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An enhanced mixed modulated Lagrange explicit time delay estimator with noisy input*

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Abstract: The mixed modulated Lagrange explicit time delay estimation (MMLETDE) algorithm provides an efficient time delay estimation between narrowband or sinusoidal signals. However, it does not explicitly consider the additive measurement noise at the input, which actually exists in practice. Aiming at this issue, an enhanced MMLETDE algorithm is proposed for noisy inputs based on the unbiased impulse response estimation technique, assuming that the noise power ratio is known a priori. Simulation results show that for narrowband signals or sinusoids over a wide frequency range, the proposed algorithm with a small filter order performs well in moderate and high noise scenarios.

Key words: Time delay estimation, Adaptive filter, Noisy input, Modulated Lagrange, Unbiased impulse response estimation

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1 Introduction

Time delay estimation (TDE) between signals received by spatially separated sensors is essential in many applications, including synchronization in communications, array signal processing, direction finding, radar and sonar ranging, target localization and tracking, and exploration geophysics (Chen and Ho, 2013). Recently, TDE has attracted renewed attention in the context of wireless sensor networks (Jamalabdollahi and Zekavat, 2015), as well as geolocation of mobile ad-hoc network nodes (Patwari *et al.*, 2005; Sadler and Kozick, 2006).

Several algorithms have been proposed to effectively tackle the TDE problem over the years (Knapp and Carter, 1976; Carter, 1987; Benesty *et al.*, 2004; Li *et al.*, 2012; Zhong *et al.*, 2014; 2015). For explicit TDE, several algorithms have been proposed to obtain a time delay estimate of fractional times of the sampling interval, such as sub-sample time delay estimation based on interpolation technologies (Benesty *et al.*, 2004), high-resolution methods (Li *et al.*, 2012; Zhong *et al.*, 2013), and frequency-domain TDE (Piersol, 1981).

Among the TDE algorithms, the well-known explicit time delay estimator (ETDE) (So *et al.*, 1994) is especially attractive, since TDE is explicitly parameterized in the time delay filter coefficients in the adaptive iterations. It has been shown that the TDE obtained by ETDE is unbiased for broadband white noise like signals (So *et al.*, 1994). However, for narrowband signals, ETDE is far from optimal (Dooley and Nandi, 1999).

By combining the ETDE algorithm and the unbiased impulse response estimation technique (So,

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2001), So (2002) further developed a least-mean-square-type (LMS-type) TDE algorithm for the scenario in which both the input and output signals are corrupted by the additive Gaussian noise, with the assumption that the noise power ratio at the output and input is known a priori. This TDE algorithm is demonstrated to outperform the conventional LMS-type time delay estimator, e.g., for autoregressive signals (So *et al.*, 1994) as well as illustrative real speech data (So, 2002). However, the TDE therein is indirectly obtained with the time delay filter coefficients estimated in advance through a grid search. Hence, the estimation performance might degrade remarkably due to an improper selection of the search grid. Moreover, this algorithm might still not be suitable for TDE of narrowband signals.

For narrowband and sinusoidal signals commonly used in radar, sonar, and digital communications, the so-called mixed modulated Lagrange ETDE (MMLETDE) algorithm (Cheng and Tjhung, 2003) has been proposed, which could obtain an unbiased TDE with as small a filter order as possible. Hence, MMLETDE is endowed with characteristics of easy implementation. It is demonstrated that MMLETDE behaves well for narrowband signals or sinusoids under a relatively high signal-to-noise ratio (SNR) with the filter order as small as 1 or 2 (Cheng and Tjhung, 2003).

In another related work (Chakraborty and So, 2007), an adaptive algorithm was developed for direct estimation of the time delay between two noisy replicas of a sinusoidal signal received at spatially separated sensors. The key idea of the algorithm is to use a specific sampling frequency that results in a two-tap finite impulse response (FIR) filter model for the delay process, which is identified by updating the time delay directly. However, since the algorithm exploits the prior knowledge of the specific forms of the system coefficients and the corresponding precondition of the adaptive filter for sinusoids, it would be difficult to apply this algorithm in the scenarios of non-sinusoidal narrowband signals.

In this work, motivated by the unbiased impulse response estimation approach (So, 2001; 2002), we develop an enhanced MMLETDE algorithm for the TDE of narrowband signals corrupted by additive white Gaussian noise and under the precondition that the power ratio of the noise at the output and input is known a priori. Similar to other computationally efficient LMS-type TDE processors, e.g., those proposed by So *et al.* (1994) and Cheng and Tjhung (2003), the proposed time delay estimate is explicitly parameterized in the coefficients of the time delay estimate filter, and is directly obtained through adaptation. In contrast to the cited algorithms (So *et al.*, 1994; Cheng and Tjhung, 2003), the time delay estimate is unbiased for both narrowband and sinusoidal signals with moderate or high noise power profiles. Since the noise effect at the input is explicitly considered in the derivation of the proposed algorithm, the proposed algorithm would promisingly outperform the existing MMLETDE (Cheng and Tjhung, 2003) in moderate- and low-SNR scenarios, as is validated through the simulation results presented. Moreover, the proposed algorithm retains likewise most characteristics of MMLETDE, such as good performance for narrowband and sinusoidal signals with small filter orders. Furthermore, involving limited extra computations, the proposed algorithm is still easy to implement.

2 Problem formulation

We consider the complex-valued discrete-time signals received at two spatially separated sensors:

$$\begin{cases} x[n] = s[n] + q_i[n], \\ y[n] = s[n-D] + q_o[n], \end{cases} \tag{1}$$

where $s[n] = A[n]\exp(\mathrm{j}\omega_0 n)$ is the narrowband signal with a known center frequency ω_0, D is the normalized time delay by the sampling interval T_s, and $q_i[n]$ and $q_o[n]$ are uncorrelated zero-mean, stationary, complex-valued white Gaussian noises with variances σ_i^2 and σ_o^2, respectively. Furthermore, both $q_i[n]$ and $q_o[n]$ are assumed to be independent of $s[n]$. Here, the ratio $\gamma \triangleq \sigma_o^2/\sigma_i^2$ is assumed to be known a priori. The main purpose of this work is to estimate the sub-sample time delay D explicitly and iteratively with the narrowband noisy observation $x[n]$ and its noisy delayed replica $y[n]$.

Consider the normalized time delay D to be a positive real number, which can be split into an integer part and a fractional part of the time delay. Thus, the noise-free delayed signal $s[n-D]$ in Eq. (1) may be approximated by a truncated fractional time

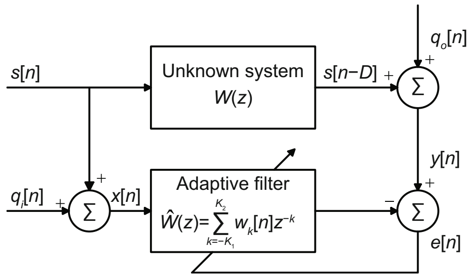

Fig. 1 Adaptive time delay estimator considering noise at both input and output

delay filter (Cheng and Tjhung, 2003)

$$s[n-D] \simeq \sum_{k=-K_1}^{K_2} \operatorname{sinc}(k-D)s[n-k], \qquad (2)$$

where $\operatorname{sinc}(v) \triangleq \sin(\pi v)/(\pi v)$, $K_1 = K_2 = K/2$ for an even integer K, $K_1 = (K-1)/2$, $K_2 = (K+1)/2$ for an odd integer K, and $K+1$ is the length of the truncated time delay filter ($K \geq 1$).

As illustrated in Fig. 1, the estimation of the non-integer delay D may be formulated as the following minimization problem:

$$\hat{D} = \arg\min_D \left\{ \mathcal{J}_1(D) \triangleq E\left\{ |e[n]|^2 \right\} \right\}, \qquad (3)$$

where $E\{\cdot\}$ is the mathematical expectation operator, $|\cdot|$ denotes the absolute value, and $e[n]$ is the estimation error in the nth iteration, i.e.,

$$e[n] = y[n] - \sum_{k=-K_1}^{K_2} \hat{w}_k[n]x[n-k]. \qquad (4)$$

To obtain the MMLETDE algorithm (Cheng and Tjhung, 2003), the weight coefficient $\{\hat{w}_k[n]\}$ of the time delay estimate filter in Eq. (4) is given by

$$\hat{w}_k[n] = \mathrm{e}^{\mathrm{j}\omega\nu}\operatorname{sinc}(\nu), \quad -K_1 \leq k \leq K_2, \qquad (5)$$

where $\nu \triangleq k - \hat{D}[n]$, and $\hat{D}[n]$ is the time delay estimate in the nth iteration.

With the gradient decent of the instantaneous squared error $\hat{\mathcal{J}}_1(n) \triangleq |e[n]|^2$, the iterative procedure of MMLETDE to obtain $\hat{D}[n]$ may be formulated as (Cheng and Tjhung, 2003)

$$\hat{D}[n+1] = \hat{D}[n] - 2\mu \cdot \Re\left\{ e^*[n] \left[\sum_{k=-K_1}^{K_2} g(k-\hat{D}[n])x[k-n] \right] \right\}, \qquad (6)$$

where μ is the step size, and $\Re\{\cdot\}$ and the superscript '$*$' denote the real part and complex conjugate of a complex value, respectively. The function $g(\nu) \triangleq g(k-\hat{D}[n])$ is the first-order derivative of the coefficient of the time delay estimate filter given in Eq. (5), i.e.,

$$g(\nu) = \mathrm{e}^{\mathrm{j}\omega_0\nu}\left[f(\nu) - \mathrm{j}\omega_0\operatorname{sinc}(\nu)\right], \qquad (7)$$

where $f(\nu)$ is referred to as the coefficient adaptation factor (Cheng and Tjhung, 2003),

$$f(\nu) = \frac{\partial\operatorname{sinc}(\nu)}{\partial\hat{D}[n]} = -\frac{\cos(\pi\nu) - \operatorname{sinc}(\nu)}{\nu}. \qquad (8)$$

We now explicitly consider the noise effect at the input, and briefly address possible performance deterioration of MMLETDE in low-SNR scenarios. Substituting Eq. (1) into the $\mathcal{J}_1(D)$ in Eq. (3), and with some mathematical manipulations, we have

$$\mathcal{J}_1(D) = E\left\{ \left| \sum_{k=-K_1}^{K_2} \left(w_k - \hat{w}_k[n]\right) s[n-k] \right|^2 \right\} + \sigma_i^2 \mathcal{E}(D), \qquad (9)$$

where we have used the assumption that $q_i[n]$ and $q_o[n]$ are uncorrelated to each other, both independent of $s[n]$, and $\mathcal{E}(D)$ is given by

$$\mathcal{E}(D) \triangleq \gamma + E\left\{ \sum_{k=-K_1}^{K_2} |\hat{w}_k[n]|^2 \right\}. \qquad (10)$$

Notice that, since $\mathcal{E}(D)$ is a function of the truncated fractional TDE filter $\{\hat{w}_k[n]\}$, it is accordingly a function of the TDE $\hat{D}[n]$ as well, as indicated by Eq. (5). Obviously, with noisy input signal, i.e., when $\sigma_i^2 \neq 0$, minimizing $\mathcal{J}_1(D)$ with respect to $\hat{w}_k[n]$ would result in a biased estimate of D. Furthermore, the bias of time delay estimate would increase with the increase of the noise power. Thus, the MMLETDE algorithm would deteriorate by using the noise-corrupted input signal $x[n]$, especially in scenarios of moderate or high noise power, as is validated in the forthcoming simulations.

3 Proposed algorithm

To improve the TDE accuracy of narrowband signals in low-SNR scenarios, we consider the elimination of the negative effect of the input noise. Motivated by the unbiased impulse response estimate method in So (2001), we consider the weighted cost function by normalizing Eq. (9) with $\mathcal{E}(D)$, i.e.,

$$\mathcal{J}(D) \triangleq \frac{1}{\mathcal{E}(D)}\mathcal{J}_1(D). \tag{11}$$

Substituting Eq. (9) into the above equation, we have

$$\begin{aligned}\mathcal{J}(D) &= \frac{1}{\mathcal{E}(D)} \\ &\quad\cdot E\left\{\left|\sum_{k=-K_1}^{K_2}(w_k[n]-\hat{w}_k[n])\,s[n-k]\right|^2\right\}+\sigma_i^2 \\ &\triangleq \tilde{\mathcal{J}}(D)+\sigma_i^2\end{aligned} \tag{12}$$

with an obvious definition of $\tilde{\mathcal{J}}(D)$. Thus, minimizing $\tilde{\mathcal{J}}(D)$ in Eq. (12) is equivalent to minimizing the weighted cost function $\mathcal{J}(D)$. Since $\mathcal{J}(D)$ is independent of the weight coefficient $\{\hat{w}_k[n]\}$ of the time delay estimate filter, an unbiased estimate can be obtained by minimizing $\mathcal{J}(D)$ even with a noise-corrupted input $x[n]$. Note that minimizing the weighted mean-squared error $\tilde{\mathcal{J}}(D)$ is equivalent to minimizing $\mathcal{J}_1(D)$ subject to a constant-norm constraint, namely, $\mathcal{C}\left(1+E\left\{\sum_{k=-K_1}^{K_2}(\mathrm{sinc}(\nu))^2\right\}\right)=1$, where $\mathcal{C}$ is a positive constant (Regalia, 1994).

We now formulate the TDE algorithm of LMS-type (Widrow and Steams, 1985). By incorporating the instantaneous counterparts of each term in the weighted cost function in Eq. (11), we have the corresponding instantaneous weighted cost function

$$\hat{\mathcal{J}}(n) \triangleq \hat{\mathcal{J}}\left(\hat{D}[n]\right)=\frac{|e[n]|^2}{\hat{\mathcal{E}}(n)}, \tag{13}$$

where $\hat{\mathcal{E}}(n) \triangleq \gamma+\sum_{k=-K_1}^{K_2}|\hat{w}_k[n]|^2$ corresponds to the TDE $\hat{D}[n]$. Taking the partial derivative of Eq. (13) with respect to $\hat{D}[n]$, we can obtain the gradient of $\hat{\mathcal{J}}(n)$:

$$\frac{\partial\hat{\mathcal{J}}(n)}{\partial\hat{D}[n]}=\frac{\frac{\partial|e[n]|^2}{\partial\hat{D}[n]}\hat{\mathcal{E}}(n)-\frac{\partial\hat{\mathcal{E}}(n)}{\partial\hat{D}[n]}|e[n]|^2}{\hat{\mathcal{E}}^2(n)} \tag{14}$$

with

$$\frac{\partial|e[n]|^2}{\partial\hat{D}[n]}=2\Re\left\{e^*[n]\sum_{k=-K_1}^{K_2}g(k-\hat{D}[n])x[k-n]\right\}, \tag{15}$$

$$\frac{\partial\hat{\mathcal{E}}(n)}{\partial\hat{D}[n]}=-2\Re\left\{\sum_{k=-K_1}^{K_2}g(k-\hat{D}[n])\hat{w}_k^*[n]\right\}. \tag{16}$$

Thus, the TDE iteration may be readily obtained as

$$\hat{D}[n+1]=\hat{D}[n]-\tilde{\mu}\frac{\partial\hat{\mathcal{J}}(n)}{\partial\hat{D}[n]}, \tag{17}$$

where $\tilde{\mu} \triangleq \mu\hat{\mathcal{E}}(n)$ is the step size. By substituting Eqs. (14)–(16) into Eq. (17), we obtain the iterative TDE:

$$\begin{aligned}\hat{D}[n+1] &= \hat{D}[n]-2\mu \\ &\quad\cdot\Re\left\{e^*[n]\left[\sum_{k=-K_1}^{K_2}g(k-\hat{D}[n])x[k-n]\right.\right. \\ &\quad\left.\left.+\frac{e[n]}{\hat{\mathcal{E}}(n)}\left(\sum_{k=-K_1}^{K_2}\hat{w}_k^*[n]g(k-\hat{D}[n])\right)\right]\right\}.\end{aligned} \tag{18}$$

In contrast to the MMLETDE (Cheng and Tjhung, 2003) update formula reiterated in Eq. (6), there is an extra additive bias-removal term in the proposed TDE iteration in Eq. (18), which is related to the input noise and used to alleviate the noise effect.

In order for the proposed TDE processor given in Eq. (18) to achieve optimal performance, sufficient iterations are needed along with a proper initial guess, as addressed in So *et al.* (1994) and Cheng and Tjhung (2003). Moreover, the transient and steady-state performance of the proposed algorithm is primarily influenced by the step size μ, as in other LMS-type TDE algorithms (So *et al.*, 1994; 1995; Cheng and Tjhung, 2003). Note that MMLETDE requires only a small order of the time delay estimate filter without noticeable estimation bias over a wide frequency range (Cheng and Tjhung, 2003). As is validated through computer simulations in Section 4, the proposed algorithm retains the property of a small filter length, with enhanced performance in low-SNR scenarios.

Further, notice that the noise power ratio γ is assumed to be known a priori. Otherwise, it has to be estimated in advance with the noise power estimates of σ_i^2 and σ_o^2. This premise is popular for TDE enhancement; e.g., the knowledge (or estimate) of the signal and noise spectra is required by the classical generalized cross-correlator (GCC) (Patwari *et al.*, 2005; Sadler and Kozick, 2006). The factor $(\sigma_s^2+\sigma_i^2)/\sigma_s^2$ is adaptively tracked to minimize the mean-squared error (So *et al.*, 1995; So and Ching, 2001). The TDE performance is enhanced between noisy signals with the prior knowledge of noise powers (So, 2002). Nevertheless, this precondition is slack for the proposed algorithm, as suggested by the illustrative simulation results presented hereafter.

4 Simulation results

In this section, we evaluate the performance of the proposed enhanced MMLETDE algorithm, as well as those of MMLETDE (Cheng and Tjhung, 2003) and ETDE (So *et al.*, 1994) for comparison. We consider the eight-tone narrowband and sinusoidal signals, respectively. In the following experiments, the actual time delay is set to be $0.35T_{\rm s}$, and the initial guess of the time delay estimates of all three algorithms are set to be zero. We employ the empirical mean-squared delay error (MSDE) $\mathrm{MSDE}[n]=\sum_{l=1}^{L}(\hat{D}_l[n]-D)^2/L$ to measure the accuracy of delay estimate as in So (2002), where $\hat{D}_l[n]$ is the time delay estimate in the lth Monte-Carlo trial, and $L=400$ is the total number of Monte-Carlo trials. The SNRs at $x[n]$ and $y[n]$ are set to be the same for simplicity.

In the first experiment, we evaluate the performance of the proposed algorithm with different parameters, namely step size μ and time delay filter length K, for the narrowband and sinusoidal signals, respectively. The center frequencies of the narrowband and sinusoidal signals are set to be 0.7π, and the bandwidth of the narrowband signals is 0.1π. As illustrated in Figs. 2 and 3, both the initial convergence rate and the steady-state performance of the proposed algorithm are largely dominated by the step size. Steady-state performance improvement can be obtained with a reduced step size at the cost of initial convergence rate slowdown, as is consistent with the existing results for the LMS-type TDE processors. Further results on the steady-state performance of the algorithms are given.

We also justify the TDE performance degradation due to imperfect prerequisite of the noise power ratio γ with a relatively small deviation ($\varDelta=0.15$); i.e., we incorporate $(1+\varDelta)\gamma$ in the time delay estimation iteration Eq. (18). Negligible performance degradation can be observed in Figs. 2 and 3 due to the imprecise noise power ratio.

In the second experiment, we compare the performance of the proposed algorithm with that of MMLETDE and ETDE. To make a fair comparison, we set the step sizes of the three algorithms to be

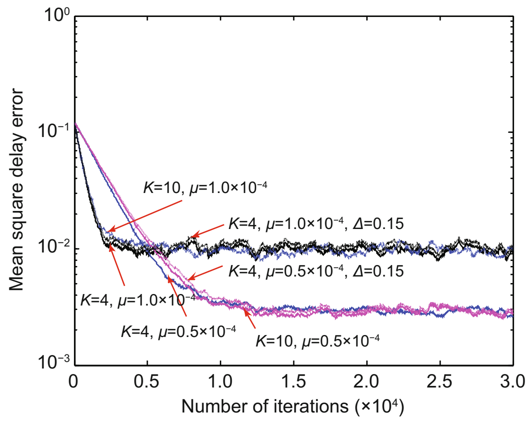

Fig. 2 Learning curves with different parameter settings for sinusoidal signals (SNR=−10 dB)

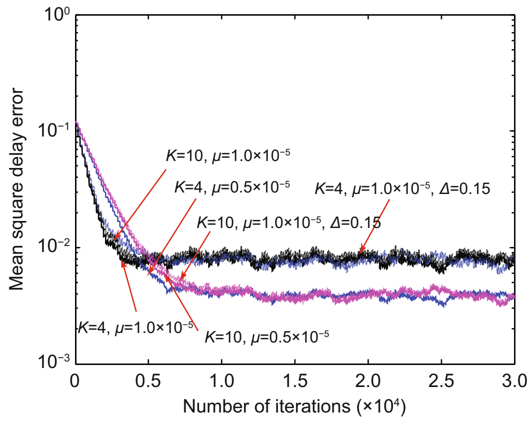

Fig. 3 Learning curves with different parameter settings for narrowband signals (SNR=−10 dB)

1×10^{-4} and 1×10^{-5} for the two input signals above, respectively, such that the initial convergence rates of the algorithms are similar. It is obvious in Fig. 4 that, in the low-SNR scenario, the TDEs obtained by ETDE and MMLETDE are biased with a relatively large length of the truncated time delay filter, while the proposed algorithm could attain rather accurate TDE with a smaller filter length. The steady-state MSDEs, which are calculated through 15 000 iterations after convergence, are shown in Fig. 5 for low and moderate SNR scenarios. It is observed that although the steady-state performance of MMLETDE approaches that of the proposed algorithm in the relatively high SNR range, the steady-state performance of the proposed algorithm is obviously superior to that of its counterparts of the same small filter order.

In the third experiment, we compare the performance of the algorithms for the sinusoidal signal with different center frequencies in a relatively low

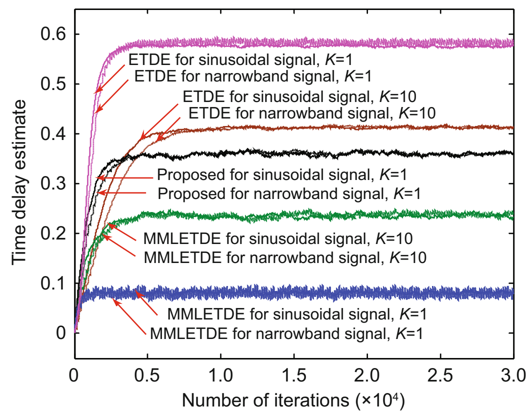

Fig. 4 Time delay estimate of the three algorithms for sinusoidal and narrowband signals (SNR=−10 dB)

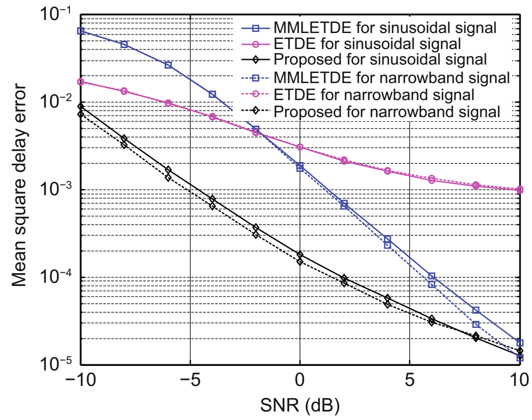

Fig. 5 Steady-state performance for sinusoidal and narrowband signals at different SNRs ($K = 2$)

SNR. The step sizes of the three algorithms are set to be 2×10^{-4}, such that the initial convergence rates of the algorithms are similar. The steady-state MSDEs of the three algorithms for different center frequencies are shown in Fig. 6. It is evident that, under the large input noise, the proposed algorithm markedly outperforms its counterparts over $0.3\pi \le \omega_0 \le 0.9\pi$, which is a relatively wide frequency range.

In the final experiment, we compare the performance of MMLETDE and the proposed algorithms for SNR $= -5$ dB and 5 dB, respectively, with different numbers of time delay filter taps, which are all relatively small. The MSDE of each independent simulation is obtained by averaging 15 000 iterations after convergence. The results for narrowband and sinusoidal signals are shown in Figs. 7 and 8, respectively. It is observed that the proposed algorithm achieves improved accuracy for a wide range of K values, compared to its counterpart. Further, the performance of the MMLETDE algorithm levels off and gets closer to that of the proposed algorithm for the larger SNR with the increase of K.

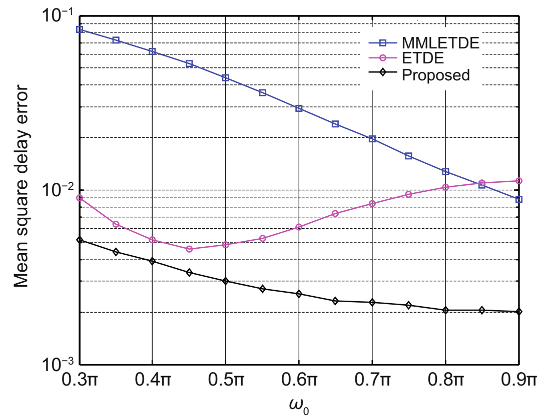

Fig. 6 Steady-state performance with different center frequencies (SNR $= -5$ dB, $K = 2$)

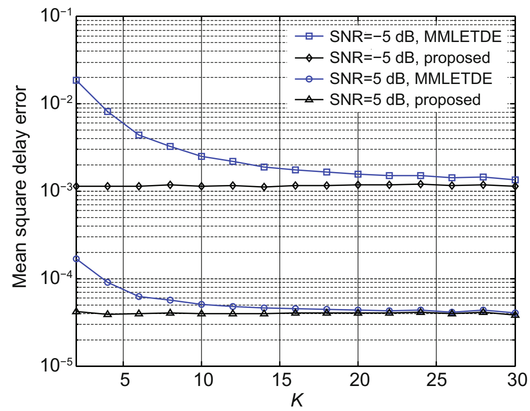

Fig. 7 Steady-state performance with $2 \le K \le 30$ for sinusoidal signals ($\mu = 1.0 \times 10^{-4}$)

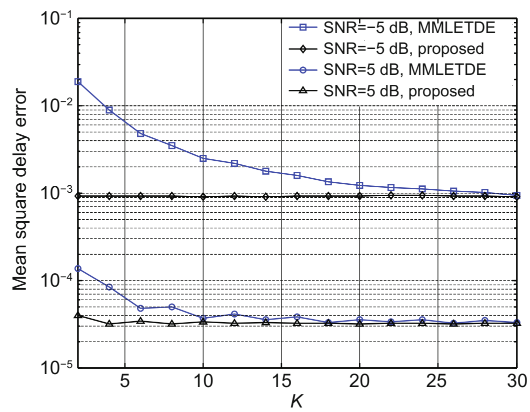

Fig. 8 Steady-state performance with $2 \le K \le 30$ for narrowband signals ($\mu = 1.0 \times 10^{-5}$)

5 Conclusions

An enhanced mixed modulated Lagrange explicit time delay estimator (MMLETDE) algorithm is proposed for noisy input. Simulation results show that, when the input is corrupted by noise, especially under low SNR scenarios, the proposed algorithm can directly obtain an unbiased explicit TDE for narrowband and sinusoidal signals with a smaller steady-state estimation error than those of ETDE and MMLETDE in the premise of almost the same initial convergence rate. For sinusoids, the proposed algorithm with a small filter order obviously obtains TDE over a wide frequency range with improved accuracy.

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