LP-Based Blind Adaptive Channel Identification and Equalization with Phase Offset Compensation

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ABSTRACT

Blind channel identification and equalization attempt to identify the communication channel and to remove the inter-symbol interference caused by a communication channel without using any known training sequences. In this paper, we propose a blind adaptive channel identification and equalization algorithm with phase offset compensation for single-input multiple-output (SIMO) channel. It is based on the one-step forward multichannel linear prediction error method and can be implemented by an RLS algorithm. Phase offset problem is inherent part of any second-order statistics-based blind identification and equalization. To solve this problem, we use a blind adaptive algorithm called the constant modulus derotator (CMD) algorithm based on constant modulus algorithm (CMA). Moreover, unlike many known subspace (SS) methods or cross relation (CR) methods, our proposed algorithms do not require channel order estimation. Therefore, our algorithms are robust to channel order mismatch.

Key words: Blind equalization, blind identification, multichannel linear prediction, phase offset Compensation

Ⅰ. Introduction

In recent years, the interest in blind channel estimation problem has received considerable attention. The basic blind channel estimation problem involves the channel model where only the observation signal is available for processing in the estimation channel. Earlier blind channel estimation approaches mostly depend on higher order statistics (HOS), because the second order statistics (SOS) does not contain phase information for stationary signal [1], [2]. Using HOS-based methods, it has been shown that the performance index as the optimization criterion is nonlinear with respect to estimation parameters and these methods require a large amount of data samples. Therefore, these methods have the disadvantage that their computational complexity may be large. See, for example, [1], [2] and references therein.

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 signal processing and communication fields. This is achieved by exploiting assumed cyclostationary properties, induced by oversampling or antenna array at the receiver part [3], [4]. Among many SOS-based methods, the subspace (SS) methods [5], the cross relation (CR) method [6], and the linear prediction (LP) methods [7]-[11] are the three main categories. When the channel order is known, the SS-based approaches can provide accurate estimations. However, SS-based methods 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 [12]. However, the LP-based methods are very robust to order overdetermination. Moreover, with respect to computational complexity, the SS-based methods require eigenvalue decomposition, and the

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high computational complexity becomes disadvantageous for their adaptive implementation.

The LP-based channel estimation or equalization, which was first introduced by Slock et al. [7], followed by Slock and Papadias [8], [9], Meraim et al. [10] and, more recently, by Li and Fan [11]. The work discussed by Slock et al. mainly focused on blind channel equalization. The approach presented in [10] is a block based algorithm rather than adaptive algorithms. Therefore, the computation of the correlation matrix and its inverse problem is inevitable. Li and Fan proposed a blind channel estimation algorithms as a by product of an blind channel equalizer [11], but the channel estimation was performed after the equalizer was obtained.

Up to date, the implementation of SOS-based methods has been mostly block based algorithm rather than adaptive algorithms. Most communication channels are time-varying in practice. Therefore, the algorithms should be able to track the change of the channel impulse response. Moreover, in a fast fading channel, the multipath channels in wireless communications vary rapidly, and we only have a few data samples corresponding to the same channel characteristics.

In this paper, we propose a blind adaptive channel identification and equalization algorithm for SIMO channel. The proposed algorithm is based on multichannel linear prediction that is less sensitive to the channel order length. Most notations are standard: vectors and matrices are boldface small and capital letters, respectively; the matrix transpose, the Hermitian, and the Moore-Penrose pseudoinverse are denoted by $(.)^T$, $(.)^H$, and $(.)^{\dagger}$, respectively; $\mathbf{I}_P$ is the $P\times P$ identity matrix; $E[.]$ is the statistical expectation.

This paper is organized as follows. The system model is presented in Section Ⅱ. In Section Ⅲ, we discuss multichannel linear prediction problem for blind channel identification and equalization. Simulation results are presented in Section Ⅳ. Section Ⅴ concludes our results

Ⅱ. System Model and Multichannel Linear Prediction

Let $x(t)$ be the signal at the output of a noisy channel at time kT_s, T_s being the symbol period. The continuous time received signal is

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

where $s(k)$ denotes the transmitted symbol at time kT_s, $h(t)$ 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 [3]. Here we consider the oversampling technique. With an oversampling factor P, $x(t)$ is sampling at $t=nT_s/P$. The received signal is

$$x(n)=\sum_{k=-\infty}^{\infty}s(k)h\left(\frac{nT_s}{P}-kT_s\right)+v\left(\frac{nT_s}{P}\right) \tag{2}$$

The ith subchannel response is defined as $h_i(n)\equiv h(t+iT_s/P+nT_s)$, $n=0,\cdots,L$, where L is the sub-channel length. Its output signal $x_i(n)\equiv x(t+iT_s/P+nT_s)$ is

$$x_i(n)=\sum_{k=0}^{L}h_i(k)s(n-k)+v_i(n) \tag{3}$$

where $i=0, \cdots, P\text{-}1$ and the symbol period is normalized to $T_s=1$. The received signal $x(nT_s/P)$ is cyclostationary, which enables blind identification and equalization of the channel from the SOS of the received signal, if the subchannels $h_i(n)$ have no common zero [3].

Let

$$\begin{aligned}\mathbf{x}(n)&=[x_0(n),\cdots,x_{P-1}(n)]^T\\ \mathbf{h}(n)&=[h_0(n),\cdots,h_{P-1}(n)]^T\\ \mathbf{v}(n)&=[v_0(n),\cdots,v_{P-1}(n)]^T\end{aligned} \tag{4}$$

The scalar cyclostationary process $x(n/T_s)$ is thus transformed into a wide-sense stationary vector process. We represent $x_i(n)$ in a vector form as

$$\mathbf{x}(n)=\sum_{k=0}^{L}s(k)\mathbf{h}(n-k)+\mathbf{v}(n) \tag{5}$$

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

$$\mathbf{x}_N(n)=\mathbf{H}\mathbf{s}(n)+\mathbf{v}_N(n) \tag{6}$$

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.

$$\begin{aligned}\mathbf{s}(n)&=[s(n),\cdots,s(n-L-N+1)]^T\\ \mathbf{x}_N(n)&=[\mathbf{x}^T(n),\cdots,\mathbf{x}^T(n-N+1)]^T\\ \mathbf{v}_N(n)&=[\mathbf{v}^T(n),\cdots,\mathbf{v}^T(n-N+1)]^T\end{aligned} \tag{7}$$

and

$$\mathbf{H}=\begin{bmatrix}\mathbf{h}(0)&\cdots&\mathbf{h}(L)&\cdots&\mathbf{0}\\ \vdots&\ddots&\vdots&\ddots&\vdots\\ \mathbf{0}&\cdots&\mathbf{h}(0)&\cdots&\mathbf{h}(L)\end{bmatrix} \tag{8}$$

We assume the following used through the paper.

1) The input sequence $s(n)$ is zero-mean and white with unit variance.
2) The additive noise $v(n)$ is zero-mean and white with variance σ_v^2.
3) The sequence $s(n)$ and $v(n)$ are uncorrelated.
4) The matrix $\mathbf{H}$ has full rank, i.e., the subchannels $h_i(n)$ have no common zeros to satisfy the Bezout equation [3]. Also, $h_i(0)\neq 0$ for some i.
5) The dimensions of $\mathbf{H}$ obey $NP\geq N+L$

Let us define $\mathbf{r}(k)=E[\mathbf{x}(n+k)\mathbf{x}^H(n)]$ and $\mathbf{R}_N=E[\mathbf{x}_N(n+k)\mathbf{x}_N^H(n)]$. Using assumptions A1)-A3), we can write the exact correlation matrix of $\mathbf{x}_N(n)$ as

$$\mathbf{R}_N=E[\mathbf{x}_N(n)\mathbf{x}_N^H(n)]=\mathbf{H}\mathbf{H}^H+\sigma_v^2\mathbf{I}_{NP} \tag{9}$$

An one-step ahead forward predictor of order N produces an estimate $\hat{\mathbf{x}}(n)$ of the received signal $\mathbf{x}(n)$ based on previous signal $\mathbf{x}_{N-1}(n-1)$. The one-step ahead forward prediction error is then

$$\begin{aligned}\mathbf{f}(n)&=\mathbf{x}(n)-[\mathbf{p}_1\mathbf{x}(n-1)+\cdots+\mathbf{p}_{N-1}\mathbf{x}(n-N-1)]\\ &=[\mathbf{I}_P\ \ -\mathbf{P}_N]\mathbf{x}_N(n)=\mathbf{A}_N\mathbf{x}_N(n)\end{aligned} \tag{10}$$

where $-\mathbf{p}_k$ for $k=1,\cdots,N-1$ are $P\times P$ matrices of a FPEF of order N-1. The FPEF coefficients are selected such that mean square value of $\mathbf{f}(n)$, i.e., $E[|\mathbf{f}(n)^2|]$, is minimized. The filter coefficients $\mathbf{P}_N$ are obtained from the Wiener-Hopf equations

$$\mathbf{P}_N=\mathbf{r}_1\mathbf{R}_{N-1}^{-1} \tag{11}$$

where $\mathbf{r}_1=[\mathbf{r}(1),\mathbf{r}(2),\cdots,\mathbf{r}(N-1)]$. When the FPEF is optimum in the sense of MSE, the input signal vector $\mathbf{x}_{N-1}(n-1)$ and the prediction error $\mathbf{f}(n)$ are orthogonal. Consider the noise free case. As shown in [7]-[11], we obtain

$$\mathbf{f}(n)=\mathbf{h}(0)s(n) \tag{12}$$

Ⅲ. Blind Adaptive Equalization and Identification Based on Linear Prediction

1. Blind Channel Equalization and Identification

We consider blind ZF-equalizer that are based on multichannel linear prediction. A ZF-equalizer can be obtained from (12) that in the absence of additive channel noise. The transmitted symbol can be extracted as following

$$\hat{s}(n)=\frac{\hat{\mathbf{h}}^H(0)\mathbf{f}(n)}{\|\hat{\mathbf{h}}(0)\|^2} \tag{13}$$

$\hat{\mathbf{h}}(0)$ can be estimated from the correlation matrix $\mathbf{P}_f=E[\mathbf{f}(n)\mathbf{f}^H(n)]$ [9]-[11]. Let us denote the unit-norm eigenvector corresponding to the nonzero eigenvalue of $\mathbf{P}_f$ by $\mathbf{u}$ and the corresponding eigenvalue λ. In the absence of additive channel noise, $\mathbf{P}_f=\mathbf{h}(0)\mathbf{h}^H(0)$. Then correlation matrix $\mathbf{P}_f$ is a rank-one matrix. Therefore, $\hat{\mathbf{h}}(0)=\sqrt{\lambda}\,\mathbf{u}$ up to a unitary complex constant $(\hat{\mathbf{h}}(0)=\mathbf{h}(0)e^{j\theta})$.

Blind identification and equalization can only be performed up to a multiplicative constant $e^{j\theta}$ so that for ZF-equalization, the extracted symbol is $\hat{s}(n)=s(n)e^{-j\theta}$. This scalar rotation is an inherent part of any SOS-based blind identification and equalization [10], [11].

From (6), (10) and (12), we know that

$$[\mathbf{I}_P - \mathbf{P}_{N-1}]\mathbf{H}\mathbf{s}(n) = \mathbf{h}(0)s(n) \tag{14}$$

Postmultiflying by $\mathbf{s}^H(n)$ and taking expectation operator, we get

$$[\mathbf{I}_P - \mathbf{P}_{N-1}]\mathbf{H} = [\mathbf{h}(0)\ 0\ \cdots\ 0] \tag{15}$$

Rewrite the matrix $\mathbf{P}_{N-1}$ as $\mathbf{P}_{N-1}$ = $[\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_{N-1}]$. Noting the special structure of $\mathbf{H}$, we can obtain

$$\begin{aligned}\mathbf{h}(1) &= \mathbf{p}_1\mathbf{h}(0)\\ \mathbf{h}(2) &= \mathbf{p}_1\mathbf{h}(1)+\mathbf{p}_2\mathbf{h}(0)\\ \mathbf{h}(3) &= \mathbf{p}_1\mathbf{h}(2)+\mathbf{p}_2\mathbf{h}(1)+\mathbf{p}_3\mathbf{h}(0)\\ &\vdots\\ \mathbf{h}(L) &= \mathbf{p}_1\mathbf{h}(L-1)+\mathbf{p}_2\mathbf{h}(L-2)+\cdots+\mathbf{p}_L\mathbf{h}(0)\end{aligned} \tag{16}$$

Suppose that $\mathbf{P}_{N-1}$ is the optimal multichannel linear predictor, $N \geq L$; then channel coefficients $\mathbf{h}(1)$, $\mathbf{h}(2)$, $\cdots$, $\mathbf{h}(L)$ can be determined from $\mathbf{P}_{N-1}$ and $\mathbf{h}(0)$.

We propose the adaptive algorithms for updating the multichannel linear prediction error filter coefficients. We are required to compute the multichannel prediction matrices $\mathbf{P}_{N-1}$ and to estimate the multichannel prediction error $\mathbf{f}(n)$. In order to fast convergence, we can use the RLS algorithm to update the multichannel linear prediction as following [15]

- Compute output:

$$\mathbf{x}(n) = \mathbf{P}_{N-1}(n)\mathbf{x}_{N-1}(n-1) \tag{17}$$

- Compute FPE:

$$\mathbf{f}(n) = \mathbf{x}(n) - \hat{\mathbf{x}}(n) \tag{18}$$

- Compute Kalman gain:

$$\mathbf{K}(n) = \frac{\mathbf{Q}(n-1)\mathbf{x}(n-1)}{\lambda + \mathbf{x}^H(n-1)\mathbf{Q}(n-1)\mathbf{x}(n-1)} \tag{19}$$

- Update inverse of the correlation matrix:

$$\mathbf{Q}(n) = \frac{\mathbf{Q}(n-1) - \mathbf{K}(n)\mathbf{x}^H(n-1)\mathbf{Q}(n-1)}{\lambda} \tag{20}$$

- Update FPEF coefficients:

$$\mathbf{P}_{N-1}(n) = \mathbf{P}_{N-1}(n-1) + \mathbf{f}(n)\mathbf{K}^H(n) \tag{21}$$

The term $\lambda(0 \leq \lambda \leq 1)$ 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 [15]. From the covariance matrix of FPE in (18), its estimation of adaptive manner is given by

$$\mathbf{F}(n) = \lambda\mathbf{F}(n-1) + \mathbf{f}(n)\mathbf{f}^H(n) \tag{22}$$

Compared with (18), $\mathbf{h}(0)$ is the column of $\mathbf{F}(n)$ with the largest norm.

2. Blind Phase Offset Compensation

The performance of channel identification depends on the accuracy of $\mathbf{h}(0)$. An eigenvalue decomposition of $\mathbf{P}_f$ will allow us to identify $\hat{\mathbf{h}}(0)=\mathbf{h}(0)e^{j\theta}$ for noise-free case. Blind identifi-cation and equalization can only be performed up to a multiplicative constant $e^{-j\theta}$ so that for ZF-equalization, the extracted symbol is

$$\hat{s}(n) = s(n)e^{-j\theta} \tag{23}$$

In order to estimated θ and directly remove this phase offset, consider the single tap derotator shown in Fig. 1, where $\hat{\theta}$ represents an estimate of θ. This can be viewed as the problem of

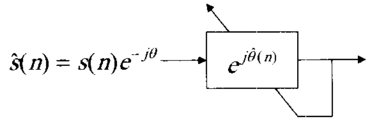

Fig. 1. A single tap derotator.

equalizing a complex scalar channel. Moreover, some HOS-based blind phase recovery methods are proposed, but these ones are not appropriate for adaptive implementation [13]. Therefore, we use a blind adaptive scheme called the constant modulus derotator (CMD) for removing phase offset, which is based on constant modulus algorithm (CMA) of [14].

In the absence of noise, and if $\hat{\theta}$ were exactly equal to θ, then the projection of $\hat{s}(n)$ onto the real axis would consist of a collection of points at the symbol values defined by the constellation from which $s(n)$ were drawn. The projection will consist of a number of clusters as these symbol values. Similarly, when $\hat{\theta}$ is offset somewhat from θ, the clusters widen. Thus, a criterion for estimating θ is to try and minimize the dispersion of the projection of the constellation onto the real axis. Consider the cost function

$$J(\hat{\theta}) = E[(\mathrm{Re}(\hat{s}(n)e^{j\hat{\theta}})^2 - \gamma)^2] \qquad (24)$$

where γ is any real constant and Re(·) denotes the real projection operator. For QAM or PSK constellation, the $\hat{\theta}$ that minimizes $J(\hat{\theta})$ will be equal to θ. Using a stochastic gradient algorithm to minimize (18) gives the CMD algorithm

$$\hat{\theta}(n+1) = \hat{\theta}(n) - \mu(\mathrm{Re}(\hat{s}(n)e^{j\hat{\theta}(n)})^2 - \gamma)\cdot \mathrm{Re}(\hat{s}(n)e^{j\hat{\theta}(n)})\,\mathrm{Im}(\hat{s}(n)e^{j\hat{\theta}(n)}) \qquad (25)$$

See [14] for more details on CMD algorithm. Table 1 briefly summaries the proposed algorithm, in which the linear prediction is implemented by using an RLS adaptation algorithm [6].

Ⅳ. Simulation Results

In this section, we use computer simulations to evaluate the performance of the proposed algorithm. The performance criterion is achieved by examining the root mean square error (RMSE) for blind channel identification.

Table 1. Summary of the proposed algorithm.

Initialize the algorithm at time n=0, set

$$\mathbf{Q}(0) = \delta^{-1}\mathbf{I}$$
$$\mathbf{P}_{N-1}(0) = \mathbf{0}$$
$$\mathbf{F}(0) = \mathbf{0}$$
$$\theta(0) = 0$$

For n = 1, 2, 3, ... , do the following

$$\mathbf{K}(n) = \frac{\mathbf{Q}(n-1)\mathbf{x}_{N-1}(n-1)}{\lambda + \mathbf{x}_{N-1}^H(n-1)\mathbf{Q}(n-1)\mathbf{x}_{N-1}(n-1)}$$
$$\mathbf{f}(n) = \mathbf{x}(n) - \mathbf{P}_{N-1}(n-1)\mathbf{x}_{N-1}(n-1)$$
$$\mathbf{P}_{N-1}(n) = \mathbf{P}_{N-1}(n-1) + \mathbf{f}(n)\mathbf{K}^H(n)$$
$$\mathbf{Q}(n) = \lambda^{-1}\mathbf{Q}(n-1) - \lambda^{-1}\mathbf{K}(n)\mathbf{x}_N^H(n-1)\mathbf{Q}(n-1)$$
$$\mathbf{F}(n) = \lambda\mathbf{F}(n-1) + \mathbf{f}(n)\mathbf{f}^H(n)$$

The column of $\mathbf{F}(n)$ with the largest norm is taken as the estimate of $\mathbf{h}(0)$, $\hat{\mathbf{h}}(0)$

$$\hat{s}(n) = \frac{\hat{\mathbf{h}}^H(0)\mathbf{f}(n)}{\|\hat{\mathbf{h}}(0)\|^2}$$
$$\hat{\theta}(n) = \hat{\theta}(n-1) - \mu(\mathrm{Re}(\hat{s}(n-1)e^{j\hat{\theta}(n-1)})^2 - \gamma)\cdot \mathrm{Re}(\hat{s}(n-1)e^{j\hat{\theta}(n-1)})\cdot \mathrm{Im}(\hat{s}(n-1)e^{j\hat{\theta}(n-1)})$$
$$\tilde{\mathbf{h}}(0) = e^{j\hat{\theta}(n)}\hat{\mathbf{h}}(0)$$
$$\tilde{s}(n) = e^{j\hat{\theta}(n)}\hat{s}(n)$$
$$\mathbf{h}^{(n)}(1) = \alpha\mathbf{h}^{(n-1)}(1) + (1-\alpha)\mathbf{p}_1\tilde{\mathbf{h}}^{(n)}(0)$$
$$\mathbf{h}^{(n)}(2) = \alpha\mathbf{h}^{(n-1)}(2) + (1-\alpha)[\mathbf{p}_1\mathbf{h}^{(n)}(1) + \mathbf{p}_2\tilde{\mathbf{h}}^{(n)}(0)]$$
$$\vdots$$
$$\mathbf{h}^{(n)}(L) = \alpha\mathbf{h}^{(n-1)}(L) + (1-\alpha)[\mathbf{p}_1\mathbf{h}^{(n)}(L-1) + \cdots + \mathbf{p}_L\tilde{\mathbf{h}}^{(n)}(0)]$$

$$\mathrm{RMSE} = \frac{1}{\|\mathbf{h}\|^2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\|\mathbf{h}_i - \mathbf{h}\|^2} \qquad (26)$$

where N is number of Monte Carlo trials, $\mathbf{h}$ is the optimal channel coefficients, and $\mathbf{h}_i$ is the estimate of the channels from the ith trial. A total number of 50 independent trials is performed. The coefficients of the impulse response used in simulations is given in Table 2. Subdividing the received signal (3) according to $x_i(n) = a_i(n) + v_i(n)$, we can define the SNR as $E[\|\mathbf{a}^2(n)\|]/E[\|\mathbf{v}^2(n)\|]$. For all simulation, the source symbol is drawn from a 16-QAM constellation

Table 2. Channel coefficients for simulations.

	$i=0$	$i=1$
$h_i(0)$	$+0.2890-0.0772j$	$+0.8911-0.2260j$
$h_i(1)$	$+0.9616+0.2323j$	$+0.2557+0.0493j$
$h_i(2)$	$-0.1946-0.0380j$	$-0.0219+0.0030j$
$h_i(3)$	$+0.0878+0.0101j$	$-0.0197-0.0126j$
$h_i(4)$	$-0.0336-0.0036j$	$+0.0198+0.0077j$
$h_i(5)$	$+0.0099+0.0033j$	$-0.0109-0.0011j$
$h_i(6)$	$+0.0031+0.0055j$	$+0.0164+0.0066j$
$h_i(7)$	$+0.0040+0.0022j$	$-0.0007-0.0020j$

with a uniform distribution. The noise is drawn

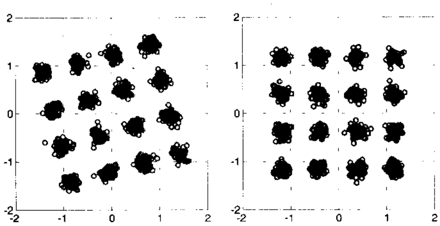

Fig. 2 Scatter plots after equalized received signal with phase offset and after phase offset compensation.

from a white Gaussian distribution at a varying SNR. Algorithm initialization parameters used in RLS algorithm are $\delta = 10^{-3}$, $\lambda = 0.995$.

We examine the effect of the first channel coefficient on equalizer performance. Scatter plots of the equalized received signal with phase offset and its compensation are presented in Fig. 2 for an SNR of 20dB. The convergence of $\hat{\mathbf{h}}(0)$ is shown in Fig. 3, both when $\hat{\mathbf{h}}(0)$ is estimated with the eigen-pair tracking algorithm and when it is blind phase compensation with CMD algorithm.

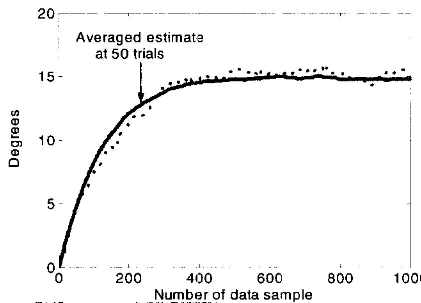

Fig. 4. Phase offset tracking.

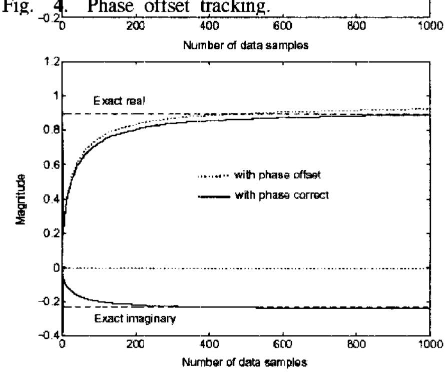

Fig. 3 Real and imaginary part of the exact, estimate and phase corrected estimate value of the $h_0(0)$ and $h_1(0)$.

Fig. 3 confirms that CMD algorithm compensates the phase offset, while Fig. 4 shows that the estimated phase offset track the true value ($\theta = \pi/12$) well. Fig. 3 and Fig. 4 are presented under SNR=20dB.

We investigate the performance of the proposed algorithm for channel identification. When the channel order is assumed to be known, Fig. 5 shows the RMSE curves as a function of the data samples size for the proposed method under SNR=16dB and 30dB. Convergence occurs after approximately 600 and 400 samples, respectively. Fig. 6 shows the performance of the proposed method under difference SNR situations. Aforementioned advantage of the prediction-based blind identification and equalization is robust to channel order overdetermination. Performing experiment for an SNR of 30dB, we examined the RMSE achieved after 600 samples for prediction orders N=6,⋯,12. The channel order is L=8. From Fig. 7, we can conclude that the exact

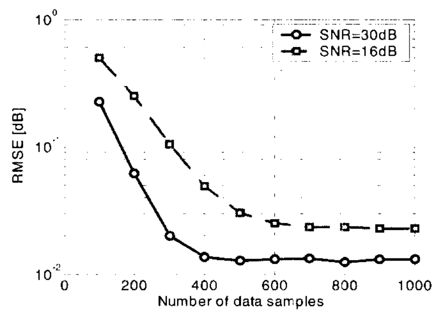

Fig. 5. RMSE curves for the proposed algorithm.

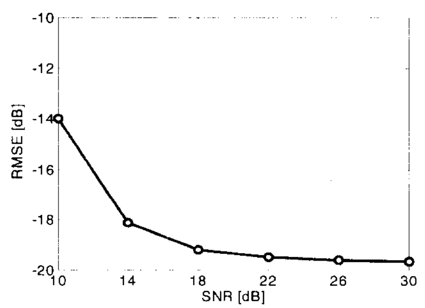

Fig. 6 Performance of the proposed algorithm under different SNR.

order is not needed in the proposed method.

Moreover, cross-correlation (CR) method as shown in [17], this algorithm is sensitive to channel order mismatch.

V. Conclusion

This paper presents blind adaptive channel identification and equalization using multichannel linear forward prediction error. A block-type algorithm is developed the correlation matrices of the received signal. Then, we have developed the RLS algorithm for obtaining the multichannel linear prediction error. Furthermore, we have used the CMD algorithm for tracking the unknown phase offset which is inherent problem of any SOS-based algorithm. Our proposed algorithm do not require the exact channel order estimation and are robust to channel order mismatch. Simulation results show that the proposed algorithm have these advantages.

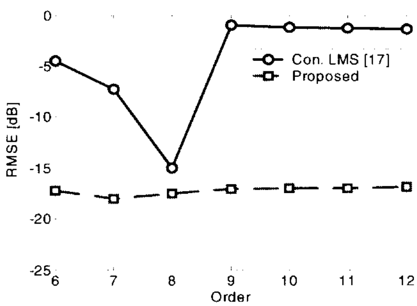

Fig. 7 RMSE performance for several prediction orders.

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