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Adaptive sparse system identification using normalized least mean fourth algorithm

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SUMMARY

Normalized least mean square (NLMS) was considered as one of the classical adaptive system identification algorithms. Because most of systems are often modeled as sparse, sparse NLMS algorithm was also applied to improve identification performance by taking the advantage of system sparsity. However, identification performances of NLMS type algorithms cannot achieve high-identification performance, especially in low signal-to-noise ratio regime. It was well known that least mean fourth (LMF) can achieve high-identification performance by utilizing fourth-order identification error updating rather than second-order. However, the main drawback of LMF is its instability and it cannot be applied to adaptive sparse system identifications. In this paper, we propose a stable sparse normalized LMF algorithm to exploit the sparse structure information to improve identification performance. Its stability is shown to be equivalent to sparse NLMS type algorithm. Simulation results show that the proposed normalized LMF algorithm can achieve better identification performance than sparse NLMS one. Copyright © 2013 John Wiley & Sons, Ltd.

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KEY WORDS: least mean square (LMS); least mean fourth (LMF); adaptive system identifications (ASI); adaptive sparse system identifications (ASSI); sparse penalty

1. INTRODUCTION

1.1. Background and motivation

Adaptive system identification (ASI) has been applied in many applications, such as channel estimation [1, 2] and echo cancelation [3]. Least mean square (LMS) algorithm is one of the popular methods for ASI [4]. Because of its sensitivity to random scaling of input signal, normalized least mean square (NLMS) was also proposed to improve identification performance [4]. In many scenarios, impulse responses of unknown systems are often modeled as sparse, consisting of only a few large coefficients and many small ones, which are below noise floor. Taking advantage of such sparse prior information can improve the system identification performance [1, 5–8]. In [1], ℓ_0-norm sparse penalty function was introduced to NLMS to exploit system sparsity. However, NLMS type algorithm cannot achieve high-identification performance, especially in low signal-to-noise ratio (SNR) regime [9].

Least mean fourth (LMF) algorithm [10] outperforms the well-known NLMS algorithm [4] in achieving a better balance between convergence and steady-state performances of ASI as shown in Figure 1. It is well known that the stability is one of the key factors for ASI. Standard LMF algorithm is unstable due to the fact that its stability depends on the following three factors: *input signal power*, *noise power*, and *weight initialization* [11]. In general, for a given gradient descend

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step-size, NLMS algorithm is stable and depends solely on the input signal power [4]. However, more and more systems, such as broadband wireless channels, were confirmed that exhibits sparse structures [12, 13]. NLMS-based ASI may degrade the identification performance because of neglecting the sparsity. To exploit sparse structure information in unknown system, sparse NLMS algorithm [1] were proposed for adaptive sparse system identifications (ASSI). Note that finite impulse response (FIR)-based sparse system vector is only supported by few nonzero coefficients. An example of sparse system is given as shown in Figure 2, the length of FIR-based system is 16, whereas the number of nonzero coefficients is only 2.

To improve ASSI performance, sparse LMF was proposed in low SNR regime [14]. However, the proposed method cannot work stable in high SNR regime. Inspirited by traditional LMF algorithm, stable normalized LMF (NLMF) algorithm for ASI was also proposed in [9]. The stability of NLMF is controlled by a variable step-size. For a better understanding about the stability, we will explain in detail in third section in this paper.

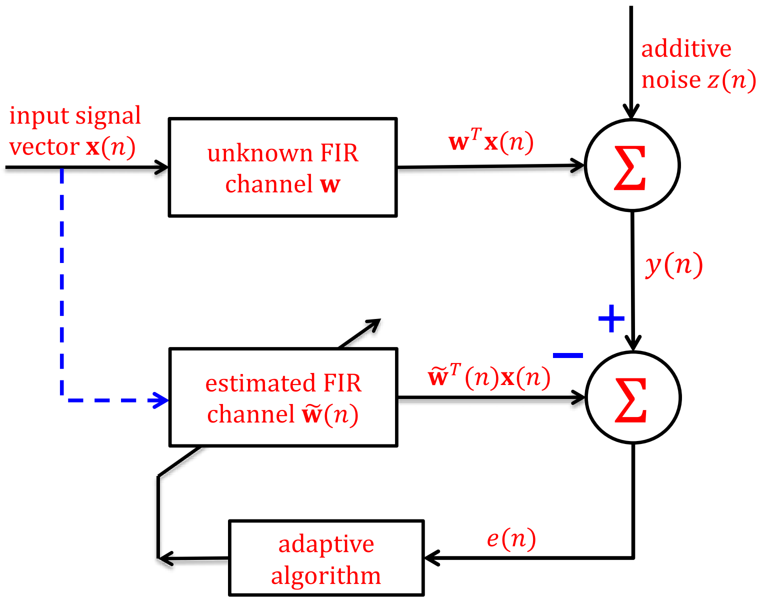

Figure 1. Adaptive system identification using adaptive algorithm.

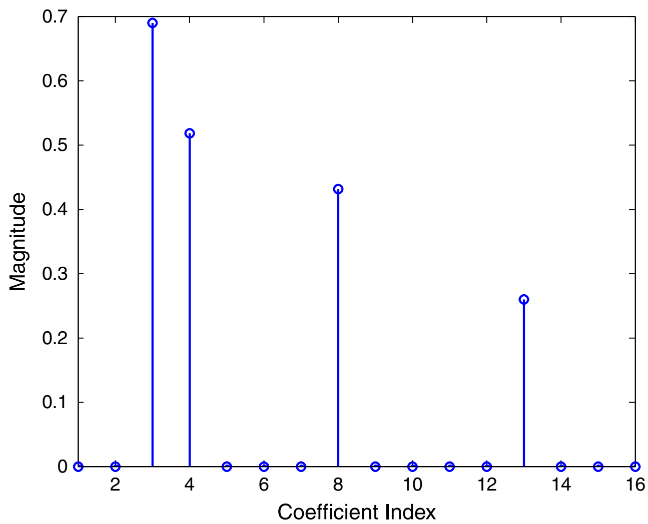

Figure 2. An example of sparse finite impulse response system.

1.2. Main contribution

On the basis of standard NLMF algorithm, we propose a stable sparse NLMF algorithm, which provides better identification performance than sparse NLMS one. To improve the stability of sparse NLMF algorithm, normalized version of the algorithm using sparse penalty is considered. The proposed sparse algorithm is effective for exploiting system sparsity and stable for all statistics of input signal, noise, and initial setting of the algorithm. For one thing, the updating normalization stabilizes the algorithm against increasing input power and the infinity of the input distribution. For another, the estimation error normalization term stabilizes the algorithm against increasing noise power and increasing initial weight deviation. At last, the approximated ℓ_0-norm sparse penalty is utilized so that ASSI replaces small system coefficients with zero. In other words, system sparsity can be exploited. Note that when the values of variable step-size in the range (0, 2), stability of the sparse NLMF algorithm is similar to that of the sparse NLMS one [1]. Performance of the proposed algorithm is evaluated by the computer simulation.

1.3. Relates to previous works

In [15], a faster proportionate PNLMS algorithm was proposed for ASSI for improving convergence speed. In other words, the proposed method can reduce computational complexity for sparse system. Unlike this method, our proposed method can exploit the system sparsity to improve the identification performance. In [14], sparse LMF for ASI was proposed in low SNR regime (e.g., less than 5 dB). By means of computer simulations, identification performance of sparse LMF improved is much better than sparse LMS [1, 16]. However, sparse LMF is not more stable if the SNR beyond low SNR regime. In [17], reweighted zero-attracting NLMF was proposed for ASSI by using ℓ_1-norm sparse penalty function for taking the advantage of system sparsity. Different from the proposed algorithm, we utilized an approximated ℓ_0-norm sparse penalty function to exploit stronger system sparsity than ℓ_1-norm one [18, 19].

Remainder of the rest paper is organized as follows. A system model is described and problems are formulated in Section 2. In section 3, sparse NLMF algorithm is proposed, and variable step-size controlling algorithm stability is highlighted. Simulation results are presented in Section 4 in order to verify the effectiveness of the proposed algorithm for ASI. Finally, we conclude the paper in Section 5.

2. SYSTEM MODEL AND PROBLEM FORMULATION

Assume that an input signal $x(n)$ is input to the system with unknown sparse FIR coefficients vector $w = [w_1, w_2, \ldots, w_N]^T$, then its observed output signal $y(n)$ is given by

$$y(n) = w^T x(n) + z(n), \tag{1}$$

where $x(n) = [x(n), x(n-1), \ldots, x(n-N+1)]^T$ denotes the vector of input signal $x(n)$, and $z(n)$ is the observation noise assumed to be independent with $\mathbf{x}(n)$. The objective of the algorithm is to adaptively identify the unknown FIR coefficients vector $\mathbf{w}$ using the input signal $\mathbf{x}(n)$ and the desired output $y(n)$. One of the effective identification methods is adopting the traditional NLMS algorithm. The system mismatching identification error is defined as $e(n) = y(n) - \widetilde{\mathbf{w}}^T(n)\mathbf{x}(n)$, where $\widetilde{w}(n) = [\widetilde{w}_1(n), \widetilde{w}_2(n), \ldots, \widetilde{w}_N(n)]^T$ denotes n-th filter updating weight vector. Hence, the cost function and corresponding update equation of NLMS are given by

$$\begin{cases} \textit{Cost function}: G_1(n) = \dfrac{1}{2}e^2(n) \\ \textit{Update equation}: \widetilde{\mathbf{w}}(n+1) = \widetilde{\mathbf{w}}(n) + \dfrac{\mu}{\|\mathbf{x}(n)\|_2^2}\cdot\dfrac{\partial G_1(n)}{\partial \widetilde{\mathbf{w}}(n)} = \widetilde{\mathbf{w}}(n) + \mu\dfrac{e(n)\mathbf{x}(n)}{\|\mathbf{x}(n)\|_2^2}. \end{cases} \tag{2}$$

where step-size $\mu \in (0, 1/\gamma_{\max})$ controls the steady-state performance and stability of NLMF and $\gamma_{\max}$ is maximal eigenvalue of covariance matrix $\mathbf{R} = E\{\mathbf{x}(n)\mathbf{x}^T(n)\}$.

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To exploit the system sparsity, ASSI using L0-NLMS algorithm was proposed in [1]. The cost function $G_2(n)$ of L0-NLMS is given by

$$G_2(n) = \frac{1}{2}e^2(n) + \lambda_1\|\widetilde{\mathbf{w}}(n)\|_0, \tag{3}$$

where λ_1 is a regularization parameter, which balances matching error and sparseness of the system; $\|\widetilde{\mathbf{w}}\|_0$ denotes zero-norm operator, which counts the number of nonzero coefficient of $\widetilde{\mathrm{w}}$. Because solving zero-norm algorithm is a non-deterministic polynomial-time hard problem [20], $\|\widetilde{\mathbf{w}}\|_0$ in Eq. (3) can be approximated by $J(\widetilde{\mathbf{w}}) = [J(\widetilde{w}_0), \dots, J(\widetilde{w}_i), \dots, J(\widetilde{w}_{N-1})]^T$, and $J(\widetilde{w}_i)$ is given by

$$J(\widetilde{w}_i) = \begin{cases} 2\varepsilon^2\widetilde{w}_i - 2\varepsilon\mathrm{sgn}(\widetilde{w}_i), & when\ |\widetilde{w}_i| \le 1/\varepsilon \\ 0, & others \end{cases}, \tag{4}$$

where sgn(w_i) is a component-wise function, which is defined as: sgn(w_i) $= w_i/|w_i|$ when $w_i \neq 0$ and sgn (w_i) $= 0$ when $w_i = 0$; and ε is a threshold, which controls sparseness of $\mathbf{w}$. In this letter, we set $\varepsilon = 10$ in computer simulation which was suggested by [21]. Then, update equation of sparse NLMS algorithm is given by

$$\widetilde{\mathbf{w}}(n+1) = \widetilde{\mathbf{w}}(n) + \mu\frac{e(n)\mathbf{x}(n)}{\|\mathbf{x}(n)\|_2^2} - \beta_1 J(\widetilde{\mathbf{w}}(n)), \tag{5}$$

where $\beta_1 = \mu\lambda_1$; $\mu \in (0,2)$ is a gradient descend step-size, which controls convergence speed and steady-state performance; $\|\cdot\|_2$ is the Euclidean norm operator and $\|\mathbf{x}\|_2^2 = \sum_{i=1}^{N}|x_i|^2$.

3. ADAPTIVE SPARSE SYSTEM IDENTIFICATIONS USING SPARSE NORMALIZED LEAST MEAN FOURTH ALGORITHM

3.1. *Sparse normalized least mean fourth algorithm*

It is well known that four-order error cost function can achieve better performance than second-order error one in ((2)) [14]. The cost function and corresponding update equation of LMF are constructed by

$$\begin{cases} \text{Cost function} : G_3(n) = \frac{1}{4}e^4(n) \\ \text{Update equation} : \widetilde{\mathbf{w}}(n+1) = \widetilde{\mathbf{w}}(n) + \frac{\mu}{\|\mathbf{x}(n)\|_2^2}\cdot\frac{\partial G_3(n)}{\partial \widetilde{\mathbf{w}}(n)} = \widetilde{\mathbf{w}}(n) + \mu\frac{e^3(n)\mathbf{x}(n)}{\|\mathbf{x}(n)\|_2^2}. \end{cases} \tag{6}$$

Similarly, the cost function of sparse LMF algorithm [14] can also be written as

$$G_3(n) = \frac{1}{4}e^4(n) + \lambda_2\|\widetilde{\mathbf{w}}(n)\|_0, \tag{7}$$

where $\lambda_2 > 0$ is a regularization parameter, which trades off the fourth-order mismatching error and sparseness of system. Then, updating equation of sparse NLMF algorithm can be written as

$$\widetilde{\mathbf{w}}(n+1) = \widetilde{\mathbf{w}}(n) + \mu\frac{e^3(n)\mathbf{x}(n)}{\|\mathbf{x}(n)\|_2^2} - \beta_2 J(\widetilde{\mathbf{w}}(n)), \tag{8}$$

where $\beta_2 = \mu\lambda_2$. However, stability of Eq. (8) still depends on input signal power, noise power, and weight initialization of sparse NLMF. To ensure its stability, the updating equation in Eq. (8) is modified as

$$\begin{aligned}\widetilde{\mathbf{w}}(n+1) &= \widetilde{\mathbf{w}}(n) + \frac{\mu e^2(n)}{\|\mathbf{x}(n)\|_2^2 + e^2(n)} \cdot \frac{e(n)\mathbf{x}(n)}{\|\mathbf{x}(n)\|_2^2} - \beta_2 J(\widetilde{\mathbf{w}}(n)),\\ &= \widetilde{\mathbf{w}}(n) + \mu(n)\frac{e(n)\mathbf{x}(n)}{\|\mathbf{x}(n)\|_2^2} - \beta_2 J(\widetilde{\mathbf{w}}(n)),\end{aligned} \tag{9}$$

where the variable step-size $\mu(n)$, which is decided by $e^2(n)$.

3.2. Stability analysis

Unlike the traditional sparse NLMF algorithm in (8), the proposed sparse NLMF algorithm in (9) behaves more like sparse NLMS algorithm in (5). The main difference between the two algorithms is their step-sizes. It was well known that the necessary condition of stable sparse NLMS algorithm is $0 < \mu < 2/\gamma_{\max}$. According to the Eq. (9), the variable step-size $\mu(n)$ is equals to

$$\mu(n) = \frac{\mu e^2(n)}{\|\mathbf{x}(n)\|_2^2 + e^2(n)}, \tag{10}$$

where the input signal vector $\mathbf{x}(n)$ is invariable. Hence, variable step-size $\mu(n)$ in Eq. (10) depends only on the system identification error $e^2(n)$.

Theorem 1

The necessary condition of sparse NLMF algorithm is $\mu(n) \in (0, \mu)$, where $\mu \in (0, 2/\gamma_{\max})$.

Proof

According to Eq. (10), when $e^2(n) \gg \|\mathbf{x}(n)\|_2^2$ then $\mu(n) \to \mu$; when $e^2(n) \approx \|\mathbf{x}(n)\|_2^2$ then $\mu(n) \to \mu/2$; and when $e^2(n) \ll \|\mathbf{x}(n)\|_2^2$ then $\mu(n) \to 0$. Obviously, $\mu(n) \in (0, \mu)$ is necessary condition to ensure sparse NLMF algorithm stable. ■

For example, two step-sizes of NLMS type are set as $\mu = 0.5$ and 1, $\|\mathbf{x}(n)\|_2^2 = 16$, variable step-sizes of NLMF can be depicted as in Figure 3. As the identification error $e^2(n)$ increases, $\mu(n)$

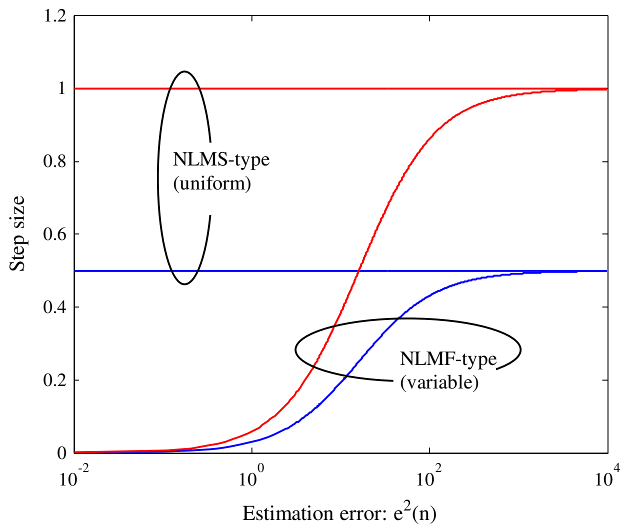

Figure 3. Variable step-size depends on estimation error.

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approaches to μ to improve convergence speed of NLMF; and as the identification error $e^2(n)$ decreases, $\mu(n)$ approaches to 0 to ensure stability of the NLMF.

4. COMPUTER SIMULATION AND DISCUSSION

In this section, computer simulation adopts 1000 independent Monte-Carlo runs for achieving average. Four algorithms, that is, NLMS, NLMF, sparse NLMS, and sparse NLMF will be evaluated by mean square deviation (MSD), which is defined as

$$MSD\{\mathbf{w}(n)\} = E\left\{\|\mathbf{w} - \widetilde{\mathbf{w}}(n)\|_2^2\right\}, \tag{11}$$

where $E\{\cdot\}$ denotes expectation operator, $\mathbf{w}$ and $\widetilde{\mathbf{w}}(n)$ denote actual system coefficient vector and its estimator, respectively. The FIR system length is set as $N = 16$ and its number of nonzero coefficients

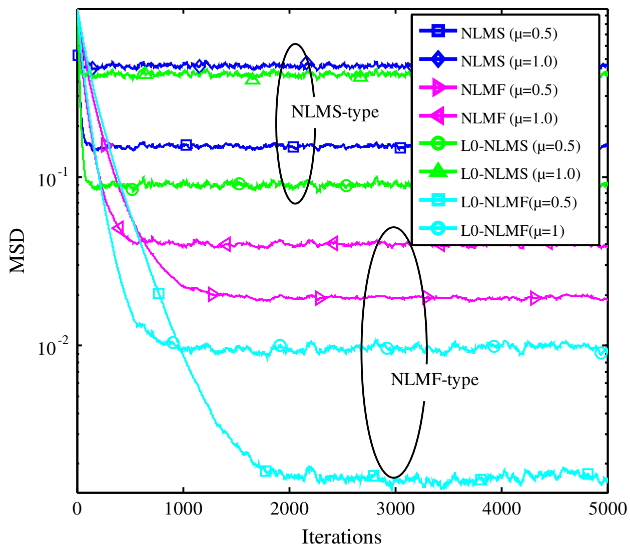

Figure 4. Performance comparison (K = 1 and SNR = 2 dB).

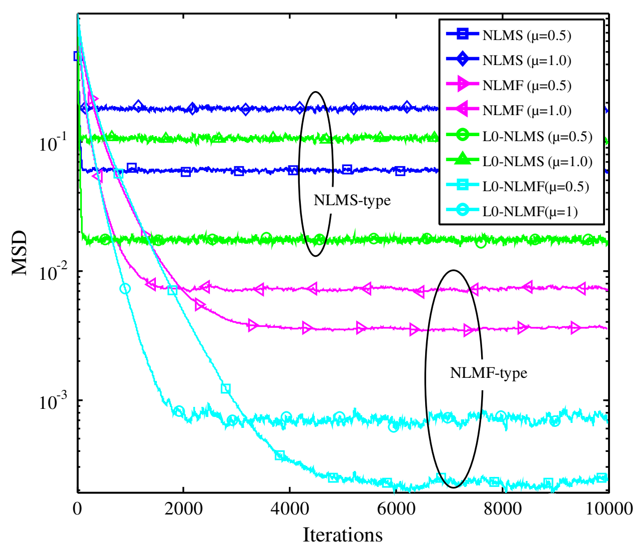

Figure 5. Performance comparison (K = 1 and SNR = 4 dB).

is set as $K=1$ and 4, respectively. The values of the nonzero FIR coefficients follow Gaussian distribution and the positions of coefficients are randomly allocated within the FIR system **w**, which is subjected to $\|\mathbf{w}\|_2^2=1$. The received SNR is defined as $SNR=10\log\left(E_0/\sigma_n^2\right)$, where $E_0=1$ is normalized transmitted power and the noise power is given by $\sigma_n^2=10^{-SNR/10}$. These algorithms use the same step-size each time and two step-sizes, that is, $\mu=0.5$ and 1 are considered. The regularization parameters are set as $\lambda_1=0.02\sigma_n^2$ and $\lambda_2=0.0002\sigma_n^2$, respectively. Please note that effective regularization parameters selection methods via Monte-Carlo simulations. Interesting authors can find the detail selection methods in our paper [22, 23]. Experiments have been designed to demonstrate their convergence speed (or iterative times) and steady-state performance (measured by MSD) in different SNR regimes.

In the first experiment, $K=1$, number of nonzero coefficients of FIR system, as well as different SNR cases are considered for comparison. MSD performance curves of two type algorithms, that is,, NLMS, sparse NLMS, NLMF, and sparse NLMF, are depicted in Figures 4–7. These figures

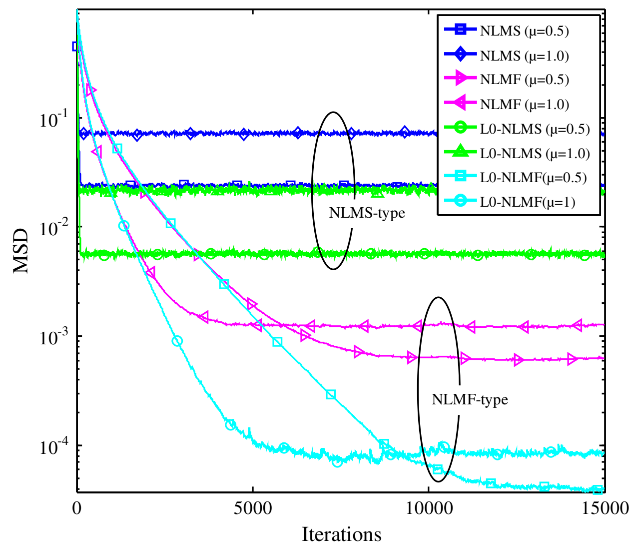

Figure 6. Performance comparison (K = 1 and SNR = 6 dB).

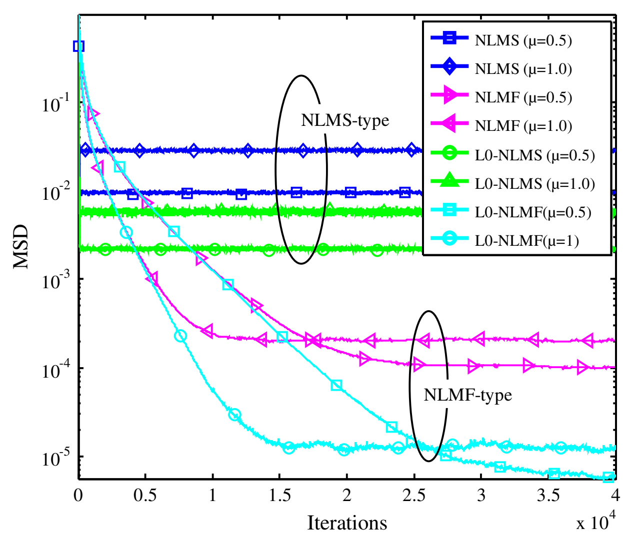

Figure 7. Performance comparison (K = 1 and SNR = 8 dB).

show that the proposed sparse NLMF algorithm is stable at two different step-sizes, that is, $\mu = 0.5$ and 1. On the one hand, because sparse NLMF algorithm has taken the advantage of system sparsity, sparse NLMF algorithm obtained better identification performance than standard NLMF algorithm. On the other hand, the proposed algorithm achieved much better performance than sparse NLMS one at two different step-sizes, that is, $\mu = 0.5$ and 1. It was worth mentioning that sparse NLMF algorithm has to run more iterative times than sparse NLMS. The main reason is that variable step-size $\mu(n)$ decreases adaptively to ensure sparse NLMF algorithm stable as the identification error $e^2(n)$ reducing. One can also find that its gradient descend speed is always slower than sparse NLMS algorithm in Figures 4–7.

In the second experiments, to confirm the effectiveness of proposed method in different sparse systems, Figures 8–11 depict MSD performance curves of the proposed method at $K = 4$. According to these figures, proposed sparse NLMF algorithm achieves better estimation performance than sparse NLMS. Compare with all of simulation figures, that is, Figures 4–11, we can find that sparse filters relates with sparseness of system. In other words, sparser system vector may obtain better performance and vice versa.

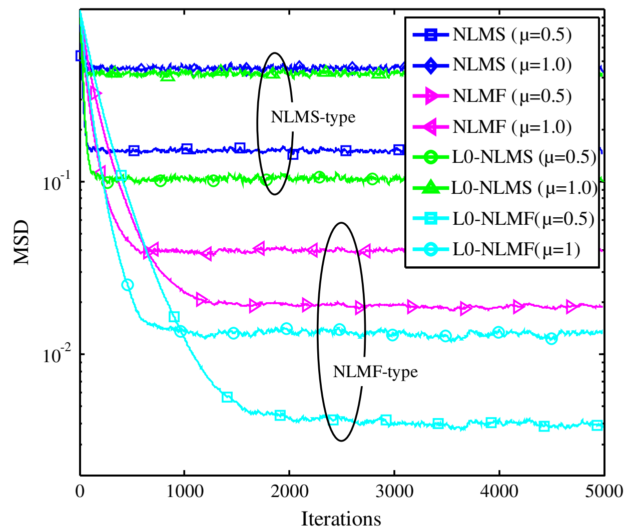

Figure 8. Performance comparison (K = 4 and SNR = 2 dB).

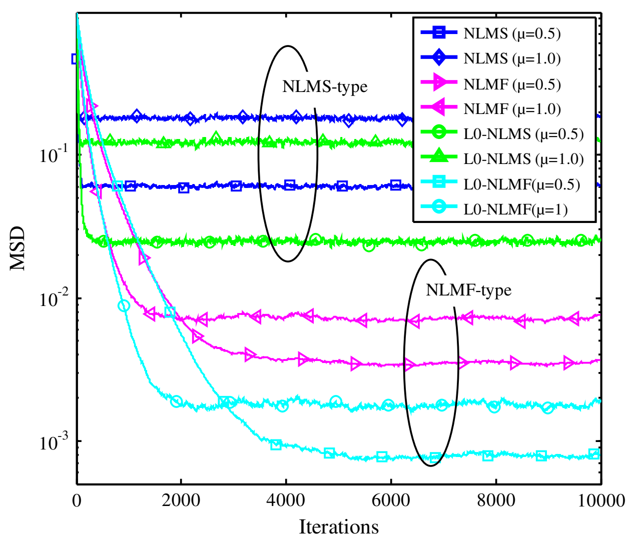

Figure 9. Performance comparison (K = 4 and SNR = 4 dB).

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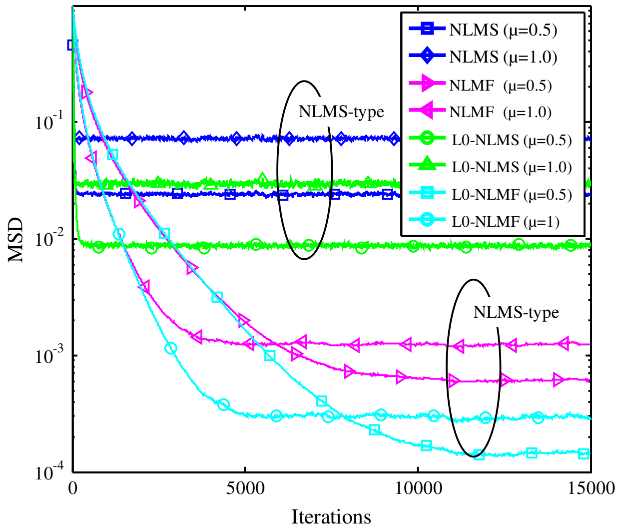

Figure 10. Performance comparison (K = 4 and SNR = 6 dB).

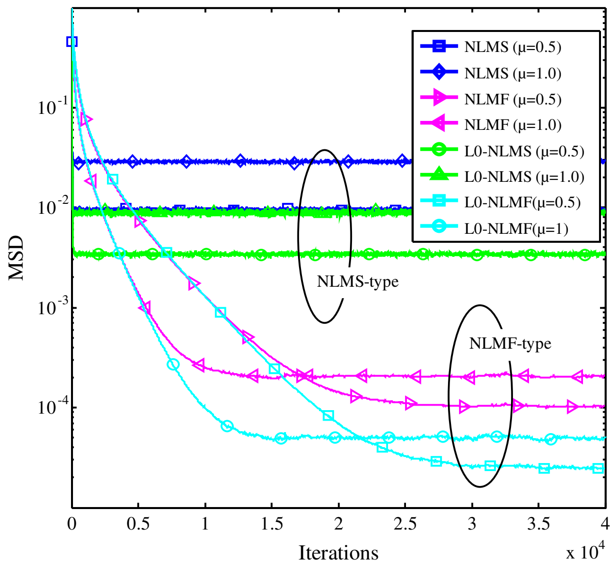

Figure 11. Performance comparison (K = 4 and SNR = 8 dB).

5. CONCLUSION

Normalized least mean square type algorithm was considered as one of effective methods for ASSI. Because NLMF adopts four-order statistical in cost function, hence, it can achieve better identification performance than NLMS. Motivated by this idea, first of all, in this paper, we applied the NLMF algorithm to ASI so that it can improve identification performance. To exploit the system sparsity, we proposed a stable sparse NLMF algorithm to further improve the identification performance. In addition, equivalent stability between NLMS and NLMF was also discussed. Simulation results have shown the superior performance of the proposed algorithm compared with the existing algorithms.

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