

The application research of blind adaptive filter

Li Lin¹ Chen Shanji

Abstract. This paper described the principle and basic structure of blind deconvolution filter, it used blind adaptive algorithm, and adjusted coefficient automatically with the changed signal, in order to track the change of signal and realize the filtering finally. at last the performance of designed filter was verified using the Matlab simulation platform.

Keywords: Blind adaptive filter Bussgang algorithm Digital signal processing;

1.1 Introduction

Adaptive signal processing is an important branch discipline of the signal and information processing subject. It can track the non-stationary random change of external environment without prior condition.

With the rapid development of science and technology, The signal processing of real-time, accuracy and flexibility of the demand is higher and higher, and the position of adaptive filter in signal processing is more important. Because of good filtering performance, it used widely in communication, control, radar, sonar, etc. The target of blind signal processing is to recover original signal from a group of observed data without any source signal and mixed prior technology or only a little. Considering the time delay, the observed signal is the convolution of source signal and channel response. Blind separated the convolution aliasing signal is called blind deconvolution.

¹Lilin

College of Physics and Electronic Information Engineering, Qinghai University for Nationalities Xining, Qinghai China
e-mail: qinghaili_06@yahoo.com.cn

1.2 Theory of Blind Deconvolution Adaptive Filter

1.2.1 Theory of Blind Equalizer

In blind deconvolution, the input signal and system is known, it commands reconfiguration the input signal. However, in blind deconvolution (without supervision), only the output is known, the input signal and system should be determined. Assumed a linear time invariant system with has a input signal of $x(n)$, if it is minimum phase system, that is its zero-points and pole-points are in the unit circle, so it is stable and its inverse system is stable too. So the $x(n)$ can be considered the information of output of $u(n)$, and the inverse system is a whitening filter, so the problem of blind deconvolution is settled [1]-[3]. But it is not a minimum phase system generally, so the adaptive equalizer needs an initial stage of training, when the training is over, the equalizer switched the mode of facing decision. Blind deconvolution only needs received signal and some additional information described with probability form. It can work in unsupervised mode [2].

1.2.2 Theory of Blind Equalizer

The steps of blind separation is to establish a model, objective function and find a appropriate algorithm. Firstly, to establish a model according to the researched problem, secondly, to establish a objective function $J(w)$ to w for variable, lastly to find a suitable algorithm [2]-[3].

For signal of linear convolution mixed, the observed signal can be shown as:

$$u(n) = H * x(n) = \sum_{p=-\infty}^{\infty} H_p x(n-p)$$

Where the H is impulse response of mixed channel and $x(n) = [x_1(n), x_2(n), \dots, x_n(n)]^T$ is a $n \times 1$ vector composed by n source signal, and H_p is the p th delay node matrix and meet the condition of $\sum_{p=-\infty}^{\infty} \|H_p\| < \infty$.

In order to express easily, it can be transformed in z-domain,

$$U(z) = H(z)X(z).$$

The aim of linear convolution blind source separation is to find a filter with impulse response w , the observed signal after filtering can be shown as:

$$y(n) = W * u(n) = \sum_{p=-\infty}^{\infty} W_p u(n-p)$$

And the expression in z-domain is

$$Y(z) = W(z)U(z) = W(z)H(z)X(z) = C(z)X(z)$$

Where $C(z)$ is product of a switching matrix and a nonsingular diagonal matrix, blind source separation has the fussiness of time delay, that is compared with separated signal and source signal, the delay maybe exist.

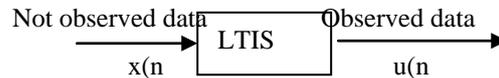


Fig. 1.1 schematic diagram of blind deconvolution

1.3 To Design a Adaptive Filter

1.3.1 Bussgang algorithm

The mode of Bussgang algorithm is composed of a linear communication channel and a group of cascaded equalizer. The channel is consist of transmitted filter, transmission medium and received filter. The channel can be characterized a slow time-varying impulse response h_n , the convolution can be shown as

$$u(n) = \sum_{k=-\infty}^{\infty} h_k x(n-k) \quad n=0, \pm 1, \pm 2, \pm 3 \dots$$

Where $x(n)$ is input data before the channel, and $u(n)$ is the output of channel being processed.

The problem is that the output is known, how to reconfiguration the input data $x(n)$.

Assumed that w_i is the impulse response of desired inverse filter, so the relation with channel impulse response h_i can be shown as:

$$\sum_i w_i h_{l-i} = \delta_l$$

This inverse filter can reconfiguration the transmitted data $x(n)$, the convolution of $w_i(n)$ and $u(n)$ cancel inter symbol interference entirely or partly, so after n th iteration, a approximate deconvolution sequence is obtained:

$$y(n) = \sum_{i=-L}^L w_i(n)u(n-i) \quad (3.0)$$

The approximate inverse filter can be get through iteration, the output of inverse is $y(n)=x(n)+v(n)$.where $v(n)$ is called convolution noise, it is residual inter symbol interference, $y(n)$ is added to zero-memory nonlinear estimator, and the estimated value $\hat{x}(n)$ of $x(n)$ is emerged:

$$\hat{x}(n) = g(y(n)) \quad (3.1)$$

Where g is a nonlinear function. The estimated value is non reliable through n times iteration, but an adaptive way can use in order to get good estimated value after $n+1$ iteration, LMS algorithm is a good choice. The input of i th tap of transversal filter in i th iteration is $u(n-i)$, the nonlinear estimation $\hat{x}(n)$ as desired response, and the output of transversal filter is $y(n)$, the estimated error can be shown as:

$$e(n) = \hat{x}(n) - y(n) \quad (3.2)$$

The i th tap weight means the past value of parameter estimation, so the weight of i th tap is updated in $(i+1)$ th as:

$$\hat{w}_i(n+1) = \hat{w}_i(n) + \mu u(n-i)e(n) \quad i = 0, i = \pm 1, \dots, i = \pm n \quad (3.3)$$

Where μ is step length. The expression of 3.0~3.3 is the iterative algorithm of blind equilibrium in channel, every iteration corresponds transmitted a data symbol, the during time is known in receiver.

The expression of algorithm in 3.1~3.3 is called Busgang algorithm.

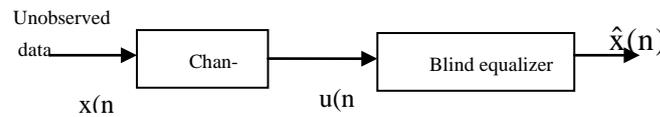


Fig. 1.2 cascaded of unknown channel and blind equalizer

1.3.2 Theory of Blind Equalizer

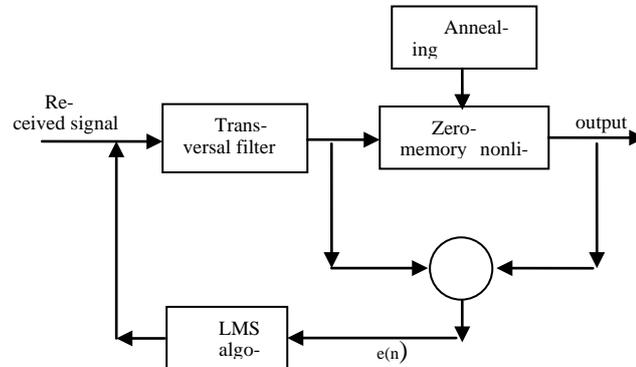


Fig. 1.3 diagram of blind equalizer with Annealing Controller

Blind equalization algorithm used MMSE, when the noise of convolution is high, nonlinear estimator has the robustness to the change of variance of convolution noise, especially, it can express the characteristics of input/output accurately when the ratio of noise and noisy signal is high[3]-[4].

The hyperbolic tangent function can be used in estimating of zero-memory for data sequence.

$$\hat{x} = a_1 \tanh(a_2 y / 2), \text{ where } a_1 = 1.945, a_2 = 1.25.$$

It needed an annealing process in bussgang algorithm so that with the equilibrium step by step, the equalizer can use it to process the different grade noise of convolution. When the noise is high, the $\hat{x} = a_1 \tanh(a_2 y / 2)$ can be a good approximation device of zero-memory nonlinear function in blind equalizer. The aim of annealing process is to change slope a_2 while the scale parameter is fixed[5].

1.3.3 LMS Algorithm

LMS is based on the steepest descent algorithm. It predicts instantaneous estimation and updates the filter coefficients sample by sample in a mode to minimize the MSE [6]. The LMS algorithm's significant feature is its simplicity as neither has it required measurements relevant to the auto correlation, cross correlation nor it needs to compute matrix inversion[5]-[6]. Hence it is faster than basic Weiner filter algorithm [6]. Two basic processes works behind the LMS filtering algorithm: filtering process-calculates the output response of the filter relating to the input signal and generates an estimation error of the output pertaining to the desired response and adaptive process- adjusts the parameters automatically regarding the estimation error[1]-[4].

With transversal structure filter, the error can be defined as follow:

$$e(n) = d(n) - y(n) \quad (3-4)$$

Where $d(n)$ is designed signal and $y(n)$ is output signal. The Mean Square Error is shown as (3-5):

$$\mathcal{E} = E[e^2(n)] = E[d(n) - y(n)]^2 \quad (3-5)$$

To minimize the \mathcal{E} and obtain the optimization weight vector $w(n)$, the equation is shown as [8]:

$$\left. \frac{\partial \mathcal{E}}{\partial w(n)} \right|_{w(n)=w_{opt}(n)} = 0 \quad (3-6)$$

The $w_{opt}(n)$ can be shown as:

$$W_{opt}(n) = R_{xx}^{-1} R_{xd} \quad (3-7)$$

$$R_{xx} = \begin{bmatrix} r_{xx}(0) & r_{xx}(1) & \cdots & r_{xx}(N-1) \\ r_{xx}(1) & r_{xx}(0) & \cdots & r_{xx}(N-2) \\ \vdots & \vdots & \ddots & \vdots \\ r_{xx}(N-1) & r_{xx}(N-2) & \cdots & r_{xx}(0) \end{bmatrix}$$

$$R_{xd} = [r_{xd}(0) \quad r_{xd}(1) \quad \cdots \quad r_{xd}(N-1)]^T$$

R_{xx} is a $N \times N$ matrix and R_{xd} is $N \times 1$ matrix, R_{xx} is correlated matrix of $x(n)$ and R_{xd} is cross-correlated of $x(n)$ and $d(n)$.

As LMS is based on the steepest descent algorithm weight update vector at time $k+1$ should be as follows [2]:

$$W(n+1) = W(n) + \mu \nabla(n) \quad (3-8)$$

Where $W(n)$ is the n -th weight vector, $\nabla(n)$ is the gradient vector composed in equation (3-8) and μ controls the rate of convergence. Replacing the value of $\nabla(n)$ [2]:

$$W(n+1) = W(n) + 2\mu x(n)[d(n) - w^T(n)x(n)] \quad (3-9)$$

Algorithm can be performed as follows:

Parameter : M: length of filter

μ :step factor

$$0 < \mu < (MP)^{-1} \quad P = E[|x_i(n)|^2]$$

Initial condition: $W(n) = 0$

Operation: For $n=0,1,\dots$

To obtain $x(n),d(n)$;

Filtering $y(n) = w^T(n)x(n)$

Error estimate $e(n) = d(n) - y(n)$

Update weight coefficient

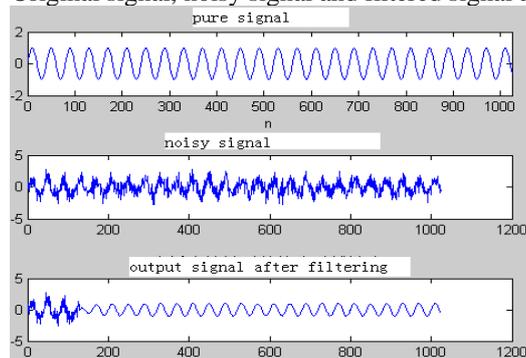
$$w(n+1) = w(n) + 2\mu x(n)[d(n) - w^T(n)x(n)]$$

LMS doesn't require any knowledge about correlation matrix instead it uses instantaneous estimation [8]-[9]. At first stage weights may be deviated from expectation but gradually it incline towards good adjustment. In this way, it performs the adaptation through learning the signal characteristics.

1.4 Simulation and Result

A noisy sine signal and a noisy speech signal was sent to adaptive filter in experiment 1 and 2 respectively.

Original signal, noisy signal and filtered signal are shown in Fig.1.4.



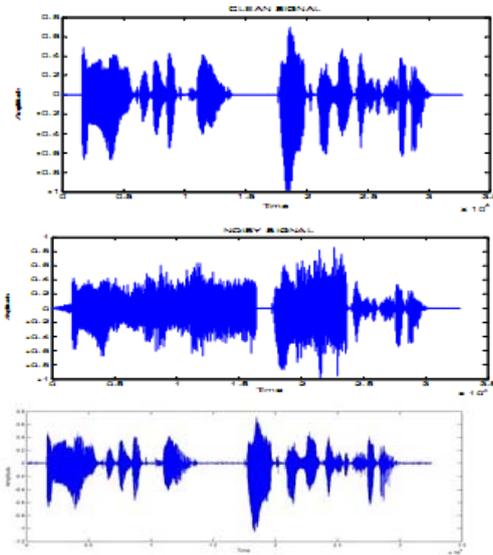


Fig. 1.4Wave of Original, Noisy and Filtered signal

The blind signal processing is important and active subject in signal processing domain, and it used in many field. In this paper, the theory of blind deconvolution filter is described and a basic structure model is given, and verified the effectiveness of adaptive algorithm. Of course, to study the blind adaptive algorithm, structure of adaptive and its using is a lasting work.

1.6 References

1. Cardoso J F, Paris CNRS. Blind signal separation: statistical principle[J]. *Proceeding of IEEE*, 1998, 86(10): 2009-2025.
2. Almeida L B. The fractional Fourier transform and time-frequency representations[J]. *IEEE trans Signal Processing*, 1994, 42(11): 3084-3091.
3. Deepa, Dr. A. Shanmugam, "Dual Channel Speech Enhancement Using Hadamard-LMS Algorithm With Dct PREPROCESSING TECHNIQUE". *International Journal of Engineering Science and Technology*, Vol. 2(9), 2010, 4418-4423.
4. N. J. Bershad and P. L. Feintuch, "Non-Wiener solutions for the LMS algorithm—A time domain approach," *IEEE Trans. Signal Processing*, vol. 43, pp. 1273–1275, May-1995.
5. E. R. Ferrara, Jr., "Fast Implementation of LMS Adaptive Filter," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-28, pp. 474-475, 1980.
6. M. J. Shensa, "Non-Wiener solutions for the adaptive canceller with a noisy reference," *IEEE Trans. Acoustic, Speech, Signal Processing*, vol- ASSP-28, pp. 468–473. August-2000.
7. P. Clarkson and P. White, "Simplified analysis of the LMS adaptive filter using a transfer function approximation," *IEEE Trans. Acoustic., Speech, Signal Processing*, vol. ASSP-35, pp. 987–993, July 1987.