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Simulation-based adaptive filter MATLAB

This article described the working principle of adaptive filter and deduced the well-known LMS algorithm. Take an example to demonstrate the adaptive filters filtering effects. The results show that the filter has an effective way to filter signal.
criteria.
Key words: LMS algorithm, Adaptive Filter, Matlab, digital filter IIR, FIR digital filter.

С. Далабаев, С.Т. Мухамбетжанов, З.М. Абдиахметова
MATLAB-та адаптивті фильтр негізінде пішімдеу

Осы мақала адаптивті фильтр жұмысын сипаттап, белгілі LMS алгоритмін шығарады. Фильтрация фильтрлерінің адаптивті әсерлерін көрсететін мысал келтірілген. Нәтижелер бойынша, фильтр сигналды фильтрациялаудың тиімді әдісін ұсынатыны байқалды. Практикалық нәтижелер келтірілген.
Түйін сөздер: MS алгоритмі, адаптивті фильтр, Matlab, IIR сандық фильтрі, FIR сандық фильтрі.

С. Далабаев, С.Т. Мухамбетжанов, З.М. Абдиахметова
Моделирование на основе адаптивного фильтра на MATLAB

Эта статья описывает принцип работы адаптивного фильтра и выводит хорошо известный алгоритм LMS. Приводится пример, демонстрирующий адаптивные эффекты фильтров фильтрации. Результаты показывают, что фильтр имеет эффективный способ фильтрации сигнала.
Ключевые слова: алгоритм LMS, адаптивный фильтр, Matlab, цифровой фильтр IIR, цифровой фильтр FIR.

Introduction. Adaptive filter theory put forward by the Widrow B, etc., is one of the best filtering method developed in linear filter-based Wiener filtering, Kalman filtering on. Because it has more adaptable and better filtering performance, which is widely used in communications, system identification, echo cancellation, adaptive line enhancement, adaptive channel equalization, speech linear prediction and adaptive antenna arrays and many other areas [1]. Maximum advantage of the adaptive filter does not need to know a priori knowledge that the statistical properties of the signal and noise filtering can be optimal signal. In this paper, a specific example and the results demonstrated the filtering effect of the adaptive filter.

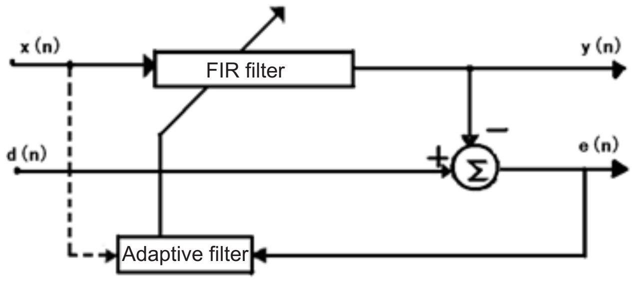

Figure 1. Schematic adaptive filtering

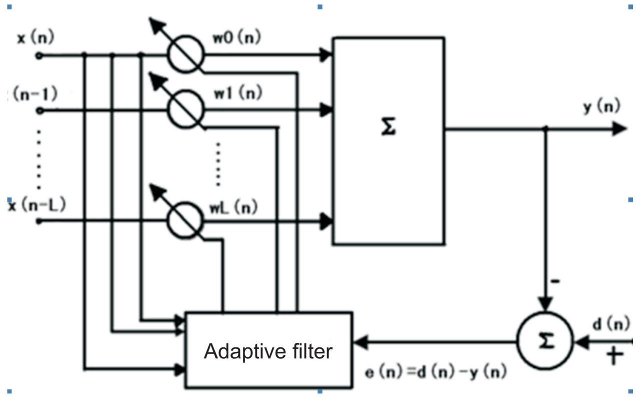

Figure 2. L-order weighted adaptive transversal filter

1. Principles and LMS adaptive filtering algorithm. Principles of adaptive filtering

In the adaptive filter, the number of adjustable parameters for the FIR filter is generally a digital filter, IIR digital filter or a lattice digital filter. Adaptive filtering of two processes. First, the input signal is thought x(n) through the adjustable parameters of a digital filter output signal y(n), y(n) with a reference signal d(n) may compare the error signal e(n); II to adjust the parameters of the digital filter parameters adjustable by an adaptive algorithm, and x(n) and e(n) value, i.e. the weighting coefficients to make the best filtering effect.

2. LMS algorithm and associated parameters

LMS algorithm is the core idea is that instead of using the squared error mean square error [2]. Therefore, this algorithm is simplified calculation. In the adaptive noise cancellation system, such as the adaptive filter parameters properly, will not have the proper filtering effect, but also may get the opposite effect. So for different signal and noise should select the appropriate parameters [3]. Seen, the filtering effect of the choice of parameters is essential. Here only the L-order weighted adaptive transversal filter, for example, the LMS algorithm is derived formulas. L weighted adaptive transversal filter. Stage shown in Figure 2.

LMS algorithm formula is derived: Set up

$$x(n) = [x(n) * x(n-1) - x(n-L)]^T; \tag{1}$$

$$w(n) = [w_0(n) * w_1(n) - w_L(n)]^T; \tag{2}$$

Among x(n) Input signal,w(n) Weighting coefficients. The error signal:

$$b(n) = d(n) - y(n) = d(n) - x^T(n) * w(n) = d(n) - w^T(n) * x(n); \tag{3}$$

Equation (3), d (n) is the reference signal, y (n) is the output signal. Mean square value of the error signal

$$\xi(n) = E[e^2(n)]; \tag{4}$$

By equation (3) and equation (4) to give: MSE performance surface gradient:

$$\nabla(n) \approx \overline{\nabla}(n) = \frac{\partial\overline{\xi}(n)}{\partial w} = 2b(n)\frac{\partial\underline{}(n)}{\partial w} = -2b(n) * x(n); \tag{5}$$

The steepest descent method iteration full-vector equation

$$w(n+1) = w(n) - \mu\nabla(n); \tag{6}$$

Equation (6) in order to control the parameters of stability and convergence rate. By equation (5) and equation (6) to give:

$$w(n+1) = w(n) + 2\mu * b(n)x(n); \tag{7}$$

Equation (7) describes the LMS algorithm is a core rough estimate of each iteration instead of the actual exact value, which greatly simplifies the calculation, but it is undeniable, accurate weighting coefficients can not descend along the steepest ideal path toad just its parameters and weighting coefficient μ has a close relationship. Therefore, an appropriate choice of the adaptive filter is particularly important performance parameter μ.

3. MATLAB simulation

By designing this embodimenta second-order transverse weighting coefficients of the adaptive FIR filter, a sinusoidal signal plus noise signal filter[4].To implement this function, Mr. sine wave signal to a standard obtained s(n) and a random noise signal n(n),then s(n)and n(n) is obtained by adding a sinusoidal signal plus noise after x(n), then follow the LMS algorithm is derived out of the equation (7), the design of adaptive filtering algorithms for noise signal filtering, and finally get the signal e (n) filtered to achieve the program code is as follows:

```
clear t=0:1/10000:1-0.0001 ;s=sin(2*pi*t);n=randn(size(t));x=s+n;
w=[0,0.5];
u=0.00026;
for i=1:9999;
y(i+1)=n(i:i+1)*w';
e(i+1)=x(i+1)-y(i+1);
w=w+2*u*e(i+1)*n(i:i+1);
end;
figure(1)
subplot(4,1,1)
```

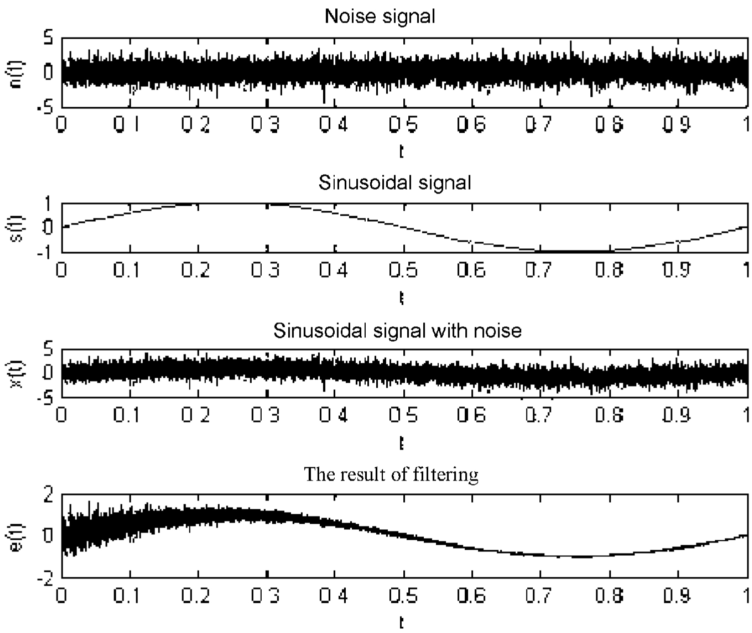

Figure 3. μ filter renderings when taken 0.00026

```
plot(t,n);
title('Noise signal');xlabel('t');ylabel('n(t)');
subplot(4,1,2)
plot(t,s);
title('Sinusoidal signal');xlabel('t');ylabel('s(t)');
subplot(4,1,3)
plot(t,x);
title('Sinusoidal signal with noise');xlabel('t');ylabel('x(t)');
subplot(4,1,4)
plot(t,e);
title('the result of filtering');xlabel('t');ylabel('e(t)');
```

When μ when taking 0.00026 get better. A time earlier than the blurred because the filter parameter is not adjusted to the optimum, illustrated in Figure 3.The figure shows that when take 0.5, has found the best weighting coefficients.

When taking 0.000026 μ , the results are almost linear filter, and the line is very thick, indicating to find the weighting factor is too slow, as shown in Figure 4.

When μ takes 0.26, the result is a linear shape, and very fine lines in some places there are glitches, indicating that the system parameters change too fast, the system has not yet adjusted to the optimum weighting coefficients shown in Figure 5.

Take the μ 1, the system out put confusion shown in Figure 6.

The results showed that: the type of μ is worth to different filtering effect. Experimental data obtained by observation: when μ is too large, adaptive shorter the time, the faster the adaptation process, but it causes greater imbalance, resulting in very vague filtering results, the larger the output signal changes when μ greater than a values, the chaotic system output; when μ is small, the system is stable, a small change in the output signal, the off set is small,

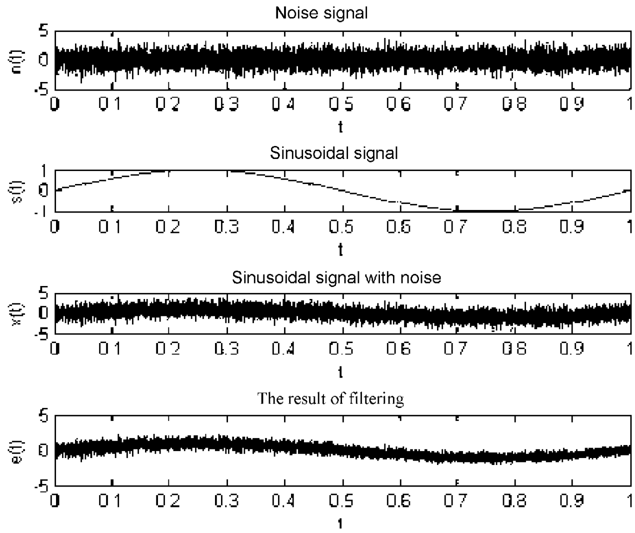

Figure 4. μ filter renderings when taken 0.000026

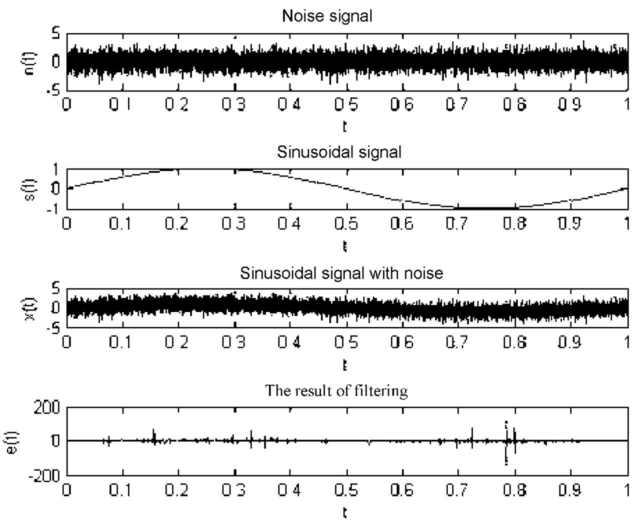

Figure 5. μ filtering effect when taken 0.26

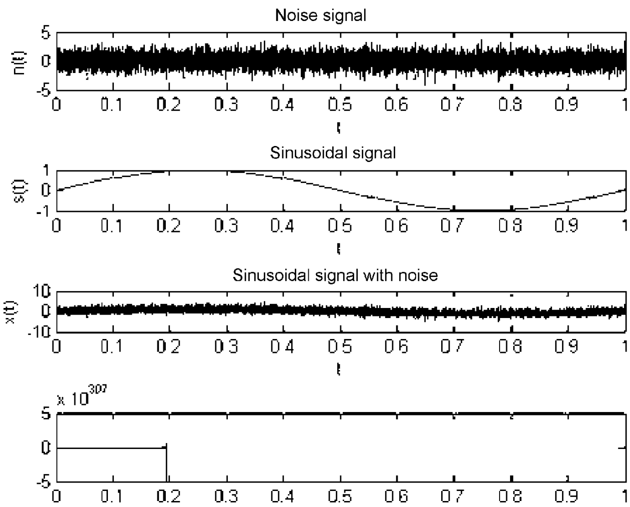

Figure 6. μ take the filtering effect of Figure 1

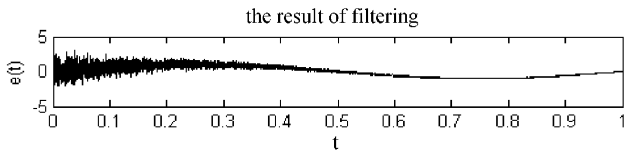

Figure 7. W(n)=[0, 0]

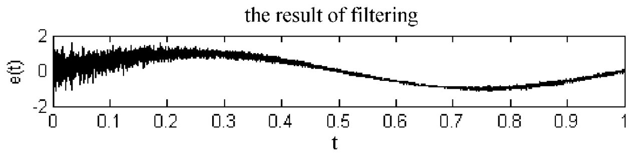

Figure 8. W(n)= [0, 0.5]

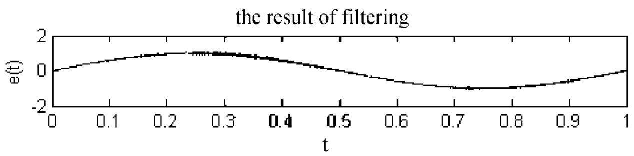

Figure 9. W(n)= [0, 1]

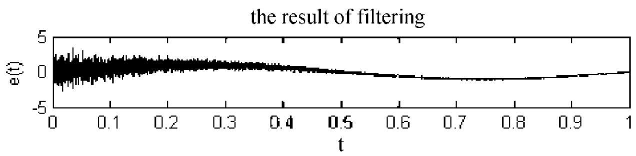

Figure 10. W(n)= [0.5, 0]

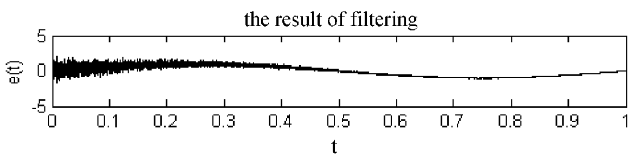

Figure 11. W(n)= [0.5, 0.5]

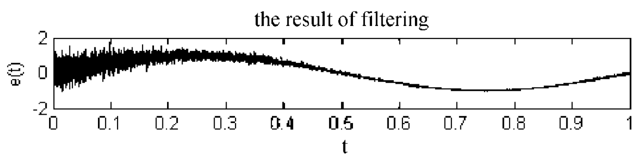

Figure 12. W(n)= [0.5, 1]

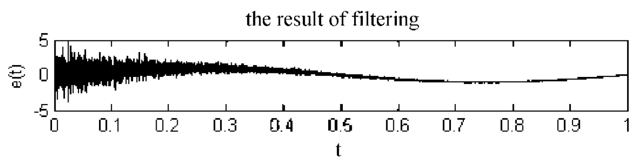

Figure 13. W(n)= [1, 0]

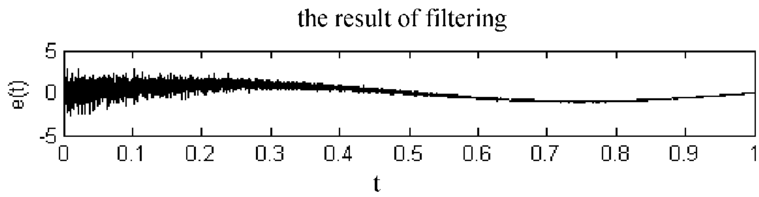

Figure 14. W(n)= [1, 0.5]

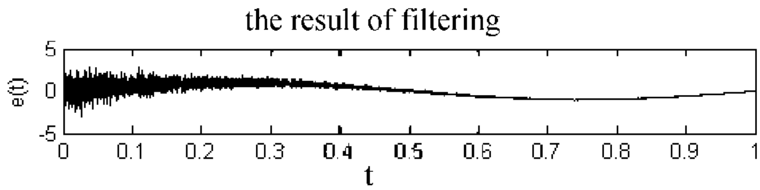

Figure 15. W(n)= [1, 1]

but has a corresponding length ending of the adaptive process, so the choice of the parameter μ should the system requirements, the accuracy requirements are met under the premise of minimizing adaptive time.

Finally, by taking appropriate μ , changing the w(n) initial value can always find an optimal weighting factor. The program of iterations is 10000. Therefore, concluded: When μ a, large number of iterations, the weighting coefficients can always find the optimal solution.

The following is the image W(n) changing the initial value of the time.

Summary

Through this example, so we understand the working principle of adaptive filters, and how to use adaptive signal processing filter to do the work. MATLAB has a powerful digital signal processing simulation, through this experiment, again review some instruction usage. This experiment is worth noting that there is a problem, and that is how to find? FIR filter with stable and easy to implement strict linear phase, the signal processing phase distortion is not generated, and widely applied in practice [5].

References

[1] *Ye Hua, Wu Borepair* Studyvariable step filtering algorithm. China: Adaptive Journal of Electronics, 1990. — P. 63–69.

[2] *Yao Tianren, Sun Hong* Modern digital signal processing. Wuhan:Huazhong University of Science and Technology Press, 1999. – P. 123–130.

[3] *Wuyi Gang, Fan Meng* Adaptive filter parameter selection and simulation results. Jilin Institute of Technology, 2001. – P. 25–29.

[4] *Luo Zhen Hui* MATLAB applications such as digital signal processing. – Beijing: Mechanical Industry Press, 2005.

[5] *Zhang Yani* Wavelet video image processing technology. Liaoning University of Engineering and Technology, 2004. – P. 230–232.