ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Automatic Modulation Classification and Blind Equalization for Cognitive Radios

P.Yashwanth Reddy
M.Tech Student,
Department of Electronics and Instrumentation Engineering,
GITAM University, Visakhapatnam,
Andhra Pradesh, India.

G.Naresh Kumar
Associate Professor,
Department of Electronics and Instrumentation Engineering,
GITAM University, Visakhapatnam,
Andhra Pradesh, India.

ABSTRACT:

Cognitive radio (CR) is a developing wireless communication technology that addresses the inefficiency of current radio spectrum management. The automatic modulation classifier (AMC) is an important signal processing component that helps the CR in identifying the modulation format occupied in the detected signal. A blind equalizer is another important signal processing component that a CR must carry since there are no training or pilot signals available in many applications. In a typical wireless communication area the transmitted signals are subjected to noise and multipath fading. Multipath fading is not only affects the performances of symbol detection by causing inter symbol interference (ISI) but also affects the performance of the AMC.

The blind equalizer that removes ISI from the received signal, thus improving the symbol detection performance.AMC can be broadly classified into are two categories: Likelihood based and Feature based. Cumulants based AMC was categorized in featured based and it was considered because of its ability to classify a wide variety of modulation schemes with easy implementation. This will involve formulating a cost function that is related to the performance of the chosen AMC and adapting the weights of the equalizer such that the cost function is optimized. Depending on the type of feature based AMC, it may be required to use nonlinear optimization techniques like a genetic algorithm (GA).

INTRODUCTION:

Cognitive Radio (CR), basically introduced by Mitola [2], has become a key research area in the field of communications. CR is a hopeful technology that is capable of achieving better spectrum utilization by opportunistically finding and utilizing vacancy frequency bands [1]. AMC, as the name suggests is the automatic recognition of modulated signals present in a particular band of frequency. AMC is an important component of cognitive radio that improves spectral efficiency by modifying transmission and reception according to the spectral environment. CRs are basically intended to form an ad-hoc network known as a Cognitive Radio Network (CRN) [3], which has potential military and commercial applications.

In public safety and military applications, the CRs must be capable of performing fixed and on-the move communications between highly different elements in a harsh environment which may also be susceptible to jamming attacks and malicious interference [4]. For the secure and reliable operation of a CRN, CRs must be able to identify all users in the frequency band simultaneously. Feature based AMCs [5] are widely used because of easy implementation and better performance. The multiuser AMC using fourth order cumulant based approach is recently proposed in [6].
By using multiple antennas at the receiver the CR can identify the number of transmitting users which is generally not possible while using a single antenna receiver.

Also, by using multiple antennas the CR can harness the flexibility offered by traditional multi-input multi-output (MIMO) communication schemes separate from classifying the signals from multiple users. The cumulant based multiuser AMC [6] requires the knowledge of the multiuser channel impulse response. However, channel knowledge or pilot sequence for estimating the channel is not available in a CR scenario. Therefore, one needs toestimate the channel blindly. In blind channel estimation, the channel impulse response is estimated using only the received data sequence withpilot sequence or no knowledge of the transmitted. Most of the blind multi-channel identification algorithms are proposed in[8]-[19]are batch processing algorithms.

Due to the presence of multiple signals in a frequency band, any transmitted signal is subjected to the inter user interference (IUI).The transmitted signals are subjected to inter symbol interference (ISI) due to the multipath fading. Since there is no training sequence available in a CR scheme, 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 local minimum. Convergence of MIMO blind equalizer to local minimum not only affects symbol detection performance but also the performance of multiuser AMC.

Mostly, blind equalizers are designed to improve the performance of symbol detection. In a CR, AMC is an important component and hence it is better to design a blind equalizer that improves the performance of both symbol detection and AMC. In this paper, we propose the MIMO blind equalizer that improves the performance of both multiuser AMC and multiuser symbol detection. In order to do so, we design a cost function that is related to the performance of the multiuser AMC and then choose the parameters of the blind equalizer such that the cost function is maximized. 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 multiuser AMC and multiuser symbol detection. For designing the blind equalizer we can also use the MIMO channel estimates provided by the multiuser AMC.

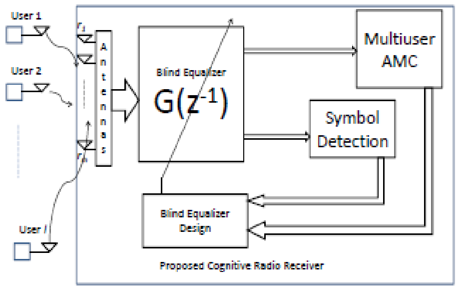

Figure 1: Block diagram of the proposed system.

2. Channel Model and Assumptions

As mentioned earlier, multiple receiving antennas are used for classifying signals from multiple users. Let l and m are the number of transmitting users and the number of receiving antennas respectively and it is required that m > l. Usually in a CR scheme, l is not known and needs to be estimated using algorithms like the one proposed in [20]. The multipath channel between the i^{th} receiving antenna and j^{th} user 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, . . . , L) is the fading coefficients of the corresponding multipaths. Now, the overall system can be represented by the following model

$$y(i) = x(i) + w(i),\ i = 0, 1, 2, \ldots \quad (2)$$

$$x(i) = H(z^{-1})s(i),$$

Where s(i) is the $l \times 1$ transmission vector whose elements $s_k(i)$ (k = 1, 2 . . . l) denote the k^{th} transmitting user and y(i) is the $m \times 1$ reception vector whose elements $y_k(i)$ (k = 1, 2 . . . m) denote the

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

received signal at the k^{th} receiving antenna, $w(i)$ denotes the $m \times 1$ noise vector and $H(z^{-1})$ is given by

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

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 $k = 1, 2 \,.\,. L$) is the $m \times l$ scalar matrix. We make the following assumptions regarding the system model (2).

Assumption A21: rank$[H(z^{-1})]$=l, for all complex z=0, i.e. $H(z^{-1})$ is irreducible.Assumption A21 is valid for any practical wireless channel with reasonable spatial diversity. Also we assume that the signals transmitted by various users are uncorrelated and each element of the noise vector $w(i)$ is zero mean white Gaussian with variance σ^2_w.

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 $H(z^{-1})$. As mentioned earlier, in this paper we design a blind equalizer that takes into consideration the performance of the multiuser AMC. In order to do so, we consider the following theorem from [17].

Theorem 1:[17] For the system given in (2) under Assumption A21 there exists $(l \times m)$ polynomial matrix $G(z^{-1})$ such that

$$G(z^{-1})H(z^{-1}) = I_l. \quad (5)$$

Since $G(z^{-1})$ is not unique, so we can choose $G(z^{-1})$ such that both multiuser AMC performance andsymbol detection performances are improved.

According to [18], $G(z^{-1})$ in (5) can be factorized as follows

$$G(z^{-1}) = G_2(z^{-1})G_1(z^{-1}), \quad (6)$$

where $G_2(z^{-1})$ is a $l \times m$ polynomial matrix and $G_1(z^{-1})$ is an arbitrary $m \times m$ polynomial matrix with the condition $\det[G_1(z^{-1})] \neq 0$, f or $|z| \geq 1$. Since $G_1(z^{-1})$ is an arbitrary polynomial matrix, we design $G_1(z^{-1})$ such that the multiuser AMC performance is improved. To do so, we first construct a cost function J_{amc} which is related to the performance of the multiuser AMC. Then We can choose the parameters of $G_1(z^{-1})$ such that J_{amc} is maximized. The overall design of $G_1(z^{-1})$ can be viewed as the following constrained optimization problem

$$\max_{G1(z-1)} J_{amc}$$

$$\text{s.t.}\det[G_1(z^{-1})] = 0, \text{ f or } |z| \geq 1 \quad (7)$$

The rest of the paper is about formulating the cost function J_{amc} and solving for the polynomial matrices $G_1(z^{-1})$ and $G_2(z^{-1})$.

2.1 Cost Function for the Multiuser AMC

In this subsection we develop the cost function J_{amc} for designing blind equalizer polynomials $G_1(z^{-1})$ and $G_2(z^{-1})$. 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 [6] one can see that the normalized cumulant values of each received signal $\tilde{C}_{yi(n,m)}$ (for $i = 1, 2 \,.\,.\,.\, m$)is a weighted sum of the normalized cumulant values of all the transmitting users. The weighting coefficients are given by $w_{ij} = \gamma_{ij}$(for i= 1,2. . . m, j= 1,2. .l) [6]. It can be easily shown that

$$|w_{ij}| = |\gamma_{ij}\Delta^2{}_i| < 1 \quad (\text{f or } i = 1, 2 \,.\,.\,.\, m, \quad j = 1,2. \,.l) \quad (8)$$

Since the magnitude of the 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 [6] to distinguish between the features. Thus the coefficients of the matrix polynomial $G_1(z^{-1})$ must be chosen in such a way that the features are unclustered. For this reason we propose the following cost function

$$J_{amc} = \sum^{m}_{j=1} |C_{x2j(n,m)}|, \quad (9)$$

Where $x_2(i) = G_1(z^{-1})y(i)$ and $C_{x2j(n,m)}$ is the cumulant value of the j_{th} component in the vector signal $x_2(i)$. The above cost function maximizes the magnitude of the normalized cumulant values of the signals so that the classifier can distinguish between the features.

3 Designing the Matrix Polynomials

In this section, we propose the algorithm for designing the polynomials $G_1(z^{-1})$ and $G_2(z^{-1})$. We also present the overall step by step procedure for designing the blind equalizer. The cost function in (9) can be expressed as follows

$$J_{amc} = \sum^{m}_{j=1}|C_{x2(j)(n,k)}| = J_1 + \ldots + J_m, \quad (10)$$

Where $J_i = |C_{x2(i)(n,k)}|$ (for $i = 1 \ldots m$). Now we choose $G_1(z^{-1})$ to be the diagonal

matrix given by

$$G_1(z^{-1}) = \text{diag } C_1(z^{-1}), \ldots, C_m(z^{-1}), \quad (11)$$

Where the elements of diagonal matrix are the FIR filters given by

$$C_p(z^{-1}) = c_{p1}z^{-1} + \ldots + c_{pL1}z^{-L1} \quad (12)$$

$$\text{for } p = 1 \ldots m$$

Where L1 is the length of the filter and c_{ij} (for $i = 1, \ldots, m$, $j = 1, \ldots, L1$) are the filter weights. Since $G_1(z^{-1})$ is chosen to be a diagonal matrix, the constraint on $G_1(z^{-1})$(refer[21]-[25]) implies that the FIR filter $C_p(z^{-1})$ (for $p = 1 \ldots m$) must be minimum phase. That is, the filter must not have any zeros on or outside the unit circle. Let us denote the weight vector as $c_p = [c_{p1}, \ldots, c_{pL}]$ (for $p = 1, \ldots, m$) then, for updating weights we use the following constrained gradient search technique. Due to the constraint on $G_1(z^{-1})$ we reduce the search space to the region where the weights form a minimum phase polynomial.Let$c_p(k)$denote the coefficient vector during the iteration $k = 0, 1, 2, \ldots$.

• **Step 1**: For $k = 0$ initialize $c_p(0)$ to a random value from the search space.

• **Step 2**: For $k = 1, 2, \ldots$ calculate the output of the filter

$$x_{2p}(n) = \sum^{L}_{m=0} c_p(m) y_p(n - m) \quad (13)$$

$$\text{for } p = 1 \ldots m$$

• **Step 3:** Update the coefficient vector using the following equation

$$c_p(k) = c_p(k - 1) - \mu\, \partial J_p/\partial c_p$$

$$\text{for } p = 1 \ldots m \quad (14)$$

where μ is step size. The weights are updated only if the new weights lies in the search space. If not, repeat step 2.

• **Step 4:** If $|J_p(c_p(k)) - J_p(c_p(k-1))| \,/\, J_p(c_p(k-1)) < \zeta$ terminate the iteration and go to step 5. If not, repeat step 2, where ζ is chosen to be a small number less than one.

• **Step 5:** Calculate the output $x_2(i)$ using $G_1(z^{-1})$.

Now the cumulant features of the $(m \times 1)$ signal vector x_2 are maximized and not clustered around zero, therefore x2 is given to the MAMC shown for classification[6]. Let us denote

$$F(z^{-1}) = G_1(z^{-1})H(z^{-1}) = \sum^{L+L1-1}_{k=0} F_k z^{-k}. \quad (15)$$

It can be seen from [6], that a blind MIMO channel estimator forms an integral part of the multiuser AMC Since $x_2(i)$ is fed to the multiuser AMC, we can obtain the estimate of the polynomial $F(z^{-1})$. Using the estimate of $F(z^{-1})$,we design $G_2(z^{-1})$ by solving the following equation

$$G_2(z^{-1})F(z^{-1}) = I_l, \quad (16)$$

where I_l is the $(l \times l)$ identity matrix. Let us denote $G_2(z^{-1})$ as

$$G_2(z^{-1}) = \sum^{L2-1}_{k=0} G_{2k} z^{-k}, \quad (17)$$

where G_{2k} (for $k = 0, 2 \ldots (L2 - 1)$) are the $l \times m$ scalar matrix. Now the solution to (16) is given by [17],[18]

$$[G_{21}\ G_{22}\ G_{23} \ldots\ldots] = [I_l \ldots] S^{\dagger}, \quad (18)$$

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International Journal & Magazine of Engineering,
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Where S† is the pseudo inverse of the S matrix given by

$$S = \begin{pmatrix} F_0 & F_1 & F_2 \ldots & \ldots \\ 0 & F_0 & F_1 \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ 0 \quad 0 & 0 & F_0 & \ldots \end{pmatrix} \quad (19)$$

3.1.Overall Classification and Equalization Algorithm

In this section we can present the step by step implementation of the overall proposed system.

• **Step 1:** Given the (m × 1) received signal vector y(i) estimate the number of transmitting users l using the method proposed in [20].•

Step 2: Choose the length of the matrix polynomials L1 and L2. Since the length of channel impulse response is not known,choose a sufficiently large length so that

the system is over modeled.

• **Step 3:** $G_1(z^{-1})$ is chosen to be a diagonal matrix given by (11) and its coefficients are adapted by using the gradient search algorithm given by (14).

• **Step 4:** The signal $x_2(i)$ is sent to the MAMC for classification. The multiuser AMC provides an estimate of the matrix polynomial $F(z^{-1})$.

• **Step 5:** Using the estimated $F(z^{-1})$, then design the (l × m) matrix polynomial $G_2(z^{-1})$ by solving (16). The output of $G_2(z^{-1})$ is used for symbol detection.

4 Simulation results

In this section, we demonstrate the performance of the constant modulus algorithm (CMA) optimization and the performance of the proposed MIMO blind equalizer using Monte Carlo simulation. Since the performance of the multiuser AMC is also considered while designing the blind equalizer, we can analyze the performance of both the multiuser AMC and symbol detection. For the Monte Carlo simulation, 1,000 trials are considered.

4.1 CMA Optimization performance

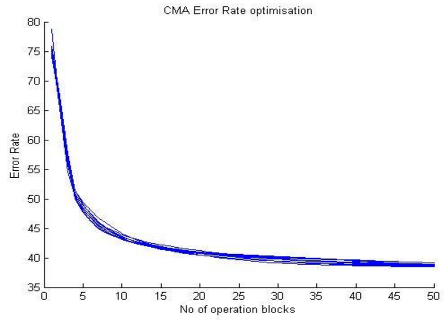

Figure 2: Performance of the CMA optimization

The above figure represents the maintenance of the error rate as no of operational blocks are going to increase in CMA optimization.

4.2 Multiuser AMC Performance

In this subsection we can determine the performance of the MAMC using computer simulation. The performance measure considered is the probability of correct classification P_{cc}. 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 $D = \{d_1, \ldots, d_{L1}\}$. The probability of correct classification P_{cc} is defined as

$$P_{cc} = \sum_{i=1}^{L1} P(d_i|d_i)P(d_i) \quad (20)$$

Where $P(d_i)$ is the probability to that the particular transmission scenario occurs and $P(d_i|d_i)$ is the correct classification probability when scenario d_i has been transmitted. For the simulation we assumeP (di) =1/ L1, ∀ i, where all scenarios are equally probable.

Two-user three-class problem (Fourth order cumulants)

In this experiment we can consider l = 2 transmitting users and m = 3 receiving antennas. The 3 × 2 channel matrix $H(z^{-1})$ is modeled as a realistic three tap MIMO FIR channel. Three modulation schemes are considered for this experiment and they are Ω =

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International Journal & Magazine of Engineering, Technology, Management and Research
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{BPSK, QAM(4), PSK(32)}. Since three modulation schemes are considered, there are nine possible scenarios. The Monte Carlo simulation results are summarized in Figure 3. In Figure 3, the curve labeled P_{cc2} shows the performance of the multiuser AMC without the proposed blind equalizer. The curve labelled P_{cc1} illustrates the performance of the AMC using the proposed system.

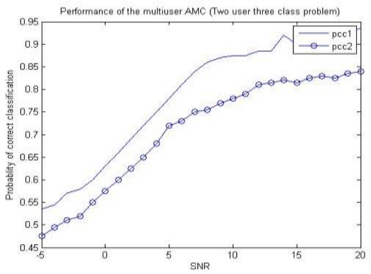

Figure 3: Performance of the multiuser AMC (Two-user three-class problem).

Two-user four-class problem (Fourth order cumulants)

In this experiment we can consider l = 2 transmitting users and m = 3 receiving antennas. The 3 × 2 channel matrix $H(z^{-1})$ is modeled as a realistic three tap MIMO FIR channel. Three modulation schemes are considered for this experiment and they are Ω = {BPSK, QAM (4), QAM (16), PSK(32)}. Since four modulation schemes are considered, there are sixteen possible scenarios. The Monte Carlo simulation results are summarized in Figure 4. In Figure 4, the curve labeled P_{cc2} showsthe performance of the multiuser AMC without the proposed blind equalizer. The curve labelled P_{cc1} illustrates the performance of the AMC using the proposed system.

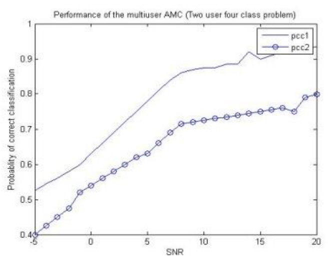

Figure 4: Performance of the multiuser AMC (Two-user four-class problem)

Four-user five-class problem (Sixth order cumulants)

In this experiment we can consider l = 4 transmitting users and m = 5 receiving antennas. Each entry of the 5 × 4 channel matrix $H(z^{-1})$ is modeled as a realistic three tap MIMO FIR channel.Five modulation schemes are considered for this experiment and they are Ω = {BPSK, QAM (4), QAM (16), PSK(8), PSK(32)}. The Monte Carlo simulation results are summarized in Figure 5. In Figure 5, the curve labeled Pcc1 shows the performance of the MAMC without the proposed blind equalizer. The curve labelled P_{cc2} illustrates the performance of the AMC using the proposed system.

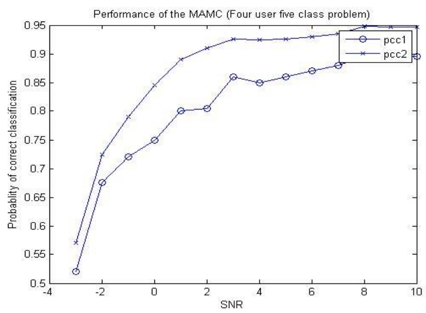

Figure 5: Performance of the MAMC (Four-user five-class problem) .

Four-user five-class problem (Realistic channel II)

This problem is the same as the previous one except four modulation schemes are considered. The modulation schemes considered are Ω = {BPSK, QAM (4), QAM (64), PSK (8), PSK(32)}. The channel considered was a realistic MIMO multipath channel. The Monte Carlo simulation results are summarized in Figure 6. In Figure 6 the curves labelled P_{cc1}, and P_{cc2} have the same meaning as that of Figure 5. From Figures 4 - 5, it can be seen that the proposed MIMO blind equalizer enhances the performance of the MAMC.

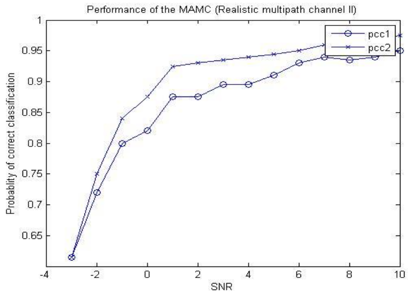

Figure 6: Performance of the MAMC (Realistic multipath channel II)

4.3 Symbol Detection Performance

In order to analyze the symbol detection performance, we can consider the same 2-input/3-output FIR random channel considered in the previous experiment. The normalized mean square error (NMSE) and symbol error rate (SER) are taken as performance measures. The simulation results are shown in Figure 7 and Figure 8. In Figure 7 and Figure 8 the curve labeled sd1 illustrates the symbol detection performance of the proposed system. The curve labeled sd2 illustrates the symbol detection performance of MIMO blind equalizer when the channelimpulse response is known (non-blind equalizer). From the figures it can be seen that the symbol detection performance of the proposed system is close to that of the non-blind MIMO equalizer.

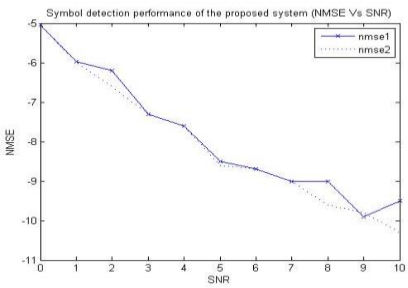

Figure 7: Symbol detection performance of the proposed system(NMSE Vs SNR).

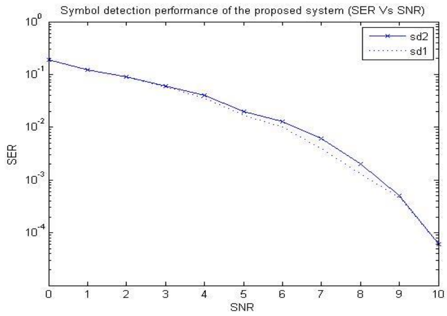

Figure 8: Symbol detection performance of the proposed system (SER vs SNR)

4.4 Performance of Multiuser AMC with Genetic algorithm

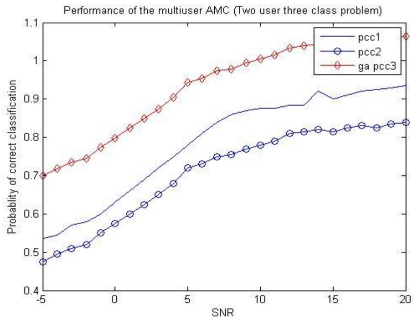

Figure 9: Performance of the multiuser AMC (Two-user three-class problem)

In the above figure9 genetic algorithm optimization gives better correct classification probability than other methods in two user and three class problem.

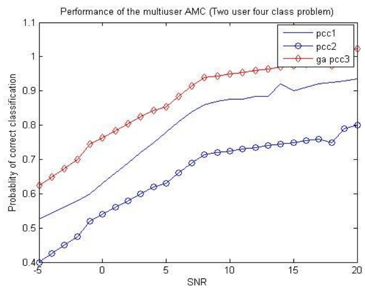

Figure 10: Performance of the multiuser AMC (Two-user four-class problem)

In the above figure10 genetic algorithm optimization gives better correct classification probability than other methods in two user and four class problem.

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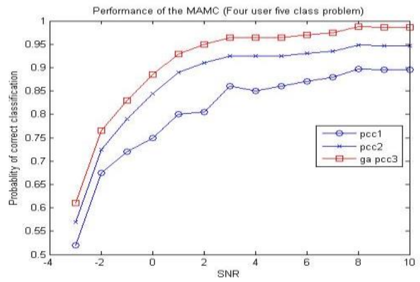

Figure 11: Performance of the multiuser AMC (Four-user five-class problem)

In the above figure11 genetic algorithm optimization gives better correct classification probability than other methods in four users and five class problem.

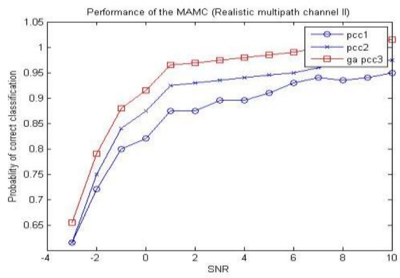

Figure 12: Performance of the MAMC (Realistic multipath channel II)

In the above figure12 genetic algorithm optimization gives better correct classification probability than other methods in realistic multipath channel II.

5.Conclusion:

In this paper, the proposed MIMO blind equalizer was tested under different scenarios. From the simulation results it can be seen the MIMO blind equalizer improves the performance of both multiuser AMC and multiuser symbol detection with Genetic algorithm. Irrespective of the kind of channel and the type of feature used, it can be seen from the simulation results that we get 15% improvement at higher SNR's and atleast 10% improvement in performance at 0dB SNR. The performance of proposed equalizer was analyzed using computer simulations and yielded promising results.

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