International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Performance Analysis of LMS, RLS, CMA Algorithms for Beamforming in Smart Antenna Systems

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***Abstract:** Smart antenna systems strengthen wireless mobile communication, with enhancement over conventional systems, by projecting the signal power in narrow beams towards the desired users and suppressing the signal power towards unwanted users or interferers. Different DOA estimation and beamforming algorithms play crucial role in smart antenna system. In beamforming algorithms, using different techniques complex weights are calculated and applied to the signals from the smart antenna array elements to enhance signals of interest and suppress signals not of interest. In this article Least Mean Square(LMS) technique, Recursive Least Square(RLS)technique and Constant Modulus (CMA)technique adaptive beamforming algorithms are implemented, analyzed and compared using MATLAB simulations to help users to choose amongst them as per the their need, ease and suitability.*

***Keywords :** smart antenna, DOA, beamforming, LMS, RLS, CMA.*

I. INTRODUCTION

Smart antenna systems have become need of the hour in communication systems as they allow for maximum utilization of the frequency spectrum by giving service to maximum number of users. Smart antenna systems use an array of antenna elements and a smart signal processing hardware and software implementing suitable direction of arrival (DOA) and beamforming algorithms. These algorithms give smart antennas the ability to give service to desired users and reject the undesired or unwanted users or interferers. These algorithms also help to mitigate multipath and noise fading effects. It results in overall enhancement of the communication channel by improving the quality of signal and rendering service to optimum number of users.

This is achieved by determining the direction of arriving signals accurately, and from these signals, forming beams in the direction of desired users and applying nulls or suppressing the signal in the direction of remaining unwanted users. Thus by beamforming, the smart antenna system transmits the signal only in the direction of desired user.

Manuscript published on November 30, 2019.
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Simultaneously it avoids the interferers or unwanted users. This saves the power utilized in the transmission and also improves signal to noise ratio by eliminating interferers and noise.

Several DOA estimation and beamforming algorithms already exist and are working satisfactorily. Here consideration is given to beamforming algorithms, presenting a brief overview and their classification and mainly focusing on LMS, RLS and CMA algorithms along with their implementation, analysis and comparison.[1][2][3]

II. CLASSIFICATION OF BEAMFORMING ALGORITHMS

Basically there are two types of beamforming algorithms called Fixed beam and Adaptive beamforming algorithms which are again classified into non-blind and blind beamforming algorithms. In today's world adaptive beamforming is mostly preferred.

As shown in figure 1, adaptive beamforming algorithms can be classified into two categories: 1.) Non-Blind Adaptive Algorithms and 2.) Blind Adaptive Algorithms.

Non-blind adaptive algorithms need statistical knowledge of the transmitted signal in order to converge to a weight solution. This is typically accomplished through the use of a pilot training sequence sent over the channel to the receiver to help identify the desired user. LMS, RLS, SMI and CGM are some of the examples of the non-blind algorithms.

On the other hand, blind adaptive algorithms do not need any training, hence the term " blind" . They attempt to restore some type of characteristic of the transmitted signal in order to separate it from other users in the surrounding environment. CMA and DDA are some of the examples of non-blind algorithms. [1][8]

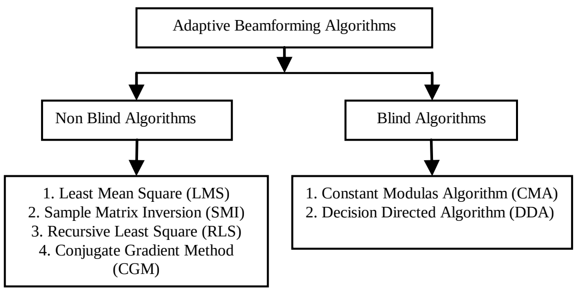

Figure 1 Classification of adaptive beamforming algorithms

III. ADAPTIVE BEAMFORMING ALGORITHMS

If the incident angles of the desired signal arriving at antenna array elements keep varying with respect to time it is required to calculate the optimum array weights instantaneously, on-the-fly and keep recalculating the optimum array weights with respect to the variations in the angles of arrival in real time. The receiver algorithm must continuously keep updating weights according to the variations in the electromagnetic environment. The adaptive beamforming thus progresses by continuously calculating the updated weights by adapting to the variations in angles of arrival.[4] Many beamforming methods fulfilling certain optimization criterion are then devised.

As shown in figure 2, the desired signal s(k) at angle θ_0, interfering unwanted signals $i_1(k)$, $i_2(k)$,…$i_N(k)$ are incident on a uniform linear array of M antenna elements. It results in the input signals $x_1(k)$, $x_2(k)$,…, $x_M(k)$ respectively on each of the M antenna elements. Complex weights are calculated for each antenna element signal and are applied to these signals so as to strengthen the desired signal and null the interferers. Then all these signals are combined to deliver the combined received signal, y(k). The difference between this received signal and the desired signal (also called reference or training signal) is called the error, ε(k), which is used as a controlling parameter by control system or adaptive algorithm to calculate the complex adaptive weights. Here reference signal, d(k) is required which has high correlation with the desired signal. The complex weights are then multiplied with the corresponding array element signals respectively to deliver a combine output and the control system and the adaptive algorithm try to reduce the error so as to make the output, combined received, signal equal to the desired signal. Non-blind adaptive algorithms use the reference or training signal but blind algorithms attempt to restore some type of characteristic of the transmitted signal in order to separate it from other users in the surrounding environment.[3]

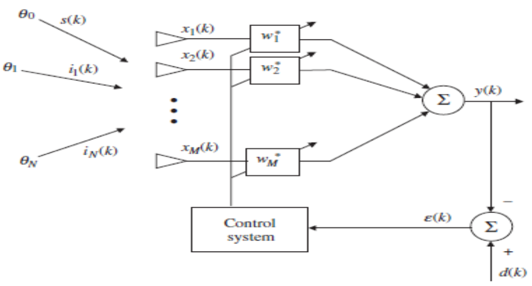

Figure 2 Adaptive beamforming

Least Mean Squares (LMS)

The least mean square (LMS) is a gradient based technique. Here, we can find the cost function by finding MSE. The error as shown in figure 2 is ,

$$\varepsilon(k) = d(k) - \bar{w}^H(k)\bar{x}(k) \qquad (1)$$

Hence,

$$|\varepsilon(k)|^2 = |d(k) - \bar{w}^H(k)\bar{x}(k)|^2 \qquad (2)$$

Momentarily suppressing the time dependence the cost becomes,

$$J(\bar{w}) = D - 2\bar{w}^H\bar{r} + \bar{w}^H\bar{R}_{xx}\bar{w} \qquad (3)$$

Where,

$$D = E[|d|^2]$$

By employing the gradient method to locate minimum we have,

$$\nabla_{\bar{w}}\big(J(\bar{w})\big) = 2\bar{R}_{xx}\bar{w} - 2\bar{r} \qquad (4)$$

When gradient is zero, the minimum occurs. Hence Wiener solution determines the optimum weight and are given as,

$$\bar{w}_{opt} = \bar{R}_{xx}^{-1}\bar{r} \qquad (5)$$

In equation (5) we require the knowledge of all signal statistics for calculation of the correlation matrix. Actually we don't know the signal statistics and should calculate the array correlation matrix ($\bar{R}_{xx}$) along with the signal correlation vector ($\bar{r}$). This is done for a range of snapshots representing each instant in time. There instantaneous values are given by,

$$\hat{R}_{xx}(k) \approx \bar{x}(k)\bar{x}^H(k) \qquad (6)$$

And

$$\hat{r}(k) \approx d^*(k)\bar{x}(k) \qquad (7)$$

By applying the steepest descent iterative approximation we get,

$$\bar{w}(k+1) = \bar{w}(k) - \frac{1}{2}\mu\nabla_{\bar{w}}\big(J(\bar{w}(k))\big) \qquad (8)$$

Where, μ is a step size and $\nabla_{\bar{w}}$ is the gradient of the cost function. Hence, from equations (5), (8) we have LMS solution as,

$$\bar{w}(k+1) = \bar{w}_k - \mu[\hat{R}_{xx}\bar{w} - \hat{r}] \quad = \bar{w}_k + \mu e^*(k)\bar{x}(k) \qquad (9)$$

where,

$\varepsilon(k) = d(k) - \bar{w}^H(k)\bar{x}(k) =$ error signal

As presented in equation (9) the convergence of the LMS algorithm is directly proportional to the step-size μ. For very small step size the convergence is slow. For the convergence slower than the changes in the angles of incidence or arrival, there is a possibility that the adaptive array will not acquire the desired signal fast enough to track the changing source-signal. For too large step size, there will be an overshoot in optimum weights, making the convergence too fast. In this case the weights tend to oscillate about optimum weights but do not attain the desired solution. Thus it is important to choose correct step size that will allow proper convergence. This can be achieved by meeting following condition.

$$0 \le \mu \le \frac{1}{2\lambda_{max}} \qquad (10)$$

Here, λ_{max} is the largest eigen value associated with $\hat{R}_{xx}$.

All the eigen values are positive as the correlation matrix positive and definite. With only one signal of interest and all the interfering signals to be noise above condition approximates to,

$$0 \le \mu \le \frac{1}{2trace[\hat{R}_{xx}]} \qquad (11)$$

The LMS algorithm requires many iterations before achieving satisfactory convergence. In the environment where the signal characteristics change rapidly it may not track desired signal satisfactorily. Eigen value spread of the array correlation matrix decides the rate of convergence of the weights.

Recursive Least Squares (RLS)

In recursive least square (RLS) method we can eliminate the computational load by recursively calculating the required correlation vector and required correlation matrix.

We know that,

$$\hat{R}_{xx} = \sum_{i=1}^{k}\bar{x}(i)\bar{x}^H(i) \qquad (12)$$

$$\hat{r} = \sum_{i=1}^{k} d^*(i)\bar{x}(i) \qquad (13)$$

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DOI:10.35940/ijrte.D4424.118419
Journal Website: www.ijrte.org

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Where k is a block length with last time sample k and $\hat{R}_{xx}$ and $\hat{r}$ are correlation estimates ending at time sample k. For changing source positions, we can forget earlier time samples as they are of no use for current source position. Above two equations can be modified to forget the early time samples by a weighted estimate. Thus,

$$\hat{R}_{xx}(k) = \sum_{i=1}^{k} \alpha^{k-i} \bar{x}(i)\bar{x}^H(i) \quad (14)$$

$$\hat{r}(k) = \sum_{i=1}^{k} \alpha^{k-i} d^*(i)\bar{x}(i) \quad (15)$$

Where α is the forgetting factor also called exponential weighting factor and 0 ≤ α ≤ 1. For α = 1 we go for the ordinary least squares algorithm. This value also points to infinite memory. Now we split the above two equations into two terms, as,

$$\hat{R}_{xx}(k) = \alpha \sum_{i=1}^{k-1} \alpha^{k-1-i} \bar{x}(i)\bar{x}^H(i) + \bar{x}(k)\bar{x}^H(k) = \alpha \hat{R}_{xx}(k-1) + \bar{x}(k)\bar{x}^H(k) \quad (16)$$

$$\hat{r}(k) = \alpha \sum_{i=1}^{k-1} \alpha^{k-1-i} d^*(i)\bar{x}(i) + d^*(k)\bar{x}(k) = \alpha \hat{r}(k-1) + d^*(k)\bar{x}(k) \quad (17)$$

In this way using previous values array correlation and the vector correlation estimate can be found for future values.

From Sherman Morrison-Woodbury theorem we know that,

$$(\bar{A} + \bar{z}\bar{z}^H)^{-1} = \bar{A}^{-1} - \frac{\bar{A}^{-1}\bar{z}\bar{z}^H\bar{A}^{-1}}{1+\bar{z}^H\bar{A}^{-1}\bar{z}} \quad (18)$$

From equations (18) an (16) we get the recursion formula,

$$\hat{R}_{xx}^{-1}(k) = \alpha^{-1}\hat{R}_{xx}^{-1}(k-1) - \frac{\alpha^{-2}\hat{R}_{xx}^{-1}(k-1)\bar{x}(k)\bar{x}^H(k)\hat{R}_{xx}^{-1}(k-1)}{1+\alpha^{-1}\bar{x}^H(k)\hat{R}_{xx}^{-1}(k-1)\bar{x}(k)} \quad (19)$$

If we define a gain vector $\bar{g}(k)$ as,

$$\bar{g}(k) = \frac{\alpha^{-1}\hat{R}_{xx}^{-1}(k-1)\bar{x}(k)}{1+\alpha^{-1}\bar{x}^H(k)\hat{R}_{xx}^{-1}(k-1)\bar{x}(k)} \quad (20)$$

Therefore,

$$\hat{R}_{xx}^{-1}(k) = \alpha^{-1}\hat{R}_{xx}^{-1}(k-1) - \alpha^{-1}\bar{g}(k)\bar{x}^H(k)\hat{R}_{xx}^{-1}(k-1) \quad (21)$$

Above equation is called the Riccati equation for RLS method. By multiplying by denominator the equation(20) simplifies to,

$$\bar{g}(k) = [\alpha^{-1}\hat{R}_{xx}^{-1}(k-1) - \alpha^{-1}\bar{g}(k)\bar{x}^H(k)\hat{R}_{xx}^{-1}(k-1)]\bar{x}(k) \quad (22)$$

Thus,

$$\bar{g}(k) = \hat{R}_{xx}^{-1}(k)\bar{x}(k) \quad (23)$$

To derive a recursion relation for updating weight vectors optimum Wiener solution is repeated for k iterations. Then using equation (17) we get,

$$\bar{w}(k) = \hat{R}_{xx}^{-1}(k)\hat{r}(k) = \alpha\hat{R}_{xx}^{-1}(k)\hat{r}(k-1) + \hat{R}_{xx}^{-1}(k)\bar{x}(k)d^*(k) \quad (24)$$

From equations (21) and (24) we get,

$$\bar{w}(k) = \hat{R}_{xx}^{-1}(k-1)\hat{r}(k-1) - \bar{g}(k)\bar{x}^H(k)\hat{R}_{xx}^{-1}(k-1)\hat{r}(k-1) + \hat{R}_{xx}^{-1}(k)\bar{x}(k)d^*(k) = \bar{w}(k-1) - \bar{g}(k)\bar{x}^H(k)\bar{w}(k-1) + \hat{R}_{xx}^{-1}(k)\bar{x}(k)d^*(k) \quad (25)$$

By substituting equation (23) in above equation we get,

$$\bar{w}(k) = \bar{w}(k-1) - \bar{g}(k)\bar{x}^H(k)\bar{w}(k-1) + \bar{g}(k)d^*(k) = \bar{w}(k-1) + \bar{g}(k)[d^*(k) - \bar{x}^H(k)\bar{w}(k-1)] \quad (26)$$

In RLS it is not required to invert large correlation matrix as in SMI and it converges much faster than the LMS algorithm. The recursive equations of RLS easily update the inverse of correlation matrix.

Constant Modulus Algorithm(CMA)

In a communication system many a times the signal are frequency or phase modulated keeping the amplitude of the signal ideally constant. This signal has a constant magnitude or modulus. But in fading channels due to multipath, the received signal is a composite of all the multipath signals. Thus the signal magnitude faces amplitude variation due to channel. Frequency selective networks destroy the constant modulus parameter of the signal. With the information that the arriving signals of interest are having constant modulus, an algorithm can be devised to equalize or restore the amplitude of the signal.

Dominique Godard used the constant modulus (CM) property to form blind equalization algorithms for phase modulated waveforms. As a cost function he used a dispersion function of order p to get the optimum weights after minimization. This cost function is,

$$J(k) = E\left[\left(|y(k)|^p - R_p\right)^q\right] \quad (27)$$

where,
p is a positive integer,
q is a positive integer = 1

According to Godard for following value of R_p the gradient of the cost function is zero.

$$R_p = \frac{E[|s(k)|^{2p}]}{E[|s(k)|^p]} \quad (28)$$

where s(k) is zero memory value of y(k). The resultant error signal is,

$$\varepsilon(k) = y(k)|y(k)|^{p-2}(R_p - |y(k)|^p) \quad (29)$$

The error signal in LMS can be replaced by this error signal to give,

$$\bar{w}(k+1) = \bar{w}(k) + \mu\varepsilon^*(k)\bar{x}(k) \quad (30)$$

For p = 1 the cost function reduces to,

$$J(k) = E[(|y(k)| - R_1)^2] \quad (31)$$

where,

$$R_1 = \frac{E[|s(k)|^2]}{E[|s(k)|]} \quad (32)$$

By scaling the output estimate s(k) to unity, the error signal in equation (29) becomes,

$$\varepsilon(k) = \left(y(k) - \frac{y(k)}{|y(k)|}\right) \quad (33)$$

For p = 1 the weight vector will be,

$$\bar{w}(k+1) = \bar{w}(k) + \mu\left(1 - \frac{1}{|y(k)|}\right)y^*(k)\bar{x}(k) \quad (34)$$

For p = 2 the cost function reduces to,

$$J(k) = E[(|y(k)|^2 - R_2)^2] \quad (35)$$

where,

$$R_2 = \frac{E[|s(k)|^4]}{E[|s(k)|^2]} \quad (36)$$

By scaling the output estimate s(k) to unity, the error signal in equation (29) becomes,

$$\varepsilon(k) = y(k)(1 - |y(k)|^2) \quad (37)$$

For p = 2 the weight vector will be,

$$\bar{w}(k+1) = \bar{w}(k) + \mu(1 - |y(k)|^2)y^*(k)\bar{x}(k) \quad (38)$$

The cases at p = 1 or 2 are called constant modulus algorithms (CMA). For p=1 case CMA converges faster than for p=2.

It is worth knowing that CMA suppresses multipath but does not eliminate it. Godard CMA algorithm converges slowly. Slow convergence puts limits to performance where the signals change rapidly and it is required to capture these signals quickly. It incorporates the method of steepest descent by taking the gradient of the cost function.[1][2]

IV. SIMULATION RESULTS, PERFORMANCE ANALYSIS AND COMPARISON

LMS, RLS and CMA algorithms are implemented in MATLAB and their simulation results are used for the performance analysis and comparison of the individual algorithm by varying different parameters like number of array elements, spacing between array elements and step-size (for LMS and CMA) one after another and keeping other parameters the same. Effects of variation of these parameters along with simulation results and analysis are given below.

LMS:

Least Mean Square (LMS) algorithm uses gradient based approach of steepest descent. From the available data estimates of the gradient vector are determined and used by LMS algorithm. By iterative procedures successive corrections are applied to the weight vector in the direction pointing towards negative of the gradient vector. Ultimately it results in the minimum square error. LMS algorithm is comparatively simple to implement and does not require calculations for correlation function or the matrix inversions.

Following parameters for LMS algorithm are considered for simulation and realization for two desired signals and one interferer.

Angle of arrival for first desired signal: 15^0
Angle of arrival for second desired signal: 60^0
Angle of arrival for interfering signal: - 60^0
N=8 = number of antenna array elements
d = λ/2= interelement spacing

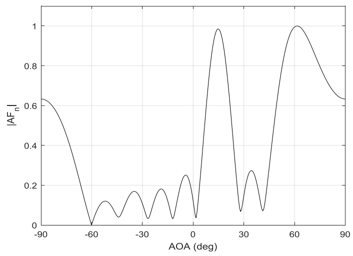

Figure 3 LMS algorithm Array factor plot for two users at 15^0,60^0 and one interferer at -60^0 with d=λ/2, N=8

Figure 3 shows the array factor plot for LMS algorithm for the desired angles at 15^0,60^0 and one interferer at -60^0 with d=λ/2, N=8. The step size μ approximates to 0.02. The plot shows that, the LMS algorithm has placed deep null at -60^0 and maximum at 15^0 and 60^0.

- **Effect Of Variation In Inter-element Distance, d In Antenna Array**

d = λ/4

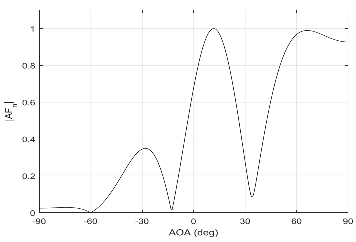

Figure 4 LMS algorithm Array factor plot for two users and one interferer with d=λ/4, N=8

Figure 4 shows the array factor plot for LMS algorithm for variation in inter-element spacing, d between the array elements given by d= λ /4 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation results show that as the inter-element spacing, d decreases, the main lobes become broader reducing the resolution of the LMS algorithm. Although the null at -60^0 seems to be exact.

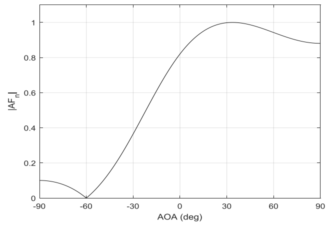

Figure 5 LMS algorithm Array factor plot for two users and one interferer with d=λ/8, N=8

Figure 5 shows the array factor plot for LMS algorithm for variation in inter-element spacing, d between the array elements given by d= λ /8 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation results show that as the inter-element spacing, d decreases further the main lobes merge and do not form separate beams for desired angles of 15^0 and 60^0, instead there appears a single main lobe covering the desired spectrum reducing the resolution of the LMS algorithm. Here also the null at -60^0 seems to be exact.

Considering this to be a worst case where LMS algorithm seems to lose its resolving capability between the two desired signals, if the number of array elements are increased to 20, it gives the remedial solution to this problem. Figure 6 reveals this fact where the desired angles seem to be well resolved and null is also well placed.

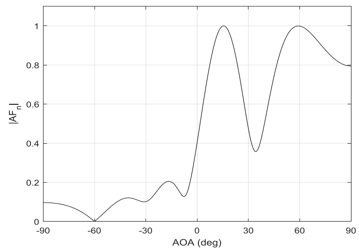

Figure 6 LMS algorithm Array factor plot for two users and one interferer with d=λ/8, N=20

- **Effect Of Variation In Number Of Array Elements, N**

N = 6

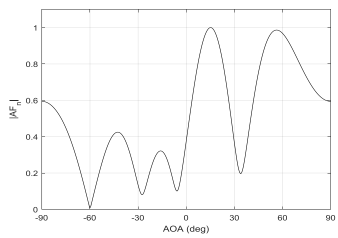

Figure 7 LMS algorithm Array factor plot for two users and one interferer with d=λ/2, N=6

Figure 7 shows the array factor plot for LMS algorithm for variation in number of array elements given by N=6 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation result shows that as the number of array elements decreases, the main lobes and the side lobes become broader reducing the resolution of the LMS algorithm. Although the null at -60^0 seems to be exact.

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DOI:10.35940/ijrte.D4424.118419
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N = 20

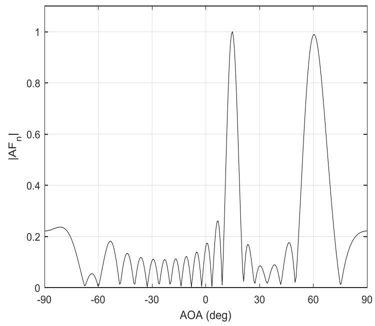

Figure 8 LMS algorithm Array factor plot for two users and one interferer with d=λ/2, N=20

Figure 8 shows the array factor plot for LMS algorithm for variation in number of array elements given by N=20 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation result shows that as the number of array elements increases, the main lobes and the side lobes become narrower increasing the resolution and accuracy of the LMS algorithm. The null at -60^0 also seems to be exact and with smaller side lobes.

RLS:

The problem of slow convergence of LMS algorithm for large Eigen value spread is solved in RLS algorithm by using inverse of gain matrix in place of step-size μ in LMS algorithm.

Following parameters for RLS algorithm are considered for simulation and realization for two desired signals and one interferer.

Angle of arrival for first desired signal: 15^0
Angle of arrival for second desired signal: 60^0
Angle of arrival for interfering signal: $- 60^0$
N=8 = number of antenna array elements
d = λ/2= interelement spacing
σ^2 =0.01= noise variance
α = 0.9 = forgetting factor
k = 50 = samples

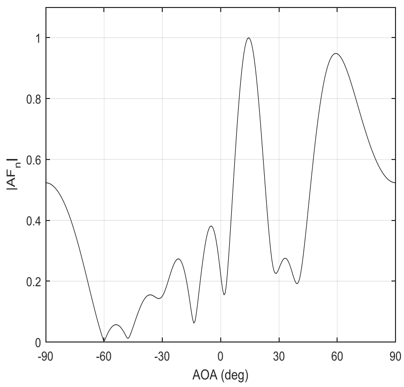

Figure 9 RLS algorithm Array factor plot for two users at 15^0,60^0 and one interferer at -60^0 with d=λ/2, N=8

Figure 9 shows the array factor plot for RLS algorithm for the desired angles at 15^0,60^0 and one interferer at -60^0 with d=λ/2, N=8. The plot shows that, the RLS algorithm has placed deep null at -60^0 and maximum at 15^0 and 60^0.

- **Effect Of Variation In Inter-element Distance, d In Antenna Array**

d = λ/4

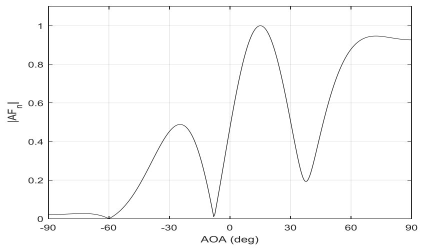

Figure 10 RLS algorithm Array factor plot for two users and one interferer with d=λ/4, N=8

Figure 10 shows the array factor plot for RLS algorithm for variation in inter-element spacing, d between the array elements given by d= λ /4 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation results show that as the inter-element spacing, d decreases, the main lobes become broader reducing the resolution of the RLS algorithm. Although the null at -60^0 seems to be exact.

d = λ/8

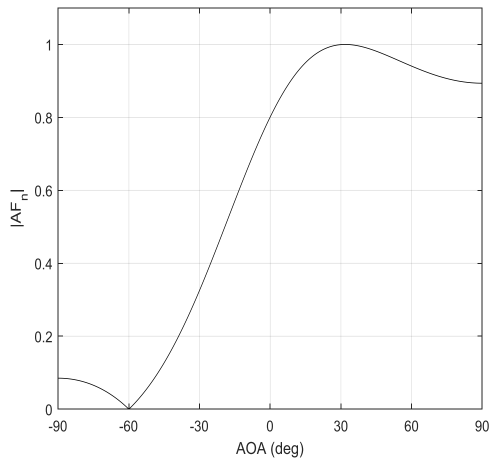

Figure 11 RLS algorithm Array factor plot for two users and one interferer with d=λ/8, N=8

Figure 11 shows the array factor plot for RLS algorithm for variation in inter-element spacing, d between the array elements given by d= λ /8 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation results show that as the inter-element spacing, d decreases further the main lobes merge and do not form separate beams for desired angles of 15^0 and 60^0, instead there appears a single main lobe covering the desired spectrum reducing the resolution of the RLS algorithm. Here also the null at -60^0 seems to be exact.

Considering this to be a worst case where RLS algorithm seems to loose its resolving capability between the two desired signals, if the number of array elements are increased to 20, it gives the remedial solution to this problem. Figure 12 reveals this fact where the desired angles seem to be well resolved and null is also well placed.

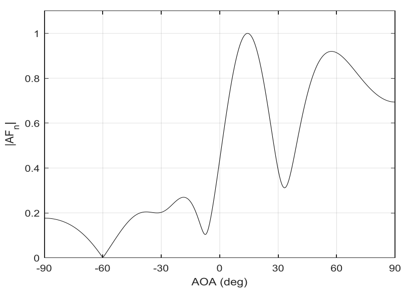

Figure 12 RLS algorithm Array factor plot for two users and one interferer with d=λ/8, N=20

- **Effect Of Variation In Number Of Array Elements, N**

N = 6

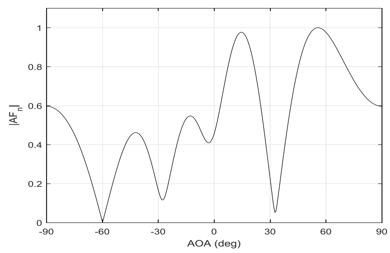

Figure 13 RLS algorithm Array factor plot for two users and one interferer with d=λ/2, N=6

Figure 13 shows the array factor plot for RLS algorithm for variation in number of array elements given by N=6 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation result shows that as the number of array elements decreases, the main lobes and the side lobes become broader reducing the resolution of the RLS algorithm. Although the null at -60^0 seems to be exact.

N = 20

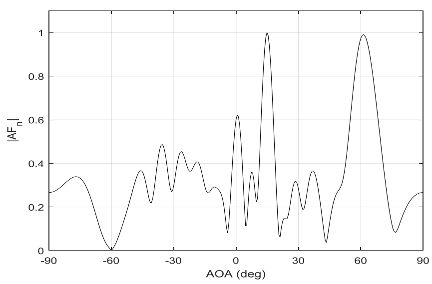

Figure 14 RLS algorithm Array factor plot for two users and one interferer with d=λ/2, N=20

Figure 14 shows the array factor plot for RLS algorithm for variation in number of array elements given by N=20 for the desired input angles of 15^0 and 60^0 and for interferer at -60^0.

The simulation result shows that as the number of array elements increases, the main lobes and the side lobes become narrower increasing the resolution and accuracy of the RLS algorithm. The null at -60^0 also seems to be exact and with smaller side lobes.

CMA:

The frequency or phase modulated signal should ideally have constant magnitude or modulus. However in fading environments due to multipath signals amplitude variation in signal amplitude is observed. By the knowledge that the received signal has constant modulus, to restore the amplitude of the original signal CMA algorithm is used.

Following parameters algorithm are considered for simulation and realization for two desired signals and one interferer.

Angle of arrival for first desired signal: 45^0

Angle of arrival for second desired signal: 60^0

Angle of arrival for first multipath signal that is 30 percent of direct path signal: 0^0

Angle of arrival for first multipath signal that is 10 percent of direct path signal: -30^0

N=8 = number of antenna array elements

d = λ/2= inter element spacing

μ = 0.5= step size

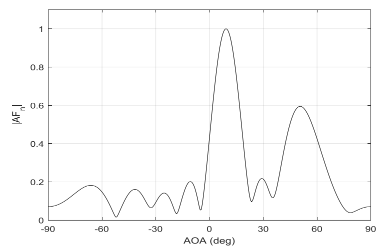

Figure 15 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/2, N=8

Figure 15 shows the array factor plot for CMA algorithm for the desired angles at 10^0,50^0 and the first multipath signal at 0^0 which is 30 percent of the direct path signal and the second multipath signal at -30^0 which is 10 percent of the direct path signal with d=λ/2, N=8. The plot shows that, the CMA algorithm has placed maximum at 15^0 and 60^0 and has suppressed the multipath signals but it does not cancel them fully.

- **Effect Of Variation In Inter-element Distance, d In Antenna Array**

d = λ/4

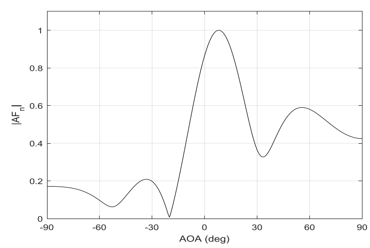

Figure 16 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/4, N=8

Figure 16 shows the array factor plot for CMA algorithm for variation in inter-element spacing, d between the array elements given by d= λ /4 for the desired input angles of 10^0 and 50^0 and for multipath signals at 0^0 , -30^0.

The simulation results show that as the inter-element spacing, d decreases, the main lobes become broader and the multipath signals also seem less suppressed.

Retrieval Number: D4424118419/2019©BEIESP
DOI:10.35940/ijrte.D4424.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
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d = λ/8

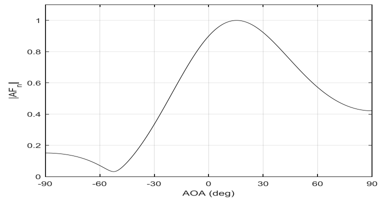

Figure 17 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/8, N=8

Figure 17 shows the array factor plot for CMA algorithm for variation in inter-element spacing, d between the array elements given by d= λ /8 for the desired input angles of 10^0 and 50^0 and for multipath signals at 0^0, -30^0.

The simulation results show that as the inter-element spacing, d decreases further the main lobes merge and do not form separate beams for desired angles of 10^0 and 50^0 , instead there appears a single main lobe covering the desired spectrum reducing the resolution of the CMA algorithm. Here the multipath signals also seem to be merged in that single main lobe and are less suppressed.

Considering this to be the worst case where CMA algorithm seems to loose its resolving capability between the two desired signals and the multipath signals, if the number of array elements are increased to 20, it gives the remedial solution to this problem. Figure 18 reveals this fact where the desired angles seem to be resolved though not to satisfaction and multipath signals are suppressed but not to a satisfactory level. Further improvement in this scenario is possible by altering the step size and this is shown by figure 19.

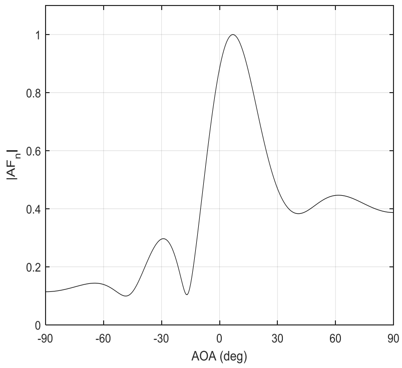

Figure 18 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/8, N=20

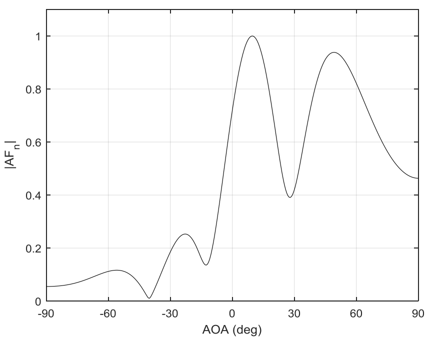

Figure 19 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/8, N=20 and μ=0.15

- **Effect Of Variation In Number Of Array Elements, N**

N = 6

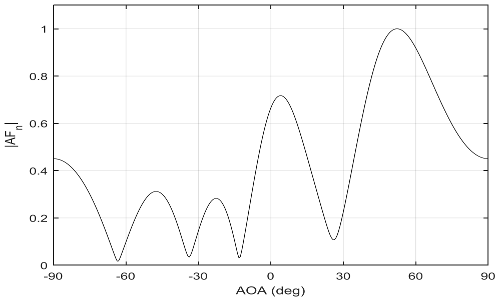

Figure 20 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/2, N=6

Figure 20 shows the array factor plot for CMA algorithm for variation in number of array elements given by N=6 for the desired input angles of 10^0 and 50^0 and for multipath signals at 0^0, -30^0.

The simulation result shows that as the number of array elements decreases, the main lobes and the side lobes become broader and the multipath signals also seem less suppressed.

N = 20

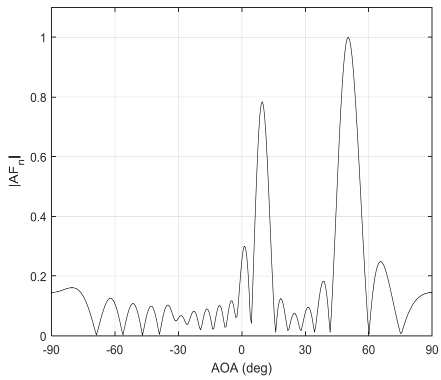

Figure 21 CMA algorithm Array factor plot for two users and two multipath signals with d=λ/2, N=20

Figure 21 shows the array factor plot for CMA algorithm for variation in number of array elements given by N=20 for the desired input angles of 10^0 and 50^0 and and for multipath signals at 0^0, -30^0.

The simulation result shows that as the number of array elements increases, the main lobes and the side lobes become narrower increasing the resolution and accuracy of the CMA algorithm. The multipath signals seem to be suppressed to greater extent.

V. COMPARISON

From the simulation results it is quite clear that all the algorithms perform well for an inter-element spacing (d) of half the wavelength. Also for a satisfactory performance of all the algorithms at least eight number of antenna array elements are required. In case of LMS and CMA algorithms alterations in the step-size within its limits can be used for bringing the improvement in the performance.[5]

LMS and RLS algorithms require a reference signal whereas the CMA does not require a reference signal. LMS has gained popularity due to its low computational complexity and robustness. One of the drawbacks encountered in LMS algorithm is its slow convergence under high eigen value spread.

Table 1: Comparison of LMS, RLS, CMA algorithm

Parameter	LMS	RLS	CMA
Reference signal requirement	Required	Required	Not Required
Computational complexity	Low	High	Moderate
Convergence time	More	Less	Slow Convergence.
Co-channel Interference Rejection	Low	Satisfactory	Low
Beamwidth	Narrow with lesser sidelobe levels	Narrow with more sidelobe levels	Wider

RLS algorithm improves its convergence substantially by replacing the step-size in LMS algorithm by the inverse of the gain matrix. It is computationally complex than LMS algorithm.

CMA algorithm can be easily implemented by a simple search algorithm like steepest- descent method. But its convergence is not guaranteed.CMA algorithm suppresses the multipath signals but does not cancel them. For CDMA systems where power control is necessary CMA is not suitable.CMA does not require a pilot signal. If the arriving signal has constant amplitude then it maintains and restores the amplitude of the desired signals. In the absence of any reference signal CMA on its own fixes one or several multipaths as the desired reference signal. [1]

VI. CONCLUSION

LMS algorithm minimizes the mean square error between the training or reference signal and the received signal. Its convergence depends on the correlation matrix eigenvalue spread and could be slow (for large eigenvalue spread). The convergence of LMS algorithm takes more time as it depends on the step-size. LMS algorithm is quite simple and can be easily implemented. Its computational complexity is very low. LMS has smaller sidelobes as compared to RLS. LMS algorithm can generate main lobes and nulls in specified directions but it exhibits unsatisfactory response in nullifying co-channel interference.LMS algorithm requires a reference signal. RLS algorithm minimizes the mean square error between the reference signal and the output, combined received signal. Thus it requires a training or reference signal. It is independent of the eigenvalue spread of the correlation matrix. Its convergence rate is faster than LMS algorithm. The recursive equations applied in RLS algorithm allow for faster updates of array weights. Though the RLS algorithm exhibits high convergence rate, sidelobes are not fully eliminated. RLS gives narrower beamwidths, satisfactory rejection of interference and faster convergence at the cost of added computational load but as compared to LMS, it has greater power in sidelobes. It is found to have minimum error signal magnitude and BER. It gives satisfactory response towards main lobe and a better response towards co-channel interference. RLS finds its applications where quick signal tracking is required. It is the best choice among the three algorithms considered.

Many a times a reference signal is not available, in that case CMA algorithm is used. CMA does not require a reference training signal.CMA algorithm is suitable for constant envelope modulations and restores signal by minimizing the interference effect on the modulus. Its nonconvex function might result in false minima. CMA algorithm suppresses the multipath signals but does not cancel them to full extent. CMA algorithm produces wider beamwidth in desired direction, produces interference suppression to some extent and has unstable behavior related to convergence. It bears maximum error but considering the co-channel interference its results are more reliable as compared to LMS and RLS. CMA finds its application only where complex envelope of the signal remains ideally constant.

For all the above algorithms, optimum spacing between antenna array elements is found to be half the wavelength. Also for a satisfactory performance of all the algorithms at least eight number of antenna array elements are required. At last it can be easily concluded that RLS algorithm has upper hand over LMS and CMA algorithms.

REFERENCES

1. S.F. Shaukat, Mukhtar ul Hassan, R. Farooq, H.U. Saeed and Z. Saleem, "Sequential Studies of Beamforming Algorithms for Smart Antenna Systems", World Applied Sciences Journal 6 (6): 754-758, 2009 ISSN 1818-4952 IDOSI Publications, 2009.
2. Amara Prakasa Rao, N.V.S.N. Sarma, "Adaptive Beamforming Algorithms For Smart Antenna Systems", Wseas Transactions On Communications E-ISSN: 2224-2864 44 Volume 13, 2014.
3. Ch. Santhi Rani, P. V. Subbaiah, K. Chennakesava Reddy, and S. Sudha Rani, "LMS And RLS Algorithms For Smart Antennas In A W-CDMA Mobile Communication Environment", ©2006-2009 Asian Research Publishing Network (ARPN) VOL. 4, NO. 6, AUGUST 2009 ISSN 1819-6608.
4. Suraya Mubeen, Dr.Am.Prasad, Dr.A.Jhansi Rani ," Smart Antenna its Algorithms and Implementation", International Journal of Advanced Research in Computer Science and Software Engineering", Volume 2, Issue 4, April 2012 ISSN: 2277 128X
5. Chintan S. Jethva and Dr. R.G. Karandikar," Algorithms of Adaptive Beam Forming for Smart Antenna: A Comparative Study", IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) e-ISSN: 2278-2834,p- ISSN: 2278-8735. Volume 8, Issue 1 (Sep. - Oct. 2013), PP 27-30
6. Miss Nayan B. Shambharkar, Prof. Prakash M. Mainkar, Dr. G. N. Mulay, "Implementation of RLS Beamforming Algorithm for Smart Antenna System", Volume-4, Issue-2, April-2014, ISSN No.: 2250-0758.
7. Hang Ruan and Rodrigo C. de Lamare, "Robust Adaptive Beamforming Based on Low-Rank and Cross-Correlation Techniques", 2016.
8. Taco Kluwer, "Development of a test-bed for smart antennas, using digital beamforming" Thesis submitted in August 2001 at University of Twenty.

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