Analysis and Synthetic Model of Adaptive Beamforming for Smart Antenna Systems in Wireless Communication

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Abstract —Adaptive beamforming is one of the radio resource controlling systems and define as a process by which an adaptive spatial signal processing are performed on array of antennas. By the addition of the signals weights constructively in the preferred direction of signal, adaptive beamforming technique creates radiation pattern on antenna array thereby nulling pattern in the unwanted direction that is interference. These arrays are antennas in the smart antenna context. Adaptive beamforming are normally used to achieve spatial selectivity at transmitting and receiving ends. In this research work, adaptive beamforming algorithms techniques (Least Mean Square and Recursive Least Square) are considered for the smart antennas. Uniform array of isotropic elements *M (10, 15, and 20)* are considered having their coordinate system in the direction of *y*. The spacing of the antenna elements are varied at *d (0.5λ, 0.6λ and 2λ)*. The angles at which the grating lobe appears, steering angle, and the antenna element's effect spacing on beamforming has been examined. The following are the observation as the antenna element spacing are increasing: (i) narrower main lobe, (ii) grating lobes, (iii) reduction in beamwidth (thus making the array more directional), and (iv) reduction in sidelobe level, thus improving beamforming. It has been also observed that there is no grating lobe when $d/\lambda = 0.5$, which we have considered as the optimal design spacing for the array antenna elements in the smart antenna..

Index Terms—Adaptive beamforming; complex weights; null-steering; radiation pattern; smart antenna; wireless communication

I. Introduction

One of the prominent techniques that can proffer solution for the mitigation of multipath and co-channel interference signals as the wireless communication systems is at the advanced stage is smart antenna [1]-[3]. Smart antenna has the capacity to improve signal-to-interference-plus-noise-ratio and suppress jamming signal [4].

The adaptive beamforming is a combination of several antenna elements inputs from the antennas array using the signal processing capacity to produce a narrow beams so as to allow certain frequency range for separate users within the cell at a particular point in time [5]. To improve a system capacity, one of the factors to consider is to suppress the co-channel interference. This can be achieved through the implementation of adaptive beamforming. Hence, system immunity to multipath fading is improved. To achieve a better SNR through adaptive beamforming, each antennas weights are varied in the array. In the direction of users, co-channel interference, and noise, adaptive beamforming can still estimates the signal coming from that particular direction using direction-of-arrival (DOA) algorithm [2]. The adaptive beamformer can also be known as adaptive/smart antennas. Adaptive Beamformer adjusts the complex weights that are present at every antenna array output end and form a pattern that optimizes directed signals reception at a precise direction with statistical sense.

A smart antenna arrays system geometry Fig. 1 comprises of uniform linear antenna array *M* at the cellular sites. The adaptive beamforming algorithms of the array adjust the amplitudes current by the complex weights [6]. The array output beam pattern is optimized by the algorithm so as to produce the radiated power in the directions of signals of interest and put nulls in the direction of co-channel interference. The centrality of smart antenna arrays is smart algorithms choice in an adaptive manner. With beamforming algorithms, antenna arrays' weight are adjusted to generate adaptive beam so as to locate corresponding users dynamically and concurrently reduce any interference coming from other consumers by putting nulls in their respective directions [7]. Least Mean Squares (LMS), Sample Matrix Inversion (SMI), and Recursive Least Squares (RLS) are frequently use in adaptive algorithm [8]. LMS algorithm is simple and robust [2], [4], [5-7], [9-13]. RLS algorithm converges faster than LMS algorithm. It stipulates nulls in the angle corresponding to the interferences signals but it is complex. For anti-jamming purpose, RLS is one of the best algorithms [4].

Various researches on adaptive beamforming algorithms [6] established in the literature for the aim of studying the performance of smart antenna systems [4]-[11]. *Ali, et al.* [4], examined three types of beamforming algorithms (LMS, Optimized-LMS and RLS) with emphasis on anti-jamming. In *ref.* [6] several conventional algorithms adaptation are used for the smart antenna arrays weights so as to maximize the output power in the direction of signal of interest and minimize the power in the interference direction [14]. Various adaptive beamforming algorithms were investigated in [7].

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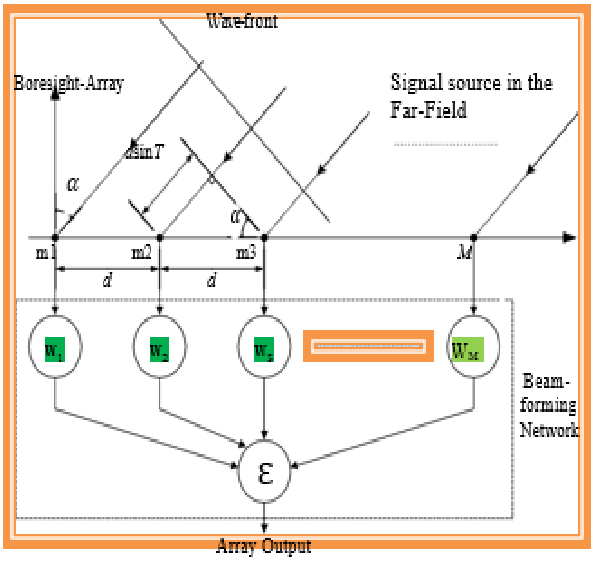


Fig. 1. Uniform linear array (M) geometry.

The antenna elements' displacement are adjusted in each algorithm to select the best. *Shubair and Merri* [9] examined a convergence study of adaptive beamforming algorithms by investigating the effect of changing a number of parameters such as interference signals, number of iterations/antenna elements, LMS step size, and RLS weighting factor. *Kawitkar and Wakde* [10] analyzed and computed smart antenna arrays using LMS algorithm based on Minimum Square Error criterion. Adaptive beamforming algorithm using variable step-size were investigated in [11] for the improvement of adaptive beamforming in smart antenna.

This research work examines an adaptive beamforming and its algorithms as an excellent performance for smart antennas in wireless communication systems. The each antenna elements and the displacement between them in the system are compared. The algorithms efficiency is analyzed and the equation governing them in terms of beamforming stability, beamwidth (thus making the array more directional), maximum reduction in sidelobe level (thus improving beamforming), nulls depth, and rate of convergence are derived. Optimum algorithm using LMS and RLS algorithms are examined and studied.

The study takes the following organization. The theory for the signal modeling and adaptive beamforming algorithm for the systems are formulated in Section II. In Section III, the simulated results and discussions for the LMS and RLS algorithms are presented. Finally, Section IV gives a synopsis of the study.

II. Signal Modeling and Adaptive Beamforming Mathematical Problem Formulation

Fig. 2 shows adaptive beamformer which comprises of multiple antenna elements; complex weights, and a summer. The purpose of the complex weights is for signals amplification/attenuation and signals delay from each antenna elements, while the summer takes the summation of all the processed signals, so as minimize the interference signals, while increasing the desired signals. The beamformer indicates the antenna capability (control signals in a specified direction), and its ability receive signals emanating from a desired direction by placing nulls in the direction of interferers.

III. Signal Modeling Formulation

Fig. 1 comprises of linear array of *M* antennas (uniform), $S_m(u)$ signal source with *k* narrowband from signal of interest directions ($\alpha_1, \alpha_2, \ldots, \alpha_k$), and interferers from directions ($\alpha_1, \alpha_2, \ldots, \alpha_I$) as it receives source signals $S_i(u)$ of narrowband *I*. At specific time, u = 1, 2,…, J, where J is the sum of time taken.

Mathematically, the desired users signal vector $\mathbf{X}_n(v)$ can be written as [15].

$$\mathbf{X}_n(u) = \sum_{n=1}^{N} \mathbf{q}(\alpha_n) S_n(v) \tag{1}$$

α_n (array response) can be written as

$$\mathbf{q}(\alpha_n) = e^{[i(k-1)\varphi_n]^V}\ 1 \le k \le k \tag{2}$$

φ_n (electrical phase shift) is

$$\varphi_n = 2\pi\left(\frac{d}{\lambda}\right)\sin(\alpha_n) \tag{3}$$

From equation (1), $\mathbf{X}_n(v)$

$$\mathbf{X}_n(v) = \mathbf{A}_n \mathbf{S}(v) \tag{4}$$

$\mathbf{X}_n(v)$ direction vectors

$$\mathbf{A}_n = [\mathbf{q}(\alpha_1), \mathbf{q}(\alpha_2), \ldots, \mathbf{q}(\alpha_k)] \tag{5}$$

$\mathbf{S}(v)$ waveform vector is written as

$$\mathbf{S}(v) = [s_1(v)\ s_2(v)\ ..\ \ ..\ s_k(v)]^V \tag{6}$$

The interference users signal vector $\mathbf{X}_I(v)$ is

$$\mathbf{X}_I(v) = \mathbf{A}_I \mathbf{i}(v) \tag{7}$$

$$\mathbf{A}_I = [\mathbf{q}(\alpha_1), \mathbf{q}(\alpha_2), \ldots, \mathbf{q}(\alpha_I)] \tag{8}$$

The interference users' source waveform vector defined is

$$\mathbf{I}(v) = [i_1(v)\ \ i_2(v)\ ..\ \ ..\ i_I(v)]^V \tag{9}$$

Equation (7), (8), and (9) can be combined as

$$\mathbf{x}(v) = q_o \mathbf{S}(v)[q_1\ q_2\ \cdots\ q_N] \cdot \begin{bmatrix} I_1(v) \\ I_2(v) \\ \vdots \\ I_N(v) \end{bmatrix} + \mathbf{n}(v)$$

Hence,

$$\mathbf{X}(v) = \mathbf{X}_k(v) + \mathbf{n}(v) + \mathbf{X}_I(v) \tag{10}$$

Its covariance matrix is expressed as

$$\mathbf{R}_{k+1} = E\{\mathbf{X}_{K+1}(v)\mathbf{X}^H_{k+1}(v)\} \tag{11}$$

To approximate Equation (11), averaging process over D snapshots taken from signals that are incident on the antenna array leads to form a spatial correlation matrix $\mathbf{R}_{k+1}$ given by [12, 15-16]:

$$\mathbf{R}_{K+1} = \mathbf{D}^{-1}\sum_{d=1}^{J}\mathbf{X}(d)\mathbf{X}_{k+1}^{H}(d) \tag{12}$$

$$\mathbf{R} = \mathbf{A}_k\mathbf{R}_{ss}\mathbf{A}_k^H + \mathbf{n}(k) + \mathbf{A}_I\mathbf{R}_{ii}\mathbf{A}_I^H \tag{13}$$

The summation of the array antenna in direction α, Fig. 1 is given as:

$$y_k(v) = \sum_{n=1}^{M} w_{N-1}e^{j(2\pi fv+\varphi_n k)} \tag{14}$$

The output of the narrowband beamforming is:

$$Y(v) = W^H X(v) \tag{15}$$

The defined SINR is:

$$SINR = \frac{W^H R_s W}{W^H R_{i+n} W} \tag{16}$$

To achieve optimum (SINR), the optimal weight vector W is needed. Hence Equation (2) must be solved to, optimal weight vector W for:

$$W_{opt} = \frac{R_{i+n}^{-1}A}{A^H R_{i+n}^{-1}A} \tag{17}$$

At this time the corresponding $SINR_{opt}$ is:

$$SINR_{opt} = P_s^2 A^H R_{i+n}^{-1} A \tag{18}$$

IV. Mathematical Formulation for Beamforming Algorithm

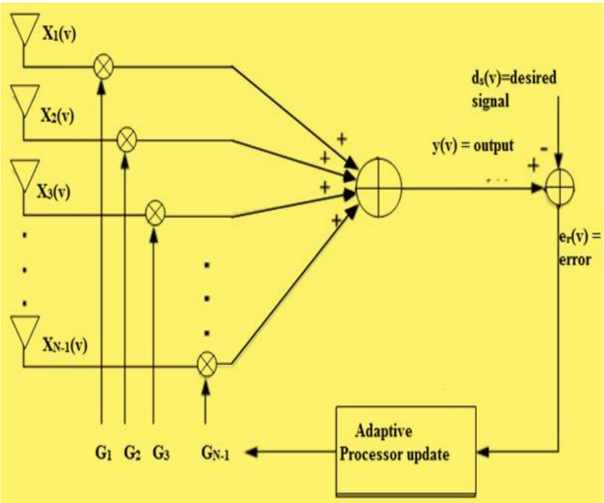


Fig. 2. Adaptive beamforming and algorithm

Beamforming algorithms are used for system updating parameters ($G_1, G_2,\ldots, G_{N-1}$) Fig. 2. Weights computation normally takes place by minimizing the error between the output array and desired signal while waiting for the weights to attain their optimal set of values [5]. G is the weight vector and can be expressed by input X(v) received via multiple antennas. The adaptive processor update minimize the errors $e_r(v)$ between the array output y(v) and desired signal ds(v). The individual element's weights adjust the phase shift and the amplitude attenuation of the received signal so that the outputs of the individual antennas are combined in a linear form once being scaled through consistent weights adjusting the antenna array to form gain in the direction of desired signal and nulls in the interferers direction [4], [7], [14]. The LMS and RLS algorithms are used in this context.

A. LMS Algorithm Formulation

The LMS algorithm updates its weights at every iteration by calculating approximately the quadratic Mean Square Error gradient at the instant time. The updated weights are moved in the negative direction of the gradient by the step size parameter [2, 4-7, 9, 11-12]. Let the weights for the mathematical analysis be equal to G.

Consider the output of the beamformer at time u, *y(u)* is specified through a linear summation of the numbers of *M* antennas $[X_1, X_2, X_3, \ldots, X_{N-1}]$, with $\boldsymbol{c}(u)$ as input vector and $\boldsymbol{G}(u)$ as weight vector.

The output response for the array can be expressed as

$$y(u) = \mathbf{G}^H\mathbf{C}(u), \tag{19}$$

$$e(u) = d(u)-\mathbf{G}^H\mathbf{c}(u) \tag{20}$$

To avoid matrix inverse operation for the LMS algorithm, the gradient vector $\nabla \boldsymbol{J}(t)$ for weight vector upgradation can be used. The weight vector at time *(u+1)* can be expressed as

$$\boldsymbol{G}(u+1) = \boldsymbol{G}(u) + \frac{1}{2}\mu[-\nabla \boldsymbol{J}(u)] \tag{21}$$

µ operates on the adoption rate and is being referred to as the step-size parameter, correlation matrix, and determines how close the weights are moving. Its value is in the range of 0 and 1 [6]. For small values of step-wise parameter, there will be slow convergence. Hence, cost function are approximately in a good sense. However, large values of step-wise parameter leads to a faster convergence but the stability could be lost at the lowest value [7].

When LMS algorithm is started with random weight vector, it converges and stable in the range of $0 < \mu < \frac{1}{\lambda_{max}}$ [7]. For slow convergence values, it means the eigenvalues of the correlation matrix is widespread.

From equation (18), to estimate the instantaneous gradient vector $\nabla \boldsymbol{J}(u)$. Covariance matrix **X** and cross-correlation vector **Y** previous information is required. The LMS algorithm conversely simplifies this with the help of instantaneous values of covariance matrices **X** and **Y** in preference to their actual values.

$$\nabla(u) = \partial\left(\frac{J(u)}{\partial(G(u))}\right)$$

$J(u)$ is a squared error

Hence,

$$\nabla \mathbf{J}(\mathrm{u}) = -2\mathbf{Y}(\mathrm{u}) + 2\mathbf{X}(\mathrm{u})\mathbf{G}(\mathrm{u}) \tag{22}$$

The weight vector update is found to be

$$\mathbf{G}(\mathrm{u}+1) = \mathbf{G}(\mathrm{u}) + \mu[\mathbf{Y}(\mathrm{u}) - \mathbf{X}(\mathrm{u})\mathbf{G}(\mathrm{u})] \tag{23}$$

$$= \mathbf{G}(\mathrm{u}) + \mu\mathbf{c}(\mathrm{u})[\mathbf{d}^*(\mathrm{u})(\mathrm{u}) - \mathbf{c}^{\mathrm{H}}(\mathrm{u})\mathbf{G}(\mathrm{u})]$$

$$= \mathbf{G}(\mathrm{u}) + \mu\mathbf{c}(\mathrm{u})\mathbf{e}^*(\mathrm{u}) \tag{24}$$

Equation (23) and (24) are the estimated weight vector and reference signal used for weights update at individual iteration [6]. This weight vector correction gives the minimum value of the mean square error. Stability is determined by [2, 4-7].

$$0 \le \mu \le \frac{1}{2\lambda_{max}}$$

B. RLS Algorithm Formulation

RLS is one of the greatest adaptive filter algorithms. It computes the requisite correlation matrix and vector repeatedly to lessen the computational intricacy with fast conversion rate [7]. For the tap input vector *c(u)* the autocorrelation of the order *M*-by-*M* is given by [4,13]

$$\boldsymbol{\vartheta} = \sum_{k=1}^{\mathrm{u}} \lambda^{\mathrm{n}-1}\,\mathbf{c}(\mathrm{b})\mathbf{c}^{\mathrm{H}}(\mathrm{b}) + \delta\lambda^{\mathrm{n}}\mathbf{I}$$

where λ and δ are forgetting factor (positive constant) and the regularizing term. The tap input vector autocorrelation matrix and desire response can be expressed as

$$\mathbf{Y}(\mathrm{u}) = \sum_{\mathrm{b}=1}^{\mathrm{u}} \frac{1}{\lambda}\cdot[\mathbf{c}(\mathrm{b})\mathrm{d}^*(\mathrm{b})] \tag{25}$$

For RLS tricky, tap weight vector ***G(u)*** could be approached as

$$\boldsymbol{\vartheta}(\mathrm{u}) = \frac{\mathbf{Y}(\mathrm{u})}{\mathbf{G}(\mathrm{u})} \tag{26}$$

Matrix inversion Lemma is applied to avoid computationally inefficient calculations of $\boldsymbol{\vartheta}^{-1}(n)$ [13]. Hence,

$$\boldsymbol{\vartheta}^{-1}(\mathrm{u}) = \lambda^{-1}\frac{\mathbf{G}(\mathrm{u})}{\mathbf{Y}(\mathrm{u})}(\mathrm{u}-1) - \frac{\lambda^{-2}\frac{\mathbf{G}(\mathrm{u})}{\mathbf{Y}(\mathrm{u})}(\mathrm{u}-1)\mathbf{c}(\mathrm{u})\mathbf{c}^{\mathrm{H}}(\mathrm{u})\frac{\mathbf{G}(\mathrm{u})}{\mathbf{Y}(\mathrm{u})}(\mathrm{u}-1)}{1+\lambda^{-1}\mathbf{c}^{\mathrm{H}}(\mathrm{u})\frac{\mathbf{G}(\mathrm{u})}{\mathbf{Y}(\mathrm{u})}(\mathrm{u}-1)\mathbf{c}(\mathrm{u})} \tag{27}$$

Let **b**(u) represents M-by-1 vector defined by the tap input vector as **c**(u). This can also be referred to as gain vector. The transformed inverse of the correlation matrix of $\frac{\mathbf{G}(\mathrm{u})}{\mathbf{Y}(\mathrm{u})}(\mathrm{u})$ results in

$$\mathbf{b}(\mathrm{u}) = \boldsymbol{\vartheta}^{-1}(u)\boldsymbol{u}(u) \tag{28}$$

The weight upgradation equation in RLS is obtained [13]

$$\mathbf{G}(\mathrm{u}) = \frac{\mathbf{G}(\mathrm{u})}{\sum_{\mathrm{b}=1}^{\mathrm{u}}\frac{1}{\lambda}\cdot[\mathbf{c}(\mathrm{b})\mathrm{d}^*(\mathrm{b})]}(\mathrm{u})\mathbf{z}(\mathrm{u}-1)$$

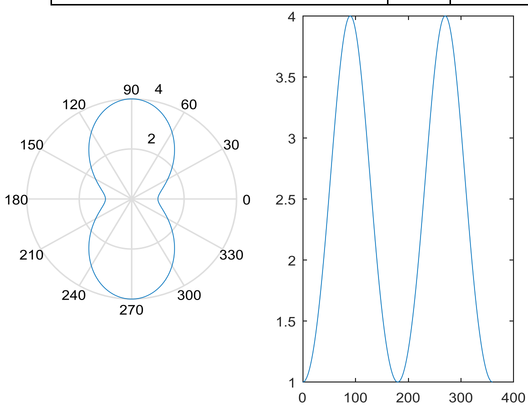
$$+\frac{\mathrm{G}(\mathrm{u})}{\sum_{\mathrm{b}=1}^{\mathrm{u}}\frac{1}{\lambda}\cdot[\mathrm{c}(\mathrm{b})\mathrm{d}^*(\mathrm{b})]}(\mathrm{u})\mathrm{c}(\mathrm{u})\mathrm{d}^*(\mathrm{u}) - \mathrm{b}(\mathrm{u})\mathrm{c}^{\mathrm{H}}(\mathrm{u})\frac{\mathrm{G}(\mathrm{u})}{\sum_{\mathrm{b}=1}^{\mathrm{u}}\frac{1}{\lambda}\cdot[\mathrm{c}(\mathrm{b})\mathrm{d}^*(\mathrm{b})]}(\mathrm{u}-1)\mathrm{z}(\mathrm{u}-1) \tag{29}$$

V. Simulation Results and Discussion

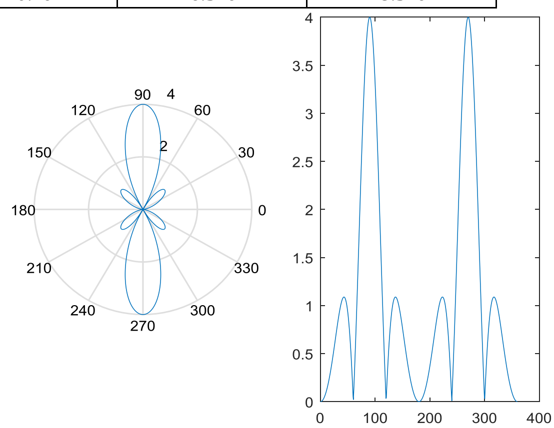
In this work, the LMS and RLS algorithms results have been evaluated for their convergence rate and beamforming. The performance of null steering such as: beamwidth, null depths and maximum sidelobe level has been examined and computed. Table 1 shows the results these algorithms. LMS and RLS nearly show equal dependence on SNR and SIR. The weights of the estimated system is nearly identical with the real one.

TABLE I. RESULTS OF THE ALGORITHMS

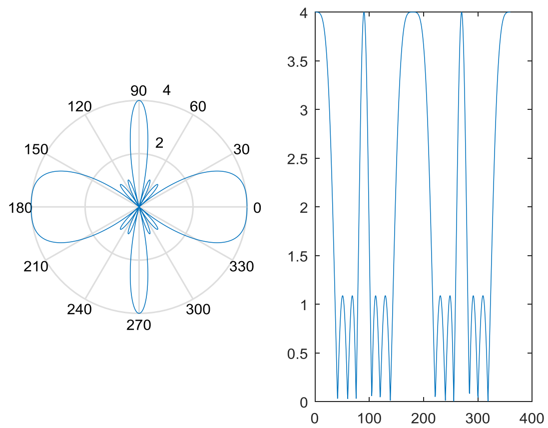
Beamforming Algorithm Analysis	M	Beamwidth	Sidelobe Level	Null depth (-18^0)	Null depth (35^0)
LMS	10	14^0	-9.5dB	-32dB	-38dB
	15	6^0	-9.8dB	-28dB	-32dB
	20	7^0	-13dB	-29dB	-27dB
RLS	10	13.57^0	-5.3dB	-21.37dB	-38.25dB
	15	6^0	-5.5dB	-25.23dB	-36.73dB
	20	7^0	-10.7dB	-16.31dB	-48.37dB



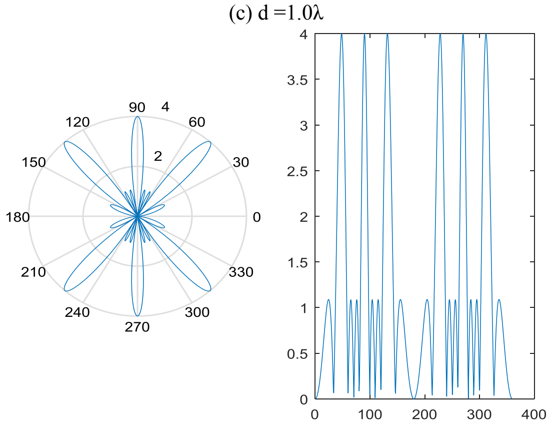
(a) d =0.2λ



(b) d =0.5λ



(c) d =1.0λ

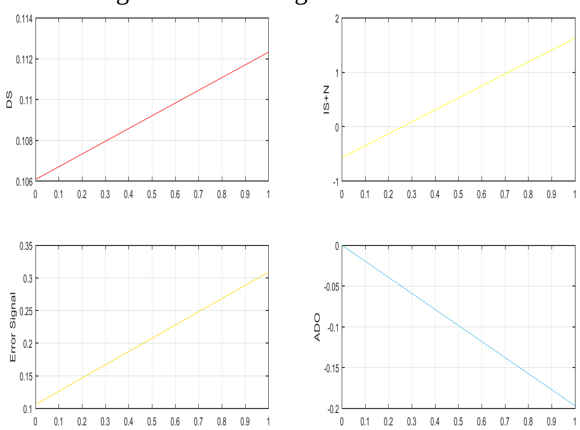


(d) d =1.5λ

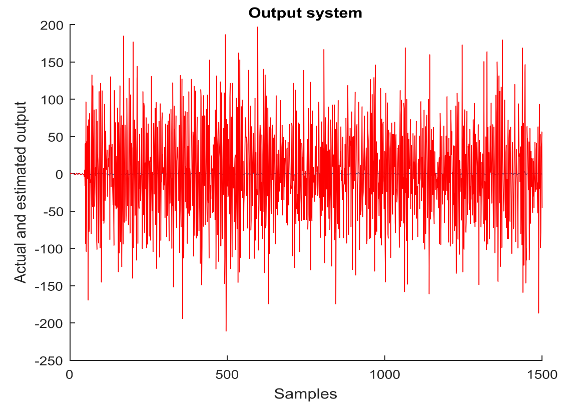
Fig. 3. Antenna element's spacing.

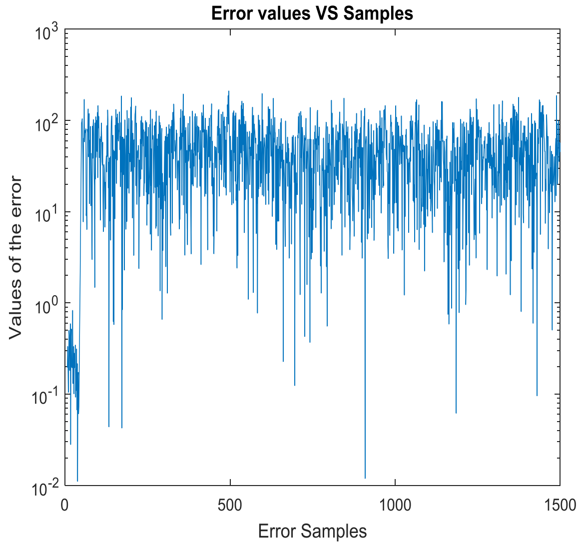
From Fig. 3, we observed that when the antenna element spacing is increasing we have a: (i) narrower main lobe, (ii) grating lobes, (iii) reduction in beamwidth (thus making the array more directional), and (iv) reduction in sidelobe level, thus improving beamforming. It has also been observed that there is no grating lobe when d/λ = 0.5, which is the optimal design spacing for the array antenna elements in the smart antenna.

We observed in Fig. 4 (a) that equal number of antenna elements inputs (N and mu), the desired signal (DS) and the adaptive desired output (ADO) starts from the origin and takes the same shape i.e. a straight line curve. If N > mu, all the shapes takes zig-zag curve. If mu > N, only the desired signal takes a straight line curve.



(a) LMS adaptive algorithm simulated curve





(b) LMS adaptive algorithm filtering curve.

Fig. 4. LMS adaptive algorithm and filtering curve

To minimize the error signal, we need adaptive filtering. This process is referred to as convergence. It is observed in Fig. 4 (b) that adaptive filter takes a short time to calculate the error signal.

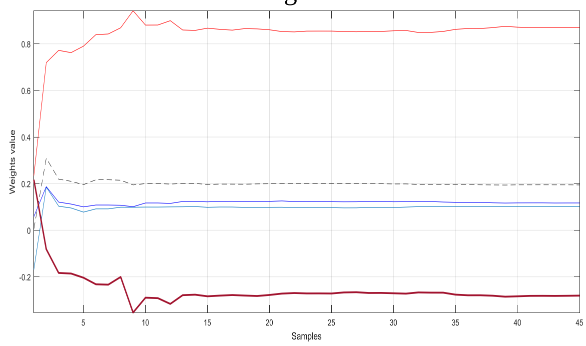


Fig. 5. RLS adaptive algorithm curve.

Fig. 5 shows the estimated weights convergence of the weights value and samples for the Recursive Least Square (RLS) algorithm. RLS algorithm takes less number of iteration to achieve a steady state error with mean square error.

VI. Conclusions

In this work, LMS and RLS algorithms have been examined and analyzed. d =0.5λ has been used as the optimal distance between the antenna in this work. It has been observed that LMS algorithm has better realization apart from the slow rate of convergence and inability to nullify co-channel interference. Hence, RLS is chosen to improve the convergence rate of LMS at the expense of higher Sidelobe Level and lower null depths. RLS algorithm has better response towards co-channel interference, generates better main lobe in desired direction and has faster convergence with order of magnitude rate than LMS, hence the best of all

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