Multistep Prediction을 이용한 블라인드 등화기와 효율적인 적응 알고리듬

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Multistep Prediction-Based Blind Equalization and Efficient Adaptive Implementation

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요 약

통신 채널에서 블라인드 채널 등화는 훈련신호나 채널의 사전 정보가 필요하지 않기 때문에 전송 효율을 높일 수 있는 매우 중요한 문제이다. 선형 예측 오차 방법은 블라인드 등화기의 차수 추정 오차에 대하여 강인하며 적응 알고리듬을 이용하여 효율적으로 구현할 수 있는 장점이 있다. 시스템 지연은 등화기의 성능에 많은 영향을 끼치지만 기존의 one-step 선형 예측은 등화기의 임의의 시스템 지연에 대해서는 구현할 수 없는 단점이 있다. 순방향 선형 예측과 역방향 선형 예측은 각각 시스템 지연이 0과 최대인 블라인드 등화와 관련이 있다. 그러나 Multistep 예측은 임의의 시스템 지연을 갖는 블라인드 등화기를 구현할 수 있는 장점이 있다. 본 논문에서는 최적의 시스템 지연을 구한 후 RLS 알고리듬과 LMS 알고리듬을 이용한 multistep 선형 예측을 이용한 블라인드 채널 등화기를 제안하였다. 그리고 기존의 알고리듬들과 본 논문에서 제안한 알고리듬의 성능을 모의실험을 통하여 기존의 알고리듬들과 비교·평가하였다.

ABSTRACT

Blind equalization of transmission channel is important in communication areas and signal processing applications because it does not need training sequence, nor does it require a priori channel information. The linear prediction error method perhaps the most attractive in practice due to the insensitive to blind equalizer length mismatch as well as for its simple adaptive filter implementation. Unfortunately, the previous one-step prediction error method is known to be limited in arbitrary delay. Consequently, multistep prediction error method has been suggested as a solution to the problem. In this paper, we induce the optimal delay, and propose the multistep prediction-based adaptive blind equalizer using RLS- and LMS-type algorithm. Simulation results are presented to demonstrate the proposed algorithm and to compare it with existing algorithms.

I. INTRODUCTION

Multipath propagation appears to be a typical limitation in mobile digital communication where it leads to severe inter- symbol interference (ISI). The classical techniques to overcome this problem use either periodically sent training sequences or blind techniques exploiting higher order statistics (HOS). Adaptive equalization using training sequence wastes the bandwidth efficiency but in blind equalization, no training is no needed and the equalizer is obtained only with the utilization of the received

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signal. Since the seminal work by Tong *et al.* the problem of estimating the channel response of multiple FIR channel driven by an unknown input symbol has interested many researchers in the signal processing areas and communication fields[3][4].

For the most part, algebraic and second-order statistics (SOS) techniques have been proposed that exploit the structural techniques (Hankel, Toeplitz matrix, *et al.*) of the single-input multiple-output (SIMO) channel or data matrices. The information on channel parameters or transmitted data is typically recovered though subspace decomposition of the received data matrix (deterministic method) or that of the received data correlation matrix (stochastic method). Although very appealing from the conceptual and signal processing techniques point of view, the use of the aforementioned techniques in real world applications faces serious challenges. Subspace-based techniques lay in the fact that they relay on the existence of numerically well-defined dimensions of the noise-free signal or noise subspaces. Since these dimensions are obviously closely related to the channel length, subspace-based techniques are extremely sensitive to channel order mismatch[6].

The prediction error methods (PEM) offer an alternative to the class of techniques above. PEM, which were first introduced by Slock *et al.* and later refined by Meraim *et al.* exploited the i.i.d. property of the transmitted symbols and apply a linear prediction error filter on the received data. The PEM offers great practical advantages over most other proposed techniques. First, channel estimation using the PEM remains consistent in the presence of the channel length mismatch. This property guarantees the robustness of the technique with respect to the difficult channel length estimation problem. Another significant advantage of the PEM is that it lends itself easily to a low-cost adaptive implementation such as adaptive lattice filters. But the delay cannot be controlled with existing one-step linear prediction method[7][8][11].

In this paper, we propose a novel adaptive blind equalizer algorithms based on multistep prediction method. This paper makes two results. First, we demonstrate that a multistep prediction method which can be viewed as a certain generalization of the previous PEM. Second, we derive an adaptive algorithm for ZF blind equalization. Most notations are standard: vectors and matrices are boldface small and capital letters, the matrix transpose, the Hermitian, and the Moore-Penrose pseudoinverse are denoted by $(\,)^T$, $(\,)^H$, and $(\,)^+$, respectively; $\mathbf{I}_P$ is the $P\times P$ identity matrix; $E[\,]$ is the statistical expectation.

This paper is organized as follows. In section Ⅱ, we present models for the channel and blind equalizer, and we introduce the concepts of signal vectors and matrices. In section Ⅲ, we discuss multistep prediction-based blind equalization with flexible delay control and propose adaptive algorithms based on least-squares method. In section Ⅳ, we present simulation results comparing the proposed method and existing algorithms. We conclude our results in section Ⅴ.

Ⅱ. SYSTEM MODEL AND BLIND ZF EQUALIZATION

1. Multichannel Communication Model

Let $x(t)$ be the continuous-time signal at the output of a noisy communication channel

$$x(t)=\sum_{k=-\infty}^{\infty} s(k)h(t-k)+v(t) \tag{1}$$

where $s(k)$ denotes the transmitted symbol at time kT, $h(t)$ denotes the continuous-time channel impulse response, and $v(t)$ is additive noise. The fractionally spaced discrete-time model can be obtained either by oversampling or by the sensor array at the receiver[8]. The oversampled single-input single-output (SISO) model results SIMO model as in Figure 1. The corresponding SIMO model is described as follows

$$x_i(n)=\sum_{k=0}^{L-1} s(k)h_i(n-k)+v_i(n),\ i=0,\cdots,P-1 \tag{2}$$

where P is the number of channel, and L is the maximum order of the P channels.

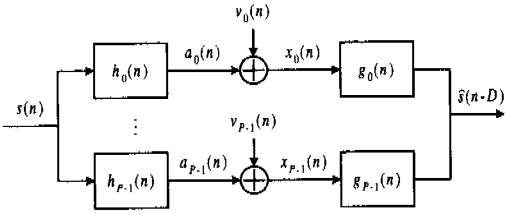

Fig. 1 A SIMO communication system model.

Let

$$\begin{aligned} \boldsymbol{x}(n) &= [x_0(n) \cdots x_{P-1}(n)]^T \\ \boldsymbol{h}(n) &= [h_0(n) \cdots h_{P-1}(n)]^T \\ \boldsymbol{v}(n) &= [v_0(n) \cdots v_{P-1}(n)]^T \end{aligned} \tag{3}$$

We represent $x_i(n)$ in a vector form as

$$\boldsymbol{x}(n) = \sum_{k=0}^{L-1} s(k)\, \boldsymbol{h}(n-k) + \boldsymbol{v}(n) \tag{4}$$

Stacking N received vectors samples into an ($NP\times 1$)-vector, we can write a matrix equation as

$$\boldsymbol{X}_N(n) = \boldsymbol{H}\, s(n) + \boldsymbol{V}_N(n) \tag{5}$$

where $\boldsymbol{H}$ is a $NP\times(N+L)$ channel convolution matrix, $s(n)$ is $(N+L)\times 1$, $\boldsymbol{X}_N(n)$ and $\boldsymbol{V}_N(n)$ are $NP\times 1$ vectors.

$$\begin{aligned} s(n) &= [s(n) \cdots s(n-L-N+2)]^T \\ \boldsymbol{X}_N(n) &= [\ \boldsymbol{x}^T(n) \cdots \boldsymbol{x}^T(n-N+1)]^T \\ \boldsymbol{V}_N(n) &= [\ \boldsymbol{v}^T(n) \cdots \boldsymbol{v}^T(n-N+1)]^T \\ \boldsymbol{H} &= \begin{bmatrix} \boldsymbol{h}(0) & \cdots & \boldsymbol{h}(L-1) & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{h}(0) & \cdots & \boldsymbol{h}(L-1) \end{bmatrix} \end{aligned} \tag{6}$$

We assume the following throughout in this paper.

A1) The input sequence $s(n)$ is zero mean and white with variance σ_s^2.

A2) The additive noise $v(n)$ is stationary with zero mean and white with variance σ_v^2..

A3) The sequences $s(n)$ and $v(n)$ are uncorrelated.

A4) The matrix $\boldsymbol{H}$ has full rank, i.e., the subchannels $h_i(n)$ have no common zeros to satisfy the Bezout equation.

A5) The dimension of $\boldsymbol{H}$ obey $NP > L+N$.

2. Multichannel Blind ZF Equalization

The ith subchannel $h_i(n)$ is equalizer by the filter $g_i(n)$, as shown in Figure 1. A ZF equalizer whose subchannels are order L_K is described by

$$\sum_{i=0}^{P-1} \sum_{k=0}^{L_K-1} h_i(n-k) g_i(k) = \delta(n-D) \tag{7}$$

Above equation can be written in matrix form as follows

$$\boldsymbol{g}^T \boldsymbol{H} = \boldsymbol{e}_{D+1}^T \tag{8}$$

where $\boldsymbol{e}_{D+1}$ is a $(N+L)\times 1$ vector with a 1 as the $(D+1)$th element and zeros elsewhere[9]. A ZF equalizer is proved in [3]-[5] and we consider noise-free case. Using assumptions A1)-A3), we can write the exact correlation matrix of $\boldsymbol{X}_N(n)$ as

$$\boldsymbol{R} = E[\ \boldsymbol{X}_N \boldsymbol{X}_N^H] = \sigma_s^T \boldsymbol{H}\ \boldsymbol{H}^H \tag{9}$$

From (8), we induce the zero-delay equalizer

$$\begin{aligned} \boldsymbol{g}_0^T &= \sigma_s^2 \boldsymbol{H}(0)\ \boldsymbol{R}^+ \\ &= \sigma_s^2[\ \boldsymbol{h}^H(0)\ \ 0]\ \boldsymbol{R}^+ \end{aligned} \tag{9}$$

where $\boldsymbol{H}(0)$ is the first column of matrix $\boldsymbol{H}$. Considering that an arbitrary-delay blind equalizer, it is proved in [5] that an equalizer $\boldsymbol{g}_D$ with D-delay can be obtained from $\boldsymbol{g}_0$ as

$$\boldsymbol{g}_D^T = \boldsymbol{g}_0^T \boldsymbol{R}_D\ \boldsymbol{R}^+ \tag{10}$$

where $\boldsymbol{R}_D = E[\ \boldsymbol{X}_N(n-D)\ \boldsymbol{X}_N^H(n)]$

Ⅲ. LS APPROACH TO MULTISTEP PREDICTION AND BLIND ADAPTIVE EQUALIZER

1. Multistep Prediction-Based Blind Equalizer

A zero-delay ZF equalizer based on linear prediction is proposed in [6]-[8]. We know that

$$\boldsymbol{g}_0^T = \boldsymbol{h}^H(0)[\ \boldsymbol{I}_P\ \ -\boldsymbol{P}_{N-1}] \tag{12}$$

where $-\boldsymbol{P}_{N-1}$ is $P\times P(N-1)$ prediction coefficient matrix. It is obtained by minimizing the prediction error variance in [8] or using least-squares lattice (LSL) algorithm[7]. And a D-step forward predictor of order N produces an estimation of the received signal $x(n)$ based on the N previous signal $x_N(n-D)$[11].

$$\hat{x}(n) = a_1 x(n-D) + \cdots + a_N x(n-N-D+1) \quad (13)$$

The D-step forward prediction error is given by

$$\begin{aligned} f_D(n) &= x(n) - \hat{x}(n) \\ &= [\, I_P \;\; 0_{P\times P(D-1)} \;\; -A_N] \, X_{N+D}(n) \\ &= K_D \, X_{N+D}(n) \end{aligned} \quad (14)$$

Using well-known orthogonality principle between prediction error and input sequences, it comes from (5)

$$\begin{aligned} & E[\, X_N(n-D) \, f_D^H(n)] \\ &= E[\, H_N \, s_N(n-D) \; X_{N+D}(n)] \, K_D \\ &= H_N E[\, s_N(n-D) \, s_N^H(n)] \, H_{N+D}^H \, K_D \\ &= H_N [\, 0_{N\times D} \;\; I_N \,] H_{N+D}^H \, K_D \\ &= 0 \end{aligned} \quad (15)$$

Hence, it produces

$$\begin{aligned} & [\, 0_{N\times D} \;\; I_N \,] H_{N+D}^H \, K_D = 0 \\ & K_D^H \, H_{N+D} = [\, h(0) \cdots h(D-1) \; 0 \cdots 0] \end{aligned} \quad (16)$$

then

$$f_D(n) = K_D^H \, X_{N+D}(n) = \sum_{j=0}^{D-1} h(j) s(n-j) \quad (17)$$

The D-delay blind equalizer method considered here is based on the output of D- and (D+1)-step prediction error filters. A D-delay ZF equalizer can be obtained after acknowledging from (17)

$$\begin{aligned} & f_{D+1}(n) - f_D(n) \\ &= (\, K_{D+1} - K_D)^H \, X_{N+D}(n) \\ &= \sum_{j=0}^{D} h(j) s(n-j) - \sum_{j=0}^{D-1} h(j) s(n-j) \\ &= h(D) s(n-D) \end{aligned} \quad (18)$$

Therefore, the transmitted symbol can then be extracted as follow

$$s(n-D) = \frac{h^H(D)}{\| h(D) \|^2} \, (\, f_{D+1}(n) - f_D(n)) \quad (19)$$

The predictor coefficients are selected such that the mean square value of $f_D(n)$, i.e., $E[|\, f_D(n)|^2]$, is minimized. Therefore, for any set of predictor coefficients a_k $(1 \le k \le N)$

$$\frac{\partial E[\, f_D(n) \, f_D^H(n)]}{\partial \, a_k^N} = 0, \text{ for } 0 \le k \le N \quad (20)$$

Due to the linearity of the expectation and differentiation operators we can interchange these two operators and (20) can be written as

$$\begin{aligned} & E\left[\frac{\partial |\, f_D(n)|^2}{\partial \, a_k^N} \right] = \\ & E\Big[\Big\{ x(n) - \sum_{k=1}^{N} a_k^N x(n-D-k+1) \Big\}^H \\ & \quad \cdot (\, a_k^N)^H \, x^H(n-D-k+1) \\ & \quad + \Big\{ x(n) - \sum_{k=1}^{N} a_k^N x(n-D-k+1) \Big\} \\ & \quad \cdot \, a_k^N x(n-D-k+1) \Big] \end{aligned} \quad (21)$$

Therefore, from (20) and (21) we can write,

$$\begin{aligned} & 2\,\mathrm{Re}\Big[(\, a_k^N)^H \Big\{ r(D+l-1) - \sum_{k=1}^{N} a_k^N r(l-k) \Big\} \Big] = 0 \\ & \Rightarrow r(D+l-1) - \sum_{k=1}^{N} a_k^N r(k-1) = 0, l = 1, \cdots, N \end{aligned} \quad (22)$$

We can rewrite above equation using matrix form

$$R_N \, a_N = r_{N+D} \quad (23)$$

where $r_{N+D} = [\, r(D) \cdots r(D+N-1)]^T$ and $a_N = [\, a_1^N \cdots a_N^N]^T$

$$\begin{aligned} R_N &= E[\, X_N(n) \, X_N^H(n)\,] \\ &= \begin{bmatrix} r(0) & r(1) & \cdots & r(N-1) \\ r^H(1) & r(0) & \cdots & r(N-2) \\ \vdots & \vdots & \ddots & \vdots \\ r^H(N-1) & r^H(N-2) & \cdots & r(0) \end{bmatrix} \end{aligned} \quad (24)$$

where $r(i-j) = E[\, x(n+i) \; x^H(n+j)]$

To solve the prediction error filter coefficients matrix in D-step predictor, it requires matrix inverse calculation for Yule-Walker equation.

2. Proposed Method using Projection Matrix

The D-delay equalizer g_D in (11) can be estimated by linear prediction. Consider the following LS method

$$\begin{aligned} e_d(n) &= x(n-D) - p_1\, x(n) \\ e_{d+1}(n) &= x(n-D-1) - p_1\, x(n-1) \\ &\vdots \\ e_{d+N-1}(n) &= x(n-D-N+1) - p_N\, x(n-N+1) \end{aligned} \tag{25}$$

where p_k is coefficients matrix for prediction at the kth stage. Eq. (25) is rewritten with matrix form as

$$E(n) = X_N(n-D) - P_N\, X_N(n) \tag{26}$$

where $E(n)$ is an $PN\times 1$ prediction error vector and P_N is a $PN\times PN$ projection matrix. The optimal P_N is obtained by minimizing as following cost function.

$$J = \mathrm{tr}\{E[\, E(n)\; E^H(n)]\} \tag{27}$$

Letting the derivative of (27) with respect to projection matrix equal to zero as following

$$\frac{\partial J}{\partial P_N^H} = E[\; -X_N(n-D)\, X_N^H(n) + P_N\, X_N(n)\, X_N^H(n)] \tag{28}$$

So we get as

$$\begin{aligned} P_N R - R_D &= 0 \\ P_N &= R_D\, R^+ \end{aligned} \tag{29}$$

Comparing (11) with (29) we get as following equation.

Table 1. RLS algorithm for zero-delay blind equalizer.

Initialization the algorithm at time $n=0$, set

$$\begin{aligned} Q_1(0) &= \delta^{-1}\, I_{P(N-1)} \\ P_{N-1}(0) &= \mathbf{0} \end{aligned}$$

For $n=1,2,\cdots$ do the following

(1) First linear prediction computation.

$$\begin{aligned} X_N(n) &\equiv [\, X_{N,1}^H \;\; X_{N,2}^H\,] \\ K_1(n) &= \frac{\lambda^{-1}\, Q_1(n-1)\; X_{N,2}(n)}{1+\lambda^{-1}\, X_{N,2}(n)\; Q_1(n-1)\; X_{N,2}(n)} \\ e(n) &= X_{N,1}(n) - P_{N-1}(n-1)\; X_{N,2}(n) \\ P_{N-1}(n) &= P_{N-1}(n-1) + e(n)\, K_1^H(n) \\ Q_1(n) &= \lambda^{-1}\, Q_1(n-1)\; K_1(n)\, X_{N,2}^H\; Q_1(n-1) \end{aligned}$$

(2) Estimation of $h(0)$ in [10].

(3) Computation g_0 in (12).

$$g_D^T = g_0^T\, P_N \tag{30}$$

It should be noted that the blind equalizer is designed for transmitted signal recovery at a given delay D. Thus, different delay can result in difference performance. To get best delay choice, [9] proposes the minimizing MSE is given by

$$\mathrm{MSE}(D) = 1 - H^H(D)\;\, R^+\; H(D) \tag{31}$$

where $H(D)$ is $(D+1)$th block column of the channel convolution matrix H. Hence, the optimum delay can be found by

$$\arg\max_D\, H^H(D)\;\, R^+\; H(D) \tag{32}$$

3. Adaptive Implementation

One advantage of the prediction approach is the ability to develop computationally efficient adaptive algorithm for estimating the blind equalizers. Although the methods of [5] and [7] can be implemented as adaptive manners, [5] requires the sensitive correlation matrix Moore- Penrose pseudoinverse computations, whereas [7] may be weak approach because equalizers of arbitrary delay cannot be obtained. In this section, we propose the adaptive algorithm for updating the multistep linear prediction error filter coefficients.

Table 2. RLS algorithm for D-delay blind equalizer.

Initialization the algorithm at time $n=0$, set

$$\begin{aligned} Q_2(0) &= \delta^{-1}\, I_{PN} \\ P_N(0) &= \mathbf{0} \end{aligned}$$

For $n=1,2,\cdots$ do following

(1) Projection matrix computation.

$$\begin{aligned} K_2(n) &= \frac{\lambda^{-1}\, Q_2(n-1)\; X_N(n)}{1+\lambda^{-1}\, X_N(n)\; Q_2(n-1)\; X_N(n)} \\ E(n) &= X_N(n-D) - P_N(n-1)\; X_N(n) \\ P_N(n) &= P_N(n-1) + E(n)\, K_2^H(n) \\ Q_2(n) &= \lambda^{-1}\, Q_2(n-1)\; K_2(n)\, X_N^H\, Q_2(n-1) \end{aligned}$$

(2) Compute the zero-delay blind equalizer g_0

(3) Computation g_D in (30).

To solve (30), we are required to compute the first linear prediction in (12) and to estimate the $\boldsymbol{h}(0)$. To estimate $\boldsymbol{h}(0)$, we use eigen-tracking method in [10]. A zero-delay blind equalizer is obtained in (12). The second linear prediction in (26) is computed and then D-delay blind equalizer can be computed in (30) with predetermined zero-delay blind equalizer.

Zero-delay and D-delay blind equalizer are obtained as described in Table 1 and Table 2. Also, D-delay blind equalizer based on LMS algorithm is described in Table 3.

Table 3. LMS algorithm for D-delay blind equalizer.

Initialization the algorithm at time $n=0$, set

$$P_{N-1}(0) = 0$$
$$P_N(0) = 0$$

Compute $n=1,2,\cdots$ do following

(1) First linear prediction computation.

$$\begin{aligned} X_N(n) &\equiv [\, X_{N,1}^H \;\; X_{N,2}^H \,] \\ e(n) &= X_{N,1}(n) - P_{N-1}(n-1)\, X_{N,2}(n) \\ E(n) &= X_N(n-D) - P_N(n-1)\, X_N(n) \\ P_{N-1}(n) &= P_{N-1}(n-1) + \mu_1\, e(n)\, X_{N,2}^H(n) \\ P_N(n) &= P_N(n-1) + \mu_2\, E(n)\, X_N^H(n) \end{aligned}$$

(2) Estimation of $\boldsymbol{h}(0)$ in [10].

(3) Computation $\boldsymbol{g}_0$ and $\boldsymbol{g}_D$ in (12) and (30).

Ⅳ. EXPERIMENTAL RESULTS

In this section, we use computer simulations to examine the performance of the proposed method described in previous section. In addition, we compare the performance of the proposed methods with some existing SOS algorithms and CMA for blind channel equalization. In this simulation, as an approximation of a three-ray multipath environment, the channel impulse response is given by

$$h_c(t) = c(t,0.45)W(t) + 0.8c(t-0.25T,0.45)\,W(t-0.25T) - 0.4c(t-2T,0.45)\,W(t-2T) \quad (39)$$

where $c(t,\alpha)$ is a raised cosine pulse with the roll-off factor α, and $W(t)$ is a rectangular window of duration 6 symbol intervals spanning $[-0.85T \;\; 5.14T]$. There are four subchannels. As a performance index, the MSE of symbol estimation is defined as in [3].

$$\mathrm{MSE} = E[\,|\,\hat{s}(n-D) - s(n)|^2] \quad (40)$$

For the simulations, the SNR is defined to be at the input to the equalizer in Figure 1.

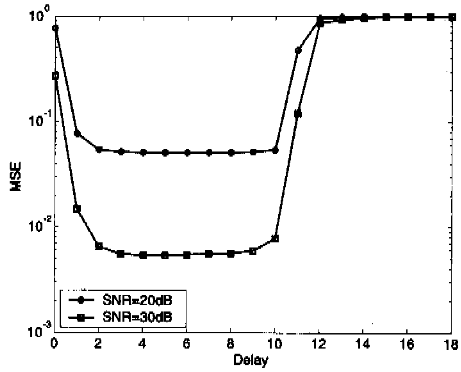

Fig. 2 MSE curves versus the different delay D under SNR=20dB and 30dB.

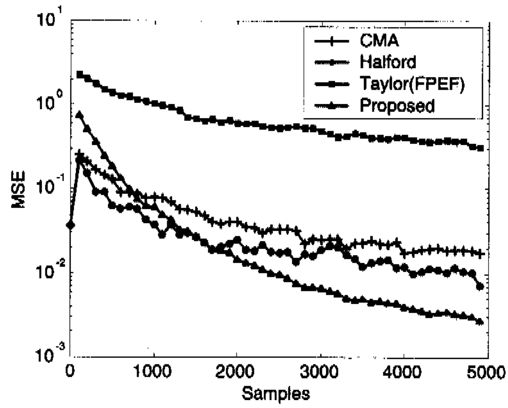

Fig. 3 Comparison of MSE curves for existing algorithms and proposed algorithm under SNR=30dB.

$$\mathrm{SNR} = \frac{E[\,|a(n)|^2]}{E[\,|v(n)|^2]} \quad (41)$$

For each simulation, we have used an i.i.d. input sequence drawn from a 16-QAM constellation. The noise is generated from a white Gaussian distribution at varying SNR's.

An MSE of the blind equalizer is affected by a different selection of delay D. In Figure 2, we whow the MSE of the output for different delay D and the MSE obtained from (32) under SNR=20dB and 30dB. The number of subchannels is four. Let the equalizer order be $L_g=8$. In this simulation, we compare the proposed algorithm with FS-CMA, RLS algorithm proposed by Halford *et al.* (denotes Halford algorithm)[5], and LSL algorithm with forward prediction error filter (FPEF) proposed by Taylor *et al.* (denotes Taylor algorithm)[7]. Let the equalizer order be $L_g=8$ for proposed method, $L_g=12$ for Taylor algorithm, and $L_g=18$ for CMA in each subchannels. To verify optimal equalizer length, see [5] and [7]. Figure 3 and 4 show the MSE curves for MSE of the proposed RLS and existing algorithms under SNR=20dB and 30dB, respectively. It is shown that the proposed algorithm has faster convergence speed than the others, whereas the Taylor algorithm has poor performance because equalizers of arbitrary delay cannot be controlled. This simulation tests the BER performance of proposed algorithm together with existing algorithms under various levels of SNR. The result of the simulation is shown in Figure 5. The data input signal is i.i.d. 16-QAM and oversampling factor is $P=4$. The number of output data samples is $N=5000$. We can see that BER performance of the proposed algorithm is better than the others.

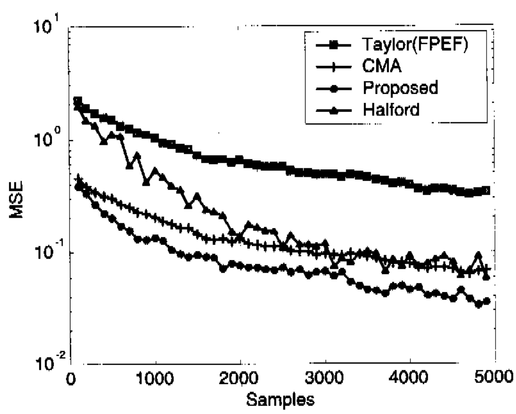

Fig. 4 Comparison of MSE curves for existing algorithms and proposed algorithm under SNR=30dB.

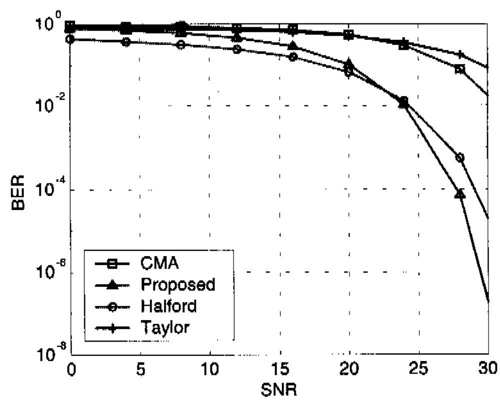

Fig. 5 Comparison of BER curves of existing algorithms and proposed algorithm.

V. CONCLUSIONS

This paper presents adaptive blind equalizer based on multichannel linear prediction with optimum delay. We have developed RLS- and LMS-type algorithm for updating prediction coefficient matrix as projection matrix. Our proposed method ensures flexible delay control and provides flexibility for a practical implementation since various well-known adaptive filtering algorithms, including RLS and LMS, can be used to implement the method. Furthermore, our algorithms are robust to channel order overdetermination in nature of linear prediction characteristics, and do not need channel length estimation. Simulation results show that our algorithms have good performance in channel equalization. Compared with HOS-based algorithm such as CMA, our algorithms are based on SOS; thus, faster convergence can be achieved. Out future works include the extension to multi-input multi-out (MIMO) blind equalizer for multiuser detection applications and the development of lattice structure for multistep prediction error filters.

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