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

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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 open 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, assumes that the signals being processed are stationary and requires a priori knowledge, or at least estimates, of their statistics which are not always available. Moreover, it is needed to solve a set of linear matrix equations to find optimum filter coefficients.

The adaptive filter, however, 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.

The Least Mean Square(LMS) adaptive algorithm have been successfully utilized for a variety of applications including system identification[3,4,5], noise cancellation[6,7], echo cancellation[8,9], channel equalization[10] during the last two decades. 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 seems partly because the analysis of the high order error based algorithms is much more difficult, and thus not much still has been known about the algorithms.

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

Walach and Widrow studied the convergence of the least mean fourth (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 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 Figure 1[3,6].

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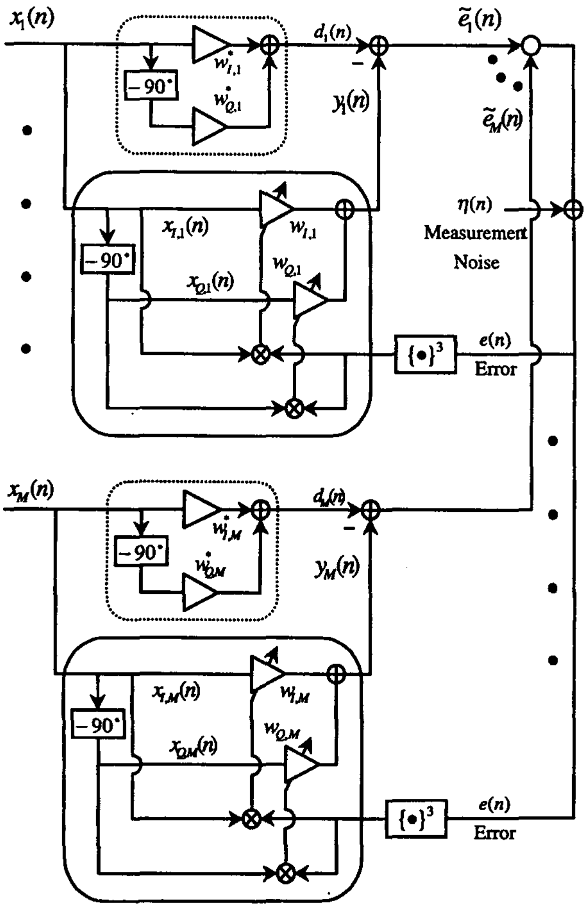


Figure 1. Adaptive digital filter for a multiple sinusoidal input under study.

For the m-th sinusoidal noise, the adaptive canceller structure also becomes to have two weights $\omega_{I,m}(n)$ and $\omega_{Q,m}(n)$, 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

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

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 Figure. 1, the error signal $e(n)$ is represented by

$$e(n) = \sum_{m=1}^{M} \{ d_m(n) - y_m(n) \} + \eta(n)$$

$$= -\sum_{m=1}^{M} A_m \left[\{ w_I(n) - w_I^* \} \cos \Psi_m(n) + \{ w_Q(n) - w_Q^* \} \sin \Psi_m(n) \right] + \eta(n) \tag{2}$$

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

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

3.1 The first moment of weight error

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

$$v_{I,m}(n) \triangleq w_{I,m}(n) - w^*_{I,m}$$

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

Inserting (4) into (3), we have

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

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

Rearranging (5) with (2), taking expectation of both sides of the resultant two weight-error equations, we can get the convergence equation based on the independent assumption on the underlying signal ; $x_m(n)$, $\eta(n)$, $v_{I,m}(n)$ *and* $v_{Q,m}(n)$.

$$E[v_{I,m}(n+1)] = (1 - 3\mu_m A_m^2 \sigma_\eta^2) E[v_{I,m}(n)] - \frac{3}{4}\mu_m A_m^4 E[v_{I,m}^3(n)] - \frac{3}{4}\mu_m A_m^4 E[v_{I,m}(n)] E[v_{Q,m}^2(n)],$$

and

$$E[v_{Q,m}(n+1)] = (1 - 3\mu_m A_m^2 \sigma_\eta^2) E[v_{Q,m}(n)] - \frac{3}{4}\mu_m A_m^4 E[v_{Q,m}^3(n)] - \frac{3}{4}\mu_m A_m^4 E[v_{I,m}^2(n)] E[v_{Q,m}(n)]. \tag{6}$$

In (6), the moment terms of order greater than 1 decrease much faster than the first order moment term in $E[v_{I,m}(n)]$ and $E[v_{Q,m}(n)]$. Therefore, ignoring the moment terms order greater than 1, the convergence equation becomes

$$E[v_{i,m}(n+1)] \cong (1-3\mu_m A_m^2 \sigma_\eta^2)\, E[v_{i,m}(n)], \quad i = I \text{ and } Q. \tag{7}$$

As it is clearly seen in (7), the mean of weight error converges exponentially to 0 under following conditions.

$$|1-3\mu_m A_m^2 \sigma_\eta^2| < 1, \quad 0 < \mu_m < \frac{2}{3A_m^2\sigma_\eta^2}. \tag{8}$$

We see that stabilizing condition of (8), unlike the Least Mean Square(LMS), is affected by variance of measurement noise signal.

In a sufficiently large time constant τ domain, time constant τ for exponential convergence can be simplified and is derived[3].

$$e^{-1/\tau_{i,m}} \cong 1-\frac{1}{\tau_{i,m}} = |1-3\mu_m A_m^2\sigma_\eta^2|, \quad i=I,\ Q. \tag{9}$$

From (9) the time constant is

$$\tau_{m,f} = \frac{1}{3\mu_m A_m^2 \sigma_\eta^2}. \tag{10}$$

3.2 The second moment of weight error

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

$$E[e^2(n)] = \sum_{m=1}^{M} e_m^2(n) + \sigma_\eta^2 = \frac{1}{2}\sum_{m=1}^{M} A_m^2\,\xi_m(n) + \sigma_\eta^2 \tag{11}$$

where

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

From (11), 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 $E[v_I^2(n+1)]$, $E[v_Q^2(n+1)]$. Since there two equations are symmetrical, we add them and assume that $E[v_{I,m}^2(n+1)] \cong E[v_{Q,m}^2(n+1)]$. Thus, elimin- ating the subscripts I and Q to simplify the second moment equation of weight error and rearranging the terms yields

$$\begin{aligned} E[v_m^2(n+1)] &= \frac{5}{4}\mu_m^2 A_m^8\{E[v_m^6(n)] + 3E[v_m^2(n)]E[v_m^4(n)]\} \\ &- \frac{3}{2}\mu_m A_m^4\{E[v_m^4(n)] + (E[v_m^2(n)])^2\} \\ &+ \frac{45}{2}\mu_m^2 A_m^6 E[\eta^2(n)]\{E[v_m^4(n)] + (E[v_m^2(n)])^2\} \\ &+ \{1-6\mu_m A_m^2 E[\eta^2(n)] + 30\mu_m^2 A_m^4 E[\eta^4(n)]\}E[v_m^2(n)] \\ &+ 2\mu_m^2 A_m^2 E[\eta^6(n)]. \end{aligned} \tag{12}$$

Assuming that $\eta(n)$ is a Gaussian with zero average and $\omega_{I,m}(n)$, $\omega_{Q,m}(n)$ are Gaussian variables, $v_m(n)$ is also a Gaussian variable. Thus, (12) 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 no zero from the beginning. Thus, a Gaussian random variable $\triangle w_m(n)$ with zero average, and its variance are adapted as follows:

$$\triangle w_m(n) \triangleq v_m(n) - V_m(n), \quad E[v_m^2(n)] = V_m^2(n) + \rho_m^2(n) \tag{13}$$

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

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

From (13), we find that during the transient state, i.e. from 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 (13) to (12) 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.

$$V_m^2(n+1)+\rho_m^2(n+1)$$
$$=5\mu_m^2A_m^8\{V_m^6(n)+9\rho_m^2(n)V_m^4(n)+18\rho_m^4(n)V_m^2(n)+6\rho_m^6(n)\}$$
$$-(3\mu_mA_m^4-45\mu_m^2A_m^6\sigma_\eta^2)\{V_m^4(n)+4\rho_m^2(n)V_m^2(n)+2\rho_m^4(n)\}$$
$$+(1-6\mu_mA_m^2\sigma_\eta^2+90\mu_m^2A_m^4\sigma_\eta^4)\{V_m^2(n)+\rho_m^2(n)\}$$
$$+30\mu_m^2A_m^2\sigma_\eta^6. \quad (14)$$

3.2.1 Convergence during the transient state

The convergence equation (14) may be examined for two different cases, First, $\rho_m^{2K}(n)$ and the last term of (14) can be removed for the transient state. Thus, the transient convergence equation is given by

$$V_m^2(n+1)\cong 5\mu_m^2A_m^8V_m^6(n)-(3\mu_mA_m^4-45\mu_m^2A_m^6\sigma_\eta^2)V_m^4(n)$$
$$+(1-6\mu_mA_m^2\sigma_\eta^2+90\mu_m^2A_m^4\sigma_\eta^4)V_m^2(n). \quad (15)$$

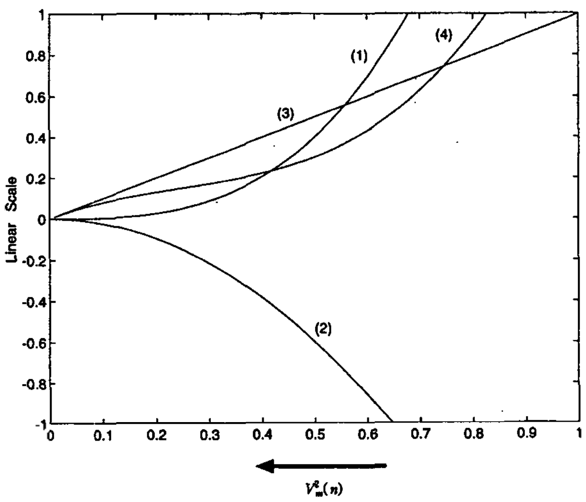


Figure 2. Learning curves for the LMF algorithm of the summed variance of weight errors at the transient state; (1) $V_m^6(n)$ term, (2) $V_m^4(n)$ term, (3) $V_m^2(n)$ term, (4) total.

Figure 2 showed the summed variance convergence curve of weight errors for the LMF algorithm at the transient state that resulted from the theoretical computation when μm = 0.2, $A_m=\sqrt{2}$, and σ_η^2 = 0.001. Taking each term on the right-hand side of (15) separately and examining them carefully, we notice that the first $V_m^6(n)$ term and the last $V_m^2(n)$ term start off as positive values and are reduced to zero. The second $V_m^4(n)$ term, however, start off as a negative value and increases to zero. It is noted from the right-hand side of (15) 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 and is given by

$$V_{m,th}^2=\sqrt{\frac{1-6\mu_mA_m^2\sigma_\eta^2+90\mu_m^2A_m^4\sigma_\eta^4}{5\mu_m^2A_m^8}} \quad (16)$$

In (16), 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 $V_m^6(n)$ V_m^2 is smaller than $V_{m,th}^2$, then the last term becomes dominant. Figure 3 is given to illustrate in terms of the convergence constant μm and the variance of measurement noise σ_η^2, 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. Point (a) is a region in which the term $V_m^6(n)$ dominates over the other and point (b) is when $V_m^2(n)$ term is the dominant one. Therefore, the transient convergence equation (15) can be written as ;

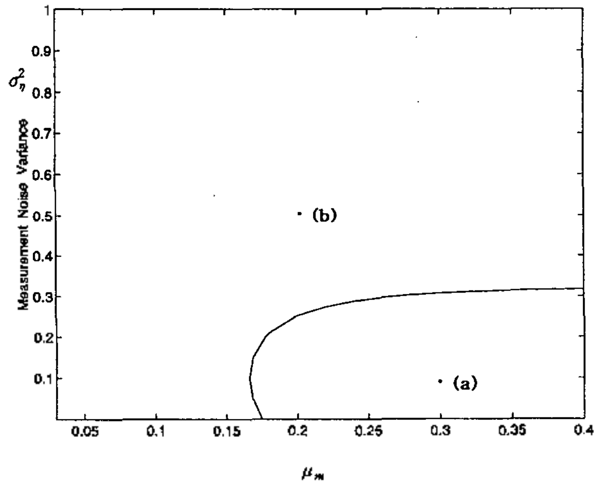


Figure 3. Dominant term decision diagram for the LMF algorithm of the summed variance of weight errors at the transient-state.
[point (a) : $\mu_m=0.3$ and $\sigma_\eta^2=0.1$. point (b) : $\mu_m=0.2$ and $\sigma_\eta^2=0.5$.]

$$V_m^2(n+1)\cong\begin{cases}5\mu_m^2A_m^8V_m^6(n) & ,\ V_m^2(n)\gg V_{m,th}^2 \quad (17a)\\ (1-6\mu_mA_m^2\sigma_\eta^2+90\mu_m^2A_m^4\sigma_\eta^4)V_m^2(n) & ,\ V_m^2(n)\ll V_{m,th}^2. \quad (17b)\end{cases}$$

Now, from (17a) we may derive the conditions for stability and the time constant by rewriting it as

$$V_m^2(n) = \{5\mu_m^2 A_m^8\}^{(3^n-1)/2}\,(V_m^2(0))^{3^n}$$
$$= \frac{1}{\sqrt{5}\,\mu_m A_m^4}\{\sqrt{5}\,\mu_m A_m^4\ \ V_m^2(0)\}^{3^n}. \qquad (18)$$

Thus, (18) is stable under the following condition ;

$$|\sqrt{5}\,\mu_m A_m^4\ \ V_m^2(0)| < 1,$$
$$0 < \mu_m < \frac{1}{\sqrt{5}\,A_m^4\ V_m^2(0)}. \qquad (19)$$

Note from the conditions for stability in (19) that the initial value of weight error acts as a limiting factor, along with the amplitude of input signal, the gain of the secondary path and the estimated gain of the secondary path. And, (17b) is stabilized when it satisfies the condition below ;

$$|1 - 6\mu_m A_m^2\sigma_\eta^2 + 90\mu_m^2 A_m^4\sigma_\eta^4| < 1,$$
$$0 < \mu_m < \frac{1}{15\,A_m^2\sigma_\eta^2} \qquad (20)$$

From (9) and (17b), the time constant is given by;

$$\tau_{m,s} = \frac{1}{6\mu_m A_m^2\sigma_\eta^2\,(1-15\mu_m A_m^2\sigma_\eta^2)} \qquad (21)$$

3.2.2 Convergence in the steady state

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 (14). The equation is then simplified as

$$\rho_m^2(n+1) \cong (1-6\mu_m A_m^2\sigma_\eta^2 + 90\,\mu_m^2 A_m^4\sigma_\eta^4)\,\rho_m^2(n) + 30\,\mu_m^2 A_m^2\sigma_\eta^6 \qquad (22)$$

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

$$\xi_m(\infty) = 2\,\rho_m(\infty) = \frac{10\,\mu_m\sigma_\eta^4}{1-15\,\mu_m A_m^2\sigma_\eta^2}. \qquad (23)$$

When the convergence constant μ_m satisfy the stability condition (20), the second term on the denominator of the right-hand side of (23) is sufficiently smaller than the first term and it is ignored to yield the following equation.

$$\xi_m(\infty) = 10\,\mu_m\sigma_\eta^4. \qquad (24)$$

3.2.3 Comparison of the LMF and LMS algorithm[1,14]

Comparing the performance of adaptive algorithms usually involves two methods. 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 while that of the LMF algorithm (14) is not a geometric series and therefore, 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 (24) and (34) in [1] we obtain as

$$\xi_{m(LMF)}(\infty) = \xi_{m(LMS)}(\infty),$$
$$10\ \mu_{m(LMF)}\,\sigma_\eta^4 = \mu_{m(LMS)}\,\sigma_\eta^2,$$
$$\mu_{m(LMF)} = \frac{\mu_{m(LMS)}}{10\,\sigma_\eta^2} \qquad (25)$$

where $\mu_{m(LMF)}$ and $\mu_{m(LMS)}$ are the convergence constants of 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 LMF algorithm in the previous section.

case 1. the convergence property of LMF algorithm.

case 2. the performance comparison of LMF and LMS.

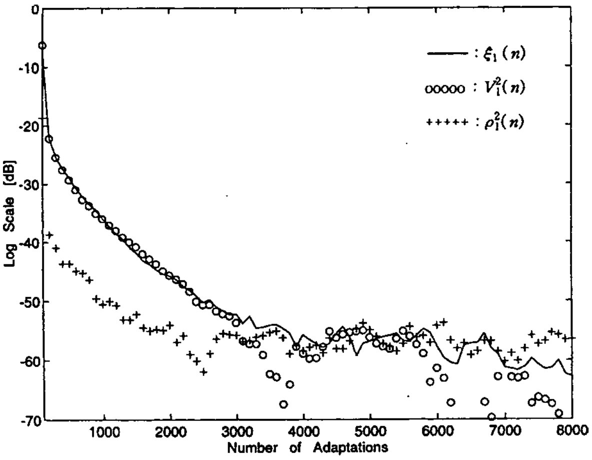
We set the frequencies of the first and second sinusoidal signal at 120Hz and 240Hz, respectively, and selected 2KHz for sampling frequency. The input signal x(n) and desired signal d(n) are given by

$$x(n) = \sum_{m=1}^{2} A_m\cos(\omega_m n + \phi_m)$$
$$= \sqrt{2}\{\cos(\frac{240\pi n}{2000} + \phi_1) + \cos(\frac{480\pi n}{2000} + \phi_2)\},$$
$$d(n) = \sum_{m=1}^{2}\{w_{I,m}^* x_{I,m} + w_{Q,m}^* x_{Q,m}\}$$
$$= 0.6x_{I,1}(n) - 0.1x_{Q,1}(n) + 0.3x_{I,2}(n) - 0.3x_{Q,2}(n). \qquad (26)$$

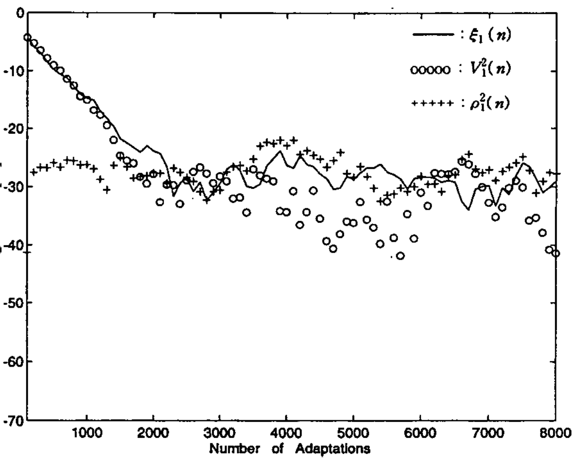
The simulation was carried out by setting 0.001 and 1 as the variances of measurement noise σ_η^2. And the initial value of weights is zero. The simulation results were obtained by ensemble averaging 1000 independent runs.

4.1 The convergence property of LMF algorithm

Figure 4 (a) and (b) showed the summed variance convergence curves of weight error for the LMF algorithm that resulted from the simulation when $\mu_{1(LMF)} = 0.2$, $\sigma_\eta^2 = 0.001$ and $\mu_{1(LMF)} = 0.0002$, $\sigma_\eta^2 = 1$, 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.



(a) $\mu_{1(LMF)} = 0.2$, $\sigma^2_\eta = 0.001$.



(b) $\mu_{1(LMF)} = 0.0002$, $\sigma_\eta^2 = 1$.

Figure 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 $\rho^2(n)$.

4.2 The comparison of LMF and LMS

We have compared the convergence behavior of LMF algorithm and that of algorithm LMS through simulation. The convergence speed of the two algorithm were compared after setting the steady-state values equal. The convergence constants of LMF and LMS algorithm were carefully chosen so that they satisfy the conditions given in (25) for a given variance of measurement signal. To be specific, we selected 0.2 and 0.0002 for $\mu_{(LMS)}$ to make the steady-state values of two algorithm equal when σ_η^2 is given as 0.001 and 1 and $\mu_{(LMF)}$ is 0.002.

In Figure 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 region of μ and σ_η^2, resulting in sufficiently small V_{th}^2 values compared to unity, the initial convert- gence of the LMF algorithm is much faster than the conventional LMS algorithm. Later on, the LMF convergence looks similar to the LMS case. This fact has not been reported yet mainly because the higher order moments have not been included in the previous analysis of the LMF transient behavior[1]. On the other hand, when V_{th}^2 is large, the LMF algorithm converges geometrically at a rate a bit slower than the LMS case.

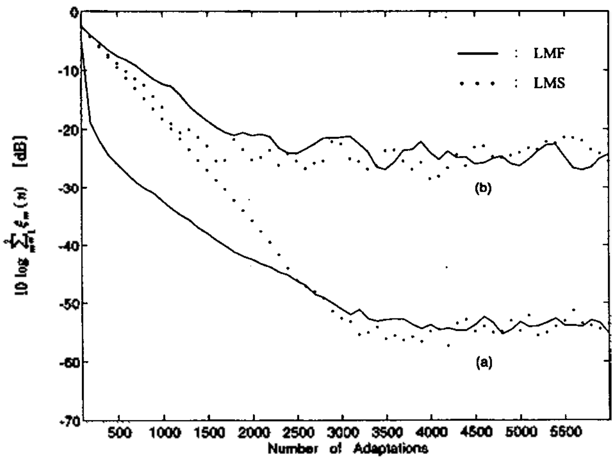


Figure 5. Comparison of the LMF and LMS algorithm learning curves of the summed variance of weight errors;

(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 shows that depending 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 logarithmic scale like the LMS algorithm; (2) the LMF algorithm converges linearly and at a slower rate than the LMS. To sum up, different convergence behavior was observed depending on the variance of Gaussian measurement noise and the magnitude of convergence constant.

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