# Convergence Analysis of IMADF Algorithm to Reduce the ISI in Fast Data Transmission

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## ABSTRACT

The convergence analysis of the improved multiplication free adaptive digital filter(IMADF) with a fractionally-spaced equalizer(FSE) to remove the intersymbol interference(ISI) in fast data transmission is presented. The IMADF structure use the one-step predicted filter in the multiplication-free adaptive digital filter(MADF) structure using the DPCM and Sign algorithm. In the experimental results, the IMADF algorithm has 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 that the IMADF algorithm is almost same as the sign algorithm, but is better than the MADF algorithm. Here, this algorithm has effective characteristics when the correlation of the input signal is highly.


## I. Introduction

The fast data transmission in many areas of digital communication, control and signal processing taking place, it is often desired to extract useful information from a set of noisy data. On way of obtaining a useful data is to solve this filter-optimization problem. A Wiener filter [1] was used first. An efficient adaptive filtering method [2-6] 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 [7,8]. This approach is a stochastic 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 [9, 10].

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[11, 12.]. 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 [13]. W.Lee, Un and C.Lee [14] has introduced the multiplication-free adaptive digital filter [MADF] that processes the differential pulse code

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modulation (DPCM) using the popular LMS algorithm.

Mathews [15] have presented the MADF algorithm including DPCM and the sign algorithm. Park, Youn and Cha [16] have showed another forms of the MADF. Especially, Cho[17] analyzed the convergence characteristics of an efficient adaptive digital filtering algorithm and structures. Mathews and Cho [18] 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 [19]. Until recently, such a equalizer have used the synchronous transversal equalizer (STE). But, the STE has the disadvantage that cant cancel the noisy completely and cant control the amplitude and phase of the signal in outer of Nyguist frequency domain. In order to solve those problems, the fractionally spaced equalizer (FSE) was proposed by Gitlin and Weistein [20]. 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 [21]. Leung, Chan and Lau [22] have proposed an efficient FSE with low computation for data transmission. Song and Yoon [23] 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 reduce the ISI is proposed and analyzed their convergence characteristics by using the mean-square error and its behavior. The characteristics parameters for estimating the performance of the algorithm are selected in the experiments.

## Ⅱ. Theory of IMADF

The problem of determining the optimum adaptive filter was solved by Nobert Wiener and others. The statement of the problem is determining a set of coefficient column vector, $H(n)$, that minimize the mean of the squared error of the filtered output as compared to some desired output[9].

The LMS algorithm as it is applied to the adaptation of time-varying FIR filters(MA systems) and IIR filters(adaptive recursive filters or ARMA systems) is the simplest and most used adaptive algorithm[9, 11, 12]. The basic LMS algorithm updates the filter coefficients based on the method of steepest descent. Besides, in some practical applications, there are modified different LMS algorithms like table 1. Where X(n) is the input signal column vector, ε (n) is the error signal and $\mu$ is a parameter that controls the rate of convergence.

Table 1. A variable LMS algorithms

| Algorithm | Equation, $H(n+1)$ |
|---|---|
| Basic LMS | $H(n) + 2\mu\varepsilon(n)X(n)$ |
| Normalized LMS | $H(n) + \mu\varepsilon(n)X(n)$ |
| Sign LMS | $H(n) + \mu X(n) sign[\varepsilon(n)]$ |
| Sign-sign LMS | $H(n) + \mu sign[X(n)] sign[\varepsilon(n)]$ |
| Leaky LMS | $rH(n) + \mu\varepsilon(n)X(n), r<1$ |

The multiplication-free adaptive digital filter (MADF) structure requiring zero-multiplication was introduced [15-17]. In particular, the MADF structure employs a differential pulse-code modulation(DPCM) system for the reference input signal, and the reference input vectors are used in the update equation for the adaptive filter coefficients[14]. The vector consisting of the reconstructed signals is used as the input vector in the coefficient update equation [17,18]. The update equation of the MADF algorithm can be written as

$$H(n+1) = H(n) + \mu sign[\varepsilon(n)]\ \hat{X}(n) \qquad (1)$$

where $\hat{X}(n)$ denote the reconstructed input signal vectors of the DPCM.

Fig. 1 shows an improved multiplication free adaptive digital filter(IMADF) structure. The IMADF algorithm uses $d'(n)$ and $e'(n-1)$ 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, $\hat{X}(n)$ and $\tilde{X}(n)$ denote the predicted and the reconstructed input signal vectors of the DPCM, respectively [18, 22]. Also, let B(n) define the vectors consisting of the quantizer outputs of DPCM as Q{ε (n)} corresponds to the vector obtained by quantizing each element of ε (n).

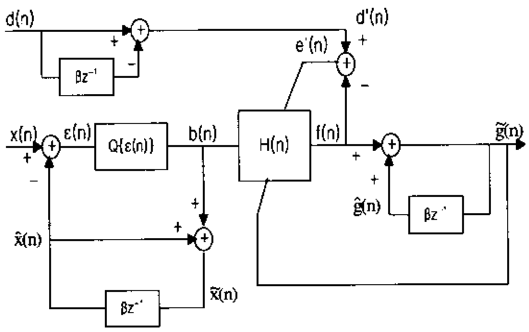


Fig. 1 Block diagram of IMADF

So, by using the set of equations describing the IMADF algorithm[23], we can obtain the final transfer equation H(n) as follows

$$H(n+1) = H(n) + \mu\tilde{X}(n)sign\{e'(n)\} \quad (2)$$

From equations f(n), $\hat{g}(n)$ and B(n), it follows that

$$\tilde{g}(n) = \beta\tilde{g}(n-1) + [\tilde{X}^T(n) - \beta\tilde{X}^T(n-1)]H(n). \quad (3)$$

where β (0<|β|<1) denotes the one-step prediction coefficient used in the DPCM system
Substituting the equation (2) in (3) yields

$$\tilde{g} = \beta\tilde{g}(n-1) + \tilde{X}^T(n)H(n) - \beta\tilde{X}^T(n-1)H(n-1)$$
$$- \mu\beta\tilde{X}^T(n-1)B(n-1)sign\{e'(n-1)\}. \quad (4)$$

Under zero initial conditions, the equation (4) can be rewritten as

$$\tilde{g}(n) = \tilde{X}^T(n)H(n)$$
$$- \mu\sum_{k=1}^{n-1}\beta^{n-k}\tilde{X}^T(k)\tilde{X}(k)sign\{e'(k)\}, \quad (5)$$

where for small values of 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 analyze of the convergence characteristics, three of assumptions will be used[15,17,18]. Then, notations of $R_{xx}$ and $R_{\tilde{x}\tilde{x}}$ denotating 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 and the reconstruction error vector $\eta(n)$ of the DPCM system at a time n , the covariance matrix that each element of $\eta(n)$ is uniformly distributed in ( $-\Delta/2, \Delta/2$ ) yields

$$R_{\eta\eta} = E\{\eta(n)\eta^T(n)\} = \sigma_\eta^2 I \quad (6)$$

By using equation (6), autocorrelation matrix $R_{d\tilde{X}}$ and $R_{\tilde{X}\tilde{X}}$ can be written as

$$R_{d\tilde{X}} = E\{d(n)[X(n) - \eta(n)]\} = R_{dX} \quad (7)$$

$$R_{\tilde{X}\tilde{X}} = E\{[X(n) - \eta(n)][X^T(n) - \eta^T(n)]\}$$
$$= R_{XX} + \sigma_\eta^2 I \quad (8)$$

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)[15, 17, 18] are given

$$H_{opt} = R_{\tilde{X}\tilde{X}}^{-1} R_{d\tilde{X}} \quad (9)$$

$$e_{min}(n) = d'(n) - \tilde{X}^T(n)H_{opt} \quad (10)$$

Note that $H_{opt}$ given by equation (9) 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[17, 24]. From the difference H(n) and $H_{opt}$, we can define the coefficient misalignment vector as

$$V(n) = H(n) - H_{opt} \tag{11}$$

and its autocorrelation matrix as

$$K(n) = E\{V(n)V^T(n) \tag{12}$$

By using equation (11) in (2), the update equation for the coefficient misalignment vector be written

$$V(n+1) = V(n) + \mu\tilde{X}(n)sign\{e'(n)\} \tag{13}$$

and substituting equation (3) in (13) yields its filter coefficient vector[4] as

$$H(n+1) = H(n) + \mu\tilde{X}(n)sign\{e(n) - \beta e(n-1)\} \\ - \mu\beta\tilde{X}(n-1)sign\{e(n) - \beta e(n-1)\} \tag{14}$$

Using Mathews[15], the expectation value of equation (13) gives

$$E\{V(n+1)\} = [I - \sqrt{\frac{2}{\pi}}\frac{\mu}{\sigma_{e'}(n)}R_{\tilde{X}\tilde{X}}]E\{V(n)\} \\ + \mu\beta\sqrt{\frac{2}{\pi}}\frac{1}{\sigma_{e'}(n)}[\mu\beta\sqrt{\frac{2}{\pi}}\frac{1}{\sigma_{e'}(n)} \\ (2R_{\tilde{X}\tilde{X}} + tr(R_{\tilde{X}\tilde{X}}) - \beta]R_{\tilde{X}\tilde{X}}E\{V(n-1)\} \tag{15}$$

and the expectation value of equations (14) gives

$$E\{H(n+1)\} = E\{H(n)\} + \mu\sqrt{\frac{2}{\pi}}\frac{1}{\sigma_{e'}(n)}[R_{d\tilde{X}} - R_{\tilde{X}\tilde{X}}E\{H(n)\}] \\ - \mu^2\beta^2\sqrt{\frac{2}{\pi}}\frac{1}{\sigma_{e'}(n)}[2R_{\tilde{X}\tilde{X}} + tr(R_{\tilde{X}\tilde{X}})][R_{d\tilde{X}} - R_{\tilde{X}\tilde{X}}E\{H(n-1)\}] \\ - \mu\ \beta^2\sqrt{\frac{2}{\pi}}\frac{1}{\sigma_{e'}(n)}[R_{d\tilde{X}} - R_{\tilde{X}\tilde{X}}E\{H(n-1)\}] \tag{16}$$

where $\sigma_{e'}(n)$ is the covariance value of estimation error. The convergence condition of the equation (15) must be considered. It is shown that the optimal coefficient Hopt in some convergence condition gives

$$H_{opt} = R_{\tilde{X}\tilde{X}}^{-1}R_{d'\tilde{X}} = R_{XX}^{-1}R_{dX} \tag{17}$$

An update equation for K(n) is now required. Substituting equation (15) into (12) yields the following expression for the mean-squared behavior of the coefficient misalignment vector [18].

$$K(n+1) = K(n) + \mu^2 R_{\tilde{X}\tilde{X}} \\ - \sqrt{\frac{2}{\pi}}\frac{\mu}{\sigma_e'(n)}[K(n)R_{\tilde{X}\tilde{X}} + R_{\tilde{X}\tilde{X}}K(n)] \tag{18}$$

In order to evaluate the steady-state response of the mean-squared estimation error[8, 17, 18], define the following limiting value :

$$\sigma_{e'}^2(\infty) \approx \xi_{\min} + \frac{\mu}{2}\sqrt{\frac{2}{\pi}}\sqrt{\xi_{\min}}tr\{R_{\tilde{X}\tilde{X}}\} \tag{19}$$

$$K(\infty) = K'(\infty) = \frac{\mu}{2}\sqrt{\frac{2}{\pi}}\sigma_e'(\infty)I \tag{20}$$

where

$$\xi_{\min}' = E\{e_{\min}'^2(n)\} = E\{d'^2(n)\} - H_{opt}^T R_{d'\tilde{X}} \tag{21}$$

Using steady-state assumption[8, 17, 23], it follows that

$$\sigma_{e'}^2(\infty) = (1+\beta^2)\sigma_e^2(\infty) \tag{22}$$

$$\xi_{\min}^{'} = (1+\beta^2)\xi_{\min} \tag{23}$$

where $\xi_{\min}$ is $E\{e_{\min}^2(n)\}$. By using $tr(R\ )$ in terms of the autocorrelation function $R_{XX}$, equations (19) and (20) give

$$tr\{R_{BB}\} = (1-\beta^2)tr\{R_{\tilde{X}\tilde{X}}\} \tag{24}$$

Therefore, expressing the equation (19)

$$\sigma_{e'}^2(\infty) = (1+\beta^2)\sigma_e^2(\infty)$$
$$= (1+\beta^2)\xi_{\min} + \frac{\mu}{2}\sqrt{\frac{\pi}{2}}\sqrt{1+\beta^2}\sqrt{\xi_{\min}}(1-\beta^2)tr\{R_{\overline{XX}}\} \tag{25}$$

As a Results, it follows that

$$\sigma_e^2(\infty) = \xi_{\min} + \frac{1-\beta^2}{\sqrt{1+\beta^2}}\frac{\mu}{2}\sqrt{\frac{\pi\xi_{\min}}{2}}[tr\{R_{XX}\} + N\sigma_e^2] \tag{26}$$

where $\sigma_e^2$ denote the quantization error in DPCM system.

The mean-squared estimation error for the MADF algorithm[18] gives

$$\sigma_e^2(\infty) = \xi_{\min} + \frac{\mu}{2}\sqrt{\frac{\pi\xi_{\min}}{2}}[tr\{R_{XX}\} + N\sigma_e^2] \tag{27}$$

On comparing equation (26) and (27), there is a modification of $(1-\beta^2)/\sqrt{1+\beta^2}$. It is shown that the IMADF algorithm converges faster than the MADF algorithm in identifical 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 fractionally spaced equalizer

The effect of an equalization is to compensate for the fast data transmission impairment such as frequency-dependent phase and amplitude distortion[19]. On considering an arbitrary impulse response, the received signal r(nT) sampled at a time nT yields

$$r(nT) = \sum_{k=-\infty}^{\infty} a_k h(nT - kT) \tag{28}$$

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[19]. In some instances, it can be advantages to sample at a multiple of the symbol rate to implement a fractionally spaced signal processing[20, 21]. To explain the ISI phenomenon, the transmitted signal replaced by $nT+t_0$ can be written as

$$r(nT+t_0) = a_n + \sum_{\substack{j\neq n\\ j=0}}^{N-1} a_j h(nT + t_0 - jT) + N(nT+t_0) \tag{29}$$

where $t_0$ is the delay time, $a_n$ is the source signal, $a_j$ 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 (29) presents the ISI phenomenon. Fig. 2 shows the block diagram of the FSE.

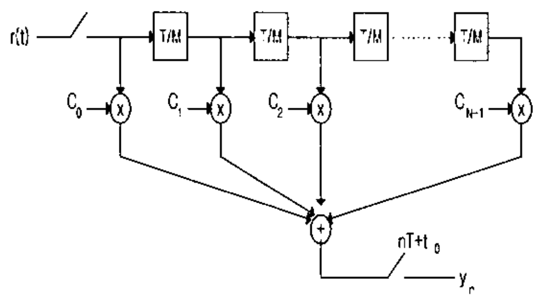


Fig. 2 The block diagram of the FSE

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

$$y_n = \sum_{k=0}^{N-1} C_n r(nT + t_0 - \frac{kT}{M}) \tag{30}$$

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+), is the prime number) gives

$$C_L(\omega) = \sum_{k=0}^{N-1} C_k e^{-j\omega kL} \tag{31}$$

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

$$F_L(\omega) = C_L(\omega)\sum_{k=0}^{N-1} H(\omega + k\frac{2\pi}{L})e^{j(\omega+2k\pi/L)\tau} \quad (32)$$

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

$$F_L(\omega) = C_L(\omega)H(\omega)e^{j\omega\tau} \quad (33)$$

Therefore, the phase and amplitude distortion due to the term $e^{j\omega\tau}$ of the equation (33) 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

$$C_k(n+1) = C_k(n) - \mu \cdot sign\{e'(n)\}r(nT + t_0 - \frac{kT}{M}) \quad (34)$$

where $C_k(n+1)$, $0 \le k \le N-1$, 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, and also reduce the computational complexity due to zero-multiplication .

## Ⅳ. Experimental Results

On comparing sign algorithm, MADF and IMADF algorithm, Table 2 shows the differences in the number of arithmetic operation. 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. Then the operation number of IMADF algorithm is increased to two.

In order to reduce the computational complexity of the equation (5) 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 △ the quantization step size of the DPCM system to be again an (possibly negative) integer power of two. Selecting $\mu$ and $\beta$ in equations (4) and (5), it is observed that the multiplications with $\mu$ can be replaced by bit-shift operation and one addition operation each[14, 16, 17]. Furthermore, since each element of B(n) is an integer multiple of quantization step △, each multiplication in equation f(n) 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 △ and 6 △ 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.

Table 2. Operation No. of each algorithm

| algorithm | No. of multiplier | No. of adder |
|---|---|---|
| Sign | N | 2N |
| MADF | 0 | 3N+5 |
| IMADF | 0 | 3N+7 |

In order to analyze the convergence characteris -tics of IMADF algorithm, we use 13 quantization levels and 22 delay taps, assuming the additive White Gaussian noise with zero-mean and independent of input signals. Table 3 shows the characteristic parameter of transmission-channel under such conditions.

In the Table 3, the parameter W is used to obtain the impulse response of channel, and controls the quantity of an amplitude distortion occurred in the transmission-channel. $r(l)$ is the autocorrelation function of reference input signals.

Table 3. Characteristic parameter

| | 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 |
| $\chi(R)$ | 3.6651 | 6.5738 | 26.1805 |

$\lambda_{min}$ is the minimum eigenvalue of autocorrelation matrix, $\lambda_{max}$ is the maximum eigenvalue of autocorrelation matrix, $\chi(R)$ is the ratio of $\lambda_{max}$ and $\lambda_{min}$. The predicted coefficient $\beta$ and quantization step $\Delta$ are given in Jayant[24]

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 3, equations (35) and (36), 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 dB or ∞ dB. Then we select $\beta = 2^{-1}$ $\Delta = 2^{-2}$. 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.

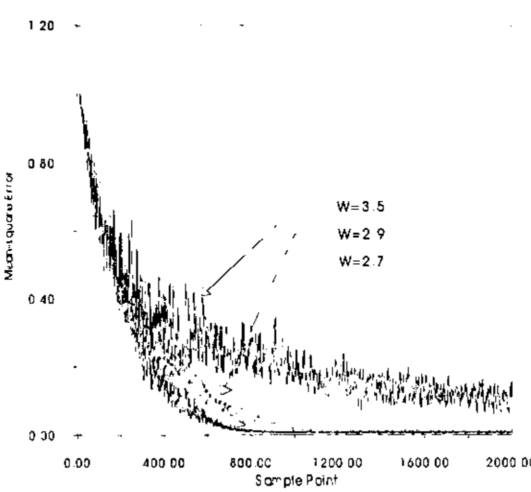


Fig. 3 The convergence characteristics of MADF algorithm

Fig. 3 present the convergence curves of the MADF algorithm by changing W on SNR = 30 dB, $\beta = 2^{-1}$, $\Delta = 2^{-2}$ and $\mu$ = 0.008. Where the MSE is the ensemble average value of recursively independent runs of 40. The vertical axis is the unit of linear size.

Fig. 4 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.

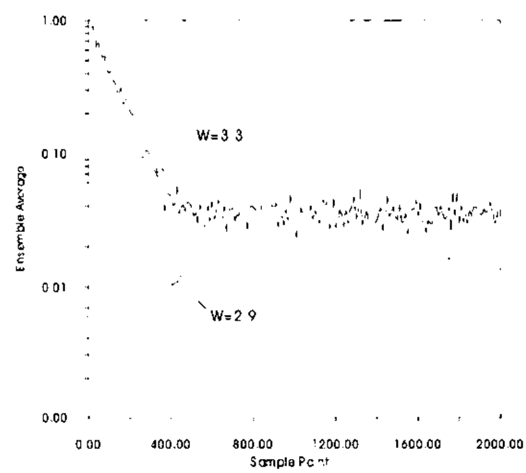


Fig. 4 The convergence characteristics of IMADF algorithm for change W.

In the Fig.4, it is shown that the convergence characteristics of the MSE in decreasing W are much better. Also, on changing SNR = ∞ dB, similar results are found in experiments. This means that the convergence characteristics are more effective for small autocorrelation values of input signals.

Fig. 5 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 $\mu$.

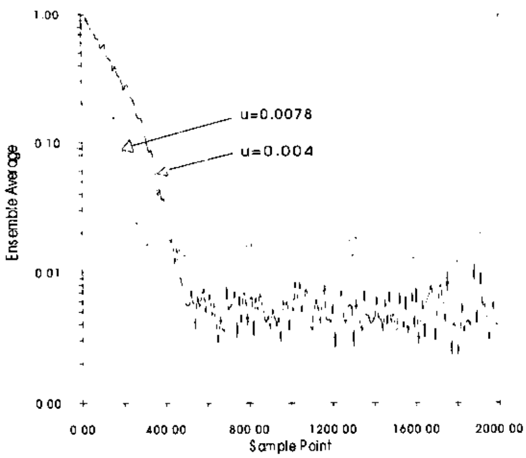


Fig. 5 The convergence characteristics of IMADF algorithm f.or change $\mu$

Fig. 5 shows that the convergence characteristics in increasing $\mu$ are much better. Also, on changing SNR = ∞ dB, similar results are found. In the Fig. 4 and Fig. 5, they shows that the convergence characteristics are more effective for W=2.9 and $\mu$ = 0.0078.

Fig. 6 compares convergence curves of Sign, MADF and IMADF algorithms for the ensemble average of recursive runs of 70 $\mu$ = 0.0078, SNR = 30 dB, $\beta = 2^{-1}, \Delta = 2^{-2}$ and W = 2.9.

In the Fig. 6, 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

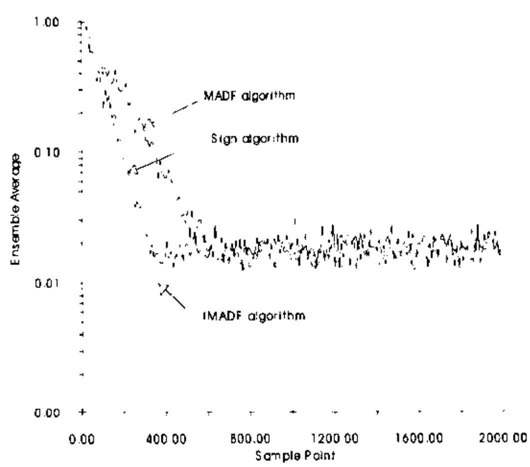


Fig. 6 Comparison of convergence characteristics of Sign, MADF and IMADF algorithms.

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 identical stationary-state with the MADF and sign algorithm, the IMADF algorithm could obtain the stabled convergence characteristics.

In the experimental results, it shows that the IMADF algorithm applying for the FSE have 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 IMADF algorithm has increased the additive operation of two more than the MADF algorithm.

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