

An Improved Constant Modulus Algorithm for Blind Signal Adaptation in Wireless Communications

Emmanuel Adotse Otsapa^{1*}, Abdoulie Momodou Sunkary Tekanyi², Kabir Ahmed Abubilal³, Mahmud Tukur Kabir⁴, Muntari Bello⁵, Emmanuel Kasai Akut⁶, Oluwatobiloba Alade Ayofe⁷, Haruna Ibrahim⁸.

¹⁻⁴Department of Electronics and Telecommunication Engineering, Ahmadu Bello University, Zaria, Nigeria.

⁵Department of Electrical and Electronics Engineering, Nigerian Defence Academy, Kaduna, Nigeria.

⁶Department of Electrical and Electronics Engineering, University of Jos, Jos, Nigeria.

⁷Department of Computer Engineering Technology, The Federal Polytechnic, Ede, Nigeria.

⁸Department of Computer Engineering, Kaduna Polytechnic, Kaduna, Nigeria.

emmaotsapa2013@gmail.com^{1*}, amtekanyi@abu.edu.ng², kabirahmed@abu.edu.ng³, mtkabir@abu.edu.ng⁴, muntaribelloh@yahoo.com⁵, eakut88@gmail.com⁶, tobiayofe@federalpolyede.edu.ng⁷, harunaebrahim@gmail.com⁸

*Corresponding Author

Abstract

While the Constant Modulus Algorithm (CMA) is the most often used blind signal equalization or adaptation technique, it converges slowly and produces excessive Side Lobe Level (SLL) radiation, which wastes energy and interferes with other equipment. Additionally, interfering signals may be picked up by side lobes, increasing the noise level in the receiver. A normalized constant-modulus method with adjustable step size was devised, which considerably increased its convergence rate. The Blackman window was also applied to the CMA to lower the SLL. The designed beamformer improved convergence rate by 40%, as observed by lower Mean Square Error (MSE) to Signal to Interference plus Noise Ratio (SINR) values. As a result, the beam former is a viable alternative in an environment where channel conditions are constantly changing. Furthermore, the use of the Blackman window had the ability to minimize the Peak Side Lobe Level (PSLL) and resulted in a 5 dB improvement over CMA for the SLL rejection gain. As compared to the conventional CMA, the Improved CMA displayed the highest reduction in PSLL with quick convergence capabilities and saved a lot of energy wastage due to side lobes minimization. These characteristics make the ICMA a potential choice for advanced wireless applications.

Keywords: Blind beamforming, Improved CMA, Equalization (or Adaptation), Convergence, Side lobe level

1. Introduction

Several adaptive beam forming techniques used in wireless communications are built around minimizing the error between the reference signal and array output. According to a priori knowledge of the nature of the incoming signals, the reference signal is frequently a training sequence used to train the adaptive array or a desired signal. When a reference signal is not available, a variety of optimization strategies that are blind to the precise content of the incoming signals must be used (Alwafie et al., 2021). The Constant Modulus Algorithm (CMA), which is used to estimate the gradient vector from the existing data, is thought of as the most traditional Blind Equalization (BE) or Blind Adaptation approach. This approach continuously corrects the weight vector in the direction of the gradient vector's negative, leading to the smallest Mean Square Error (MSE) in the end (Zheng et al., 2021). The method, however, takes longer to converge and only just manages to attain an acceptable MSE for high order transmitted signals (Kim et al., 2012). Moreover, excessive side lobe radiation from transmitting antennas using CMA wastes energy and interferes with other devices. SLL also has the drawback that private information could find up in the hands of undesired recipients. Sidelobes in receiving antennae may pick up interfering signals and raise the receiver's noise level. Hence, reducing the Side Lobe is often preferred. In order to address these issues, an Improved Constant Modulus Algorithm (ICMA) for wireless communication systems is developed in this paper. This algorithm is "normalized" (similar to the popular normalized LMS algorithm), and it has an

adjustable step size that significantly speeds up the algorithm's convergence rate. The normalized step size is inversely related to the size of the current data vector needed to attain the target modulus. Additionally, the Blackman window was used on the CMA in order to lower the SLL. Combining Hanning and Hamming windows yields the Blackman window. The Blackman window possesses a better side lobe roll-off rate than Hanning, and a superior side lobe height than both windows. It also possesses a narrower main lobe width. Computer simulations are used to show that the developed ICMA performs equalization tasks substantially better than the traditional CMA. By reducing MSE, it is demonstrated that ICMA converges more quickly than CMA and the Blackman window is successful in reducing SLL, which wastes energy and interferes with other devices. As a result, the devised algorithms have a quick convergence rate and less SLL.

2. Related Works

Since Godard (1980) first suggested the CMA, several advancements have been made to improve on it. For example, to lower the SLL, Veerendra et al. (2016) devised various reliable blind beamformers for smart antenna systems. The side lobe level of the CMA was enhanced using a number of window approaches, their system was not effective.

A generalization of the enhanced decision adjusted modulus algorithm for blind equalization of constellations with closely spaced circles was presented by Kolosovs, (2020). It is based on a hybrid of the CMA and enhanced decision adjusted modulus algorithms, and it addresses the shortcomings of both. In order to make a decision, the system employs appropriately determined detection thresholds. The optimization criterion is the lowest chance of equalizer weight misadjustment. For modulations in the constellation with closely spaced circles, the algorithm has demonstrated great efficiency. The limitation of this work was slow convergence.

A more effective CMA was created in (Zheng et al., 2021) that makes use of the clustering function of the Gaussian function to effectively suppress this artificial error and steady state misadjustment at the expense of a lower sample usage rate. The limitation of this work was slow convergence. In contrast to CMA, a concurrent modified constant modulus strategy with the Barzilai-Borwein method was developed in (Xu et al., 2021) and quickly reached convergence. One of the limitations of this work was signal separation and recovery issues.

In order to blindly equalize communication channels, Yuan et al. (2022) presented a unique Diffusion Constant Modulus Algorithm (DCMA) for networks composed of sensors placed at the receiver array. In a decentralized setting, the DCMA algorithm outperforms the traditional noncooperative CMA algorithm significantly. Blind channel equalization simulation results support the enhanced bit error rate performance of the DCMA algorithm at various SNR levels.

Signal separation and recovery were resolved by Fan et al. (2023). Their work created an orthogonality restricted analytic CMA for improving blind signal extraction. They also investigated novel ways to include the inherent statistical signal orthogonality in CMA. Both of these developments improved signal separation and recovery.

According to these literatures reviewed, several current CMAs use a variety of techniques to enhance convergence rate, SLL, bit error rate, and SINR, among other metrics. However, there is still a significant need to enhance the rate of convergence, SLL, and SINR, particularly for usage in IWSNs where a high value of SINR is required due to the critical nature of the processes. So, the Blackman window and normalization technique were utilized in this work to further improve the CMA's convergence, SLL, and SINR. As compared to other types of CMA in the literature, the research has demonstrated from the obtained results that the ICMA is more appropriate and performs better for IWSN applications when compared to other types of CMA in literatures.

3. Materials and Methodologies

The materials and methodology used in developing the Improved Constant Modulus Algorithm (ICMA) are presented in this section. The materials are discussed in the first subsection, while the methodology is covered in the second.

3.1 Materials

The list of materials that are used in this research include:

1. MATLAB 2020a Software.
2. Core i7 HP Laptop computer.

3.2 Methodology

This subsection presents the development of an ICMA. The developed improved CMA is used for blind adaptation and mitigation of multipath signal interference of radio frequency signals in a situation where the interfering signal sources come from all angles, as is typical in IWSNs. Many wireless communications and radar signals are frequency- or phase-modulated signals, such as Frequency Modulation (FM) and Phase Modulation (PM) in the analog domain as well as Phase Shift Keying (PSK), Frequency Shift Keying (FSK) and Orbit Angular Momentum (OAM) for digital signal (Veen and Paulraj, 1996). This being the case, the amplitude (magnitude or modulus) of the signal should ideally be constant to preserve its value and quality. However, if it is corrupted by noise or interference, the Constant Modulus (CM) property is lost. So, if arriving signal of interest is known to have a CM, an algorithm is simply developed to restore or equalize the amplitude of the original signal. In other words, a filter is found to restore this property without knowing the sources. This is exactly what a Constant Modulus Algorithm (CMA) does. The CMA is perhaps the most well-known blind algorithm, and it is used in many practical applications because it does not require carrier synchronization.

3.2.1 Describing the Data Model of the ICMA

An elementary problem in the area of spatial signal processing is that of blind beamforming. This problem, for example, occurs in the following wireless communications scenario illustrated in Figure 1. Consider a number of sources (“users”) at distinct locations, all broadcasting signals at the same frequency, and at the same time. The signals are received by a central platform containing an array of antennae. The beamformer interprets the incoming data information by linearly combining the antennae outputs. Its objective is to separate the signals and to “copy” each of them without interference from other signals. The task of the blind beamformer is to compute the proper weight vectors \mathbf{w}^H (amplitude and phase information) from the measured data only without the detail knowledge of the signals and the channel (Veen and Paulraj, 1996). Figure 1 describes the data model of the ICMA. This improved model multiplies the weights to each element output to achieve improved antenna array radiation pattern.

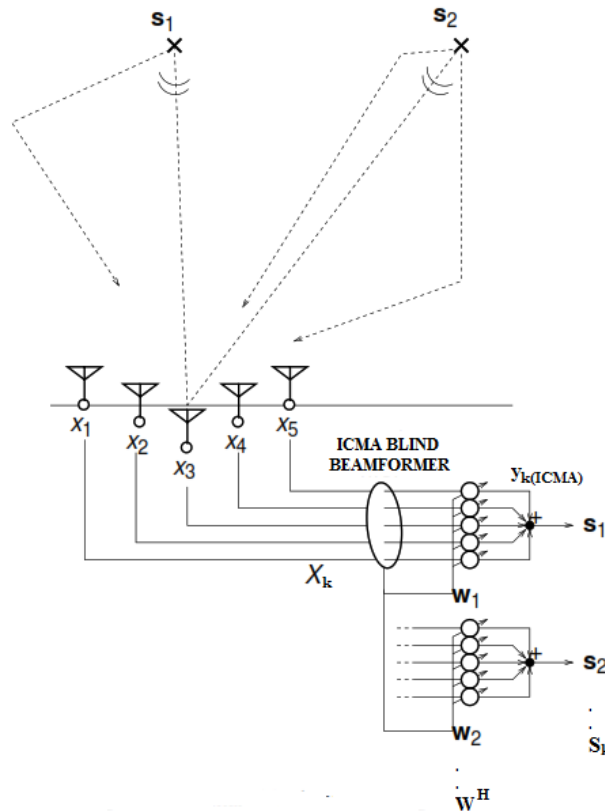


Figure 1: Data Model of the ICMA (Source: Veen and Paulraj, 1996)

The output response of the uniform linear array is given by:

$$y_{k(ICMA)} = \mathbf{W}^H \mathbf{X}_k \tag{1}$$

where;

- $y_{k(ICMA)}$ denotes the array output at the time k for the ICMA
- \mathbf{X}_k represents the incoming data information from each element output
- \mathbf{W}^H stands for the complex weights (amplitude and phase information)
- H denotes the complex conjugate transpose.

The cost function of a CMA is given by Yasin and Hussain (2016):

$$J(\mathbf{w}) = E(|y_k|^p - R_p)^q \tag{2}$$

Substituting equation (1) into equation (2) gives:

$$J(\mathbf{w}) = E(|\mathbf{W}^H \mathbf{X}_k|^p - R_p)^q \tag{3}$$

where;

- $J(\mathbf{w})$ stands for the cost function
- $|\cdot|$ denotes the modulus function
- $E|\cdot|$ represents statistical expectation
- p and q are non-negative parameters representing the modulus errors
- R is the desired modulus

By selecting different values for p and q , different families of algorithms are realized, but only the 1-1, 1-2, 2-1, and 2-2 forms are of much interest. The choices of p and q primarily depend on implementation issues such as precision

in fixed-point systems. In all cases, the filter is updated such that it produces a unity modulus with the current data vector. This work concentrates on the special case of $p = 1$ and $q = 2$ because it is less complex and converges faster with better tracking capability (Jin et al., 2018).

$$J(\mathbf{W}) = E(|\mathbf{W}^H \mathbf{X}_k| - R_1)^2 \tag{4}$$

3.2.2 Evaluating the Update Error of the ICMA.

The gradient of the cost function in equation (3) is zero when R_p is defined by Nwalozie et al., (2012) as:

$$R_p = \frac{E[|\hat{s}_k|^{2p}]}{E[|\hat{s}_k|^p]} \tag{5}$$

When p is chosen as 1, then equation (5) becomes:

$$R_1 = \frac{E[|\hat{s}_k|^2]}{E[|\hat{s}_k|]} \tag{6}$$

where;

R_p is the desired modulus of the ICMA, \hat{s}_k is the zero-memory estimate of $y_{k(ICMA)}$

The resulting error signal is given by Nwalozie et al., (2012) as:

$$e_k = y_k |y_k|^{p-2} (|y_k|^p - R_p) \tag{7}$$

If the output estimate \hat{S}_k of equation (6) is scaled down to unity, the unknown signal source has a constant modulus, $|\hat{S}_k| = 1$ for all k (Nwalozie et al., 2012), then by substituting $|\hat{S}_k| = 1$ in equation (6) results in $R_1 = 1$. Substituting $R_1 = 1$ and $p=1$, equation (7) is further reduced to:

$$e_k = y_k |y_k|^{-1} (|y_k| - R_1)$$

$$e_k = y_k |y_k|^{-1} (|y_k| - 1)$$

$$e_k = \frac{y_k}{|y_k|} (|y_k| - 1)$$

$$e_k = (y_k - \frac{y_k}{|y_k|})$$

The error signal of equation (7) is given by Yasin and Hussain, (2016) as:

$$e_{k(ICMA)} = \left(y_{k(ICMA)} - \frac{y_{k(ICMA)}}{|y_{k(ICMA)}|} \right) \tag{8}$$

The cost function of equation (4) also becomes:

$$J(\mathbf{W}) = E(|\mathbf{W}^H \mathbf{X}_k| - 1)^2 \tag{9}$$

According to the stochastic gradient descent rule, the updated formula of a CMA is given by Yasin and Hussain, (2016):

$$\mathbf{W}_{k+1(CMA)} = \mathbf{W}_{k(CMA)} + \mu e_{k(CMA)} \mathbf{X}_k \tag{10}$$

Substituting equation (8) into equation (10) yields:

$$\mathbf{W}_{k+1(ICMA)} = \mathbf{W}_{k(ICMA)} + \mu \left(y_{k(ICMA)} - \frac{y_{k(ICMA)}}{|y_{k(ICMA)}|} \right) \mathbf{X}_k \tag{11}$$

The corresponding iteration can thus be done by using equation (1) and equation (11), respectively.

3.2.3 Evaluating the Adaptive Step Size to Normalize the ICMA.

Slow convergence is a main drawback of CMA. To increase the convergence, an adaptive step size is used to adjust the step factor, μ such that the updated coefficients would achieve the desired modulus when applied to \mathbf{X}_k .

The convergence rate of a CMA is improved by using adaptive step size given by Nwalozie et al., (2012) as:

$$\mu = \frac{-\dot{\mu}}{\|\mathbf{X}_k\|^2} \tag{12}$$

where, μ is the fixed step size of the input signal

$\dot{\mu}$ is the adaptive step size that adapts the input signal

Substituting equation (12) into equation (11) gives the normalize form of the ICMA as:

$$\mathbf{W}_{k+1(ICMA)} = \mathbf{W}_{k(CMA)} - \frac{\dot{\mu}}{\|\mathbf{X}_k\|^2} \left(y_{k(CMA)} - \frac{y_{k(CMA)}}{|y_{k(CMA)}|} \right) \mathbf{X}_k \tag{13}$$

The adaptive step size ($\dot{\mu}$) prevents the weights from diverging. This feature increases the convergence rate and makes the algorithm more stable.

3. 2.4 Minimizing the SLL using Blackman Window Function and Estimating the Desired Signal for the ICMA

Apart from slow convergence, another drawback of CMA is the large Side Lobe Level (SLL). The SLL in the generated pattern is reduced by smoothly tapering the current distribution obtained from the Fourier series method using a Blackman Window (BW) function (Podder et al., 2014). According to Yasin and Hussain (2016), the Blackman weight is as follows:

$$\mathbf{W}_{k(BW\ CMA)} = \begin{cases} 0.42 - 0.5\cos\left(\frac{2\pi n}{N-1}\right) + 0.08\cos\left(\frac{4\pi n}{N-1}\right), & 0 \leq n \leq N - 1 \\ 0, & \text{Otherwise} \end{cases} \tag{14}$$

where: $n = 0, 1 \dots N$;

The BW is applied to equation (12) to further improve CMA by reducing the SLL as:

$$\mathbf{W}_{k+1(ICMA)} = \mathbf{W}_{k(BWCMA)} - \frac{\dot{\mu}}{\|\mathbf{X}_k\|^2} \left(y_{k(CMA)} - \frac{y_{k(CMA)}}{|y_{k(CMA)}|} \right) \mathbf{X}_k \tag{15}$$

Substituting equation (15) into equation (1) the output of the CMA is given by:

$$y_{k(ICMA)} = \mathbf{W}_{k(BWCMA)} \mathbf{X}_k \tag{16}$$

The desire signal is then estimated according to Yasin and Hussain (2016) as:

$$\hat{S}_k = \frac{y_{k(ICMA)}}{|y_{k(ICMA)}|} \tag{17}$$

Figure 2 and 3 show the original CMA and the Improved Constant Modulus (ICMA).

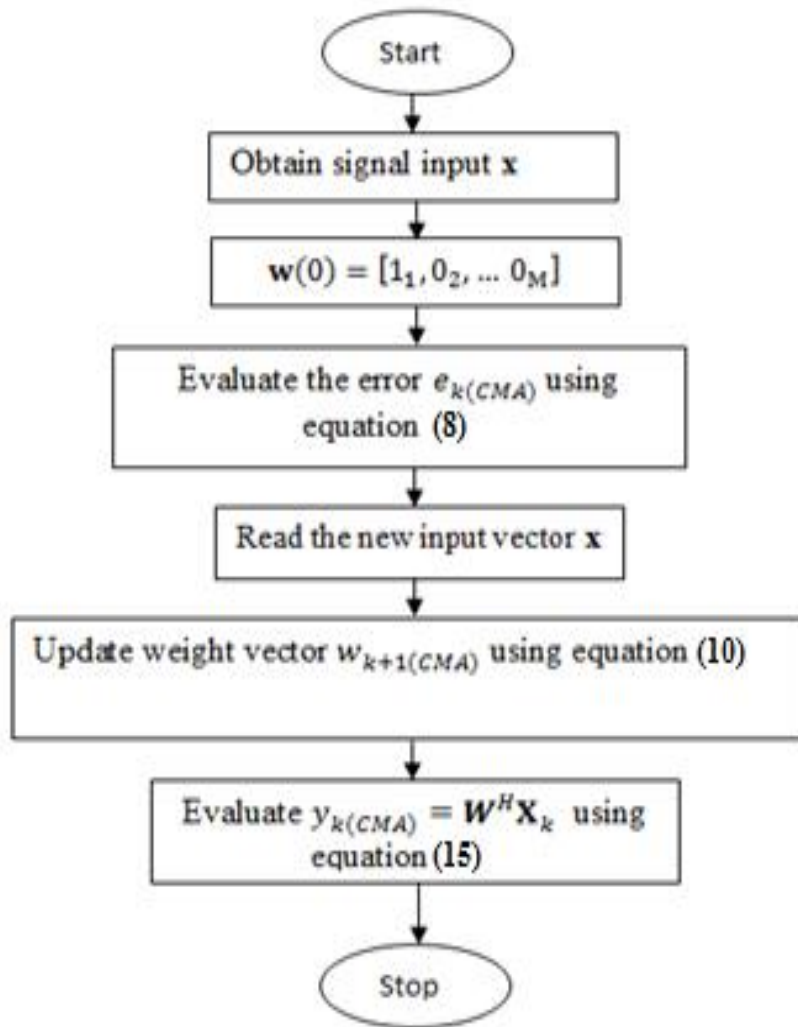


Figure 2. Constant Modulus Algorithm (Source: Zheng et al., 2020)

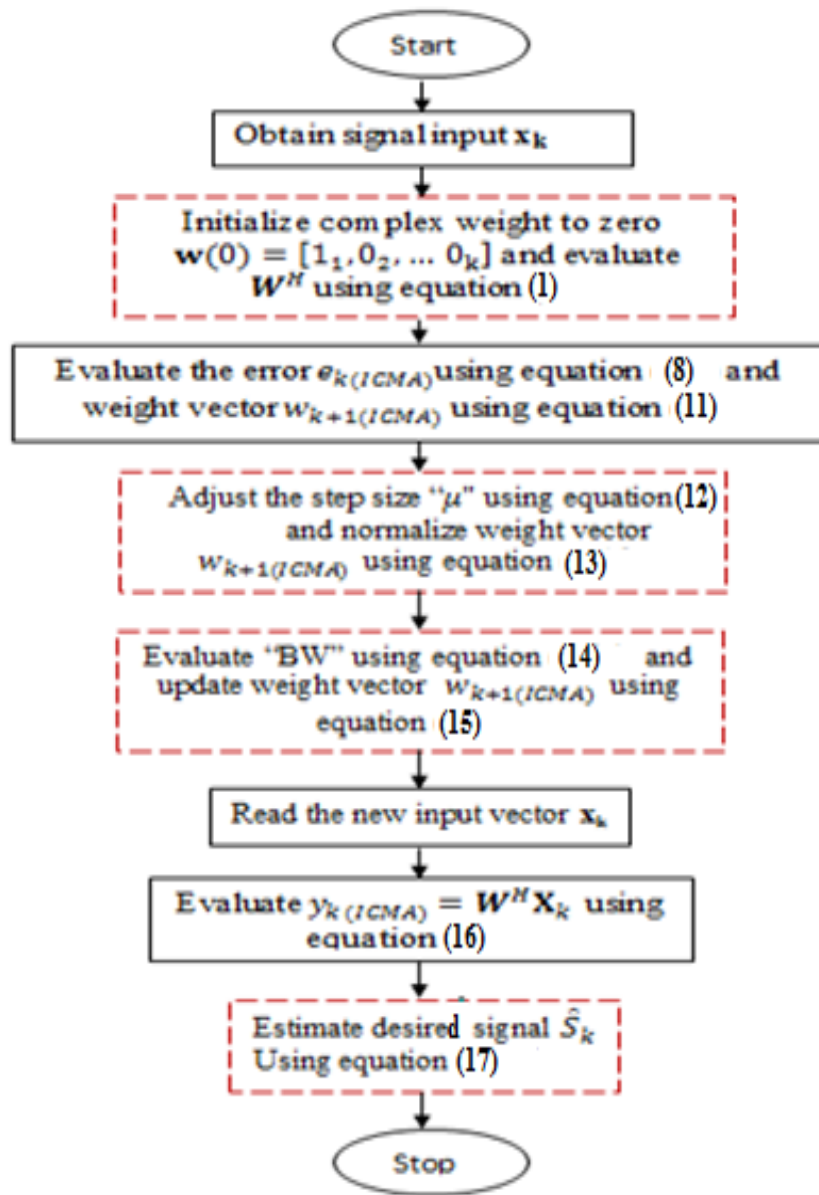


Figure 3. Improved Constant Modulus Algorithm

The modifications made to the original CMA to make it robust enough for mitigating interference in IWSNs are shown by the dotted boxes of the flowchart in Figure 3.

1. The weights are initialized to zero and the initial weight is evaluated using equation 1
2. The step size of the algorithm is changed to an adaptive step size ($\hat{\mu}$), as seen in equation 12. The variable, or "adaptive" step size, adapts to the input signal and prevents the weights from diverging, thus increasing the convergence rate and making the algorithm more stable.
3. The Blackman window has been added to the CMA. This is chosen because Blackman is a combination of Hanning and Hamming windows with a better side lobe roll-off rate than Hanning, a superior side lobe height than both windows, and a wider main lobe width (Podder et al., 2014).

The non-use of training and reference signals that add overhead to the system and thus reduce the throughput and bandwidth of the system. Instead, a constant modulus criterion implemented by feedback of the output signal is used for blind signal adaptation, which helps to increase bandwidth efficiency.

4. Simulation Results

Here, simulation is carried out for the Improved Constant Modulus Algorithm (ICMA) and its results obtained are analyzed for discussion. A baseband discrete model for a digital communication system which employs QAM signals was considered. The step size μ is chosen as $\mu = 5 \times 10^{-5}$ for 16-QAM and. The step size $\dot{\mu}$ is selected as $\dot{\mu} = 5 \times 10^{-3}$. Also, the initial BE, \mathbf{W}_0 is given by $[0, 0, 1, 0, 0, 0]^T$. The simulation is carried out for the Improved Constant Modulus Algorithm (ICMA) and the results obtained are analyzed, and the significance of the results are discussed in section 5. The developed constant modulus algorithm is simulated using MATLAB 2020a. Simulation results network performance metrics used in this research, such as the output Mean Square Error (MSE), Symbol Error Rate (SER), and Side Lobe Level (SLL) for the CMA are compared with those of the developed Improved Constant Modulus Algorithm (ICMA). The percentage improvement of ICMA over the CMA is obtained using equation (18).

$$\text{Percentage Improvement} = \frac{\text{Improved CMA} - \text{Existing}}{\text{Existing}} \times 100\% \tag{18}$$

Figures 4, 5 and 6 show the output MSE, SER and the SLL of the CMA and the ICMA. A comparative discussion of the results obtained using the improved algorithm and the existing algorithm is carried out in section 4.

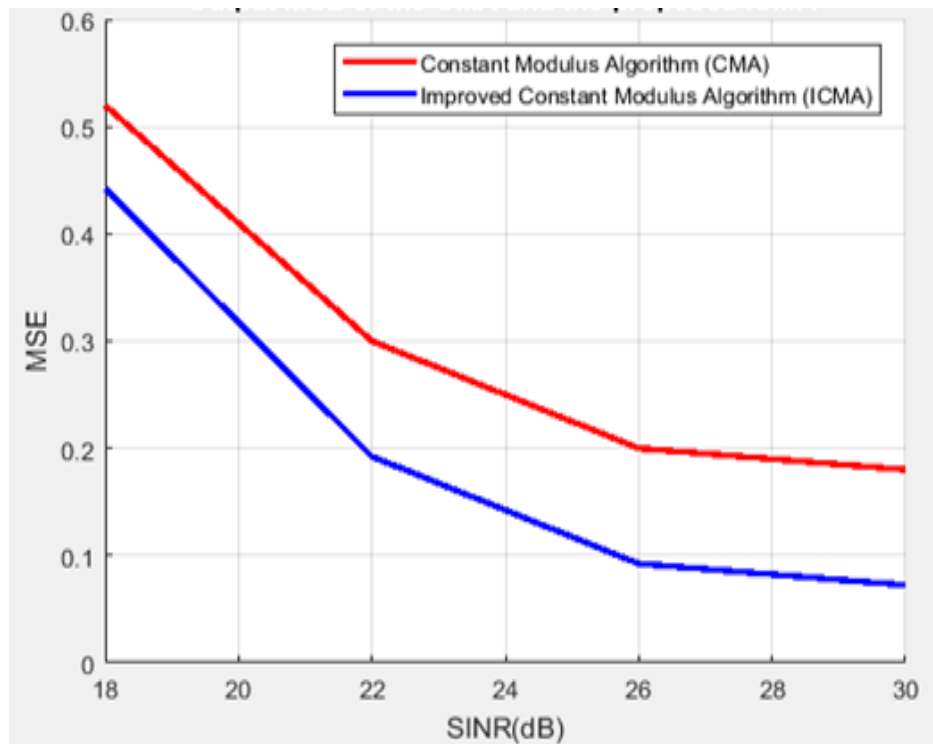


Figure 4: Output MSE of the CMA and the ICMA

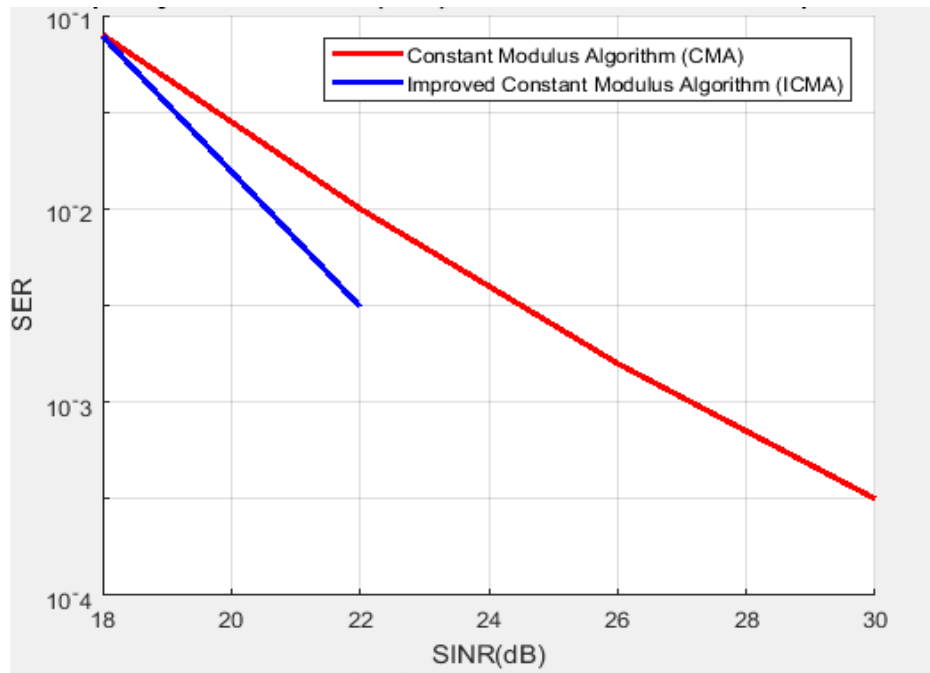


Figure 5: Output Symbol Error of the CMA and the ICMA

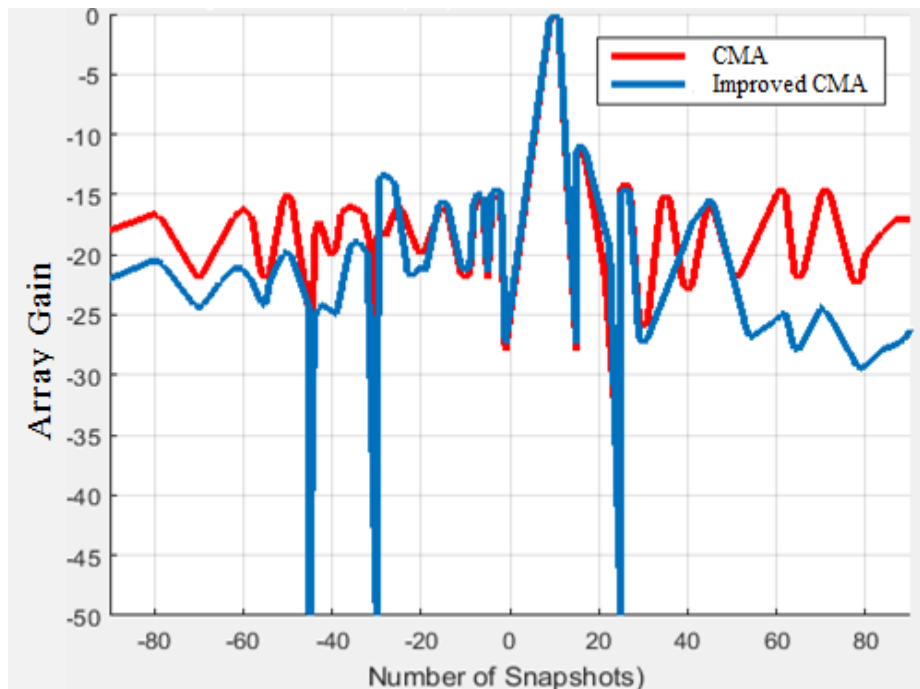


Figure 6. Array Gain of the CMA and the ICMA

5. Discussion

In all the simulations a performance comparison of the CMA and the developed ICMA was performed. As shown in Figures 4, 5 and 6, the proposed algorithm achieves much lower MSE, SER and SLL than the CMA. Figure 4 shows the faster rate of convergence of the ICMA compared to CMA with a MSE of 1.8 as against 3.0 for the same value of

SINR of 22dB. Figure 5 shows an improvement the maximum Symbol Error Rate (SER) occurring at 22 dB for ICMA compared to at 30 dB in CMA. This is due to the fact that the CMA was normalized with an adjustable step size that greatly increases the convergence rate of the CMA thus the ICMA can efficiently suppress the artificial error and the steady state maladjustments. This helps the beamformer to track the desired signal in an environment where the signal characteristics are changing rapidly. It can be observed from Figure 6 that the developed ICMA has a lower SLL and lower side lobe rejection rate. The reason for this is that the Blackman window technique which is a combination of Hanning and Hamming windows was applied to the CMA. The Blackman window a better side lobe roll-off rate than Hanning, a superior side lobe height than both windows, and a narrower main lobe width.

6. Conclusion

A robust blind beamforming algorithm has been devised for wireless communications. The ICMA with developed beamformer showed an improvement of 40% in convergence rate and interference rejection compared to the classical CMA as given by a MSE of 1.8 against 3.0 for the same value of SINR of 22 dB. This makes the beamformer a suitable candidate in an environment where the channel conditions are rapidly changing. Furthermore, side lobe levels are significantly reduced in ICMA by the application of the Blackman window function to improve CMA. All three beamformers have great potential to reduce Peak Side Lobe Level (PSLL). Figure 5 shows improvement of the maximum Symbol Error Rate (SER) occurring at 22 dB for the ICMA when compared to that of 30 dB for CMA. Also, from the Figure 6, it is clear that the addition of the Blackman window has a great potential to reduce the PSLL and caused an improvement of 5 dB over CMA for the SLL rejection gain. The developed ICMA showed the highest reduction in PSLL with fast converging capability and saves a lot of energy wastage caused by side lobes as compared to other blind beamforming algorithms. These features make the smart antenna system efficient, stable, and robust and a suitable candidate for advanced wireless network applications.

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