Blind Detection of Digital Signals in MIMO Communication

Pooya Nabavi and Murat Yuksel
Electrical and Computer Engineering, University of Central Florida, Orlando, FL USA 32816
College of Optics and Photonics, University of Central Florida, Orlando, FL USA 32816
pooya.nabavi@knights.ucf.edu, murat.yuksel@ucf.edu

2022 IEEE Wireless Communications and Networking Conference (WCNC) | 978-1-6654-4266-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/WCNC51071.2022.9771848

***Abstract*—In communication networks, the usage of multiple-input multiple-output (MIMO) systems may give advantages such as enhanced rates or diversity. This article investigates the performance of blind signal separation and symbol detection under the assumption of unavailable receiver information and the absence of a training sequence to aid in detection. The Constant Modulus Adaptive (CMA) method is assessed as the foundation technique for discussing blind source recovery in MIMO systems, demonstrating its powerful capabilities in source recovery without a training sequence. The performance and convergence speed of the Multi-Modulus Adaptive (MMA) algorithm are then compared to the CMA algorithm's low efficiency in recovering Quadrature Amplitude Modulation (QAM) signals. The Simplified Constant Modulus Adaptive (SCMA) algorithm's performance in MIMO structures with low computational complexity and a reasonable efficiency in signal estimation is further investigated as a well-known solution to reduce the computational complexity of CMA and MMA algorithms in MIMO systems with a large number of receiving antennas. Finally, using the Cross Correlation Simplified Constant Modulus Adaptive (CC-SCMA) algorithm, the non-uniqueness of the signals recovered by CMA, MMA, and SCMA algorithms is addressed.**

***Index Terms*—Adaptive Algorithm, Blind Source Separation, MIMO, Inter-symbol Interference**

I. Introduction

MIMO communication systems connect M transmitters and N receivers via $M \times N$ wireless links. These connections can be used in two distinct ways. The first approach (space multiplexing gain) [1] transmits a unique data stream from each antenna, resulting in a considerable boost in the communication system's throughput. In the second approach, a single stream of data is diverted and sent to two or more antennas and the user can enhance link reliability utilizing appropriate gain combination solutions on the receiving side. A primary challenge for such systems is detecting data signals in the receiver while dealing with multi-stream interference. This can be accomplished by using a machine learning (ML) capable receiver with a high computational complexity, as well as by utilizing MMSE, SIC-MMSE, and ZF equalizers [1]–[4]. All of these techniques necessitate precise channel information on the receiver's side.

While the availability of channel state information enables precise blind signal separation, obtaining the CSI is not always attainable in practice. For mobile links, for example, the channel behavior is constantly changing, making it impracticable to have CSI readily available for blind separation. Additionally, the transmitter must cooperate in order to accurately measure CSI. Nonetheless, there are circumstances in which the transmitter may be uncooperative. Synchronizing the transmitter and receiver is not desirable in covert communications since it may betray the existence of the communication link. Another, more difficult, scenario is when the receiver wishes to intercept the signal without alerting the transmitter. In this case, the receiver must decode the signals without having access to complete knowledge of the modulation details employed by the target transmitter. These circumstances compel the analysis of blind signal separation when the CSI is unavailable, the transmitter's modulation schemes are unknown in whole or in part, and only a generic description of the modulation method applied is accessible at the receiver.

The purpose of this paper is to assess the ability of the existing blind signal separation algorithms to eliminate Inter-Symbol Interference in MIMO systems, as well as to compare their convergence speed and performance, as well as their robustness, when different numbers of transmitting and receiving antennas are used. We presume that the receiver employed in the covert communication link does not have access to channel state information. Additionally, it is assumed that no training sequence is available to assist with channel estimates or identification. For signal detection in the presence of multi-stream interference, constant modulus blind algorithms are used. Among the contributions of our work are the following:

- We investigate the effect of changing the number of transmitting and receiving antennas on the convergence speed of blind signal detection algorithms and the Signal to Noise Interference Ratio (SINR) when recovering Phase Shift Keying (PSK) or Quadrature Amplitude Modulation (QAM) signals transmitted over a MIMO channel with flat fading.
- The performance and computational complexity of the well-known CMA, SCMA, MMA, CC-CMA, and MCC-SCMA algorithms for blind detection of PSK and QAM digital signals under multi-stream interference are analyzed.
- The impact of received Signal to Noise Ratio (SNR) on the convergence speed of blind detection algorithms is investigated.
- We determine the optimal number of transmitting and receiving antennas in order to increase SINR while lowering blind detection convergence speed without imposing excessive computational or implementation costs on the transmitter or receiver.

II. Constant Modulus Algorithm

The use of multiple antennas on both ends of the communication link considerably improves spectral efficiency, even more so when blind approaches are used. Numerous strategies have been proposed in the literature, each of which offers a different trade-off between complexity and performance. The constant modulus algorithm (CMA) is an excellent approach [5] that is extremely resilient and

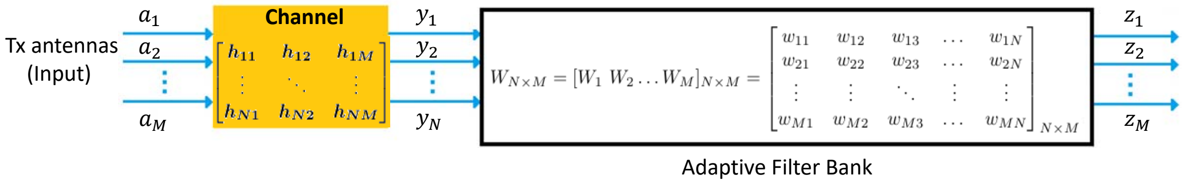

Fig. 1. Structure of an Adaptive Signal Recovery Filter at MIMO receivers

performs efficiently when estimating transmitted signals blindly. This section introduces CMA and evaluates its high convergence speed and performance under different scenarios, most notably when employing varying numbers of transmitting and receiving antennas. To enhance the effectiveness of CMA in recovering signals with a QAM constellation, the MMA algorithm is introduced as a solution [5], [6]. We examine the effectiveness of this technique and compare the SINR obtained when the total number of receiving or transmitting antennas is increased. The linear additive model for the MIMO system with flat fading can be stated as follows:

$$y(n) = Ha(n) + b(n) \tag{1}$$

where $a(n) = [a_1(n), \ldots, a_M(n)]^T$ is the $M \times 1$ vector of the source signals, $\mathrm{H}_{N\times M}$ is the MIMO channel matrix without linear memory, and M and N respectively show the number of transmitter and receiver antennas in the MIMO system. $y(n) = [y_1(n), \ldots, y_N(n)]^T$ is the $(N \times 1)$ vector of the received signals and $b(n) = [b_1(n), \ldots, b_N(n)]^T$ is the $(N \times 1)$ noise vector. We assume that H has a complete column rank of M and noise taking the form of additive white Gaussian noise independent of the source signals. The source signals are assumed independent and identically distributed. They are mutually independent $(E[aa^H] = \sigma_a^2 I_M)$ and are obtained from the PSK or QAM constellation. To simulate the flat channel fading in the MIMO system, the channel matrix H implements elements from a complex Gaussian distribution while the elements of the noise vector $b(n)$ have a complex Gaussian distribution as well.

The received signal $y(n)$ is processed by the receiving matrix W to recover the source signals. Hence, the transmitter output can be written as [7], [8]:

$$\begin{aligned} z(n) &= W^T y(n) = W^T Ha(n) + W^T b(n) \\ &= G^T a(n) + \tilde{b}(n) \end{aligned} \tag{2}$$

where $z(n) = [z_1(n), \ldots, z_M(n)]^T$ is the $M \times 1$ vector of the receiver output, $G = [g_1, \ldots, g_M] = H^T W$ is the $M \times M$ global system matrix, and $\tilde{b}(n)$ is the filtered noise at the receiver output. As shown in Fig. 1, The $W_{N\times M} = [w_1, \ldots, w_M]$ matrix is the $N \times M$ matrix of the filter coefficient bank used to recover the source signals (up to the threshold of a probable phase rotation ambiguity which can be resolved by utilizing Differential Phase Shift Keying (DPSK) instead of PSK constellation at the transmitter). Blind source separation aims to find the W matrix such that $z(n) = \tilde{a}(n)$ becomes an estimate of the source signals. To adaptively obtain the W matrix, the CMA cost function should be optimized as discussed below.

The cost function that should be minimized is:

$$\min_{w_\ell} \vartheta(w_\ell) = E\left[\left(|z_\ell(n)|^2 - R\right)^2\right], \quad \ell = 1, \ldots, M \tag{3}$$

where $|z_\ell(n)|$ is the modulus of the ℓ^{th} output of the equalizer $z_\ell(n) = w_\ell^T y(n)$ and R is the scattering constant. It is critical to note that the only information available at the receiver is the type of modulation technique employed at the transmitter (PSK or QAM), and the receiver's CSI is absolutely unknown. As a result, given a PSK-modulated transmitted symbol stream, we have implicit knowledge that the constellation of the received signal should converge to a fixed value. Thus, the objective is to decrease the dispersion of the incoming symbols such that their modulus approaches a constant iteratively during the equalization process. The optimal value for this constant R is determined using the zero forcing approach (ZF), which is based on complete equalization [8], [9]:

$$R = \frac{E\left[|a(n)|^4\right]}{E\left[|a(n)|^2\right]}. \tag{4}$$

The CMA algorithm attempts to map the equalizer's output's absolute values onto a circle with a radius of $\sqrt{R}$. This is apparent when examining the cost function in Eq. 3. Then, using the Stochastic Gradient Algorithm (SGA) to execute CMA adaptively results in an adaptive relationship for the coefficients of adaptive filter banks (Fig. 1) utilized to recover the sources. The classical SGA algorithm used to create a recovery adaptive filter with the objective of minimizing the cost function stated in Eq. 3 is as follows:

$$W(k+1) = W(k) - \frac{1}{2}\mu \nabla w(J) \tag{5}$$

where $\nabla w(J)$ represents the gradient of the cost function versus the adaptive coefficients of the recovery filter and W represents the adaptive filter bank that recovers the signals. The parameter μ can be changed to alter the convergence speed of the proposed algorithm's cost function. Increased μ allows for faster convergence at the cost of instability. The equation for upgrading the equalizer recovery filter bank at the k^{th} iteration using Eq. 5 in the CMA algorithm is as follows [7], [8]:

$$\begin{aligned} &W(k+1) = W(k) - \mu y^*(k)\left[\Delta_1(k) \ldots \Delta_M(k)\right] \\ &\Delta_i(k) = \left(|z_i(k)|^2 - R_{CMA}\right) z_i(k) \end{aligned} \tag{6}$$

where $y(k)$ is the $(N \times 1)$ vector of the received signals, W is the $(N \times M)$ matrix of the adaptive recovery filter bank, $|z_i(k)|$ is the i^{th} output of the equalizer at the k^{th} iteration where $z_i(k) = w_i^T y(k)$, w_i is the i^{th} column of the $(N \times M)$ matrix of the adaptive recovery filter bank (W), and R is obtained from Eq. 4. Then, CMA is simulated using Eqs. 3 and 6.

A. Constant Multi-Modulus Algorithms Cost Function

The previously described cost function can simply be changed to allow for the reception of QAM modulated symbols with changing amplitudes despite PSK signals. Multi-Modulus Adaptive Algorithms (MMA or CMMA) [6] are the related algorithms that minimize the cost function below.

$$\min_{w_\ell} \vartheta(w_\ell) = E\left[\left(z_{R,\ell}(n)^2 - R\right)^2 + (z_{I,\ell}(n)^2 - R)^2\right], \quad \ell = 1,\ldots,M \tag{7}$$

where $z_{R,\ell}(n)$ denotes the real part of the ℓ^{th} output of the equalizer $z_\ell(n) = w_\ell^T y(n)$ and $z_{I,\ell}(n)$ is the imaginary part of the ℓ^{th} output of the equalizer. To obtain a less computationally difficult recovery filter, the scattering constant (R) is determined using the zero forcing method on the received signal's real part:

$$R = \frac{E[a_R(n)^4]}{E[a_R(n)^2]} \tag{8}$$

where $a_R(n)$ represents the real part of the source signal $a(n)$. The filter bank (Eq. 9) for simulating MMA is obtained using the cost function (Eq. 7) and SGA [6], [7]

$$\begin{aligned} W(k+1) &= W(k) - \mu y^*(k)\left[\Delta_1(k)\ldots\Delta_M(k)\right] \\ \Delta_i(k) &= \left(z_{R,i}^2 - R\right) z_{R,i} + j\left(z_{f,i}^2 - R\right) z_{lj} \end{aligned} \tag{9}$$

where $y(k)$ is the $(N \times 1)$ vector of the received signals. The parameters $z_{R,\ell}(n)$ and $z_{I,\ell}(n)$ respectively represent the real and imaginary parts of the l^{th} output of the equalizer at the n[th] iteration. The parameter R is given by Eq. 8 and W is the $N \times M$ matrix of the adaptive filter bank used to recover the transmitted signals. Later in Section III, the simulation of this algorithm using the coefficients obtained from Eq. 9 is first discussed. Then, this method is compared with CMA to indicate its superiority over CMA for blind recovery of QAM shaped sources.

B. Simplified Constant Modulus Algorithm

For the ℓ^{th} equalizer, the cost function in Eq. 10 is introduced for the first time in [7] to be minimized:

$$\min_{w_\ell} \vartheta(w_\ell) = E\left[\left(z_{R,\ell}(n)^2 - R\right)^2\right], \quad \ell = 1,\ldots,M \tag{10}$$

where $z_{R,\ell}(n)$ is the symbol of the real part of the ℓ^{th} output of the equalizer $z_\ell(n) = w_\ell^T y(n)$ and R is the scattering constant calculated according to Eq. (8). The term on the right hand of Eq. 10 prevents the squared real part of the output of the equalizer from deviating from the constant R. Minimizing Eq. 10 allows the recovery of only one signal at each output of the equalizer. By implementing the cost function for the coefficients of the adaptive filter bank used for source recovery:

$$W(k+1) = W(k) - \frac{1}{2}\mu\nabla_w(J) \tag{11}$$

$$\begin{aligned} W(k+1) &= W(k) - \mu Y^*(k)\left[\Delta_1(k)..\Delta_M(k)\right] \\ \Delta_i(k) &= \left(z_{R,t}^2 - R\right) z_{R,t} \end{aligned} \tag{12}$$

where W is an $N\times M$ matrix of the adaptive filter bank used for signal recovery; and Y is an $N\times 1$ vector received before processing with the adaptive algorithm; then the parameter μ is selected to make the cost function convergent.

C. Cross-Correlation Constant Modulus Algorithm

The cost function proposed for CC-CMA [7], [8] is:

$$\begin{aligned} \min_{w_\ell} \vartheta(w_\ell) =& E\left[\left(|Z_\ell(n)|^2 - R\right)^2\right] \\ &+ \alpha\sum^{\ell-1}|r_{\ell i}(n)|^2, \ell = 1,\ldots,M, \end{aligned} \tag{13}$$

where $\alpha \in R^+$ is a composite parameter determining the significance of the cross-correlation term in the cost function, R is defined by Eq. 4, $a(n)$ is the $M \times 1$ vector of transmitted PSK or QAM signals, and $r_{\ell i}(n) = E(z_\ell(n)z_i^*(n))$ is the cross-correlation of the ℓ^{th} and i[th] output of the equalizer which prevents identical signal estimates in numerous outputs. Therefore, the first term in Eq. 13 guarantees recovery of only a single signal at each output branch of the equalizer while the cross-correlation term determines that each output of the equalizer is different from the other output of the equalizer. Hence, all source signals can be recovered.

To implement the cost function (13), the classical SGA is utilized. The general form of SGA is:

$$W(k+1) = W(k) - \frac{1}{2}\mu\nabla_w(J) \tag{14}$$

where $\nabla_w(J)$ is the J gradient versus W and J is the cost function of the algorithm. For CC-CMA, the coefficients for adaptive filter banks used for signal recovery in the n^{th} iteration are obtained from Eq. 15 using Eq. 12:

$$w_\ell(n+1) = w_\ell(n) - \mu e_\ell(n)y^*(n), \quad \ell = 1,\ldots,M \tag{15}$$

where $e_\ell(n)$ is the instantaneous error for the ℓ^{th} equalizer. For CC-CMA, it is given by [6], [10]–[12]:

$$e_\ell(n) = \left(|z_\ell(n)|^2 - R\right) z_\ell(n) + \frac{\alpha}{2}\sum_{m=1}^{\ell-1}\hat{r}_{\ell m}(n)z_m(n) \tag{16}$$

where R is given by Eq. 4. The scalar parameter $\hat{r}_{bm}$ is the $r_{\ell m}$ estimation calculated recursively using:

$$\hat{r}_{bn}(n+1) = \lambda\hat{r}_{\ell m}(n) + (1-\lambda)z_\ell(n)z_m^*(n) \tag{17}$$

where $\lambda \in [0,1]$ is the parameter controlling the window length of the data factored into the estimation and $\hat{r}_{\ell m}(n) = E[z_\ell(n)z_m^*(n)]$. Below, Eqs. 15, 16, and 17 are used to simulate CC-CMA for blind recovery.

D. CC-SCMA Cost Function and Adaptive Implementation

Projecting the output of the equalizers on a single dimension (real or imaginary) gives the cost function (Eq. 18) for CC-SCMA [6], [7], [11]:

$$\begin{aligned} \min_{w_\ell} \vartheta(w_e) =& E\left[\left(z_{R,\ell}(n)^2 - R\right)^2\right] \\ &+ \alpha\sum_{i=1}^{\ell-1}|r_{ei}(n)|, \quad \ell = 1,\ldots,M \end{aligned} \tag{18}$$

where $\alpha \in R^+$ is a parameter used to calculate the weight of the cross-correlation term in the cost function, R is defined by Eq. 8, and $r_{\ell i}(n) = E(z_\ell(n) z_i^*(n))$ is the cross-correlation between the equalizers' outputs ℓ^{th} and i^{th}. This term precludes the use of identical signal estimates across multiple outputs. Thus, the first term in Eq. 18 assures that only one signal is recovered at each equalizer's output, while the cross-correlation term ensures that each equalizer's output is unique. As a result, all source signals are recoverable. Additionally, $z_{R,\ell}(n)$ is the real part of the equalizer's ℓ^{th} output at the n^{th} iteration. Due to the symmetric arrangement of QAM and PSK, the imaginary portion can likewise be employed in Eq. 18. Using the SGA algorithm, the coefficients of the filter utilized for signal recovery at the n^{th} iteration of CC-SCMA are as follows:

$$w_\ell(n+1) = w_\ell(n) - \mu e_\ell(n) y^*(n), \quad \ell = 1, \ldots, M \quad (19)$$

where $e_\ell(n)$ is the instantaneous error in the ℓ^{th} equalizer. For CC-SCMA, this is given by:

$$e_\ell(n) = \left(z_{R,\ell}^2(n) - R\right) z_{R,\ell}(n) + \frac{\alpha}{2} \sum_{m=1}^{\ell-1} \hat{r}_{\ell m}(n) z_m(n) \quad (20)$$

where the scalar quantity $\hat{r}_{\ell m}$ denotes the estimated $r_{\ell m}$ that can be recursively calculated as

$$\hat{r}_{\ell m}(n+1) = \lambda \hat{r}_{\ell m}(n) + (1-\lambda) z(n) z_m^*(n) \quad (21)$$

In the above equation, $\lambda \in [0, 1]$ is the control parameter of the window length for effective estimation data while $E[\hat{r}_{\ell m}(n)] = E[z_\ell(n) z_m^*(n)]$.

E. The Cost Function of the MCC-SCMA

The cost function in Eq. 22 is provided in [5], [8] to be minimized for MCC-SCMA:

$$\min_{w_\ell} \vartheta(w_\ell) = E\left[\left(z_{R,\ell}(n)^2 - R\right)^2\right] + \alpha \sum_{m=1}^{\ell-1} \left(E^2\left[z_{R,\ell}(n) z_{R,m}(n)\right] + E^2\left[z_{R,\ell}(n) z_{I,m}(n)\right]\right), \quad \ell = 1, \ldots, M \quad (22)$$

where $\alpha \in R^+$ is a composite parameter for determining the significance of the cross-correlation term in the cost function. MCC-SCMA [6], [7] is obtained by optimizing CC-SCMA. The addition of another cross-correlation term to the CC-SCMA cost function facilitates this optimization. This extra term considerably simplifies the filter bank coefficients while preserving the CC-SCMA performance.

III. Simulation Results

In this section, for the first time, we assess and compare the convergence speed of all of the methods discussed previously, as well as their resulting SINR, in MIMO systems with varying numbers of transmitting and receiving antennas. The followings are used to calculate SINR:

$$SINR_k = \frac{|g_{kk}|^2}{\sum_{\ell, \ell \neq k} |g_{\ell k}|^2 + w_K^T R_b w_k^*} \quad (23)$$

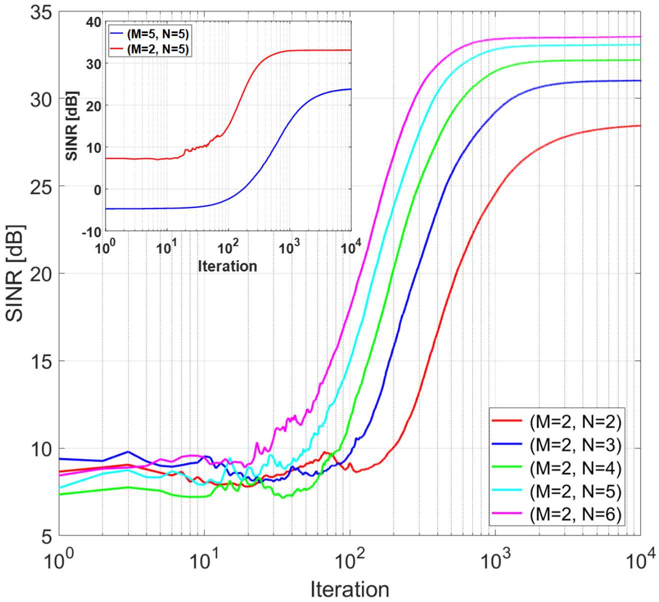

Fig. 2. The effect of the number of receiving and transmitting antennas on SINR-Iteration for 16-PSK constellation using CMA.

$$SINR = \frac{1}{M} \sum_{k=1}^{M} SINR_k \quad (24)$$

where $SINR_k$ is the SINR for the k^{th} output. In $g_{ij} = h_i^T w_j$, parameters w_j and h_i respectively represent the j^{th} and i^{th} column vector of the W and H matrices and $R_b = E|bb^H| = \sigma_b^2 I_N$ is the noise covariance matrix. SINR is estimated by calculating the mean of 1000 independent tests. Each estimate is presented by the model assuming uniformly distributed and independent system inputs acquired from 16-QAM or 16-PSK constellation. The system noise is of the complex white Gaussian noise variety with a mean of zero where the noise variance is obtained based on the desired SNR.

A. SINR-Iteration Performance

Fig. 2 shows the SINR as a function of iteration for different numbers of transmitting and receiving antennas. The uniformly distributed independent system inputs are obtained from a 16-PSK modulation scheme. The system noise is of the complex white Gaussian type with a zero mean. The noise variance is obtained based on an SNR of 30 dB. The signals with the 16-PSK constellation are transmitted by M and received by N antennas. As shown in Fig. 2, an increase in the number of transmitting antennas detrimentally affects the SINR, as it adds extra interference. However, it increases the convergence speed of the adaptive detection algorithm (Fig. 5(a)). Further, it is observed that as we increase the total number of receiving antennas, we can obtain higher SINR; however, the SINR will eventually be saturated and adding extra receiving antennas (i.e., $N > 6$) then only adds unnecessary cost to the receiver's hardware.

B. CMA and MMA for 16-QAM Constellation

Fig. 3 shows SINR for CMA and MMA, where Eqs. (6) and (9) are used as W (i.e., Filter Bank matrix), respectively. Each estimate is based on independent system inputs with uniform distribution and 16-QAM constellation. A noise

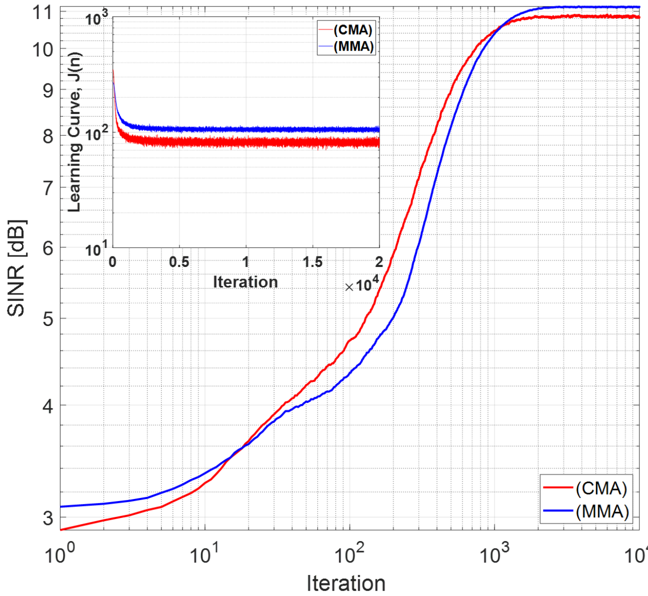

Fig. 3. Comparing SINR and Learning Curve-iteration in CMA and MMA for 16-QAM constellation in a 2×3 MIMO system at received SNR = 18 dB

of the complex white Gaussian type is considered with a zero mean. A noise variance of 18 dB is set according to the SNR. Fig. 3 shows the results for the signals with 16-QAM modulation transmitted by 2 and received by 3 antennas. The channel matrix H is modeled as an $N \times M$ matrix with complex Gaussian elements and a zero mean to represent the flat fading of the MIMO channel. A μ value of 0.005 is considered in CMA (Eq. (6)) and MMA (Eq. (9)) to make the CMA and MMA cost functions convergent. As demonstrated, when used to recover digital signals with a QAM constellation, the MMA algorithm performs comparably to the CMA method in terms of convergence speed and steady-state received SINR.

C. Computational Complexity

Table I shows the comparison of computational complexity among CMA, MMA, SCMA, CC-CMA, CC-SCMA, and MCC-SCMA. According to Table I, the following results are obtained:

- The computational complexities of MMA and CMA are identical, except that MMA outperforms CMA in the blind recovery of QAM signals.
- The computational complexities of CMA and CC-CMA were derived using Eqs. 6, 15, 16, and 17. The computational complexity of CC-CMA is more than that of CMA. However, CC-CMA performs well and nearly identically to CMA. The edge provided by CC-CMA is in rectifying the non-uniqueness of recovery filter output W against CMA, MMA, and SCMA.
- The computational complexity of MCC-SCMA is less than that of CC-CMA and CC-SCMA. The use of CC-SCMA and MCC-SCMA eliminates the non-uniqueness of the output of recovery filter W in CMA, MMA, and SCMA with low computational complexity.

TABLE I
COMPUTATIONAL COMPLEXITY OF CMA AND MMA

Algorithm	Number of multiplications	Number of additions
MMA	$2(4N+3) \times M$	$8M \times N$
CMA	$2(4N+3) \times M$	$8M \times N$
SCMA	$(4N+3) \times M$	$4 \times M \times N$
CC-CMA	$4M(M+2N-1)$	$2M(3M+4N+1)-2$
CC-SCMA	$6M(M+N)-2$	$M(4M+6N-5)+1$
MCC-SCMA	$4M(M+N)-1$	$2M(M+2N-1)$

D. Learning Speed in CMA and MMA

Fig. 3 further demonstrates the learning curves of CMA and MMA. To generate learning curve vs. iteration for CMA, for each ℓ^{th} output of the equalizer, the $(|z_\ell(n)|^2 - R)^2$ is computed in 1000 tests. By averaging the results of these tests, the learning curve of the ℓ^{th} column of the adaptive filter bank matrix W for recovering the ℓ^{th} original signal from the mixed signals $y(n)$ is obtained.

To generate the learning curve-iteration figure for MMA for the ℓ^{th} output of the equalizer, the expression $(z_{R,\ell}(n)^2 - R)^2 + (z_{I,\ell}(n)^2 - R)^2$ is computed 1000 times. The learning curve is then plotted by averaging the results of the 1,000 tests. In Fig. 3, the 16-QAM signals are transmitted by 2 and received by 3 antennas. After setting the power of the additive complex white Gaussian noise (Eq. 1), the SNR is adjusted to 18 dB. The channel matrix H is modeled as an $N \times M$ matrix with complex Gaussian elements and a zero mean to represent the flat fading of the MIMO channel. A μ value of 0.005 is considered in CMA (Eq. 6) and MMA (Eq. 9) to make their cost functions convergent. This convergence is observable after 2000 iterations in Fig. 3. As shown in Fig. 3, the convergence speed of MMA is less than that of CMA while the steady state cost function of MMA after 2000 iterations is higher than with CMA.

E. CC-CMA, CC-SMCA, MCC-SCMA Learning Speed

According to Fig. 4, the cost functions of CMA, CC-CMA, CC-SCMA, and MCC-SCMA converge to their respective minima. The convergence speed of the MCC-SCMA cost function surpasses that of all others, which

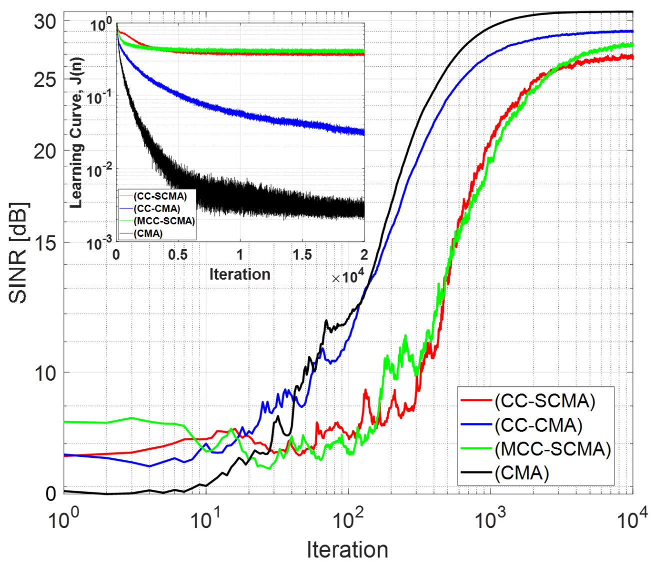

Fig. 4. Comparing SINR-iteration and Learning Curve-iteration curves of CMA, CC-CMA, CC-SCMA, and MCC-SCMA for 16-PSK constellation in a 2 × 3 MIMO system at received SNR=30 dB

gives it an edge. Despite this higher convergence speed, MCC-SCMA also has a larger steady-state cost function compared to others, which is a drawback. The steady-state cost function of the CC-SCMA nearly equals that of MCC-SCMA. Further, the fluctuations in the MCC-SCMA cost function are less than in other algorithms. Concerning MCC-SCMA, its low computational complexity, high convergence speed, and successful performance in the blind recovery of transmitted signals indicate its superiority over other adaptive algorithms in this study.

F. Learning Speed sensitivity vs. Number of transmitting antennas and received signal to noise ratio

As shown in Fig. 5(a), increasing the number of transmitting antennas delays the convergence of the CMA while decreasing the SINR as shown in Fig. 2(b). Furthermore, Fig. 5(b) demonstrates that in the presence of higher received signal strength, the CMA's cost function can achieve a lower steady-state level and therefore achieve detection performance with lower Bit Error Rate (BER). Fig. 6 shows the successful performance of CC-SCMA in recovering the transmitted signals. The advantage offered by using CC-SCMA and MCC-SCMA is in eliminating the non-uniqueness of the recovery filter output W in CMA, MMA, and SCMA with low computational complexity.

IV. Conclusion

The performance of a family of constant-modulus adaptive algorithms for blind adaptive separation of signals with QAM and PSK signals in MIMO communication systems was investigated in this article. The criteria for developing CMA algorithms were to minimize the scattering of the equalizer's output and to ensure convergence to a constant R. Due to CMA's inability to recover non-constant modulated signals such as QAM, MMA was used. This algorithm performed well in recovering QAM signals due to its simultaneous minimization of the equalizer's imaginary and real parts. CMA and MMA, on the other hand, suffered from high computational complexity and the possibility of non-unique signals being recovered from the recovery filter output. SCMA was extensively evaluated as a solution to the first issue. Rather than utilizing both the real and imaginary parts of the equalizer's output, SCMA recovers signals by minimizing the scattering of either the real or imaginary part of the output and converging it to a fixed value. This results in a reduction in computational complexity. SCMA, however, continued to suffer from the second disadvantage, which led us back to CC-CMA and MCC-SCMA. This algorithm was created by multiplying the cost function of CMA by a cross-correlation term. The resulting algorithm was capable of successfully recovering unique signals as adaptive recovery filter outputs. However, the algorithm retained the first flaw, and its high computational complexity made implementation difficult. As a result, the CC-SCMA cost function was constructed by adding a cross-correlation term to the SCMA cost function. As a result of SCMA's lower complexity in comparison to CMA, the computational complexity of CC-SCMA was reduced overall when compared to CC-CMA. Additionally, the additional cross-correlation term resolved the second issue.

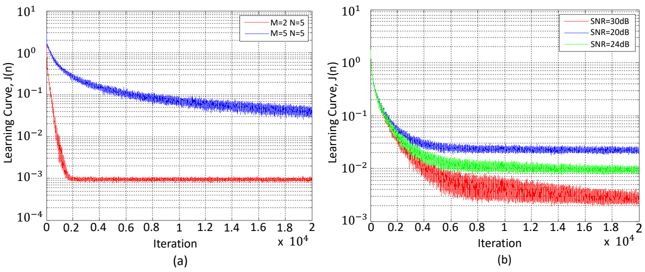

Fig. 5. The effect of (a) the number of the transmitting antennas (received SNR=30 dB) and (b) received signal to noise ratio (SNR) (M=2, N=3) on convergence speed of the Learning Curve-Iteration for 16-PSK constellation using CMA.

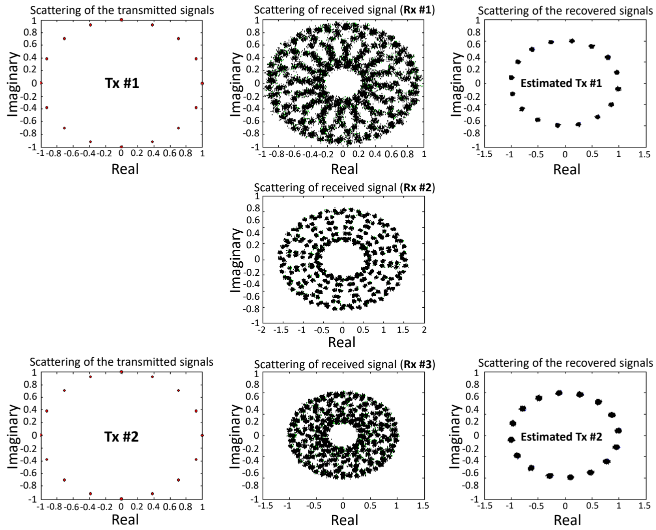

Fig. 6. The scattering diagram for 16-PSK constellation using CC-SCMA at SNR =30dB. Left: the constellation of the transmitted signals using 2 transmitting antennas (M=2); Middle: the constellation of the received (mixed) signals (N=3); Right: the constellation of recovered signals.

V. Acknowledgement

This paper was supported in part by U.S. National Science Foundation awards 2115215 and 1836741.

References

[1] H. Jafarkhani, *Space-time coding: theory and practice*. Cambridge university press, 2005.

[2] G. R. Naik, W. Wang *et al.*, "Blind source separation," *Berlin: Springer*, vol. 10, pp. 978–3, 2014.

[3] L. G. Morales, *Adaptive Filtering Applications*. BoD–Books on Demand, 2011.

[4] D. Zhang, K. Wang, and X. Zhang, "Blind adaptive affine projection algorithm-based multiuser detector over a multipath fading channel," *Signal Processing*, vol. 90, no. 6, pp. 2102–2106, 2010. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0165168409005143

[5] A. Ikhlef and D. Le Guennec, "Blind recovery of mimo qam signals: A criterion with its convergence analysys," in *2006 14th European Signal Processing Conference*. IEEE, 2006, pp. 1–5.

[6] A. Ikhlef, D. Le Guennec, and J. Palicot, "Constant norm algorithms for mimo communication systems," in *2005 13th European Signal Processing Conference*. IEEE, 2005, pp. 1–4.

[7] A. Ikhlef and D. Le Guennec, "A simplified constant modulus algorithm for blind recovery of mimo qam and psk signals: A criterion with convergence analysis," *EURASIP Journal on Wireless Communications and Networking*, vol. 2007, pp. 1–13, 2007.

[8] Y. Li and K. R. Liu, "Adaptive blind source separation and equalization for multiple-input/multiple-output systems," *IEEE Transactions on Information Theory*, vol. 44, no. 7, pp. 2864–2876, 1998.

[9] M. L. Rose, J. L. Ipson, T. K. Moon, and J. H. Gunther, "Sparse adaptive channel identification method using the cross-relation," *Physical Communication*, vol. 47, p. 101354, 2021.

[10] B. Farhang-Boroujeny, *Adaptive filters: theory and applications*. John Wiley & Sons, 2013.

[11] S. Haykin, *Adaptive filter theory*. Prentice-Hall, Inc., 1996.

[12] A. H. Sayed, *Fundamentals of adaptive filtering*. John Wiley & Sons, 2003.