COMBINED MULTIUSER SIGNAL CLASSIFICATION AND BLIND EQUALIZATION

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ABSTRACT

A Multiuser Automatic Modulation Classifier (MAMC) is an important signal processing component of a multi-antenna cognitive radio (CR) receiver that can identify the modulation format employed by multiple users simultaneously. In a typical wireless communication system, transmitted signals are subjected to multipath fading and interference from other users. Multipath fading not only affects symbol detection performance but also affects the performance of the automatic modulation classifier (AMC). A multi-input multi-output (MIMO) blind equalizer is another important component of a multi-antenna CR receiver that improves symbol detection performance by reducing inter symbol interference (ISI) and inter user interference (IUI). In a CR scenario it is preferable to consider the performance of the AMC also while adapting the parameters of the blind equalizer. A n^{th} order cumulant based MAMC was recently proposed by the authors. In this paper, we propose a MIMO blind equalizer that improves the performance of both multiuser symbol detection and n^{th} order cumulant based MAMC. Computer simulations are provided to illustrate this concept and the proposed algorithm.

1. INTRODUCTION

With the advent of Cognitive Radios (CR) and Software Defined Radios (SDR) there is an increasing need for intelligent receivers. AMC is an important component of an intelligent receiver that helps the receiver in identifying the modulation format used in the detected signal. Most of the AMC algorithms in the literature can classify only a single user present in a frequency band. The authors of this paper recently proposed a n^{th} order cumulants based MAMC in [4],[5]. The MAMC proposed in [4],[5] requires multiple receiving antennas. The MAMC was developed for a more realistic multipath channel and no assumption about the transmission powers of the user was made. With multiple transmitting users and multiple receiving antennas, the overall setup can be viewed as a classical multiple input multiple output (MIMO) communication system and is depicted in Figure 1. Thus by using multiple receiving antennas apart from classifying signals from multiple users, the CR receiver can harness the benefits offered by traditional MIMO schemes.

Due to the presence of multiple signals in a frequency band, any transmitted signal is subjected to inter user interference (IUI). Also, the transmitted signals are subjected to inter symbol interference (ISI) due to multipath fading. Since there is no training sequence available in a CR scenario, MIMO blind equalizers are used to remove IUI and ISI. Both second order statistics (SOS) and higher order statistics (HOS) of the received signal are required to achieve MIMO blind equalization. Since HOS are used, MIMO blind equalizers have the potential to converge to a undesired local minimum. Convergence of a MIMO blind equalizer to a local minimum not only affects symbol detection performance but also the performance of the MAMC.

Typically, blind equalizers are designed to improve symbol detection performance. In a CR, AMC is an important component and hence it is better to design a blind equalizer that improves the performance of both AMC and symbol detection. Two works in this direction are found in the literature. However, both works consider only a single user AMC and single input single output (SISO) blind equalizer. The first work is in [11], where a robust switching SISO blind equalizer is proposed that improves the performance of single user AMC. In the second work [12], the weights of the SISO blind equalizer are adapted in such a way that performance of the cumulants based single user is improved.

In this paper, we propose a MIMO blind equalizer that improves the performance of both multiuser symbol detection and n^{th} order cumulant based MAMC. The overall block diagram of the proposed CR receiver is shown in Figure 1. In the figure, we design the MIMO blind equalizer $G(z^{-1})$ by considering the performance of both symbol detection and MAMC. The approach in this paper is motivated by the stop and go adaptation rules proposed in [8]. The proposed approach involves formulating a cost function that is related to the performance of n^{th} order cumulants based MAMC and computing its gradient.

The paper is organized as follows. In Section II, we provide the channel model and assumptions. In Section III, we present the background theory. In Section IV, we briefly describe MAMC from [5]. The cost function related to the performance of the MAMC is also developed in this section. In Section V, we present overall design of the proposed MIMO blind equalizer. Simulation results are presented in Section VI, followed by the conclusion.

Notation: $(.)^T$ denotes the usual transpose operation; $(.)^*$ or $(.)^H$ denotes the complex conjugate transpose; I_m denotes the identity matrix of dimension $m \times m$; $|(.)|$ denotes the absolute value of the variable; $E(.)$ denotes the statistical expectation. Whenever it is clear from the context, the dimensions of the matrices will be omitted for the simplicity of presentation and can be inferred from the context.

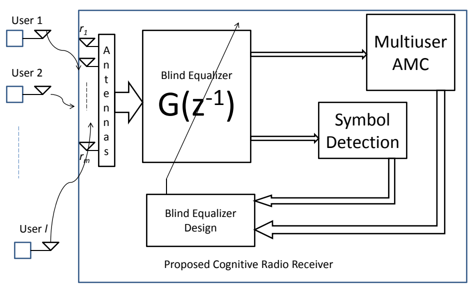

Fig. 1. Block diagram of the proposed system.

2. CHANNEL MODEL AND ASSUMPTIONS

In order to classify the signal from multiple users simultaneously, multiple antennas are used at the receiver. Let l be the number of transmitting users and m be the number of receiving antennas. It is required that $m > l$. In this paper we assume l to be known. In practice, l is estimated using the algorithms available in the literature ([18] and references therein).

The multipath channel between the j^{th} user and i^{th} receiving antenna is denoted as $h_{ij}(z^{-1})$ and is given by

$$h_{ij}(z^{-1}) = h_{ij}(0) + h_{ij}(1)z^{-1} + \ldots + h_{ij}(L)z^{-L}, \quad (1)$$

where L is the number of multipath components, z^{-1} is the unit delay operator, and $h_{ij}(k)$ (for $k = 1, \ldots, L$) are the fading coefficients of the corresponding multipaths. The overall system can now be represented by the following model

$$\begin{aligned} y(i) &= x(i) + w(i), \;\; i = 0, 1, 2, \ldots \\ x(i) &= H(z^{-1})s(i), \end{aligned} \quad (2)$$

where $s(i)$ is the $l \times 1$ transmission vector whose elements $s_k(i)$ $(k = 1, 2 \ldots l)$ denote the k^{th} transmitting user, $y(i)$ is the $m \times 1$ reception vector whose elements $y_k(i)$ $(k = 1, 2 \ldots m)$ denote the received signal at the k^{th} receiving antenna, $w(i)$ denotes the $m \times 1$ noise vector, and $H(z^{-1})$ is given by

$$H(z^{-1}) = \begin{bmatrix} h_{11}(z^{-1}) & \ldots & h_{1l}(z^{-1}) \\ \vdots & \ddots & \vdots \\ h_{m1}(z^{-1}) & \ldots & h_{ml}(z^{-1}) \end{bmatrix}. \quad (3)$$

Another representation of $H(z^{-1})$ used in this paper is

$$H(z^{-1}) = \sum_{k=0}^{L} H_k z^{-k} \quad (4)$$

where H_k (for $k = 1, 2 \ldots L$) is the $m \times l$ scalar matrix. This is also known as the MIMO FIR channel. We make the following assumptions regarding the system model (2).

Assumption A1: $rank[H(z^{-1})] = l$, for all complex $z \neq 0$, i.e. $H(z^{-1})$ is irreducible.

Assumption A2: $s(k)$ is zero mean, spatially independent and temporally white i.e.,

$$E[s(k)s^*(k+i)] = \begin{cases} I & i = 0 \\ O & i \neq 0 \end{cases}. \quad (5)$$

Non identity correlation matrices are absorbed into $H(z^{-1})$, i.e., the transmission power of the users can be different.

Assumption A3: $w(k)$ is zero-mean Gaussian with

$$E[w(k)w^*(k+i)] = \begin{cases} \sigma_w^2 I & i = 0 \\ O & i \neq 0 \end{cases}, \quad (6)$$

where O in (5) and (6) is zero matrix of appropriate dimension and σ_w^2 is the noise variance.

Assumption A1 is verified with probability one for any practical MIMO wireless channel with reasonable spatial diversity. Assumption A2 implies that signals transmitted by two different users are uncorrelated. Assumption A3 implies that that the noise vector is uncorrelated.

3. BACKGROUND THEORY

MIMO blind equalizers are used to recover the transmitted signal vector $s(i)$ using only the received signal vector $y(i)$ with no training sequence and knowledge of the channel transfer function $H(z^{-1})$. To recover the transmitted signal vector $s(i)$, we need to design $G(z^{-1})$ such that

$$G(z^{-1})H(z^{-1}) = I_l, \quad (7)$$

where $G(z^{-1})$ is a $l \times m$ matrix polynomial given by

$$G(z^{-1}) = \begin{bmatrix} g_{11}(z^{-1}) & \ldots & g_{m1}(z^{-1}) \\ \vdots & \ddots & \vdots \\ g_{l1}(z^{-1}) & \ldots & g_{lm}(z^{-1}) \end{bmatrix}. \quad (8)$$

The elements of $G(z^{-1})$ are modelled as FIR filters given by

$$g_{ij}(z^{-1}) = g_{ij}(0) + g_{ij}(1)z^{-1} + \ldots + g_{ij}(L1)z^{-L1} \quad (9)$$
$$for \ \ i = 1 \ldots l \ \ and \ \ j = 1 \ldots m.$$

In this paper, we propose to design $G(z^{-1})$ such that both symbol detection and MAMC performance is improved. In order to do so, we consider the MIMO based constant modulus algorithm (CMA) from [6] and stop and go adaptation rules proposed by [8]. In the following subsections we briefly describe stop and go adaptation rules and Tthe MIMO CMA algorithm.

3.1. Stop and Go Adaptation Rule

The output of the the MIMO blind equalizer is given by

$$z(i) = G(z^{-1})y(i), \quad (10)$$

where $z(i)$ is the $(l \times 1)$ output vector whose elements are denoted by $z_q(i)$ (for $q = 1 \ldots l$). The output of the equalizer $z(i)$ is used for both MAMC and symbol detection. It is necessary to consider the performance MAMC also while adapting the equalizer weights. Let the weights of the FIR filters in $G(z^{-1})$ during the k^{th} iteration be denoted as $\mathbf{g}_{ij}(k) = [g_{ij}(1), \ldots, g_{ij}(L1)]$ (for $i = 1 \ldots l$ and $j = 1 \ldots m$) and the regression vector as $\mathbf{y}_p(k) = [y_p(1), \ldots, y_p(L1)]$(for $p = 1 \ldots m$). Most blind equalization algorithms are designed as stochastic gradient schemes for updating the weight vector by minimizing cost functions that are related to symbol detection performance. For MIMO systems, the weights of the FIR filters in the q^{th} row of $G(z^{-1})$ are adapted by minimizing the cost function

$$\begin{aligned} J_1(z_q(k)) &= E[\Phi(z_q(k))] \quad (11) \\ &= E\left[\Phi(\sum_{p=1}^{m} \mathbf{g}_{qp}(k)\mathbf{y}_p(k)^T)\right], \end{aligned}$$

where $\Phi(z_q(k))$ is a nonlinear function of the equalizer output $z_q(k)$. Then the well known stochastic gradient decent algorithm for updating the weights of the filters in the q^{th} row is given by

$$\begin{aligned} \mathbf{g}_{qj}(k+1) &= \mathbf{g}_{qj}(k) - \mu \frac{\partial \Phi(z_q(k))}{\partial \mathbf{g}_{qj}(k)} \quad (12) \\ &= \mathbf{g}_{qj}(k) - \mu \Phi^{'}(z_q(k))) \\ &\quad (for \ \ \ j = 1 \ldots m) \end{aligned}$$

where μ is the step size and $\Phi^{'}(z_q(k))$ is the partial derivative of $\Phi(z_q(k))$ with respect to $\mathbf{g}_{qj}(k)$. Since the cost functions are non-quadratic, the weights have the potential to converge to a local minimum. From (12) it can be seen that the convergence of the blind equalizer depends on the gradient direction and more specifically the sign of the gradient $\Phi^{'}(z_q(k))$.

Since the output of the equalizer $z(i)$ is used for both symbol detection and MAMC, the convergence of the blind equalizer can be improved if the performance of the MAMC is also considered while adapting equalizer weights. In order to do so, we consider the 'stop and go' adaptation rules proposed in [8]. In the stop and go methodology, two cost functions are considered for adapting the equalizer weights. For each sample of the received signal, the equalizer weights are updated if the signs of the gradients of the two cost functions agree. Let us define the two cost functions for updating the filters in the q^{th} row as

$$\begin{aligned} J_1(z_q(k)) &= E[\Phi_1(z_q(k))] \quad (13) \\ &= E\left[\Phi_1(\sum_{p=1}^{m} \mathbf{g}_{qp}(k)\mathbf{y}_p(k)^T)\right], \end{aligned}$$

and

$$\begin{aligned} J_2(z_q(k)) &= E[\Phi_2(z_q(k))] \quad (14) \\ &= E\left[\Phi_2(\sum_{p=1}^{m} \mathbf{g}_{qp}(k)\mathbf{y}_p(k)^T)\right], \end{aligned}$$

where $\Phi_1(z_q(k))$ and $\Phi_2(z_q(k))$ are nonlinear functions of the equalizer output $z_q(k)$. Then the stop and go adaptation rule for updating the filter weights in the q^{th} row is given by

For $j = 1 \ldots m$

$$\mathbf{g}_{qj}(k+1) = \quad (15)$$
$$\begin{cases} \mathbf{g}_{qj}(k) - \mu \Phi_1^{'}(z_q(k)), \\ for \ \ sgn[\Phi_1^{'}(z_q(k))] = sgn[\Phi_2^{'}(z_q(k))] \\ \mathbf{g}_{qj}(k+1), \\ for \ \ sgn[\Phi_1^{'}(z_q(k))] \neq sgn[\Phi_2^{'}(z_q(k))] \end{cases}$$

So far in literature, both the cost functions (J_1 and J_2) are related to the symbol detection performance. In this paper, we choose the cost functions such that one of them is related to symbol detection performance and the other is related to the performance of the n^{th} order cumulants based MAMC. This ensures that the performance of the MAMC is not affected due to the blind equalizer. The rest of the paper is about formulating the cost functions (J_1 and J_2) and computing the respective gradients.

3.2. MIMO CMA

The CMA algorithm for SISO has been extended to MIMO systems in [6]. The coefficients of the FIR filters in the q^{th} row of $G(z^{-1})$ given by $g_{qj}(z^{-1})$ (for $j = 1 \ldots m$) are adapted by minimizing the following Godard cost function

$$J_1 = C[z_q(i)] = \frac{1}{4}E(|z_q(i)|^2 - 1)^2. \quad (16)$$

It is shown in [6] that each of the equalizer outputs $z_q(i)$ (for $q = 1 \ldots l$) converges to one of the transmitted signals. It is possible that some of the equalizer outputs converge to the same input. This can be avoided by using different initial weights for each filter in $G(z^{-1})$ and performing an independence test on the outputs. Also, the equalizer has the potential to converge to an undesired local minimum. Convergence to an undesired local minimum not only affects the symbol detection performance but also the MAMC performance. As mentioned earlier, in this paper we propose to use a modified version of stop and go adaptation rules to make sure that the performance of the MAMC is not affected.

4. CUMULANTS BASED MAMC

In this section, we briefly describe the higher order cumulants based MAMC. For a complex random signal $v(k)$, the n^{th} order moment is defined as

$$R_{v(n,m)}(k,\tau) = E\left[\prod_{j=1}^{n} v^{(*)_j}(k+\tau_j)\right] \tag{17}$$

where n is the order, m is the number of the conjugate factors, and $\tau = [\tau_1, \ldots, \tau_n]$ is the delay vector. In the above expression when $n = 2$ and $m = 1$ it becomes the standard auto correlation function. The n^{th} order cumulant function is defined as [13]

$$C_{v(n,m)}(k,\tau) = \sum_{P_n} K(p) \prod_{j=1}^{p} R_{v(n_j,m_j)}(k,\tau) \tag{18}$$

where the sum is over distinct partitions of the indexed set $\{1, 2 \ldots n\}$ and $K(p) = (-1)^{p-1}(p-1)!$. For example, in the above expression, when $n = 4$ and $m = 0$ we get the expression for one of the fourth order cumulants given by

$$C_{v40}(k) = E[v^4(k)] - 3E[v^2(k)]^2. \tag{19}$$

For the MAMC, the following feature is considered for classification

$$\hat{C}_{v(n,m)}(\tau) = \frac{C_{v(n,m)}(\tau)}{\left[C^2_{v(2,1)}\right]^{n/2}} \quad for\ n = 4, 6, \ldots. \tag{20}$$

The above feature is only the normalized version of the n^{th} order cumulant.

For the multiuser system defined by (2), the relationship between the normalized cumulant values of each transmitting user and normalized cumulant values of the signals received at each receiving antenna is given by

$$\begin{bmatrix} \tilde{C}_{y_1(n,m)}(\tau) \\ \vdots \\ \tilde{C}_{y_m(n,m)}(\tau) \end{bmatrix} = \tag{21}$$

$$= \begin{bmatrix} \frac{\gamma_{11}}{\Delta_1^{n/2}} & \cdots & \frac{\gamma_{1l}}{\Delta_1^{n/2}} \\ \vdots & \ddots & \vdots \\ \frac{\gamma_{m1}}{\Delta_m^{n/2}} & \cdots & \frac{\gamma_{ml}}{\Delta_m^{n/2}} \end{bmatrix} \begin{bmatrix} \tilde{C}_{s_1(n,m)}(\tau) \\ \vdots \\ \tilde{C}_{s_l(n,m)}(\tau) \end{bmatrix}.$$

or

$$\vec{C}_{y(n,m)}(\tau) = B_c \vec{C}_{s(n,m)}(\tau). \tag{22}$$

where $\tilde{C}_{y_i(n,m)}(\tau)$ (for $i = 1, 2 \ldots m$) are the normalized cumulant values of the signals at each receiving antenna, $\tilde{C}_{s_i(n,m)}(\tau)$ (for $i = 1, 2 \ldots l$) are the normalized cumulant values of the signals transmitted by each user,

$$\gamma_{ij} = \sum_{k=0}^{L-1} |h_{ij}(k)|^n \;\; (for\;\; i = 1, 2 \ldots m, \quad j = 1, 2 \ldots l) \tag{23}$$

and

$$\Delta_i = \sum_{p=1}^{l} \sum_{k=0}^{L-1} |h_{il}(k)|^2 \; (for\;\; i = 1, 2 \ldots m). \tag{24}$$

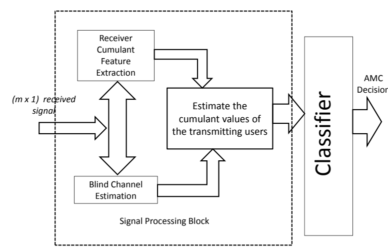

Fig. 2. Block diagram of the proposed MAMC

In [4], a blind MIMO channel estimation algorithm is proposed for estimating $H(z^{-1})$. Using the estimated channel, the elements of the B_c matrix are computed. Using the estimated B_c matrix we solve for $\vec{C}_{s(n,m)}(\tau)$, which is used as a feature for classification. The overall block diagram of the MAMC is shown in Figure 2. In Figure 2, the signal processing block extracts the features $\vec{C}_{s(n,m)}(\tau)$ which in turn is fed to the classifier. Some of the widely used classifiers are neural networks, support vector machines, etc. In [4], the classifier used was the shortest distance method. Refer to [4] for a detailed explanation.

4.1. Cost Function for the MAMC

In this subsection, we derive the cost function J_2 that is related to the performance of n^{th} order cumulants based MAMC. In order to do so, we need to understand the effect of the MIMO FIR filter on the normalized cumulant values of the received signal. From (21) one can see that the normalized cumulant values of each received signal $\tilde{C}_{y_i(n,m)}$ (for $i = 1, 2 \ldots m$) is a weighted sum of the normalized cumulant values of all the transmitting users. The weighting coefficients are given by $w_{ij} = \frac{\gamma_{ij}}{\Delta_i^2}$ (for i= 1,2…m, j= 1,2…l) (refer to (21)). It can be easily shown that

$$|w_{ij}| = |\frac{\gamma_{ij}}{\Delta_i^2}| < 1 \quad (for \;\; i = 1, 2 \ldots m, \quad j = 1, 2 \ldots l) \tag{25}$$

Since the magnitude of weighting coefficients are less than one, the magnitude of the normalized cumulant values of the received signals are driven towards zero. The MIMO FIR channel clusters all the cumulant features around zero. This clustering makes it hard for the classifier shown in Figure 2 to distinguish between the features. Thus the coefficients of the matrix polynomial $G(z^{-1})$ must be chosen in such a way that the features are unclustered. For this reason we propose the following cost function. The cost function for updating the filters in the q^{th} row is given by

$$J_2 = (C_{z_q(n,m)}(\tau))^2. \tag{26}$$

The above cost function maximizes the magnitude of the normalized cumulant values of the signals so that the classifier can distinguish between the features.

5. PROPOSED ALGORITHM

An important step in the proposed approach is to compute the gradients of J_1 and J_2.

5.1. Computing the Gradient of J_2

For the cost function J_2, we need to calculate the stochastic gradient function $\Phi_1^{'}(z_q(k))$ in order to use the stop and go adaptation rule in (15). It should be noted that the cost function (26) is non quadratic and non linear. Since only the sign of the gradient is required, we compute an approximate function for the gradient. By substituting (18) in (26), the cost function becomes

$$J_2 = \left(\frac{C_{z_q(n,m)}(k,\tau)}{C_{z_q(2,1)}(0)} \right)^2. \tag{27}$$

Now the gradient $\partial J_1 / \partial \mathbf{g}_{qj}$ (for $q = 1, 2 \ldots l$ and $j = 1, 2 \ldots m$) is given by

$$\frac{\partial J_2}{\partial \mathbf{g}_{qj}} = J_2(\mathbf{g}_{qj}) \tag{28}$$
$$[\frac{1}{C_{z_q(n,m)}(k,\tau)} \frac{\partial C_{z_q(n,m)}(k,\tau)}{\partial \mathbf{g}_{qj}^*} + \frac{1}{C_{z_q(m,n)}(k,\tau)} \frac{\partial C_{z_q(m,n)}(k,\tau)}{\partial \mathbf{g}_{qj}} - \frac{m+n}{C_{z_q(2,1)}(0)} \frac{\partial C_{z_q(2,1)}(0)}{\partial \mathbf{g}_{qj}^*}].$$

By substituting the expression for cumulants in the above equation and replacing the expectation operation by the sample estimate we obtain the expression for the stochastic gradient. Here we present the stochastic gradient function for some specific cases that were used for the simulations.

Case 1. $n = 4$, $m = 0$, and $\tau = 0$ (Fourth order cumulants)

$$\frac{\partial J_2}{\partial \mathbf{g}_{qj}} = \frac{z_q^4(k)[z_q^*(k) z_q(k) - 1]}{z_q^*(k)} \mathbf{y}_j(k)^H = \psi_2(z_q(k)) \mathbf{y}_j(k)^H \tag{29}$$

Case 2. $n = 6$, $m = 1$, and $\tau = 0$ (Sixth order cumulants)

$$\frac{\partial J_2}{\partial \mathbf{g}_{qj}} = \tag{30}$$
$$z_q^5(k) z_q^*(k) [z_q^7(k) + 5 z_q^{*7}(k) - 6 z_q^5(k) z_q^{*4}(k)] \frac{1}{z_q^{*4}(k) z_q^4(k)} \mathbf{y}_j(k)^H = \psi_2(z_q(k)) \mathbf{y}_j(k)^H$$

where $\mathbf{y}_j(k)$ (for $j = 1 \ldots m$) in the above equations is the $(1 \times L1)$ regression vector.

5.2. Computing the Gradient of J_1

The stochastic gradient of J_1 is obtained by taking the partial derivative of (16) and then replacing the expectation operation by a sample estimate. The stochastic gradient of J_1 is given by [6],

$$\frac{\partial J_1}{\partial \mathbf{g}_{qj}} = (|z_q(k)| - 1) \mathbf{y}_j(k)^H = \psi_1(z_q(k)) \mathbf{y}_j(k)^H \tag{31}$$

where $\mathbf{y}_j(k)$ (for $j = 1 \ldots m$) in the above equations is the $(1 \times L1)$ regression vector.

5.3. Overall Algorithm

The algorithm to adapt the weights of the MIMO blind equalizer is obtained by substituting the gradient functions derived in this section in (15). The overall stop and go adaptation rule for updating the filter weights in the q^{th} row of $G(z^{-1})$ is given by

For $j = 1 \ldots m$

$$\mathbf{g}_{qj}(k+1) = \begin{cases} \mathbf{g}_{qj}(k) - \mu \psi_1(z_q(k)) \mathbf{y}_j(k)^H, \\ \quad for \;\; sgn[\psi_1^{'}(z_q(k))] = sgn[\psi_2^{'}(z_q(k))] \\ \mathbf{g}_{qj}(k+1), \\ \quad for \;\; sgn[\psi_1^{'}(z_q(k))] \neq sgn[\psi_2^{'}(z_q(k))] \end{cases} \tag{32}$$

where $\psi_1(z_q(k))$ is given by (31) and $\psi_2(z_q(k))$ depends on order of the cumulants based AMC (refer to (29) and (30) for specific cases).

6. PERFORMANCE ANALYSIS

In this section, we demonstrate the performance of the proposed multi antenna CR receiver using Monte Carlo simulation. For the Monte Carlo simulation, 1000 trials are considered. In order to analyze the performance of the proposed MAMC, the probability of correct classification P_c is used as feature for classification. Suppose that there are l users and M modulation schemes which are denoted as $\Omega = \{\Omega_1, \ldots, \Omega_M\}$. Then there are $L_1 = M^l$ possible transmission scenarios denoted as $D = \{d_1, \ldots, d_{L_1}\}$. The probability of correct classification P_c is defined as [4]

$$P_c = \sum_{i=1}^{L_1} P(d_i|d_i)P(d_i) \tag{33}$$

where $P(d_i)$ is the probability that the particular transmission scenario occurs and $P(d_i|d_i)$ is the correct classification probability when scenario d_i has been transmitted. In this experiment we consider $l = 2$ transmitting users and $m = 3$ receiving antennas. This is a common scenario for CR in commercial application, where CR needs to identify whether a primary user or malicious user is present in a frequency band apart from the secondary user. For the channel, we consider the MIMO FIR channel from [6] given by

$$H(z^{-1}) = \begin{bmatrix} -1.95 + 1.06z^{-1} & -0.57 - 1.88z^{-1} \\ -0.56 - 0.79z^{-1} & 0.42 + 0.05z^{-1} \\ -1.12 + 0.35z^{-1} & 0.76 - 0.27z^{-1} \end{bmatrix}. \tag{34}$$

Case 1 (Fourth order cumulants): For this case, we consider a fourth order cumulant feature with $n = 4$, $m = 0$ and $\tau = 0$ (refer to (18)). The number of samples used to estimate the cumulant features was T1 = 5000. The stochastic gradient of the MAMC ($\Psi_1(z)$) cost function for this case is given by (29). The performance of the MAMC for the proposed system is shown in Fig. 3. In Fig. 3, $Pc2$ denotes the performance of the MAMC proposed in [4] and $Pc1$ denotes the performance of the MAMC using the proposed equalizer.

Case 2 (Sixth order cumulants): For this case, we consider a sixth order cumulant features with $n = 6$, $m = 0$, and $\tau = 0$ (refer to (18)). The number of samples used to estimate the cumulant features was T1 = 10000. The stochastic gradient of the MAMC ($\Psi_1(z)$) cost function for this case is given by (30). The performance of the AMC for the proposed system is shown in Fig. 4. In Fig. 4, $Pc1$ and $Pc2$ have the same meaning as that of Fig. 3.

From Fig. 4 and Fig. 3, it can be seen that the proposed system performs better than the MAMC proposed in [4]. The reason is that MAMC performance is also considered while adapting the weights of the equalizer. The symbol detection performance is similar to that of the MIMO CMA equalizer in [6] and hence not repeated here.

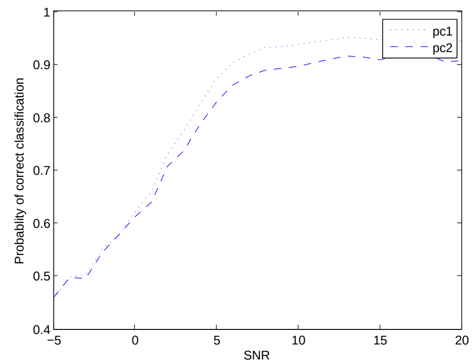

Fig. 3. Performance of the fourth order cumulant based MAMC $\{BPSK, QAM(4), PSK(8)\}$.

7. CONCLUSION

In this paper we designed a MIMO blind equalizer that improves the performance of both cumulant based MAMC and symbol detection. The performance of proposed equalizer was analyzed using computer simulations and yielded promising results.

8. ACKNOWLEDGEMENT

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9. REFERENCES

[1] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Select. Areas Commun,* vol. 23, pp. 201-220, 2005.

[2] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, "Survey of automatic modulation classification techniques: Classical approaches and new trends," *IET Communication,* vol. 1, no. 2, pp. 137-156, Apr. 2007.

[3] M. Zaerin, B. Seyfe, and H. R. Nikoofar, "Multiuser modulation classification based on cumulants in AWGN chan-

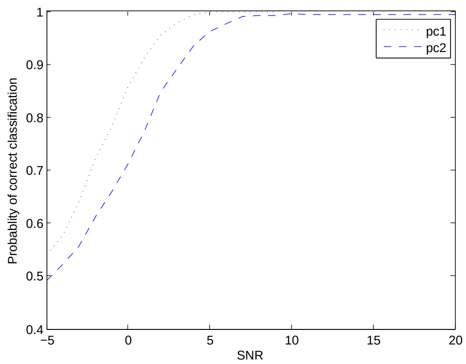

Fig. 4. Performance of the sixth order cumulants based AMC $\{BPSK, QAM(4), PSK(8), PSK(32)\}$.

nel," *Submitted to IEEE Transaction on Communications,* http://arxiv.org/abs/0908.2117.

[4] B. Ramkumar, T. Bose, and M. S. Radenkovic, "Robust multiuser automatic modulation classifier for multipath fading channels," *in Proc. IEEE Dyspan,* 2010.

[5] B. Ramkumar, T. Bose, and M. S. Radenkovic, "Robust cyclic cumulants based multiuser automatic modulation classifier for cognitive radios," *in Proc. Wireless Innovation Forum,* 2010.

[6] Y. Li and K. J. R. Liu, "Adaptive blind source separation and equalization for multiple-input/multiple-output systems," *IEEE Trnas. Info Theory,* vol. 44, no. 7, Nov. 1998.

[7] A. Swami and B. M. Sadler, "Hierarchical digital modulation classification using cumulants," *IEEE Trans. Commun.,* vol. 48, no. 3, pp. 416-429, Mar. 2000.

[8] D. Hatzinakos, "Blind equalization using stop-and-go criterion adaptation rules," *Optical Engineering,* vol. 31, pp. 1181-1198, June 1992.

[9] D. Hatzinakos, "Blind equalization," *Alta Frequenza,* vol. 7, pp. 445-450, Sep. 1988.

[10] S. Xi and H.-C. Wu, "Robust automatic modulation classification using cumulant features in the presence of fading channels," in *Proc. IEEE Wireless Communications and Networking Conference,* Apr. 2006, vol. 4, pp. 2094-2099.

[11] H.-C. Wu, Y. Wu, J. C. Principe and X. Wang, "Robust switching blind equalizer for wireless cognitive receivers," *IEEE Trans. Wireless Commun,* vol. 7, no. 5, pp. 1461-1465, May 2008.

[12] B. Ramkumar, T. Bose, and M. S. Radenkovic, "Robust automatic modulation classification and blind equalization: A novel cognitive receiver," in Proc. of Wireless Innovation Forum, 2010.

[13] C. M. Spooner, "Classification of cochannel communication signals using cyclic cumulants," *in Proc. ASILOMAR Conf.* 1995, pp. 531-536.

[14] C. M. Spooner, W. A. Brown, and G. K. Yeung, "Automatic radio-frequency environment analysis," *in Proc. ASILOMAR Conf.* 2000, pp. 1181-1186.

[15] C. M. Spooner, "On the utility of sixth-order cyclic cumulants for RF signal classification," *in Proc. ASILOMAR Conf.* 2001, pp. 890-897.

[16] O. A. Dobre, Y. Bar-Ness, and W. Su, "Higher-order cyclic cumulants for high order modulation classification," *in Proc.IEEE MILCOM* 2003, pp. 112-117.

[17] O. A. Dobre, Y. Bar-Ness, and W. Su, "Robust QAM modulation classification algorithm based on cyclic cumulants," *in Proc. IEEE WCNC* 2004, pp. 745-748.

[18] M. Shi, Y. Bar-Ness , and W. Su "Adaptive estimation of the number of transmit antennas," Proc. *IEEE MILCOM* pp. 1-5, Oct. 2007.