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Novel Robust Blind Equalizer for QAM Signals Using Iterative Weighted-Least-Mean-Square Algorithm

Kun Yan, Hsiao-Chun Wu, *Senior Member, IEEE,* Dongxin Xu, *Member, IEEE,* and S. S. Iyengar, *Fellow, IEEE*

***Abstract*—In this paper, we propose a novel blind equalizer which can deal with high-order modulated QAM (quadrature amplitude modulation) signals. This new scheme is based on the signal selection (SS) and the iterative weighted-least-mean-square (IWLMS) algorithm. The incurred additional complexity by the SS scheme is linear with respect to the sample size of the received signal and the IWLMS method is also very efficient. We employ numerous Monte Carlo experiments to compare our proposed blind equalization method with the popular constant modulus algorithm (CMA). The simulation results demonstrate that our proposed scheme is more robust than CMA especially when the QAM modulation order is large.**

***Index Terms*—Signal selection, IWLMS algorithm, blind equalization, quadrature amplitude modulation.**

I. Introduction

Signals propagating in the digital communication systems may often endure the *inter-symbol interference* (ISI). Equalization is a prevalent approach to mitigate ISI. Conventional equalizers depend on the *a priori* knowledge, mostly via the training signals, to overcome the ISI [1], [2]. However, the frequent transmission of reliable training symbols might not be viable in practice. Besides, the total throughput will reduce by the needed transmission of training sequences. Thus, many blind equalization schemes, such as constant modulus algorithm (CMA) in [3], subchannel matching in [4], and MUSIC-based subspace decomposition method in [5], have emerged in the recent decades. However, they have the difficulty to combat the blind equalization problem when a high-order modulation scheme is adopted. For example, the well-known CMA often leads to significant excessive misadjustments because the global minimum of the corresponding objective function is not guaranteed especially for many quadrature amplitude modulation (QAM) constellations.

Since its first appearance in the pioneering work by Dempster, Laird and Rubin [6], the *expectation-and-maximization* (EM) algorithm has been wildly adopted for many problems [7], [8]. Typical signal processing examples can be found in the speech recognition using hidden Markov model (HMM) with EM algorithm [9], [10], and speaker adaptation using maximum-likelihood linear-regression (MLLR) with EM algorithm [11]. Other examples can also be found in the joint channel estimation and symbol detection for digital communications using the maximum likelihood (ML) criterion with EM algorithm [12]–[15]. Similar EM schemes can also be found in the speech signal processing for the estimation of channel distortion and the speech enhancement and recognition [16]. Since it has been proved that the EM algorithm can always at least guarantee the sub-optimality [17], the EM algorithm becomes a popular optimization approach nowadays.

In this paper, we design a novel robust blind equalization scheme for the high-order QAM signals based on the EM hill-climbing algorithm. Our previously proposed blind equalizer based on the EM hill-climbing algorithm, (or the IWLMS equalizer in [7], [18]), has a strict restriction that it can be adopted for the binary phase-shift keying (BPSK) and quadrature phase-shift keying (QPSK) signals only. The IWLMS equalizer is too complex to implement directly for the high-order QAM signals since the associated probability density functions are multi-modal and very difficult to manipulate. Therefore, in this paper, we will simplify the difficult blind equalization problem for QAM signals into the simple blind equalization paradigm for QPSK signals by employing a novel signal selection scheme as a preprocessor at the receiver.

This paper is organized as follows. The transmission model is introduced in Section II. Our proposed blind equalization scheme for high-order constellations is presented in Section III. Ultimately, simulation results and conclusion will be discussed in Section IV and Section V, respectively.

Nomenclature: $\mathcal{C}$ and $\mathcal{R}$ denote the sets of complex and real numbers, respectively. $\underline{A}$, $\widetilde{A}$ indicate a vector and a matrix while $\widetilde{A}^T$ is the transpose of a matrix $\widetilde{A}$, respectively. The statistical expectation is denoted by $E\{\ \}$. The real and imaginary parts of a complex number C are denoted by $\mathbf{Re}(C)$ and $\mathbf{Im}(C)$, respectively, while $\mathbf{Re}(\underline{A})$, $\mathbf{Im}(\underline{A})$ denote the vectors containing the real and imaginary components of $\underline{A}$, respectively. Note that $j = \sqrt{-1}$.

II. Transmission Model

Figure 1 depicts a block diagram of the basic base-band digital communication system, where $s(k) \in \mathcal{C}$ is the transmitted signal, $h(k) \in \mathcal{C}$ is the channel impulse response (CIR)

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Kun Yan and Hsiao-Chun Wu are with the Department of Electrical and Computer Engineering, Louisiana State University, Baton Rouge, LA 70803, USA (e-mail: kyan2@tigers.lsu.edu, hwu1@lsu.edu). Dongxin Xu is with Infoture Inc., Boulder, CO 80301, USA (e-mail: dongxinxu@infoture.org). S. S. Iyengar is with the Department of Computer Science, Louisiana State University, Baton Rouge, LA 70803, USA (e-mail: iyengar@csc.lsu.edu).

with length M and $\eta(k) \in \mathcal{C}$ is additive white Gaussian noise (AWGN) with a variance σ^2 for both of its real and imaginary parts. We try to build a blind equalizer $w(k) \in \mathcal{C}$ with length Q to improve the quality of the received signal $r(k) \in \mathcal{C}$ accordingly. According to Figure 1, the transmission model is given by

$$r(k) = \sum_{m=0}^{M-1} h(m)s(k-m) + \eta(k), \;\; k = 1, \ldots, K. \qquad (1)$$

The high-order QAM signals are considered and the transmitted signals can be specified as $s(k) = x(k) + j\, y(k)$, where $x(k) \in \mathcal{A} \subset \mathcal{R}$ and $y(k) \in \mathcal{B} \subset \mathcal{R}$. Note that $\mathcal{A}$ and $\mathcal{B}$ correspond to the sets of the constellation's real and imaginary parts, respectively. The equalized signal in Figure 1 is given by

$$\begin{aligned} \hat{s}(k) &= \sum_{q=0}^{Q-1} w(q)\, r(k-q) \\ &= \sum_{q=0}^{Q-1} \sum_{m=0}^{M-1} w(q)h(m)s(k-q-m) \\ &\quad + \sum_{q=0}^{Q-1} w(q)n(k-q), \;\; k = 1, \ldots, K. \end{aligned} \qquad (2)$$

In this paper, we use the finite impulse response (FIR) filters to model the equalizers due to its convenient stability. Similarly, the equalized signals can be expressed as $\hat{s}(k) = \hat{x}(k) + j\, \hat{y}(k)$, where $\hat{x}(k) \in \mathcal{R}$ and $\hat{y}(k) \in \mathcal{R}$, respectively.

Suppose that $\hat{x}(k)$ and $\hat{y}(k)$ are statistically independent and the probability density function (PDF) of $\hat{s}(k)$ is a complex-valued Gaussian mixture with a mean $u^r + ju^i \in (\mathcal{A} + j\mathcal{B})$ and a covariance matrix

$$\widetilde{\Sigma} = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_i^2 \end{bmatrix}, \qquad (3)$$

where $u^r, u^i, \sigma_r^2, \sigma_i^2$ indicate the means and variances of the real and imaginary parts, respectively. We denote a vector $\underline{\hat{s}}(k) = [\hat{x}(k) \;\; \hat{y}(k)]^T$ and facilitate the PDF of $\hat{s}(k)$ as $J(\hat{s}(k)) = J(\underline{\hat{s}}(k))$. It yields

$$\begin{aligned} J(\underline{\hat{s}}(k)) &= \sum_{n=1}^{N} \frac{p_n}{\sqrt{(2\pi)^N \left|\widetilde{\Sigma}\right|}} e^{-\frac{1}{2}(\underline{\hat{s}}(k)-\underline{u}_n)^T \widetilde{\Sigma}^{-1} (\underline{\hat{s}}(k)-\underline{u}_n)} \\ &= \sum_{n=1}^{N} p_n \, G\left(\hat{s}(k), \underline{u}_n, \widetilde{\Sigma}\right), \end{aligned} \qquad (4)$$

$$G\left(\hat{s}(k), \underline{u}_n, \widetilde{\Sigma}\right) \stackrel{\text{def}}{=} \frac{e^{-\frac{1}{2}(\underline{\hat{s}}(k)-\underline{u}_n)^T \widetilde{\Sigma}^{-1} (\underline{\hat{s}}(k)-\underline{u}_n)}}{\sqrt{(2\pi)^N \left|\widetilde{\Sigma}\right|}}, \qquad (5)$$

where N is the number of the Gaussian kernels (or constellation size), and $\underline{u}_n = [u_n^r \; u_n^i]^T$ indicates the cluster mean vector for each kernel. For an equally-likely transmitted signal, we get $p_n = \frac{1}{N}, n = 1, \ldots, N$. The objective of blind equalization is to maximize the PDF function $J(\underline{\hat{s}}(k))$. Usually we take the logarithm of Eq. (4) and use it as the objective function. It yields

$$\log(J(\hat{s}(k))) = \sum_{k=1}^{K} \log\left(\sum_{n=1}^{N} p_n G(\hat{s}(k), \underline{u}_n, \widetilde{\Sigma})\right). \qquad (6)$$

III. Novel Blind Equalization Scheme for High-order QAM Constellations

The blind equalization scheme in [18] can only be applied for the BPSK or QPSK signals which have constant moduli. An IWLMS solution to the BPSK or QPSK blind equalization problem was provided thereupon. Our previous algorithm in [18] is much more efficient and effective than other existing algorithms [3], [4]. However, this IWLMS algorithm is too complex to implement especially for high-order QAM signals. In order to generalize our effective IWLMS algorithm for arbitrary QAM signals, we need to incorporate it with a preprocessor. Such a preprocessor should be capable of converting any arbitrary QAM signal constellation to a selected subset pertaining to the constant modulus. By doing so, we propose a novel signal selection scheme as the crucial component in this preprocessor as depicted in Figure 1. The high-order QAM constellations, such as 8-QAM, 16-QAM, 64-QAM, etc., can be dealt with by this preprocessor to select their subsets with constant moduli. Consequently, our previous IWLMS algorithm can be effectively employed for any QAM constellation thereby. This new preprocessor is composed by two major mechanisms, namely (i) *blind channel length estimation* and (ii) *signal selection*. We will introduce them in detail in the following subsections.

A. Blind Channel Length Estimation

The aforementioned signal selection scheme should depend on an important parameter, *channel length* or M given by Eq. (1). Note that only blind signal processing approaches can be applied in Figure 1. This channel length estimation cannot rely on the training data either. As introduced in [19], the channel length can be blindly estimated from the received signal. We just specify the input and the output of the blind channel length estimation algorithm in [19] as follows:
Input: $r(k)$.
Output: $\hat{M}$ (it is denoted by $\hat{L}_{\max}$ in [19] instead).

B. New Signal Selection Scheme

The channel $h(k)$ would induce the ISI and its statistical impact on the transmitted signal $s(k)$ is to alter its PDF. Generally speaking, such a channel effect would increase the number of the modes (kernels) in the resulted PDF. We may call it "PDF *blurring*" effect. Without loss of generality, one can easily reach the conclusion that the outlying kernels in the PDF of the received signal (having endured the channel distortion) would very probably be least sensitive to this blurring effect. Hence, we need to employ a signal selection mechanism to choose the corresponding subset to these particular kernels. Given the transmitted signal's constellation size N and the estimated channel length $\hat{M}$ resulting from

Section III-A, the PDF blurring effect would lead to as many as $N^{\hat{M}}$ distinct kernels in the PDF of the received signal. In the pessimistic scenario, we can guarantee up to 4 kernels with constant modulus, which are least sensitive to the channel distortion. Thus, we can use the standard selection algorithm in [20] to choose $\frac{400}{N^{\hat{M}}}\%$ of the received signal samples for the subsequent blind equalization. We call

$$\Upsilon \stackrel{\text{def}}{=} \frac{4}{N^{\hat{M}}} \tag{7}$$

the *signal selection ratio*. The incurred additional complexity by this selection algorithm is *linearly* proportional to the sample size K [20]. Note that one can be much more greedy to choose a larger signal selection ratio Υ to gather more information. Nevertheless, the larger Υ, the more PDF blurring effect the selected subset would endure and hence the more equalization performance degradation one could expect.

According to the aforementioned signal selection scheme, we sort the received signal samples using the corresponding magnitudes and then pre-select the subset of the received signal as $r(\Pi[1])$, $r(\Pi[2])$, $\ldots$, $r(\Pi[\Upsilon K])$, where $\Pi[k]$ is the received signal sample index corresponding to the k^{th} largest signal magnitude. Denote $K' \stackrel{\text{def}}{=} \Upsilon K$. Then construct the *viable received signal vector* as

$$\begin{aligned}\underline{R}_k &= [r(\Pi[k]), r(\Pi[k]-1), \ldots, r(\Pi[k]-Q+1)]^T, \\ & \qquad k = 1, \ldots, K'. \end{aligned} \tag{8}$$

Thus, the input and the output of the signal selection subsystem are given as follows:
Input: $r(k)$, $k = 1, \ldots, K$ and $\hat{M}$.
Output: $\underline{R}_k$, $k = 1, \ldots, K'$.

C. IWLMS Blind Equalizer

As previously discussed, the blind equalization methods including constant modulus algorithm [3], [21], soft decision-directed method [22] and kurtosis optimization method [23] all depend on the stochastic gradient search which is quite sensitive to local minima, slow convergence and step size. In our recent paper of [18], we have shown that by applying the EM algorithm, IWLMS blind equalizer can be derived for both BPSK and QPSK modulated signals. This IWLMS method facilitates the closed-form solution at each iteration free of the step-size selection problem. Moreover, for each iteration, the resulted *least mean square* (LMS) problem will share the same auto-correlation matrix of the received signal so that only one matrix inversion is necessary at the initialization step for all subsequent iterations. Here, we will employ the IWLMS blind equalizer incorporated with our proposed new preprocessor (involving the techniques stated in Sections III-A and III-B) for the high-order modulated signals.

According to Eq. (6) and [18], we can facilitate the auxiliary function as

$$\Phi(\hat{s}(k)) = \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{J_n(\hat{\underline{s}}(k))}{J(\hat{\underline{s}}(k))} \log\left(G(\hat{s}(k), \underline{u}_n, \widetilde{\Sigma})\right), \tag{9}$$

where $J_n(\hat{\underline{s}}(k)) \stackrel{\text{def}}{=} p_n G(\hat{s}(k), \underline{u}_n, \widetilde{\Sigma})$, and $J(\hat{\underline{s}}(k))$ is defined by Eq. (4). Since the real and imaginary parts are statistically independent, we get

$$\begin{aligned}\Phi(\hat{s}(k)) &= \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{J_n(\hat{\underline{s}}(k))}{J(\hat{\underline{s}}(k))} \\ & \times \log\left(\frac{e^{-\frac{1}{2}\left[\frac{(\hat{x}(k)-u_n^r)^2}{\sigma_r^2} + \frac{(\hat{y}(k)-u_n^i)^2}{\sigma_i^2}\right]}}{\sqrt{2\pi}\sigma_r\sigma_i}\right),\end{aligned} \tag{10}$$

where $\hat{x}(k), \hat{y}(k)$ are defined below Eq. (2), and $u_n^r, u_n^i, \sigma_r, \sigma_i$ are defined in Eq. (3). After neglecting the constant term, we obtain

$$\begin{aligned}\Phi_{\text{IWLMS}}(\hat{s}(k)) &= \sum_{k=1}^{K}\left(\hat{x}(k) - \sum_{n=1}^{N}\frac{u_n^r J_n(\hat{\underline{s}}(k))}{J(\hat{\underline{s}}(k))}\right)^2 \\ &+ \sum_{k=1}^{K}\left(\hat{y}(k) - \sum_{n=1}^{N}\frac{u_n^i J_n(\hat{\underline{s}}(k))}{J(\hat{\underline{s}}(k))}\right)^2.\end{aligned} \tag{11}$$

According to Eq. (11), the blind equalization becomes an LMS problem involving both real- and imaginary-parts of the received signal. We can thus relate the real- and imaginary-parts of the received signal, respectively, to

$$\begin{aligned}\bar{x}(k) &= \sum_{n=1}^{N}\frac{u_n^r J_n(\hat{\underline{s}}(k))}{J(\hat{\underline{s}}(k))}, \\ \bar{y}(k) &= \sum_{n=1}^{N}\frac{u_n^i J_n(\hat{\underline{s}}(k))}{J(\hat{\underline{s}}(k))}.\end{aligned} \tag{12}$$

The optimal solution to the LMS problem given by Eq. (11) can be derived as follows. At first, we construct the viable received signal vector $\underline{R}_k$ as stated in Section III-B, and randomly initialize the equalizer as $\underline{W} = [w(0), w(1), \ldots, w(Q-1)]^T$. For each iteration, the iterative LMS solution (for the real part) is therefore given by

$$\mathbf{Re}(\underline{W}) = \widetilde{\Omega}_r^{-1}\underline{D}_r^r, \tag{13}$$

$$\hat{x}(k) = \mathbf{Re}(\underline{W})\,\mathbf{Re}(\underline{R}_k), \tag{14}$$

where

$$\widetilde{\Omega}_r \stackrel{\text{def}}{=} \frac{1}{K}\sum_{k=1}^{K}\mathbf{Re}(\underline{R}_k)\,\mathbf{Re}(\underline{R}_k)^T, \tag{15}$$

$$\underline{D}_r^r \stackrel{\text{def}}{=} \frac{1}{K}\sum_{k=1}^{K}\mathbf{Re}(\underline{R}_k)\,\bar{x}(k). \tag{16}$$

Similarly, the solution for the imaginary part is obtained as

$$\mathbf{Im}(\underline{W}) = \widetilde{\Omega}_r^{-1}\underline{D}_r^i, \tag{17}$$

$$\hat{y}(k) = \mathbf{Im}(\underline{W})\,\mathbf{Im}(\underline{R}_k), \tag{18}$$

where

$$\widetilde{\Omega}_i \stackrel{\text{def}}{=} \frac{1}{K}\sum_{k=1}^{K}\mathbf{Im}(\underline{R}_k)\,\mathbf{Im}(\underline{R}_k)^T, \tag{19}$$

$$\underline{D}_r^i \stackrel{\text{def}}{=} \frac{1}{K}\sum_{k=1}^{K}\mathbf{Im}(\underline{R}_k)\,\bar{y}(k). \tag{20}$$

Consequently, we can employ the exactly same IWLMS algorithm in [18] for the blind equalization of QAM signals with the help of our proposed new scheme in this paper.

D. Novel Blind Equalizer for General QAM Constellations

According to Figure 1, our proposed new blind equalization scheme for any arbitrary QAM signal constellation is given as follows.

Step 1) Blindly estimate the channel length and determine the signal selection ratio according to Sections III-A and III-B.

Step 2) Sort the received signal. Then construct the *viable received signal vector* as $\underline{R}_k$.

Step 3) Since the received signal samples in the viable received signal vector are assumed to have the constant moduli, employ the exactly same IWLMS algorithm in [18] for blind equalization now, and thus construct the blind equalizer as $\underline{W} = [w(0)\ w(1)\ \cdots\ w(Q-1)]^T$.

IV. Simulation

Two major methods for combating the blind equalization of high-order QAM signals, namely CMA blind equalizer [3] and our proposed novel blind equalizer depicted in Figure 1, are compared here. Three hundred Monte Carlo trials are taken for randomly generated communication symbols and the selected signal sample size is fixed as $K' = 2,000$ in each trial. Two arbitrary complex-valued channel transfer functions are chosen for simulation as follows:

$$
\begin{aligned}
H_1(z) &= (1+j) + (0.5+0.4j)z^{-1}, \quad (21)\\
H_2(z) &= (1+j) + (-2.3-1.6j)z^{-1}\\
&- (1.91+0.91j)z^{-2} + (-0.673+0.096j)z^{-3}\\
&+ (0.084+-0.018j)z^{-4}. \quad (22)
\end{aligned}
$$

To illustrate our newly proposed signal selection scheme, Figure 2 is provided here for an example (a single random trial) of the received signal samples enduring the channel distortion characterized by $H_1(z)$ with various signal-to-noise ratios (SNRs) at 10, 20, 30, 40 dB when the 16-QAM constellation is used at the transmitter. Subject to the AWGN assumption, five different SNRs are considered in our Monte Carlo simulations, namely SNR=5, 10, 15, 25, 35 dB. For each SNR, we run 300 Monte Carlo simulations by randomly initializing the equalizer coefficients $\underline{W}$. The equalizer length is chosen as $Q = 2M-1$, where M is the channel length. The step size of the CMA method is set as 0.01 (the best value in our heuristical experience). Tables I and II demonstrate the comparative results with respect to two different channels. According to Eq. (2), the ultimate equalization performance measure, the *signal-to-interference ratio* (SIR) adopted in this paper, is defined as

$$
\text{SIR} = \frac{\max_k |w(k)\otimes h(k)|^2}{\left(\sum_{k=0}^{Q+M-2} |w(k)\otimes h(k)|^2\right) - \max_k |w(k)\otimes h(k)|^2}, \quad (23)
$$

where $\otimes$ denotes the linear convolution. It is easy to prove that the SIR is strictly proportional to the signal-to-inference-and-noise ratio (SINR) or the larger the SIR, the larger the SINR. Hence, both SIR and SINR will lead to the same performance comparison results accordingly. Obviously, our proposed new blind equalizer can greatly outperform the CMA method especially for high-order QAM constellations according to these two tables.

V. Conclusion

In this paper, we propose a novel blind equalization scheme for arbitrary high-order QAM signals. Blind channel length estimation and signal selection schemes are employed in this proposed blind equalizer. According to the simulation results, our proposed new scheme can achieve much better performance than the conventional CMA method especially when the modulation order is large.

References

[1] J. G. Proakis, *Digital communications*. McGraw-Hill, 1995.

[2] F. Petre, M. Moonen, M. Engels, B. Gyselinckx, and H. D. Man, "Pilot-aided adaptive chip equalizer receiver for interference suppression in DS-CDMA forward link," in *Proceedings of IEEE Vehicular Technology Conference*, vol. 1, September 2000, pp. 303–308.

[3] D. N. Godard, "Self-recovering equalization and carrier tracking in two-dimensional data communication systems," *IEEE Transactions on Communications*, vol. COM-28, no. 11, pp. 1867–1875, November 1980.

[4] R. Liu and G. Dong, "A fundamental theorem for multiple-channel blind equalization," *IEEE Transactions on Circuits and Systems*, vol. 44, no. 5, pp. 472–473, May 1997.

[5] K. Abed-Meraim, Y. Hua, P. Loubaton, and E. Moulines, "Subspace method for blind identification of multichannel FIR systems in noise field with unknown spatial covariance," *IEEE Signal Processing Letters*, vol. 4, no. 5, pp. 135–137, May 1997.

[6] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *J. Roy. Stat. Soc.*, vol. 39, no. 1, pp. 1–38, 1977.

[7] D. Xu, H.-C. Wu, and C. Y. Chi, "Blind separation and equalization using novel hill-climbing optimization," in *Proceedings of Asilomar Conference on Signals, Systems, and Computers*, November 2007, pp. 13–16.

[8] D. Xu and H.-C. Wu, "Robust blind adaptive beamforming by maximum likelihood with EM algorithm," in *Proceedings of IEEE AP-S International Symposium and USNC/URSI National Radio Science Meeting*, vol. 4B, July 2005, pp. 101–104.

[9] L. Rabiner and B. H. Juang, *Fundamentals of Speech Recognition*. Prentice Hall, Inc. New Jersey, 1993.

[10] F. Jelinek, *Statistical Methods for Speech Recognition*. The MIT Press, Cambridge, Massachusetts, 1997.

[11] C. J. Leggetter and P. C. Woodland, "Maximum likelihood linear regression for speaker adaptation of continuous density hidden Markov models," *Computer Speech and Language*, vol. 9, pp. 171–185, 1995.

[12] L. Tong and S. Perreau, "Multichannel blind identification: from subspace to maximum likelihood methods," *Proceedings of the IEEE*, vol. 86, no. 10, pp. 1951–1968, October 1998.

[13] V. Krishnamurthy, S. Dey, and J. P. LeBlanc, "Blind equalization of IIR channels using hidden Markov models and extended least squares," *IEEE Transactions on Signal Processing*, vol. 43, no. 12, pp. 2994–3006, December 1995.

[14] K. H. Afkhamie and Z.-Q. Luo, "Blind identification of FIR systems driven by Markov-like input signals," *IEEE Transactions on Signal Processing*, vol. 48, no. 6, pp. 1726–1736, June 2000.

[15] H. Zamiri-Jafarian and S. Pasupathy, "Adaptive MLSDE using the EM algorithm," *IEEE Transactions on Communications*, vol. 47, no. 8, pp. 1181–1193, August 1999.

[16] Y. Zhao, "An EM algorithm for linear distortion channel estimation based on observations from a mixture of gaussian sources," *IEEE Transactions on Speech and Audio Processing*, vol. 7, no. 4, pp. 400–413, July 1999.

[17] L. Ljung, *System Identification*. Prentice-Hall, New Jersey, 1999.

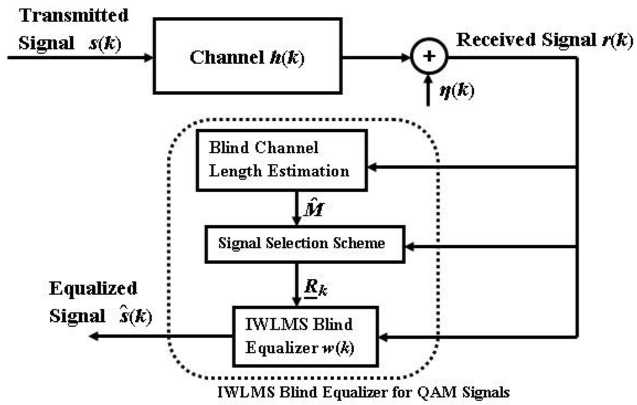

Fig. 1. Our proposed new blind equalization scheme.

[18] D. Xu, K. Yan, and H.-C. Wu, "Blind channel equalization using expectation maximization of auxiliary objective function for complex constellations," in *Proceedings of IEEE GLOBECOM Conference*, November 2009.

[19] X. B. Wang, H.-C. Wu, S. Y. Chang, Y. Y. Wu, and J. Y. Chouinard, "Efficient non-pilot-aided channel length estimation for digital broadcasting receivers," *IEEE Transactions on Broacasting*, vol. 55, no. 3, pp. 633–641, September 2009.

[20] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms*. McGraw-Hill, 2001.

[21] A. Goupil and J. Palicot, "New algorithm for blind equalization: the constant norm algorithm family," *IEEE Transactions on Signal Processing.*, vol. 55, no. 4, pp. 1436–1444, April 2007.

[22] S. J. Nowlan and G. E. Hinton, "A soft decision-directed LMS algorithm for blind equalization," *IEEE Transactions on Communications*, vol. 41, no. 2, pp. 275–279, February 1993.

[23] H.-C. Wu, Y. Y. Wu, J. C. Principe, and X. B. Wang, "Robust switching blind equalizer for wireless cognitive receivers," *IEEE Transactions on Wireless Communications*, vol. 7, no. 5, pp. 1461–1465, May 2008.

TABLE I

SIR COMPARISON FOR DIFFERENT BLIND EQUALIZATION SCHEMES (THE CHANNEL TRANSFER FUNCTION IS GIVEN BY EQ. (21)). NOTE THAT ALL THE NUMERICAL VALUES ARE IN DB AND "NEW" DENOTES OUR PROPOSED NEW SCHEME.

Scheme Constel.	New 8-QAM	New 16-QAM	New 64-QAM	CMA 16-QAM	CMA 64-QAM
5 (dB)	6.36	7.07	5.99	6.81	2.05
10 (dB)	9.90	8.76	6.01	7.93	4.92
15 (dB)	15.12	14.7	8.83	11.05	7.53
25 (dB)	18.08	17.30	10.66	14.90	8.01
35 (dB)	18.99	20.52	11.25	16.12	9.33

TABLE II

SIR COMPARISON FOR DIFFERENT BLIND EQUALIZATION SCHEMES (THE CHANNEL TRANSFER FUNCTION IS GIVEN BY EQ. (22)). NOTE THAT ALL THE NUMERICAL VALUES ARE IN DB AND "NEW" DENOTES OUR PROPOSED NEW SCHEME.

Scheme Constel.	New 8-QAM	New 16-QAM	New 64-QAM	CMA 16-QAM	CMA 64-QAM
5 (dB)	3.65	4.01	3.69	4.51	1.35
10 (dB)	4.33	4.66	6.31	6.03	4.33
15 (dB)	10.23	9.72	7.51	7.05	5.20
25 (dB)	12.07	11.30	11.01	13.76	6.34
35 (dB)	11.07	12.73	10.50	15.22	6.91

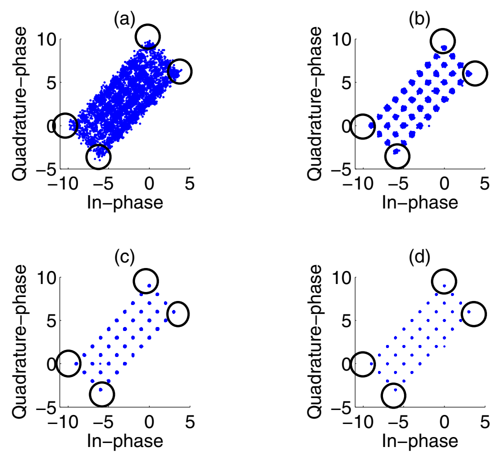

Fig. 2. Illustration of our proposed signal selection scheme: (a) Blurred transmitted signal constellation, where signal-to-noise ratio is set as 10 dB, (b) Blurred transmitted signal constellation, where signal-to-noise ratio is set as 20 dB, (c) Blurred transmitted signal constellation, where signal-to-noise ratio is set as 30 dB, (d) Blurred transmitted signal constellation, where signal-to-noise ratio is set as 40 dB. The preselected data is marked by circles. Obviously noise causes selection error. Fifty thousand received signal samples are used to generate this figure ($K = 50,000$). 16-QAM signal is employed in this example. $K' = \Upsilon K = \frac{4}{N^{\hat{M}}}K = 785$. The channel transfer function is $H_1(z) = (1 + j) + (0.5 + 0.4j)z^{-1}$.