Reduction Of Convergence Error In Adaptive Beam Forming Antenna

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ABSTRACT

Wireless communication network with much higher coverage capacity has triggered more research interest especially in beam forming techniques using smart antennas. The smart antenna adopts smart signal processing algorithms to track the location of mobile user device. However the main limitations to high-performance wireless communication are interference from other users (co-channel interference), inter-symbol interference (ISI) and signal fading caused by multipath effects. Co-channel interference limits the system capacity and is defined as the number of users which can be serviced by the system. This work therefore deploys a conjugate gradient method for mitigating convergence error in adaptive beam forming for smart antenna. The conjugate gradient method was compared with the analytical and least square modulus to validate the methodology and determine the most effective approach in terms of error minimization. The results of the research outcome showed that; the conjugate gradient method performed better than the least square method and analytical approach. The outcome of the analysis are presented in graphical results. The convergence of the conjugate gradient method was achieved with a minimum of seven iterations.

Keywords: Smart Antenna, Artificial Neural Network, Array Factor, Conjugate Gradient

INTRODUCTION

A smart antenna system is a multi-element antenna that systematically combine received signals from each antenna to better the performance of the wireless system. Smart antennas has the capability to boost signal range, mitigate signal fading, handover, suppress interfering signals, and improve the capacity of wireless systems.

Signals transmitted or received by smart antennas cannot be tracked by any other receiving device thus, this enables very high secured information to be transmitted. This paper therefore focuses on the required algorithm to achieve adaptive beam forming in the antenna radiation pattern. The antenna makes use of array gain, diversity gain and interference suppression to improve capacity of wireless network which results in increased data rate. It enhances its performance by adding more users to the system with same data rate per user.

Multipath fading results due to reflection and scattering which is avoided by smart antennas. In terms of power consumption, user capacity and noise suppression, smart antennas provide better performance than existing antennas. They can change the radiation pattern dynamically by adjusting noise, interference and multipath effects to a side lobe radiation.

The difference between smart and fixed antenna is based on the radiation pattern which have adaptive and fixed lobe respectively. The smart antennas transmit or receive signals in adaptive or spatially sensitive manner. So many operations of PC's cellular networks noticed rapid increase in signal quality and coverage. This technology is recent in the field of wireless and mobile communication which are limited by factors such as multipath and co-channel interference.

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Smart antennas are mainly of two types; the switched beam antenna and adaptive array antenna. Switched beam system have several fixed beam patterns. A decision is made as to which beam to access, at any given point in time based on system requirement. From multiple fixed beam generated, one beam is steered towards the target. Adaptive array antenna allows the beam to be continually steered to any direction to allow for the maximum signal to be received and /or the nulling of any interference.

I. Statement of the problem

High-performance wireless communications systems have some constraint when communication terminals send and receive signals. These signals are subject to mutual interference. The characteristics of the medium of propagation changes randomly, and the mobile radio channel introduces different variations in the power of the received signal. Other distortions such as frequency shifts and the spread of signals overtime are also a contributing factor. When power is radiated from an antenna, very little of it gets to the receiver. This problem is arrested by increasing transmitting power. The challenges related to signal connectivity, travel path and signal convergence has stimulated a lot of research in recent years. The constant change in the angle of arrival of signals has also limited the speed of the converging signal thereby increasing the convergence error of that signal. If attempted convergence is too fast, the weights of the signals will oscillate about the optimum weights which will lead to an inaccurate tracking of the desired solution. This work adopts a conjugate gradient method for mitigating the convergence error in adaptive beam forming for smart antenna.

II. REVIEW OF RELATED WORK.

Marwa *et al.,* (2020) undertook a study on the analysis of beam forming for smart antenna with the use of least mean square algorithm. The authors focused on the performance of LMS algorithm by adjusting the weights to reduce the mean square error that would exist in between the signal wave form. The identified drawback of least mean square approach include; many iterations before convergence is achieved.

Yigit *et al.,* (2005), worked on improvement of the performance of downlink beam forming using Adaptive Linear Neural Network (ADALINE). Auto regressive neural network was used to predict downlink vector weight with auto regressive modeling approach. Both combination resulted in improved performance of the downlink beamforming.

Zoogghby et al., (2018) looked at the issue of multiple source tracking with smart antenna. In the work, a system was proposed and implemented for communication using satellite for terrestrial system. The authors built a neural tracking system of multiple sources using an algorithm tagged RBFNN; Radical Base Functional Neural Networks. It was found out that the RBFNN algorithm had high degree of accuracy and the sources greater than the number of antenna elements was located by the system using the algorithm.

Ashraf *et al.,* (2016) carried out a performance analysis of smart antenna system using the Least mean square (LMS), Recursive least square (RLS), Sample matrix inversed (SMI), Normalized least mean square (NLMS), Hybrid Least Mean Square/Sample Matrix Inversion (HLMS/SMI) algorithms for beam forming. It was seen that, increase in the number of radiating elements increased directivity and reduced the beam width. It was also concluded that the normalized least mean square algorithm performed better than the other aforementioned in terms of speed, convergence, stability of beam forming, simplicity of computation and low side lobe level.

Sarevska et al., (2004) proposed a solution to the multiple source problems of tracking using neural network that was based on smart antenna. The authors estimated the angle of arrival and detected the signal with the help of the neural network. The authors found that the result had a very high speed.

Anil et al., (2012) noted that the method of conjugate gradient generates vector sequence of iterates, including residuals corresponding to the very iterates and then search directions used in updating both the residual and iterates.

Joseph et al., (2017) studied the performance of least mean square adaptive algorithm applied in adaptive beam forming using matlab. The work was simulated by using 30 degrees as the angle of arrival (AOA) and -50 as the angle of interference. It was concluded that when the number of antenna element was increased, narrower beams were produced.

Nabian et al., (2018) proposed a solution to the multiple source problems of tracking using neural network which is based on smart antenna. The authors estimated the angle of arrival and detected the signal with the help of the neural network. The proposed system had a very high speed when compared with ordinary neutral algorithms.

Chang, and Hu (2012) undertook the analysis of various reconfiguration components that have often been used to change antenna structure and function. Different categories of smart antenna systems were analyzed by the authors. It was proved by the authors that instead of using traditional antenna, smart antenna improved the overall performance of the system.

Arunitha et al. (2015) carried out a study of the adaptive beam forming algorithms. The authors comprehensively reviewed the different evolutionary algorithms used for adaptation. The author adopted the weight of the antenna array to maximize the expected output in the right direction while minimizing unwanted signal from undesired direction. For tracking user automatically, the authors made use of the algorithm for adaptive beam forming. Blind beam forming and non-blind beam forming algorithms were discussed, and the simulation was carried out in the matlab environment. In the simulation, the number of elements used was 8 while the separation between radiating element was 0.5.

Vavrda (2015) described digital beam formers as a way of removing wanted signal from the unwanted, interfering signals. The constraints inherent in the application of techniques for digital beam forming as well as the adaptive beam forming was highlighted. The way digital beam forming and adaptive beam forming is achieved was explained. For digital beam forming, the author noted, digital technology is combined with antenna technology. Spatiotemporal signals were converted by the antenna into temporal ones, hence the signal are available for numerous techniques for signal processing.

Mallaparapu et al (2011) investigated non-blind adaptive beam forming algorithms. The authors observed from their work that for smart antenna beam forming can be employed when there is a need for channel band width increment and capacity enhancement, especially for wireless services. As noted by the authors, channel interference can be minimized for effective communication in wireless system using beam forming

Yuanjian and Xiaohui (2016) came up with a novel adaptive algorithm for beam forming for smart antenna. This was done by the authors by making an improvement on gradient vector projection to what is called uniform linear array. The performance of the developed adaptive beam forming algorithm was compared with the least mean square algorithm. It was found by the authors that the developed algorithm performed very well when compared with the least square method.

Saad (2013) carried out research to optimize phased array antenna radiation pattern. The author employed the method of least mean squared algorithm in the optimization process. The least mean squared algorithm incorporates neural networks in its application. The research was aimed at evaluating the effectiveness of the adaptive algorithm LMS, to evolve the antenna functionality.

Using some key parameters and some equations related to antenna, simulation was performed and results obtained. Great potential was observed in using the technique of neural network in the analysis of the effectiveness of least mean squared algorithm, especially as it concerns signal processing in phased array antennas.

Frank B. Gross (2015) compared different algorithms as to their effectiveness in improving the convergence error in adaptive beam forming antennas. The author realized that when compared with constant modulus, least square constant modulus and least mean square algorithms, the conjugate gradient method performed better in reducing convergence error.

III MATERIALS AND METHODS

I. Research Methodology

The methods adopted in the study includes the following

i. Develop an adaptive beam forming antenna array model
ii. Obtain data for assigned signal weight and ANN training
iii. Develop a neural network model in Matlab
iv. Train the neural network using feed forward back propagation algorithm
v. Adaptive conjugate gradient method to minimize convergence error

II. Model Description

To analyze adaptive beam forming process we consider the propagation of a plane wave in an acoustic environment at the speed of sound (c) = 340m/s and impinges on a uniform linear sensor array consisting of M omnidirectional microphones.

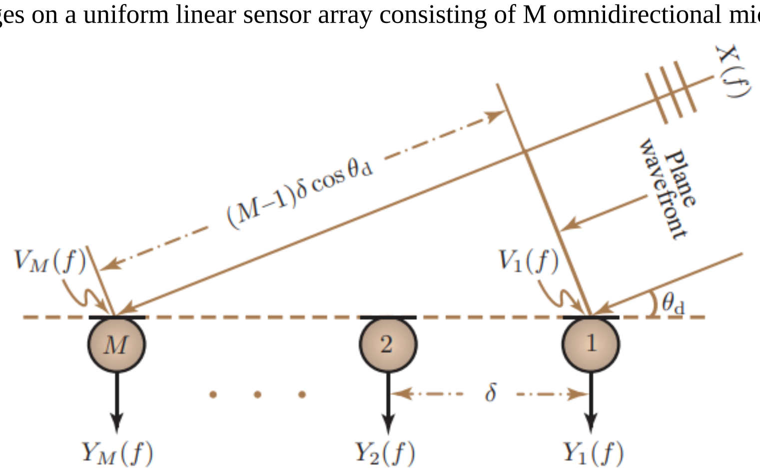

Figure 1 A uniform linear array with M sensors

The Signal model is given by

$$y(f) = x(f) + v(f)$$
$$= d(f.cos\theta_d)x(f) + v(f) \quad (1)$$

Where; $y(f)$ is observation signal vector (of length M), $d(f.cos\theta_d)$ is the steering vector associated with the desired signal $x(f)$, impinging on the array from the direction θ_d, and $v(f)$is the noise signal vector.
The correlation matrix of $y(f)$ is

$$\Phi_y(f) = \Phi_x(f) + \Phi_v(f)$$
$$= \phi x(f)d(f.cos\theta_d)d^H(f.cos\theta_d) + \Phi_v(f) \quad (2)$$

Where; $\Phi_x(f)$ and $\Phi_v(f)$are the correlation matrices of $x(f)$ and $v(f)$, respectively, and $\phi x(f)$ is the variance of $x(f)$.
Beamforming or linear filtering consists of applying a complex-valued linear filter, $h(f)$, of length M to $y(f)$

$$Z(f) = h^H(f)y(f)$$
$$= h^H(f)[x(f) + v(f)]$$
$$= X_{fd}(f) + V_{rn}(f) \quad (3)$$

Where; $Z(f)$ is, in general, the estimate of the desired signal, and $X_{fd}(f)$ and $V_{rn}(f)$ are the filtered desired signal and residual noise, respectively. Assuming that $X_{fd}(f)$ and $V_{rn}(f)$ are uncorrelated, the variance of $Z(f)$) is

$$\phi z(f) = \phi x_{fd}(f) + \phi v_{rn}(f)$$
$$= \phi x(f)|h^H(f)d(f.cos\theta_d)|^2 + h^H(f)\Phi_v(f)\, h(f) \quad (4)$$

A smart antenna system consists of array of antennas with digital signal processing techniques. The later uses two algorithms which are array factor (AF) and adaptive beam forming. The array factor algorithm (AF) is used for calculating the direction of arrival of all incoming signals. While adaptive beam forming algorithm used to update the weights of each element. Figure 2 shows the block diagram of the proposed adaptive beam forming model.

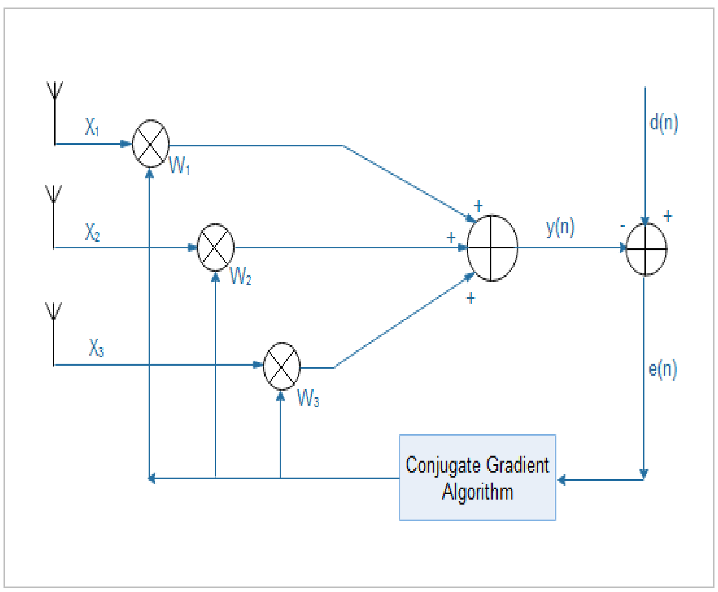

Figure 2 Block Diagram of Adaptive Beam forming Array Antenna Model

III. Data Collection

The data in this analysis were generated by writing a MATLAB code using the mathematical equation (4). Table 1-3 show the received signal, initial weight and array factor for different spacing respectively.

Table: 1 Received Signals at incident angle 30° for different spacing

N	d=1	d=0.5	d=0.25
1	1.7570 - 1.5062i	1.3785 - 0.7531i	0.6893 - 0.3765i
2	0.1416 + 0.0000i	1.5708 + 1.0000i	0.7854 + 0.0000i

3	1.7570 + 1.5062i	1.0785 + 0.7531i	0.6893 + 0.3765i
4	0.6974 + 1.6436i	0.8487 + 1.3218i	0.4244 + 0.6609i
5	0.2222 + 1.1337i	0.1111 + 1.0669i	0.0556 + 0.7834i
6	-1.3074 + 0.8566i	-0.6537 + 0.1283i	-0.3268 + 0.7142i

Table: 2 Weight of Signals at incident angle 30° for different spacing

N	d=1	d=0.5	d=0.25
1	1.0000 + 0.0000i	1.0000 + 0.0000i	1.0000 + 0.0000i
2	0.6661 - 0.7458i	-0.9127 + 0.4086i	0.2089 + 0.9779i
3	-0.1125 - 0.9936i	0.6661 - 0.7458i	-0.9127 + 0.4086i
4	-0.8161 - 0.5780i	-0.3033 + 0.9529i	-0.5902 - 0.8072i
5	-0.9747 + 0.2236i	-0.1125 - 0.9936i	0.6661 - 0.7458i
6	-0.4825 + 0.8759i	0.5087 + 0.8609i	0.8685 + 0.4956i

Table 3 Training Data

n	Input		Target
	$\lvert \boldsymbol{W}_{(n)} \rvert$	$\lvert \boldsymbol{X}_{(n)} \rvert$	$\lvert \boldsymbol{Y}_{(n)} \rvert = \lvert \boldsymbol{W}_{(n)} \rvert * \lvert \boldsymbol{X}_{(n)} \rvert$
1	1.0000	0.3142	0.3142
2	0.9830	0.1416	0.1392
3	0.9706	0.3211	0.3117
4	0.9713	0.7853	0.7628
5	1.0096	0.1553	0.1568
6	0.9905	0.5630	0.5577
1	1.0000	0.5708	0.5708
2	0.9830	0.8621	0.8474
3	0.9706	0.3154	0.3061
4	0.9713	0.5708	0.5544
5	1.0096	0.0727	0.0734
6	0.9905	0.6662	0.6599
1	1.0000	0.6935	0.6935
2	0.9830	0.5854	0.5754
3	0.9706	0.2588	0.2512
4	0.9713	0.6725	0.6532
5	1.0096	0.1002	0.1012
6	0.9905	0.1706	0.1690

IV. Mathematical Model

I. Determination of Array Factor

Array factor is used to determine the direction of arrival of all incoming signals

$$AF(\theta) = \sum_{n=0}^{N-1} w_n \, e^{j\left(\frac{-(N-1)}{2}+n\right)kd\sin\theta} \qquad 5$$

Where

AF= array factor in degree

K= wave number$\left(\frac{2\pi}{\lambda}\right)$

λ =wavelength of incident wave

w_n =weight of n^{th} radiating element

II. Determination of Incident Signals on n^{th} radiating element

Incident Signals on n^{th} (hypothetical assumption on the number of radiating element) describes the signal incident on the n^{th} sensor

$$x_n(n) = \sum_{i=0}^{N-1} S_i(n)\, e^{j\left(\frac{-(N-1)}{2}+n\right)kdsin\theta_i} + n_n(n) \quad 6$$

Where;

$S_0(n)$= desired signal

$S_{1\rightarrow(M-1)}(n)$= interference signal

$n_n(n)$= received noise signal at nth element

III. Determination of weighted sum of the output node

Weighted sum of the output node is the sum of all incident signal and associated signal weight

$$v_i = \left([w_1 \quad w_2 \quad w_3] * \begin{bmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \end{bmatrix}\right) + b \quad 7$$

$$v_i = (w_1 * x_{1i}) + (w_2 * x_{2i}) + (w_3 * x_{3i}) + b \quad 8$$

Where;

$x_1(n)$= incident signal of radiating element 1

$x_2(n)$= incident signal of radiating element 2

$x_3(n)$= incident signal of radiating element 3

w_1= weight of signals $x_1(n)$

w_2= weight of signals $x_2(n)$

w_3= weight of signals $x_3(n)$

b= bias which is associated with the storage of information

IV. Determination of Output Signal

Output Signal is a sum of all the signals to the n^{th} radiating element and the associated noise distortion

$$y(n) = \emptyset(\boldsymbol{v_i}) \quad 9$$

$$y(n) = \emptyset((w_1 * x_{1i}) + (w_2 * x_{2i}) + (w_3 * x_{3i}) + b) \quad 10$$

$$y(n) = \emptyset(v_i) = \left(\frac{1}{1+e^{-v_i}}\right) \quad 11$$

$$Ouput\ (y) = \frac{1}{1+e^{-((w_1*x_{1i})+(w_2*x_{2i})+(w_3*x_{3i})+b)}} \quad 12$$

Where;

$\emptyset$= activation function (Tan Sigmoid Function)

v_i = weighted sum of the output node

V. Determination of Error signal

Error signal is the difference between the desired signal and the output signal

$$e(n) = d(n) - y(n) \quad 13$$

$$e(n) = d(n) - \overline{w} * \bar{x}(n) \quad 14$$

Where;

$d(n)$ = desired signal

$y(n)$ =output signal

3.5 Conjugate Gradient Method

The conjugate gradient algorithm was used to update the weights by changing the phase shift and amplitude attenuation of the received signals so that the main beam is steered toward the direction of the desired signals thereby minimizing error. This method is used due to its fast convergence rate.

$$\alpha_k = \frac{r_k^T r_k}{P_k^T A P_k} \quad 11$$

$X_{x+1} = X_x + \alpha_k P_k$ 12

$\beta_k = \frac{r_{k+1}^T r_{k+1}}{r_k^T r_k}$ 13

$P_{x+1} = r_{k+1} + \beta_k P_k$ 14

Where;

α=learning rate

P_k= search direction

r_k= gradient computation

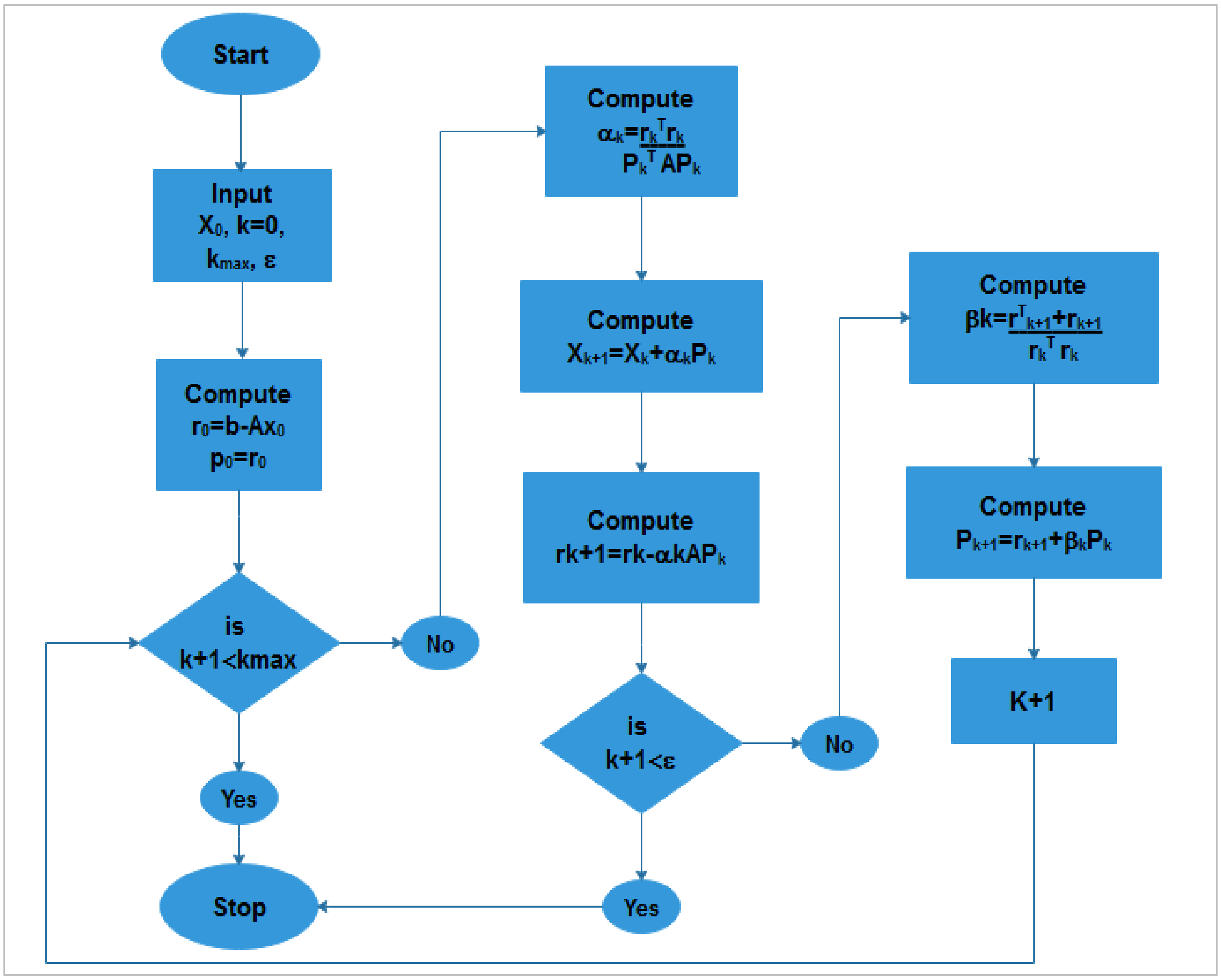

Figure 3: Flowchat of Gradient Conjugate Method

The description in figure 3 explains the programming sequence used to achieve the gradient conjugate simulation. Describing the input variables as X_0 with a range $(0, \varepsilon)$ and inputting these variables in an equation, the results are analyzed by the decision of the value of k, if undesired values are got then the process is repeated with a new equation and a condition to be achieved and the repetition is continued till the desired condition is achieved. The results at various numerically described values will be analyzed and tabularized to enable valid comparisons of the various methods.

RESULT AND DISCUSSION

Table 4 Analytical Method

Element spacing(D)	Elements in series (n)	Received Signal $\lvert x_{(n)} \rvert$	Weight $\lvert w_{(n)} \rvert$	Output Signal $\lvert y_{(n)} \rvert$	Desired Signal $\lvert d_{(n)} \rvert$	Error $\lvert e_{(n)} \rvert$
Λ	6	0.3142	1.0000	0.3142	1	0.6858
		0.1416	0.9831	0.1392	1	0.8608
		0.3211	0.9707	0.3117	1	0.6883
		0.7853	0.7167	0.5628	1	0.4372
		0.1553	1.0097	0.1568	1	0.8432
		0.5630	0.9906	0.5577	1	0.4423
0.5 λ	6	0.5708	1.0000	0.5708	1	0.4292
		0.8621	0.7510	0.6474	1	0.3526
		0.3154	0.9705	0.3061	1	0.6939
		0.5708	0.9713	0.5544	1	0.4456
		0.0727	1.0096	0.0734	1	0.9266
		0.6662	0.9905	0.6599	1	0.3401
0.25 λ	6	0.6935	1.0000	0.6935	1	0.3065
		0.5854	0.9829	0.5754	1	0.4246
		0.2588	0.9706	0.2512	1	0.7488
		0.6725	0.8226	0.5532	1	0.4468
		0.1002	1.0100	0.1012	1	0.8988
		0.1706	0.9906	0.1690	1	0.8310

Table 4 presents the result obtained analytically. A closer look at the table shows that there was an error of 0.6858 when the input signal was 0.3142° for six radiating elements, n = 6 and a spacing of λ between the radiating elements. For a spacing of 0.5λ apart and an input signal of 0.4292°, the error was 0.5708. For 0.25λ spacing, the error was 0.3065. While the least error of 0.3065 occurred when the input signal was 0.6935°, the highest error of 0.8988 occurred when the input signal was 0.1002°.

Table 5 Conjugate Gradient Method (CGM)

Element spacing(D)	Elements in series (n)	Received Signal $\lvert x_{(n)} \rvert$	Weight $\lvert w_{(n)} \rvert$	Output Signal $\lvert y_{(n)} \rvert$	Desired Signal $\lvert d_{(n)} \rvert$	Error $\lvert e_{(n)} \rvert$
λ	6	0.3142	1.7804	0.5594	1	0.4406
		0.1416	2.8100	0.3979	1	0.6021
		0.3211	1.6138	0.5182	1	0.4818
		0.7853	1.0219	0.8025	1	0.1975
		0.1553	2.6478	0.4112	1	0.5888
		0.563	1.2265	0.6905	1	0.3095
0.5 λ	6	0.5708	1.1477	0.6551	1	0.3449
		0.8621	1.0358	0.893	1	0.107
		0.3154	1.9464	0.6139	1	0.3861
		0.5708	1.2055	0.6881	1	0.3119
		0.0727	6.2531	0.4546	1	0.5454
		0.6662	1.0839	0.7221	1	0.2779
0.25 λ	6	0.6935	1.1902	0.8254	1	0.1746
		0.5854	1.2005	0.7028	1	0.2972
		0.2588	2.2249	0.5758	1	0.4242
		0.6725	1.1254	0.7568	1	0.2432
		0.1002	3.5739	0.3581	1	0.6419

		0.1706	2.4343	0.4153	1	0.5847

Table 5 is a presentation of the conjugate gradient method. The table shows that the least error of 0.107 was obtained when the input signal 0.8621°. The highest error of 0.6419 occurred when the input signal was 0.1002°. For a spacing of λ between the radiating elements the error was 0.4406. The error became 0.3449 when the radiating was separated by 0.5λ apart. When the separation between the radiating elements was 0.25λ apart, the error was 0.1746.

Table 6 Least Square Constant Modulus Method (LSCM)

Element spacing(D)	Elements in series (n)	Received Signal $\lvert x_{(n)} \rvert$	Weight $\lvert w_{(n)} \rvert$	Output Signal $\lvert y_{(n)} \rvert$	Desired Signal $\lvert d_{(n)} \rvert$	Error $\lvert e_{(n)} \rvert$
λ	6	0.3142	1.4494	0.4554	1	0.5446
		0.1416	2.0318	0.2877	1	0.7123
		0.3211	1.4235	0.4571	1	0.5429
		0.7853	0.8560	0.6722	1	0.3278
		0.1553	1.8467	0.2868	1	0.7132
		0.5630	1.0689	0.6018	1	0.3982
0.5 λ	6	0.5708	1.1887	0.6785	1	0.3215
		0.8621	0.8719	0.7517	1	0.2483
		0.3154	1.3966	0.4405	1	0.5595
		0.5708	0.9723	0.5550	1	0.4450
		0.0727	3.8281	0.2783	1	0.7217
		0.6662	0.9665	0.6439	1	0.3561
0.25 λ	6	0.6935	1.0884	0.7548	1	0.2452
		0.5854	1.1245	0.6583	1	0.3417
		0.2588	1.5429	0.3993	1	0.6007
		0.6725	0.9463	0.6364	1	0.3636
		0.1002	2.8593	0.2865	1	0.7135
		0.1706	1.7767	0.3031	1	0.6969

Table 6 gives the presentation of the least square constant modulus method. A closer look at the table shows that the least error of 0.2452 occurred when the input signal is 0.6935°. The highest error of 0.6969 was observed when the separation between antenna radiating elements was 0.25λ and the input signal was 0.1706°.

Table 7 Comparison of Output Signal

Analytical	CGM	LSCM
0.3142	0.5594	0.4554
0.1392	0.3979	0.2877
0.3117	0.5182	0.4571
0.5628	0.8025	0.6722
0.1568	0.4112	0.2868
0.5577	0.6905	0.6018
0.5708	0.6551	0.6785
0.6474	0.8930	0.7517
0.3061	0.6139	0.4405
0.5544	0.6881	0.5550

0.0734	0.4546	0.2783
0.6599	0.7221	0.6439
0.6935	0.8254	0.7548
0.5754	0.7028	0.6583
0.2512	0.5758	0.3993
0.5532	0.7568	0.6364
0.1012	0.3581	0.2865
0.1690	0.4153	0.3031

In table 7, a comparison of the outputs obtained with the analytical method, conjugate gradient method, and least square constant modulus method is presented. The table 7 shows that the conjugate gradient method had highest values of error in most cases while the analytical method had the least error values in most cases. From the table, the highest output for the analytical, the conjugate gradient, and the least square constant modulus are: 0.6935, 0.8930, and 0.7548 respectively while the least outputs were 0.0734, 0.3581, and 0.2783 respectively.

Table 8 Comparison of the Error

Analytical	CGM	LSCM
0.6858	0.4406	0.5446
0.8608	0.6021	0.7123
0.6883	0.4818	0.5429
0.4372	0.1975	0.3278
0.8432	0.5888	0.7132
0.4423	0.3095	0.3982
0.4292	0.3449	0.3215
0.3526	0.1070	0.2483
0.6939	0.3861	0.5595
0.4456	0.3119	0.4450
0.9266	0.5454	0.7217
0.3401	0.2779	0.3561
0.3065	0.1746	0.2452
0.4246	0.2972	0.3417
0.7488	0.4242	0.6007
0.4468	0.2432	0.3636
0.8988	0.6419	0.7135
0.8310	0.5847	0.6969

As can be seen from table 8 presented above, the errors for the three methods were compared. It was observed from the table that the errors for the conjugate gradient method were smaller when compared to the errors obtained from the analytical method and in the least square constant modulus method. The least error for the three methods, the analytical, the conjugate gradient and the least square constant modulus methods, were 0.3065, 0.1070, and 0.2483 respectively.

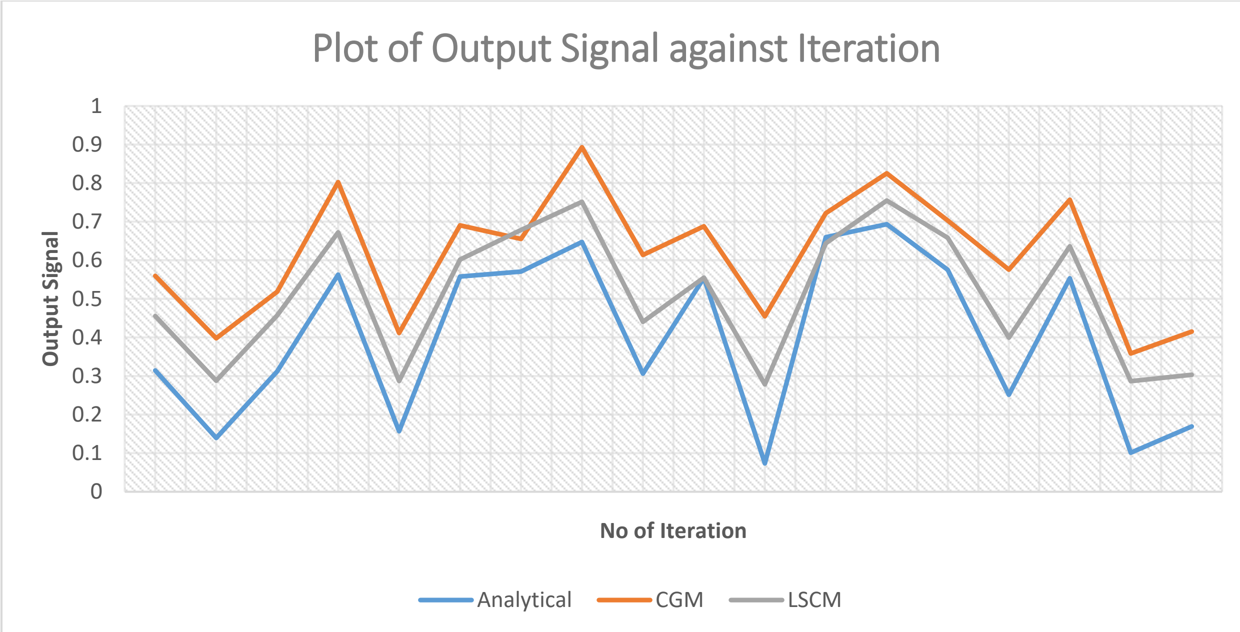

Figure 4: A Plot of Output against Iterations

Figure 4 is a plot of output signal against the number of iterations for the three methods used. The figure is a graphical representation of Table 7 and it is important to note that the iterations could be made numerically infinite so a certain range of output signal is analyzed and the link graph plot is chosen so as to visually indicate how each method performed at different iterated values. The Figure provides a graphical analysis of the output signal values. The graph shows that the analytical method has the least output signal value and the conjugate gradient method has the highest output signal value, surpassing the output signal value of the least square constant modulus method.

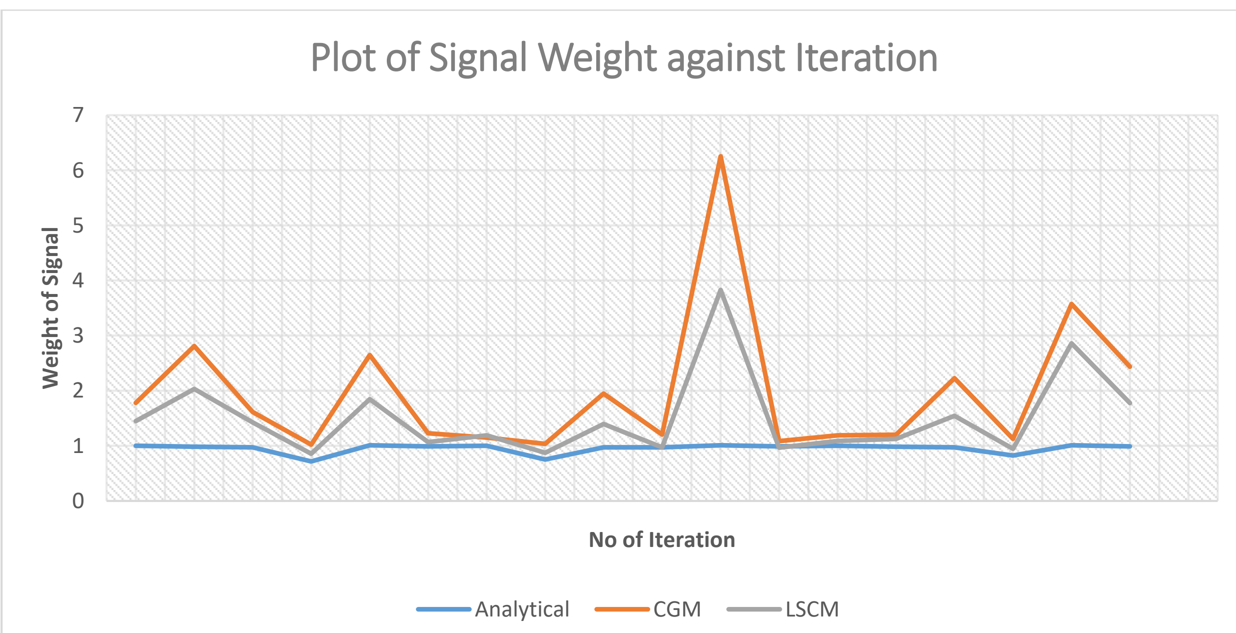

Figure 5: A Plot of Error against Iterations

Figure 5 presents a plot of signal weight against the number of iteration for the three methods used. The weight of the analytical method and that of the least square constant modulus method were closer. The constant gradient method had high weights compared to the other methods. This is because the adjustment in the phase shift and amplitude attenuation of the signal, thereby steering the main beam towards the desired signal.

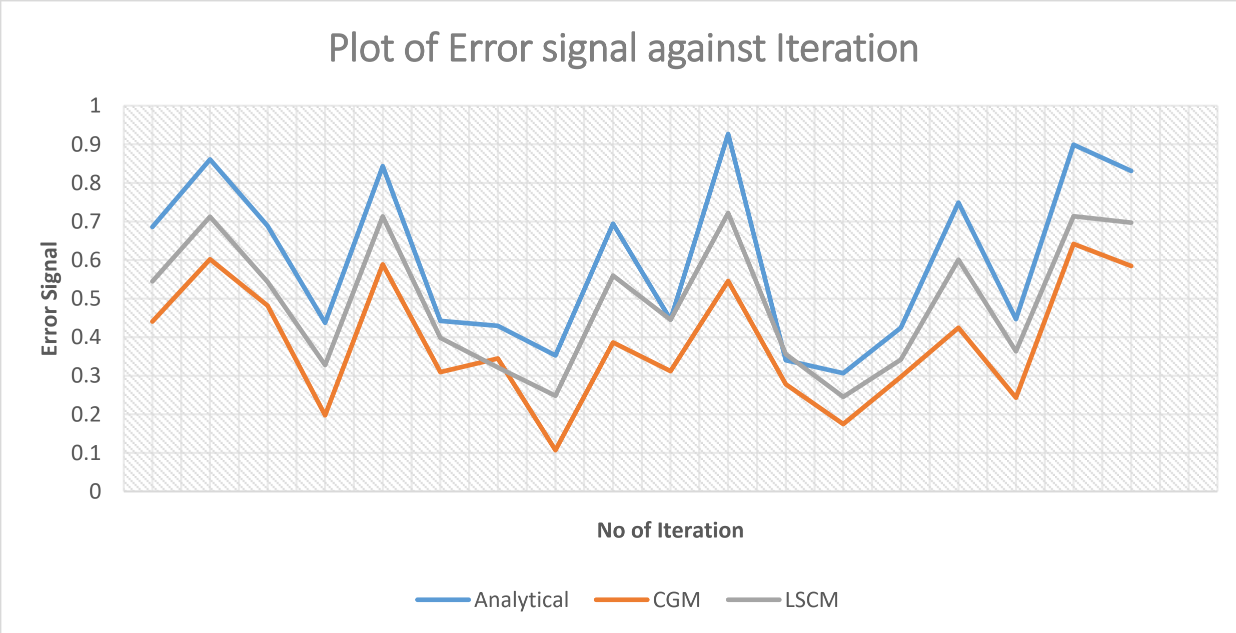

Figure 6: A Plot of Error against Iterations

Figure 6 presents the plot of error signal against the number of iterations. The figure is a graphical representation of Table 8 and the iterative value is a set of consecutive value representing numerical instances to achieve this analysis. Conjugate gradient method had the least error signal embedded in the output signal of the same iterative value. The error signal in the analytical method is the highest and that of the least square constant modulus method is intermediate but still very much higher than that of the Conjugate gradient method.

CONCLUSION

This study looked at reducing convergence error in adaptive beam forming antenna using conjugate gradient method. The research work also compared the effectiveness of the conjugate gradient method and the least square modulus method in terms of error minimization. Analysis and simulation of the conjugate gradient method were carried out in MATLAB environment. Mathematical modeling was carried to determine the output signal, error signal, input signal, etc. Training data for the artificial neural network was the input signal and the weight. The reason for the training was to obtain an anticipated output signal for all input signals fed into the system and also minimize error. For the training, supervised learning was used because the training target was known.

The result of this research work showed that the conjugate gradient method performed better than the least square method in terms of error minimization. The convergence of the conjugate gradient method was achieved with a minimum of seven iterations. Hence, researchers can rely on conjugate gradient method to reduce error in smart antenna system.

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