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IMPROVED CMA: A BEAMFORMING ALGORITHMS FOR WIRELESS SYSTEM USING SMART ANTENNA

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Abstract

The technology review indicates that performance and utility benefits could be accumulated by more control over the size and beam characteristics of the antenna. In the last couple of years smart antennas for mobile communications have received enormous interest worldwide. If the base station is to track a large number of users simultaneously, the computational cost will be large. Recently the processors with sufficient computational power are available which are used in smart antennas. In addition to increased capacity, smart antennas also introduce a number of other advantages to cellular networks, including *improved range*, *a higher level of security*, and the *possibility for new services*.
This paper aims to determine various performance measuring parameters such as beamwidth, mainlobe gain and average sidelobe gain for smart antennas used in wireless system. The channel used was Rayleigh fading and the modulation techniques were QPSK, 16 QAM, and 64 QAM. The experiments were conducted to find out the above mentioned parameters using MATLAB. The simulated results were compared with the results published in the earlier papers. It was found that Improved constant Modulus algorithm performs better than the compared Algorithms.

***Keywords**:* Smart Antenna; Beamforming; Constant modulus algorithm; Beamwidth; QAM

1. Introduction

Wireless Telecommunication technology has changed the lives during the past few decades. In the homes, offices and Educational institution the mobile portable devices gives more freedom such that the communication with each other at any time and in any place is possible. Today there are many application of wireless communication in almost in every area such as Personal Communications Services (PCS), Wireless Personal Area Networks (WPAN), Wireless Local Area Networks (WLAN) and many other Telecommunication systems, which provides reliable wireless connections between computers, portable devices and consumer electronics within a short range.

Communication system have the antennas which plays an extremely important role in wireless communication, so these system demands to design the antennas with increased functionality, better performance, reduced size and low development cost. Omni-directional antennas amplify signals in all directions for receiving and transmitting which makes them more susceptible to receive noise and more likely to generate noise for other devices. Wireless signals coming from other devices from other directions will reduce the Signal to Noise Ratio (SNR) on a dumb omni-directional antenna but not on a smart directional antenna. It is possible to get improvement using dumb directional antennas but that improvement is only aimed at a single direction. Putting a mechanical rotation device on a fixed directional antenna can solve the direction problem but it’s very costly and complex and has a very slow response time. The smart antenna uses an array of antennas facing a wide range of directions. The Digital Signal Processor (DSP) used in smart antenna

virtually points the antenna by only using the portions of the antenna that generate the highest SNR. Smart Antennas are integral part of systems due to high data throughput capability and low power requirements.
As the growing demand for mobile communications is constantly increasing, the need for better coverage, improved capacity and higher transmission quality arises. Thus, more efficient use of the radio spectrum is required. Smart Antenna Systems (SAS) are capable of efficiently utilizing the radio spectrum and assure a successful solution to the present wireless system problems while accomplishing reliable and robust high-data-rate transmission. Smart antenna systems comprise several critical areas such as individual antenna array design, signal processing algorithms, space-time processing, wireless channel modeling and coding and network performance. A Smart Antenna (SA) is a digital wireless communications antenna system that takes advantage of diversity effect at the source (transmitter), the destination (receiver), or both. Diversity effect involves the transmission and/or reception of multiple radio frequency (RF) waves to increase data speed and reduce the error rate.

2. Smart Antennas

Smart antennas consist of more than an antenna. A smart antenna is a system involving multiple antenna elements and a digital signal processor to adjust the radiation. It is an antenna system which dynamically reacts to its environment to provide better signals and frequency usage for wireless communications. There are a variety of smart antennas which utilize different methods to provide improvements in various wireless applications.

2.1 Need for Smart Antennas

Wireless communication systems, as opposed to their wireline counterparts, pose some unique challenges [1]

i. The limited allocated spectrum results in a limit on capacity.
ii. The radio propagation environment and the mobility of users give rise to signal fading and spreading in time, space and frequency.
iii. The limited battery life at the mobile device poses power constraints.

In addition, cellular wireless communication systems have to cope with interference due to frequency reuse. Research efforts investigating effective technologies to mitigate such effects have been going on for the past twenty five years, as wireless communications are experiencing rapid growth [1]. Among these methods are multiple access schemes, channel coding and equalization and smart antenna employment. Figure 1 summarizes the wireless communication systems impairments that smart antennas are challenged to combat [2].

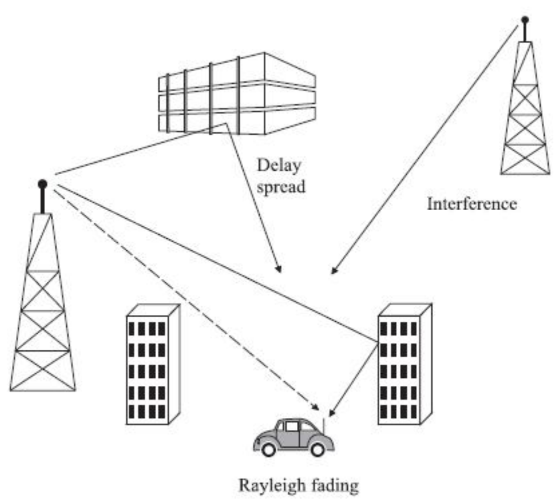

Figure 1: Wireless systems impairments.

2.2 Adaptive Antenna

The adaptive antenna systems approach communicates between a user and a base station in a different way by adding the dimension of space. By adjusting to the RF environment as it changes (or the spatial origin of signals), adaptive antenna technology can dynamically alter the signal patterns to optimize the performance of the wireless system. *Adaptive array systems* [3, 4] provide more degrees of freedom since they have the ability to adapt in real time the radiation pattern to the RF signal environment; in other words, they can direct the main beam toward the pilot signal or SOI while suppressing the antenna pattern in the direction of the interferers or SNOIs. To put it simply, adaptive array systems can customize an appropriate radiation pattern for each individual user. Adaptive array systems can locate and track signals (users and interferers) and dynamically adjust the antenna pattern to enhance reception while minimizing interference using signal processing algorithms. A functional block diagram of the digital signal processing part of an adaptive array antenna system is shown in Figure 2.
After the system downconverts the received signals to baseband and digitizes them, it locates the SOI using the DOA algorithm, and it continuously tracks the SOI and SNOIs by dynamically changing the complex weights (amplitudes and phases of the antenna elements). Basically, the DOA computes the direction-of-arrival of all the signals by computing the time delays between the antenna elements, and afterward, the adaptive algorithm, using a cost function, computes the appropriate weights that result in an optimum radiation pattern. Because adaptive arrays are generally more digital processing intensive and require a complete RF portion of the transceiver behind each antenna element, they tend to be more expensive than switched-beam systems.

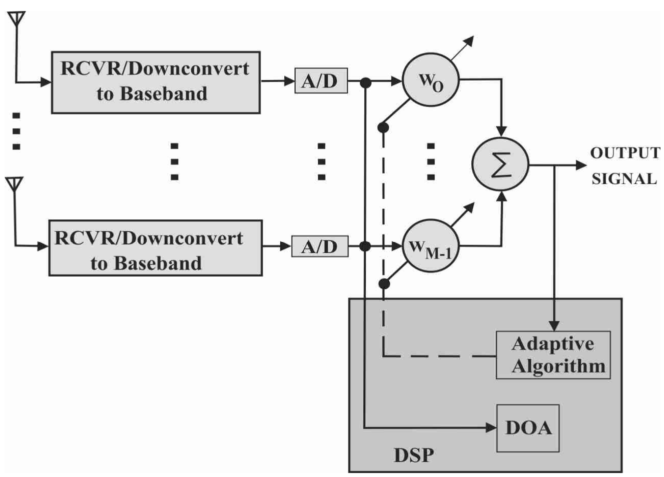

Figure 2**:** Functional block diagram of an adaptive array system.

3. Adaptive Beam forming Algorithms

For the time-varying signal propagation environment, a recursive update of the weight vector is needed to track a moving user so that the spatial filtering beam will adaptively steer to the target user's time-varying DOA, thus resulting in optimal transmission/reception of the desired signal [5]. To solve the problem of time-varying statistics, weight vectors are typically determined by adaptive algorithms which adapt to the changing environment. Figure 3 shows a generic adaptive antenna array system consisting of an N-element antenna array with a real time adaptive array signal processor containing an update control algorithm.
The data samples collected by the antenna array are fed into the signal processing unit which computes the weight vector according to a specific control algorithm. Steady-state and transient-state are the two classifications of the requirement of an adaptive antenna array. These two classifications depend on whether the array weights have reached their steady-state values in a stationary environment or are being adjusted in response to alterations in the signal environment. If the reference signal for the adaptive algorithm is obtained

by temporal reference, *a priori* known at the receiver during the actual data transmission can either continue to update the weights adaptively via a decision directed feedback or use those obtained at the end of the training period. Several adaptive algorithms can be used such that the weight vector adapts to the time-varying environment at each sample.

3.1. LMS Algorithm

The LMS algorithm can be easily realized with the advantage of simple, less operations and robust for signal statistical characteristic. Then the convergence rate and steady state error of LMS algorithm is analyzed and in order to achieve faster convergence rate and less state error a new variable step size LMS algorithm is proposed [6, 12].

By combining the signals incident on the linear antenna array and by knowing their DOA, a set of weights can be adjusted to optimize the radiation pattern. The application of the LMS algorithm to estimate the optimum weights of an antenna array is widespread. Some of the parameters are related to the array structure in terms of its size and element spacing. Others are related to the incident signals including their number and angular separation. Moreover, the SNR has an effect on the performance of the LMS beam former. The LMS algorithm involves the adjustment of a set of weights to minimize the difference between a reference signal and the antenna array output. The reference signal is used by the array to distinguish between the desired and interfering signals at the receiver. The output of the array is given by,

$$y(t) = \boldsymbol{w}^H x(t) \tag{1}$$

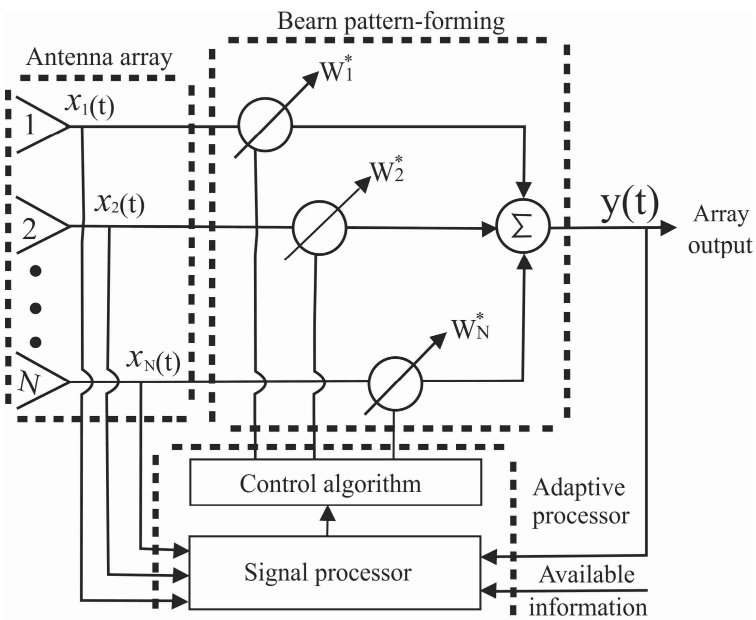

Figure 3: Functional diagram of an *N*-element adaptive array.

The LMS algorithm can be summarized in following equations;

$$\text{Output,} \quad y(n) = w^H x(n) \tag{2}$$

$$\text{Error,} \quad e(n) = b(n) - y(n) \tag{3}$$

$$\text{Weight,} \quad \boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu x(n) e^*(n) \tag{4}$$

3.2 Improved LMS (A New Variable Step LMS)

The variable step LMS is proposed based on the relationship between the performance and step μ.
During the adaptive process in smart antenna, the error between the output of antenna array and expected signal will be affected by the noise and interference. When there is serious noise and interference if μ is adjusted by only making use of the error signal LMS performance will be greatly affected. The result is that the instantaneous weight cannot be near to the optimal one, instead, it can only wave around the optimal weight. So we update the weight through the self correlation estimate of the current error and the previous to eliminate influence of irrelevance noise. A new variable step μ is proposed as follows

$$\mu(n) = \frac{\square\left(1-e^{\square\left|e(n)e(n-1)\right|}\right)}{X^{H}(n)X(n)} \tag{5}$$

$\left|e(n)e(n-1)\right|$, is introduced to adjust the weight at the stage of beginning to converge with big error, so the step *(μ) n* is big too. But for the noise is not relative and it has little impact on (μ) *n*, the steady state error caused by noise for the adaptive algorithm will be effectively reduced and the algorithm will have good performance with faster convergence rate and less error [7, 12]. The unitary method introduced warns sensitivity of the algorithm depending on the received signal a certain extent. The step μ of traditional LMS is 0.000005, and the parameters of new algorithm are □ = 0.22 and □ = 0.25.

3.3 The Constant-Modulus Algorithm (CMA)

Many communication signals, frequency or phase modulated, such as FM, CPFSK modulation, and square pulse-shaped complex pulse amplitude modulation (PAM) has a constant complex envelope [8]. This property is usually referred to as the *constant modulus* (CM) signal property. For these types of communication signals, one can take advantage of the prior knowledge of this characteristic and specify the adaptation algorithm to achieve a desired steady state response from the array. The CMA is the most well-known algorithm of this kind. It is suitable for the transmission of a modulated signal over the wireless channel, since noise and interference corrupt the CM property of the desired signal [8]. Thus, the CM provides an indirect measure of the quality of the filtered signal. It adjusts the weight vector of the adaptive array so as to minimize the variation of the desired signal at the array. After the algorithm converges, a beam is steered in the direction of the signal of interests, whereas nulls are placed in the direction of interference. In general, the CM algorithm seeks a beamformer weight vector that minimizes a cost function of the form

$$\boldsymbol{J}_{p,q} = E\left\{\left|\left|y(k)\right|^{p}-1\right|^{q}\right\} \tag{6}$$

Equation (6) describes a family of cost functions. The convergence of the algorithm depends on the coefficients *p* and *q* in (6). A particular choice of *p* and *q* yields a specific cost function called the *(p, q) CM cost function*. The (1, 2) and (2, 2) CM cost functions are the most popular. The objective of CM beamforming is to restore the array output *y* (*k*) to a constant envelope signal. Using the method of steepest descent, the weight vector is updated using the following recursive equation,

$$\boldsymbol{w}(k+1) = \boldsymbol{w}(k) - \mu\nabla_{\boldsymbol{w},\boldsymbol{w}^*}(\boldsymbol{J}_{p,q}) \tag{7}$$

When the (1, 2) CM function is used, the gradient vector is given by [9]

$$\nabla_{\boldsymbol{w},\boldsymbol{w}^*}(\boldsymbol{J}_{1,2}) = \frac{\partial \boldsymbol{J}_{1,2}}{\partial \boldsymbol{w}^*} = E\left[\boldsymbol{X}(k)\left(y(k)-\frac{y(k)}{\left|y(k)\right|}\right)^{*}\right] \tag{8}$$

Ignoring the expectation operation in (8), the instantaneous estimate of the gradient vector can be written as

$$\nabla_{w,w^*}(\boldsymbol{J}_{1,2}(k)) = \boldsymbol{X}(k)\left[y(k) - \frac{y(k)}{|y(k)|}\right]^* \tag{9}$$

Therefore, using (9), the resulting weight vector is given by

$$\boldsymbol{w}(k+1) = \boldsymbol{w}(k) - \mu\left[y(k) - \frac{y(k)}{|y(k)|}\right]^* \boldsymbol{X}(k) \tag{10}$$

$$= \boldsymbol{w}(k) + \mu e^*(k)\boldsymbol{X}(k)$$

Where,

$$e(k) = \frac{y(k)}{|y(k)|} - y(k)$$

Comparing the CM and the LMS algorithms, we notice that they are very similar to each other. The term y (k) |y (k)| in CM plays the same role as the desired signal in the LMS. However, the references signal b (k) must be sent from the transmitter to the receiver and must be known for both the transmitter and receiver if the LMS algorithm is used. The CM algorithm does not require a reference signal to generate the error signal at the receiver [9]. Several other properties of the constant modulus algorithm are discussed in [10].

3.4 Improved CMA

CMA has the disadvantages of the slow convergence rate and large steady state MSE. The objective of this work is to improve the convergence properties of the CM schemes. The convergence properties of any adaptive algorithm depend on the cost function, which is subject to minimization during the adaptation process. The cost function is a function of the equation for the error, defined as the difference between the present and the desired value of any property of the signal that is to be restored. Therefore, the cost function of an adaptive algorithm can be changed either by changing the function itself or by changing the error equation. The most commonly used definition of the cost function is the mean squared value of the error. Changing the definition of the cost function provides a lot of advantages. For example, a non-MSE criterion improves the performance of the adaptive algorithm when the interfering noise distribution is non-Gaussian. In this work, instead of changing the definition of the cost function, step size is varied to improve the performance the CM algorithm. It is shown that the performance of CMA can be improved by only changing the equation for the error signal. Some error equations provide better convergence rate, while other error equations improve performance by eliminating the probability of converging to local minima. Convergence to global minima can be confirmed by following some steps and checks during the initialization and adaptation respectively. Several new algorithms have been introduced to overcome the disadvantages of CMA. A variable step size Improved CMA (ICMA) is proposed to improve the stability of the system and convergence speed. ICMA is CMA, but the step size is changed as the correlation matrix is changed to avoid unstable system. ICMA shows the performance improvement in convergence behaviour.

The variable step CMA is proposed based on the relationship between the performance and step μ. The basic principle of Improved CMA is that at the stage of beginning to converge or change of system parameter for the weight of adaptive algorithm is far away from the optimal weight; choose a large value for μ to ensure it has faster convergence rate and tracing rate. When the weight of algorithm is near to the optimal value, in order to reduce the steady state error, choose a smaller value for μ therefore μ becomes scaling independent as given in the following equation (11)

$$\boldsymbol{w}^{(k+1)} = \boldsymbol{w}^k - \frac{\mu}{\|\boldsymbol{x}_k\|^2}\boldsymbol{x}_k(y_k - \frac{y_k}{|y_k|}) \tag{11}$$

As can be seen from Equation (11), the algorithm reduces the step size μ to make the changes large. As a result, the step size μ varies adaptively by following the changes in the input signal level. This prevents the update weights from diverging and makes the algorithm more stable and faster converging than when a fixed step size is used. In addition, the ICMA algorithm is used as the MMSE method needs to cope with the large changes in the signal levels of wireless communication systems, the new optimum ICMA algorithm update the weight vectors according to the following equations

$$R_{rr} = \sum_{1-N_1}^{N_2} x(n)x^H(n) \quad , \quad r = \sum_{1-N_1}^{N_2} b^*(n)x(n) \tag{12}$$

$$w_0 = R^{-1}r , \tag{13}$$

$$y(n) = w^H x(n) , \tag{14}$$

$$e(n) = y(n)\left[1 - \frac{1}{|y(n)|}\right] \tag{15}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n)x(n)\mu e^*(n)$$

$$= \mathbf{w}(n) + \frac{\mu}{\|x(n)\|^2} x(n)e*(n) \tag{16}$$

The final weight vector of the ICMA algorithm is estimated from equation (11). In the ICMA algorithm, advantages of both the block adaptive and sample by sample techniques are employed. In this algorithm, the initial weight vector is obtained by matrix inversion through Sample Matrix Inversion (SMI) algorithm, only for the first few samples or for a small block of incoming data instead of arbitrary value before calculating the final weight vector. The final weight vector is updated by using the ICMA algorithm.

4 Results:

In case of smart antenna the beamforming algorithm (BFA) plays a vital role. The performance of the algorithm is evaluated using various parameters. The performance parameters on the basis of radiation parameter are important to determine the effectiveness of the beamforming algorithm. The major radiation parameters are main lobe gain, average side lobe gain and beamwidth. These parameters are measured to evaluate the performance of the system. The experiment was conducted to determine the above mentioned performance measuring parameters. In this experiment the performance was evaluated for number of antenna elements and modulation schemes. The antenna elements (AE) considered for simulation were 2, 4 and 8 and modulation schemes like QPSK, 16-QAM and 64-QAM were implemented in the simulation model. The parameters were determined for different beam forming algorithms such as LMS, LLMS, ILMS, CMA and newly designed ICMA. The radiation patterns are shown in Figures 4 to 12.

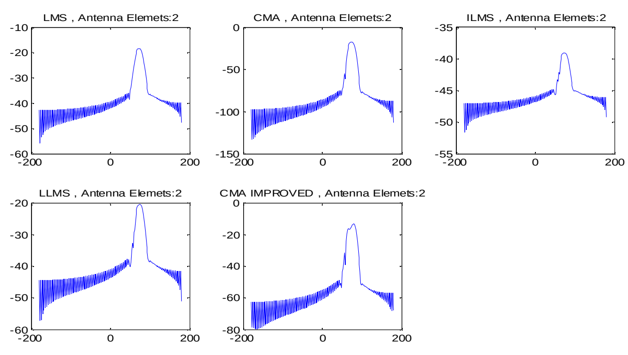

Figure 4: Radiation pattern of 2 AE for different BFA with QPSK.

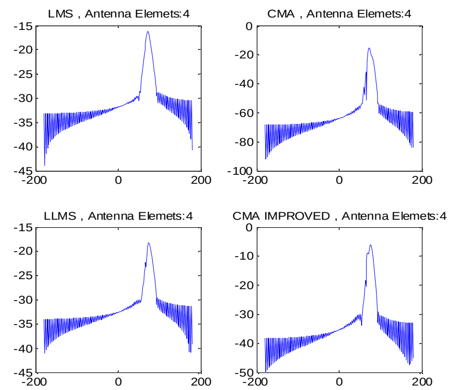

Figure 5: Plot of radiation pattern of 4 AE for different BFA with QPSK.

Figure 4, 5 and 6 shows the mainlobe gain results for 2, 4 and 8 antenna elements with various beamforming algorithms when the modulation scheme is QPSK. From the figures we observe that the main lobe gain in case of ICMA for 2 antenna elements is -13.254 dB, for 4 antenna elements it is -6.199 dB and for 8 antenna elements it is -3.05031. This observation reveals that 8 antenna elements provide 76% more main lobe gain as compared with 2 antenna elements and 53% more as compared to 4 antenna elements. Finally it is concluded that for QPSK with 8 antenna elements ICMA gives 73% more main lobe gain as compared main lobe gain of CMA. With respect to the sidelobe gain CMA outperform all other beamforming algorithms, having value of -53.7581 dB for 8 AE. Whereas of ICMA the sidelobe gain value is -14.280 dB. This is 3.5 times less as compared to CMA. The ratio of average sidelobe gain to main lobe gain of ICMA is -4.68 and for CMA it is -5.17. This result shows that the performance of ICMA is comparable with CMA. The average sidelobe gain for different beamforming algorithms with different antenna elements and modulation schemes is given in table 2 Since the mainlobe gain is higher by a factor of 3.40 the power required to achieve the same performance in case of ICMA will be very much low as compared to CMA.
The simulation was carried out to evaluate the mainlobe gain of all above beamforming algorithms by implementing 64-QAM modulation scheme. The main simulation parameters were number of antenna elements different modulation schemes and beamforming algorithms. The radiation pattern of 64-QAM with 2, 4 and 8 antenna elements for all above mentioned beamforming algorithms is shown in Figures 10 to 12. The aim of simulation is to evaluate the main lobe gain and average sidelobe gain for all algorithms with 64-QAM.

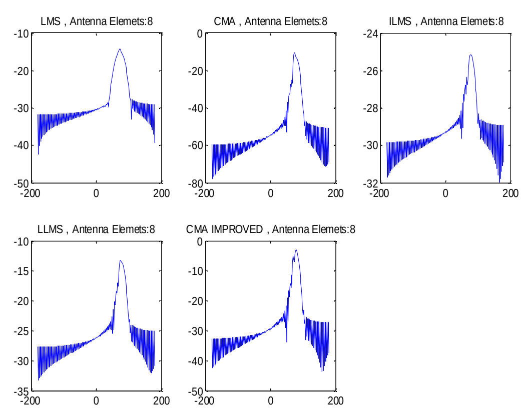

Figure 6: Radiation pattern of 8 AE for different BFA with QPSK.

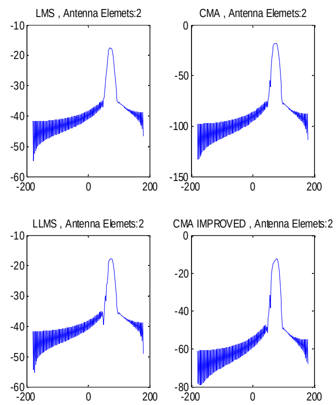

Figure 7**:** Radiation pattern of 2 AE for different BFA with 16-QAM.

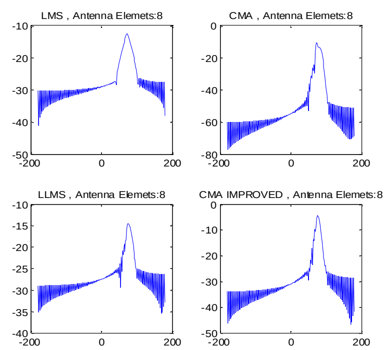

Figure 8: Radiation pattern of 4 AE for different BFA with 16-QAM.

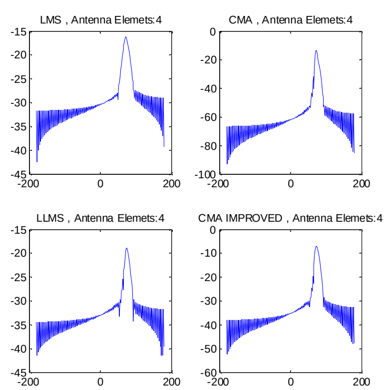

Figure 9: Radiation pattern of 8 AE for different BFA with 16-QAM.

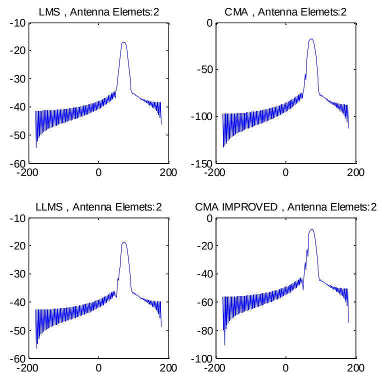

Figure 10: Radiation pattern of 2 AE for different BFA with 64-QAM.

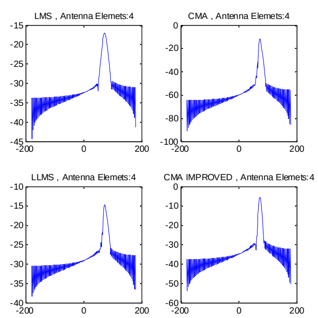

Figure 11: Radiation pattern of 4 AE for different BFA with 64-QAM.

The average sidelobe gain of CMA is lowest as compared to other algorithms which are given in table 2; the ratio of average sidelobe gain to mainlobe gain for ICMA is 6.93, whereas for CMA it is 5.11 which is compatible with ICMA**.**

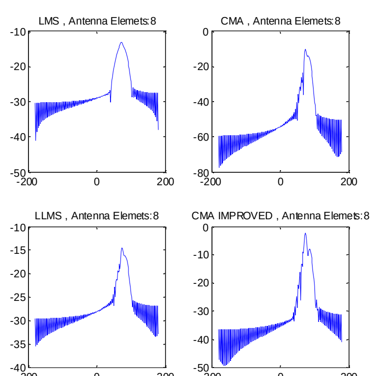

Figure 12: Radiation pattern of 8 AE for different BFA with 64-QAM.

The mainlobe gain for ICMA is 4.37 times greater than the mainlobe gain of CMA and therefore it is concluded that very less power will be required when we use ICMA algorithm as compared to CMA algorithm. From all the above discussions and observations it is concluded that the new algorithm ICMA can be used with

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64-QAM so as to achieve the high data rate capacity of 64-QAM. Hence it is concluded from all the available data from table number 1, 2 and Figures 4 to 12 that the mainlobe gain of ICMA algorithm with 8 AE and 64-QAM is very high as compared to other algorithms. The mainlobe gain for 8 AE with 64-QAM for ICMA is -2.35589 dB which is highest whereas the main lobe gain for LLMS is lowest for 2 AE with 16-QAM. It is concluded from table 2 and Figures 5 to 12 that average sidelobe suppression for CMA is better than other algorithms, but the main lobe gain of CMA is very less as compared to the main lobe gain of ICMA.

From the same experiment the beamwidth is evaluated for all algorithms by considering antenna elements as 2, 4, 8 and results are tabulated in table 3. It is observed from the Figures 4 to 12 and table 3, that the beamwidth performance improves by increasing the number of antenna elements, for all the BFA. The beamwidth performance of ICMA with 8 AE is 3.672591^0 which best as compared with the beamwidth performance of other BFA and AE combinations. Beamwidth of ILMS algorithm with 2 AE is wider as compared to 4 and 8 AE. Therefore it is concluded that beamwidth for ICMA is sharper than other algorithms.

Table: 1 Mainlobe gain in dB for different AE and BFA

BFA↓	**Modulation↓ AE→**	**2**	**4**	**8**
LMS	QPSK	-18.439	-16.280	-14.3372
	16-QAM	-17.646	-16.229	-12.5378
	64-QAM	-16.957	-17.025	-13.1712
LLMS	QPSK	-20.512	-18.254	-13.3022
	16-QAM	-17.754	-18.930	-14.4547
	64-QAM	-18.850	-14.673	-14.5363
ILMS	QPSK	-39.066	-33.607	-25.1763
	16-QAM	-39.316	-32.967	-25.0432
	64-QAM	-38.574	-33.840	-24.8491
CMA	QPSK	-17.519	-15.601	-10.3872
	16-QAM	-18.117	-13.481	-10.6038
	64-QAM	-17.787	-11.761	-10.307
ICMA	QPSK	-13.254	-6.1998	-3.05031
	16-QAM	-12.374	-6.9743	-4.46747
	64-QAM	-8.4051	-5.5652	-2.35589

Table: 2. Average sidelobe gain in dB for different AE and BFA

BFA↓	**Modulation↓ AE→**	**2**	**4**	**8**
LMS	QPSK	-40.394	-31.609	-30.4541
	16-QAM	-39.449	-30.231	-28.9605
	64-QAM	-39.062	-32.239	-28.9608
LLMS	QPSK	-41.943	-32.284	-25.8574
	16-QAM	-39.197	-32.721	-27.1985

	64-QAM	-40.293	-28.745	-27.7567
ILMS	QPSK	-46.158	-38.208	-29.2111
	16-QAM	-46.461	-37.639	-29.1643
	64-QAM	-45.678	-38.523	-28.9402
CMA	QPSK	-88.939	-62.691	-53.7581
	16-QAM	-89.529	-60.848	-53.2629
	64-QAM	-89.187	-58.868	-52.7339
ICMA	QPSK	-28.540	-17.305	-14.2804
	16-QAM	-27.888	-17.299	-15.0607
	64-QAM	-25.497	-17.095	-16.3316

The ratio of main lobe gain to first sidelobe gain of ICMA with 8 antenna elements, 64 QAM modulation with Rayleigh channel is approximately 25 where as the ratio of main lobe to the first side lobe for SMI-NCMA and NCMA (published in reference number 11) with 8 element and half wavelength spacing using Binary Phase Shift Keying (BPSK) modulation for the radio channel Additive White Gaussian Noise (AWGN) is 43 dB and 30 dB respectively.

Table 3 Beamwidth for 64-QAM with different AE

Antennas	LMS	CMA	ILMS	LLMS	ICMA
2	34.27752	29.38073	41.13302	35.76784	25.70814
4	11.42584	9.793576	13.71101	11.92261	8.569379
8	4.896788	4.197247	5.876146	5.109692	3.672591

4. Conclusion

These results shows that the performance of ICMA is comparable with SMI-CMA and NCMA and as authors have used 64 QAM and Rayleigh channel the instead of BPSK which is used in SMI-CMA, data rate will be very high and the algorithm is performing well in Rayleigh channel rather of AWGN which is used in previous publication as mentioned earlier. Therefore from the simulated results and in comparison with some previously published results it is proved that the newly developed ICMA algorithm establishes better beamwidth and main lobe gain.

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