A New Convergence Behavior of the Least Mean Fourth Adaptive Algorithm for a Multiple Sinusoidal Input

Kang Seung Lee* *Regular Member*

ABSTRACT

In this paper we study the convergence behavior of the least mean fourth(LMF) algorithm where the error raised to the power of four is minimized for a multiple sinusoidal input and Gaussian measurement noise. Here we newly obtain the convergence equation for the sum of the mean of the squared weight errors, which indicates that the transient behavior can differ depending on the relative sizes of the Gaussian noise and the convergence constant. It should be noted that no similar results can be expected from the previous analysis by Walach and Widrow[1].

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. One way of solving this filter-optimization problem is by using a Wiener filter[2]. However, this assumes that the signals being processed are stationary and it requires a priori knowledge, or at least the estimates, of their statistics which are not always available. Moreover, solving a set of linear matrix equations is needed to find optimum filter coefficients.

However, the adaptive filter makes it possible to perform satisfactorily in such environments where complete knowledge of the signal statistics is unavailable. In other words, the adaptive filter gradually learns the required correlations of the input signals and adjusts its coefficients recursively according to some suitably chosen statistical criterion.

During the last two decades, the Least Mean Square(LMS) adaptive algorithm has been successfully utilized for a variety of applications including system identification[3,4,5], noise cancellation[6,7], echo cancellation[8,9], and channel equalization[10]. Meanwhile, the adaptive filtering algorithms that are based on high order error power conditions have been proposed and their performances have been investigated[1,11,12,13,14]. Despite the potential advantages, these algorithms are less popular than the conventional LMS algorithm in practice. This is partly because the analysis of the high order error based algorithms is much more difficult, and thus little has been learned about the algorithms.

In the least mean fourth (LMF) adaptive algorithm[1] the error raised to the power of four is minimized. Here, one has to consider the possibility of the convergence to the local minimum. However, the mean of the error to the power of four is a convex function of the weight vector, so it cannot have local minima. Indeed the Hessian matrix of the error to the fourth power function can be shown to be positive definite, or positive semidefinite[15].

Walach and Widrow studied the convergence of the LMF adaptive algorithm[1]. However, in their convergence study of the mean squared weight errors, the statistical moments of the weight errors with the orders greater than two were neglected and the transient behavior was not analyzed. In

* Dept. of Computer Engineering Dongeui University (kslee@dongeui.ac.kr)
논문번호 : K01188-0827, 접수일자 : 2001년 8월 27일

this paper, we present a new result on the convergence of the least mean fourth algorithm under the system identification model with the multiple sinusoidal input and Gaussian measurement noise.

Following the introduction, we give a brief description of the underlying system model in Section II. The results of the convergence analysis and the simulation are presented in Sections III and IV, respectively. Finally we make a conclusion in Section V.

II. System Model

We consider an adaptive noise cancellation problem for the multiple sinusoidal input and Gaussian measurement noise. In that case, both the unknown system and corresponding adaptive filter can be described by the multiple in-phase (I) and quadrature (Q) weights as shown in Fig. 1[3,6].

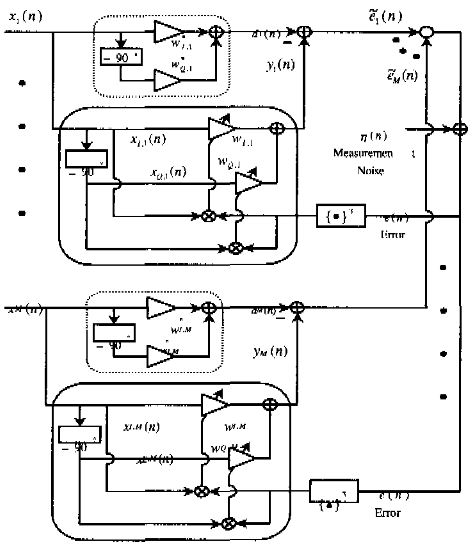


Fig. 1 Adaptive digital filter for a multiple sinusoidal input under study.

For the m-th sinusoidal input, the adaptive canceller structure also comes to have two weights $w_{I,m}(n)$ and $w_{Q,m}(n)$, with I and Q inputs, $x_{I,m}(n)$ and $x_{Q,m}(n)$, respectively. Thus the output of the m-th controller, $y_m(n)$ is expressed as

$$y_m(n)=\{ w_{I,m}(n)\, x_{I,m}(n)+w_{Q,m}(n)\, x_{Q,m}(n)\} \quad (1)$$

where

$$x_{I,m}(n)=A_m \cos(\omega_m n+\phi_m) \triangleq A_m \cos \Psi_m(n),$$
$$x_{Q,m}(n)=A_m \sin(\omega_m n+\phi_m) \triangleq A_m \sin \Psi_m(n),$$

m : branch index = $1, 2, 3, \ldots, M$,
n : discrete time index,
A : amplitude,
ω : normalized frequency,
Ψ : random phase.

Also, referring to the notation in Fig. 1, the error signal $x_{I,m}(n)$ and $e(n)$ is represented by

$$\begin{aligned} e(n) = & \sum_{m=1}^{M} [\{ w_{I,m}^{*} x_{I,m}(n) + w_{Q,m}^{*} x_{Q,m}(n)\} \\ & - y_m(n)] + \eta(n) \\ = & -\sum_{m=1}^{M} A_m [\{ w_{I,m}(n) - w_{I,m}^{*}\} \cos \Psi_m(n) \\ & + \{ w_{Q,m}(n) - w_{Q,m}^{*}\} \sin \Psi_m(n)] + \eta(n) \end{aligned} \quad (2)$$

where $\eta(n)$ is zero-mean measurement noise.

It can be shown from (1) and (2) that minimizing the fourth power error and using a gradient-descent method[3] yields a pair of the LMF weight update equations for each m as

$$w_{I,m}(n+1) = w_{I,m}(n) + 2\mu_m e^3(n)\, x_{I,m}(n)$$

and

$$w_{Q,m}(n+1) = w_{Q,m}(n) + 2\mu_m e^3(n)\, x_{Q,m}(n) \quad (3)$$

where μ_m is a convergence constant.

In the following, we analyze the convergence behavior of the mean and summed variance of weight errors of the LMF algorithm using a new analysis method.

III. Convergence Analysis

To see how the adaptive algorithm derived in (3) converges, we first investigate the convergence of the expected values of the adaptive weights. To simplify the convergence equation, we may introduce two weight errors as

$$v_{I,m}(n) \triangleq w_{I,m}(n) - w^*_{I,m} \text{ and}$$
$$v_{Q,m}(n) \triangleq w_{Q,m}(n) - w^*_{Q,m}. \tag{4}$$

Inserting (4) into (3), we have

$$v_{I,m}(n+1) = v_{I,m}(n) + 2\mu_m e^3(n)\, x_{I,m}(n) \text{ and}$$
$$v_{Q,m}(n+1) = v_{Q,m}(n) + 2\mu_m e^3(n)\, x_{Q,m}(n). \tag{5}$$

Next we investigate the convergence of the mean-square error(MSE) $E[e^2(n)]$. Using (2) and (4) we can express the MSE as

$$E[e^2(n)] = \sum_{m=1}^{M} e_m^2(n) + \sigma_\eta^2$$
$$= \frac{1}{2}\sum_{m=1}^{M} A_m^2\, \xi_m(n) + \sigma_\eta^2 \tag{6}$$

where

$$\xi_m(n) \triangleq E[v_{I,m}^2(n)] + E[v_{Q,m}^2(n)],$$
$$\sigma_\eta^2 \triangleq E[\eta^2(n)].$$

From (6) we find that studying the convergence of MSE is directly related to studying the sum of $\xi_m(n)$.

Inserting (1) and (2) into (5), and assuming that input signal $x_m(n)$, measurement noise $\eta(n)$, and weight errors $v_{I,m}(n)$, $v_{Q,m}(n)$ are independent of each other, we take the statistical average of both sides to obtain two equations for $E[v_{I,m}^2(n+1)]$ and $E[v_{Q,m}^2(n+1)]$. Since the two equations are symmetrical, we add them and assume that $E[v_{I,m}^2(n+1)] \cong E[v_{Q,m}^2(n+1)]$. This eliminates the subscripts I and Q to simplify the second moment equation of weight error, and rearranging the terms yields

$$E[v_m^2(n+1)]$$
$$= \frac{5}{4}\mu_m^2 A_m^8 \{E[v_m^6(n)] + 3E[v_m^2(n)]E[v_m^4(n)]\}$$
$$-\frac{3}{2}\mu_m A_m^4 \{E[v_m^4(n)] + (E[v_m^2(n)])^2\}$$
$$+\frac{45}{2}\mu_m^2 A_m^6 E[\eta^2(n)]\{E[v_m^4(n)] + (E[v_m^2(n)])^2\}$$
$$+\{1 - 6\mu_m A_m^2 E[\eta^2(n)] + 30\mu_m^2 A_m^4 E[\eta^4(n)]\}E[v_m^2(n)]$$
$$+ 2\mu_m^2 A_m^2 E[\eta^6(n)]. \tag{7}$$

Assuming that $\eta(n)$ is a Gaussian with a zero average, $w_{I,m}(n)$, $w_{Q,m}(n)$ are Gaussian variables, and $v_m(n)$ is also a Gaussian variable[14]. Thus (7) can be simplified by expressing $E[v_m^{2K}(n)]$ as $E[v_m^2(n)]$. Although $E[v_m(n)]$ decreases very rapidly, it is not zero from the beginning. Therefore, a Gaussian random variable $\triangle w_m(n)$ with zero average, and its variance, are adapted as follows

$$\triangle w_m(n) \triangleq v_m(n) - V_m(n),$$
$$E[v_m^2(n)] = V_m^2(n) + \rho_m^2(n) \tag{8}$$

where $V_m(n) \triangleq E[v_m(n)]$,

$$\rho_m^2(n) \triangleq E[\triangle^2 w_m(n)].$$

From (8) we find that during the transient state, i.e. from the beginning to the moment just before the steady state, $\rho_m^2(n)$ is much smaller than $V_m^2(n)$ and $E[v_m(n)]$ can be regarded as $V_m^2(n)$. On the other hand, $\rho_m^2(n)$ becomes dominant over $V_m^2(n)$ in the steady state and $E[v_m(n)]$ can be regarded as $\rho_m^2(n)$. Now, we apply (8) to (7) and use the relationship between $E[v_m^{2K}(n)]$ and $E[v_m^2(n)]$ of the Gaussian random variable[16] to arrive at the following equation

$$V_m^2(n+1) + \rho_m^2(n+1)$$
$$= 5\mu_m^2 A_m^8 \{V_m^6(n) + 9\rho_m^2(n)V_m^4(n) + 18\rho_m^4(n)V_m^2(n) + 6\rho_m^6(n)\}$$
$$-(3\mu_m A_m^4 - 45\mu_m^2 A_m^6 \sigma_\eta^2)\{V_m^4(n) + 4\rho_m^2(n)V_m^2(n) + 2\rho_m^4(n)\}$$
$$+(1 - 6\mu_m A_m^2 \sigma_\eta^2 + 90\mu_m^2 A_m^4 \sigma_\eta^4)\{V_m^2(n) + \rho_m^2(n)\}$$
$$+ 30\mu_m^2 A_m^2 \sigma_\eta^6. \tag{9}$$

The convergence equation (9) may be examined for two different cases. First, $\rho_m^{2K}(n)$ and the last term of (9) can be removed for the transient state. Thus the transient convergence equation is given by

$$V_m^2(n+1) \cong 5\mu_m^2 A_m^8 V_m^6(n) - (3\mu_m A_m^4 - 45\mu_m^2 A_m^6 \sigma_\eta^2)V_m^4(n)$$
$$+(1 - 6\mu_m A_m^2 \sigma_\eta^2 + 90\mu_m^2 A_m^4 \sigma_\eta^4)V_m^2(n). \tag{10}$$

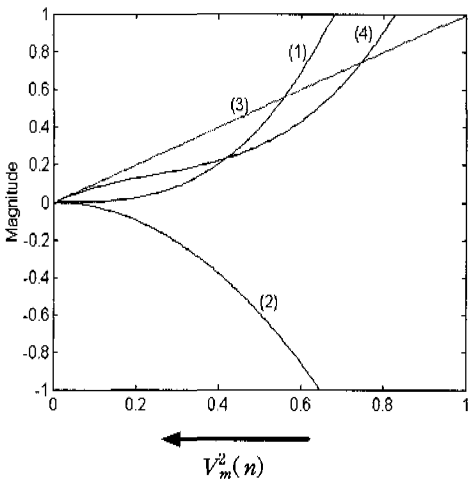


Fig. 2 Learning curves for the LMF algorithm of the summed variance of weight errors at the transient state. (1) $V_m^6(n)$ term. (2) $V_m^4(n)$ term. (3) $V_m^2(n)$ term. (4) total.

Fig. 2. shows the summed variance convergence curve of weight errors for the LMF algorithm at the transient state that resulted from a theoretical computation when μ_m = 0.2, $A_m = \sqrt{2}$, and σ_η^2 = 0.001. Taking each of the terms on the right-hand side of (10) separately and examining them carefully, we notice that the first $V_m^6(n)$ and the last $V_m^2(n)$ terms start off as positive values and are reduced to zero. However, the second $V_m^4(n)$ term starts off as a negative value and increases to zero. It should be noted from the right-hand side of (10) that in extreme cases, only one of the two terms $V_m^6(n)$ or $V_m^2(n)$ is dominant. Therefore, we may consider a particular value $V_{th,m}^2$ of $V_m^2(n)$ for which those two terms are the same. This value is given by

$$V_{m,th}^2 = \sqrt{\frac{1-6\mu_m A_m^2\sigma_\eta^2 + 90\mu_m^2 A_m^4\sigma_\eta^4}{5\mu_m^2 A_m^8}}. \qquad (11)$$

In (11) the first term $V_m^6(n)$ acts as the dominant term when $V_m^2(n)$ is greater than $V_{m,th}^2$. If V_m^2 is smaller than $V_{m,th}^2$, then the last $V_m^6(n)$ term becomes dominant.

Fig. 3 illustrates which of the two terms, the first term $V_m^6(n)$ and the last term $V_m^2(n)$, is dominant when $V_{m,th}^2(n)$ = 0.8. This illustration is in terms of the convergence constant μ_m and the variance of measurement noise σ_η^2. Point (a) is a region in which the term $V_m^6(n)$ dominates over the other and point (b) is when the $V_m^2(n)$ term is the dominant one. Therefore, the transient convergence equation (10) can be written as

$$V_m^2(n+1) \cong \begin{cases} 5\mu_m^2 A_m^8 V_m^6(n) & , V_m^2(n) \gg V_{m,th}^2 \quad (12a) \\ (1-6\mu_m A_m^2\sigma_\eta^2 + 90\mu_m^2 A_m^4\sigma_\eta^4) V_m^2(n) & , V_m^2(n) \ll V_{m,th}^2. \quad (12b) \end{cases}$$

From (12) we may derive the conditions for stability and the time constant. Expressing the general form in series, (12a) can be rewritten as

$$V_m^2(n) = \{5\mu_m^2 A_m^8\}^{(3^n-1)/2}\{V_m^2(0)\}^{3^n}$$
$$= \frac{1}{\sqrt{5}\,\mu_m A_m^4}\{\sqrt{5}\,\mu_m A_m^4 \;\; V_m^2(0)\}^{3^n}. \qquad (13)$$

Thus (13) is stable under the following condition

$$|\sqrt{5}\,\mu_m A_m^4 \;\; V_m^2(0)| < 1,$$
$$0 < \mu_m < \frac{1}{\sqrt{5}\,A_m^4 \; V_m^2(0)}. \qquad (14)$$

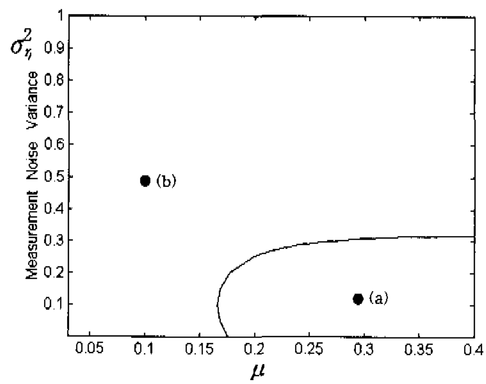


Fig. 3 Dominant term decision diagram for the LMF algorithm of the summed variance of weight errors at the transient-state.
[point (a): $\mu_m = 0.3$ and $\sigma_\eta^2 = 0.1$.
point (b) : $\mu_m = 0.2$ and $\sigma_\eta^2 = 0.5$.]

Note from the conditions for stability in (14) that the initial value of weight error acts as a limiting factor, along with the amplitude of input signal. From (12a) the time constant may not define because it is not a geometric series.

Also, (12b) is stabilized when it satisfies the condition

$$|\ 1-6\mu_m A_m^2\sigma_\eta^2+90\mu_m^2 A_m^4\sigma_\eta^4\ |<1\ ,$$
$$0<\mu_m<\frac{1}{15A_m^2\sigma_\eta^2}. \tag{15}$$

From (12b) the time constant in the second moment of weight error $\tau_{m,s}$ is given[3] by

$$\tau_{m,s}=\frac{1}{6\mu_m A_m^2\sigma_\eta^2\ \{1-15\mu_m A_m^2\sigma_\eta^2\}}. \tag{16}$$

In the steady state $V_m^2(n)$ becomes sufficiently small and the terms that include $\rho_m^4(n)$ and $\rho_m^6(n)$ can be ignored in the convergence equation (9). The equation is then simplified as

$$\rho_m^2(n+1)\cong(1-6\mu_m A_m^2\sigma_\eta^2+90\mu_m^2 A_m^4\sigma_\eta^4)\,\rho_m^2(n) + 30\mu_m^2 A_m^2\sigma_\eta^6. \tag{17}$$

Additionally, the summed variance of weight errors in the steady state $\xi_m(\infty)$ is $2\rho_m(\infty)$ and it can be written as

$$\xi_m(\infty)=2\rho_m(\infty)=\frac{10\mu_m\sigma_\eta^4}{1-15\mu_m A_m^2\sigma_\eta^2}. \tag{18}$$

When the convergence constant μ_m satisfies the stability condition (15), the second term on the denominator of the right-hand side of (18) is sufficiently smaller than the first term and it can be ignored to yield the following equation

$$\xi_m(\infty)=10\mu_m\sigma_\eta^4. \tag{19}$$

Comparing the performance of adaptive algorithms usually involves two methods[1,14]. The first method is to compare the state of convergence after setting equal values for the steady state, and the other one involves comparing the steady state values for same rate of convergence.

Summed variance of weight errors of the LMS algorithm is a geometric series and the time constant can be defined. However, the LMF algorithm (9) is not a geometric series. So, the time constant may not be defined. Then we set the steady state values of the two algorithms equal and compare the convergence rates. From (19) and (34) in [1] we obtain

$$\xi_{m(LMF)}(\infty)=\xi_{m(LMS)}(\infty),$$
$$10\ \mu_{m(LMF)}\ \sigma_\eta^4=\mu_{m(LMS)}\ \sigma_\eta^2\ ,$$
$$\mu_{m(LMF)}=\frac{\mu_{m(LMS)}}{10\,\sigma_\eta^2} \tag{20}$$

where $\mu_{m(LMF)}$ and $\mu_{m(LMS)}$ are the convergence constants of the LMF and LMS algorithms, respectively.

Ⅳ. Computer Simulations

In this section we present the results obtained from computer simulation along with the theoretical analysis of the LMF algorithm in the previous section.

We set the frequencies of the first and second sinusoidal signals at 120 Hz and 240 Hz, respectively, and selected 2 KHz for the sampling frequency. The input signal x(n) and desired signal d(n) are given by

$$x(n)=\sum_{m=1}^{2}A_m\cos(\omega_m n+\phi_m)$$
$$=\sqrt{2}\ \{\cos(\frac{240\pi n}{2000}+\phi_1)+\cos(\frac{480\pi n}{2000}+\phi_2)\},$$
$$d(n)=\sum_{m=1}^{2}\{w_{I,m}^* x_{I,m}+w_{Q,m}^* x_{Q,m}\}$$
$$=0.6x_{I,1}(n)-0.1x_{Q,1}(n)+0.3x_{I,2}(n)-0.3x_{Q,2}(n). \tag{21}$$

The simulation was carried out by setting 0.001 and 1 as the variances of measurement noise σ_η^2, and the initial value of weights were zero. The simulation results were obtained by ensemble averaging 1000 independent runs.

Fig. 4 show the summed variance convergence curves of weight error for the LMF algorithm that resulted from the simulation in case of dividing them between $V^2(n)$ and $\rho^2(n)$ when $\mu_{1(LMF)} = 0.0002$and $\sigma_\eta^2 = 1$, respectively. We see that $V^2(n)$ is the dominant term during the transient state whereas $\rho^2(n)$ becomes dominant during the steady state as we analyzed in the section III.B.

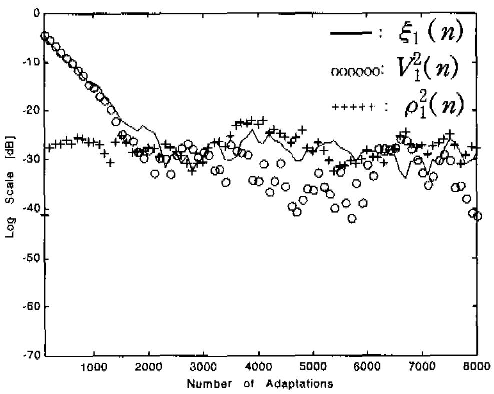


Fig. 4 Learning curves for the LMF algorithm of the summed variance of weight errors when the convergence behaviors are divided between $V^2(n)$ and $\rho^2(n)$.
[$\mu_{1(LMF)} = 0.0002$, $\sigma_\eta^2 = 1$.]

We have compared the convergence behavior of the LMF algorithm and that of the LMS algorithm through simulation. The convergence speed of the two algorithms were compared after setting the steady-state values equal. The convergence constants of the LMF and LMS algorithms were carefully chosen so that they satisfied the conditions given in (20) for a given variance of the measurement signal. To be specific, we selected 0.2 and 0.0002 for $\mu_{(LMF)}$ to make the steady-state values of the two algorithms equal when σ_η^2 was given as 0.001 and 1 and $\mu_{(LMS)}$ was 0.002.

In Fig. 5 the convergence behavior curves of summed variance of weight error obtained from simulation are compared with each other. It has been newly found that for some regions of μ and σ_η^2. The initial convergence of the LMF algorithm is much faster than the conventional LMS algorithm. This result in sufficiently small V_{th}^2 values compared to unity as the curve (a) of Fig. 5. Later on, the LMF convergence looks similar to the LMS convergence. This fact has not been reported yet, mainly because the higher order moments have not been included in the previous analyses of the LMF transient behavior[1]. On the other hand, when V_{th}^2 is large as in the curve (b) of Fig. 5, the LMF algorithm converges geometrically at a slightly slower rate than in the LMS case.

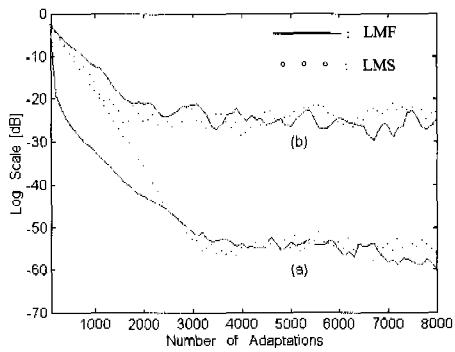


Fig. 5 Comparison of the LMF and LMS algorithm learning curves of the summed variance of weight errors.
(a) $\mu_{(LMS)}$= 0.002, $\mu_{(LMF)}$= 0.2, σ_η^2= 0.001 and V_{th}^2 =0.558.
(b) $\mu_{(LMS)}$= 0.002, $\mu_{(LMF)}$= 0.0002, σ_η^2= 1 and V_{th}^2 = 558.

V. Conclusions

We present a new result on the convergence of the least mean fourth(LMF) algorithm under the system identification model with the multiple sinusoidal input and Gaussian measurement noise. The analytical result on the mean square convergence depends on the power of Gaussian noise and the size of convergence factor. Accordingly, the transient behavior can be characterized by one of the two cases: (1) initially the LMF algorithm converges much faster than the LMS, but soon after that it converges almost linearly on a logarithmic scale like the LMS algorithm, or (2) the LMF algorithm converges linearly and at a slower rate than the LMS. To sum up, different convergence behaviors were observed depending on the variance of

Gaussian measurement noise and the magnitude of the convergence constant.

References

[1] E. Walach and B. Widrow, "The Least Mean Fourth (LMF) Adaptive Algorithm and Its Family," *IEEE Trans. on Information Theory*, Vol. 30, No. 2, pp. 275-283, March 1984.

[2] N. Wiener, Extrapolation, Interpolation and Smoothing Time Series with Engineering Application :*The MIT Press*, 1949.

[3] B. Widrow and S. D. Stearns, *Adaptive Signal Processing : Prentice-Hall*, 1985.

[4] C. P. Kwong, "Dual Sign Algorithm for Adaptive Filtering," *IEEE Trans. on Communications*, Vol. 34, No. 12, pp. 1272-1275, Dec. 1986.

[5] S. Dasgupta and C. R. Jhonson, "Some Comments on the Behavior of Sign-sign Adaptive Identifiers," *System and Letters*, Vol. 7, pp. 75-82, April 1986.

[6] B. Widrow, J. R. Glover, J. M. McCool et al., "Adaptive Noise Cancelling Principles and Applications," *Proc. IEEE*, Vol. 63, pp. 1692-1716, Dec. 1975.

[7] W. A. Harrison et al., "A New Application of Adaptive Noise Cancellation," *IEEE Trans. on Acoustics, Speech, and Signal Processing*, Vol. 34, No. 1, pp. 21-27, 1986.

[8] D. D. Falconer, "Adaptive Reference Echo Cancellation," *IEEE Trans. on Communications*, Vol. 30, No. 9, pp. 2083-2094, Sept. 1982.

[9] A. Kanemasa and K. Niwa, "An Adaptive-step Sign Algorithm for Fast Convergence of a Data Echo Canceller," *IEEE Trans. on Communications*, Vol. 35, No. 10, pp. 1102-1108, October 1987.

[10] P. F. Adam, "Adaptive Filtering in Communications", Chap. 8, *Adaptive Filters*, edited by C. F. N. Cowan and P. M. Grant, Prentice Hall, 1985.

[11] S. Pei and C. Tseng, "Adaptive IIR Notch Filter Based on Least Mean p-Power Error Criterion," *IEEE Trans. on Circuits and Systems*, Vol. II-40, No. 8, pp. 525-529, Aug. 1993.

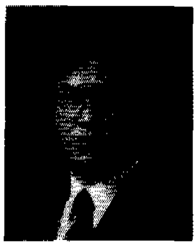
[12] J. Schroder, Rao Yarlagadda, and J. Hershey, "Lp Normed Minimization with Applications to Linear Predictive Modeling for Sinusoidal Frequency Estimation," *Signal Processing*, Vol. 24, pp. 193-216, Aug. 1991.

[13] A. Zerguine and T. Aboulnasr, "Convergence Behavior of the Normalized Least Mean Fourth Algorithm," 2000 *International Conference on Acoustics,* Speech, and Signal Processing, Vol. I, pp. 279-282, 2000

[14] K. S. Lee, "Performance Analysis of Adaptive Algorithms for Active Noise Control," *Ph. D. Thesis, Yonsei University*, Seoul, Aug. 1995.

[15] A. Gersho, "Some Aspects of Linear Estimation with Non-Mean-Square Error Criteria, "*Proc. Asilomar Ckts. and System Conf.*, 1969.

[16] J. S. Bendat, *Nonlinear System Analysis and Identification from Random Data : Jhon Wiley & Sons*, 1990.



Kang Seung Lee was bone in Korea, in 1962. He received the B. S., M. S., and Ph. D. degree in electronic engineering from Yonsei University, Seoul, Korea, in 1985, 1991 and 1995, respectively.

From 1991 to 1995, he served as a Research Associate at Yonsei University. From 1987 to 1996, he served as a Senior Member of Research Staff at Korea Electric Power Research Center, Taejeon City. Since 1996, he has been with the Department of Computer Engineering, Dongeui University, Pusan, as an Assistant Professor. His research interests include adaptive digital signal processing, image processing, multimedia signal processing and digital communications.

He is a member of IEEE(the Institute of Electrical and Electronics Engineers), AES(Audio Engineering Society), the Korea Institute of Telematics and Electronics, the Korean Institute of Communication Sciences, and the Acoustical Society of Korea.