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ORIGINAL RESEARCH

An adaptive beamforming algorithm for millimeter wave MIMO system

B. Rajarajeswarie[1] · R. Sandanalakshmi[1]

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Abstract In the realm of 5G and beyond, the evolution of wireless communication technologies demands efficient solutions to overcome challenges in Massive Multiple-Input Multiple-Output (MIMO) systems for enhanced Mobile Broadband (eMBB) services. The adaptive beamforming technique leverages the spatial domain to enhance the performance of communication systems by forming directional beams toward desired signals while suppressing interference. In a Massive MIMO scenario, where the number of antennas at the base station is significantly increased, adaptive beamforming becomes crucial for mitigating the interference. This paper explores the application of adaptive beamforming using the conventional Least Mean Squares (LMS) and adaptive gradient (Adagrad) algorithm in the context of MIMO for eMBB use cases. It focuses on the design and optimization of beamforming weights in a Massive MIMO setup, considering the challenges posed by interference. Simulations and performance evaluations are conducted to assess the effectiveness of the adaptive beamforming approach in enhancing the array gain and nullifying the interference signal.

Keywords Adaptive Beamforming · Least Mean Square Error · Adagrad · SystemVue software

✉ B. Rajarajeswarie
rajarajeswarie.b@pec.edu

[1] Department of Electronics and Communication Engineering, Puducherry Technological University, Pondicherry, Puducherry, India

1 Introduction

In today's millimeter wave MIMO communication systems, the antenna plays a major role in transmitting and receiving the signal [1]. In wireless communication, the antennas are categorized into isotropic, omnidirectional, directional, and adaptive. For the theoretical purpose, the isotropic antenna is utilized to radiate equal power of radiation in all directions [2]. Whereas in practical conditions, omnidirectional and directional antennas were implemented. However, the drawback of omnidirectional antennas is that they radiate the signal equally in all directions thereby energy is wasted. Therefore, directive characteristics must be upgraded to overcome this and reduce energy waste. This can be achieved by the directional antenna as it directs more energy in the favoured direction and reduces/nullifies the energy in the other direction. To achieve a higher directivity antenna array is required as it consists of multiple elements [3]. The antenna array contains the information for transmission that is transmitted in the form of a beam. Where the main lobe carries the useful information and the interference signal is generated by the side lobes. Hence, to produce an antenna array, the adaptive antenna is required with signal processing to form a beam in an appropriate direction by the corresponding weights using conventional beamforming or adaptive beamforming techniques [4]. In a conventional beamformer, the weight vector is fixed while in the adaptive beamformer, the weight vector changes adaptively based on the adaptive algorithm [5]. The adaptive algorithm is divided into 2 categories: blind and non-blind adaptive algorithms [6]. In a non-blind adaptive algorithm, the reference signal is required whereas no reference signal is required in a blind adaptive algorithm. The objective of the adaptive beamforming algorithm is to increase the capacity and provide better coverage by suppressing the interference in the unwanted direction [7]. The author in [8, 9] used deterministic and adaptive beamforming techniques. To minimize the array output power, a Capon beamformer is utilized. The adaptive beamforming algorithm is mainly used to enhance the nulling level control by various optimization techniques. A stochastic gradient method based adaptive version of the radial basis function neural network has proposed in [10] to map the pattern features of the control chart patterns in different categories to recognize their belonging class. The author in [11] implemented a Fibonacci Branch Search based optimization algorithm to reduce the probability of reaching into local optimal. The author in [12] proposes a novel Hierarchical Bayesian model based on multinomial distribution and Dirichlet prior to refine the weights for solving such multi-objective route optimization problems. After the literature survey, it is noticed that many worked on LMS algorithm for various applications such as optical communication, radar communication, etc. In wireless communication it is noticed that for short-distance communication the propagation characteristic of mm wave is very poor. Therefore, to overcome this extreme directive antennas are needed [13]. Therefore, adaptive beamforming plays a major role in 5 G. It is implemented in two ways, which include the estimation of direction of arrival (DOA) based beamforming algorithm and the other way is based on the beam reference signal [14]. The traditionally, LMS adaptive beamforming works by adjusting the weights of the antenna elements such that the beam is focused on a signal coming from one way while trying to evade disturbance from other directions with constant step size.Hence this paper emphasises the beam reference signal based method that uses the LMS algorithm with Adagrad method.

1.1 Contribution

The novelty of this paper is to design and analysed adaptive beamforming algorithms using machine learning.

- The first step is to generate the desire and interference signal using ESL System Vue software. Consider three different scenarios, each scenario consists of the desired and the interfering eMBB user with the intended and interfere angle in electronic system level (ESL) System Vue software.
- Collect the intended and interference angle signal from the System Vue software.
- Implement the beamforming algorithm such as least mean square and adaptive gradient method techniques.
- Calculate the array gain, half power beam width, null depth and effective isotropic radiated power (EIRP)

1.2 Organization of the paper

The remaining paper is organized in such a way that section 2 describes the signal model. The non-blind adaptive algorithm such as the least mean square and Adagrad algorithm is explained in section 3. Section 4 emphasises the simulation scenario and the result analysis. Finally, section 5 gives a brief conclusion and future work.

2 Signal model

Consider a uniform linear antenna array (ULA) composed of M antenna elements and the spacing between each antenna elements be $d = 0.5\lambda$, where λ is the wavelength. Assume that the incident array signal source is unrelated to each other and the noise signal is the Gaussian white noise. The received signal consist of desired angle signal, interference and noise signal. The received signal at the m^{th} antenna is given by

$$x_m(t) = \sum_{k=1}^{K} (s_k(t).a_m(\theta_k) + v_m(t)) \tag{1}$$

were:

$x_m(t)$ is the received signal at m^{th} antenna at time t. $s_k(t)$ is the signal from the k^{th} the source. $a_m(\theta_k)$ is the steering vector for the m^{th} antenna corresponding to the k^{th} source. $v_m(t)$ is the additive white noise at the m^{th} antenna.

At time t the overall received signal vector can be $X(t) = [x_1(t), x_2(t), ..., x_M(t)]^T$ and the entire array of the steering vector denoted by $a(\theta_k) = [a_1(\theta_k), a_2(\theta_k), ..., a_M(\theta_k)]^T$ The received signal can be expressed in terms of vectors

$$X(t) = As(t) + V(t) \tag{2}$$

3 Non-blind adaptive algorithm-Least Mean Square (LMS) algorithm

This section describes the LMS algorithm which is a non-blind adaptive beamforming technique for the smart antenna. The Fig. 1 shows the implementation of the LMS algorithm. To analyse the performance of the LMS algorithm, Uniform Linear Array (ULA) type antenna is considered with M antenna elements and the space between each antenna element is denoted by d. The blue dash line represents the beamforming, where $X(t)$ denotes the output signal of the M antenna elements and W is the complex conjugate weight. The beamformer output [15]is given by

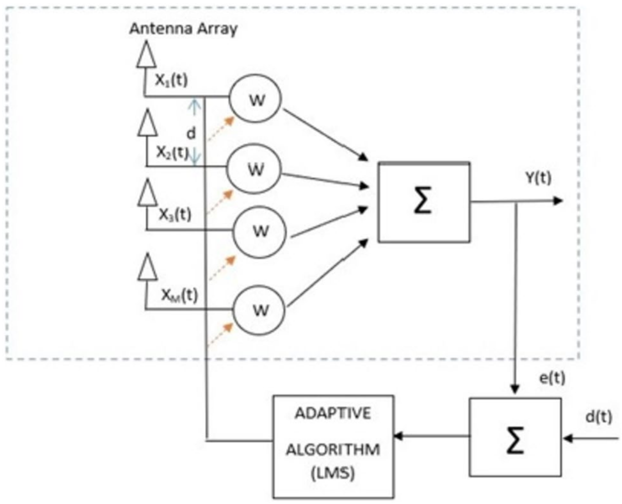

Fig. 1 Uniform Linear Array with Adaptive Beamforming (LMS)

$$Y(t) = \sum_{m=1}^{M} (W_m(t)^T X_m(t)) \tag{3}$$

To avoid matrix inversion, the LMS algorithm utilized the gradient vector $\nabla G(t)$ to upgrade the weight vector. Therefore, the weight vector is given by,

$$W(t+1) = W(t) + \frac{1}{2}\mu[-\nabla G(t)] \tag{4}$$

In the above equation μ denotes the step size, the value of step size varies between 0 to 1 for controlling the convergence speed. The gradient vector $\nabla G(t)$ is given by,

$$\nabla G(t) = -2p(t) + 2R(t)W(t) \tag{5}$$

$$R(t) = X(t)X^H(t)$$
$$p(t) = d^*(t)X(t)$$

By substituting the above equation in the weight updating equation

$$W(t+1) = W(t) + \mu[p(t) - R(t)W(t)] \tag{6}$$

$$= W(t) + \mu X(t)[d^*(t) - X^H(t)W(t)$$
$$= W(t) + \mu X(t)e^*(t)$$

The error between the reference signal and the beamformer signal $y(t)$is minimum as it implements steepest descend gradient vector to update the weight vector. Therefore, the beamformer signal and the error signal are denoted by

$$y(t) = W^H(t)X(t) \tag{7}$$

$$e(t) = d(t) - y(t) \tag{8}$$

The main drawback of this algorithm is that the learning rate μ is identical [16, 17]. Therefore, in the proposed algorithm the learning rate is updated based on the past gradient.

3.1 Adaptive gradient (adagrad) algorithm

This section explains the LMS with Adagrad algorithm, to update the learning rate based on the past gradient. The weight vector representation of the proposed LMS with Adagrad algorithm is denoted by

$$W(t+1) = W(t) - \frac{\mu}{\sqrt{(G_t + \epsilon)}}[g_t] \tag{9}$$

$$\nabla G(t) = g_t$$

In the above equation G_t signifies the diagonal matrix of the gradient and to avoid the denominator term zero, ϵ is added which is termed as the smoothing term. From the equation, it is observed that the learning rate divides the square root of the diagonal matrix of the gradient. Therefore, during the training period the learning rate is reduced. Hence, the benefit of this algorithm is to eradicates the need of the physical tuning learning rate.

Algorithm 1 LMS algorithm

```
Training Samples: Input signal x(n) and Desired signal d(n)
Initialization: weight w(0) = 0
Computation:
for n=1, 2... do
e(n) = d(n) − wᵀ(n)x(n)
w(n + 1) = w(n) + μx(n)e(n)
end for
```

Algorithm 2 Modified LMS (Adagrad) Algorithm

Training Samples: Input signal $x(n)$ and Desired signal $d(n)$
Initialization: weight $w(0) = 0$
Computation:
for n=1, 2... **do**
$e(n) = d(n) - w^T(n)x(n)$
$W(n+1) = W(n) - \frac{\mu}{\sqrt{(G_n+\epsilon)}}[g_n]$
$\nabla G(n) = g_n$
end for

Table 1 Simulation parameters and their values

Parameters	Values
Carrier frequency	28 GHz
Bandwidth	100 MHz
Element spacing	$\lambda/2$
Modulation	16 QAM

Table 2 Simulation parameters and their values

Parameters	Case 1	Case 2	Case 3
Desired Angle	30°	30°	-2° and 20°
Interfere Angle	45°	-12° and 45°	9°

4 Simulation scenario and parameters

This section gives a brief description of the simulation scenario created in the ESL System Vue software. In this software, the 5G library has an NRDL Source GUI block which is used to generate the 5G NR signals. This signal is then modulated. The signal is in the form of a random bit sequence. This signal is passed to the 5G NR downlink source, where the system parameters are defined such as carrier frequency, bandwidth, modulation. The uniform linear antenna array consists of 8 elements, that are shared by using shared array architecture by RF beamformer to generate a signal at the desired direction. The Table 1 provides the simulation parameters.

The proposed algorithm is assessed based on the three different cases with single and multiple interference. The algorithm is validated by verifying the beam pattern for 3 different cases.

In the first case scenario, the desired signal is at an angle of 30° and the interference is at the 45°. The simulation results are analysed in terms of simulation metric (Table 2). The Fig. 2 describes the beam pattern performance for the LMS and modified LMS algorithm. From the Fig. 2 it is observed that the level of nullifying the interference is large in the case of Adagrad algorithm. From the Table 3 it is noticed that the Adagrad algorithm nullify the interference angle at 45° by 10 dB when compared to the LMS algorithm.

In the second case scenario, two interfere signal are considered -12° and 45°. The desired angle is at 30 degrees. From the Fig. 3 it is observed that the level of nullifying the interference is large in the case of Adagrad algorithm. From the Table 4 it is noticed that the Adagrad algorithm nullify the interference angle at -12° and 45° by 12 dB and 10 dB when compared to the LMS algorithm. It shows the proposed algorithm provides the narrow beam towards 30°.

In the third case scenario, the desired signal is at an angle of -2° and 20°. Whereas the interference is at the 9°. The simulation results are analysed in terms of simulation metric such as Gain, EIRP, Null Depth and Half power beamwidth. The Fig. 4 describes the beam pattern performance for the LMS and modified LMS algorithm. From the Fig. 4 it is observed that the level of nullifying the interference is large in the case of Adagrad algorithm. From the Table 5 it is noticed that the

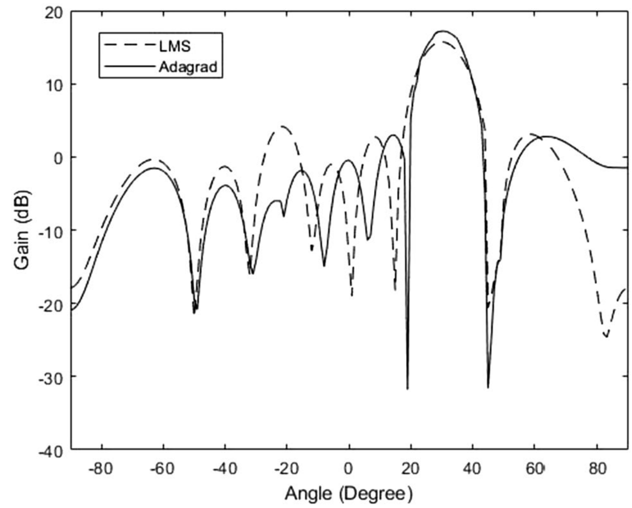

Fig. 2 Beam pattern Performance for the case 1 scenario

Table 3 Performance analysis for first scenario

Parameters	Case1	
	LMS	Adagrad
Gain (dB)	15.71	17.2
Null depth (dB)	−20.584	−31.6
Half power bandwidth (degree)	15	13
EIRP (dBm)	52.71	54.2

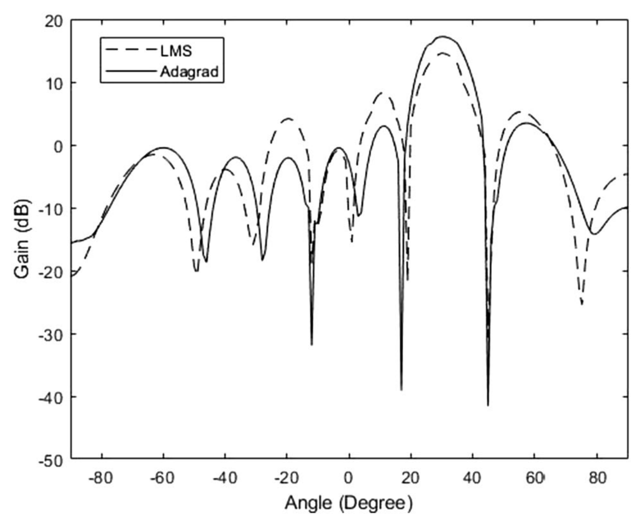

Fig. 3 Beam pattern Performance for the case 2 scenario

Table 4 Performance Analysis for second scenario

Parameters	Case2	
	LMS	Adagrad
Gain (dB)	14.589	16.98
Null depth (dB)	−18.84,−30.62	−31.9,−41.58
Half power bandwidth (degree)	15	12
EIRP (dBm)	51.589	53.9

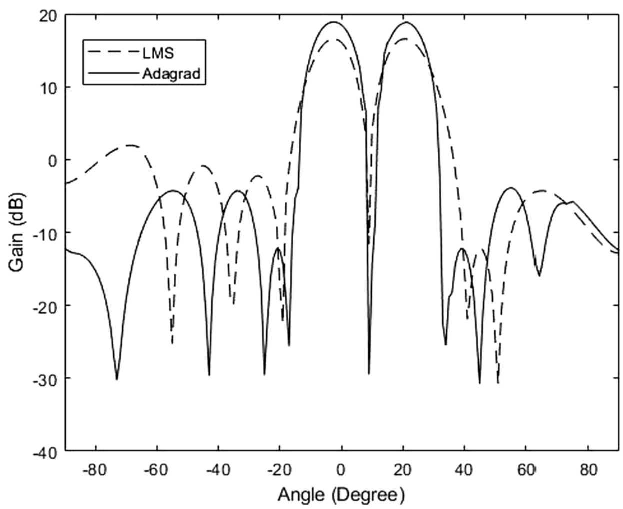

Fig. 4 Beam pattern Performance for the case 3 scenario

Table 5 Performance Analysis for third scenario

Parameters	Case3	
	LMS	Adagrad
Gain (dB)	16.5	18.6
Null depth (dB)	−11.66	−28.48
Half power bandwidth (degree)	14.2	12.5
EIRP (dBm)	53.5	55.6

Adagrad algorithm nullify the interference angle at 9° by 15 dB when compared to the LMS algorithm.

From the Fig. 5 it is noticed that the adaptive gradient method has the fastest convergence rate over the other conventional adaptive beamforming algorithm. The LMS algorithm requires 60 iterations while Adagrad requires 25 iterations to converge. The adaptive gradient method has about 58% of improvement over the conventional LMS.

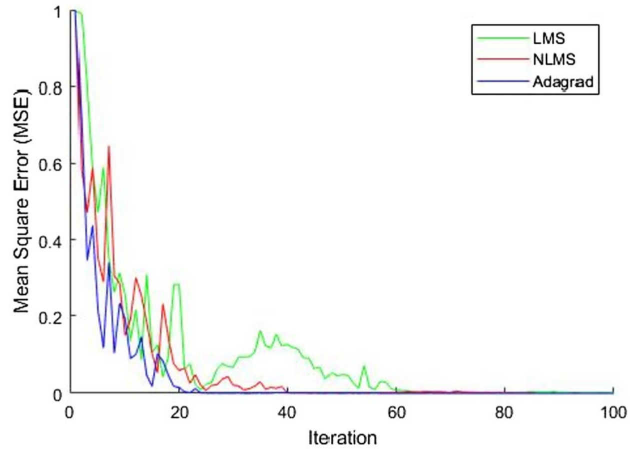

Fig. 5 Performance of iteration vs MSE

5 Conclusion

In this paper, a modified LMS algorithm (Adagrad) is used in mm wave MIMO system. For 3 different cases, this algorithm was investigated. From the result it is observed that the Adagrad algorithm provides better null steering in the interfere direction when compared to the conventional LMS algorithm. That is the suppress of side lobe level is 20dB in the first case scenario and 13 dB in the second and third cases. The adaptive gradient method has about 58% of improvement over the conventional LMS.This significantly reduces the processor speed. Hence this method is most suitable for 5G low latency communication. The main application of the adaptive beamformer consists of autonomous vehicles, radar, military applications and sonar. Therefore, the future work of this algorithm is to incorporate in autonomous vehicles.

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Data availability Data is available from the corresponding author [Rajarajeswarie B] upon reasonable request.

Declarations

Conflict of interest The authors declare no Conflict of interest.

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