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LETTER

Transform-Domain Adaptive Constrained Normalized-LMS Filtering Scheme for Time Delay Estimation

Chi-Hui HUANG[†a)], ***Member***, **Shyh-Neng LIN**[††b)], ***Nonmember***, **Shiunn-Jang CHERN**[†c)], ***Affiliate Member***, ***and*** **Jiun-Je JIAN**[†], ***Nonmember***

SUMMARY The convergence speed of the conventional adaptive LMS algorithms for time delay estimation (TDE) is highly dependent on the spectral distribution of the desired random source signals of interest, thus the performance of TDE might be degraded, dramatically. To solve this problem, in this letter, a DCT-transform domain constrained adaptive normalized-LMS filtering scheme, referred to as the adaptive constrained DCT-LMS algorithm, is devised for TDE. Computer simulation results verify that the proposed scheme can be used to achieve desired performance, for input random signals with different spectral distributions; it outperforms the unconstrained DCT-LMS and time-domain constrained adaptive LMS algorithms.

key words: *time-delay estimation, adaptive constrained DCT-LMS algorithm, spectral distributions*

1. Introduction

The need to estimate time delay (or difference) between random signals received at two spatially separated sensors arises in many applications, e.g., delay lock-loop for direct sequence code division multiple access (DS-CDMA) systems [1]–[4]. As an introduction, let us consider the output signals of two sensors to be defined as

$$x(n) = s(n) + w_1(n) \tag{1}$$

and

$$y(n) = s(n - D) + w_2(n), \tag{2}$$

where the source $s(n)$ is a band-limited signal, and D is the discrete time delay between outputs of two sensors. Background noises, $w_1(n)$ and $w_2(n)$, corresponding to each related sensor, are assumed to be band-limited mutually independent white Gaussian random processes with identical distribution, which has zero-mean and with the same variance or power. Also, both $w_1(n)$ and $w_2(n)$ are statistically independent of $s(n)$. The goal of TDE is to extract the value of true time delay, D, from $x(n)$ and $y(n)$. To reduce the effect due to background noise, the time-domain adaptive LMS filtering algorithms with tap-weights constraint were suggested in Refs. [3] and [4], under the assumption that the desired source signal is white random process (or with flat spectral distribution). However, in most practical applications, the desired random source signals of interest may be highly correlated. In such cases, due to the large eigenvalue spread of input signal auto-correlation matrix, the convergence speed, using the time-domain adaptive LMS filtering algorithms, might become too slow and results in dramatic performance degradation of TDE.

To speed up the convergence rate, the transform-domain adaptive LMS filtering algorithms [5]–[9] have been suggested, when the random source signals are highly correlated (spectral distribution is no longer flat). Although, with the transform-domain adaptive LMS filtering algorithms [6]–[9], we are able to speed up the convergence rate; they may not have the capability to reduce the effect due to background noises, simultaneously. As verified in Refs. [3] and [4], the background noises would affect the estimated values of the filter's weight coefficients, and producing a large variance of TDE. To circumvent the above-described problems for TDE, in this letter, a new adaptive constrained DCT-LMS (CDCT-LMS) algorithm, with constraint that the sum of the squares of the transformed tap weights equals unity, will be devised for TDE. As proved in Ref. [4], the time domain constrained optimal tap-weights could converge to the true weights; it could be used to alleviate the effect due to background noises. We will show later that this is also true for the constrained optimal tap-weights in transformed domain. To demonstrate the advantage for the proposed algorithm, the TDE performance and the convergence rate, are compared with the conventional approaches, viz., the unconstrained DCT-LMS and the time-domain constrained LMS algorithms.

2. Adaptive Constrained DCT-LMS (CDCT-LMS) Filtering Algorithm for TDE

As an introduction the block diagram of the proposed adaptive constrained DCT-LMS filtering scheme for TDE is illustrated in Fig. 1. The input signal vector, $\mathbf{x}(n)$, is transformed by an orthogonal matrix $\mathbf{Q}$ (e.g., DCT) into new transform-domain signal vector, $\mathbf{u}(n)$, i.e.,

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[†]The authors are with the Department of Electrical Engineering, National Sun Yat-Sen University, Kaohsiung, 80424, Taiwan, R.O.C.
[††]The author is with the Department of Electrical Engineering, Nan-Joen Institute of Technology, Yenshui Tainan County 73701, Taiwan, R.O.C.
a) E-mail: d8831819@studet.nsysu.edu.tw
b) E-mail: shyhneng@ms48.hinet.net
c) E-mail: chern@ee.nsysu.edu.tw

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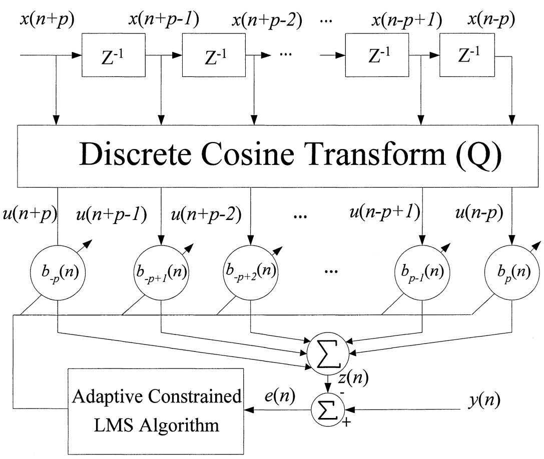


Fig. 1 Block diagram of the adaptive constrained DCT-LMS filtering scheme for TDE.

$$\mathbf{u}(n) = \mathbf{Q}\mathbf{x}(n) \tag{3}$$

where $\mathbf{x}(n) = [x(n+p), \ldots x(n), \ldots x(n-p)]^T$ and $\mathbf{u}(n) = u(n+p), \ldots, u(n), \ldots, u(n-p)^T$, respectively. The error signal $e(n)$ of Fig. 1, is defined by

$$e(n) = y(n) - z(n) = y(n) - \mathbf{b}^T\mathbf{u}(n) \tag{4}$$

where $\mathbf{b}(n) = [b_{-p}(n), \ldots, b_0(n), \ldots, b_p(n)]^T$ is the transformed weight vector of adaptive filter. The mean square value of the error signal, $E[e^2(n)]$, is denoted as

$$E[e^2(n)] = E[y^2(n)] - 2\mathbf{b}^T\mathbf{p}_{yu} + \mathbf{b}^T\mathbf{R}_{uu}\mathbf{b} \tag{5}$$

where $\mathbf{R}_{uu} = E[\mathbf{u}(n)\mathbf{u}(n)^T]$ and $\mathbf{p}_{yu} = E[y(n)\mathbf{u}(n)]$ are designated as the transformed domain input signal autocorrelation matrix and the cross-correlation vector of $\mathbf{u}(n)$ and $y(n)$, respectively.

Next, as suggested in Ref. [4], due to the inherent property of *sinc* function and the DCT matrix is an orthogonal matrix, to further alleviate the effect of background noises the sum of the squares of the transformed weight coefficients is constrained to be unity. We recalled that, ideally, the true values of the time-domain weight coefficients are defined as a *sinc*(.) function, e.g., $\mathbf{h}_s = [sinc(-p-D), \ldots, sinc(D), \ldots, sinc(p-D)]^T$ (for the case without noises) [4], i.e.,

$$\mathbf{h}_s^T\mathbf{h}_s = 1 = \mathbf{b}_s^T\mathbf{Q}\mathbf{Q}^T\mathbf{b}_s = \mathbf{b}_s^T\mathbf{b}_s \tag{6}$$

where $\mathbf{b}_s$ is the transformed domain true weight vector and $\mathbf{b}_s = \mathbf{Q}\mathbf{h}_s$. As in Ref. [4], the constrained optimization in transform-domain can be performed by minimizing the mean square error of Eq. (5), subject to the constraint of Eq. (6). That is, the cost function can be defined by

$$J(n) = E[y^2(n)] - 2\mathbf{b}^T\mathbf{p}_{yu} + \mathbf{b}^T\mathbf{R}_{uu}\mathbf{b} + \alpha(\mathbf{b}^T\mathbf{b} - 1) \tag{7}$$

where α is the Lagrange multiplier. Taking the derivative of Eq. (7) with respect to $\mathbf{b}$ and setting to null, the constrained optimal weight vector in transform-domain, $\mathbf{b}_o$, can be obtained

$$\mathbf{b}_0 = (\mathbf{R}_{uu} + \alpha\mathbf{I})^{-1}\mathbf{p}_{yu}. \tag{8}$$

Under the assumption that the orthogonal matrix, $\mathbf{Q}$, can be used to have a diagonal matrix, $\mathbf{R}_{uu} = diag(\lambda_1, \lambda_2, \ldots, \lambda_{2p+1})$, with its entries being the eigenvalue, λ_i, $i = 1, \ldots, 2p+1$ of $\mathbf{R}_{xx} = \mathbf{E}[\mathbf{x}(n)\mathbf{x}(n)^T]$. These can be viewed as the average power of the corresponding components of the transformed domain input signal, i.e., $\lambda_i = \sigma^2_{s'_i} + \sigma^2_{w'_{1_i}}$. Here, $\sigma^2_{s'_i}$ and $\sigma^2_{w'_{1_i}}$ are defined as the averaged power of the ith component of the transformed domain desired source signal vector $\mathbf{s}'(n)(\mathbf{s}'(n) = \mathbf{Q}\mathbf{s}(n))$ and the transformed domain noise vector $\mathbf{w}'_1(n)(\mathbf{w}'_1(n) = \mathbf{Q}\mathbf{w}_1(n))$, respectively. Accordingly, we have $\mathbf{p}_{yu} = diag(\sigma^2_{s'_1}, \sigma^2_{s'_2}, \ldots, \sigma^2_{s'_{2p+1}})\mathbf{b}_s$ thus Eq. (8) can be rewritten as

$$\begin{aligned}
\mathbf{b}_o &= (\mathbf{R}_{uu} + \alpha\mathbf{I})^{-1}\mathbf{p}_{yu} \\
&= (\mathbf{R}_{uu} + \alpha\mathbf{I})^{-1} diag(\sigma^2_{s'_1}, \sigma^2_{s'_2}, \ldots, \sigma^2_{s'_{2p+1}})\mathbf{b}_s \\
&= diag[(\sigma^2_{s'_1} + \sigma^2_{w'_{1_1}} + \alpha)^{-1}, (\sigma^2_{s'_2} + \sigma^2_{w'_{1_2}} + \alpha)^{-1}, \\
&\quad \ldots, (\sigma^2_{s'_{2P+1}} + \sigma^2_{w'_{1_{2p+1}}} + \alpha)^{-1}]. \\
&\quad diag(\sigma^2_{s'_1}, \sigma^2_{s'_2}, \ldots, \sigma^2_{s'_{2p+1}})\mathbf{b}_s.
\end{aligned} \tag{9}$$

Solving Eq. (9) for α by applying the constraint defined in Eq. (6), we get

$$\alpha\mathbf{I} = -\sigma^2_{w'_1}\mathbf{I} \tag{10}$$

or $\alpha = -\sigma^2_{w'_1}$. Ideally, we assume that all elements of the transformed noise vector, $\mathbf{w}'_1(n)$, have the same value of average power. From Eqs. (9) and (10), we have the constrained optimal weight vector

$$\mathbf{b}_o = \mathbf{b}_s = \mathbf{Q}\mathbf{h}_s. \tag{11}$$

This implies that the equivalent time-domain expression of $\mathbf{b}_o$ is equal to the true weight vector $\mathbf{h}_s$. Therefore, by using the transformed domain constrained approach, we may be able to reduce the effect due to background noises. However, this is not the case when the conventional transformed domain unconstrained optimization approach is adopted; it can be viewed as the special case of Eq. (9) with $\alpha = 0$ (i.e., $\mathbf{b}_o \neq \mathbf{b}_s$).

Proceed in a similar manner as the time-domain adaptive constrained LMS (CLMS) algorithm developed in Ref. [4], the new adaptive constrained DCT-LMS (CDCT-LMS) algorithm for TDE can be derived

$$\begin{aligned}
\mathbf{b}(n+1) &= \mathbf{b}(n) + \gamma_c\hat{\mathbf{R}}^{-1}_{uu}(n)[e(n)\mathbf{u}(n) - \alpha\mathbf{b}(n)] \\
&= [1 + \gamma_c\hat{\mathbf{R}}^{-1}_{uu}(n)\sigma^2_{w'_1}]\mathbf{b}(n) + \gamma_c\hat{\mathbf{R}}^{-1}_{uu}(n)e(n)\mathbf{u}(n)
\end{aligned} \tag{12}$$

where $\gamma_c \times \hat{\mathbf{R}}^{-1}_{uu}(n)$ denotes the normalized (time-varying) step-size, where $\hat{\mathbf{R}}_{uu}(n)$ is a diagonal matrix having its diagonal elements to be the averaged power estimated from the elements of the transformed signal vector $\mathbf{u}(n)$, i.e.,

$$\hat{\mathbf{R}}_{uu}^{-1}(n) = diag\{\hat{U}_{-p}^{-1}(n), \ldots, \hat{U}_0^{-1}(n), \ldots, \hat{U}_p^{-1}(n)\} \quad (13)$$

where the entries are estimated by the following equation:

$$\hat{U}_i(n) = \beta\hat{U}_i(n-1) + (1-\beta)u^2(n-i), \quad for\ i = -p, \ldots, 0, \ldots, +p, \quad (14)$$

where β is the smoothing factor, $0 < \beta < 1$.

Since in practical applications, the noise power, $\sigma^2_{w_1'}$, in Eq. (12) is not available, and needs to be estimated. In what follows, a simple scheme for estimating the noise power is provided. By definition, from Eqs. (2) and (4), the cross-correlation between $y(n)$ and $z(n)$ is given by

$$\begin{aligned}\sigma_{yz}^2 &= E[y(n)z(n)] \\ &= E\{(\mathbf{b}_s^T\mathbf{Q}\mathbf{s}(n) + w_2(n))(\mathbf{b}^T\mathbf{Q}[\mathbf{s}(n) + \mathbf{w}_1(n)])\}, \quad (15) \\ &= E\{[\mathbf{b}_s^T\mathbf{s}'(n)][\mathbf{b}^T\mathbf{s}'(n)]\} \\ &= \mathbf{b}_s^T\mathbf{R}_{ss}'\mathbf{b}\end{aligned}$$

where $\mathbf{R}_{ss}' = E[\mathbf{s}'(n)\mathbf{s}'^T(n)]$ denotes the auto-correlation matrix of the transformed desired source signal $\mathbf{s}'(n)$. Also, the average power of signal $y(n)$ is defined by

$$\begin{aligned}\sigma_y^2 &= E[y^2(n)] \\ &= E\{(\mathbf{b}_s^T\mathbf{Q}\mathbf{s}(n) + w_2(n))(\mathbf{b}^T\mathbf{Q}\mathbf{s}(n) + w_2(n))\}, \quad (16) \\ &= \mathbf{b}_s^T\mathbf{R}_{ss}'\mathbf{b} + \sigma_{w2}^2\end{aligned}$$

where $\sigma_{w2}^2 = E[w_2(n)w_2(n)]$ is the noise power of the second sensor. From Eqs. (15) and (16), we have

$$\sigma_y^2 - \sigma_{yz}^2 = \mathbf{b}_s^T\mathbf{R}_{ss}'(\mathbf{b}_s - \mathbf{b}) + \sigma_{w2}^2. \quad (17)$$

It is noted that, ideally, when $\mathbf{b}$ converges to the true value of the transformed domain weight vector $\mathbf{b}_s$, parameter $G = \mathbf{b}_s^T\mathbf{b}$ would converge to unity. The noise power of the second sensor can be obtained as $\sigma_{w2}^2 = \sigma_y^2 - \sigma_{yz}^2$. Since, in general, $\sigma_{w1}^2 = \sigma_{w2}^2$, we may use Eq. (17) to estimate the noise power of the first sensor, σ_{w1}^2, and apply it to Eq. (12), during the adaptation process. From Eq. (17), we learn that the accuracy of estimating σ_{w1}^2 depends on the estimation results of parameters, σ_y^2 and σ_{yz}^2. One possibility of estimating both σ_y^2 and σ_{yz}^2 was employed in Refs. [3] and [4]:

$$\hat{\sigma}_y^2(n) = f\hat{\sigma}_y^2(n-1) + (1-f)y^2(n) \quad (18)$$

and

$$\hat{\sigma}_{yz}^2(n) = f\hat{\sigma}_{yz}^2(n-1) + (1-f)y(n)z(n) \quad (19)$$

where f is the smoothing factor, $0 < f < 1$.

After the weight coefficients of the FIR filter being estimated by the adaptive CDCT-LMS algorithm of Eq. (12), we apply the inverse transformation to Eq. (11) to obtain equivalent time-domain weight coefficients (i.e., $\mathbf{h}_s = \mathbf{Q}^{-1}\mathbf{b}_s = \mathbf{Q}^T\mathbf{b}_s$). The obtained time-domain weight coefficients, h_i, are applied to the so-called direct delay estimation (DDE) formula (only need three significant weights) [4] for extracting the integer or non-integer time delay, D, i.e.,

$$\hat{D}(n) = m(n) + \frac{h_{m+1}(n)}{h_{m+1}(n) + h_m(n)}, if\ h_{m+1}(n) \geq 0. \quad (20)$$

Otherwise, the following formula is employed

$$\hat{D}(n) = m(n) - \frac{h_{m-1}(n)}{h_{m-1}(n) + h_m(n)} \quad (21)$$

where $\hat{D}(n)$ is an estimated time delay, $h_m(n)$ is denoted as the weight with the largest value among weights, h_i , $i = -p, \ldots, 0, \ldots + p$, and $m(n)$ is the integer index related to $h_m(n)$ at time index n.

In the latter computer simulation, for performance comparison, the conventional DCT-LMS filtering algorithm [6]–[8] is given in Eq. (22) and can be viewed as the case of Eq. (12) with $\alpha = 0$.

$$\mathbf{b}(n+1) = \mathbf{b}(n) + \gamma_d\hat{\mathbf{R}}_{uu}^{-1}(n)e(n)\mathbf{u}(n), \quad (22)$$

where $\gamma_d\hat{\mathbf{R}}_{uu}^{-1}(n)$ is the normalized (time-varying) step-size. The time-domain adaptive CLMS algorithm is [4]

$$\begin{aligned}\mathbf{h}(n+1) =& [1 + (\gamma/\hat{\sigma}_x^2(n))\sigma_{w1}^2(n)]\mathbf{h}(n) \\ &+ (\gamma/\hat{\sigma}_x^2(n))e(n)\mathbf{x}(n), \quad (23)\end{aligned}$$

where $\mathbf{h}(n)$ denotes the time-domain weight vector, $\gamma/\hat{\sigma}_x^2(n)$ is the normalized (time-varying) step-size, and $\hat{\sigma}_x^2(n)$ is the averaged power estimated from the input signal $x(n)$. The details regarding the estimation formula of the noise power, $\sigma_{w1}^2(n)$, was addressed in Ref. [4].

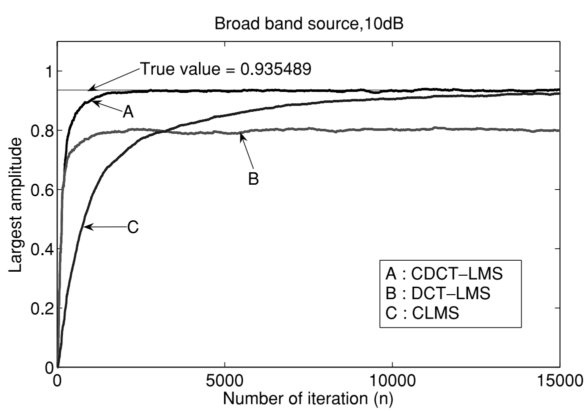
3. Simulation Results

To verify the merits of our proposed adaptive CDCT-LMS filtering algorithm for TDE, the convergence speed of the weight with the largest value, $h_m(n)$, and the result of TDE are investigated and compared with the conventional methods, under different environments. The desired source signal $s(n)$ is assumed to be a 2nd order auto-regressive (AR(2)) random process, e.g., $s(n) = a_1s(n-1) + a_2s(n-2) + v(n)$, where $v(n)$ is a white Gaussian random process, with zero-mean. With different parameter set of a_1 and a_2, various spectral density distribution of source signal can be generated [5]. Here, two cases are investigated. In the first case, a broadband source signal is considered with $a_1 = 0.6$ and $a_2 = -0.25$, while in the second case, a narrow-band source signal is generated with $a_1 = 1.5$ and $a_2 = -0.8$. On the other hand, as described in Sec. 1, the background noises, $w_1(n)$ and $w_2(n)$, were assumed to be mutually independent white Gaussian random processes with identical distribution (e.g., zero-mean with the same power, i.e., $\sigma_{w1}^2 = \sigma_{w2}^2$). Also, for a band-limited signal $s(n)$, the delayed signal $s(n-D)$ could be expressed as $s(n-D) = \sum_{i=-\infty}^{\infty} sinc(i-D)s(n-i)$ [3], [4], [10]. For simplicity, in simulation, the delayed signal $s(n-D)$ is obtained by passing $s(n)$ through a FIR filter of order 41 (i.e., $2N+1 = 41$), that is, $i = -N, \ldots, 0, \ldots + N$, with its impulse response being the samples of a *sinc* function [3], [4], [10]. We note that in this paper the order of adaptive filter is chosen to be

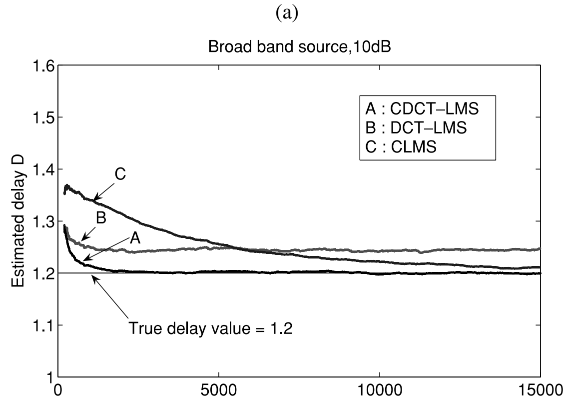
$2p+1 = 31$ (should be less than the order of weight coefficients of the FIR filter, $2N+1$). As discussed in Ref. [10] if the value of p satisfied the following condition, $p > |D| + 6$, the truncation errors, due to the limit of number of weight coefficients (of adaptive filter) for delay estimation, could be neglected. Moreover, the simulation results are the average of 50 independent realizations (or runs).

For comparison, in our simulation results, the parameters $D = 1.2$ (constant delay) and SNR=10 dB are adopted. We note that for time delay $D = 1.2$, by definition, the value of the true weight coefficient with the largest amplitude will be $h_m = h_1 = sinc(1-1.2) = 0.935489$. For fair comparison, the normalized (time-varying) step-size is denoted as $\gamma_c \times \hat{\mathbf{R}}_{uu}^{-1}(n)$ for the adaptive CDCT-LMS algorithm. Similarly, we have $\gamma_d \times \hat{\mathbf{R}}_{uu}^{-1}(n)$ for the DCT-LMS algorithm, and $\gamma/\hat{\sigma}_x^2(n)$ for the CLMS algorithm. Under the same convergence range, $0 < \gamma_c, \gamma, \gamma_d < 2/(2p+1) = 0.0645$, the positive constants of the normalized step-size for three algorithms employed in this paper are chosen to be $\gamma_c = \gamma = \gamma_d = 0.001$. Further, the smoothing factors in Eqs. (14) and (19) are chosen to be $\beta = 0.995$ and $f = 0.995$, respectively.

First, for a broadband source signal case, the results are shown in Figs. 2(a) and 2(b). From Fig. 2(a), we found that using the proposed CDCT-LMS scheme, the value of $h_1(n)$ could converge to the true value much faster than the conventional approaches (i.e., DCT-LMS and CLMS algorithms). This is true when the results of TDE is considered as evident from Fig. 2(b). It is noted that, in Fig. 2(a), using the unconstrained DCT-LMS algorithm, the tap weight could not converge to the true weight because of the effect of background-noise; it is the case of Eq. (9) with $\alpha = 0$ (i.e., $\mathbf{b}_o \neq \mathbf{b}_s$). Consequently, the bias of TDE would induce, as discussed in Refs. [3] and [4]. The similar results for the case of narrowband source signal are given in Figs. 3(a) and 3(b). From Fig. 3, we observed that the unconstrained DCT-LMS and time-domain CLMS algorithms could not work properly, which are mainly due to the effect of background noise, and the relatively large eigenvalue spread, respectively. Finally, it is important to verify the convergence behavior of the parameter $G = \mathbf{b}_s^T\mathbf{b}$ (see three lines below Eq. (17)). From Fig. 4, for both broadband and narrowband source signals cases, the parameter G could converge to unity, in steady state. This means that the weight vector $\mathbf{b}$ of the proposed scheme, in steady-state, could converge to the true weight vector $\mathbf{b}_s$, which did verify the description of Eq. (17).

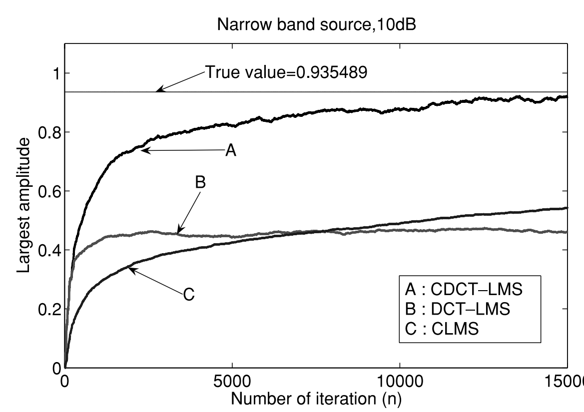


(a)

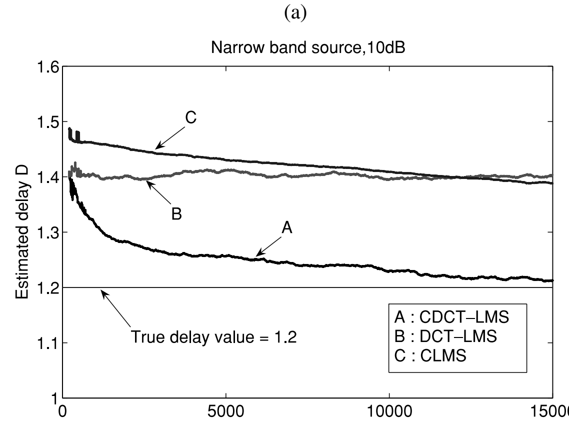


(b)

Fig. 2 Performance comparison of TDE for broadband source signal with SNR=10 dB. (a) Learning curves of the weight with the largest amplitude. (b) Time delay estimation.



(a)



(b)

Fig. 3 Performance comparison of TDE for broadband source signal with SNR=10 dB. (a) Learning curves of the weight with the largest amplitude. (b) Time delay estimation.

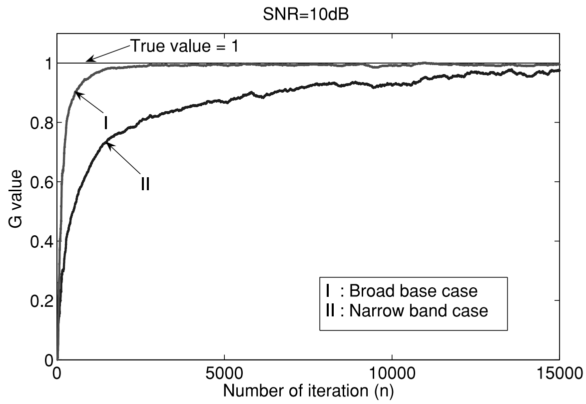


Fig. 4 Convergence behavior of the parameter $G = \mathbf{b}_s^T\mathbf{b}$ with proposed CDCT-LMS algorithms for SNR=10 dB.

4. Conclusions

In this letter, a new adaptive constrained CDCT-LMS filtering algorithm has been proposed for TDE. As confirmed by the simulation results, the new proposed scheme could be employed for TDE to achieve desired performance over the conventional unconstrained DCT-LMS and time-domain CLMS algorithms, for random signals with different spectral characteristics. In fact, the proposed scheme could be employed not only to alleviate the effect due to background noise, but also to reduce the eigenvalue spread, yields achieving better TDE results. But, this is not the case when conventional DCT-LMS and time-domain CLMS filtering algorithms are employed.

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