents the  $k_{th}$  filter coefficient of recursive  $(n+1)_{th}$  values,  $\mu$  is the convergence constant. So, by using FSE in the IMADF algorithm, this can prevent the ISI effects from the fast data transmission-channel, and also reduce the computational complexity due to zero-multiplication.

#### IV. Experimental Results

On comparing sign algorithm, MADF and IMADF algorithm, the MADF and IMADF algorithm has zero-multiplication, the additive operations of the two algorithms are increased more than the sign algorithm. Let it consider only additive operation in MADF and IMADF. Then the additive operation number of an IMADF algorithm is  $3N+7$  and one of the MADF is  $3N+5$ , increased to two.

In order to analyze the convergence characteristics of IMADF algorithm, we use 13 quantization levels

표 1. 전송채널의 특성파라미터

Table 1. Characteristic parameter of transmission-channel.

	W		
	2.7	2.9	3.3
$r(0)$	1.0493	1.0974	1.23
$r(1)$	0.3205	0.4482	0.6867
$r(2)$	0.0451	0.0672	0.1310
$\lambda_{\min}$	0.4709	0.3149	0.1069
$\lambda_{\max}$	1.7259	2.0701	2.7987
$\chi(R) = \lambda_{\max} / \lambda_{\min}$	3.6651	6.5738	26.1805

and 22 delay taps, assuming the additive White Gaussian noise with zero-mean and independent of input signals. Table 1 shows the characteristic parameter of transmission-channel under such conditions.

In the Table 1,  $W$  is the parameter that controls the quantity of an amplitude distortion occurred in the transmission-channel and the coefficients to obtain the impulse response of channel.  $\gamma(l)$  is the autocorrelation function of reference input signals, and is written as

$$r(l) = E\{x(k)x(k+l)\} \quad (41)$$

$\lambda_{\min}$  is the minimum eigenvalue of autocorrelation matrix,  $\lambda_{\max}$  is the maximum eigenvalue of autocorrelation matrix, and  $\chi(R)$  is the ratio of  $\lambda_{\max}$  and  $\lambda_{\min}$ . The predicted coefficient  $\beta$  and quantization step  $\Delta$  in Jayant<sup>[23]</sup> is given by

$$\beta = r(1)/r(0) \quad (42)$$

$$\Delta = 0.43 \cdot \{[1 - (r(1)/r(0))^2]r(0)\}^{1/2} \quad (43)$$

We have used input signals of 2000 samples, and found the ensemble average (or MSE) obtained by recursively independent runs of 40 or 70. Utilizing data of Table 1, equations (42) and (43), and the experimental results in the lower condition is processed. First, we find the MSE during  $W = 2.7, 2.9$  or  $3.3$ ,  $\mu = 0.0078(2^{-7})$ , SNR = 30 or dB. Then we select the  $\beta = 2^{-1}$  and  $\Delta = 2^{-2}$ . Second, we select the convergence constant  $\mu$  considering the stationary state error, and analyze the convergence characteristics by changing the SNR in the value  $W$ .

Fig. 3 present the convergence curves of the IMADF algorithm by changing  $W$  on SNR = 30 dB,  $\beta = 2^{-1}$ ,  $\Delta = 2^{-2}$  and  $\mu = 0.0078$ . Where the ensemble average(or MSE) is the average value of recursively independent runs of 70. The vertical axis is the unit of logarithm.

In the Fig.3, it is shown that the convergence

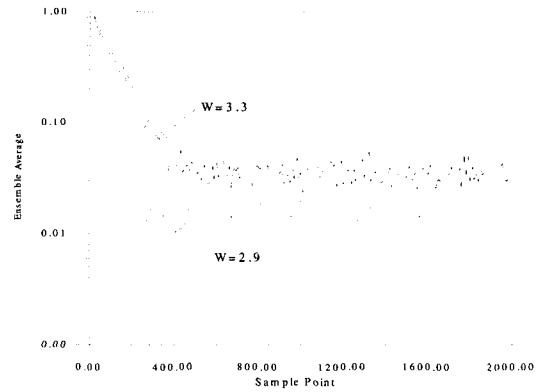


그림 3.  $W$  변화에 대한 IMADF 알고리즘의 수렴특성  
Fig. 3. The convergence characteristics of IMADF algorithm for change  $W$ .

characteristics of the MSE in decreasing  $W$  are much better. Also, on changing SNR =  $\infty$  [dB], similar results are found in experiments. This means that the convergence characteristics are more effective for small autocorrelation values of input signals.

Fig. 4 presents the ensemble average of the IMADF algorithm averaged by recursively independent runs of 70. The experimental conditions are SNR = 30 dB,  $\beta = 2^{-1}$ ,  $\Delta = 2^{-2}$ ,  $W = 2.9$ . Then, the experimental results are given by changing  $\mu$ .

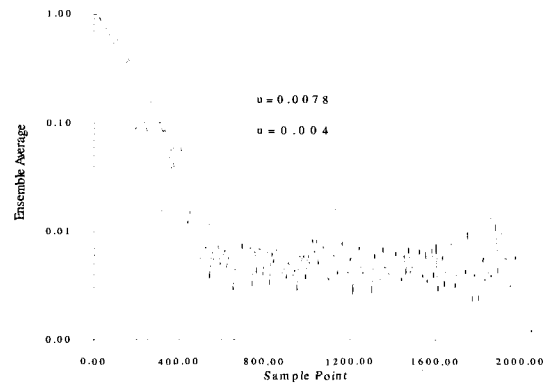


그림 4.  $\mu$  변화에 대한 IMADF 알고리즘의 수렴특성  
Fig. 4. The convergence characteristics of IMADF algorithm for change  $\mu$ .

Fig. 4 shows that the convergence characteristics in increasing  $\mu$  are much better. Also, on changing SNR =  $\infty$  [dB], similar results are found. In the Fig.

3 and Fig. 4, they shows that the convergence characteristics are more effective for  $W=2.9$  and  $\mu = 0.0078$ .

Fig. 5 compares convergence curves of Sign, MADF and IMADF algorithms for the ensemble average of recursive runs of 70 on  $\mu = 0.0078$ , SNR = 30 dB,  $\beta = 2^{-1}$ ,  $\Delta = 2^{-2}$  and  $W = 2.9$ .

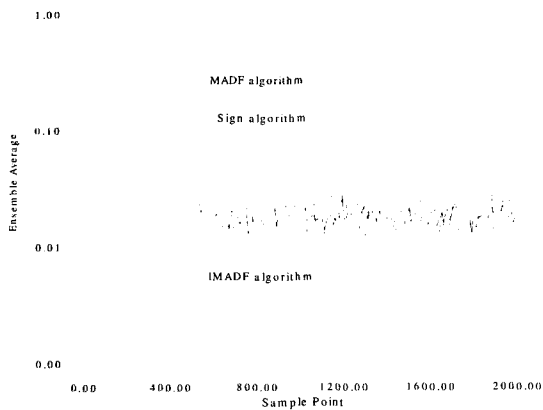


그림 5. Sign, MADF 및 IMADF 알고리즘의 수렴특성 비교

Fig. 5. Comparison of convergence characteristics of Sign, MADF and IMADF algorithms.

In the Fig.5, it is shown that the IMADF algorithm applying for the FSE has more stable performance than other algorithms. Therefore, in the experimental results, the IMADF algorithm has not multiplicative operation and almost identical convergence characteristics as the sign algorithm. In comparison with MADF algorithm, the convergence characteristics of IMADF algorithm are better than that of MADF algorithm, but that has the increased additive operation.

## V. Conclusion

The IMADF algorithm is the structure with one-step predicted filter in the MADF structure using the DPCM and sign algorithm. When the reconstructed error  $\sigma^2$  and the  $\mu$  are small, the algorithm has effective characteristics. But, the arithmetic operation of the FSE by oversampling has

increased more or less, the IMADF algorithm could have reduced the computational complexity by use of only the addition operation without a multiplier. Also, under the condition of identical stationary-state error, it could obtain the stabled convergence characteristics.

On comparing algorithms, it shows that the IMADF algorithm applying for the FSE has more stable performance than other algorithms. The IMADF algorithm has almost identical convergence characteristics as the sign algorithm, and is better than the convergence characteristics of the MADF algorithm, but the algorithm has the increased additive operation.

## Reference

- [1] N. Wiener, *Extrapolation, Interpolation, and Smoothing of stationary Time series with Engineering Application*, Cambridge, MA : The MIT Press, 1949.
- [2] M. L. Honing and D. G. Messerschmitt, *Adaptive Filters : Structures, Algorithms, and Applications*, Hingham, MA : Kluwer Academic Publishers, 1984.
- [3] G. C. Goodwin and K. S. Sin, *Adaptive Filtering, Prediction, and Control*, Englewood Cliffs, NJ : Prentice-Hall, 1985.
- [4] B. Widrow and S. D. Stearns, *Adaptive Signal Processing*, Englewood Cliffs, NJ : Prentice-Hall, 1985.
- [5] S. Haykin, *Adaptive Filter Theory*, Englewood Cliffs, NJ : Prentice-Hall, 1986.
- [6] B. Mulgrew and C. F. N Coean, *Adaptive Filters and Equalizers*, Hingham, MA : Kluwer Academic Publishers, 1988.
- [7] B. Widrow, *Adaptive Filters*, in R. Kalman and N. De Claris, Eds, *Aspects of Network and System Theory*, Newyork, NY : Rinehart, and Winstom, pp .563~589, 1971.
- [8] B. Widrow, "Stationary and Nonstationary Learning Characteristics of the LMS Adaptive



- Filter,” Proceeding of the IEEE, Vol.64, No.8, pp. 1151~1162, Aug.1976.
- [9] N. A. M Verhoeckx and T. A. C. M Classen, “Some Consideration on the Design of Adaptive Digital Filters Equipped with the Sign Algorithm,” IEEE Trans. Communication, Vol. COM-32, No.3, pp. 258~266, Mar.1984.
- [10] Sen Kuo and Chein Chen, “An implementation of adaptive filters with the TMS320C25 or the TMS320C30,” in Digital Signal Processing Solutions, Texas Instruments, 1997.
- [11] Leor Brenman, “Setting up TMS320 DSP interrupts in C,” Texas Instruments, Application Report, 1995.
- [12] A. Peled and B. Liu, “A New Approach to the Realization of Nonrecursive Digital Filters,” IEEE Trans. Audio and Electroacoustics, Vol. AU-21, No.6, pp. 477~487, Dec.1973.
- [13] I. W. Lee, C. K. Un and J. C. Lee, “Adaptive Digital Filtering of Differentially Coded Signal,” Proc. of the IEEE ICASSP, Tampa, FL, pp. 1257~1260, Mar.1985.
- [14] V. J. Mathews, “An Efficient FIR Adaptive Filter using DPCM and the Sign Algorithm,” IEEE Trans. ASSP, Vol.37, No.1, pp. 128~133, Jan.1989.
- [15] T. H. Park, D. H. Youn and I. W. Cha, “Multiplication-free Adaptive Filters,” Proc. Of IEEE, Vol.76, No.5, pp. 632~634, May 1988.
- [16] Sung Ho Cho, “Convergence Analysis Efficient Adaptive Digital Filtering Algorithms and Structures,” A dissertation submitted to the faculty of the University of Uath, Aug.1989.
- [17] V. J. Mathews and S. H. Cho, “Improved Convergence Analysis of Stochastic Gradient Adaptive Filters using the Sign Algorithm,” IEEE Trans. On Acoustics, Speed, and Signal Processing, Vol.Assp-35, No.4, pp. 450~454, April 1987.
- [18] D. Smalley, “Equalization Concepts : A tutorial,” Texas Instrument, Application Report, Oct. 1994.
- [19] R. D. Gitlin and S. B. Weinstein, “Fractionally Speed Equalization ; An Improved Digital Transversal Equalizer,” B. S. T. J., Vol.60, No. 2, Feb, 1981.
- [20] F. Ling, “On Training Fractionally Spaced Equalizers Using Intersymbol Interpolation,” IEEE Trans. Communication, Vol.COM-37, pp. 1096~1099, Oct.1989.
- [21] S. H. Leung, B. L. Chan and S. M. Lau, “An Efficient Fractionally-Spaced Equalizer with Low Computations for Data transmission,” Proc, Int. Symp. On signal processing and it App : Gold Coast, Australia, pp. 311~314, Aug.1990.
- [22] S. Y. Song and D. H. Yoon, “Convergence Characteristics of MMADF Algorithm with the ISI Reduction for Data Transmission,” Proc. Of the 1999 International Technical Conference on Circuits/systems, Computers and Communications.(ITC-CSCC'99) Vol.2, pp. 1294~1297, July 1999.
- [23] N. S. Jayant, *Digital Coding of Waveforms Principles and Applications to Speech and Video*, Englewood Cliffs, NJ : Prentice-Hall, 1984.
- [24] T. Koh and E. J. Powers, “Efficient Methods to Estimate Correlation Functions of Gaussian Processes and Their Performance Analysis,” IEEE Trans. on Acoustics, Speech, and Signal Processing, Vol. ASSP-33, No.4, pp. 1032~1035, Aug. 1985.

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