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Adaptive Blind MMSE Equalization for SIMO Channel

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ABSTRACT

Blind equalization of transmission channel is important in communication areas and signal processing applications because it does not need training sequences, nor does it require a priori channel information. In this paper, an adaptive blind MMSE channel equalization technique based on second-order statistics is investigated. We present an adaptive blind MMSE channel equalization using multichannel linear prediction error method for estimating cross-correlation vector. They can be implemented as RLS or LMS algorithms to recursively update the cross-correlation vector. Once cross-correlation vector is available, it can be used for MMSE channel equalization. Unlike many known subspace methods, our proposed algorithms do not require channel order estimation. Therefore, our algorithms are robust to channel order mismatch. Performance of our algorithms and comparisons with existing algorithms are shown for real measured digital microwave channel.

I. Introduction

Multipath propagation appears to be a typical limitation in mobile digital communication where it leads to severe intersymbol interference (ISI). The classical techniques to overcome this problem use either periodically sent training sequences or blind techniques exploiting higher order statistics (HOS) [1]. Adaptive equalization using training sequence wastes the bandwidth efficiency but in blind equalization, no training is needed and the equalizer is obtained only with the utilization of the received signal. A well-known HOS-based algorithm is constant modulus algorithm (CMA). A main disadvantage of this algorithm is the possibility of local convergence [2]. The fractionally-spaced CMA (FS-CMA) was shown in [3] to guarantee global convergence with finite length equalizers. 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 [4]–[8].

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 through 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], [7].

The prediction error method (PEM) offers an alternative to the class of techniques above. PEM, which was first introduced by Slock *et al.* and later refined by Meraim *et al.* exploited the i.i.d. property of the transmitted symbols and applies a

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linear prediction error filter on the received data [7], [8]. 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 [8]−[11]. These algorithms calculate ZF or MMSE equalizers based on channel identification.

In this paper, we propose adaptive blind MMSE channel equalization algorithm that is less sensitive to the equalizer order length. This paper makes three results. First, we estimate the multichannel prediction-based cross-correlation vector estimation between the channel output signal and the transmitted signal. Estimated cross-correlation vector can then be used to calculate the MMSE blind equalizer. Second, we develop an efficient algorithm to perform this cross-correlation vector tracking. A simple iterative algorithm can be used to find the cross-correlation vector. Third, we derive an LMS and RLS type adaptive algorithms for MMSE blind equalization. Most notations are standard: vectors and matrices are boldface small and capital letters, respectively; the matrix transpose, the Hermitian, the Moore-Penrose pseudoinverse are denoted by $(\cdot)^T$, $(\cdot)^H$, and $(\cdot)^+$, respectively; $\mathbf{I}_P$ is the $P\times P$ identity matrix; $E[\cdot]$ is the statistical expectation.

This paper is organized as follows. In section Ⅱ, we present models for the channel and blind MMSE equalizer, and we introduce the concepts of signal vectors and matrices. In section Ⅲ, we discuss multichannel linear prediction problem for cross-correlation vector estimation. Simulation results and performance comparisons of our proposed algorithms with some well-known existing algorithms are presented in section Ⅳ. We conclude our results in section Ⅴ.

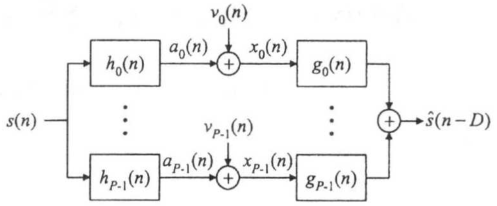

Fig. 1 Linear equalization for fractionally-spaced channel.

Ⅱ. Problem Formulation

1. System Model

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

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

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 time oversampling or by the sensor array at the receiver [4]. The oversampled single-input single-output (SISO) model results SIMO model as in Fig. 1. The corresponding SIMO model is described as follows

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

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

Let

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

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

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

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

$$\mathbf{x}_N(n) = \mathbf{H}\mathbf{s}(n) + \mathbf{v}_N(n) \tag{5}$$

where $\mathbf{H}$ is a $NP \times (N+L)$ block Toeplitz matrix, $\mathbf{s}(n)$ is $(N+L)\times 1$, $\mathbf{x}_N(n)$, and $\mathbf{v}_N(n)$ are $NP\times 1$ vectors.

$$\begin{aligned} \mathbf{s}(n) &= [s(n),\cdots,s(n-L-N+1)]^T \\ \mathbf{x}_N(n) &= [\mathbf{x}^T(n),\cdots,\mathbf{x}^T(n-N+1)]^T \\ \mathbf{v}_N(n) &= [\mathbf{v}^T(n),\cdots,\mathbf{v}^T(n-N+1)]^T \end{aligned} \tag{6}$$

and

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}(0) & \cdots & \mathbf{h}(L-1) & \cdots & \mathbf{0} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{h}(0) & \cdots & \mathbf{h}(L-1) \end{bmatrix} \tag{7}$$

We assume the following in this paper.

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

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

(A3) The sequences $\mathbf{s}(n)$ and $\mathbf{v}(n)$ are uncorrelated.

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

Consider an FIR linear MMSE equalizer shown in Fig. 1, where $g_i(n)$ for i=0, 1, $\cdots$, $P-1$ is the order N equalizer of the ith subchannel and the symbol is estimated from

$$\hat{s}(n-d) = \mathbf{g}^H\mathbf{x}_N(n) \tag{8}$$

According to (5)−(7), $\mathbf{x}_N(n)$ has nonzero correlation with only $s(n),\cdots,s(n-L-N+1)$. Therefore, decision delay d is usually in the interval $[0,\ N+L-1]$. For finite SIMO channels, MMSE equalizer of the finite length can be found if assumption (A4) holds and the equalizer length $N\geq L$ [8]. An MMSE equalizer minimize the following cost function

$$J_{\text{MMSE}} = E[|\hat{s}(n-d)-s(n-d)|^2] \tag{9}$$

MMSE blind equalizer with delay d is given by

$$\mathbf{g}_{\text{MMSE}} = \arg\min_{\mathbf{g}} E[|\mathbf{g}^H\mathbf{x}_N(n)-s(n-d)|^2] \tag{10}$$

The minimum MSE filter to estimate $\hat{s}(n-d)$ is the solution to the Wiener-Hopf equation [12]

$$E[\mathbf{x}_N(n)\mathbf{x}_N^H(n)]\mathbf{g} = E[\mathbf{x}_N(n)\mathbf{s}^*(n-d)] \tag{11}$$

Using assumptions (A1)−(A3), we can write the exact correlation matrix of $\mathbf{x}_N(n)$ as

$$\mathbf{R} = E[\mathbf{x}_N(n)\mathbf{x}_N^H(n)] = \sigma_s^2\mathbf{H}\mathbf{H}^H + \sigma_v^2\mathbf{I} \tag{12}$$

whereas the cross-correlation vector equals

$$\mathbf{R} = E[\mathbf{x}_N(n)\mathbf{x}_N^H(n)] = \sigma_s^2\mathbf{H}\mathbf{H}^H + \sigma_v^2\mathbf{I} \tag{13}$$

where $\mathbf{H}(d)$ denotes the $(d+1)$th block column of the channel convolution matrix $\mathbf{H}$ [12]. Based on assumption that $s(n)$ has unit variance, the blind MMSE equalizer with delay d is given by

$$\mathbf{g} = \mathbf{R}^+\mathbf{H}(d) \tag{14}$$

Ⅲ. Proposed Method

1. Multichannel Linear Prediction

Consider the noise-free case. For convenience, we can rewrite (5) as

$$\mathbf{x}_N(n) = \mathbf{H}\mathbf{s}(n) = [\mathbf{H}_1 \quad \mathbf{H}_2 \quad \mathbf{H}_3]\begin{bmatrix} \mathbf{s}_1(n) \\ \mathbf{s}_2(n) \\ \mathbf{s}_3(n) \end{bmatrix} \tag{15}$$

where $\mathbf{H}_1$ is of dimension $NP\times d$, the $NP\times 1$ vector $\mathbf{H}_2$ is the $(d+1)$th column of $\mathbf{H}$, and the last part of $\mathbf{H}$ is denoted by $\mathbf{H}_3$ with dimension $NP\times(N+P-d-1)$ [13].

An $NP\times 1$ multichannel linear prediction error vector can be obtained as [13]

$$\mathbf{f}_1(n) = [\mathbf{I} \quad -\mathbf{P}_1(n)]\begin{bmatrix} \mathbf{x}_N(n) \\ \mathbf{x}_M(n-d) \end{bmatrix} = \mathbf{H}_1\mathbf{s}_1(n) \tag{16}$$

where $\mathbf{P}_1$ is an $NP\times MP$ matrix. $\mathbf{x}_N(n)$ is defined in (6), and $\mathbf{x}_M(n-d)$ is defined as

$$\mathbf{x}_M(n-d) = \begin{bmatrix} \mathbf{x}(n-d) \\ \vdots \\ \mathbf{x}(n-d-M+1) \end{bmatrix} \tag{17}$$

The optimal $\mathbf{P}_1(n)$ is obtained by minimizing as following cost function

$$J_1 = \mathrm{tr}[E[\mathbf{f}_1(n)\mathbf{f}_1^H(n)]] \quad (18)$$

Letting the partial derivative of (18) with respective to $\mathbf{P}_1$ equals to zero as following

$$\frac{\partial J_1}{\partial \mathbf{P}_1} = E[-\mathbf{x}_N(n)\mathbf{x}_M(n-d) + \mathbf{P}_1\mathbf{x}_M(n-d)\mathbf{x}_M^H(n-d)] = 0 \quad (19)$$

We get as

$$\mathbf{P}_1 = [E[\mathbf{x}_M(n-d)\mathbf{x}_M^H(n-d)]]^+ E[\mathbf{x}_N(n)\mathbf{x}_M(n-d)] \quad (20)$$

Consider another multichannel linear prediction problem

$$\mathbf{f}_2(n) = [\mathbf{I} \ \ -\mathbf{P}_2(n)]\begin{bmatrix} \mathbf{x}_N(n) \\ \mathbf{x}_M(n-d-1) \end{bmatrix} = [\mathbf{H}_1 \ \ \mathbf{H}_2]\begin{bmatrix} \mathbf{s}_1(n) \\ \mathbf{s}_2(n) \end{bmatrix} \quad (21)$$

The proof is again provided in [13]. Compared with (18), (19), and (20), we can know that the optimal $\mathbf{P}_2$ is obtained as following

$$\mathbf{P}_2 = \left[E\left[\mathbf{x}_M(n-d-1)\mathbf{x}_M^H(n-d-1)\right]\right]^+ \cdot E\left[\mathbf{x}_N(n)\mathbf{x}_M(n-d-1)\right] \quad (22)$$

In order to consider $\mathbf{H}_2$, we can compute

$$\mathbf{f}(n) = \mathbf{f}_2(n) - \mathbf{f}_1(n) = \mathbf{H}_2\mathbf{s}_2(n) \quad (23)$$

The transmitted signal with delay d is written as

$$s(n-d) = \frac{\mathbf{H}_2^H}{\mathbf{H}_2^H\mathbf{H}_2}[\mathbf{0} \quad \mathbf{H}_2 \quad \mathbf{0}]\mathbf{s}(n) \quad (24)$$

Substitute (8) and (24) back to (9), we get

$$J_{\mathrm{MMSE}} = 1 - \mathbf{g}^H\mathbf{H}_2 - \mathbf{H}_2^H\mathbf{g} + \mathbf{g}^H\mathbf{R}\mathbf{g} \quad (25)$$

Then, minimizing J_{MMSE} yields

$$\mathbf{g}_{\mathrm{MMSE}} = \mathbf{R}^+\mathbf{H}_2 = \mathbf{R}^+\mathbf{H}(d) \quad (26)$$

From (23), we know that

$$E[\mathbf{f}(n)\mathbf{f}^H(n)] = \sigma_s^2\mathbf{H}_2\mathbf{H}_2^H = \sigma_s^2\mathbf{H}(d)\mathbf{H}^H(d) \quad (27)$$

Then, the rank of the matrix $E[\mathbf{f}(n)\mathbf{f}^H(n)]$ is one. Therefore, $\mathbf{H}(d)$ is the singular vector corresponding to the largest singular value of matrix $E[\mathbf{f}(n)\mathbf{f}^H(n)]$. Substituting this estimated cross-correlation vector into (26), MMSE blind equalizer is obtained. If the delay d equals channel length, then we can obtain channel coefficient since $\mathbf{H}_2$ is just the channel coefficient vector.

The block style algorithm for MMSE blind equalizer estimation can be summarized.

1. Compute correlation and prediction matrices (20) and (22).
2. Compute the multichannel prediction vectors (16), (21) and (23).
3. Compute $\mathbf{R}^+$ and $\mathbf{H}(d)$.
4. Compute MMSE blind equalizer $\mathbf{g}_{\mathrm{MMSE}}$.

2. Adaptive Implementation

We propose the adaptive algorithms for updating the multichannel linear prediction error filter coefficients. Two multichannel linear prediction problems are required in estimating the MMSE blind equalizer. We are required to compute the multichannel prediction matrices in (20) and (22) and to estimate the multichannel prediction errors in (16), (21), and (23). In order to fast convergence, we can use the RLS algorithm to update the multichannel linear prediction as following

- Compute multichannel linear prediction error vector:

$$\mathbf{f}_1(n) = \mathbf{x}_N(n) - \mathbf{P}_1(n-1)\mathbf{x}_M(n-d)$$
$$\mathbf{f}_2(n) = \mathbf{x}_N(n) - \mathbf{P}_2(n-1)\mathbf{x}_M(n-d-1) \quad (28)$$

- Compute Kalman gain:

$$\mathbf{K}_1(n) = \frac{\lambda^{-1}\mathbf{Q}_1(n-1)\mathbf{x}_M(n-d)}{1+\lambda^{-1}\mathbf{x}_M^H(n-d)\mathbf{Q}_1(n-1)\mathbf{x}_M(n-d)}$$
$$\mathbf{K}_2(n) = \frac{\lambda^{-1}\mathbf{Q}_2(n-1)\mathbf{x}_M(n-d-1)}{1+\lambda^{-1}\mathbf{x}_M^H(n-d-1)\mathbf{Q}_2(n-1)\mathbf{x}_M(n-d-1)} \quad (29)$$

- Update inverse of the correlation matrix:

$$\mathbf{Q}_1(n) = \lambda^{-1}\mathbf{Q}_1(n-1) - \lambda^{-1}\mathbf{K}_1(n)\mathbf{x}_M^H(n-d)\mathbf{Q}_1(n-1)$$
$$\mathbf{Q}_2(n) = \lambda^{-1}\mathbf{Q}_2(n-1) - \lambda^{-1}\mathbf{K}_2(n)\mathbf{x}_M^H(n-d-1)\mathbf{Q}_2(n-1) \quad (30)$$

• Update multichannel linear prediction coefficient matrix:

$$\mathbf{P}_1(n) = \mathbf{P}_1(n-1) + \mathbf{f}_1(n)\mathbf{K}_1^H(n)$$
$$\mathbf{P}_2(n) = \mathbf{P}_2(n-1) + \mathbf{f}_2(n)\mathbf{K}_2^H(n) \quad (31)$$

• Compute another prediction error vector:

$$\mathbf{f}(n) = \mathbf{f}_1(n) - \mathbf{f}_2(n) \quad (32)$$

The term λ ($0<\lambda \leq 1$) is intended to reduce the effect of past values on the statistics when the filter operates in nonstationary environment. It affects the convergence speed and the tracking accuracy of the algorithm [14]. From the covariance matrix of $\mathbf{f}(n)$ in (27), its estimation of adaptive manner is given by

$$\mathbf{F}(n) = \lambda\mathbf{F}(n-1) + \mathbf{f}(n)\mathbf{f}^H(n) \quad (33)$$

To update the correlation estimates recursively, we can use the sample estimator

$$\mathbf{R}(n) = \sum_{k=0}^{n-1}\lambda^{n-k}\mathbf{x}_N(k)\mathbf{x}_N^H(k) + \mathbf{x}_N(n)\mathbf{x}_N^H(n)$$
$$= \lambda\mathbf{R}(n-1) + \mathbf{x}_N(n)\mathbf{x}_N^H(n) \quad (34)$$

Defining $\mathbf{B}(n) = \mathbf{R}^{+}(n)$ and using the matrix inversion lemma (e.g., [14], p. 565) with (34), we can write

$$\mathbf{B}(n) = \lambda^{-1}\mathbf{B}(n-1) - \lambda^{-1}\mathbf{K}(n)\mathbf{x}_N^H(n)\mathbf{B}(n-1) \quad (35)$$

and

$$\mathbf{K}(n) = \frac{\lambda^{-1}\mathbf{B}(n-1)\mathbf{x}_N(n)}{1+\lambda^{-1}\mathbf{x}_N^H(n)\mathbf{B}(n-1)\mathbf{x}_N(n)} \quad (36)$$

Notice that (35) and (36) do not require a matrix inverse problem and thereby provide a recursive method for computing $\mathbf{B}(n)$. From (26), we can use the following equation to obtain the MMSE equalizer estimation

$$\mathbf{g}(n) = \mathbf{B}(n)\mathbf{H}(d) \quad (37)$$

The above multichannel linear prediction problems can be computed by an LMS algorithm. The first one can be updated by

$$\mathbf{f}_1(n) = \mathbf{x}_N(n) - \mathbf{P}_1(n-1)\mathbf{x}_M(n-d)$$
$$\mathbf{f}_2(n) = \mathbf{x}_N(n) - \mathbf{P}_2(n-1)\mathbf{x}_M(n-d-1) \quad (38)$$

The second one is updated by

$$\mathbf{P}_1(n) = \mathbf{P}_1(n-1) + \mu_1\mathbf{f}_1(n)\mathbf{x}_M^H(n-d)$$
$$\mathbf{P}_2(n) = \mathbf{P}_2(n-1) + \mu_2\mathbf{f}_2(n)\mathbf{x}_M^H(n-d-1) \quad (39)$$

3. Cross-Correlation Vector Tracking Algorithm

A simple iterative algorithm known as the power method can be used to find the largest eigenvector and its associated eigenvector [15], [23]. Let $\mathbf{F}$ be a matrix with eigenvalues ordered as $\lambda_1 > \lambda_2 \geq \cdots \geq \lambda_{NP}$, with corresponding eigenvectors $\mathbf{e}_1, \mathbf{e}_2, \cdots, \mathbf{e}_{NP}$. Let $\mathbf{e}(0)$ be a normalized vector that is assumed to be not orthogonal to $\mathbf{e}_1$. The vector $\mathbf{e}(0)$ can be written in terms of the eigenvector as

$$\mathbf{e}(0) = a_1\mathbf{e}_1 + a_2\mathbf{e}_2 + \cdots + a_{NP}\mathbf{e}_{NP} \quad (40)$$

for some set of coefficient a_i, where $a_1 \neq 0$. We define the power method recursion by

$$\mathbf{e}(n+1) = \frac{\mathbf{F}\mathbf{e}(n)}{\|\mathbf{F}\mathbf{e}(n)\|} \quad (41)$$

Then

$$\mathbf{e}(1) = \frac{a_1\lambda_1\left(\mathbf{e}_1 + \frac{a_2}{a_1}\left(\frac{\lambda_2}{\lambda_1}\right)\mathbf{e}_2 + \cdots + \frac{a_{NP}}{a_1}\left(\frac{\lambda_{NP}}{\lambda_1}\right)\mathbf{e}_{NP}\right)}{\|\mathbf{F}\mathbf{e}(0)\|}$$
$$\mathbf{e}(2) = \frac{a_1\lambda_1\left(\mathbf{e}_1 + \frac{a_2}{a_1}\left(\frac{\lambda_2}{\lambda_1}\right)^2\mathbf{e}_2 + \cdots + \frac{a_{NP}}{a_1}\left(\frac{\lambda_{NP}}{\lambda_1}\right)^2\mathbf{e}_{NP}\right)}{\|\mathbf{F}\mathbf{e}(1)\|}$$
$$\vdots$$
$$\mathbf{e}(n) = \frac{a_1\lambda_1\left(\mathbf{e}_1 + \frac{a_2}{a_1}\left(\frac{\lambda_2}{\lambda_1}\right)^{n-1}\mathbf{e}_2 + \cdots + \frac{a_{NP}}{a_1}\left(\frac{\lambda_{NP}}{\lambda_1}\right)^{n-1}\mathbf{e}_{NP}\right)}{\|\mathbf{F}\mathbf{e}(n-1)\|} \quad (42)$$

Because of the ordering of the eigenvalues, as $n \to \infty$

$$\mathbf{e}(n) \to a_1\mathbf{e}_1 \quad (43)$$

which is the eigenvector of $\mathbf{F}$ corresponding to

Table 1. RLS-based adaptive algorithm for the proposed method.

Initialize the algorithm at time n=0, set	
$\mathbf{Q}_1(0)=\mathbf{Q}_2(0)=\delta^{-1}\mathbf{I}$	$MP \times MP$
$\mathbf{P}_1(0)=\mathbf{P}_2(0)=\mathbf{0}$	$NP \times MP$
$\mathbf{F}(0)=\mathbf{0}$	$NP \times NP$
$\mathbf{R}(0)=\delta^{-1}\mathbf{I}$	$NP \times NP$
$\mathbf{e}(0)=[1,0,\cdots,0]$	$NP \times 1$
For n=1, 2, 3, $\cdots$, do the following	
$\mathbf{K}_1(n)=\dfrac{\lambda^{-1}\mathbf{Q}_1(n-1)\mathbf{x}_M(n-d)}{1+\lambda^{-1}\mathbf{x}_M^H(n-d)\mathbf{Q}_1(n-1)\mathbf{x}_M(n-d)}$	$MP \times 1$
$\mathbf{K}_2(n)=\dfrac{\lambda^{-1}\mathbf{Q}_2(n-1)\mathbf{x}_M(n-d-1)}{1+\lambda^{-1}\mathbf{x}_M^H(n-d-1)\mathbf{Q}_2(n-1)\mathbf{x}_M(n-d-1)}$	$MP \times 1$
$\mathbf{f}_1(n)=\mathbf{x}_N(n)-\mathbf{P}_1(n-1)\mathbf{x}_M(n-d)$	$NP \times 1$
$\mathbf{f}_2(n)=\mathbf{x}_N(n)-\mathbf{P}_2(n-1)\mathbf{x}_M(n-d-1)$	$NP \times 1$
$\mathbf{P}_1(n)=\mathbf{P}_1(n-1)+\mathbf{f}_1(n)\mathbf{K}_1^H(n)$	$NP \times MP$
$\mathbf{P}_2(n)=\mathbf{P}_2(n-1)+\mathbf{f}_2(n)\mathbf{K}_2^H(n)$	$NP \times MP$
$\mathbf{Q}_1(n)=\lambda^{-1}\mathbf{Q}_1(n-1)-\lambda^{-1}\mathbf{K}_1(n)\mathbf{x}_M^H(n-d)\mathbf{Q}_1(n-1)$	$MP \times MP$
$\mathbf{Q}_2(n)=\lambda^{-1}\mathbf{Q}_2(n-1)-\lambda^{-1}\mathbf{K}_2(n)\mathbf{x}_M^H(n-d-1)\mathbf{Q}_2(n-1)$	$MP \times MP$
$\mathbf{f}(n)=\mathbf{f}_2(n)-\mathbf{f}_1(n)$	$NP \times 1$
$\mathbf{F}(n)=\lambda\mathbf{F}(n-1)+\mathbf{f}(n)\mathbf{f}^H(n)$	$NP \times NP$
$\mathbf{e}(n)=\mathbf{F}\mathbf{e}(n-1)$	$NP \times 1$
$\lambda(n)=\mathbf{e}^H(n)\mathbf{F}\mathbf{e}(n)$	1×1
$\hat{\mathbf{H}}_2=\sqrt{\lambda(n)}\cdot\mathbf{e}(n)$	$NP \times 1$
$\mathbf{R}(n)=\lambda\mathbf{R}(n-1)+\mathbf{x}_N(n)\mathbf{x}_N^H(n)$	$NP \times NP$
$\mathbf{B}(n)=\lambda^{-1}\mathbf{B}(n-1)-\lambda^{-1}\mathbf{K}(n)\mathbf{x}_N^H(n)\mathbf{B}(n-1)$	$NP \times NP$
$\mathbf{K}(n)=\dfrac{\lambda^{-1}\mathbf{B}(n-1)\mathbf{x}_N(n)}{1+\lambda^{-1}\mathbf{x}_N^H(n)\mathbf{B}(n-1)\mathbf{x}_N(n)}$	$NP \times 1$
$\mathbf{g}(n)=\mathbf{B}(n)\hat{\mathbf{H}}(d)$	$NP \times 1$

the largest eigenvalue. The eigenvalue itself is found by a Rayleigh quotient,

$$\frac{\mathbf{e}^H(n)\mathbf{F}\mathbf{e}(n)}{\|\mathbf{e}(n)\|}\rightarrow\lambda_1 \tag{44}$$

It should be noted that the MMSE equalizer is designed for transmitted symbol recovery at specific decision delay. Thus, different decision delay can result in different performance. A recursive form to get best decision delay is discussed in [12] and [22]. To get best decision delay choice, [12] proposes the minimizing MSE is given by

$$J_{\mathrm{MMSE}}(d)=1-\mathbf{H}^H(d)\mathbf{R}^{+}\mathbf{H}(d) \tag{45}$$

If the transmitted symbols have constant modulus (CM) property, which is practical case in digitally modulated signal such as QAM or PSK, the best

Table 2. LMS-based adaptive algorithm for the proposed method.

Initialize the algorithm at time n=0, set	
$\mathbf{P}_1(0)=\mathbf{P}_2(0)=\mathbf{0}$	$NP \times MP$
$\mathbf{F}(0)=\mathbf{0}$	$NP \times NP$
$\mathbf{R}(0)=\delta^{-1}\mathbf{I}$	$NP \times NP$
$\mathbf{e}(0)=[1,0,\cdots,0]$	$NP \times 1$
For n=1, 2, 3, $\cdots$, do the following	
$\mathbf{f}_1(n)=\mathbf{x}_N(n)-\mathbf{P}_1(n)\mathbf{x}_M(n-d)$	$NP \times 1$
$\mathbf{f}_2(n)=\mathbf{x}_N(n)-\mathbf{P}_2(n)\mathbf{x}_M(n-d-1)$	$NP \times 1$
$\mathbf{P}_1(n)=\mathbf{P}_1(n-1)+\mu_1\mathbf{f}_1(n)\mathbf{x}_M^H(n-d)$	$NP \times MP$
$\mathbf{P}_2(n)=\mathbf{P}_2(n-1)+\mu_2\mathbf{f}_2(n)\mathbf{x}_M^H(n-d-1)$	$NP \times MP$
$\mathbf{f}(n)=\mathbf{f}_2(n)-\mathbf{f}_1(n)$	$NP \times 1$
$\mathbf{F}(n)=\lambda\mathbf{F}(n-1)+\mathbf{f}(n)\mathbf{f}^H(n)$	$NP \times NP$
$\mathbf{e}(n)=\mathbf{F}\mathbf{e}(n-1)$	$NP \times 1$
$\lambda(n)=\mathbf{e}^H(n)\mathbf{F}\mathbf{e}(n)$	1×1
$\hat{\mathbf{H}}_2=\sqrt{\lambda(n)}\cdot\mathbf{e}(n)$	$NP \times 1$
$\mathbf{R}(n)=\lambda\mathbf{R}(n-1)+\mathbf{x}_N(n)\mathbf{x}_N^H(n)$	$NP \times NP$
$\mathbf{B}(n)=\lambda^{-1}\mathbf{B}(n-1)-\lambda^{-1}\mathbf{K}(n)\mathbf{x}_N^H(n)\mathbf{B}(n-1)$	$NP \times NP$
$\mathbf{K}(n)=\dfrac{\lambda^{-1}\mathbf{B}(n-1)\mathbf{x}_N(n)}{1+\lambda^{-1}\mathbf{x}_N^H(n)\mathbf{B}(n-1)\mathbf{x}_N(n)}$	$NP \times 1$
$\mathbf{g}(n)=\mathbf{B}(n)\hat{\mathbf{H}}(d)$	$NP \times 1$

decision delayed blind equalizer can be determined by the following CM index [22]:

$$J_{\mathrm{CM}}=\sum\left(\left|\mathbf{g}_d^H\mathbf{x}_N(n)\right|^2-1\right)^2 \tag{46}$$

where $\mathbf{g}_d$ is a d-delay blind equalizer. The blind equalizer having the smallest J_{MMSE} or J_{CM} value will be considered as the best decision delayed blind equalizer. In many practical channels, it has been observed [1] that selecting $d \simeq (N+L)/2$ results in good performance. RLS- and LMS-based adaptive algorithms for the proposed method are summarized in Table 1 and Table 2, respectively. The computational complexity of the RLS-based proposed algorithm is approximately

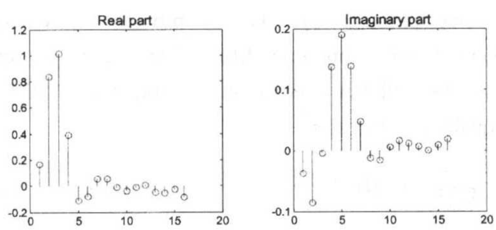

Fig. 2 Real and imaginary part of the shortened real measured channel impulse response.

$9(MP)^2 + 11(NP)^2 + 4(MP)(NP)$. Moreover, the computational complexity of the LMS-based proposed algorithm is reduced to about $11(NP)^2 + 4(MP)(NP)$.

Ⅳ. Simulation Results

In this section, we use computer simulations to evaluate the performance of the proposed algorithm. We compare the performance of the proposed algorithm with some existing algorithms. The SNR is defined to be at the input to the equalizer as shown in Fig. 1.

$$\text{SNR} = E\left[\sum_{j=0}^{P-1} |a_j(n)|^2\right] \Big/ E\left[\sum_{j=0}^{P-1} |v_j(n)|^2\right] \tag{47}$$

As a performance index, we estimate the residual ISI over 50 independent Monte Carlo runs. The residual ISI is defined as

$$\text{ISI} = \frac{\sum_n |q(n)|^2 - \max_n |q(n)|^2}{\max_n |q(n)|^2} \tag{48}$$

where

$$q(n) = \sum_{i=0}^{P-1} \sum_{j=0}^{L-1} g_i(j) h_i(n-j) \tag{49}$$

The source symbols are drawn from a 16-QAM constellation with a uniform distribution. The noise is drawn from white Gaussian distribution at a varying SNR. The simulated channel is a length-16 version of an empirically measured (T/2)-spaced (P=2) digital microwave radio channel with 230 taps, which we truncated to obtain a channel with L=8. The Microwave channel chan1.mat is founded at http://spib.rice.edu/spib/microwave.html. The shortened version is derived by linear decimation of the FFT of the full-length (T/2)-spaced impulse response and taking the IFFT of the decimated version (see [16] for more details on this channel). The overall channel impulse response is shown in Fig. 2.

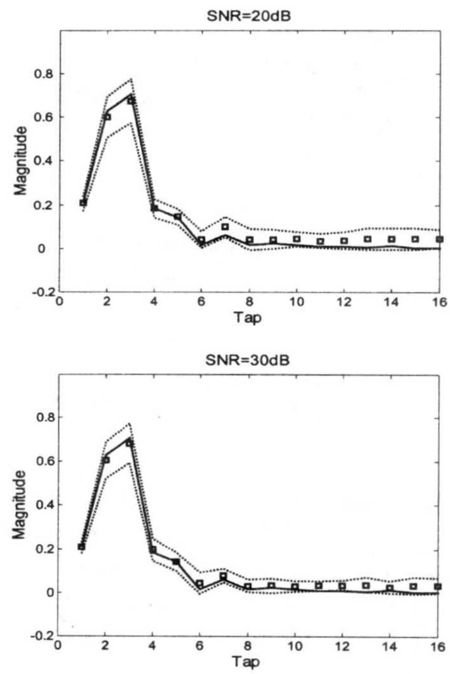

Fig. 4 Magnitude of the estimated channel under SNR = 20dB and SNR = 30dB at 50 trials, the original channel (solid line), the averaged estimated±standard deviation (dotted line), and the mean value of 50 estimates (square symbol).

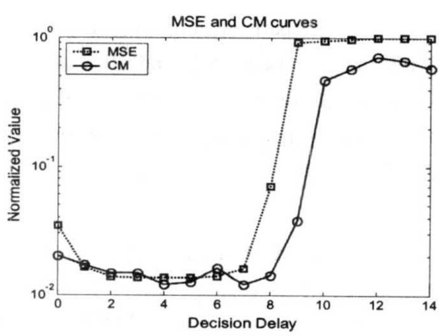

Fig. 3 The best decision delay choice rule.

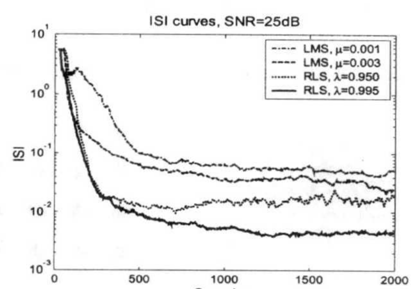

Fig. 5 Comparison of residual ISI for the proposed algorithm, SNR = 25dB.

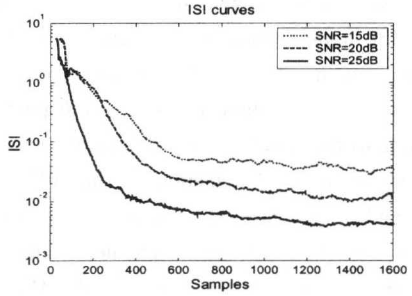

Fig. 6 ISI curves of the proposed RLS algorithm for different SNR's.

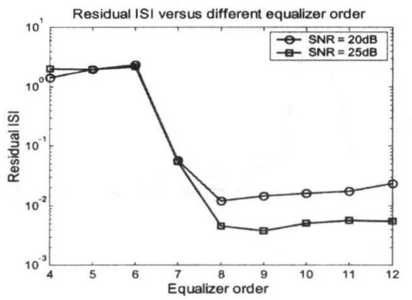

Fig. 7. Residual ISI curves versus the different equalizer order, SNR = 20dB and SNR = 25dB.

We consider the performance of the proposed RLS and LMS algorithms for blind MMSE equalizer. Let the equalizer order $N=8$, and let the delay be $d=7$. In Fig. 3, we show the J_{MMSE} and J_{CM} versus decision delay d under SNR = 30dB. Fig. 4 shows 50 estimates of the cross-correlation vector under SNR = 20dB and 30dB, respectively. We have discussed earlier that we can obtain channel coefficient vector if delay equals to channel length. From this figure, we can obtain the channel estimation from the

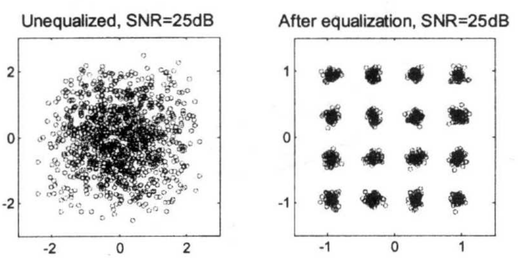

Fig. 8 Scatter plots before and after equalization for the proposed RLS algorithm, SNR=25dB.

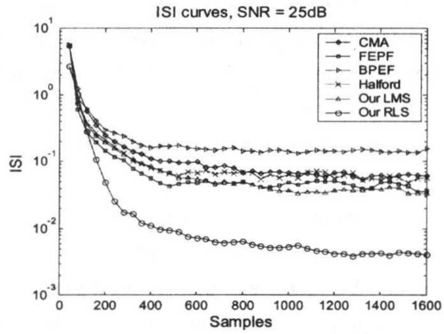

Fig. 9 ISI comparisons of existing algorithms and the proposed algorithm, SNR = 25dB.

cross-correlation vector with delay corresponding to the channel length. The performance of the proposed RLS and LMS algorithms are shown in Fig. 5. It is found from the results that the proposed RLS and LMS algorithms and achieve sufficiently low ISI after 1000 samples. Fig. 6 shows the ISI curves of the proposed RLS algorithm under SNR = 15dB, 20dB, and 25dB. Fig. 7 presents the performance of the proposed RLS algorithm after 2000 samples for several equalizer orders under SNR = 20dB and 25dB. From this figure, we can conclude that the exact order estimation is not needed in the proposed algorithm. Fig. 8 shows the received constellation and the equalized constellation at SNR = 25dB for 1000 samples. We compare the performance of the proposed algorithm with some existing algorithms: the CMA of [17], least-squares lattice (LSL) one-step forward prediction of [9] (denotes FPEF), LSL one-step backward prediction of [9] (denotes BPEF), and RLS equalizer of [18] (denote Halford). Let the all equalizer orders be $N=8$ for fair comparison. Fig. 9 shows the ISI curves for the proposed LMS and RLS algorithms and existing algorithms at SNR = 25dB. It is shown that the proposed algorithms perform better than the others.

V. Conclusion

This paper presents blind MMSE channel equalization using multichannel prediction-based cross-correlation vector estimation. A block-type algorithm is developed using the correlation matrices of the received signal. Then, we have developed the RLS and LMS type algorithm for obtaining the multichannel linear prediction error. Furthermore, we have used the iterative power method for tracking the cross-correlation vector. Our proposed algorithms do not require the exact channel order estimation and are robust to channel order mismatch in nature of linear prediction characteristics. Moreover, cross-correlation vector estimation algorithm can be used for partial or complete channel estimation via delay control. Simulation results show that the proposed algorithms outperform many existing algorithms.

References

[1] J. G. Proakis, *Digital Communication*, 4th ed. New York: McGraw Hill, 2001.

[2] Z. Ding, R. A. Kennedy, B. D. O. Anderson, and C. R. Johnson, Jr., "Ill-convergence of Godard blind equalizers in data communication systems," *IEEE Trans. Signal Processing*, vol. 39, no. 9, pp. 1313-1327, Sept. 1991.

[3] Y. Li and Z. Ding, "Global convergence of fractionally-spaced Godard (CMA) adaptive equalizers," *IEEE Trans. Signal Processing*, vol. 44, no. 4, pp. 818-826, Apr. 1996.

[4] L. Tong, G. Xu, and T. Kailath, "Blind identification and equalization based on second-order statistics: A time domain approach," *IEEE Trans. Inform. Theory*, vol. 40, no. 2, pp. 340-349, Mar. 1994.

[5] L. Tong, G. Xu, B. Hassibi, and T. Kailath, "Blind channel identification based on second-order statistics: A frequency- domain approach," *IEEE Trans. Inform. Theory*, vol. 41, no. 1, pp. 329-334, Jan. 1995.

[6] E. Moulines, P. Duhamel, J. F. Cardoso, and S. Mayrargue, "Subspace methods for the blind identification of multichannel FIR filter," *IEEE Trans Signal Processing*, vol. 43, no. 2, pp. 516-525, Feb. 1995.

[7] K. Abed-Meraim, E. Moulines, and P. Loubaton, "Prediction error method for second-order blind identification," *IEEE Trans. Signal Processing*, vol. 45, no. 3, pp. 694-704, Mar. 1997.

[8] C. B. Papadias and D. T. M. Slock, "Fractionally spaced equalization of linear polyphase channels and related blind techniques based on multichannel linear prediction," *IEEE Trans. Signal Processing*, vol. 47, no. 3, pp. 641-653, Mar. 1999.

[9] J. Mannerkoski and D. P. Taylor, "Blind equalization using least-squares lattice prediction," *IEEE Trans. Signal Processing*, vol. 47, no. 3, pp. 630-640, Mar. 1999.

[10] J. Mannerkoski, V. Koivunen, and D. P. Taylor, "Performance bounds for multistep prediction-based blind equalization," *IEEE Trans. Signal Processing*, vol. 49, no. 1, pp. 84-93, Jan. 2001.

[11] D. T. Slock and C. B. Papadias, "Further results on blind identification and equalization of multiple FIR channels," in *Proc. ICASSP*, 1995, pp. 1964-1967.

[12] J. Shen and Z. Ding, "Direct blind MMSE channel equalization based on second order statistics," *IEEE Trans. Signal Processing*, vol. 48, no. 4, pp. 1015-1022, Apr. 2000.

[13] X. Li and H. Fan, "Direct estimation of blind zero-forcing equalizers based on second-order statistics," *IEEE Trans. Signal Processing*, vol. 48, no. 8, pp. 2211-2218, Aug. 2000.

[14] S. Haykin, *Adaptive Filter Theory*, 3rd ed. Upper Saddle River, NJ: Prentice-Hall, 1996.

[15] G. H. Golub and C. F. Van Loan, *Matrix Computations*, 3rd ed. Baltimore, MD: Johns Hopkins Univ. Press, 1996.

[16] J. Endres, S. D. Halford, C. R. Johnson, and G. B. Giannakis, "Simulated comparisons of blind equalization algorithms for cold startup applications," *Int. J. Adaptive Contr. Signal Process.*, vol. 12, no. 3, pp. 283-301, May 1998.

[17] T. R. Treichler, I. Fijalkow, and C. R. Johnson, "Fractionally spaced equalizers: how long should they be?," *IEEE Signal Processing Mag.*, vol. 13, no. 3, pp. 65-81, May 1996.

[18] G. B. Giannakis and S. D. Halford, "Blind

fractionally spaced equalization of noisy FIR channels: direct and adaptive solutions," *IEEE Trans. Signal Processing*, vol. 45, no. 9, pp. 2277-2292, Sept. 1997.

[19] B. Yang, "Projection approximation subspace tracking," *IEEE Trans. Signal Processing*, vol. 43, no. 1, pp. 95-107, Jan. 1995.

[20] P. Common and G. H. Golub, "Tracking a few extreme singular values and vectors in signal processing," *Proc. IEEE*, vol. 78, no. 8, pp. 1327-1343, Aug. 1990.

[21] D. Gesbert and P. Duhamel, "Robust blind channel identification and equalization based on multi-step predictors," in *Proc. ICASSP*, 1997, pp. 3621-3624.

[22] H. Luo and R. Liu, "Blind equalizers for multipath channels with best equalization delay," in *Proc. ICASSP*, 1999, pp. 2511-2513.

[23] T. K. Moon and W. C. Stirling, *Mathematical Methods and Algorithms for Signal Processing.* Upper Saddle River, NJ: Prentice-Hall, 2000.

[24] K. S. Ahn, J. P. Cho, and H. K. Baik, "Multistep prediction-based blind equalization and efficient adaptive implementation," *Journal of the KICS*, vol. 26, no. 6B, pp. 776-783, June 2001.

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