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PAPER *Special Section on Digital Signal Processing*

Adaptive Line Enhancers on the Basis of Least-Squares Algorithm for a Single Sinusoid Detection

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SUMMARY This paper proposes adaptive line enhancers with new coefficient update algorithms on the basis of least-square-error criteria. Adaptive algorithms by least-squares are known to converge faster than stochastic-gradient ones. However they have high computational complexity due to matrix inversion. To avoid matrix inversion the proposed algorithms adapt only one coefficient to detect one sinusoid. Both FIR and IIR types of adaptive algorithm are presented, and the techniques to reduce the influence of additive noise is described in this paper. The proposed adaptive line enhancers have simple structures and show excellent convergence characteristics. While the convergence of gradient-based algorithms largely depend on their stepsize parameters, the proposed ones are free from them.
key words: *adaptive line enhancer, least-squares algorithm, frequency estimation*

1. Introduction

Adaptive line enhancers (ALEs) are one realization of adaptive filters, which are used to detect the frequency of unknown sinusoids corrupted by noise and to filter additive noise. Second-order IIR filters are often used to realize ALEs because of their simple structures. The Gauss-Newton algorithms were first adopted as adaptive algorithms for IIR ALEs [1]. They require very complicated computations. Later, simple gradient-based ALEs were proposed, and many research efforts have been devoted to such ALEs so far [2]–[9]. ALEs with stochastic-gradient algorithms have low computational complexity and are suitable for real-time implementation. However, their convergence of adaptation is not always fast, and is dependent on the amplitude of a sinusoidal input. The fluctuation of adaptive coefficients after convergence also depends on the amplitude of a sinusoidal input. Moreover, the tracking property of this type of ALEs in the case of a non-stationary input is poor. ALEs with normalized stochastic-gradient algorithms converge faster than unnormalized ones, but require additional computations for the normalization of stochastic-gradients, which are implemented as division. The convergence of gradient-based algorithms largely depend on their stepsize parameters.

This paper proposes ALEs with new coefficient update algorithms, which adapt more quickly than conventional ALEs and have simple structures. The proposed algorithms solve least-squares problems directly and have no stepsize parameter, while conventional stochastic-gradient-based ones use the steepest descent method for iterative coefficient update. Generally speaking, adaptive algorithms by least-squares converge faster than stochastic-gradient-based ones. However they have high computational complexity due to matrix inversion. In order to reduce this complexity, the proposed algorithms adapt only one coefficient to detect one sinusoid for altering matrix inversion to division. For tracking a non-stationary input forgetting factors are introduced to estimate least-squares errors. The forgetting factors are time-weight coefficients which make it possible to treat non-stationary signals as stationary signals approximately. In addition to these properties, the proposed ALEs show that their convergence of adaptation is independent of the amplitude of a sinusoidal input.

One type of ALEs which has an excellent noise-reduction characteristic is separated-structure ALEs (SALEs) [9]. SALEs contain two parts, 'estimator' and 'discriminator'. An estimator is an ALE which is used to estimate the frequency of an unknown sinusoidal input, and a discriminator is a narrow-band bandpass filter with the same center frequency as the estimator. In the design of an estimator, the examination of a noise-reduction characteristic is not required. For this reason this paper concentrates its discussion on the design of ALEs with a good convergence property for the use of estimators.

In this paper an FIR type of algorithm is first presented. An IIR type is secondly presented, which is less sensitive to noise than the FIR one. The additive algorithms to suppress the influence of noise in very low SNR environments, is also described. Finally it is demonstrated by simulations that the proposed algorithms show better performance in convergence speed and trackability than conventional ALEs.

2. Frequency Estimation Using FIR Adaptive Notch Filters

In this section, a frequency estimation algorithm for ALEs using FIR adaptive notch filters on the basis of

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least-squares is described. The input signal to ALEs is the summation of an unknown sinusoid $f(k)$ and noise $n(k)$ written as

$$x(k) = f(k) + n(k) \tag{1}$$

where k is time index. The sampling period is normalized to 1. An unknown sinusoid is represented by

$$f(k) = A\cos(\omega_0 k + \theta) \tag{2}$$

where A, ω_0 and θ denote amplitude, angular frequency and initial phase, respectively. The noise $n(k)$ is assumed to be a sequence of a white Gaussian random variable with zero-mean and variance σ_n^2.

When the notch frequency of notch filters equal to the frequency of single sinusoidal input, their output is minimized. The input frequency can be evaluated from their coefficients if it is unknown. General second-order FIR adaptive filters have three adaptive coefficients, and their zeros can be located anywhere in the z-plane. However, it is sufficient for the estimation of the frequency of an unknown sinusoid using a second-order FIR adaptive notch filter that its zeros related to its notch frequency are located on the unit circle in the z-plane. Such an adaptive notch filter can be controlled by only one adaptive coefficient and the computational complexity for coefficient update is greatly reduced. Its transfer function is expressed as

$$H_N(z) = 1 - 2\alpha_1(k)z^{-1} + z^{-2} \tag{3}$$

where $\alpha_1(k)$ is an adaptive coefficient which determines its notch frequency by $\cos\omega_c = \alpha_1(k)$. When $x(k)$ denotes its input, its output $e(k)$ is obtained as

$$e(k) = x(k) - 2\alpha_1(k)x(k-1) + x(k-2). \tag{4}$$

When $e(k)$ is close to zero, the notch frequency is close to the sinusoid frequency. Hence, $e(k)$ can be regarded as an adaptation error in updating the coefficient $\alpha_1(k)$. The proposed algorithm is used to minimize this error. The derivative of $e(k)$ with respect to $\alpha_1(k)$ is given by

$$\begin{cases} \dfrac{\delta e(m)}{\delta \alpha_1(k)} = -2x(m-1) & \text{for } m = k \\ \dfrac{\delta e(m)}{\delta \alpha_1(k)} = 0 & \text{for } m < k. \end{cases} \tag{5}$$

It is noted that the changes of the adaptive coefficient $\alpha_1(k)$ do not affect $e(m)$ for $m < k$. This shows that the error $e(m)$ is not evaluated except $m = k$. Under stationary conditions, it is effective for the robustness to noise that the adaptation error $e(m)$ is available in the case of $m < k$. Therefore $e(m)$ is modified to $\hat{e}(k,m)$ as follows;

$$\hat{e}(k,m) = x(m) - 2\alpha_1(k)x(m-1) + x(m-2). \tag{6}$$

From this modification, the derivative of $\hat{e}(k,m)$ of $\alpha_1(k)$ is obtained as

$$\frac{\delta \hat{e}(k,m)}{\delta \alpha_1(k)} = -2x(m-1) \quad \text{for m} \le \text{k}. \tag{7}$$

The estimation of total adaptation error is defined by

$$J(\alpha_1(k)) = \sum_{m=0}^{k} \lambda^{k-m} \hat{e}^2(k,m). \tag{8}$$

where λ is a forgetting factor and is set less than 1 and near to 1. The use of this factor has the following merit. Though the proposed algorithm is introduced under stationary conditions, it is applicable to non-stationary input if the input signal does not vary so quickly and the proper value is set to this factor. Moreover, the use of this factor prevents the estimation $J(\alpha_1(k))$ from overflowing in the calculation of its summation.

The frequency of an input sinusoid is estimated by searching optimum adaptive coefficient $\alpha_1(k)$ which minimizes $J(\alpha_1(k))$. When the estimation function has only one relative minimum, the equation to be solved for getting the optimum $\alpha_1(k)$ is

$$\frac{\delta J(\alpha_1(k))}{\delta \alpha_1(k)} = 0. \tag{9}$$

This becomes

$$\begin{aligned} \frac{\delta J(\alpha_1(k))}{\delta \alpha_1(k)} &= 2\sum_{m=0}^{k} \lambda^{k-m} \hat{e}(k,m) \frac{\delta \hat{e}(k,m)}{\delta \alpha_1(k)} \\ &= 4\sum_{m=0}^{k} \lambda^{k-m} \Big\{ 2\alpha_1(k)x^2(m-1) \\ &\qquad - x(m-1)(x(m) + x(m-2)) \Big\} \\ &= 0. \end{aligned}$$

It is easy to solve Eq. (9), because it contains only one unknown variable and no matrix inversion is needed. Therefore optimum $\alpha_1(k)$ is obtained as

$$\alpha_1(k) = \sum_{m=0}^{k} \lambda^{k-m} x(m-1)\Big(x(m) + x(m-2)\Big) \times \frac{1}{2\displaystyle\sum_{m=0}^{k} \lambda^{k-m} x(m-1)^2}. \tag{10}$$

The simulation results are given in Fig. 1 when the signal-to-noise ratio(SNR) are 20[dB], 10[dB], and the forgetting factor λ is 0.95. SNR is defined by

$$\text{SNR} = \frac{A^2}{2\sigma_n^2}. \tag{11}$$

It should be noted that $\alpha_1(k)$ (thus the frequency) is estimated even without the FIR notch filter because Eq. (10) does not refer to the output signal $e(k)$.

This algorithm has very high-speed convergence

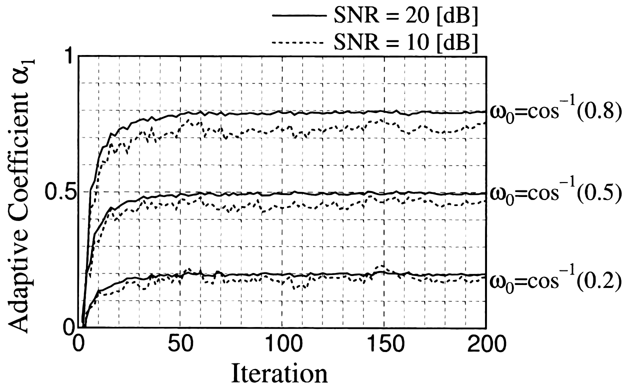

Fig. 1 The convergence property of frequency estimation using FIR filter.

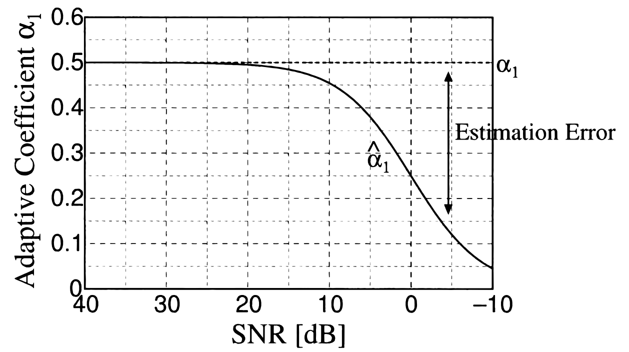

Fig. 2 The estimation error due to the noise.

because of solving the solution of least-squares directly. However there exist two problems due to additional input noise. One is the fluctuation of the adaptive coefficient. It is easily smoothed by using a low-pass filter. The other is the bias of the estimated frequency. Because the noise $n(k)$ have no correlation to the sinusoid $f(k)$, the relation of the noise variance and the estimated frequency $\hat{\alpha}$ is given by

$$\hat{\alpha}_1(k) = \frac{\sum_{m=0}^{k} f(m-1)\Big\{f(m)+f(m-2)\Big\}}{2\Big\{\sum_{m=0}^{k} f^2(m-1) + \sum_{m=0}^{k} n^2(m-1)\Big\}}$$
$$= \alpha_1(k)\frac{\sum_{m=0}^{k} f^2(m-1)}{\sum_{m=0}^{k} f^2(m-1) + \sum_{m=0}^{k} n^2(m-1)}$$
$$= \alpha_1(k)\frac{A^2}{A^2+2\sigma_n^2} = \alpha_1(k)\frac{\text{SNR}}{\text{SNR}+1}. \quad (12)$$

This shows that the frequency bias is proportional to the noise power. For example, Fig. 2 shows the plot of frequency estimation versus noise power when $\cos\omega_0 = \alpha_1 = 0.5$ holds.

Because it is desirable to be robust to the increasing noise power, another adaptive algorithm using IIR filters which has less influence to frequency bias is described in the next section.

3. Frequency Estimation Using Adaptive IIR Filters

In this section, the idea used in the previous section is applied to second-order IIR filters which have sharper amplitude characteristics. It is difficult to solve least-squares directly because recursive terms are contained in IIR filters. An approximated solution is proposed to reduce the difficulty.

The transfer functions of second-order IIR notch filter $H_N(z)$ and bandpass filter $H_B(z)$ are written as

$$H_N(z) = \frac{(1+\alpha_0)\{1-2\alpha_1(k)z^{-1}+z^{-2}\}}{2\{1-\alpha_1(k)(1+\alpha_0)z^{-1}+\alpha_0 z^{-2}\}} \quad (13)$$
$$H_B(z) = 1 - H_N(z)$$
$$= \frac{(1-\alpha_0)(1-z^{-2})}{2\{1-\alpha_1(1+\alpha_0)z^{-1}+\alpha_0 z^{-2}\}} \quad (14)$$

respectively, where α_0 is a constant which determines bandwidth and $\alpha_1(k)$ is an adaptive coefficient which determines center frequency. $\alpha_1(k)$ is related to $\cos\omega_c$ by $\cos\omega_c = \alpha_1(k)$. $e(k)$ and $y(k)$ denote the output of $H_N(z)$ and $H_B(z)$, respectively, whose input is $x(k)$. $e(k)$ is written as

$$e(k) = \frac{1+\alpha_0}{2} \times \Big\{x(k) - 2\alpha_1(k)x(k-1) + x(k-2)\Big\} + \alpha_1(k)(1+\alpha_0)e(k-1) - \alpha_0 e(k-2). \quad (15)$$

By differentiating Eq. (15) $\delta e(k)/\delta\alpha_1(k)$ is obtained as

$$\frac{\delta e(k)}{\delta\alpha_1(k)} = -(1+\alpha_0)y(k-1) + \alpha_1(k)(1+\alpha_0)\frac{\delta e(k-1)}{\delta\alpha_1(k-1)} - \alpha_0\frac{\delta e(k-2)}{\delta\alpha_1(k-2)}. \quad (16)$$

The second and third terms of Eq. (16) are recursive factors. These make the computation of Eq. (16) difficult. $\Psi(z)$ and $\Psi_r(z)$ which are the transfer functions corresponding to $\delta e(k)/\delta\alpha_1(k)$ and recursive factors in Eq. (16) respectively, are defined as

$$\Psi(z) \equiv \mathcal{Z}\left[\frac{\delta e(k)}{\delta\alpha_1(k)}\right]/X(z) \quad (17)$$

$$\Psi_r(z) \equiv \mathcal{Z}\left[\alpha_1(k)(1+\alpha_0)\frac{\delta e(k-1)}{\delta\alpha_1(k-1)} - \alpha_0\frac{\delta e(k-2)}{\delta\alpha_1(k-2)}\right]/X(z). \quad (18)$$

According to Tellegen's theorem, $\Psi(z)$ can be represented by

$$\Psi(z) = G(z)H_B(z) \tag{19}$$

where

$$G(z) = \frac{-(1+\alpha_0)z^{-1}}{1-\alpha_1(k)(1+\alpha_0)z^{-1}+\alpha_0 z^{-2}}. \tag{20}$$

Applying the z-transform to each side of Eq. (16),

$$\Psi(z) = -(1+\alpha_0)z^{-1}H_B(z) + \Psi_r(z) \tag{21}$$

is obtained. The ratio of the recursive term to the non-recursive term in Eq. (16) is given by

$$\begin{aligned}\left|\frac{\Psi_r(z)}{\Psi(z)-\Psi_r(z)}\right| &= \left|\frac{\Psi_r(z)}{-(1+\alpha_0)z^{-1}H_B(z)}\right| \\ &= \left|\frac{G(z)+(1+\alpha_0)z^{-1}}{-(1+\alpha_0)z^{-1}}\right| \\ &= \left|\frac{1}{1-\alpha_1(1+\alpha_0)z^{-1}+\alpha_0 z^{-2}}-1\right|.\end{aligned} \tag{22}$$

If it is small enough, it can be neglected in Eq. (16). Figure 3 shows the frequency characteristics of Eq. (22).

The recursive term strongly depends on α_0 and the influence increases when α_0 approaches to 1. This factor can be neglected when α_0 is much smaller than 1. In order to reduce computational complexity, it is desirable to neglect this factor. However, in order to have good notch property, α_0 is desired to be close to 1. Therefore α_0 is determined to be as large as possible on the condition of being able to be neglected in comparison to 1 by computer simulations.

By means of this strategy, Eq. (16) is approximately written as

$$\frac{\delta e(k)}{\delta\alpha_1(k)} \simeq -(1+\alpha_0)y(k-1). \tag{23}$$

Then, the IIR type of adaptive algorithm is derived by the same way as the FIR type. The optimized $\alpha_1(k)$ is obtained as

$$\begin{aligned}\alpha_1(k) = \sum_{m=0}^{k}\lambda^{k-m}y(m-1)\Big[&x(m)+x(m-2) \\ &+\alpha_0\{x(m)-x(m-2)+2y(m-2)\}\Big] \\ \times\, &\frac{1}{2(1+\alpha_0)\sum_{m=0}^{k}\lambda^{k-m}y(m-1)^2}.\end{aligned} \tag{24}$$

The simulation results are shown in Fig. 4 when the signal-to-noise ration(SNR) are 20[dB], 10[dB], the forgetting factor λ is 0.95, and α_0 is 0.7. The lattice realization of $H_B(z)$ is shown by Fig. 5, and the estimator realization of the proposed algorithm is shown by Fig. 6.

It is found from Fig. 4 that the IIR type of algorithm is more stable to the noise power than the case of FIR. The denominator of Eq. (24) contains only $y(k)$ terms which are the output of the bandpass filter and

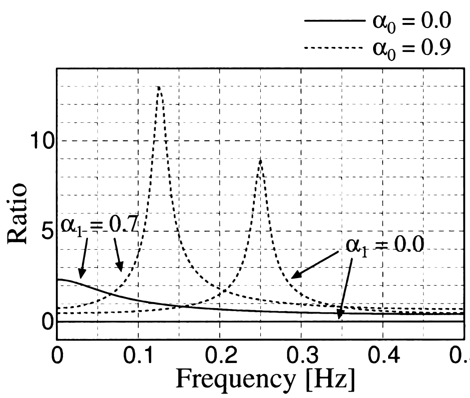

Fig. 3 The ratio of recursive terms to non-recursive ones of Eq. (16).

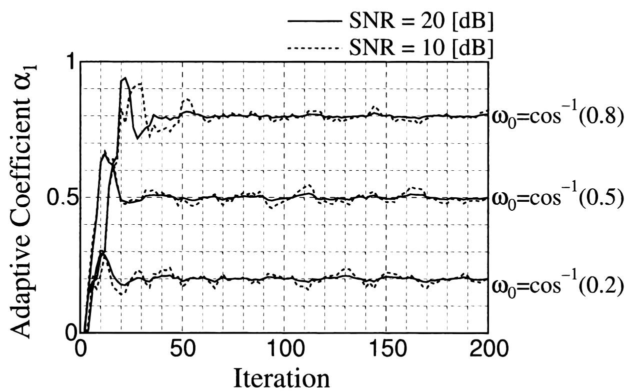

Fig. 4 The convergence property of frequency estimation using IIR filter.

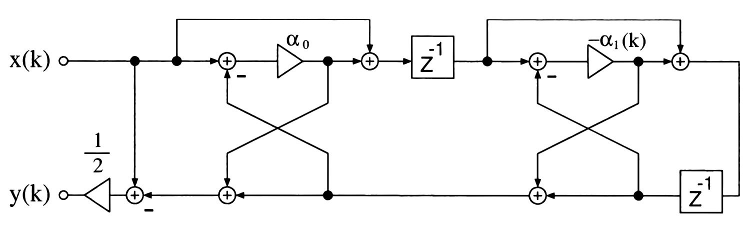

Fig. 5 The realization of lattice filter $H_B(z)$.

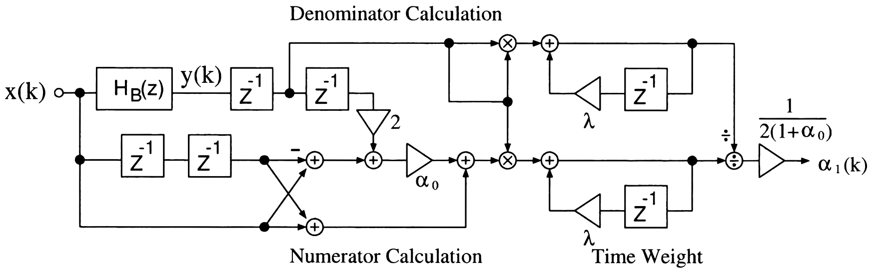

Fig. 6 The frequency estimator realization for the IIR adaptive filter.

have small noise power. On the other hand, the numerator cancels its noise owing to the characteristics of noise, that is, the zero-mean and no correlation.

4. Suppression of Noise Influence

The proposed IIR adaptive algorithm has an advantage of small frequency bias. However, it has a problem of coefficient fluctuations when the SNR of input signals is small. In this section, some applicable methods to solve this problem are proposed.

4.1 Coefficient Smoothing with Lowpass Filters

It is necessary for good noise rejection that the vibration of adaptive coefficients after its convergence is small. If the coefficient $\alpha_1(k)$ has little bias, lowpass filtering to $\alpha_1(k)$, which is sequentially obtained from Eq. (10) or Eq. (24), can suppress the vibration of $\alpha_1(k)$. However it will make the convergence a little slow. Experimentally first-order IIR lowpass filters are sufficient for this purpose because higher-order ones do not show the remarkable suppression of the vibration compared to first-order ones. The realization of above mentioned lowpass filters is shown in Fig. 7. An example of the convergence property with the proposed coefficient smoothing applied to proposed IIR estimator is shown in Fig. 8, where the SNR of input signals is equal to 3 [dB].

4.2 Prefilter Technique for Noise Reduction

The output SNR of bandpass filters whose center frequency is equal to the frequency of sinusoidal component of input signals is improved. If such bandpass filters are used at the input of estimators as prefilters, the noise power becomes small and the coefficient fluctuations are reduced. However it is not easy to apply this technique strictly. The reason is that it is necessary to equalize their center frequency to the sinusoid frequency although it is unknown and the function of ALEs is to estimate it. If the adaptive coefficients of ALEs can converge when the center frequency of prefilters is far from the sinusoid frequency and the frequency equalization is achieved after their convergence,

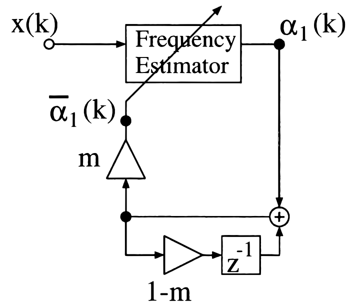

Fig. 7 A typical realization of a lowpass filter for a coefficient smoothing.

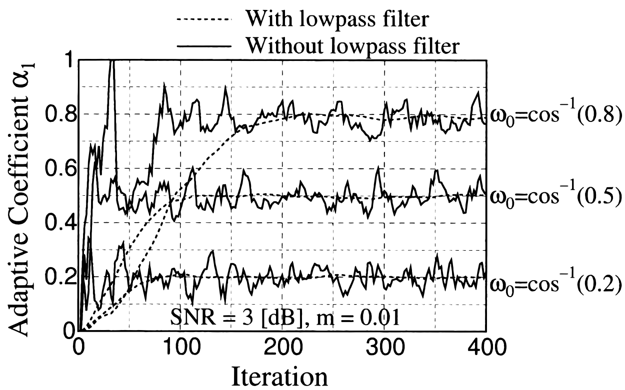

Fig. 8 A convergence property with/without a coefficient smoothing.

then the effects of additional noise such as the coefficient vibration can be reduced. A simple and practical realization of this method is shown in Fig. 9, where ρ is named 'bypass coefficient' and is a small constant. The center frequency of the prefilter is also controlled by $\alpha_1(k)$. When the bandpass filter $H_B(z)$ in the prefilter has narrow bandwidth, it attenuates not only noise but also sinusoid. Without the bypass coefficient the attenuation of sinusoid causes the degradation of the convergence characteristics of ALEs. The bypass coefficient transmits the input signal to the estimator for compensating the attenuation of sinusoid. The SNR of $x'(k)$ is calculated and plotted in Fig. 10 when the SNR of the input $x(k)$ is 0[dB] and two parameters $\alpha_1(k)$ and α_0 of $H_B(z)$ in the prefilter are 0 and 0.7 respectively. Figure 10 shows that excessively small values of ρ degrade the SNR of $x'(k)$. Since this results in the slow convergence of adaptive coefficients as well as the reduction of their fluctuations after their convergence, it is required to determine ρ appropriately except for excessively small and large values. To confirm the effectiveness of the proposed prefilter, a convergence property with $\rho = 0.01$ is shown in Fig. 11, where the SNR of the input signal is 3[dB] and the sinusoidal frequency is $\omega_0 = \cos^{-1} 0.7$. α_0 of $H_B(z)$ in the prefilter is equal to 0.7. In Fig. 11 the FIR estimator is used because the FIR ones more suffer from additional noise than the IIR ones and the effectiveness of the prefilter is more remarkable.

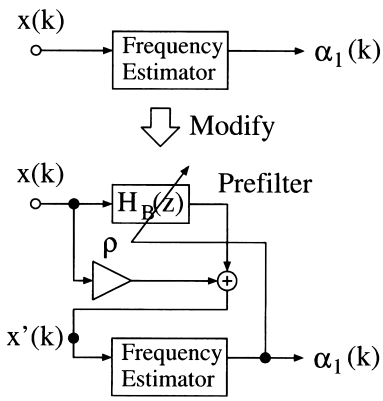

Fig. 9 A prefilter for noise reduction.

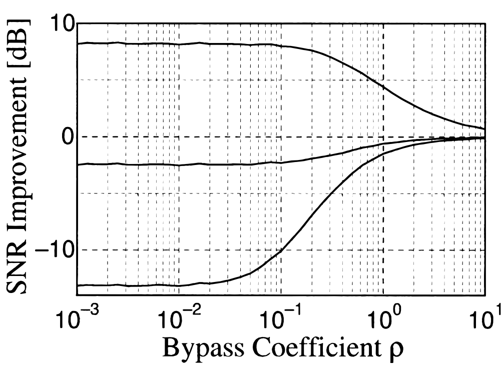

Fig. 10 SNR improvement with respect to bypass coefficient ρ.

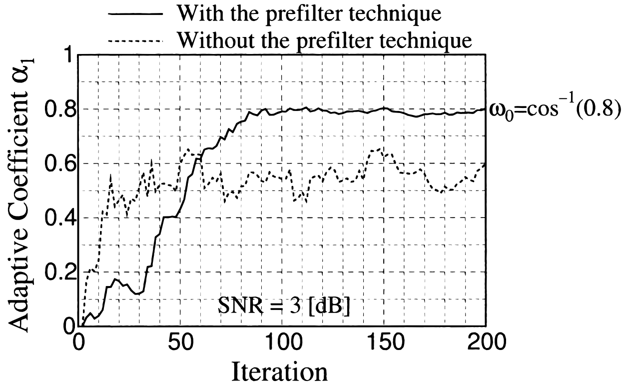

Fig. 11 Convergence property with/without the prefilter technique.

5. Simplification of Divisions

The proposed algorithm requires one division per one sampling period. The execution of divisions requires longer time than other arithmetical operations like multiplications. To avoid divisions, the technique which is introduced for the normalized stochastic-gradient algorithms is applicable to the proposed method [4]. It is an approximate expression of divisions by using multiplications and additions. The inverse of d can be obtained from the recursive equations described by

$$a(n+1) = a(n)\Big(2 - \Big(d + P_{min}\Big)a(n)\Big) \tag{25}$$

where P_{min} is a small constant to avoid divisions by zero and $a(n)$ is a sequence which is initialized to be a positive value less than $d/2$ and converges to $1/d$. The circuitry realization of Eq. (25) is shown in Fig. 12. It is recommended to initialize the denominator of Eq. (10) or Eq. (24) to some positive value, otherwise this algorithm may be unstable for zero-divisions.

With this simplifications, one division is replaced by three multiplications. The remarkable difference of the convergence property between the use of real divisions and proposed iterative divisions are not recognized from simulation results.

6. Simulation Results

In this section some simulations demonstrate the effectiveness of the proposed algorithms by comparison with conventional algorithms. The IIR types of the ones with the noise suppression techniques and the division simplification are examined. The parameters are set respectively as follows;

$$\rho = 0.01, \qquad \lambda = 0.95, \qquad \alpha_0 = 0.7,$$
$$m = 0.05, \quad P_{min} = 0.001.$$

Simulated conventional algorithms are the stochastic gradient one [6] and the normalized stochastic gradient one [3].

1. Convergence Speed

   The parameters of the input signal are presented

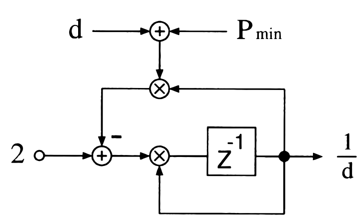

Fig. 12 The simplifed division by multipliers.

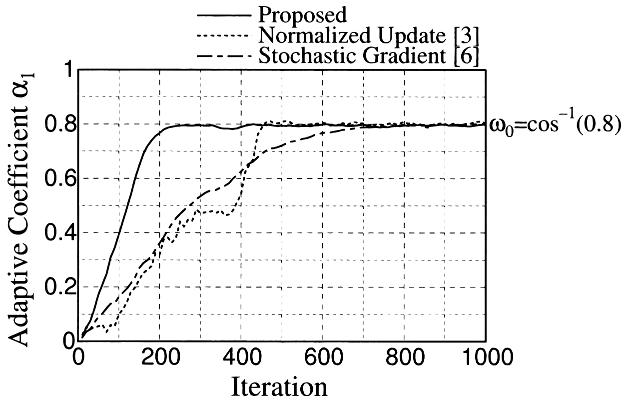

Fig. 13 Comparison of the convergence speed.

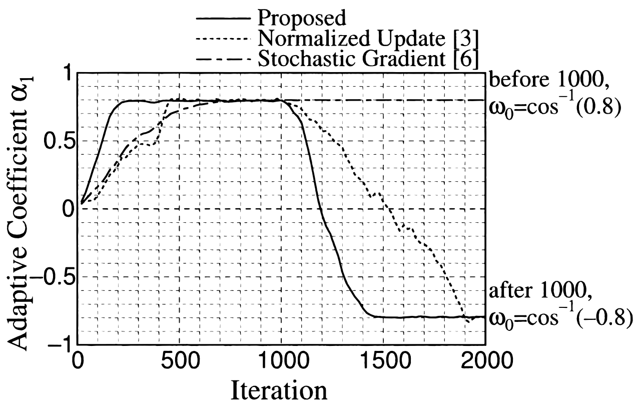

Fig. 14 Comparison of the tracking ability.

by $A = 1$, $\omega_0 = \cos^{-1} 0.8$, and SNR = 3[dB]. The results are shown in Fig. 13.
The proposed algorithm has faster adaption than the others. The reason is that it evaluates approximately the direct solutions of least-squares problems whereas conventional algorithms use iterative update methods by gradient calculations.

2. Tracking Property to Non-stationary Signals
   The parameters of the input signal are presented by $A = 1$, SNR = 3[dB], signal frequency $\omega_0 = \cos^{-1} 0.8$ before time index 1000 and $\omega_0 = \cos^{-1}(-0.8)$ after 1000. The results are shown in Fig. 14.
   The proposed algorithm has a good convergence even in the case of non-stationary signals. This is provided by the use of the forgetting factor. Some of the ALE algorithms have miserable property but most ALEs can incorporate a forgetting factor to improve tracking performance.
3. Computational Complexity
   Table 1 compares computational complexity per sampling period for the proposed and two known ALE algorithms. The proposed algorithm requires 40% less multiplications at the expense of move additions. Note that a multiplication is in general much more computationally expensive than an addition.

Table 1 Comparison of the computation load.

	Addition	Multiplications
Proposed	24	15
SFSVSA [6]	16	26
NSFSVSA [7]	13	24

7. Conclusion

In this paper, new adaptive algorithms for ALEs on the basis of least-squares criteria have been described. To avoid computations of matrix inversion, the proposed algorithms adapt only one coefficient to detect one sinusoid. This makes it possible to realize the proposed ALEs without extra computation compared with conventional ALEs. For tracking a non-stationary input, forgetting factors are introduced to estimate least-squares errors. In low SNR case, the additive algorithms to reduce the influence of noise is also described. It is certified by simulations that the proposed algorithms show better performance in convergence speed and trackability than conventional ALEs.

The extensions of the proposed algorithms for the detection of multiple sinusoids still remains to be studied.

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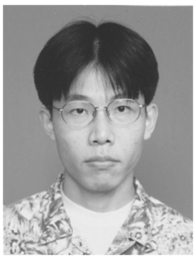

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