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Research of an improved variable step size and forgetting echo cancellation algorithm[1]

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Abstract. In communication systems, the received signal may be interfered by various additive noises. They occur in many places of communication network and reduce the communication quality. Based on the adaptive filter theory, according to the ITU-T G.165 standard, combined with the advantages of forgetting factor and variable step algorithm, a new adaptive echo cancellation algorithm, which is the improved variable step size LMS forgetting factor algorithm, was verified. Through the MATLAB analysis, it was proved that it has a better performance in echo cancellation.

Key words. Adaptive filter, LMS, variable step, forgetting factor, MATLAB.

1. Introduction

In a communication system, the signal at the receiving end is usually interfered by various additive noises. As a kind of communication noise, echo appears in many parts of the communication network [1], [2]. It will affect the speech dialogue naturalness and clarity [3], and sometimes produces shrill voice [4], reduces the signal-to-noise ratio [5], and even interferes with the normal work of the system communication [6]. Therefore, a signal processing technique called echo cancellation (EC) has been developed and flourished [5], [6].

The basic principle of adaptive echo cancellation is to use an adaptive filter to identify and simulate the echo path, generate a copy of the echo, and then subtract the copy from the received signal, and then get the desired signal [7], [8]. Figure 1 shows the principle of adaptive echo cancellation system.

In Fig. 1, after the remote signal $x(n)$ sent by the caller A passes through the

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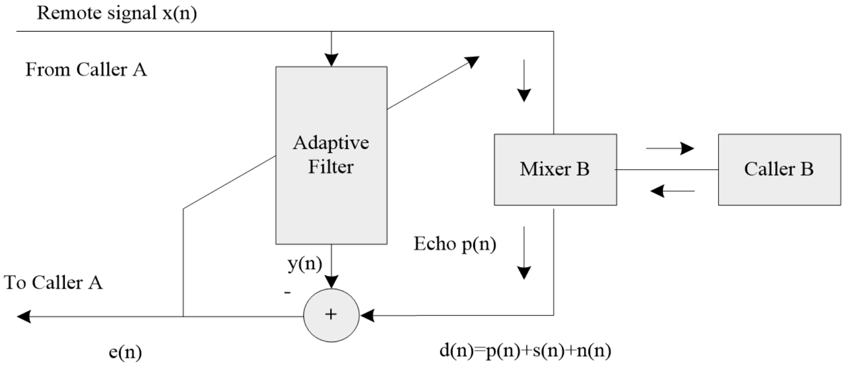

Fig. 1. Principle of adaptive echo cancellation system

adaptive filter, the false echo $y(n)$ is duplicated, and then will generate echo signal $p(n)$ after mixer B. When $p(n)$ meets the signal $s(n)$ (generated by caller B) and noise $n(n)$ (in order to simplify the analysis, sometimes it is accepted that $n = 0$), they will be superimposed to the desired signal $d(n)$, as is shown in formula (1). The signal generated by the elimination of false echo is shown in formula (2).

$$d(n) = p(n) + s(n) + n(n)\,, \tag{1}$$

$$e(n) = d(n) - y(n) = p(n) + s(n) + n(n) - y(n)\,. \tag{2}$$

In practice, when the unit impulse response of the adaptive filter can better simulate the transfer function of the echo path, it is considered that the amplitude of $y(n)$ is equal to that of $x(n)$, and the phase is opposite, so the echo $p(n)$ is basically offset.

2. 2. Analysis of the advantages of forgetting method and variable step method

The advantage of the method is to enhance the anti noise performance of the system, so that the adaptive filter on the basis of the gradient direction can maintain the correction of the direction of convergence [9], and can also restrain the tendency of convergence direction deviating from the gradient direction [10]. To some extent, it improves the drawback of LMS algorithm which has a wide dispersion and slow convergence, so the convergence speed and robustness are increased [11].

The advantage of variable step size algorithm lies in the initial stage of adaptive process [9]. At this point, the error $e(n)$ is large, but the convergence factor $\mu(n)$ is variable and large too, so the convergence rate is accelerated. When the error is gradually reduced, $\mu(n)$ is gradually reduced too, and finally a small steady-state error can be obtained [11].

3. New algorithm based on forgetting and variable step size method

Combining the advantages of the above two methods, a new minimum mean square error (LMS) algorithm is proposed.

Algorithm inputs include the weighted coefficient filter vector $\boldsymbol{w}(n)$, gradient estimation $\boldsymbol{\gamma}(n)$, variable step length convergence factor $\mu(n)$, adaptive filter input vector $\boldsymbol{x}(n)$, and expected output is $d(n)$.

Algorithm outputs include that adaptive filter output $y(n)$, altered variable step size convergence factor $\mu(n+1)$, and altered adaptive filter weight vector $\boldsymbol{w}(n+1)$.

The new algorithm steps are as follows:

1) Adaptive filtering.

$$y(n) = \boldsymbol{w}^{\mathrm{T}}(n)\boldsymbol{x}(n)\,. \tag{3}$$

2) Error estimation.

$$e(n) = d(n) - y(n)\,. \tag{4}$$

3) Gradient vector estimation of forgetting factor.

$$\boldsymbol{\gamma}(n) = \rho\boldsymbol{\gamma}(n-1) + e(n)\boldsymbol{x}(n) \tag{5}$$

4) Parameter estimation of variable step size.

$$p(n) = \beta p(n-1) + (1-\beta)e(n)e(n-1) \tag{6}$$

5) Updating of variable step size convergence factor.

$$\mu(n+1) = \alpha\mu(n) + \xi p(n) \tag{7}$$

(6) Renewal of weight coefficient vector

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu(n)\boldsymbol{\gamma}(n) \tag{8}$$

When $\rho = 0$, amnesia disappears, and the algorithm will degenerate into the basic variable step size LMS algorithm.

4. Simulation and performance evaluation

4.1. Simulation settings

The frequency of the remote input signal is 300 Hz, and the amplitude is 1 according to the formula

$$x(n) = \sin(600\pi n)\,. \tag{9}$$

The near-end sine input signal frequency is 1000 Hz and the amplitude is 1/6 according to the formula

$$s(n) = \frac{1}{6}\sin(2000\pi n)\,. \tag{10}$$

The echo signal frequency is 300 Hz, and the amplitude is 0.8, see the formula

$$p(n) = 0.8\sin(600\pi n)\,. \tag{11}$$

The expected signal is

$$d(n) = p(n) + s(n) = \frac{1}{6}\sin(2000\pi n) + 0.8\sin(600\pi n)\,. \tag{12}$$

Assuming the Gauss white noise is $N(\frac{10}{p+1}, 0.001)$, the order of the adaptive filter is 10 ($p = 9$), and variable step sizes are $\alpha = 0.97$, $\xi = 6\times10^{-3}$, and $\beta = 0.99$. The lower bound of the boundary value is $\mu_{\min} = 10^{-5}$, and the upper bound is $\mu_{\max} = 5\times10^{-3}$.

4.2. Simulation results analysis

The simulation results of variable step size LMS algorithm with forgetting factor are as follows:

Figure 2 displays that the convergence of variable step size LMS algorithm without forgetting factor spent 0.54 s.

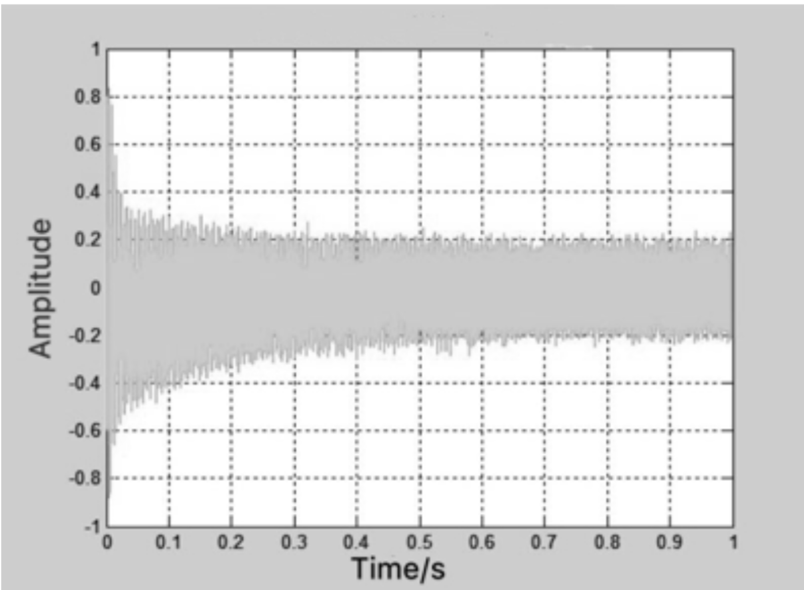

Fig. 2. Convergent results of variable step size LMS algorithm

Figure 3 shows that the convergence time of the variable step size LMS algorithm with forgetting factor 0.89 is 0.26 s, and the convergence rate is obviously faster than that of the variable step size LMS algorithm without forgetting factor. This is easier to observe in Figs. 4 and 5.

Figures 6 and 7 show that the variable convergence factor of the variable step LMS

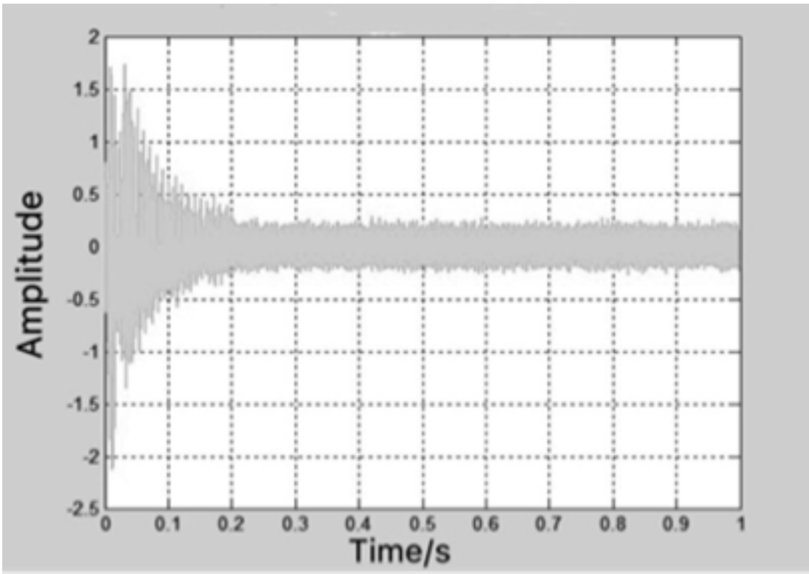

Fig. 3. Convergence time of the variable step size LMS algorithm with forgetting factor 0.89

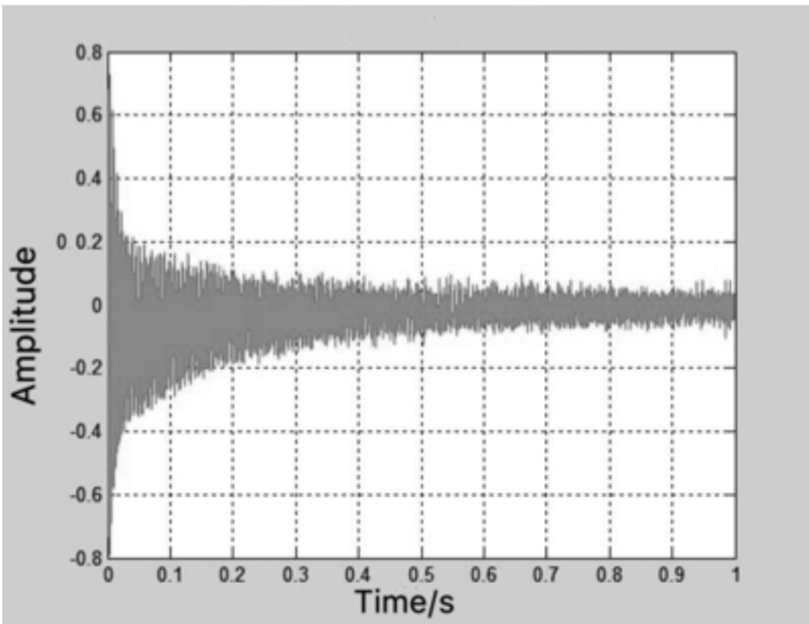

Fig. 4. Convergent process of variable step size LMS algorithm

algorithm with forgetting factor 0.89 changes from 0.005 to 0.002 and stabilized, and the maximum step size is not more than the upper value 0.005, so its steady-state

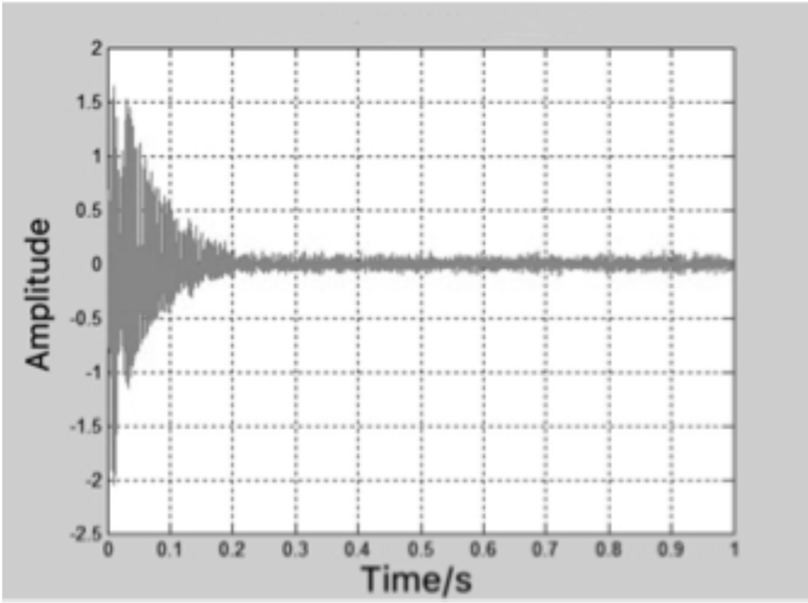

Fig. 5. Convergence process of the variable step size LMS algorithm with forgetting factor 0.89

error is smaller, and convergence speed of the variable step convergence factor $\mu(n)$ is faster than that without forgetting factor algorithm.

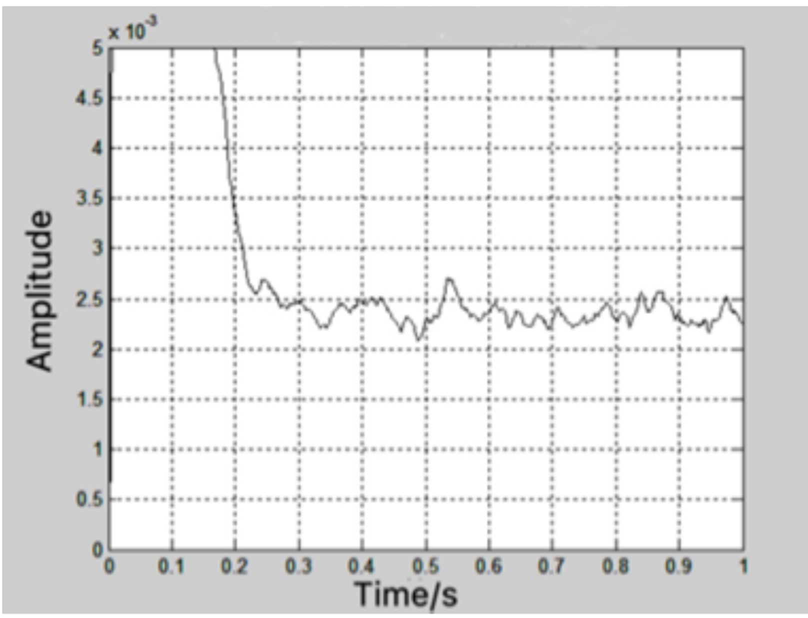

Fig. 6. Step change in the variable step size LMS algorithm

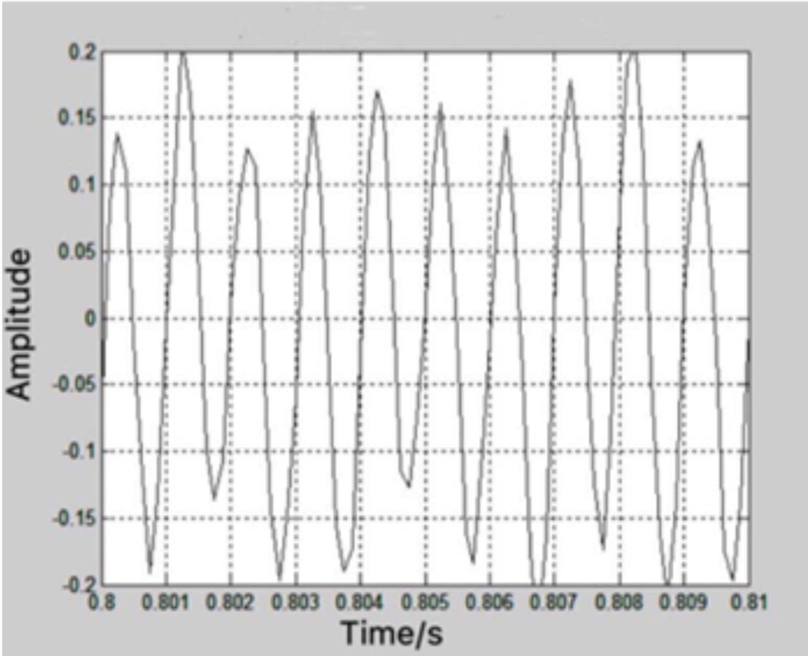

Fig. 7. Step change in the variable step size LMS algorithm with forgetting factor 0.89

Figures 8 and 9 shows that the echo cancellation effect of the forgetting factor is close to the signal from the near end, and the anti-noise ability is better than that of the variable step size algorithm without forgetting factor.

Figure 10 shows that the performance of the algorithm is worse than that of the median forgetting factor ρ_{m}, and leads to wave attenuation. Figure 11 shows that the algorithm becomes divergent when the radius of convergence is exceeded. After many experiments, the convergence radius of forgetting factor was determined, its value $\rho_{\mathrm{c}} = 0.931$.

Compared with the variable step size LMS algorithm without introducing forgetting factor, the convergence speed and noise immunity (robustness) of the variable step size LMS algorithm with forgetting factor are greatly improved.

5. Conclusion and future work

In this paper, a new adaptive echo cancellation algorithm, the improved variable step size LMS forgetting algorithm, is proposed, which is based on the two ideas of forgetting and variable step size. It can not only keep the convergence speed, the steady state error and the low algorithm complexity of the variable step size algorithm, but also absorb the anti-noise performance and fast convergence speed of the forgetting algorithm. So it is proved that this is an effective method.

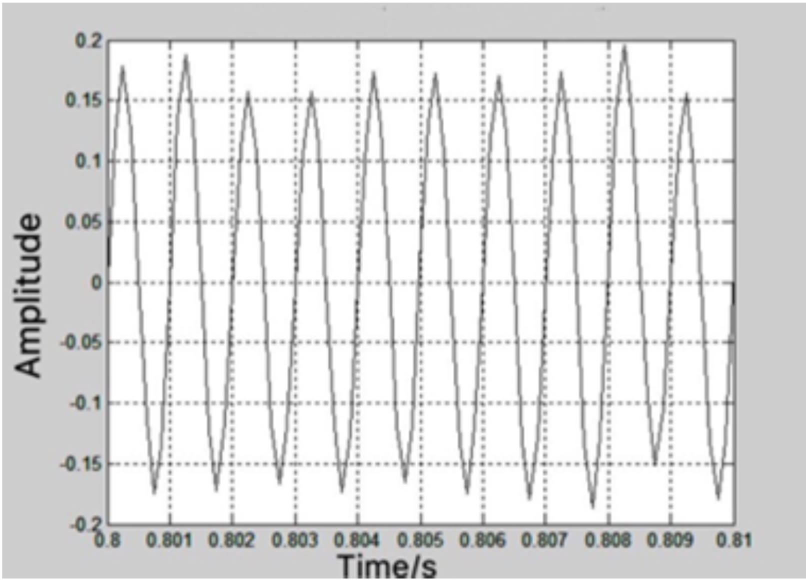

Fig. 8. Echo cancellation results of variable step size LMS algorithm

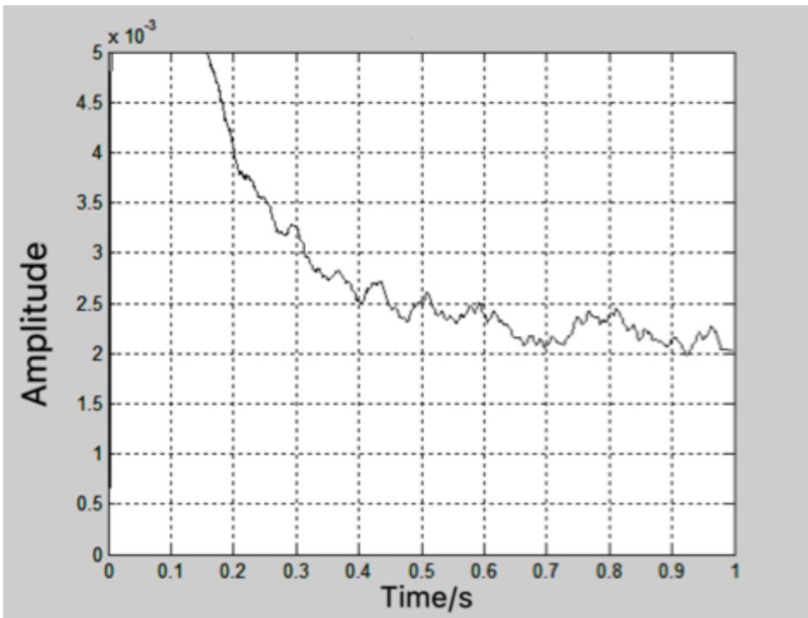

Fig. 9. Echo cancellation results of variable step size LMS algorithm with forgetting factor 0.89

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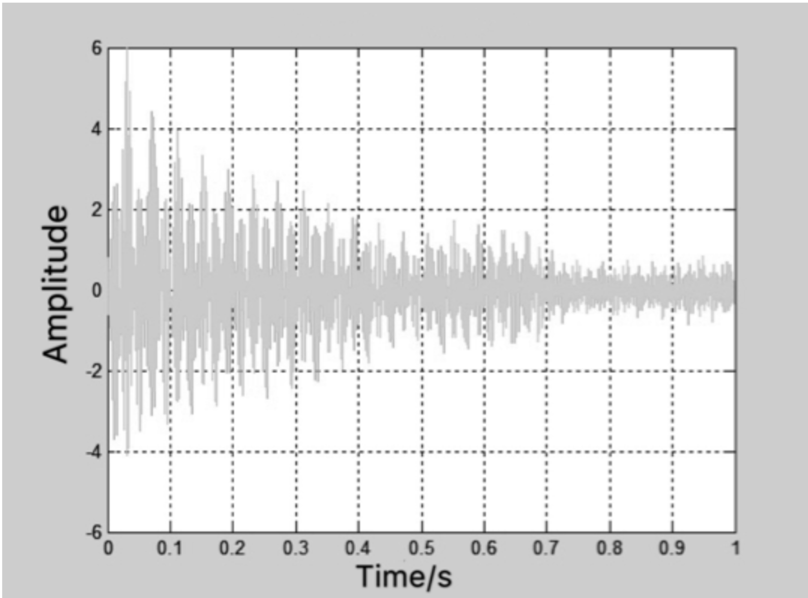

Fig. 10. Wave of forgetting factor 0.9285

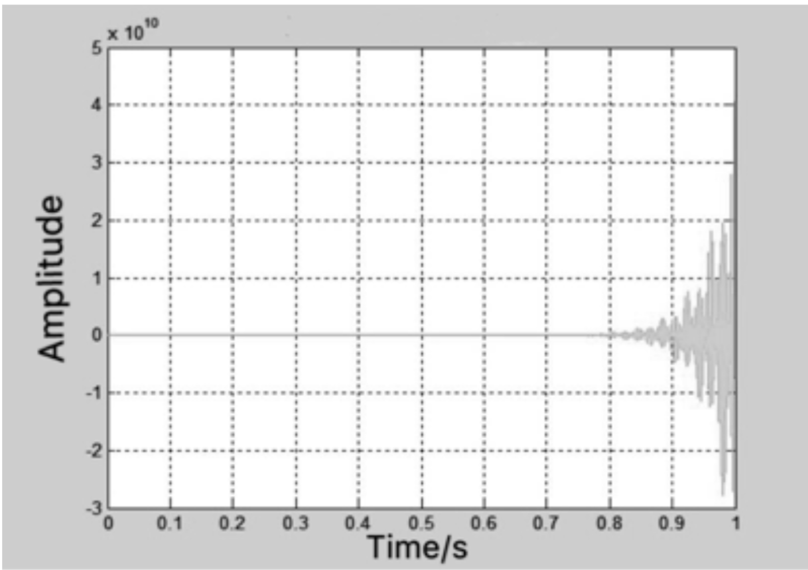

Fig. 11. Divergence of forgetting factor 0.94

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