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Smart Antenna its Algorithms and Implementation

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ABSTRACT: ***"Smart Antenna" generally refers to any antenna array, terminated in a sophisticated signal processor, which can adjust or adapt its own beam pattern in order to emphasize signals of interest and to minimize interfering signals. Smart antennas generally encompass both switched beam and beam formed adaptive systems. Switched beam systems have several available fixed beam patterns. A decision is made as to which beam to access, at any given point in time, based upon the requirements of the system. Beam formed adaptive systems allow the antenna to steer the beam to any direction of interest while simultaneously nulling interfering signals. The rapid growth in demand for smart antennas is fueled by two major reasons. First, the technology for high speed analog-to-digital converters (ADC) and high speed digital signal processing is burgeoning at an alarming rate. Now the smart antennas its algorithms and its MATLAB onward flow is discussed and being implemented in my research paper.***

KEYWORDS: *LMS, SMI,ADAPTVE BEAMFORMING,WEIGHTS*

I. INTRODUCTION

Smart antenna systems are rapidly emerging as one of the key technologies that can enhance overall wireless communications system performance. By making use of the spatial dimension, and dynamically generating adaptive receive and transmit. There are two basic types of smart antennas. As shown in Fig1, the first type is the phased array or multi beam antenna, which consists of either a number of fixed beams with one beam turned on towards the desired signal or a single beam (formed by phase adjustment only) that is steered toward the desired signal. The other type is the adaptive antenna array as shown in Fig 2, which is an array of multiple antenna elements, with the received signals weighted and combined to maximize the desired signal to interference plus noise power ratio.

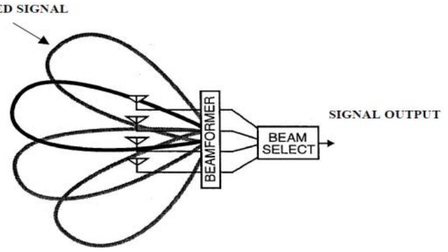

Fig 1 : PHASED ARRAY

This essentially puts a main beam in the direction of the desired signal and nulls in the direction of the interference antenna patterns, a smart antenna can greatly reduce interference, increase the system capacity, increase power efficiency as well as reduce overall infrastructure costs. A smart antenna is therefore a phased or adaptive array that adjusts to the environment. That is, for the adaptive array, the beam pattern changes as the desired user and the interference move; and for the phased array the beam is steered or different beams are selected as the desired user moves.

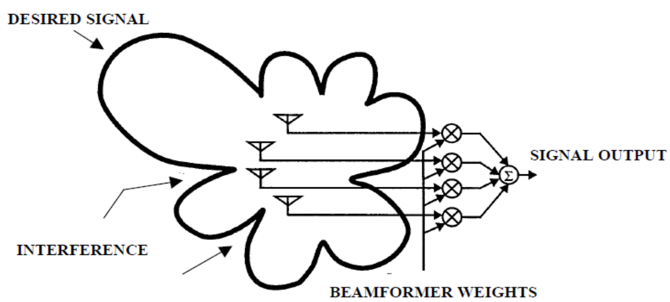

Fig 2: ADAPTIVE ARRAY

II. SMART ANTENNA ALGORTHIMS

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 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 .Further work on the LMS algorithm, 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. SMI algorithm for adaptively adjusting the array weights, 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].

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. Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 [12] is an adaptive algorithm, which uses a gradient-based method of steepest decent [10]. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions.

Consider a Uniform Linear Array (ULA) with N isotropic elements, which forms the integral part of the adaptive beam forming system as shown in the figure below. The output of the antenna array is given by,

$x(t) = s(t)\,a(\theta_0) + \sum_{i=1}^{N_u} u_i\ (t)\,a(\theta_i) + n(t)$ [1]

Weight, w (n+1) = w(n) + μ x(n)e* (n) [2]

Error, e(n) = d*(n) – y(n) [3]

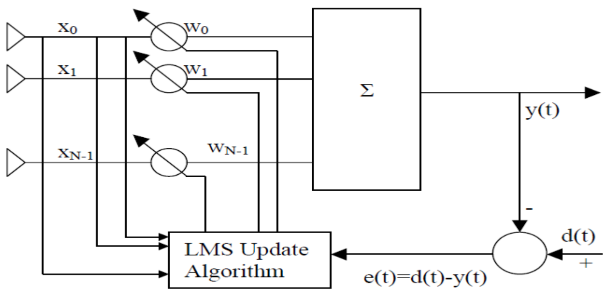

Fig 3: LMS Adaptive beam forming network

As shown above the outputs of the individual sensors are linearly combined after being scaled using corresponding weights such that the antenna array pattern is optimized to have maximum possible gain in the direction of the desired signal and nulls in the direction of the interferers. The weights here will be computed using LMS algorithm based on Minimum Squared Error (MSE) criterion. Therefore the spatial filtering problem involves estimation of signal from the received signal (i.e. the array output) by minimizing the error between the reference signal , which closely matches or has some extent of correlation with the desired signal estimate and the beam former output y(t) (equal to w x(t)).

III.SIMULATION RESULTS FOR THE LMS ALGORITHM

For simulation purposes a 4-element linear array is used with its individual elements spaced at half-wavelength distance. The desired signal arriving s(t) is a simple complex sinusoidal-phase θ_o modulated signal of the following form, Two examples are provided to show the beam forming abilities of the LMS algorithm. Each example has a normalized array factor plot and corresponding LMS error plot.

Case 1: In the first case the desired angle is arriving at 30 degrees and there are three interfering signals arriving at angles –20, 0 and 60 degrees respectively. The array factor plot in Figure 6.2a shows that the LMS algorithm is able to iteratively update the weights to force deep nulls at the direction of the interferers and achieve maximum in the direction of the desired signal. It can be seen that nulls are deep at around 40dB level below the maximum. The LMS error plot in figure shows that the LMS algorithm converges. In this case the LMS error is almost 0.025 at around 3000 samples.

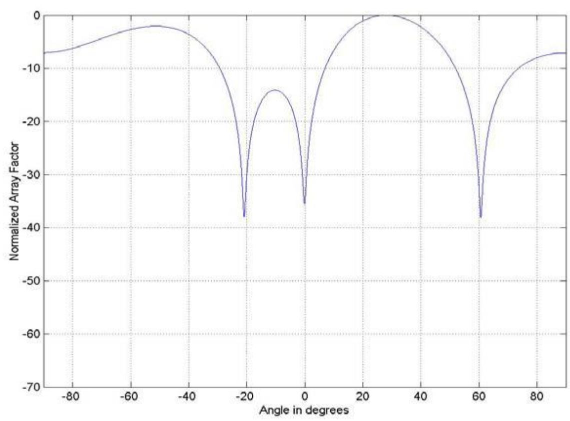

Fig 4: Normalized Array Factor plot for case1

Case 2:

Another example shown in figure.6.3a is provided for the case where the desired signal is arriving at an angle and there are four interferers (compared to three interferers in previous case) arriving at angles –40, -10, 30 and 60 degrees respectively. It is seen that nulls are deeper when the number of interferers are larger at around the 50dB level from the maximum value. However, from the LMS error plot in figure 6, it is quite evident that it takes longer to converge, it takes about 6000 samples to converge where the error is less than 2%.

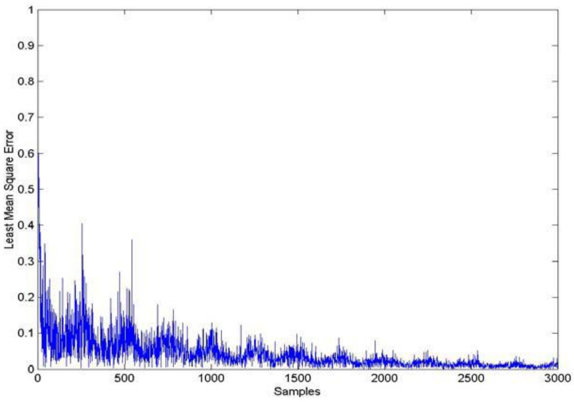

Fig 5: LMS error plot for case 1

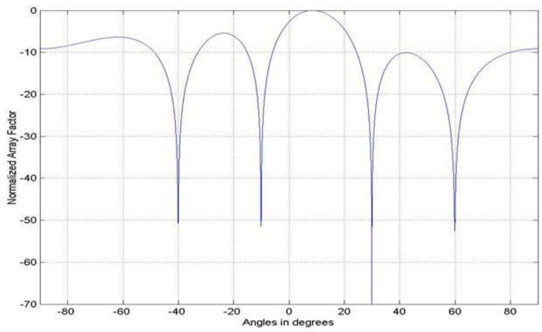

Fig 6 : Normalized Array Factor plot for case2

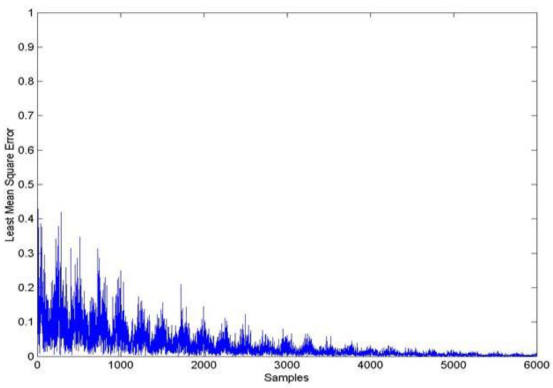

Fig 7: LMS error plot for case 1

III. SMI ALGORTHIM:

One such algorithm is the Sample Matrix Inversion (SMI) which 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.

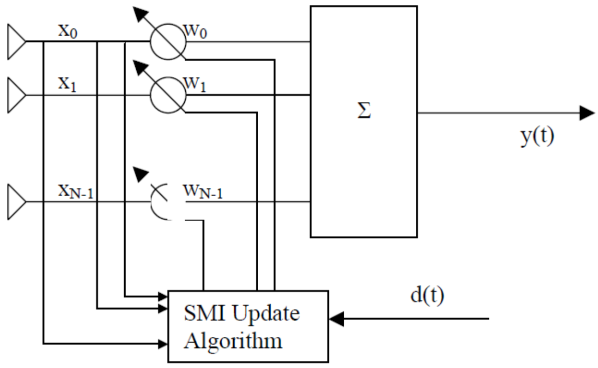

Fig 8:SMI ADAPTIVE BEAMFORMING NETWORK

The SMI algorithm has a faster convergence rate since it employs direct inversion of the covariance matrix R. Let us recall the equations for the covariance matrix and the correlation matrix r. $R = E[x(t)x^H\ (t)]$ [4]

$$r = E[(d(t)\,x(t)] \qquad [5]$$

If a priori information about the desired and the interfering signals is known, then the optimum weights can be calculated directly

$$w_{opt} = R_{xx}{}^{-1} r_{xd} \qquad [6]$$

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 $R_{XX} = \frac{1}{K}\sum_{k=1}^{K} x(k)x^H(k)$ [7]

The stability of the SMI algorithm depends on the ability to invert the large covariance matrix. In order to avoid a singularity of the covariance matrix, a zero- mean white Gaussian noise is added to the array response vector. It creates a strong additive component to the diagonal of the matrix. In the absence of noise in the system, a singularity occurs when the number of signals to be resolved is less than the number of elements in the array. Since SMI employs direct matrix inversion the convergence of this algorithm is much faster compared to the LMS algorithm. However, huge matrix inversions lead to computational complexities that cannot be easily overcome.

Weight adaptation in the SMI algorithm can be achieved in different ways

1. Block adaptation

The above-mentioned block adaptive approach, where the adaptation is carried over disjoint intervals of time, is the most common type. This is well suited for a highly time varying signal environment as in mobile communications

2. Overlapping block adaptation

This approach is computational intensive as adaptation intervals are not disjoint but overlapping. It provides better performance but has an increased number of inversions when compared to the above method.

3. Block adaptation with memory

This method utilizes the matrix estimates computed in the previous blocks. This approach provides faster convergence for spatial channels that are highly time-correlated. It works better when the signal environment is stationary.

V. SIMULATION RESULTS AND ANALYSIS FOR SMI

For simulation purposes, a similar scenario is considered as with the LMS simulation discussed in the previous session. The SMI algorithm discussed here uses the Block Adaptation approach, the size of the block being equal to 10 time samples.

A 4-element linear array is used with its individual elements spaced at half-wavelength distance. The desired signal s(t) arriving at θ_0 simple sinusoidal-phase modulated signal of the same form as in equation The interfering signals arriving at angles are also of the same form. By doing so it can be shown in the simulations how interfering signals of the same frequency as the desired signal can be separated to achieve rejection of co-channel interference. However, Rayleigh fading is added to the incoming interfering signals. Simulation results with illustrations are provided to give a better understanding of different aspects of the SMI algorithm with respect to adaptive beam forming. For simplicity sake the reference signal d(t) is considered to be same as the desired signal. In the example provided here, the desired angle is arriving at 30 degrees and there are three interfering signals arriving at angles –20, 0 and 60 degrees respectively. The array factor plot in Figure shows that the SMI algorithm is able to update the weights block wise to force deep nulls in the direction of the interferers and achieve a maximum in the direction of the desired signal. The angular parameters for the desired and interfering signals used here are identical to that used in the LMS simulation in the previous chapter. It can be seen that nulls are deeper in the case of SMI when compared to LMS. The null levels are at around 50dB-60dB below the maximum.

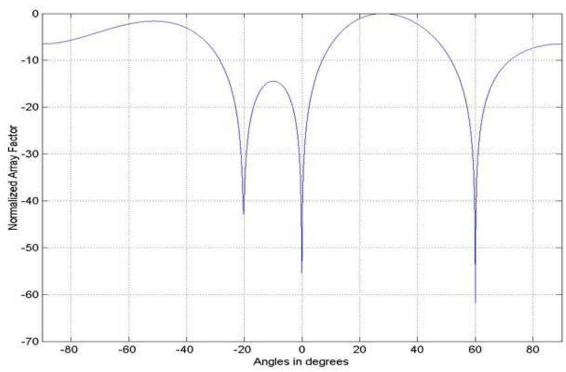

Fig 9: Normalized Array Factor plot

The error plot for this situation is shown in figure When compared to the LMS error SMI error is small. However, this error is uniform and is present throughout the acquisitions. This is because SMI does not require the error information to update the weights. These observations indicate that SMI algorithm converges almost immediately during the first block itself but there is a small amount of residual error throughout. This residual error comes from the fact that the covariance matrices are estimated values and not accurate values.

If the block size is increased from 10 to 30 as shown in figure we see that error tends to increase. If the signal environment is changing then each block will have its own optimal solution for weights. If a highly mobile signal environment is under consideration it is better to have a small block size to enable to better adaptation.

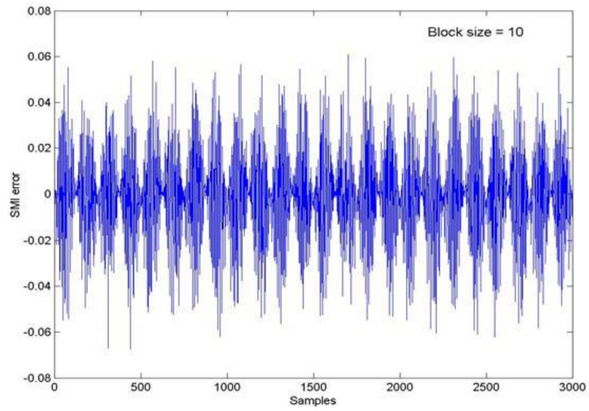

Fig 10: SMI error plot when block size = 10

It quite evident from the simulation analysis that SMI has a fast convergence rate. It is suitable for burst traffic adaptation where it is unlikely that signal environment will change during block acquisition. SMI algorithm is based on matrix inversion, which tends to be computationally intensive. the high convergence rate property of the SMI algorithm is best made use of when it is used in conjunction with other algorithms. Again like LMS, SMI algorithm requires information about the desired signal.

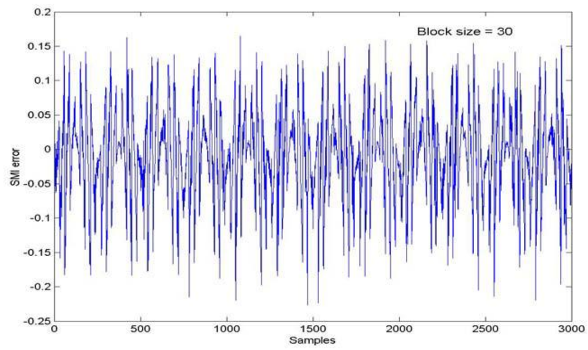

Fig 11 : SMI error plot when block size = 30

VI.COMPARISON OF BOTH WEIGHTS FOR LMS AND SMI

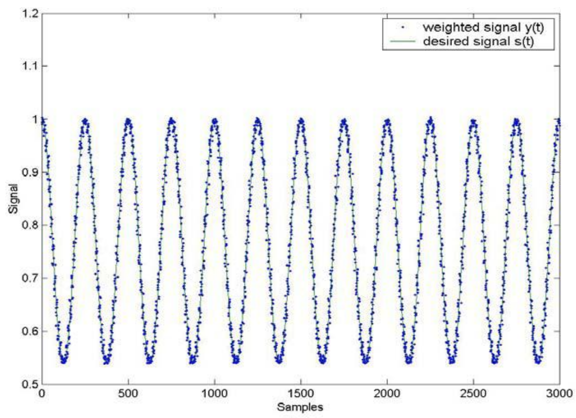

Fig 12:SMI Weighted signal vs. desired signal response

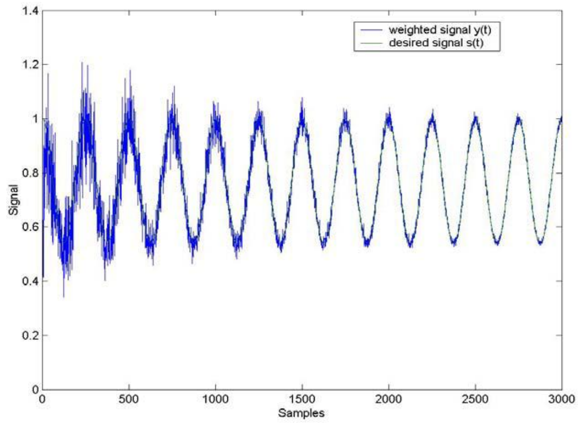

Fig 13: LMS Weighted signal vs. desired signal response

VII. CONCULSION:

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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