ITC-CSCC 2010

The 25th International Technical Conference on Circuits/Systems, Computers and Communications

Program and Abstracts

July 4-7, 2010

Pattaya, Thailand

Information

Table Of Contents

Search This CD-ROM

CD-ROM Help

Exit

ECTI Association

사단법인 대한전자공학회 The Institute of Electronics Engineers of Korea

EiC

A NEW ADAPTIVE ALGORITHM FOR CHANNEL EQUALIZATION IN PERPENDICULAR RECORDING CHANNELS

Khemmakorn Srisang[1], *Sopapun Suwansawang*[2], *Piya Kovintavewat*[3] *and Apinunt Thanachayanont*[4]

[1] *Department of Data Storage Technology, Faculty of College of Data Storage Technology and Application, King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand*
[2,3] *Data Storage Technology Research Unit, Faculty of Science and Technology, Nakhon Pathom Rajabhat University, Nakhon Pathom 73000, Thailand*
[4] *Department of Electronic Engineering, Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand*
E-mail: [1]*s1068904@kmitl.ac.th,* [2]*sopapun@gmail.com,* [3]*piya@npru.ac.th,* [4]*ktapinun@kmitl.ac.th*

ABSTRACT

Perpendicular magnetic recording systems have played an important role to support an enormous demand for storage capacity. As the recording density keeps increasing, the perpendicular recording channels will inevitably encounter intersymbol interference (ISI), and nonlinear and additive distortions such as media jitter noise and pulse broadening. To solve this problem, an adaptive finite impulse response equalizer has been used because it is stable and no special adjustments are needed for implementation. This paper proposes a new adaptive algorithm for channel equalization in perpendicular recording channels to combat media jitter noise and pulse broadening. This algorithm is denoted as a VL-adaline, whose variable learning step size is controlled by an adaline neural network. The proposed algorithm differs from the existing adaline algorithm in a sense that it utilizes the estimated energy and the auto-correlation of the equalizer outputs as parameters to update the step size. Results indicate that the proposed algorithm performs better than other adaptive algorithms in terms of bit-error rate (BER) at the output of the detector.

Index Terms**—**Adaptive filter, adaline network, LMS algorithm, media jitter noise, pulse broadening

1. INTRODUCTION

Practically, a read-channel chip utilizes a finite impulse response (FIR) equalizer to shape the readback signal to a predetermined target before performing maximum-likelihood equalization by the Viterbi detector [1]. This technique is known as partial-response maximum-likelihood (PRML) [2], which can efficiently combat the intersymbol interference (ISI). However, at high recording density, the channel will face with many nonlinearity problems, such as media jitter noise and pulse broadening. To deal with this problem, an adaptive filter based on a least mean square (LMS) algorithm [3] is usually used for channel equalization in perpendicular recording channels because of its simplicity. Nevertheless, Nair and Moon [4] have shown that a nonlinear equalizer based on a neural network can perform better than a linear FIR equalizer. This motivates us to develop a new equalizer so as to improve overall system performance.

To improve the system performance, we propose the VL-adaline (variable learning rate and adaptive linear neural network) algorithm for channel equalization. The proposed algorithm employs an adaline neural network [5] to update a learning step size. It will be shown in simulation that the proposed algorithm can help improve the system performance if compared with an FIR equalizer, especially when the channel experiences severe ISI and distortions.

The rest of this paper is organized as follows. After explaining the system model in Section 2, Section 3 describes a design of an adaline algorithm. Section 4 gives simulation results. Finally, Section 5 concludes this paper.

2. SYSTEM MODEL

The channel model along with the equalizer is shown in Fig. 1. The binary input sequence to be stored in the recording disk is denoted by $a_k \in \{\pm 1\}$, with bit period T is filtered by an ideal differentiator $(1 - D)/2$ to form a transition sequence $b_k \in \{-1,0,1\}$, where D is a unit delay operator, $b_k = \pm 1$ corresponds to a positive or a negative transition, and $b_k = 0$ corresponds to the absence of the transition. The transition b_k passes through the magnetic recording channel represented by $g(t)$. The transition response for perpendicular recording is given by [6]

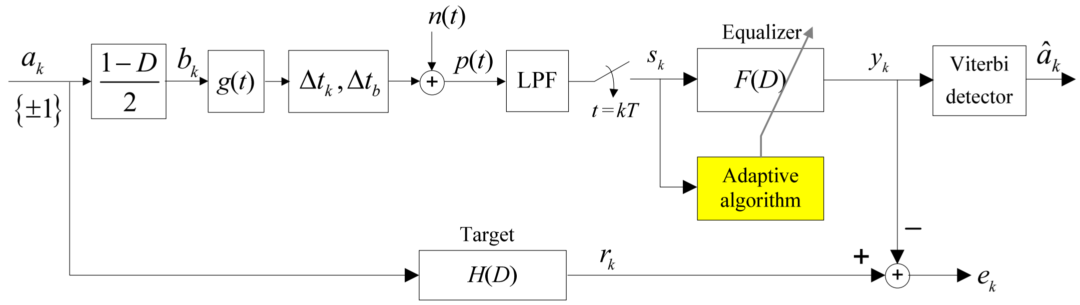

Fig. 1. A channel model with an adaptive equalizer.

$$g(t) = \mathrm{erf}\left(\frac{t\sqrt{\ln 16}}{\mathrm{PW}_{50}}\right) \tag{1}$$

where $\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-z^2}dz$ is an error function, and PW_{50} determines the width of the derivative of $g(t)$ at half its maximum. In the context of magnetic recording, a normalized recording density is defined as ND = PW_{50}/T, which determines how many data bits can be packed within the resolution unit PW_{50}.

The readback signal, $p(t)$, can then be written as [7]

$$p(t) = \sum_{k=1}^{N} b_k g(t - kT + \Delta t_k + \Delta t_b) + n(t) \tag{2}$$

where N is the length of a data sequence b_k, and $n(t)$ is additive white Gaussian noise (AWGN) with two-sided power spectral density $N_0/2$. The media jitter noise, Δt_k, is modeled as a random shift in the *transition position* with a Gaussian probability distribution function with zero mean and variance $|b_k|\sigma_j^2$ truncated to $T/2$ [6], where $|c|$ takes the absolute value of c, whereas the bloom parameter, Δt_b, is modeled as random pulse broadening [8] with a Gaussian probability distribution function with zero mean and variance $|b_k|\sigma_b^2$. This bloom parameter can also be thought of as the change in the location of a domain edge measured along the track center.

In conventional setting, the read-back signal $p(t)$ is filtered by a seventh-order Butterworth low-pass filter (LPF) and is then sampled at time $t = kT$, assuming perfect synchronization. The sample output s_k is equalized by an equalizer $F(D)$, where D is a delay operator, such that the output sequence y_k resembles the desired sequence r_k. Finally, the Viterbi detector performs sequence detection to determine the most likely input sequence.

3. DESIGN OF ADALINE ALGORITHM

3.1 The LMS-adaline algorithm

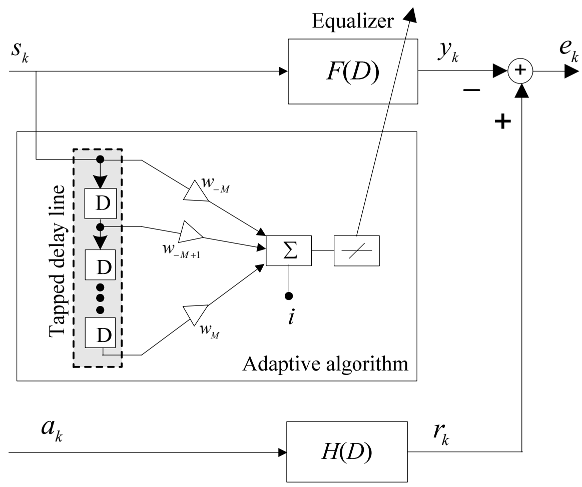

Fig. 2. An adaline adaptive filter.

Based on the adaline network that uses the Widrow-Hoff learning rule or an LMS algorithm [3], finding a suitable learning step size (μ) is an essential problem in the LMS algorithm. Generally, if μ is too small, a convergence speed of the algorithm will be very slow. On the other hand, if μ is too large, it will cause severe mis-adjustment for channel equalization, which can in turn result in system instability. In practice, a suitable μ should be in the range of $0 < \mu < 1/\lambda_{\max}$ [3], where $\lambda_{\max}$ is the maximum eigenvalue of the auto-correlation matrix of the equalizer inputs.

The design of adaline algorithm can be described by a block diagram as shown in Fig. 2. Assuming that the PR target $H(D)$ is known, meaning that r_k is also known. Let the PR target $H(D)$ be of the form

$$H(D) = \sum_{k=0}^{v} h_k D^k \tag{3}$$

where h_k is coefficients of the channels, and v is memory of channel. Then, the desired signal $r_k = a_k * h_k$, where * denotes the convolution operator. The error output e_k is the difference between the desired signal and the equalizer output, which can be expressed as

$$e_k = r_k - \mathbf{s}_k^{\mathrm{T}}\mathbf{w}_k, \quad (4)$$

where $\mathbf{w}_k = [w_{-M} \ldots w_{-1}\ w_0\ \mathrm{w}_1 \ldots w_M]^{\mathrm{T}}$ is a $(2M+1)$-element column vector of the equalizer weights at time k, $\mathbf{s}_k = [s_k\ s_{k-1}\ s_{k-2} \ldots s_{k-2M}]^{\mathrm{T}}$ is a $(2M+1)$-element column vector, M is an integer, and $[.]^{\mathrm{T}}$ is a transpose operator. In this paper, we use $K = 5$ for our simulation so that the equalizer has 11 taps as used in today's hard disk drive.

The update equation of the existing LMS-adaline algorithm is given by [3]

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \mu e_k \mathbf{s}_k, \quad (5)$$

and the bias update is given by

$$i_{k+1} = i_k + 2\mu e_k, \quad (6)$$

where i_k is a bias parameter at time k. However, for perpendicular recording channels, we found that using a fixed bias parameter $i_k = i = 0.004$ can yield better performance than using an updated bias parameter from (6). Thus, we will use $i = 0.004$ in our simulation.

In addition, if a fixed μ is used in this channel, it might lead to poor performance. To solve this problem, we utilize the variable step-size LMS algorithm based on an adaline algorithm as illustrated in Fig. 2. This proposed algorithm is denoted as VL-adaline, where the step size is updated by the energy and the auto-correlation of the equalizer outputs. Generally, the VL-adaline algorithm can help reduce the output error and achieves a faster convergence rate in many applications [9].

3.2 The VL-adaline algorithm

In the VL-adaline algorithm, the fixed step size μ is replaced by μ_k, which is a variable step size at time k. Then, the coefficient vector $\mathbf{w}_k$ is updated according to

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \mu_k e_k \mathbf{s}_k, \quad (7)$$

The VL-adaline algorithm uses a new variable learning step size adaline algorithm (i.e, VL-adaline) so as to improve the performance of the LMS algorithm. This can be achieved by employing large step sizes at the early stages of the adaptive process and small step sizes after the system approaches the convergence speed of the algorithm. Based on our proposed method, the mathematical formulations of the updates of the variable step size μ_k is given by

$$\mu_{k+1} = \alpha\mu_k + \gamma p_k^2 g_k^2, \quad (8)$$

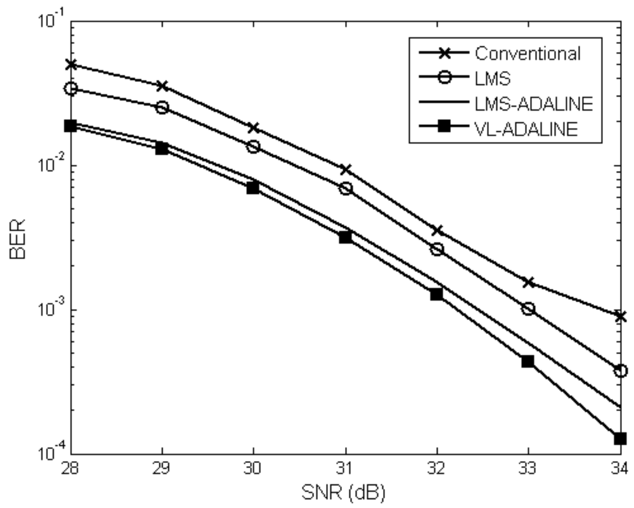

Fig. 3. BER performance of different algorithms.

where p_k controls the speed of convergence of the VL-adaline algorithm, which can be obtained from [9]

$$p_k = \sigma p_{k-1} + (1-\sigma) y_k^2, \quad (9)$$

and g_k controls the adaptation of the step size μ_k, which can be obtained from [9]

$$g_k = \lambda g_{k-1} + (1-\lambda) y_k y_{k-1}, \quad (10)$$

where α, γ, σ, and λ are positive constants between 0 and 1.

It will be shown in simulation that the proposed VL-adaline algorithm can significantly improve the performance of the adaptive equalizer.

4. SIMULATION RESULTS

Consider a perpendicular recording channel at ND = 3 and a fixed bias $i = 0.004$. The signal-to-noise ratio (SNR) is defined as

$$\mathrm{SNR} = 10\log_{10}\left(\frac{E_i}{N_0}\right), \quad (8)$$

in decibel (dB), where E_i is the energy of the channel impulse response (the derivative of the transition response scaled by 2). The 11-tap equalizer was designed based on the MMSE approach [4] to match the EPR2 target $H(D) = 1 + 3D + 3D^2 + D^3$. We compute the BER of the system based on a minimum number of 1000 data sectors and 500 error bits.

The system using a fixed equalizer (referred to as "Conventional") will be compared with that using adaptive

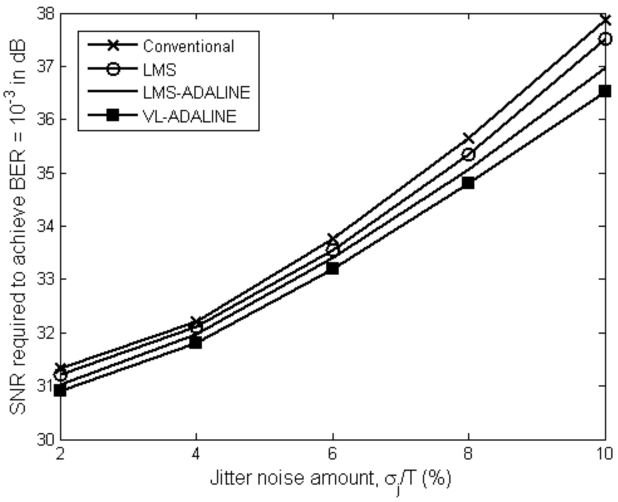

Fig. 4. Performance comparison as a function of σ_j/T's.

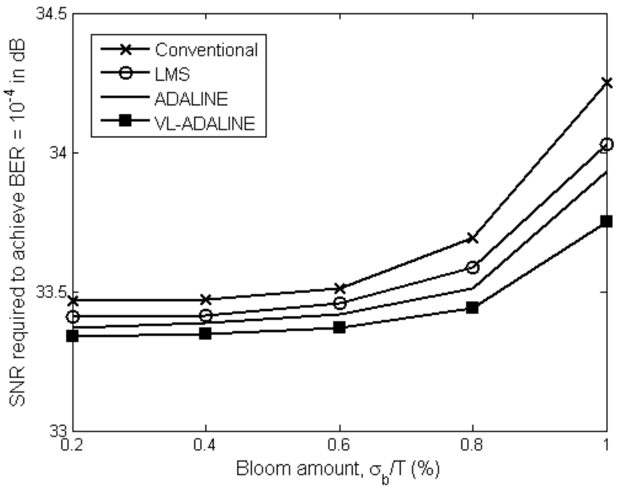

Fig. 5. Performance comparison as a function of σ_b/T's.

equalizers based on LMS, LMS-adaline, and VL-adaline algorithms. Fig. 3 compares the BER performance of different algorithms as a function of SNRs for the system with 5% media jitter noise (i.e., σ_j/T = 5%) and 3% bloom parameter (i.e., σ_b/T = 3%). It is apparent that the proposed VL-adaline algorithm performs better than other algorithms.

We also compare the performance of different algorithms by plotting the SNR required to achieved BER = 10^{-3} as a function of jitter noise amounts in Fig. 4, where a bloom parameter of σ_b = 0.2% is utilized. Again, the proposed algorithm performs the best for all jitter noise amounts because it requires the lowest SNR to achieve the same BER as other algorithms do. Finally, Fig. 5 plots the SNR required to achieved BER = 10^{-4} as a function of bloom amounts, where we use media jitter noise of σ_j/T = 3%. Again, the proposed algorithm performs better than other algorithms for all bloom amounts, especially when a bloom parameter is large.

5. CONCLUSION

At ultra high recording density, perpendicular recording channels experiences severe intersymbol interference and many nonlinearity problems, such as media jitter noise and pulse broadening. This paper proposes a new adaptive algorithm for channel equalization to combat media jitter noise and pulse broadening. This algorithm is denoted as a VL-adaline, whose variable learning step size is controlled by an adaline neural network. It has been illustrated in simulation that the proposed algorithm performs better than existing algorithms, especially when media jitter noise is high or when a bloom parameter is large.

6. REFERENCES

[1] G. D. Forney, "Maximum-likelihood sequence estimation of digital sequences in the presence of intersymbol interference," *IEEE Trans. Inform. Theory*, vol. IT-18, no. 3, pp. 363 – 378, May 1972.

[2] R. D. Cideciyan *et al*., "A PRML system for digital magnetic recording," *IEEE J. Selected Areas Commun*., vol. 10, pp. 38 – 56, Jan 1992.

[3] B. Widrow and M.E. Hoff, Jr., "Adaptive switching circuits," *IRE WESCON Convention Record*, pp. 96 – 104, 1960.

[4] S. K. Nair and J. Moon, "A theoretical study of linear and nonlinear equalization in the nonlinear magnetic storage channels," *IEEE Trans. Neural Networks*, vol. 8, pp. 1106 – 1118, Sept 1997.

[5] B.Widrow and S.D. Stearns, *Adaptive Signal Processing*. Prentice – Hall, Englewood Cliffs, NJ, USA, 1985.

[6] P. Kovintavewat *et al*., "Generalized partial response targets for perpendicular recording with jitter noise," *IEEE Trans. Magn*., vol. 38, no. 5, pp. 2340 – 2342, September 2002.

[7] P. Kovintavewat, et al., "A new timing recovery architecture for fast convergence," in *Proc. of ISCAS 2003*, vol. 2, pp. 13 – 16, May 2003.

[8] I. Ozgunes and B.V.K. Vijaya Kumar, "Signal-to-noise ratio performance of Magneto-Optic read channels in the presence of bloom," in *Proc. of SPIE*, vol. 2338, pp. 319 – 327, 1994.

[9] C. Benjangkaprasert, S. Teerasakworakun and K. Janchitra-pongvej, "Implementation of variable step-size algorithm for lattice structure for echo cancellation," in *Proc. of IEEE Asia-Pacific Conference on Circuit and systems*, vol. 1, pp. 291 – 294, October 2002.