

Performance Analysis of Smart Antenna Beam forming Techniques

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Abstract: The wireless cellular base station antenna system employs switched beam technology which suffers from its inefficiency to track the user and limited capacity. The Smart antenna tracks the mobile user more efficiently by directing the main beam towards the user and forming nulls in the directions of the interfering signal. Smart antennas include the design of antenna array and adjusting the incoming signal by changing the weights of the amplitude and phase using efficient DSP algorithms [1]. This paper mainly focuses on the adaptive beam forming algorithms such as LMS, SMI, RLS, CGA, CMA and LSCMA applied for uniform linear array antenna. The above adaptive algorithms are simulated using MATLAB. Results obtained are then compared.

Keywords: Smart antenna, Adaptive beamforming, Switched beam, Uniform Linear Arrays, Interference, Least mean square, Recursive mean square, Sample matrix inversion, Constant modulus algorithm, CGA and LSCMA.

I. Introduction

Smart antennas are antenna arrays or group of antenna with smart processing algorithms used to identify direction of arrival signal. Diversity effect involves the transmission and reception of multiple radio frequency waves to reduce the error rate and increase data speed. Smart antenna improves capacity and signal quality. Smart antenna also called adaptive array antennas.

The increasing demand for wireless communication services without a corresponding increase in Radio frequency (RF) spectrum allocation and a better performance motivates the need for new techniques to improve spectrum utilization and system performance. Consequently, future wireless applications are characterized by a better performance and adaptive. Fixed beam forming is employing at the base station of wireless communication system which has a drawback of system performance and lack of adaptive techniques. For increasing these requirements uses spatial processing with adaptive antenna array. Smart antennas have two main functions: direction of arrival estimation (DOA) and Beamforming.

II. Beam Forming

Beam forming is the method used to create the radiation pattern of the antenna arrays by adding constructively the phase of the signals in the direction of desired targets and nulling the pattern of undesired targets. In Beamforming, both the amplitude and phase of each antenna elements are controlled. Combined amplitude and phase control can be used to adjust side lobe levels and steer nulls better than can be achieved by phase control alone [2, 3, 4]. Beam forming in a smart antenna array makes use of a number of individual antennas and associated signal processors to create a desired transmission radiation pattern. The major benefits to using a smart, active antenna system come from a reduction in overall system power, reduction in communication interference, increase in system capacity and increase in power efficiency.

2.1 Switched Beamforming

Switched beam antenna systems from multiple fixed beams with heightened sensitivity in particular directions. These antenna systems detect signal strength, choose from one of several predetermined, fixed beams and switch from one beam to another as the mobile moves throughout the sector. Instead of shaping the directional antenna pattern with the metallic properties and physical design of a single element, switched beam systems combine the outputs of multiple antennas in such a way as to form finely directional beams with more spatial selectivity than can be achieved with conventional, single-element approaches [5]. Figure 1 shows the switch beamforming in this technique same strength beam form in all direction.

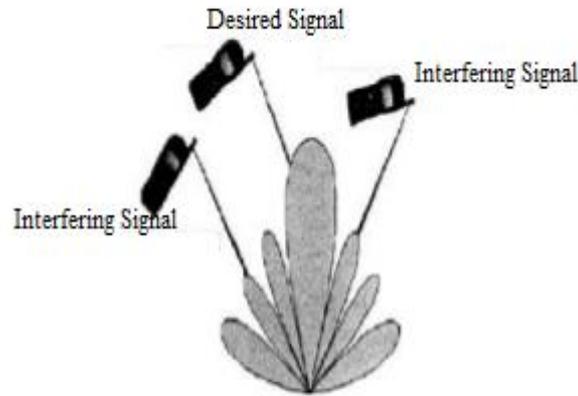


Fig.1: Switched Beam Antenna

2.2 Adaptive Beamforming

Adaptive Beamforming is a technique in which an group or array of antennas is used to achieve maximum reception in a specified direction while forming nulls in the directions of the interfering signal. The weights are computed and adaptively updated in real time based on signal samples. The adaptive process permits narrower beams in look direction and reduced output in other directions, which results in significant improvement in Signal to Interference Noise Ratio [6]. Figure 2 shows the adaptive beamforming in this technique maximum radiation in the direction of user and null in direction of interference signal form.

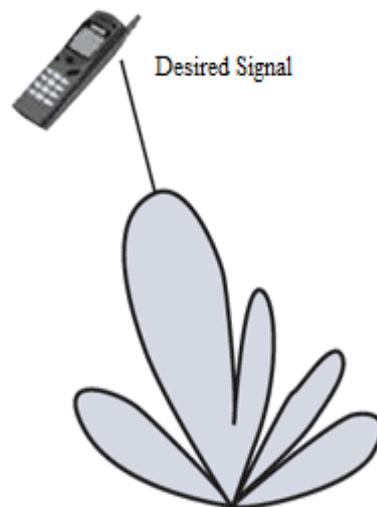


Fig.2: Adaptive Array antennas

2.2.1 Least mean squares (LMS) algorithms

Least mean square algorithm is most commonly used adaptive algorithms. LMS is a gradient descent and it is also known as stochastic gradient descent (SGD) algorithm. The name SGD comes from the fact the gradient estimate typically used in steepest descent algorithm is replaced with an instantaneous and hence noisy estimate of the gradient. Steepest algorithm iteratively finds the weight vector 'w' that minimize a cost of function J(w).

$$w(k + 1) = w(k) - \mu \nabla_w J(W)$$

Here μ is a positive step size

∇_w is gradient operator with respect to the weight factor.

When the cost function is given by

$$J(w) = \varepsilon \{ |w^H(n) - s(n)|^2 \}$$

LMS weight vector is given by

$$w(k + 1) = w(k) - \mu x(n)e^*(n)$$

Error signal $e(n)$ is given by

$$e(n) = y(n) - s(n)$$

The LMS algorithm initiated with some arbitrary value for the weight vector is seen to converge and stay stable for

$$0 < \mu < \frac{1}{\lambda_{\max}}$$

Here λ_{\max} is the largest eigenvalue. If μ is taken to be very small then the algorithm converges very slowly. A large value of μ may lead to a faster convergence but less stable around the minimum value.

LMS have low computational complexity and its main disadvantage is slow convergence rate. LMS algorithm is one of the most popular algorithms in adaptive signal processing, due to its simplicity and robustness [6, 7].

2.2.2 Sample Matrix Inversion Algorithm

SMI algorithm is given by Reed Mallett and Brennan in 1974. SMI is a time average estimate of the array correlation matrix using k -time samples. If the random process is ergodic in the correlation, the time average estimate will equal the actual correlation matrix. SMI also overcome problems of LMS scheme [7, 8].

We can estimate the correlation matrix by calculating the time average such that

$$R_{xx} = \frac{1}{k} \sum_{k=1}^k x(k)x^H(k)$$

x is arrival signal, given by

$$x = [x_1(n), x_2(n), \dots, x_m(n)]^T$$

Output signal

$$y = w^H x$$

Here k is observation interval and correlation vector r

$$r(k) = \frac{1}{k} \sum_{k=1}^k d^*(k)x(k)$$

The k -length block of data is called a block adaptive approach.

The SMI weights given by

$$W_{SMI} = R_{xx}^{-1}(k)r(k)$$

2.2.3 Recursive Least Square Algorithm

SMI overcome the problems of LMS algorithm but SMI have the computational burden and potential singularities that cause problems. For removing the problems of SMI a new algorithm was given known as RLS algorithm. In RLS the correlation matrix and the correlation vector omitting K as

$$R_{xx}(k) = \sum_{i=1}^k x(i)x^H(i)$$

$$r(k) = \sum_{i=1}^k d^*(i)x(i)$$

Here k , is the block length and last time sample k and $R_{xx}(k)$, $r(k)$ is the correlation estimates ending at time sample k [7, 9].

$$R_{xx}^{\wedge}(k) = \sum_{i=1}^k \alpha^{k-i} x(i)x^H(i)$$

$$r_{xx}^{\wedge} = \sum_{i=1}^k \alpha^{k-i} d^*(i)x(i)$$

here α is the forgetting factor or exponential weighting factor. α is a positive constant such that $0 < \alpha <= 1$. When also $\alpha=1$ indicates infinite memory.

2.2.4 Conjugate Gradient Method

CGA method improves the convergence rate. CGA is an effective method for symmetric positive definite systems. The aim of Conjugate Gradient method is to iteratively search for the optimum solution by choosing perpendicular path for new iteration. This method provides faster convergence [9].

The covariance matrix of the input vector X for a finite sample size is defined as the maximum likelihood estimation of matrix R and can be calculate as

$$R(N) = \frac{1}{N} \sum_{k=1}^N X(k) X(k)^H$$

Here

$X(t)$ = received signal

w^H = output of the beam form antenna.

$(.)^H$ = Hermetian operator.

The optimum weight vector that is given by

$$W = R^{-1}V$$

Here

$$V = [e^{j\xi d \sin \theta} \ e^{2j\xi d \sin \theta} \ \dots \ e^{j(k-1)\xi d \sin \theta}]$$

where k = no. of antennas.

The difference in length between the paths is $d \sin \theta$, the signal that arrives at antenna k , leads in phase with $\xi k d \sin \theta$, where $\xi = 2\pi/\lambda$ and λ is the wavelength.

W = weight vector

V = Array propagation vector.

2.2.5 Constant Modulus Algorithm

CMA is a blind algorithm. The idea behind it to reduce systems overhead and maintain gain on the signal while minimizing the total output energy. As per name of algorithm it gives constant amplitude. This method enhances the performance of system. Consider a signal of magnitude α within the received data vector X [9,10]. 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. Dominique Godard used a cost function called a dispersion function of order p which is given by,

$$J(k) = E[(|y(k)|^p - R_p)^q]$$

Where $y = w^H X(k)$ is the array output at the time k and p is the positive integer and q is a positive integer =1.

The gradient of this cost function is zero when R_p is defined by

$$R_p = \frac{E[|S(k)|^{2p}]}{E[|S(k)|^p]}$$

Where $s(k)$ is the zero-memory estimate of $y(k)$. the resulting error signal is given by

$$e(k) = y(k) |y(k)|^{p-2} (R_p |y(k)|^p)$$

LMS weight vector is given by

$$w(k+1) = w(k) - \mu x(k) e^*(k)$$

By selecting values of 1 or 2 for p different version of CMA may be obtained.

$$J(k) = E[(|y(k)| - R_1)^2]$$

The case of $p = 1$, the cost function will be reduced to

where

$$R_1 = \frac{E[|S(k)|^2]}{E[|S(k)|]}$$

If we scale the output estimate $s(k)$ to unity we can write the error signal of equation $e(k)$ as

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

Thus the weight vector becomes

$$w(k+1) = w(k) - \mu \left(1 - \frac{1}{|y(k)|} \right) y^*(k) x(k)$$

Similarly when $p = 2$ the cost function will reduce to

$$J(k) = E[(|y(k)| - R_1)^2]$$

The case of $p = 1$, the cost function will be reduced to

Where

$$R_2 = \frac{E[|S(k)|^4]}{E[|S(k)|^2]}$$

If we scale the output estimate $s(k)$ to unity we can write the error signal of equation $e(k)$ as

$$e(k) = y(k) (1 - |y(k)|^2)$$

Thus the weight vector becomes

$$w(k+1) = w(k) - \mu (1 - |y(k)|^2) y^*(k) x(k)$$

One of the attractive features of the CMA is that carrier synchronization is not required; furthermore it can be applied successfully to non-constant modulus signal if the Kurtosis of the beam former output is less than two. This means that CMA can be applied to for example PSK signals that have non-rectangular pulse shape. This is important because it implies that the CMA is also robust to symbol timing error when applied to pulse-shaped PSK signals. Pulse shaping typically is used to limit the occupied bandwidth of the transmitted signal.

2.2.6 Least Square-Constant Modulus Algorithm

LSCMA is improved version of CMA it provide fast convergence. It is a block update iterative algorithm that is guaranteed to be stable and easily implemented [10].

Output is given as

$$y_n(k) = W^H X(k)$$

Weight vector W_n

The initial weight vector W_0 can be taken as

$$W_0 = [1 \ 0 \ 0 \ \dots \ 0]^T$$

If no a priori information is available, the nth signal estimate is then hard limited to yield

$$d_n(k) = \frac{y_n(k)}{|y_n(k)|}$$

New weight vector is formed according to

$$W_{(n+1)} = R_{xx}^{-1} r_{xd}$$

Where,

$$R_{xx} = (X(k)X^H(k))_N$$

$$r_{xd} = (X(k)d_n^*(k))_N$$

Equations denote a time average over $0 \leq k \leq N-1$. Weight vector $W_{(n+1)}$ minimizes the mean square error.

III. Simulation Results And Discussion

The simulation of different Beamforming algorithm has been done with MATLAB™. The incident signal is obtained from linear array antenna containing of 16 elements. In terms of wavelength the element are separated from each other by distance of about 0.5. We have considered the value of signal to noise ratio is 20dB and we have taken 100 snapshots from 16 elements antenna array.

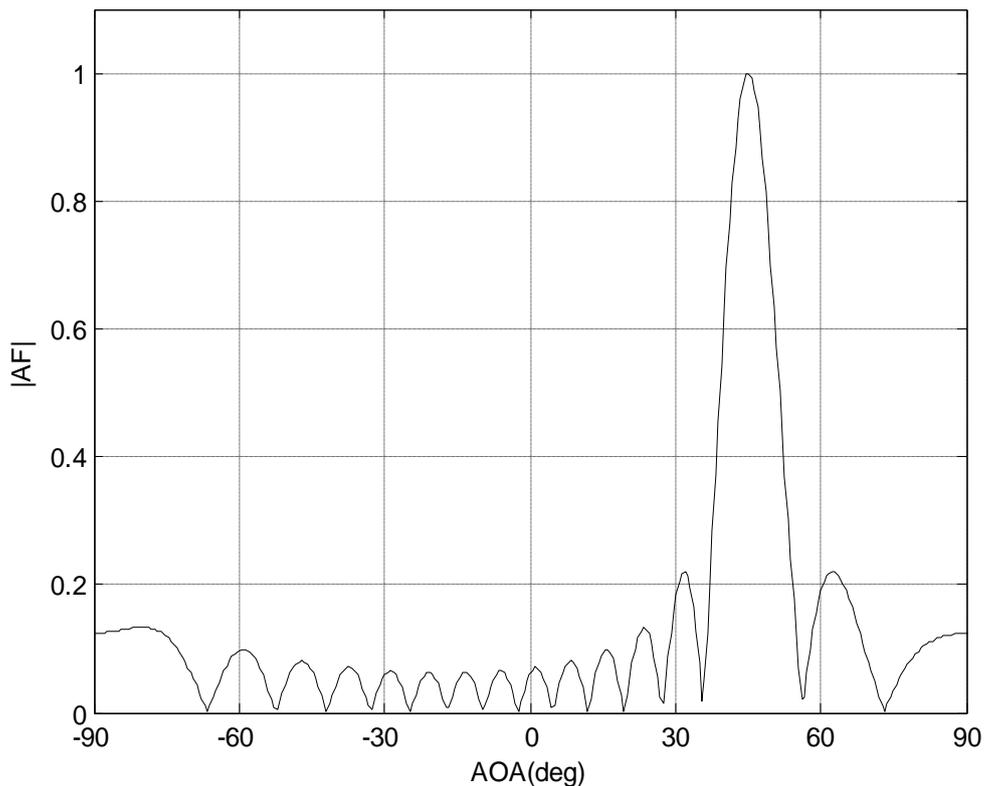


Fig.3: Array factor plot for LMS algorithm when the desired user with AOA 45, the spacing between the elements is 0.5λ , SNR is 20dB and no. of elements is 16.

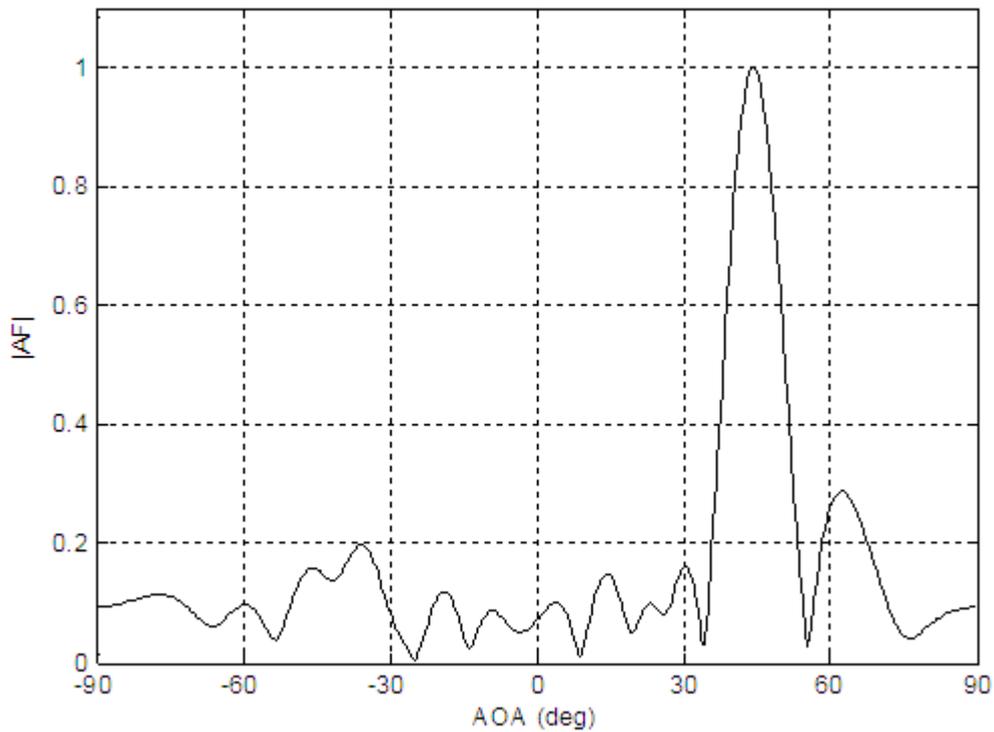


Fig.4: Array factor plot for SMI algorithm when the desired user with AOA 45, the spacing between the elements is 0.5λ , SNR is 20dB and no. of elements is16.

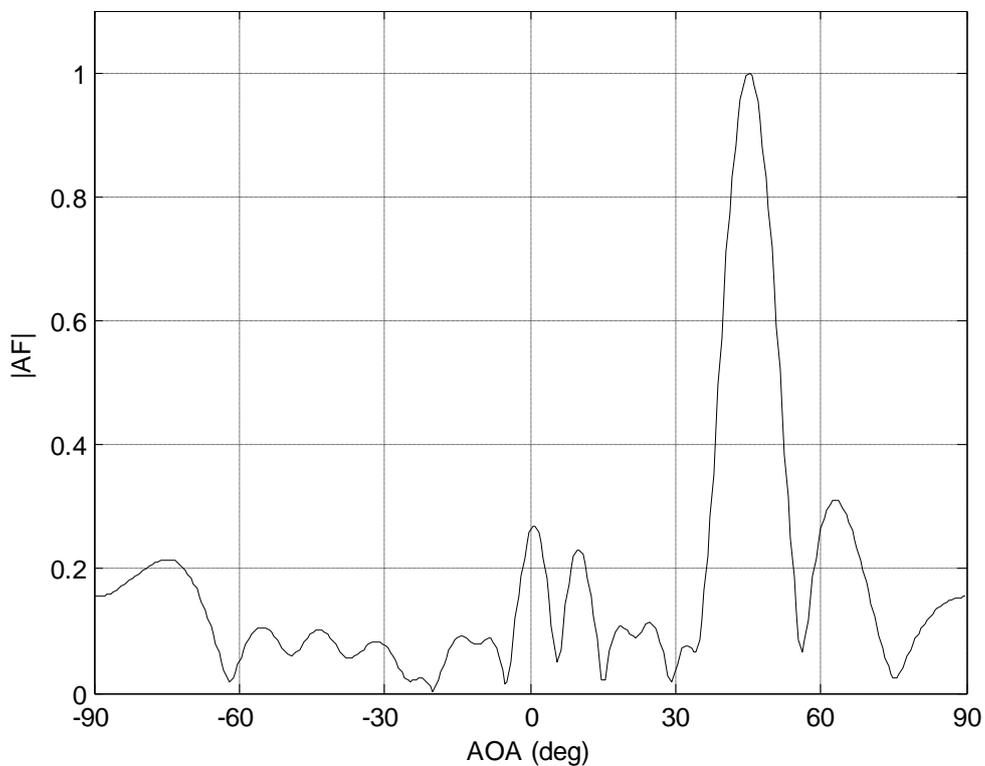


Fig.5: Array factor plot for RLS algorithm when the desired user with AOA 45, the spacing between the elements is 0.5λ , SNR is 20dB and no. of elements is16.

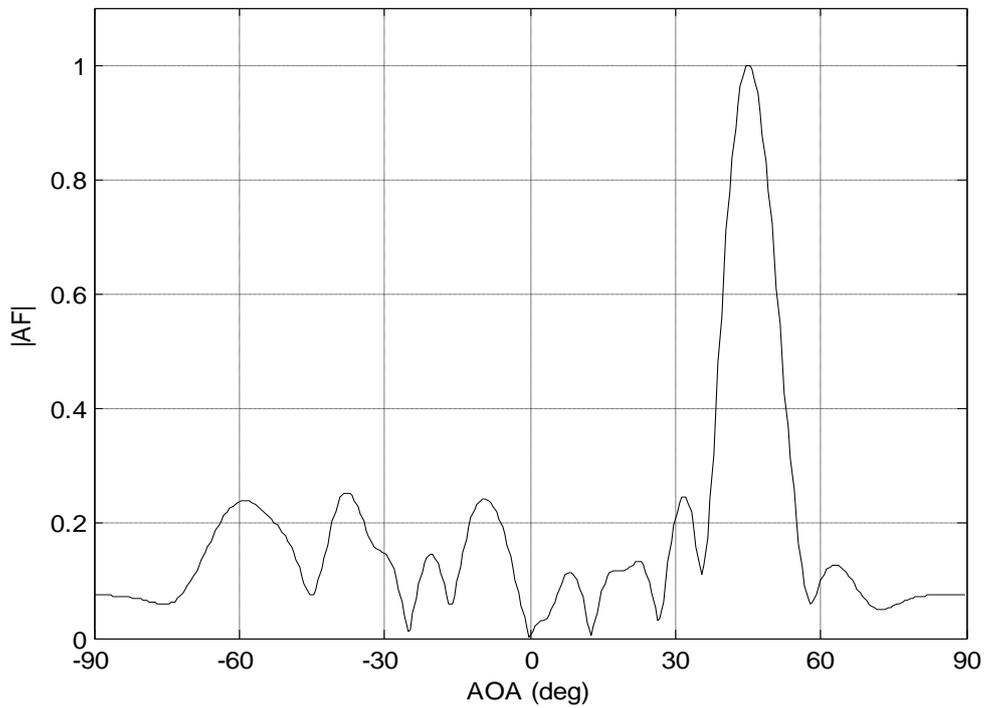


Fig.6: Array factor plot for CG algorithm when the desired user with AOA 45, the spacing between the elements is 0.5λ , SNR is 20dB and no. of elements is 16.

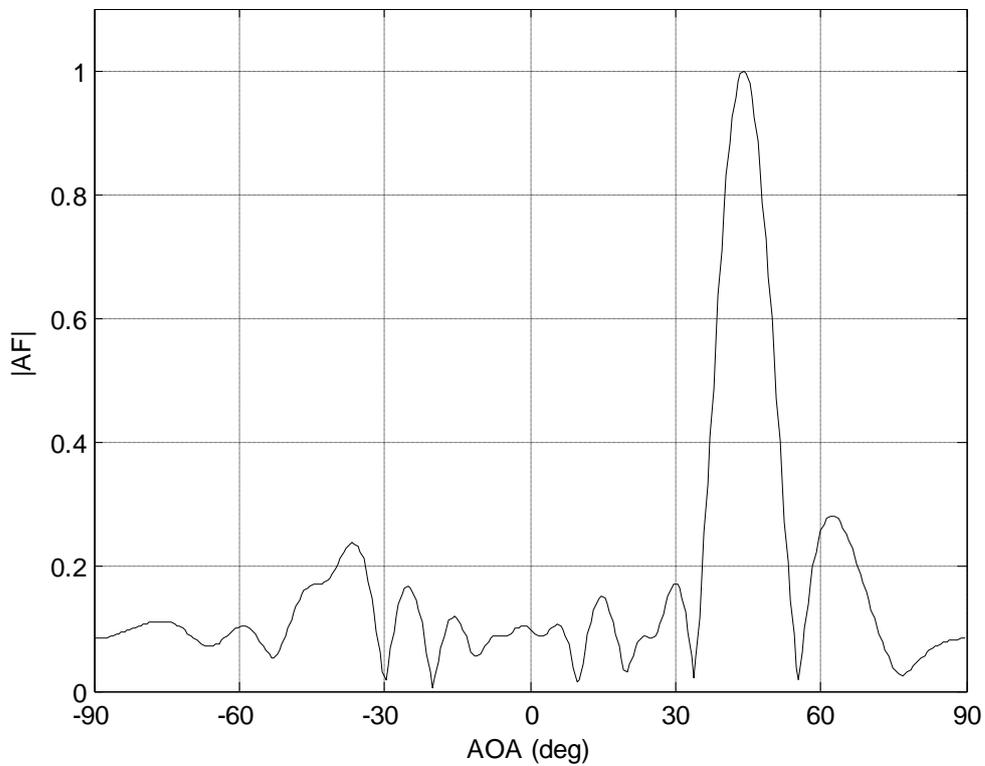


Fig.7: Array factor plot for CMA algorithm when the desired user with AOA 45, the spacing between the elements is 0.5λ , SNR is 20dB and no. of elements is 16.

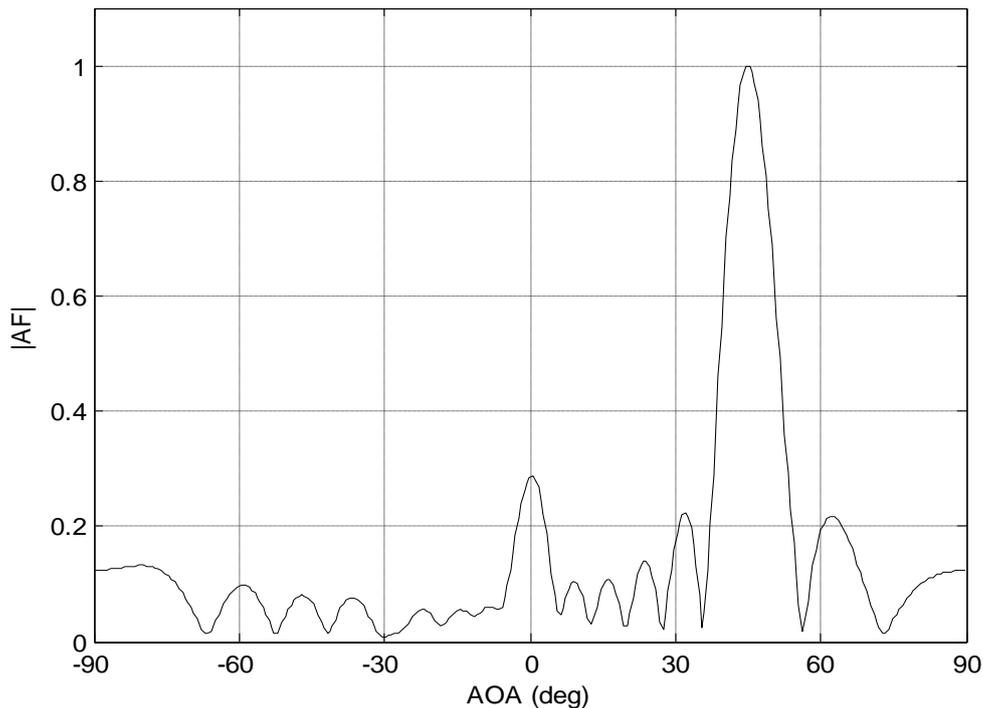


Fig.8: Array factor plot for LS-CM algorithm when the desired user with AOA 45, the spacing between the elements is 0.5λ , SNR is 20dB and no. of elements is 16.

For reliable comparison between the LMS, SMI, RLS, CG, CM, LS-CM algorithms 100 trials were run for each case and their result were averaged before comparison. The LMS, RLS, SMI, CM and LSCM algorithms are simulated using MATLAB.

LMS algorithm has good response towards desired direction and has better capability to place null towards interferer. Recursive Least Square (RLS) converges with slow speeds when the environment yields a correlation matrix R possessing a large Eigen spread. RLS has fastest convergence at the cost of high computational burden when compared to LMS. RLS is the best choice and has also its application where quick tracking of the signal is required. The RLS algorithm does not require any matrix inversion computations as the inverse correlation matrix is computed directly. It requires reference signal and correlation matrix information. It is almost ten times faster compared to LMS. The SMI algorithm has a faster convergence rate since it employs direct inversion of the covariance matrix R . It provides good performance in a discontinuous traffic. However, it requires that the number of interferers and their positions remain constant during the duration of the block acquisition. Since SMI employs direct matrix inversion the convergence of this algorithm is much faster compared to the LMS algorithm. CGM algorithm by replacing the gradient step size with a gain matrix, noticed that increasing the number of elements of the antenna array ensures better performance. The CMA algorithm is important because it does not require carrier synchronization. One severe disadvantage of the Godard CMA algorithm is the slow convergence time. The slow convergence time limits the usefulness of the algorithm in dynamic environment where the signal must be captured quickly. A fast converging CMA is the Least Square CMA (LS-CMA) which is a block update iterative algorithm that is guaranteed to be stable and easily implemented. Static LSCMA can converge 100 times faster than the conventional CMA. However, the computational load makes the LSCMA impractical for a real-time application.

The simulation result shows performance of LSCM algorithm improves with increase of elements in the array and we get the better performance. We have found improvement in result after changing other parameters like SNR, Element Number. From results LSCM is found to be more accurate, stable and give faster convergence than the other methods.

IV. Conclusion

In this paper, we have presented the theory of smart antenna and studied different beamforming technology like switched beamforming and adaptive beamforming. We studied algorithms of adaptive beamforming technology. LSCMA method is found to be better than other method. It provides better efficiency on higher no of sources; it gives more accuracy, stability and better coverage.

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