

A Novel Blind Frequency Domain Equalizer For SIMO Systems

Iman Moazzen¹, Ali Mohammad Doost-Hoseini², Mohammad Javad Omidi³
Isfahan University of Technology, Isfahan, 84156, Iran
(1) i.moazzen@ec.iut.ac.ir, (2) alimdh@cc.iut.ac.ir, (3) omidi@cc.iut.ac.ir

Abstract— A novel blind equalization method is introduced for SIMO systems. In the proposed design method, based on the blindly estimated characteristics of Rician fading channels, a realizable equalizer which is constructed to minimize the mean square error (MSE) from the frequency domain perspective is designed to recover the transmitted sequence. Diversity techniques and equalization methods are combined to enhance the performance. Illustrative simulations demonstrate the improvement in the proposed method.

Key Words— Single Input Multiple Output (SIMO), Rician Fading Channels, Mean Square Error (MSE)

I. INTRODUCTION

The recovery of transmitted signals in the presence of noise and InterSymbol Interference (ISI) is an important research topic in digital communications. In low quality channels, ISI increases Symbol Error Rate (SER) drastically. In meeting the increasing demand of high-speed communications, equalizer employed at the receiver plays an important role in mitigating ISI. So, equalization of communication channels has attracted intensive research activity over the past few decades. Particularly in severely fading channels, Single-Input Multiple-Output (SIMO) transmission is widely replacing Single-Input Single-Output (SISO) approach to enhance the performance via diversity combining [1]. A SIMO system consists of a single-antenna transmitter and a receiver equipped with multiple antennas.

Frequency domain approach has some advantages compared to its time domain counterpart. So, it has been frequently utilized to design optimal equalizers [2, 4-5]. In [2], a fixed robust DFE which gives an acceptable performance over a range of perturbations of channel parameters is proposed. Multipath fading channels with Rician (or Rayleigh) distribution have been used to characterize the statistical properties of time-varying channels for a long time [3-5]. In [4], based on [2], a realizable transversal filter is constructed to minimize the MSE from the frequency domain perspective in Rician fading Channels. In [5], this strategy was expanded to design an optimal DFE. In [5], a training sequence was used in order to estimate the statistical characteristics of fading channels and, consequently a fixed equalizer is designed. Only SISO systems were considered in [2,4-5]. By combining diversity techniques and equalization methods in the frequency domain, a novel blind SIMO equalizer is proposed.

Considerations are made to decrease the implementation complexity as much as possible. One main advantage of the proposed design method is that only a fixed equalizer is required to treat the equalization problem. The organization of this paper is as follows: In Section 2, the mathematical description of the channels is presented. In Section 3, based on the dynamics of fading channels, an optimal and realizable equalizer that minimizes the MSE is derived. Illustrative simulations are presented in Section 4 to demonstrate the performance of this method. Finally, Section 5 concludes the paper.

II. MATHEMATICAL DESCRIPTION

In severely fading channels, SIMO transmission is widely replacing the SISO approach to enhance the performance via diversity combining. The number of antennas in the receiver is shown by M . The i.i.d equiprobable input sequence $u(n)$ with zero mean and variance σ_u^2 is transmitted every T_s seconds through a communication system. The transmitter sends the same data in different spatial directions and different antennas capture the signals. The receiver employs all the information to reconstruct the transmitted data. In this study, all channels are multipath Rician fading. So, the mathematical description for one channel (SISO) is presented. Following the nomenclature, symbols and procedure of [5], a SISO system for the m^{th} channel is depicted in Fig.1. $h_{m,k}(n)$ is the time-varying impulse response of the overall system including transmitter filters, receiver filters and fading channel. The received discrete-time signal from each channel can be written in the following form:

$$y_m(n) = \sum_{k=0}^{L_m} h_{m,k}(n)u(n-k) + w_m(n) \quad (1)$$

where $w_m(n)$ denotes the additive white circular complex-valued Gaussian noise with zero mean and known variance σ_w^2 , and L_m is the channel order that is assumed to be known [6]. $h_{m,k}(n)$ can be expressed in the following form:

$$h_{m,k}(n) = h_{m,k} + \tilde{h}_{m,k}(n) \quad (2)$$

where $h_{m,k}$ is a constant mean and $\tilde{h}_{m,k}(n)$ is wide-sense stationary and uncorrelated scattering (WSSUS) with:

$$\tilde{h}_{m,k}(n) = \sum_{j=1}^p \phi_{m,kj} \tilde{h}_{m,k}(n-j) + v_{m,k}(n) \quad (3)$$

$v_{m,k}(n)$ is a white Gaussian sequence with zero mean and variance $\sigma_{v_{m,k}}^2$, p is the order of the AR model, and $\phi_{m,kj}$ are selected so that (4) is the specified low-pass filter having a cutoff frequency equal to the maximum Doppler frequency [5].

$$\varphi_{m,k}(z^{-1}) = 1/(1 - \sum_{j=1}^p \phi_{m,kj} z^{-j}) \quad (4)$$

Combining (3) and (4) we get (The backward shift operator is shown by q^{-1} i.e. $q^{-1}u(n) = u(n-1)$):

$$\tilde{h}_{m,k}(n) = \frac{v_{m,k}(n)}{(1 - \sum_{j=1}^p \phi_{m,kj} q^{-j})} = v_{m,k}(n) \varphi_{m,k}(q^{-1}) \quad (5)$$

The following two assumptions are made:

As.1: Both $w_m(n)$ and $\tilde{h}_{m,k}(n)$ are uncorrelated with the input sequence $u(n)$.

As.2 : $w_m(n)$ is uncorrelated with $v_{m,k}(n)$ for $k = 0, 1, \dots, L_m$. Consequently, $w_m(n)$ is uncorrelated with $\tilde{h}_{m,k}(n)$ and $h_{m,k}(n)$ for $k = 0, 1, \dots, L_m$.

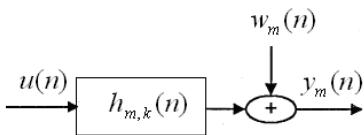


Figure 1. SISO communication system

III. PROPOSED METHOD

A novel equalizer is depicted in Fig.2. For each antenna, a transversal filter is used. Then, all outputs are summed to form a unique output. Finally, only a feedback filter is used to compensate ISI more. Using a single feedback filter instead of M filters can decrease the implementation complexity dramatically.

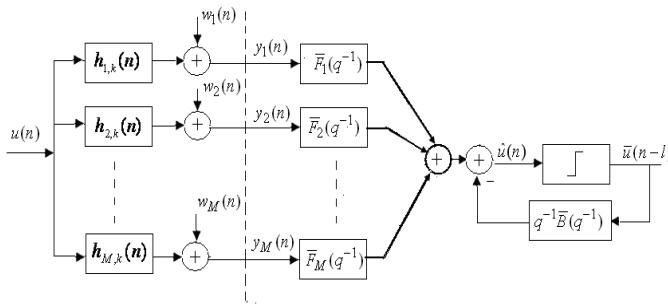


Figure 2. The structure of the proposed method

Let's denote $H_m(q^{-1}) = \sum_{k=0}^{L_m} h_{m,k} q^{-k}$, $H_m(q^{-1}; n) = \sum_{k=0}^{L_m} \tilde{h}_{m,k}(n) q^{-k}$.

The received signal in each antenna is:

$$y_m(n) = H_m(q^{-1})u(n) + \tilde{H}_m(q^{-1}; n)u(n) + w_m(n) \quad (6)$$

And the input to the decision device is:

$$\begin{aligned} \hat{u}(n) &= \bar{F}_1(q^{-1})y_1(n) + \bar{F}_2(q^{-1})y_2(n) + \cdots + \\ &\quad \bar{F}_M(q^{-1})y_M(n) - q^{-l} \bar{B}(q^{-1})\bar{u}(n-l) \end{aligned} \quad (7)$$

The error sequence is defined by:

$$e(n-l) = u(n-l) - \hat{u}(n) \quad (8)$$

where l is the number of smoothing lags. The assumption of sufficiently accurate detection of the transmitted symbol, i.e. $\bar{u}(n-l) = u(n-l)$, is necessary and often is satisfied in the proposed method at a high SNR. Following the procedure of [5], all filters are designed so that the following index is minimized:

$$J = E_{h,u,w} \left[|e(n-l)|^2 \right] = E_{h,u,w} \left[|u(n-l) - \hat{u}(n)|^2 \right] \quad (9)$$

By combining $H_m(q^{-1}; n) = \sum_{k=0}^{L_m} \tilde{h}_{m,k}(n) q^{-k}$ and (5) we get:

$$H_m(q^{-1}; n) = \sum_{k=0}^{L_m} v_{m,k}(n) \varphi_{m,k}(q^{-1}) q^{-k}. \quad (10)$$

By combining (6), (7), (8), and (10) and according to Parseval's theorem, the reconstruction performance index J can be written as (under the condition AS1, AS2 and WSSUS):

$$\begin{aligned} J &= \frac{1}{2\pi j} \oint_{|z|=1} \{ [z^{-l} - \bar{F}_1(z^{-1})H_1(z^{-1}) - \bar{F}_2(z^{-1})H_2(z^{-1}) - \cdots - \\ &\quad \bar{F}_M(z^{-1})H_M(z^{-1}) + z^{-l-1} \bar{B}(z^{-1})] \times [z^l - \bar{F}_1^*(z^*)H_1^*(z^*) - \\ &\quad \bar{F}_2^*(z^*)H_2^*(z^*) - \cdots - \bar{F}_M^*(z^*)H_M^*(z^*) + z^{l+1} \bar{B}^*(z^*)] \sigma_u^2 + \\ &\quad + \bar{F}_1(z^{-1})\bar{F}_1^*(z^*) (\sum_{k=0}^{L_1} \varphi_{1,k}(z^{-1}) \varphi_{1,k}^*(z^*) \sigma_{v_{1,k}}^2) \sigma_u^2 + \\ &\quad \bar{F}_2(z^{-1})\bar{F}_2^*(z^*) (\sum_{k=0}^{L_2} \varphi_{2,k}(z^{-1}) \varphi_{2,k}^*(z^*) \sigma_{v_{2,k}}^2) \sigma_u^2 + \cdots + \\ &\quad \bar{F}_M(z^{-1})\bar{F}_M^*(z^*) (\sum_{k=0}^{L_M} \varphi_{M,k}(z^{-1}) \varphi_{M,k}^*(z^*) \sigma_{v_{M,k}}^2) \sigma_u^2 \\ &\quad + \bar{F}_1(z^{-1})\bar{F}_1^*(z^*) \sigma_{w_1}^2 + \bar{F}_2(z^{-1})\bar{F}_2^*(z^*) \sigma_{w_2}^2 + \cdots + \\ &\quad \bar{F}_M(z^{-1})\bar{F}_M^*(z^*) \sigma_{w_M}^2 \} \frac{dz}{z} \end{aligned} \quad (11)$$

Where $\oint_{|z|=1}$ denotes the counter-clockwise integration around the unit circle. Both transversal filter and single feedback filter are considered as $\bar{F}_m(z^{-1}) = F_m(z^{-1}) + \epsilon_m \eta_m(z^{-1})$ ($1 \leq m \leq M$), and $\bar{B}(z^{-1}) = B(z^{-1}) + \epsilon_{M+1} \eta_{M+1}(z^{-1})$ respectively. $F_m(z^{-1}), B(z^{-1})$ are the candidates of the optimal filters. $\eta_m(z^{-1})$ ($1 \leq m \leq M+1$) are arbitrary realizable rational functions with all poles in $|z| < 1$, and ϵ_m ($1 \leq m \leq M+1$) are small variational parameters. These forms are substituted into (11). Let us denote (for $1 \leq m \leq M$):

$$\sum_{k=0}^{L_m} \varphi_{m,k}(z^{-1}) \varphi_{m,k}^*(z^*) \sigma_{v_{m,k}}^2 = G_m(z^{-1}) G_m^*(z^*) \quad (12)$$

Based on the calculus of variation technique, the performance index must satisfy the following conditions:

$$\frac{\partial J}{\partial \epsilon_m} \Big|_{\epsilon_1, \epsilon_2, \dots, \epsilon_{M+1}} = 0, \quad \text{for } 1 \leq m \leq M+1 \quad (13)$$

There are $M+1$ differential equations. Based on the symmetry property $\oint_{|z|=1} [F^*(z^*) + F(z^{-1})] dz / z = \oint_{|z|=1} 2F(z^{-1}) dz / z$

[2, 4-5], we get:

$$\begin{aligned} \frac{\partial J}{\partial \epsilon_m} \Big|_{\epsilon_1, \epsilon_2, \dots, \epsilon_{M+1}} &= 0 \quad \text{for } 1 \leq m \leq M \Rightarrow \\ &\frac{2}{2\pi j} \oint_{|z|=1} \{(-\eta_m^*(z^*) H_m^*(z^*)) \times [z^{-l} - F_1(z^{-1}) H_1(z^{-1}) - \\ &F_2(z^{-1}) H_2(z^{-1}) - \dots - F_M(z^{-1}) H_M(z^{-1}) + z^{-l-1} B(z^{-1})] \sigma_u^2 \\ &+ F_m(z^{-1}) \eta_m^*(z^*) G_m(z^{-1}) G_m^*(z^*) \sigma_u^2 + F_m(z^{-1}) \eta_m^*(z^*) \sigma_{w_m}^2\} \frac{dz}{z} = 0 \quad (14) \\ \frac{\partial J}{\partial \epsilon_{M+1}} \Big|_{\epsilon_1, \epsilon_2, \dots, \epsilon_{M+1}} &= 0 \Rightarrow = \frac{2}{2\pi j} \oint_{|z|=1} \eta_{M+1}^*(z^*) \times \\ &[1 - z^l F_1(z^{-1}) H_1(z^{-1}) - z^l F_2(z^{-1}) H_2(z^{-1}) \\ &- \dots - z^l F_M(z^{-1}) H_M(z^{-1}) + z^{-l} B(z^{-1})] \sigma_u^2 dz = 0 \quad (15) \end{aligned}$$

$Q^*(z^*)$ is defined as follows:

$$\begin{aligned} Q^*(z^*) &= 1 - z^l F_1(z^{-1}) H_1(z^{-1}) - z^l F_2(z^{-1}) H_2(z^{-1}) \\ &- \dots - z^l F_M(z^{-1}) H_M(z^{-1}) + z^{-l} B(z^{-1}) \quad (16) \end{aligned}$$

By neglecting the coefficient $2/2\pi j$, (15) can be written as:

$$\oint_{|z|=1} \eta_{M+1}^*(z^*) Q^*(z^*) \sigma_u^2 dz = 0 \quad (17)$$

From (16), it can be seen that since $F_1(z^{-1}), \dots, F_M(z^{-1}), H_1(z^{-1}), \dots, H_M(z^{-1}), B(z^{-1})$ are analytic outside the unit circle in the z -plane, based on Cauchy's residue

theorem the only choice of $Q^*(z^*)$ satisfying condition (17) is a polynomial in z with degree l , i.e.,

$$Q^*(z^*) = q_0 + q_1 z + \dots + q_l z^l \quad (18)$$

By defining $C_m(z^{-1}) C_m^*(z^*) = G_m(z^{-1}) G_m^*(z^*) \sigma_u^2 + \sigma_{w_m}^2$, and substituting (16) into (14) we easily get ($1 \leq m \leq M$):

$$\begin{aligned} \oint_{|z|=1} \{F_m(z^{-1}) C_m(z^{-1}) C_m^*(z^*) - \\ z^{-l} H_m^*(z^*) Q^*(z^*) \sigma_u^2\} \eta_m^*(z^*) \frac{dz}{z} = 0 \quad (19) \end{aligned}$$

In (19), a rational function is defined as follows ($1 \leq m \leq M$):

$$\begin{aligned} P_m^*(z^*) &= \\ [F_m(z^{-1}) C_m(z^{-1}) C_m^*(z^*) - z^{-l} H_m^*(z^*) Q^*(z^*) \sigma_u^2] / z \quad (20) \end{aligned}$$

Based on Cauchy's residue theorem, (19) is satisfied only if $P_m^*(z^*)$ is analytic inside the unit circle in the z -plane. Multiplying both sides of (20) by the inverse of $C_m^*(z^*)$:

$$\begin{aligned} z P_m^*(z^*) (C_m^*(z^*))^{-1} &= \\ F_m(z^{-1}) C_m(z^{-1}) - z^{-l} H_m^*(z^*) Q^*(z^*) (C_m^*(z^*))^{-1} \sigma_u^2 \quad (21) \end{aligned}$$

We divide $z^{-l} H_m^*(z^*) Q^*(z^*) (C_m^*(z^*))^{-1} \sigma_u^2$ into the causal and stable part shown by $\{\}_{+}$ which is analytic outside the unit circle in the z -plane, and anti-causal and stable part shown by $\{\}_{-}$ which is analytic inside the unit circle in the z -plane:

$$\begin{aligned} z P_m^*(z^*) (C_m^*(z^*))^{-1} + \{z^{-l} H_m^*(z^*) Q^*(z^*) (C_m^*(z^*))^{-1} \sigma_u^2\}_{-} &= \\ F_m(z^{-1}) C_m(z^{-1}) - \{z^{-l} H_m^*(z^*) Q^*(z^*) (C_m^*(z^*))^{-1} \sigma_u^2\}_{+} \quad (22) \end{aligned}$$

Note that the left-hand side of (22) is analytic inside the unit circle, while the right-hand side is analytic outside the unit circle. As a result, the only solution to (22) is that both of them are zero simultaneously. Therefore, $F_m(z^{-1})$ can be obtained as follows ($1 \leq m \leq M$):

$$\begin{aligned} F_m(z^{-1}) &= \\ \{z^{-l} H_m^*(z^*) Q^*(z^*) (C_m^*(z^*))^{-1} \sigma_u^2\}_{+} C_m^{-1}(z^{-1}) \quad (23) \end{aligned}$$

We utilize the method introduced in [5] to find optimal filters. Based on (23), let us denote (for $1 \leq m \leq M$):

$$S_m(z^{-1}) = \{z^{-l} H_m^*(z^*) Q^*(z^*) (C_m^*(z^*))^{-1} \sigma_u^2\}_{+} \quad (24)$$

Since the poles of $H_m(z^*)Q^*(z^*)(C_m^*(z^*))^{-1}$ are in $|z| > 1$, the only choice of $S_m(z^{-1})$ is a polynomial in z^{-1} with degree l , i.e.

$$S_m(z^{-1}) = s_{0,m} + s_{1,m}z^{-1} + \cdots + s_{l,m}z^{-l} \quad (25)$$

We perform the polynomial spectral factorization on the denominator and numerator of the $C_m(z^{-1})C_m^*(z^*)$, and we get $C_m(z^{-1})$. By using $H_m(z^{-1})$ and $C_m(z^{-1})$ we get (for $1 \leq m \leq M$):

$$H_m(z^{-1})C_m^{-1}(z^{-1}) = \sum_{i=0}^{\infty} r_{i,m}^* z^{-i} \quad (26)$$

By substituting (18), (25) and (26) into (24) and comparing the coefficients of orders from z^0 to z^l we get:

$$\begin{bmatrix} S_{0,m} \\ S_{1,m} \\ \vdots \\ S_{l,m} \end{bmatrix} = \sigma_u^2 \begin{bmatrix} r_{0,m} & r_{1,m} & r_{2,m} & \cdots & r_{l,m} \\ 0 & r_{0,m} & r_{1,m} & \cdots & r_{l-1,m} \\ 0 & 0 & \ddots & \cdots & \vdots \\ 0 & 0 & 0 & \ddots & r_{1,m} \\ 0 & 0 & 0 & 0 & r_{0,m} \end{bmatrix} \begin{bmatrix} q_l \\ q_1 \\ \vdots \\ q_0 \end{bmatrix} \quad (27)$$

Matrices A_m are defined as follows:

$$A_m = \begin{bmatrix} r_{0,m} & r_{1,m} & r_{2,m} & \cdots & r_{l,m} \\ 0 & r_{0,m} & r_{1,m} & \cdots & r_{l-1,m} \\ 0 & 0 & \ddots & \cdots & \vdots \\ 0 & 0 & 0 & \ddots & r_{1,m} \\ 0 & 0 & 0 & 0 & r_{0,m} \end{bmatrix} \quad (28)$$

So, (23) can be rewritten in the following forms ($1 \leq m \leq M$):

$$F_m(z^{-1}) = S_m(z^{-1})C_m^{-1}(z^{-1}) \quad (29)$$

Base on (16) we get:

$$B(z^{-1}) = z[Q^*(z^*) - 1 + z^l F_l(z^{-1})H_l(z^{-1}) + z^l F_2(z^{-1})H_2(z^{-1}) + \cdots + z^l F_M(z^{-1})H_M(z^{-1})] \quad (30)$$

Since $B(z^{-1})$ is stable and causal, by comparing the coefficients of the powers z^0 to z^l we easily get:

$$\begin{bmatrix} q_l \\ \vdots \\ q_1 \\ q_0 \end{bmatrix} = (\mathbf{I} + \sigma_u^2 [A_1^H A_1 + A_2^H A_2 + \cdots + A_M^H A_M])^{-1} \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix} \quad (31)$$

The whole process is summarized as follows:

Step1: Obtain $G_m(z^{-1})G_m^*(z^*)$ from (12) for each channel.

Step2: Obtain $C_m(z^{-1})$ by performing the spectral factorization in $C_m(z^{-1})C_m^*(z^*) = G_m(z^{-1})G_m^*(z^*)\sigma_u^2 + \sigma_{w_m}^2$ (for $1 \leq m \leq M$).

Step3: Drive the impulse response and form A_m by using (26), (28) respectively for each sub-channel (for $1 \leq m \leq M$).

Step4: $Q^*(z^*)$ is constructed by using (31) and (18).

Step5: Obtain $S_1(z^{-1})$, $S_2(z^{-1})$, ..., and $S_M(z^{-1})$ by using (25), (27).

Step6: Transversal filters and a single feedback filter are designed via (29) (for $1 \leq m \leq M$), (30).

During the design procedure all parameters of each channel are considered to be known. However, in a practical case these parameters must be estimated. In [5], one training sequence is transmitted and the required parameters are estimated via the Least-Squares method. However, in some cases transmitting a training sequence is not possible. So, a blind method is utilized to estimate the required parameters. One of the famous classes of blind equalization is blind sequence estimation [9]. In this group, the approximate maximum likelihood estimates for the channel and data are obtained. In [9], Chen proposed a fast blind equalization based on Bayesian DFE for joint data and channel estimation. Chen's algorithm may not converge to the correct estimate without a suitable initialization requiring some pre-known channel characteristics. In [10], Parallel Bayesian DFE (PBDFE) was proposed to solve this problem which has high accuracy and reliability. Moreover, its fast convergence to the real channel is considerable. In time-varying channels the equalizer converges to paths' means. Although, the computational complexity of PDE is drastically increased if the alphabet size of modulation is high or channel impulse response length is long. In this study, channels with short length are considered. So, the latter is not noticeable here. On the other hand, PBDFE with small alphabet size requires reasonably complex computations with high accuracy. In order to estimate channel parameters here, first a binary PAM sequence is utilized. Then larger alphabet size can be selected. In fact, at first a binary PAM sequence with a short period (because of the fast convergence of PBDFE) is transmitted, and the sub-channels are estimated. Then, larger constellation can be selected. In the blind practical systems, channel is usually estimated by binary sequences. Hence, this strategy is justifiable. In short, to blindly estimate the channel parameters, PBDFE [19] is used for each channel to estimate the constant paths means and data jointly. Based on the blindly reconstructed data, $\phi_{m,kj}$ and $\sigma_{v_{m,k}}^2$ are estimated

via the method introduced in [5]. In other words, [5] uses a training sequence to estimate the channel parameters, but we employ PBDFE, and utilize the blindly estimated data instead. In fact, the detected data is considered as a training sequence with high accuracy provided PBDFE converges to the right channel state. This is guaranteed in a high Signal to Noise Ratio (SNR). Based on the estimated parameters for each sub-channel, the proposed equalizer is implemented. Because of the fixed form, the implementation complexity decreases significantly. The optimal filters have IIR forms which are converted to FIR ones. The denominator order is p introduced in (3). Since all filters are stable and causal, their poles are inside the unit circle ($|b(k)| < 1$). Each denominator can be expressed as the summation of p rational functions. Each rational function can be implemented by a K -length FIR filter. K is selected so that the neglected terms in the approximation are insignificant, e.g. $K = \lceil \log(\xi)/\log(b(k)) \rceil + 1$ in which $\lceil \cdot \rceil$ denotes the integer part. ξ is an accuracy control factor, which can be normally selected as $\xi = 0.01$ [7]. When $b(k)$ is close to unity, the large value of K increases implementation complexity drastically. In this case, efficient Laguerre structure for equalizer design is employed [7-8]. It can be seen that the Laguerre architecture requires significantly fewer multipliers in the implementation when there is a pole near to the unit circle. When the pole is far from the unit circle, an FIR implementation is a suitable choice [7]. It is shown that when the filter pole is in the following range, the Laguerre implementation is preferred over an FIR structure [7] (a is the pole of Laguerre structure):

$$\frac{1 - \sqrt{1 - a^2}}{a} \leq |b(k)| \leq \frac{1 + \sqrt{1 - a^2}}{a} \quad (32)$$

We assume $a = 0.75$ and then check (32) for each $b(k)$. If $|b(k)|$ satisfies this relation, Laguerre architecture is selected for implementation. Otherwise, FIR form is the better choice. It is noted again that all filters are implemented in a fixed form. Hence, there are no adaptive rules.

IV. SIMULATION

To illustrate the performance of the proposed method, a SIMO system is considered. All sub-channels are normalized to have unity gain, and each figure is the result of averaging over 50 independent trials. In each figure SNR=30 db, $l = 6$ and the order of the AR model in (3), i.e. p is supposed to be one. So, only $\phi_{m,1}$ ($1 \leq m \leq M$) is important. The proposed method is compared with two blind methods; Constant Modulus Algorithm (CMA) and

CMA-DD [1] that is an improvement for CMA. In fact, the steady state performance of the CMA in terms of its mean square error (MSE) may not be sufficiently low for the system to achieve an adequate bit error rate performance. So, a standard solution is to switch to decision directed (DD) adaptation. CMA and CMA-DD are implemented in adaptive forms, but the proposed method has a fixed form. The learning steps are as large as possible for CMA and CMA-DD (the stability of adaptive method must be guaranteed). The number of transmitted symbols is 10000. A SIMO system has two channels ($M = 2$) whose zeros are depicted in Fig.3. Due to severe proximity of the zeros to the unit circle in the channels, the SIMO system is quite hard to be equalized. For the proposed method, a 500 long binary PAM is transmitted and the required parameters are blindly estimated as mentioned previously. For comparison, MSE is depicted that is calculated as follows ($MSE(start) = 1$, λ is a forgetting factor and is set 0.99):

$$MSE(k) = \lambda \times MSE(k-1) + (1-\lambda) \times |\hat{u}(k) - \bar{u}(k-1)|^2 \quad (33)$$

We set $\phi_{m,1} = 0.95$ and $\sigma_{v_{m,k}}^2 = 2 \times 10^{-4}$, and consider normalized ($\sigma_u^2 = 1$) 8-QAM and 16-QAM modulations in Fig.4 and Fig.5, respectively. Although for the proposed method we need to transmit a short PAM sequence more, it is worth mentioning again that the proposed method is implemented in a fixed form. So, it doesn't need adaptive rules like CMA and CMA-DD. As a result, it can be inferred that the proposed method requires much less complex implementation compared to CMA and CMA-DD. From Fig.4 and Fig.5 it can be concluded that the proposed method has better performance in MSE and, consequently, SER.

V. CONCLUSION

In this paper, a novel blind equalizer is proposed for SIMO systems. It has as many forward filters as the number of receivers and employs only one feedback filter for further ISI compensation. This structure decreases the implementation complexity significantly. Both diversity and equalization concepts are employed to enhance the performance. First, some required parameters are blindly estimated. Then, the proposed equalizer is designed in the frequency domain. The illustrative simulations show better performance in MSE and consequently, SER. Moreover, the proposed equalizer has a fixed structure and there is no adaptive rule which causes implementation complexity to decrease significantly.

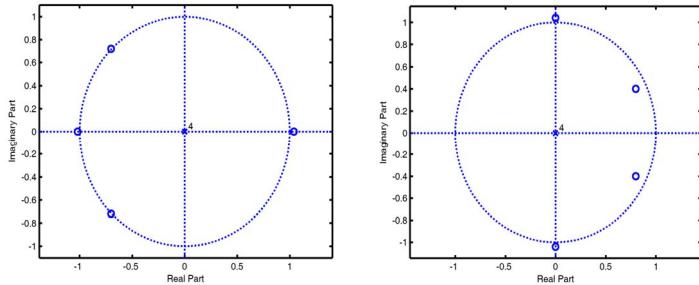


Figure 3. Zeros location of the SIMO system

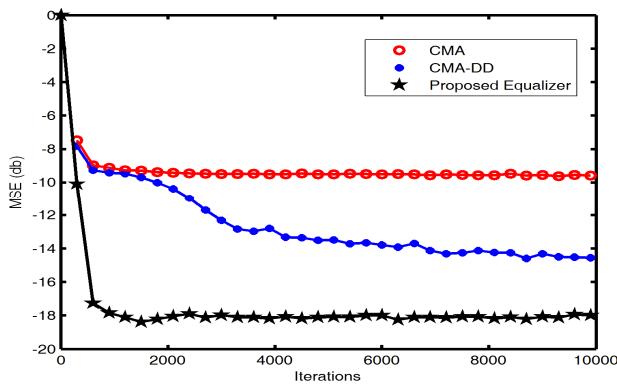


Figure 4. The compared performance (MSE) of the proposed method with CMA and CMA-DD for 8-QAM

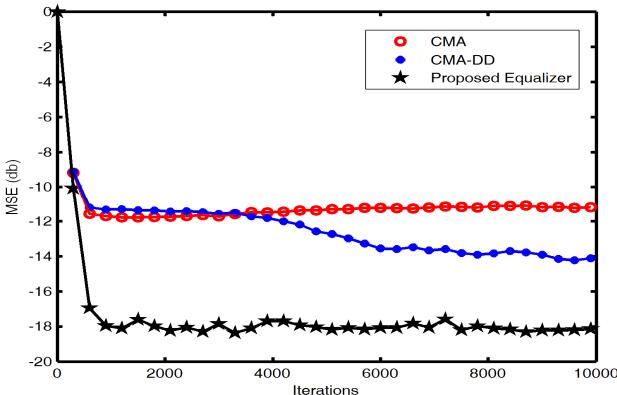


Figure 5. The compared performance (MSE) of the proposed method with CMA and CMA-DD for 16-QAM

REFERENCES

- [1] Chen, S., Wolfgang, A., Hanzo, L., "Constant modulus algorithm aided soft decision directed scheme for blind space-time equalization of SIMO channels," *Elsevier, Signal Processing*, Vol.87, Issue.11, pp.2587-2599, 2007.
- [2] Chen, B.S., Lin, C.W., Yang, T.Y., "Robust decision-feedback equalizer design method under parameter perturbation in a transmission channel," *Elsevier, Signal Processing*, Vol.44, Issue.1, pp.39-49, 1995.
- [3] Ling.F. , Proakis.J.G. , "Adaptive lattice decision feedback equalizer - Their performance and application to time variant multipath channels," *IEEE Trans. Comm.* Vol.33, No.4, pp.348-356, 1985.
- [4] Chen, B.S., Huang, Y.J., Chen, S.C., "Estimation and equalization of multipath Rician fading channels with stochastic tap coefficients," *Elsevier, Signal Processing*, Vol.68, Issue.1, pp.43-57, 1998.
- [5] Huang, Y.J., Chen, B.S., "Decision feedback equalization of frequency-selective Rician fading channels," *Elsevier, Signal Processing*, Vol.76, Issue.2, pp.117-133, 1999.
- [6] Stoica.P, Selen.Y, "Model-order selection," *IEEE Signal Process. Mag.* 21, pp. 36-47, 2004.
- [7] Ye, Y., Abeysekera, S.S., "Efficient blind estimation and equalization of non-minimum phase communications channels via the use of a zero forcing equalizer," *Elsevier, Signal Processing*, Vol.86, Issue.5, pp.1019-1034, 2006.
- [8] Abeysekera, S.S., "Implementation of a zero-forcing residue equalizer using a Laguerre filter architecture," *International Symposium on Circuits and Systems, ISCAS*, Vancouver, Canada, pp. 385-388, 2004.
- [9] Chen, S., McLaughlin, S., Grant, P.M., Mulgrew, B., "Fast blind equalization based on a Bayesian decision feedback equalizer" *IEE Electron. Lett.* 29, No.10, pp.891-893, 1993.
- [10] Lin, H., Yamashita, K., "Blind equalization using parallel Bayesian decision feedback equalizer" *Elsevier, Mathematics and Computers in Simulation*, Vol.56, Issue.3, 4, pp.247-257, 2001.
- [11] Proakis, J., Salehi, M., Digital Communications, 5th ed. McGraw-Hill, New York, 2008.