INTERFERENCE REJECTION OF ADAPTIVE ARRAY ANTENNAS BY USING LMS AND SMI ALGORITHMS

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ABSTRACT

In this study, the LMS (least mean square) and the SMI (sample matrix inversion) algorithms are presented for the interference rejection of adaptive array antennas. Interference rejection is achieved by optimally determining the array weights. LMS algorithm, which is based on the steepest-descent method, is the most common technique used for continuous adaptation. SMI algorithm based on an estimate of the correlation matrix is a method of directly calculating the antenna array weighs. Performance results of LMS and SMI algorithms are investigated and given for different interference angles, step size of LMS, block size of SMI and interference-to-noise ratios (INRs) for a three elements uniformly spaced linear array.

I. INTRODUCTION

An adaptive antenna is a multi-beam adaptive array with its gain pattern being adjusted dynamically [1-3]. In recent decades, it has been widely used in different areas such as mobile communications, radar, sonar, medical imaging, radio astronomy etc. Especially with the increasing demand for improving the capacity of mobile communications, adaptive antenna is introduced into mobile systems to mitigate the effect of interference and improve the spectral efficiency. Adaptive antennas have the ability of separating automatically the desired signal from the noise and the interference signals and continuously updating the element weights to ensure that the best possible signal is delivered in the face of interference [4-8].

The first fully adaptive array was conceived in 1965 by Applebaum [9], which was designed to maximize the signal-to-noise ratio (SNR) at the array's output. An alternative approach to canceling unwanted interference is LMS error algorithm of Widrow *et al.* [10]. Further work on the LMS algorithm, by Frost [11] and Griffiths [12], is introduced constraints to ensure that the desired signals were not filtered out along with the unwanted signals. LMS algorithm uses continuous adaptation. The weights are adjusted as the data is sampled such that the resulting weight vector sequence converges to the optimum solution. In 1974, Reed *et al.* [13] proposed SMI algorithm for adaptively adjusting the array weights. SMI algorithm uses block adaptation. The statistics are estimated from a temporal block of array data and used in an optimum weight equation. In the literature, there have been many studies about different versions of LMS and SMI algorithms used in adaptive antennas [14-21].

In this paper, LMS and SMI algorithms were used for interference rejection problem of the adaptive antennas. The performance of these algorithms was investigated for different interference angles, step size of LMS, block size of SMI and INRs. In the simulation process, a uniformly spaced linear array with three elements was used.

II. ARRAY ANTENNA MODEL

Consider a uniformly spaced linear array with M omni-directional antenna elements shown in Figure 1. Interelement spacing is d and the plane wavefront is impinging upon the array at an angle of θ with respect to the array normal.

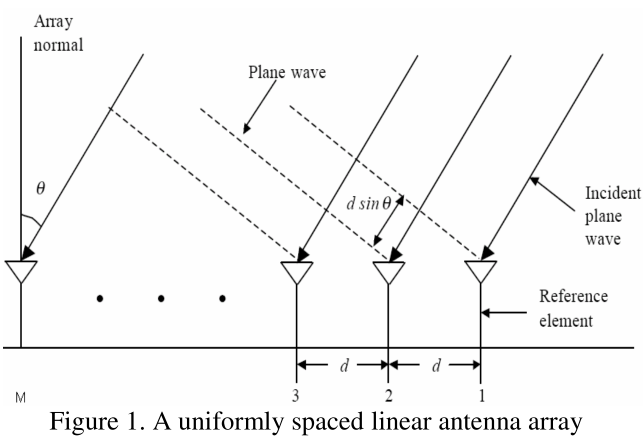


Figure 1. A uniformly spaced linear antenna array

The receiving beamformer is shown in Figure 2. In this receiving beamformer, each signal x is multiplied by a complex weight w and summed to form the output of the array denoted by y.

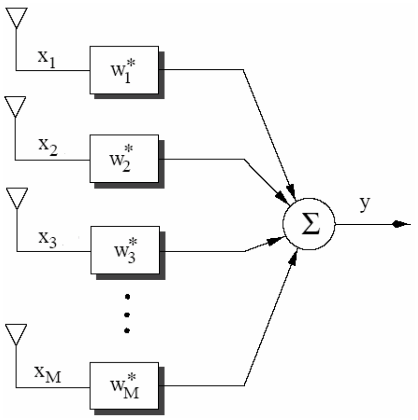


Figure 2. Receiving beamformer

The output of beamformer at time n is given by

$$y(n) = \sum_{m=1}^{M} w_m^* x_m(n) = w^H x \quad (1)$$

where * denotes the complex conjugate and $(.)^H$ denotes hermitian (complex conjugate) transpose operation. The vectors w and x, referred to as array weight vector and the array signal vector, respectively, are

$$w = \left[w_1, w_2, ..., w_M\right]^T \quad (2)$$

$$x = \left[x_1(n), x_2(n), ..., x_M(n)\right]^T \quad (3)$$

where $(.)^T$ denotes the transpose operation. The array signal vector x can also be written as:

$$x(n) = s_d(n)a(\theta_d) + \sum_{i=1}^{L} s_i(n)a(\theta_i) + N(n) \quad (4)$$

where s_d and s_i are the desired and interfering signals arriving at the array at an angle θ_d and θ_i, respectively, L is the number of interfering signals, and N is the gaussian noise at the array elements. $a(\theta_d)$ and $a(\theta_i)$ are the steering vectors for the desired and interfing signals, respectively. $a(\theta)$ is given by

$$a(\theta) = \left[1, e^{-j\frac{2\pi}{\lambda}d\sin(\theta)}, ..., e^{-j\frac{2\pi}{\lambda}d(M-1)\sin(\theta)}\right]^T \quad (5)$$

where λ is the wavelength.

III. ADAPTIVE ALGORITHMS

Figure 3 shows a block diagram representation of an adaptive antenna array. The weighted signals are summed and the output is fed to a controller that adjusts the weights to satisfy an optimization criterion.

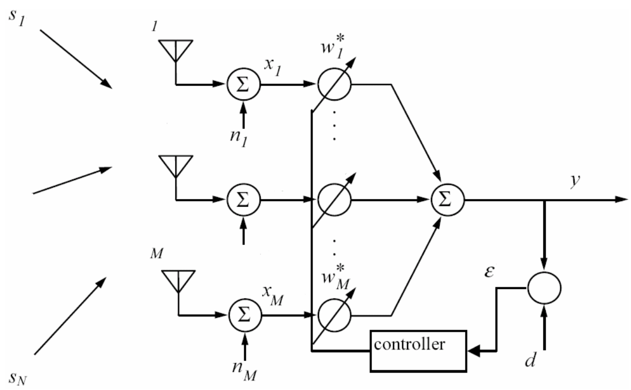


Figure 3. Adaptive antenna array

In order to minimize the mean square error between the array output y(n) and the reference (desired) signal d(n), the optimum weights can be chosen by using the following equation [1–3, 10]

$$w_{opt} = R_{xx}^{-1} r_{xd} \quad (6)$$

where $R_{xx}=E[x(n)\ x^H(n)]$ is the correlation matrix, $r_{xd}=E[x(n)\ d(n)]$ is the cross correlation vector, and E(.) is the expectation operator.

The optimum weights can be estimated with LMS algorithm at time (n+1) as

$$w(n+1) = w(n) + \mu x(n)\varepsilon^*(n) \quad (7)$$

where μ is the step size which controls the rate of convergence. ε* is the error between the reference signal and the array output, which is formulated as

$$\varepsilon^*(n) = d(n) - x^H(n)w(n) \quad (8)$$

Array weights can be calculated directly by SMI algorithm. This algorithm is based on an estimate of the correlation matrix and cross correlation vector of the adaptive array output samples. The estimate of the correlation matrix is given by

$$\hat{R}_{xx} = \frac{1}{K}\sum_{k=1}^{K} x(k)x^{H}(k) \tag{9}$$

The estimate of the sample cross-correlation vector can be evaluated by the following formula

$$\hat{r}_{xd} = \frac{1}{K}\sum_{k=1}^{K} x(k)d^{*}(k) \tag{10}$$

where K is the block size. The details on LMS and SMI adaptive algorithms can be found in [1–3, 6].

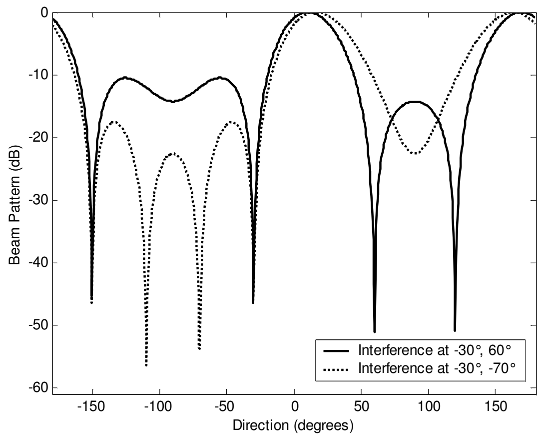


Figure 4. Beam pattern of SMI algorithm

IV. SIMULATION RESULTS

In this section, several computer simulation results for interference rejection performance of LMS and SMI algorithms are presented. The performance of these algorithms is investigated for different interference angles, step size of LMS, block size of SMI, and different INR values. Four examples of a linear array having three equispaced omnidirectional elements with λ/2 interelement spacing are carried out. For these examples, the desired (source) signal is located at 10° and the SNR value of this desired signal is 10 dB.

In the first example, it is assumed that the INR for all interferers is 20 dB, step size of LMS is 0.001, block size of SMI is 16, and the interferers are located at (-30°, 60°) and (-30°, -70°). The beam patterns are then obtained by SMI and LMS algorithms and illustrated in Figures 4 and 5. It is clear from the Figures 4 and 5 that the achieved null depths for both algorithms have very good performance. However, the null depth level of SMI algorithm is deeper than that of LMS algorithm.

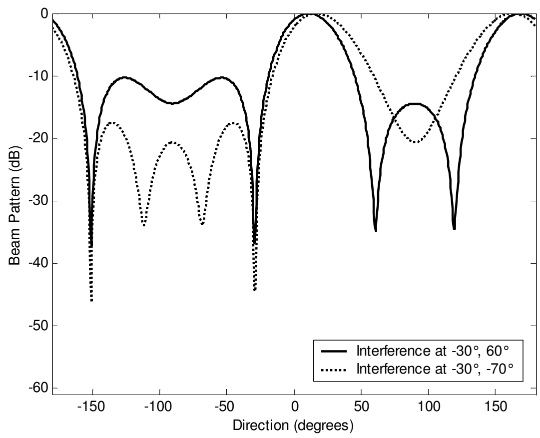
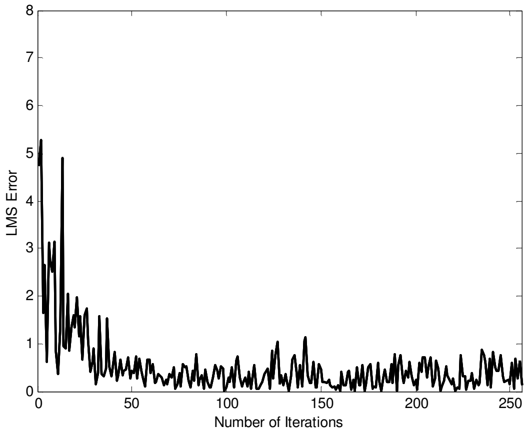


Figure 5.Beam pattern of LMS algorithm

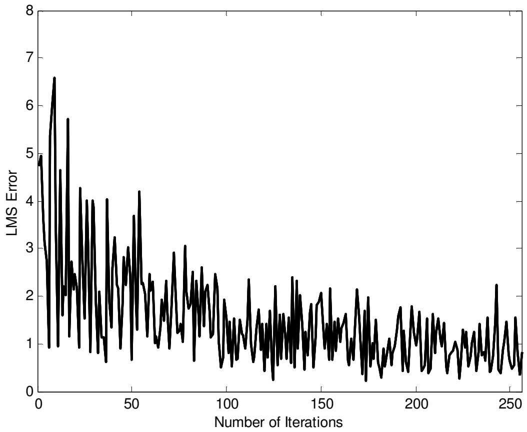
In the following three examples, it is assumed that the interferers are located at (-30°, 60°). To show the effects of the step size μ on the error ε* of LMS algorithm, the step size values are selected as 0.01, 0.001, 0.0005 for the second example, while the other design parameters are the same as those of the first example. The results obtained for three different step size values are shown in Figure 6. It is clear from Figure 6 that the convergence is slow for μ = 0.0005, but the convergence is rapid for μ = 0.01. These results illustrate that a larger step size causes to a faster convergence.

In the third example, the patterns are obtained for six different block sizes of SMI algorithm, and the resultant patterns are shown in Figure 7. In this figure, it can be seen that the increase in the value of block size increases the level of interference rejection.

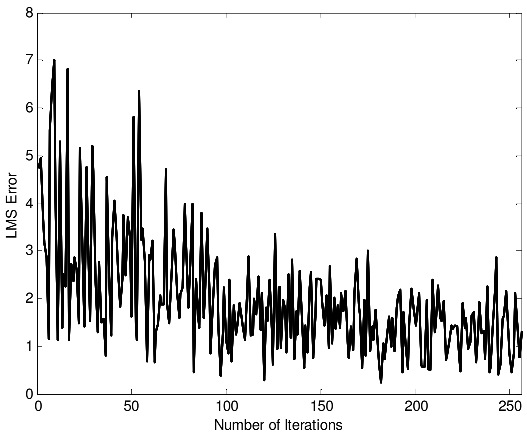
In the last example, we examined the effect of the INR values on interference rejection of SMI and LMS algorithms. Figures 8 and 9 show the beam patterns achieved for 20 dB and 30 dB INR values. It is evident from Figures 8 and 9 that as the value of INR increases, the interference rejection capability increases as well.



(a) μ=0.01



(b) μ=0.001



(c) μ=0.0005

Figure 6. Convergence performance of LMS algorithm for (a) μ=0.01, (b) μ=0.001, and (c) μ=0.0005

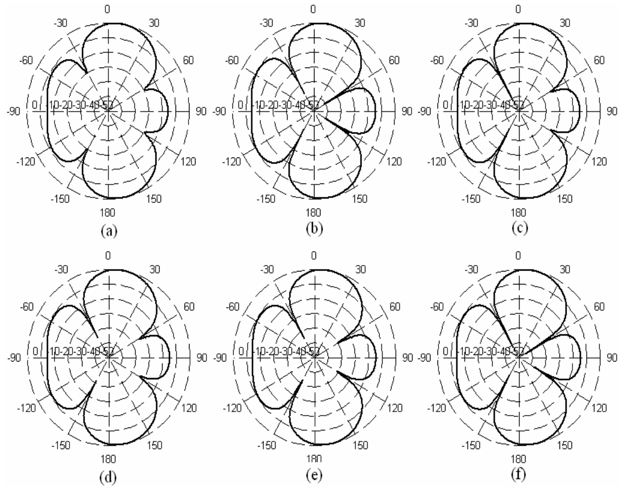


Figure 7. Beam patterns of SMI algorithm for (a) K=8, (b) K=16, (c) K=32, (d) N=64, (e) N=128, and (f) N=256.

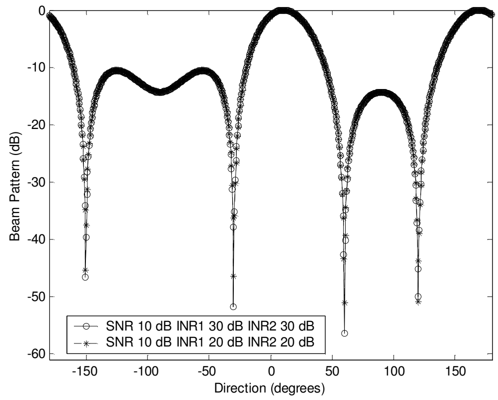


Figure 8. Beam pattern of SMI algorithm for two different INR values.

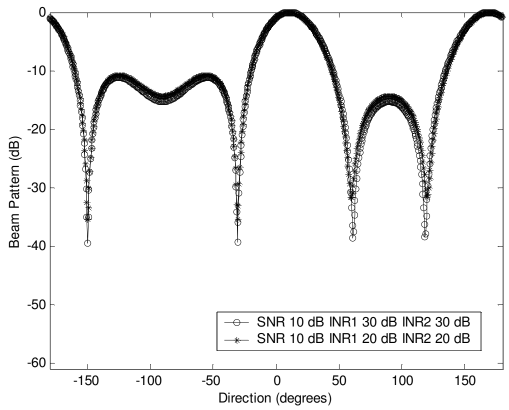


Figure 9. Beam pattern of LMS algorithm for two different INR values.

V. CONCLUSION

In this work, the LMS and SMI algorithms are used for the interference rejection of the adaptive antenna array with three-elements. The effects of some design specifications such as the interference angles, the step size of LMS, and the block size of SMI and INRs on the interference rejection are investigated. Simulation results show that both algorithms, LMS and SMI, are capable of nulling the interference sources even the interference sources close to each other. The null depth performance of the SMI algorithm is better than that of the LMS algorithm.

The weighting factors of LMS and SMI algorithms give greater flexibility and control over the actual pattern. The antenna designer should make a trade-off between the achievable and the desired pattern. By adjusting the factors it is possible to obtain very reasonable approximations and trade-offs.

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