A New Variable Step-size LMS Algorithm and Its Analysis

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Abstract. *The LMS (least mean square) algorithm is an adaptive filtering algorithm widely used in the fields of signal processing and system identification. To avoid the compromise between the convergence speed and the steady-state error for fixed step-size LMS algorithm, a variable step-size LMS algorithm (named ELVSLMS algorithm) based on error autocorrelation estimation and logarithmic function is proposed and analyzed in this paper. In the proposed algorithm, the variable step-size filter is replaced by a filter whose step-size function is a modified function based on error autocorrelation estimation and logarithmic function. Thus, logarithmic nonlinear relationship between the step-size and the error autocorrelation is constructed. Therefore, the slow convergence speed and the weak anti-jamming ability of fixed step-size LMS are conquered. Simulation results show that the proposed ELVSLMS algorithm, compared to LMS algorithm, SVSLMS algorithm (whose step-size adjustment function is based on sigmoid function), TLVSLMS algorithm (whose step-size adjustment function is based on versoria function) and HSVSLMS algorithm (whose step-size adjustment function is based on hyperbolic secant function), not only has superior capability of tracking in the presence of noise and in a stable and even non-stable environment, but also can maintain a better convergence and smaller steady-state error.*

Keywords

Least mean square (LMS) filter, error autocorrelation estimation, logarithmic function, performance analysis

1. Introduction

The step-size of the filter plays a significant role in the convergence process of LMS algorithm [1–3]. It not only controls the convergence speed of the initial stage but also determines the steady-state performance of the convergence stage [4]. The compromise between convergence speed and steady-state error influences filtering performance. In order to avoid different requirements of the step-size for satisfying convergence speed and steady-state error in a single filter [5–7], many variable step-size LMS algorithms are proposed. These variable step-size algorithms are different in the changing way of step-size. A few algorithms obtain the current moment step-size by modifying the previous moment step-size [8], [9]. Most algorithms adjust the step-size by constructing the nonlinear function relationship between the step-size and the error [10–12], and they get more attention. SVSLMS algorithm [10] constructs nonlinear relationship between the step-size and the error by sigmoid function. It has fast convergence speed, small steady-state error and good tracking ability, while its steady-state error is not ideal because sigmoid function changes rapidly near minimum zero. TLVSLMS algorithm [11] uses versoria function to construct the nonlinear relationship between the step-size and the error, whose performance is better than SVSLMS algorithm, but it is vulnerable to noise in steady-state. In [12], HSVSLMS algorithm uses hyperbolic secant function to construct the nonlinear relationship between the step-size and the error. The effect of noise in steady-state is reduced by introducing error autocorrelation estimation, and the HSVSLMS algorithm has good filtering result. Similar to GSVSLMS algorithm, the performance of HSVSLMS algorithm is poor at low SNR (Signal to Noise Ratio). Thus, how to make variable step-size LMS algorithm have better filtering performance in low SNR case and noise environment is a problem worthy of study.

Motivated by this, we introduce error autocorrelation estimation to the adjustment of step-size and a new variable step-size LMS algorithm named ELVSLMS is proposed based on logarithmic function. The proposed algorithm constructs logarithmic nonlinear relationship between the step-size and the error autocorrelation. Thus, it can effectively accelerate convergence speed and reduce steady-state error. Besides, this algorithm can also coordinate the deficiency that other variable step-size LMS algorithms are susceptible to noise jamming in steady-state, and it also can perform well at low SNR.

The remainder of this paper is organized as follows. Section 2 analyzes step-size adjustment rules of some variable step-size LMS algorithm, providing ideas for the research of the new algorithm. Section 3 describes the pro-

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posed algorithm in detail and analyzes its anti-jamming ability theoretically. Section 4 gives the dataset description and shows Monte Carlo simulation results. Section 5 concludes the paper.

2. Step-size Adjustment Rules of Some Variable Step-size LMS Algorithm

Table 1 shows the step-size functions of some variable step-size LMS algorithms, and numerical curves of step-size functions are shown in Fig. 1.

It is easy to see that the step-size and the error of variable step-size LMS algorithms have a nonlinear relationship in Fig. 1. When the error is big, the step-size should be big to accelerate convergence speed. When the error is small, the step-size should be small to reduce steady-state error. Thus, at the initial filtering stage, the variable step-size LMS algorithm needs a big step-size error to converge. At the stable filtering stage, the variable step-size LMS algorithm needs a small step-size error to ensure steady-state performance. Besides, the step-size function should have the characteristic of slow change to ensure the stability of convergence when the error tends to zero, and it can be realized by adjusting some parameters in the step-size function.

Algorithm	Step-size function	Adjustment parameters
SVSLMS [10]	$\mu(n)=\beta(\frac{1}{1+\exp(-\alpha\|e(n)\|)}-0.5)$	β , α
TLVSLMS [11]	$\mu(n)=a(1-\frac{1}{be^2(n)+1})$	a , b
HSVSLMS [12]	$\mu(n)=\frac{\beta(1-\exp(-\alpha\|e(n)e(n-1)\|))^2}{1+h\exp(-2\alpha\|e(n)e(n-1)\|)}$	β , α , h

Tab. 1. The step-size functions of some variable step-size LMS algorithms.

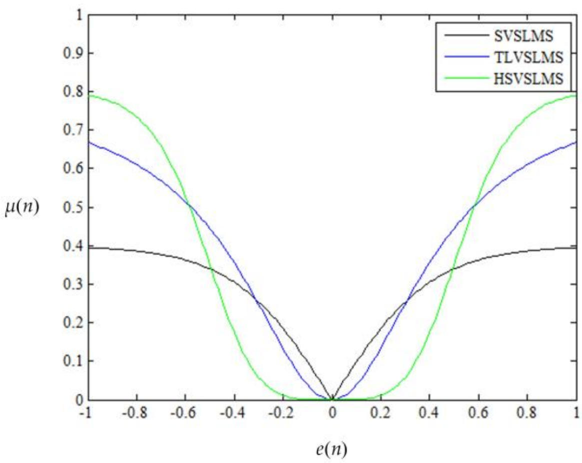


Fig. 1. Numerical curves of step-size functions with parameters $\beta = a = 0.8$, $\alpha = b = 5$ and $h = 2$.

3. Proposed ELVSLMS Algorithm

3.1 Algorithm Description

Although many variable step-size LMS algorithms adjust the step-size by constructing the nonlinear function relationship between the step-size and the error to conquer the deficiency of fixed step-size LMS algorithm, they bring new shortcomings. Logarithmic function has simple form and less computation, fulfilling the step-size adjustment rules, and it has some application in variable step-size LMS algorithms [13–15].

Under the idea of variable step-size LMS algorithms, the ELVSLMS algorithm is proposed in this paper. In this algorithm, the step-size adjustment function is a variable function of logarithmic function, which can be expressed as

$$\mu(n)=\frac{\beta\lg(1+\alpha e^{2\gamma}(n))}{1+\lg(1+2\alpha e^2(n))}. \tag{1}$$

In (1), β controls the span of step-size and α controls the changing shape of step-size, while γ controls the smoothness of step-size round zero. It adds a smoothness adjustment parameter γ compared with SVSLMS algorithm, GSVSLMS algorithm and TLVSLMS algorithm. But equation (1) cannot conquer the problem that variable step-size algorithm is vulnerable to noise in steady-state. So, we use the error autocorrelation estimation $|e(n)e(n-1)|$ to replace instantaneous square $e^2(n)$ in (1), which can mitigate the influence of noise and improve the ability of anti-jamming. Equation (1) can be changed as

$$\mu(n)=\frac{\beta\lg(1+\alpha|e(n)e(n-1)|^{\gamma})}{1+\lg(1+2\alpha|e(n)e(n-1)|)}. \tag{2}$$

Thus, the proposed ELVSLMS algorithm is summarized in Tab. 2.

Inputs Input vector: $\mathbf{x}(n)$ Desired signal: $d(n)$ Weight coefficient vector: $\mathbf{w}(n)$	**Outputs** Output of filter: $y(n)$ Updating weight coefficient vector: $\mathbf{w}(n+1)$
Initialization: $\mathbf{w}(0)=\mathbf{0}$, β , α , γ ; For each iteration time n 1. Output of LMS filter, $y(n)=\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}(n)$, 2. Error of LMS filter, $e(n) = d(n) - y(n)$, 3. Step-size adjustment, $\mu(n)=\frac{\beta\lg(1+\alpha\|e(n)e(n-1)\|^{\gamma})}{1+\lg(1+2\alpha\|e(n)e(n-1)\|)}$, 4. Updating weight coefficient vector, $\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)e(n)\mathbf{x}(n)$, end	

Tab. 2. The summary of proposed ELVSLMS algorithm.

3.2 Performance Analysis of Anti-jamming Ability

The ELVSLMS algorithm is based on error autocorrelation estimation and logarithmic function. The step-size adjustment controlled by logarithmic function is similar to other variable step-size LMS algorithms, which needs to comprehensively consider the influence of β, α and γ to get a best performance. Using the error autocorrelation estimation $|e(n)e(n-1)|$ to replace instantaneous square $e^2(n)$ can ameliorate performance in noise environment and improve the anti-jamming ability of the proposed algorithm. In this subsection, we analyze the anti-jamming performance of the ELVSLMS algorithm. We make the following assumptions and notations [16]:

- $d(n)$ and $\mathbf{x}(n)$ are related in a linear attenuation model

$$d(n)=\hat{\mathbf{w}}^{\mathrm{T}}\mathbf{x}(n)+\varepsilon(n) \tag{3}$$

where $\hat{\mathbf{w}}$ is the weight vector of an unknown system with length N and $\varepsilon(n)$ is independent modeling of observed noise with mean zero and variance σ_ε^2.

- $\mathbf{w}(0)$ is independent of $\{d(n), \mathbf{x}(n), \varepsilon(n)\}$ for all n.
- $E[d(n)]=0$, $E[\mathbf{x}(n)]=\mathbf{0}$ and $E[\mathbf{x}(n)\mathbf{x}^{\mathrm{T}}(n)]=\mathbf{R}$.

According to step 1 and step 2 in Tab. 2, the desired signal can be expressed as

$$d(n)=\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}(n)+e(n)\,. \tag{4}$$

Making an assumption

$$\mathbf{h}^{\mathrm{T}}(n)=\mathbf{w}^{\mathrm{T}}(n)-\hat{\mathbf{w}}^{\mathrm{T}}\,. \tag{5}$$

Combining equation (3)~(5), we get

$$e(n)=\varepsilon(n)-\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)\,. \tag{6}$$

Thus, we can derive the following relation

$$\begin{aligned}&E[|e(n)e(n-1)|]=E[e(n)e(n-1)]\\&=E\{[\varepsilon(n)-\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)][\varepsilon(n-1)-\mathbf{h}^{\mathrm{T}}(n-1)\mathbf{x}(n-1)]\}\\&=E[\varepsilon(n)\varepsilon(n-1)-\varepsilon(n)\mathbf{h}^{\mathrm{T}}(n-1)\mathbf{x}(n-1)\\&\quad-\varepsilon(n-1)\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)+\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)\mathbf{x}^{\mathrm{T}}(n-1)\mathbf{h}(n-1)].\end{aligned} \tag{7}$$

In view of the independent of $\varepsilon(n)$ and $\mathbf{x}(n)$, there is a fact that

$$\begin{aligned}&E[\varepsilon(n)\varepsilon(n-1)]=E[\varepsilon(n)\mathbf{h}^{\mathrm{T}}(n-1)\mathbf{x}(n-1)]\\&=E[\varepsilon(n-1)\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)]=0.\end{aligned} \tag{8}$$

So, equation (7) can be simplified to

$$E[|e(n)e(n-1)|]=E[\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)\mathbf{x}^{\mathrm{T}}(n-1)\mathbf{h}(n-1)]\,. \tag{9}$$

At the same time, we can derive the following relation from (6)

$$\begin{aligned}&E[e^2(n)]=E\{[\varepsilon(n)-\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)]^2\}\\&=E[\varepsilon^2(n)-2\varepsilon(n)\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)+\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)\mathbf{x}^{\mathrm{T}}(n)\mathbf{h}(n)]\\&=E[\varepsilon^2(n)+\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)\mathbf{x}^{\mathrm{T}}(n)\mathbf{h}(n)]\\&=E[\varepsilon^2(n)]+E[\mathbf{h}^{\mathrm{T}}(n)\mathbf{x}(n)\mathbf{x}^{\mathrm{T}}(n)\mathbf{h}(n)].\end{aligned} \tag{10}$$

Comparing (9) and (10), it can be seen that $E[|e(n)e(n-1)|]$ is not affected by the independent modeling of observed noise $\varepsilon(n)$, but $E[\varepsilon^2(n)]$ has influence to $E[e^2(n)]$. Thus, $\mu(n)$ cannot accurately reflect the adaptive state of ELVSLMS algorithm if we use $e^2(n)$ to adjust step-size according to (1). However, we can use $|e(n)e(n-1)|$ to adjust step-size according to (2), and the independent modeling of observed noise can be ignored, leading to improving anti-jamming ability of ELVSLMS algorithm.

4. Simulation Analysis and Results

In this section, we verify the convergence performance, steady-state performance and tracking performance of the proposed ELVSLMS algorithm for system identification through Monte Carlo simulation. The performance of ELVSLMS is compared with that of LMS, SVSLMS, TLVSLMS and HSVSLMS in 200 times Monte Carlo simulation, and we make an average. In the following simulations, the unknown system and the adaptive filter have the same length of $N = 8$. The used adaptive filter is a digital FIR (Finite Impulse Response) filter. It is an all-zero and non-recursive filter which is very stable, flexible and adaptable [17–19]. It is currently the most commonly used adaptive filter and its standard structure is shown in Fig. 2.

According to Fig. 2, weight vector of FIR filter ($N = 8$) can be expressed as

$$\mathbf{w}(n)=\left[w_0(n),w_1(n),w_2(n),...,w_7(n)\right]^{\mathrm{T}}. \tag{11}$$

The input signal $x(n)$ builds input vector $\mathbf{x}(n)$ as

$$\mathbf{x}^{\mathrm{T}}(n)=[x(n),x(n-1),...,x(n-7)]\,. \tag{12}$$

Output of FIR filter can be expressed as

$$y(n)=\mathbf{w}^{\mathrm{T}}(n)\mathbf{x}(n)\,. \tag{13}$$

Error of FIR filter can be expressed as

$$e(n)=d(n)-y(n)\,. \tag{14}$$

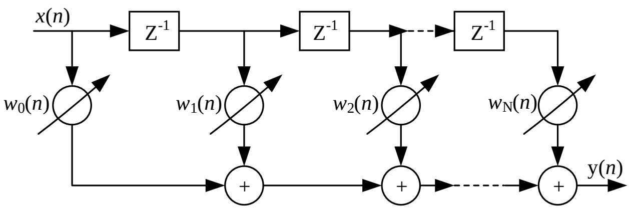


Fig. 2. Standard structure of the FIR filter.

The parameter of unknown system is set to $\hat{\mathbf{w}}^{\mathrm{T}} = [0.8783, -0.5806, 0.6537, -0.3223, 0.6577, -0.0582, 0.2895, -0.2710]$. When the iteration time reaches to 1000, $\hat{\mathbf{w}}$ is suddenly changed to $\hat{\mathbf{w}}^{\mathrm{T}} = [0.6537, -0.3223, 0.6577, -0.0582, 0.2895, -0.2710, 0.1278, -0.1508]$ to study the ability of reacting to changes. The input signal $x(n)$ is zero-mean white Gaussian noise with variance $\sigma_x^2 = 1$. According to (3), $\varepsilon(n)$ is zero-mean white Gaussian noise as well with variance σ_ε^2, independent of $x(n)$. We consider two cases that $\sigma_\varepsilon^2 = 0.01$ and $\sigma_\varepsilon^2 = 0.1$, namely, SNR = 20 dB and 10 dB.

4.1 Simulation Analysis of ELVSLMS with Different Parameters

In this section, we discuss how β, α and γ in (2) influence the MSE (mean-square error) performance of ELVSLMS. SNR is set to 20 dB and $\hat{\mathbf{w}}$ is assumed to be stable until a sudden change occurs after 1000 iteration time.

The MSE performance of ELVSLMS with $\alpha = 1000$ and $\gamma = 2$ while $\beta = 0.01, 0.02, 0.06, 0.1$ is illustrated in Fig. 3. It is clear to see that the convergence speed of ELVSLMS increases as β rises from 0.01 to 0.1; meanwhile, the steady-state error has some reduction. When the unknown system is suddenly changed after 1000 iteration, ELVSLMS algorithm still has good tracking ability. In fact, we find that the performance remains the same when β varies between 0.1 and 0.16 in the simulation; it cannot converge when β is bigger than 0.16. Therefore, the optimal β is around 0.1 in our simulation; 0.1 is selected.

In Fig. 4, the MSE performance of ELVSLMS with $\beta = 0.1$ and $\gamma = 2$ while $\alpha = 10, 100, 1000, 10000$ is displayed. It can be seen that the convergence speed of ELVSLMS increases when α rises from 10 to 1000; meanwhile, the steady-state error has some reduction. When α is bigger than 10000, the convergence speed has no obvious variation but the steady-state error has a certain extent. Thus, the optimal α is around 10000 in our simulation; 10000 is selected.

The MSE performance of ELVSLMS with $\beta = 0.1$ and α =10000 while $\gamma = 5, 4, 3, 2, 1$ is shown in Fig. 5. It can be found that the convergence speed of ELVSLMS increases when γ declines from 5 to 2, and the steady-state error has some reduction at the same time. When γ is 1, the algorithm has faster convergence speed but bigger steady-state error compared to $\gamma = 2$. In fact, we find that it cannot converge when γ is bigger than 5; it accelerates convergence speed but enlarges steady-state error when γ is smaller than 2. Therefore, the optimal γ is 2 in our simulation; 2 is selected.

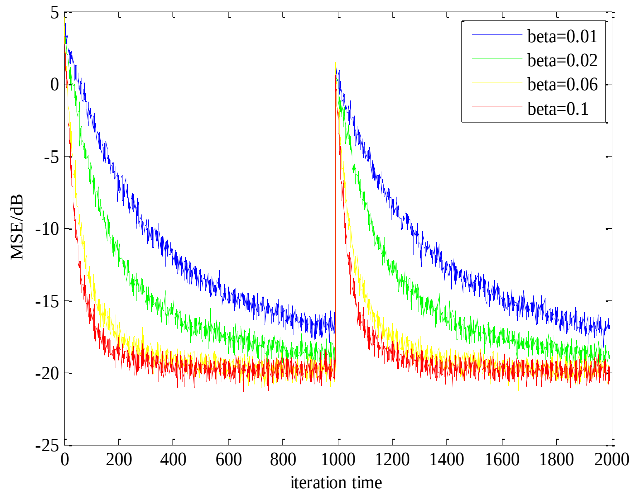


Fig. 3. Performance of ELVSLMS changes when β is different.

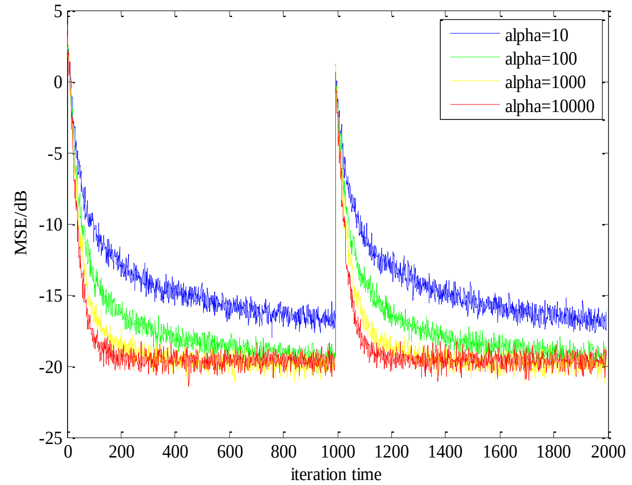


Fig. 4. Performance of ELVSLMS changes when α is different.

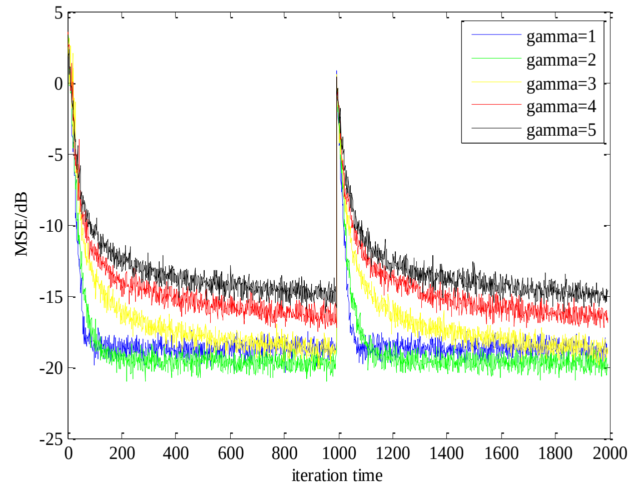


Fig. 5. Performance of ELVSLMS changes when γ is different.

4.2 Simulation Analysis of Different Algorithms in a Stable Environment

In a stable environment, $\hat{\mathbf{w}}$ would not change. Referring to Sec. 4.1 and relative study in mentioned references, we get the relative optimal parameters as shown in Tab. 3 by many simulations.

The MSE performance of different algorithms with two SNRs in a stable environment is illustrated in Fig. 6. The number of iterations each algorithm needs to converge and the steady-state MSE values are shown in Tab. 4. It is clear to see that all variable step-size LMS algorithms have faster convergence speed compared to fixed step-size LMS algorithm in two SNRs cases when steady-state errors have no obvious difference from Fig. 6 and Tab. 4. The number of convergence iterations is reduced by more than 210 when SNR is 20 dB; the number of convergence iterations is reduced by more than 140 when SNR is 10 dB. This is because that fixed step-size LMS algorithm cannot update the step-size on the basis of error and has a weak tracking updating ability. Meanwhile, the convergence speed of ELVSLMS algorithm has a slight improvement compared to the other three variable step-size LMS algorithms. The number of convergence iterations is reduced by more than 5 when SNR is 20 dB; the number of convergence iterations is reduced by more than 20 when SNR is 10 dB. When the unknown system is suddenly changed after 1000 iteration, ELVSLMS algorithm can be quickest to steady-state again, proving it has a good tracking ability. When SNR declines from 20 dB to 10 dB, all algorithms can effectively accelerate convergence speed with more than 30 times iterations of reduction, but leading to bigger steady-state error approaching to –10 dB. ELVSLMS still has the best performance.

4.3 Simulation Analysis of Different Algorithms in a Non-stable Environment

In a non-stable environment, $\hat{\mathbf{w}}$ would change when iteration advances. The model of a time-varying system is given as [2]

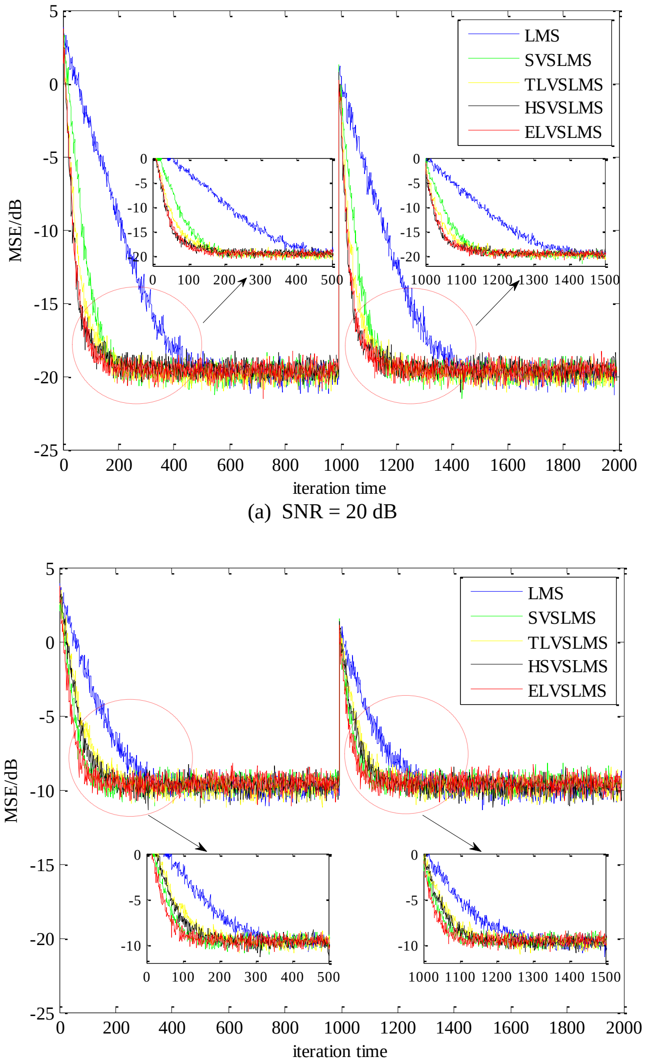
$$\hat{\mathbf{w}}(n+1)=\hat{\mathbf{w}}(n)+c(n) \tag{13}$$

where $c(n)$ is zero-mean white Gaussian noise with variance $\sigma_c^2 = 0.0001$. Other simulation conditions and algorithm parameters are the same as Sec. 4.2.

The MSE performance of different algorithms with two SNRs in non-stable environment is shown in Fig. 7. The number of iterations each algorithm needs to converge and the steady-state MSE values are shown in Tab. 5. It can be obviously found that ELVSLMS still has the best performance in non-stable environment from Fig. 7 and Tab. 5: the fastest convergence speed and the smallest steady-state error. When the unknown system is suddenly changed, ELVSLMS still has the best tracking performance. In a non-stable environment, LMS is most affected and has a biggest steady-state error. When SNR declines from 20 dB to 10 dB, the convergence speed of SVSLMS, TLVSLMS and HSVSLMS has slowed down with more than 10 times iterations of increase especially for HSVSLMS, while the convergence speed of LMS algorithm actually speeds up with more than 20 times iterations of reduction. Compared to Fig. 5, the steady-state errors of all algorithms are relatively bigger at the same SNR in a non-stable environment (MSE is more than 4.9 dB when SNR is 20 dB and MSE is more than 0.9 dB when SNR is 10 dB), but the convergence speeds are relatively faster, while it has no effect on the good ability of ELVSLMS in a non-stable environment.

Algorithm	Parameters	SNR=20dB	SNR=10dB
LMS	μ	0.008	0.008
SVSLMS	β , α	0.05, 10	0.05, 10
TLVSLMS	a , b	0.06, 5	0.02, 5
HSVSLMS	β , α , h	0.1, 25, 2	0.02, 25, 2
ELVSLMS	β , α , γ	0.1, 10000, 2	0.05, 10000, 2

Tab. 3. Parameters for different algorithms in a stable environment.



(a) SNR = 20 dB

(b) SNR = 10 dB

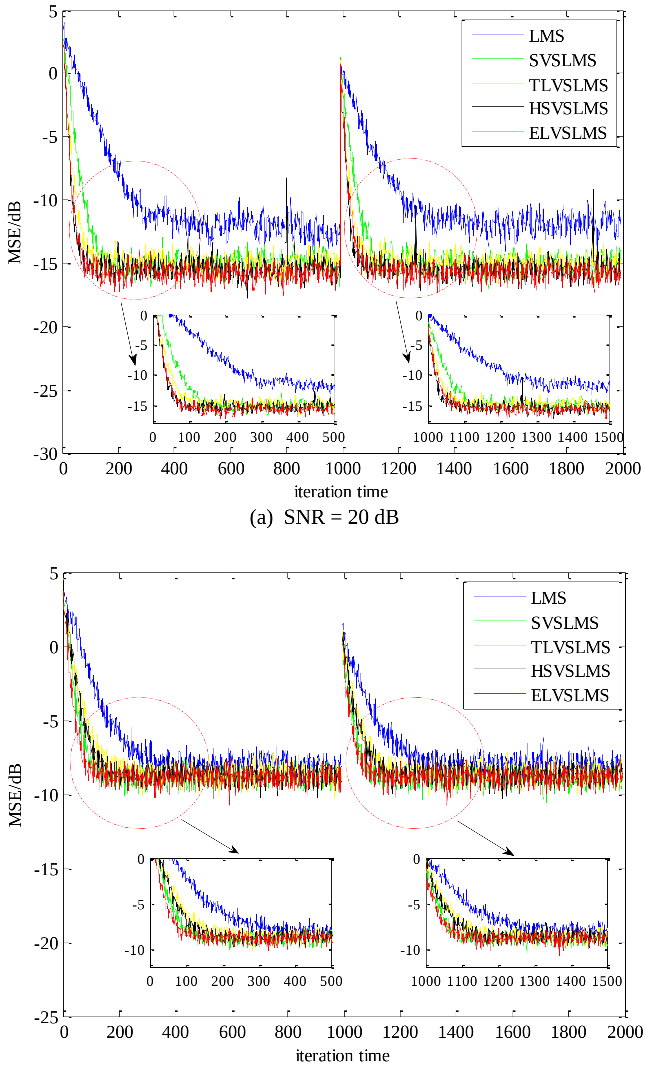
Fig. 6. Performance of different algorithms in a stable environment.

Algorithm	SNR = 20 dB		SNR = 10 dB	
	Convergence iterations(first/second)	MSE/dB	Convergence iterations(first/second)	MSE/dB
LMS	430/390	–19.6	320/280	–9.7
SVSLMS	185/180	–19.7	120/110	–9.8
TLVSLMS	185/180	–19.6	150/140	–9.8
HSVSLMS	180/175	–19.6	150/140	–9.7
ELVSLMS	175/170	–19.7	100/90	–9.8

Tab. 4. Number of convergence iterations and steady-state MSE in a stable environment.

Algorithm	SNR = 20 dB		SNR = 10 dB	
	Convergence iterations(first/second)	MSE/dB	Convergence iterations(first/second)	MSE/dB
LMS	420/300	–11.8	320/280	–7.8
SVSLMS	150/120	–15.0	110/130	–8.6
TLVSLMS	130/110	–15.2	160/150	–8.2
HSVSLMS	110/80	–15.6	150/140	–8.2
ELVSLMS	100/80	–15.8	110/100	–8.9

Tab. 5. Number of convergence iterations and steady-state MSE in a non-stable environment.



(a) SNR = 20 dB

(b) SNR = 10 dB

Fig. 7. Performance of different algorithms in a non-stable environment.

All in all, the performance of ELVSLMS has some promotion no matter in a stable or non-stable environment compared to other three variable step-size algorithms, obvious better than fixed step-size LMS, getting characteristics of small steady-state error, fast convergence speed and good tracking ability. No matter at low SNR or in a noise environment, ELVSLMS has good filtering performance, indicating its effectiveness.

5. Conclusion

In this paper, a new variable step-size LMS algorithm named ELVSLMS algorithm has been proposed. The proposed algorithm has introduced error autocorrelation estimation to the adjustment of step-size, constructing logarithmic nonlinear relationship between step-size and error autocorrelation. It has effectively accelerated convergence speed and reduced steady-state error. Besides, the MSE performance of different algorithms is compared in the stable and non-stable environment through simulation respectively. Results show that ELVSLMS has better performance compared to LMS, SVSLMS, TLVSLMS and HSVSLMS no matter in a noise environment or at low SNR.

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