Performance Enhancement of Smart Antennas Algorithms for Mobile Communications System

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Research Article

Date of Submission: 01-05-2025 Date of Acceptance: 09-05-2025 Date of Publication: 10-06-2025

Abstract—In order to improve the performance of mobile communications systems, this research suggests two novel smart antenna algorithms based on a combined approach. The first suggested combination approach combines the pure Normalized Least Mean Square (NLMS) and Conjugate Gradient Method (CGM) algorithms to create a new algorithm known as CGM-NLMS. The second suggested technique, known as the CGM-MLLMS algorithm, will combine the pure CGM and Modified NLMS algorithms. One variable regularization parameter that is fixed in the traditional NLMS technique is the MNLMS algorithm. Rather than using a fixed regularization parameter, the regularization parameter makes use of a reciprocal of the estimate error square of the update step size of NLMS. The estimated weight coefficients obtained from the first stage of the CGM algorithm are kept and then used as starting weight coefficients for processing the NLMS (or MNLMS) algorithm using the newly suggested CGM-NLMS and CGM-MNLMS algorithms. According to simulation results of an adaptive beamforming system using a fading channel and a Jakes power spectral density channel model, the two newly suggested algorithms outperform the pure CGM and pure NLMS algorithms in terms of speedy convergence, increased interference suppression, and low levels of mean square deviation (MSD) and minimum mean square error (MSE) at steady state.

I. Introduction

The simplicity of the Least Mean Square (LMS) method developed by Widrow and Hoff in 1960 is its key characteristic [1]. Furthermore, neither a matrix inversion nor measurements of the relevant correlation functions are needed [1]. The LMS algorithm's very sluggish rate of convergence is its primary drawback [1]. Normalized LMS (NLMS) is a modification of the LMS algorithm that uses normalization to improve the convergence rate [1, 2]. The normalized LMS algorithm may be thought of as an LMS algorithm with a step-size parameter that varies over time [1]. Error Normalized Step Size LMS (ENSS), Robust Variable Step Size LMS (RVSS) [3], and Error-Data are some of the time-varying step size techniques for the NLMS algorithm. There are reports of the Normalized Step Size LMS (EDNSS) [3] and others [3–15]. In 2004, the generalized normalized gradient descent (GNGD) method [6] updated the NLMS step size using a gradient adaptive term. In 2006, the first free tuning method was presented [7], which updated the step size using the anticipated noise power and the mean square error [7]. A normalized gradient is used to regulate the regularization parameter update in the resilient regularized NLMS (RR-NLMS) filter, which was developed in 2006 [8]. To improve the GNGD's performance, a different hybrid filter structure technique was put out in 2007 [9]. Considered a time-varying step size NLMS, the noise restricted normalized least mean squares (NC-NLMS) adaptive filtering was suggested in 2008

[10]. The generalized square error regularized NLMS method (GSER) [10,11] is another free tuning NLMS technique that was developed in 2008 [11,12]. In 2008, the variable step size NLMS technique was introduced to use the inverse of weighted square error [13]. In 2010, it was proposed to update a variable step size NLMS algorithm using the Euclidian vector norm of the output error [14]. In 2012, another nonparametric approach was introduced that made use of the estimated noise power and mean square error [15]. All of these techniques have considerable computational cost or suffer from pre selection of ertain constant parameters in the early adaptive processing stage. This study proposes a tuned-free (i.e., nonparametric) version of the Modified Normalized Least Mean Square method (MNLMS). Instead of using a constant value (), it used time changing regularization [16]. In some situations, the gradient-based directions approach has a sluggish rate of convergence. Hestenes and Stiefel created the conjugate gradient technique (CGM) in the early 1950s to address this issue [17]. The problem with the CGM is that the rate of convergence is dependent on the matrix's conditional number. As a result, several changes have been suggested to enhance the CG algorithm's performance for various applications [18]. A constant value or a normalized step size may be used in lieu of the step size in [19]. Additionally, by altering the distribution of the eigenvalues and clustering them around a single point, the preconditioning procedure is utilized to speed up the CGM algorithm's rate of convergence. An method for smart antennas in mobile communication systems was developed in 1997 using the spatial and temporal diversity for the CGM algorithm [20]. They proposed new forward and backward algorithms in 1999 to address the issue of applying CGM for a limited amount of both pictures and array items. multilayer (WBCGM) and CGM (FBCGM) techniques [21]. An technique based on the conjugate gradient was used in 2013 to achieve interference alignment in time-varying MIMO (multiple input and multiple output) interference channels. With is the signal vector that is wanted. is a signal vector that interferes.

is each channel's mean Gaussian noise. approach in conjunction with metric projection is used for [22]. To minimize the mean square error (MSE) of the linear system, the adaptive block least mean square method (B-LMS) was introduced in 2013 [23]. It uses conjugate gradient search directions to determine the ideal step size. Even though a pure CGM algorithm performs better than a pure NLMS algorithm, combining both techniques into a single algorithm may still improve performance. A novel method for achieving low levels of MSD and MSE, rapid convergence, and increased interference suppression capabilities is presented in this study. The suggested methods combine the NLMS (or MNLMS) algorithm as the second stage with CGM as the first stage. Thus, the variable step size method's strong tracking ability, low level of MSD, and MSE of the NLMS (or MNLMS) algorithm are paired with the desired quick convergence and good interference suppression capabilities of CGM. The following parts make up the paper: A summary of traditional adaptive algorithms is presented in the next section. The suggested method (MNLMS) will be introduced in part III, and an analysis of the algorithm's time-varying step size will be provided in section IV. The CGM algorithm will be introduced in section V. The two combination algorithms that are suggested will be provided in Section VI. The simulation results of the suggested algorithms, as well as those of the pure

CGM and pure NLMS algorithms, are shown in section VII. An understandable rationale for the suggested two algorithms' improved performance will be provided in section VIII. Lastly, we wrap up the article based on the simulation findings in the last section.

II. A NOVE RVIEW OF CLASSICAL ADAPTIVE ALGORITHMS

The M-element array smart antenna system may be shown as shown in Fig. 1. This graphic illustrates how the weight vector has to be adjusted to reduce error while iterating the array weights [24]. An array of M elements with M potential weights receives the signal and interferers [24]. Additive Gaussian noise is also included in every received signal at element m. The kth time samples are used to represent time. As a result, the weighted array output may be shown as follows [24]: 1) When the input signal vector is equivalent to the following and the operator T indicates the vector transposed:

is the steering vector for the direction of arrival in an M-element array.

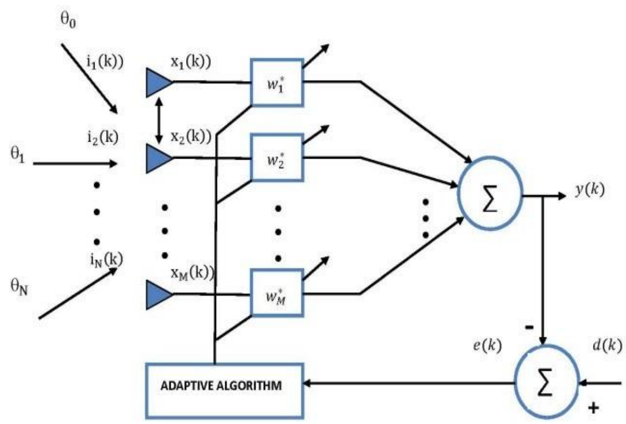

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Fig.1.BlockdiagramofSmartAntennasSystem.

The disparity between the output signal and the intended signal is known as an error signal [24].

$$e(k) = d(k) - \bar{w}^T(k)\,\bar{x}(k) \quad (3)$$

By using the gradient of cost function, the weight vector of LMS is:

$$\bar{w}(k+1) = \bar{w}(k) + \mu\, e(k)\,\bar{x}(k) \quad (4)$$

This constant parameter is called the step size [24]. The step size parameter should be constrained by [25] to ensure the stability of the LMS algorithm.

$$0 < \mu < \frac{2}{tr\,[\bar{R}]} \quad (5)$$

Where $\bar{R}$isthe correlation matrix. Note thatallthe components that are equal on the major diagonal. is itself equal to the input's mean square value at each of the FIR filter's M-taps, thus

$$tr\,[\bar{R}] = M\, r(0) \quad (6)$$

A constant step size µ proportionate to the stability constraint is used by the LMS algorithm:

A constant step size µ proportionate to the stability constraint is used by the LMS algorithm:

(7) $\mu_{MAX} = \frac{2}{M\,r(0)}$

$$\bar{x}(k) = \bar{a}_0 \bar{s}(k) + [\bar{a}_1 \bar{a}_2 \ldots \bar{a}_N] . \begin{bmatrix} i_1(k) \\ i_2(k) \\ \vdots \\ i_N(k) \end{bmatrix} + \bar{n}(k)$$

$$= \bar{x}_s(k) + \bar{x}_i(k) + \bar{n}(k) \quad (2)$$

$\frac{1}{M}\,\bar{x}^T(k)\bar{x}(k$

GORITHMrate. To achieve a low degree of misadjustment at steady state, as seen in Fig. 2, the step size is small and the error signal is significant when the error signal is small. This prevents the update weights from diverging and makes the MNLMS more stable and converges faster than NLMS
Since this is the maximum step size, the practical formula for the step size used to NLMS is [25]:

$$\mu_{NLMS}(k) = \frac{u_0}{\varepsilon + \bar{x}^T(k)\bar{x}(k)} \quad (10)$$

where is a little positive constant that has to be limited in order to ensure that the NLMS algorithm converges [25],

$$\bar{w}(k+1) = \bar{w}(k) + \frac{\mu_0}{\varepsilon + \|\bar{x}(k)\|^2}\, e(k)\bar{x}(k) \quad (11)$$

Where $\|\bar{x}(k)\|^2 = \bar{x}^T(k)\bar{x}(k)$

To get around the issue of dividing by a tiny number for the, the fixed regularization parameter is introduced [24].

III. MODIFIEDNORMALIZEDLEASTMEANSQUAREALGORITHM (MNLMS)

A novel approach to step size selection is presented by the suggested MNLMS algorithm [16]. The step size update parameter may see a decrease in value due to the tiny constant in the NLMS algorithm. This decrease in step size has an impact on the NLMS algorithm's weight stability and pace of convergence. To prevent the denominator from becoming zero and to regulate the step size in each iteration, the MNLMS algorithm may use the error signal [16]. Using this method, the parameter may be set as follows:

$$\varepsilon(k) = \frac{1}{e(k)^2} \quad (12)$$

algorithms.

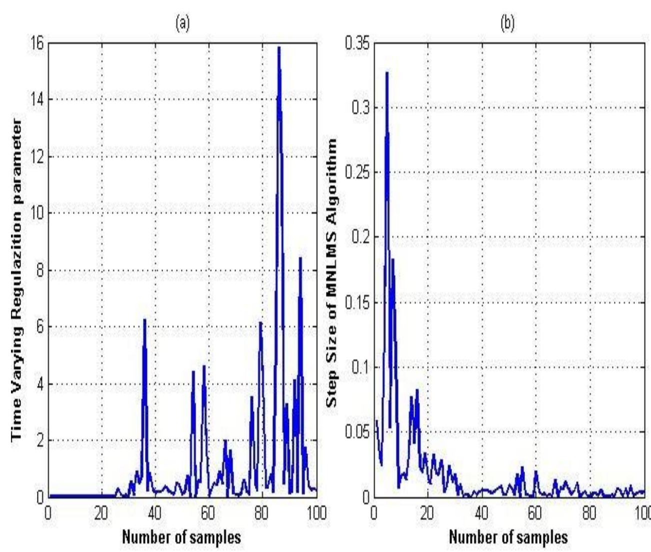


Fig.2. (a) Profile change of parameter and (b) Profile change of step size parameters ( )ofMNLMSalgorithm.

IV. ANALYSIS OF THE PROPOSE DMNLMS ALGORITHM

Using a methodology like to that used in [4, 25], this section will provide an estimated performance analysis for the suggested MNLMS algorithm. The suggested algorithm's weight coefficients are changing as shown in (17). The new version of this is:

(15) $$\bar{w}(k+1) = \bar{w}(k) + \mu_{mnlms}(k)e(k)\bar{x}(k)$$

Let $\bar{w}(k)^*$ represents the time varying optimal weightvector that is computed as [4]:

Theproposednewstepsizeformulacanbewrittenas

$$\mu_{mnlms}(k) = \frac{\mu_0}{\varepsilon(k)+\|\bar{x}(k)\|^2}$$

Where is the zero-mean white process disturbance located [4]? Additionally, let denotes the ideal estimation error procedure, which is defined as [4]:

Evidently, is governed by the normalization of both reciprocal of the input or data vector squared with the estimating error. Consequently, the MNLMS weight vector (17) (18) The algorithm is

(14)

$$\bar{w}(k+1) = \bar{w}(k) + \frac{u_0}{\varepsilon(k)+\|\bar{x}(k)\|^2}e(k)\bar{x}(k)$$

Let representsthecoefficientmisadjustmentvector (error vector) defined as [25]:

The reciprocal of the squared estimate error and input tap vectors causes the MNLMS step size to decrease and rise, as shown in (13). To put it another way, if the error signal is high at the start of the adaptation process, the step size is modest and big to improve convergence.

$$\bar{v}(k) = \bar{w}(k) - \bar{w}(k)^*$$

Substitutes(18and19) in(3)for$d(k)$and respectively, then e(k)in (3) becomes:

$$\begin{aligned} e(k) &= \\ e(k) &\quad \zeta(k) + \bar{x}^T(k)\bar{w}(k)^* - \bar{x}^T(k)\bar{w}(k) \\ &= \zeta(k) - \bar{v}^T(k)\bar{x}^T(k) \end{aligned}$$

Takingexpectedvalueof(20)aftersquaringit,then

$$E[e^2(k)] = \xi_{min} + \sigma^2(\bar{x})tr[\bar{G}(k)]$$

Alinearsearchisusedtodetermineα(k)which minimizes$j(\bar{w}(k))$.

(33) $$E[\bar{v}(k+1)] = [\boldsymbol{I} - E[\mu_{mnlms}(k)]E[\bar{x}^T(k)\bar{x}(k)]]E[\bar{v}(k)]$$

(23) $$\alpha(k) = \frac{\bar{r}^H(k+1)\bar{A}\bar{A}^H\bar{r}(k+1)}{\bar{r}^H(k)\bar{A}\bar{A}^H\bar{r}(k)}$$

If the predicted value of the step size parameter falls within the following range, the suggested method will converge.

$$0 < E[\mu_{mnlms}(k)] < 2 \quad (24)$$

V. CONJUGATEGRADIENTMETHOD(CGM)

With each subsequent iteration, the CGM algorithm selects conjugate (perpendicular) pathways in an iterative search for the optimal solution [24]. The objective of the iterative CGM technique is to minimize the quadratic cost function [24].

$$J(\bar{w}) = \frac{1}{2}\bar{w}^H \bar{A}\,\bar{w} - \bar{d}^H \bar{w} \qquad (25)$$

where K is the number of snapshots and M is the number of array elements, and is the K x M matrix of array snapshots.
is K snapshots' intended signal vector. The cost function's gradient may be shown to be [24]:

$$\nabla_w J(\bar{w}) = \bar{A}\,\bar{w} - \bar{d} \qquad (26)$$

Beginning with a first estimate for the weights, the first residual value after the first estimate (iteration = 1) is provided as [24]:

$$\bar{r}(1) = -J'(\bar{w}(1)) = \bar{d} - \bar{A}\bar{w}(1) \qquad (27)$$

The new conjugate direction vector $\bar{D}$ to iterate toward the optimum weight is [24]:

Finding the residual and the associated weights, then updating until convergence is achieved, is the process for using CGM.

VI. TWO NEW PROPOSED COMBINATION ALGORITHMS

The two proposed algorithms can summarized as the following

1. 1. The CGM-NLMS algorithm, which combines the CGM and NLMS techniques, is the first suggested algorithm. To get the final ideal weight1, the NLMS method starts with the weight vector determined by the CGM algorithm.
2. CGM-MNLMS is the name of the second algorithm that has been suggested. Based on the CGM and the suggested MNLMS algorithms, it employs two distinct algorithm phases.
3. The calculated weight coefficients from the first CGM algorithm are stored in the suggested (CGM-NLMS) and (CGM-MNLMS) algorithm schemes, and they are then employed as starting weight coefficients for processing NLMS (or MNLMS) algorithms. In this manner, previously calculated values derived from the first method (CGM) will be used to start the NLMS weight coefficients rather than zero. The step sequence for the two suggested methods is shown in Table 1.

VII. SIMULATIONRESULTS

This section simulates and examines the CGM-NLMS, CGM-MNLMS, pure CGM, and pure NLMS algorithms for use in mobile communications systems with smart antennas.

$$\bar{D}(1) = \bar{A}^H \bar{r}(1) \qquad (28)$$

Thegeneralweightupdateexpressionisgivenby[24]:

Table1CGM-NLMSandCGM-MNLMSalgorithm

Set the parameters: K , AOA0, AOA1, AOA2, the order of the FIR and the number of array elements ; Generate the desired and interference signals; Step0:Initialization(CGMasthefirststage)

$\overline{w(0)} = [0,0,\ldots\ldots,0]^T$

$\bar{d} -$

For a hundred average ensemble runs, the Mean Square Error (MSE) is also calculated.

$\mu_{CGM}(k)$ *TheSimulationoftheRayleighFadingChannelwith Jakes Model*

$\bar{x}(:,k)$

$\bar{w}(k) + \mu_{CGM}(k)\bar{D}(k)$

$\bar{r}(k+$ $\bar{D}(k+$

$\bar{w}(K/2)$

A deterministic technique for modeling time-correlated Rayleigh fading waveforms, the Jakes fading model—also referred to as the Sum of Sinusoids (SOS) model—is used in the simulations and is still in use today. Assuming that N equal-strength rays reach a moving receiver with uniformly dispersed arrival angles, the model predicts that ray n will undergo a Doppler shift, where v is the vehicle speed, c is the speed of light, and v is the carrier frequency. Consequently, the No + 1 complex oscillator, where No = (N/2 - 1) /2, may be used to simulate the fading waveform. The equation is the result of this [26].

$$T_k(t) = \sqrt{\frac{1}{2N+1}}\left\{2\sum_{n=1}^{N_0}(\cos\beta_n + j\sin\beta_n)\cos(\omega_n\cos\alpha_n t + \theta_{nh}) + \sqrt{2}\cos(\omega_m t + \theta_{0h})\right\} \quad (38)$$

$e(k) \qquad - \bar{w}^T(k)\,\bar{x}(k)$

$$\bar{w}(k+1) = \bar{w}(k) + \frac{\mu_0}{\varepsilon + \|\bar{x}(k)\|^2} e(k)\,\bar{x}(k)$$

$$\bar{w}(k+1) = \bar{w}(k) + \frac{u_0}{\varepsilon(k) + \|\bar{x}(k)\|^2} e(k)\,\bar{x}(k)$$

Where h=1, 2…, and h is the waveform index. The wavelength of the transmitted carrier frequency is denoted by N0 and λ. Here. In order to create the various waveforms, Jakes recommends using [26].Every algorithm's performance is examined in relation to (34) All algorithms' performance is examined in terms of their (34) ability to reduce interference, MSD, and MSE learning curve. A linear array with M=10 isotropic elements and element spacing is utilized in all of the simulations shown here. A cosine input signal with a frequency of MHz is the desired signal, and 200 iterations are specified. The intended signal's desired angle of arrival (AOA) is set to and two interfering signals with AOAs, respectively. 30 dB is the signal to noise ratio (SNR), and 10 dB is the signal to interference ratio (SIR). For every 200 iterations, the ensemble run average is 100. For a 100 average ensemble run, the Mean Square coefficients deviation (MSD) is calculated using the following formulas: dB interference suppression capabilities, MSD, and MSE learning curve. A linear array with M=10 isotropic elements and element spacing is utilized in all of the simulations shown here. A cosine input signal with a frequency of MHz is the desired signal, and 200 iterations are specified. Two conflicting signals with AOAs are tuned to the desired signal's Desired Angle of Arrival (AOA). in turn. 30 dB is the signal to noise ratio (SNR), and 10 dB is the signal to interference ratio (SIR). For every 200 terations, the ensemble run average is 100.For a 100 average ensemble run, the Mean Square coefficients deviation (MSD) is calculated as follows: dB

34)

In this case, the ideal weight vector may be calculated as [1]:-, and the predicted weight is vector.

$$\bar{w}^* = \hat{R}_x^{-1}\,\hat{r} \quad (35)$$

Where $\hat{R}_x$ is the estimation of input correlation matrix and $\hat{r}$ is the estimation correlation vector respectively.

$$\hat{R}_x = \bar{x}(k)^T \, \bar{x}(k) \quad (36)$$

$$\hat{r} = \bar{x}(k)^T \bar{d} \quad (39)$$

$$\theta_{nh} = \frac{\pi n}{N_0+1} + \frac{2\pi(h-1)}{N_0+1}$$

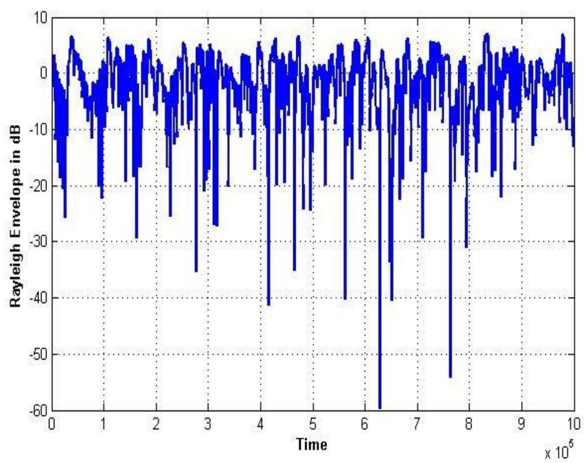
The result was shown as a power spectrum, with the sampling time (or sample number) on the x axis and the fluctuation of the signal strength on the y axis [26]. With the sampling time (or sample number) on the x axis and the fluctuation of the signal strength on the y axis, the result was shown as a power spectrum [26].

$$T_h(t) = \sqrt{\frac{2}{N_0}} \left\{ \sum_{n=1}^{N_0} (\cos\beta_n + j\sin\beta_n) \cos(\omega_n \cos\alpha_n t + \theta_{nh}) \right\} \quad (40)$$

A. The speed of an automobile is set to 80 km/h at 900 MHz to illustrate a typical case situation. Figure 3 displays the Rayleigh Envelope that arises with inputs of v = 80 km/h, = 900 MHz, = 500 kbps, U = 3, and M = 1000000, where M is the number of channel coefficients and U is the number of sub-channels.

B. LinearRadiationPatternofalgorithms

It is necessary to use an Additive White Gaussian Noise (AWGN) channel model, which accounts for just additive, zero mean Gaussian noise in each received signal at element m in Fig. 1, in order to accurately evaluate the performance of smart antennas for mobile communication systems.



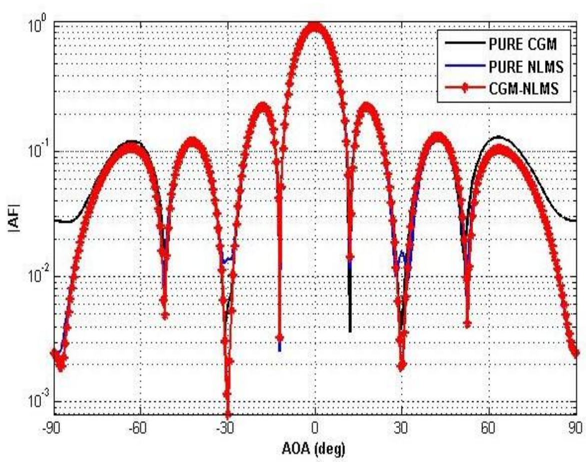


Fig.3SimulationofJakes fadingmodelwithv=80km/h.

The linear plot of the radiation pattern for the pure NLMS and pure CGM algorithms is shown in Fig. 4. According to this figure, at interference angles of -30o and 30o, respectively, the pure CGM produces a deeper null of around -28 dB. Conversely, at interference angles, NLMS produces a null of around -19 dB.

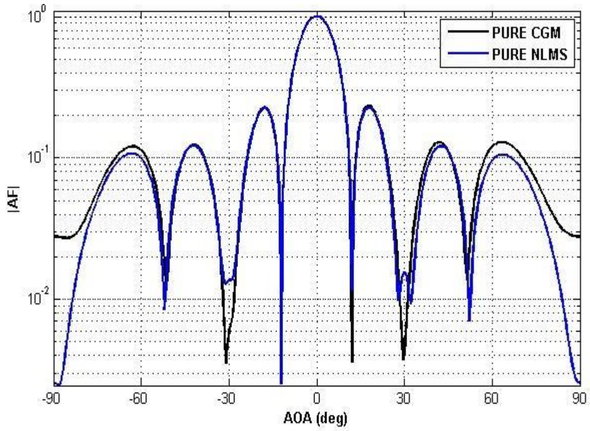


Fig.4LinearradiationpatternsforpureCGM,andNLMS algorithms/Rayleigh channel

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The radiation pattern's linear plot for the pure CGM, pure NLMS, and CGM-NLMS algorithms is shown in Fig. 5. In comparison to both pure CGM and pure NLMS algorithms, the CGM-NLMS method produces a deeper null of around -32 dB and -29 dB for interference angles of -300 and 300, respectively, as this figure illustrates. This indicates that, in comparison to pure CGM and pure NLMS algorithms, the suggested CGM-NLMS method improves interference suppression by an average of around 2.5 and 11 dB, respectively. The linear plot of the radiation pattern for the CGM-MNLMS, pure NLMS, and pure CGM algorithms is shown in Fig. 6. In comparison to the pure CGM and CGM-NLMS algorithms, the CGM-MNLMS algorithm produces a deeper null of around -32 dB for interference angles of -300 and 300, respectively, as seen in this figure.

Fig.5LinearradiationpatternsforpureCGM,pureNLMSandCGM- NLMS algorithms/Rayleigh channel

This indicates that when compared to pure CGM and NLMS algorithms, the second suggested CGM-MNLMS method improves interference suppression by an average of 4 dB and 13 dB. To put it another way, the second suggested algorithm outperformed the previous one in terms of performance.

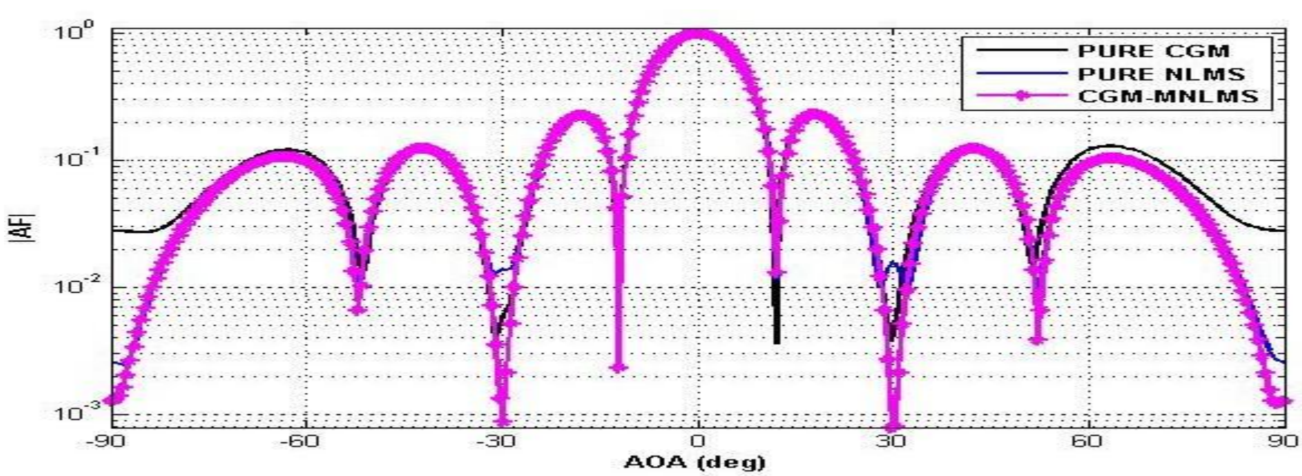

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Fig.6LinearradiationpatternsforpureCGM,pureNLMSandCGM- MNLMS algorithms/Rayleigh channel

C. EstimationOneWeight

For the first 20 iterations and a single run, the magnitude estimate for one element weight () is shown in Fig. 7. This chart shows that the CGM-MNLMS performs better than the other algorithms in terms of low degree of misadjustment in steady state and quick convergence rate. Furthermore, the CGM-NLMS method performs better than both pure algorithms.

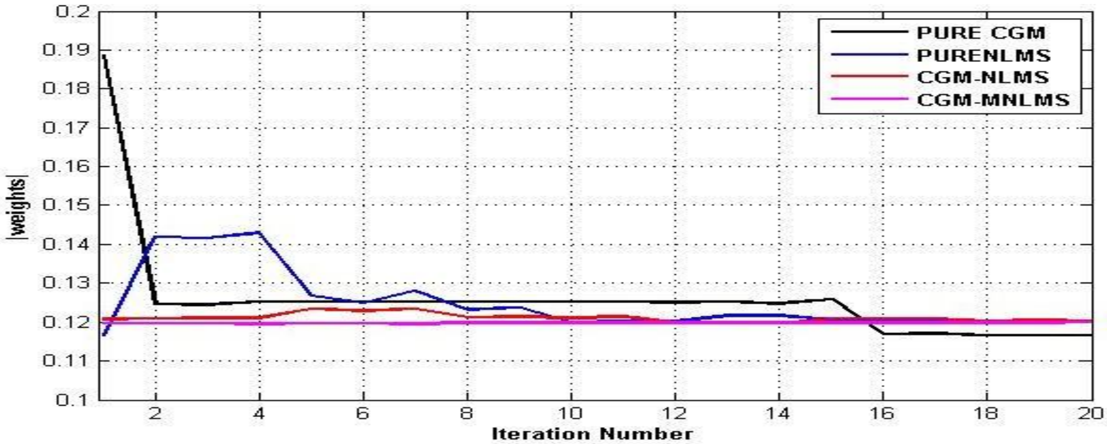

Fig.7Oneweighttrackingforallalgorithms/Rayleigh channel.

D. MSDandMSELearning Curve

Fig.8and9showsthe(MSD)andMSElearningcurvesfor all algorithms using ensemble average run of 100 for 200 iterations.

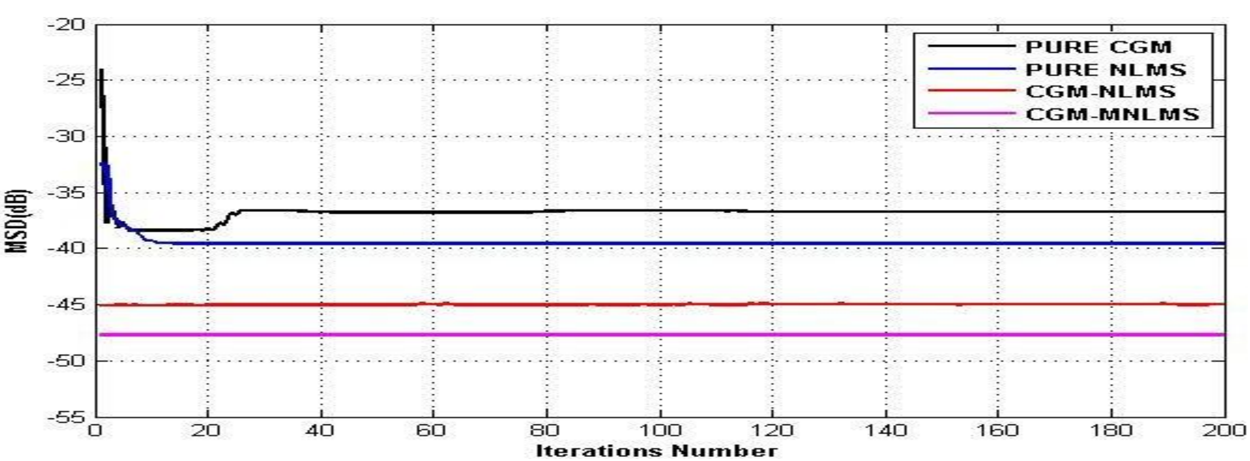

Fig.8MSDplotforallalgorithms/Rayleigh channel.

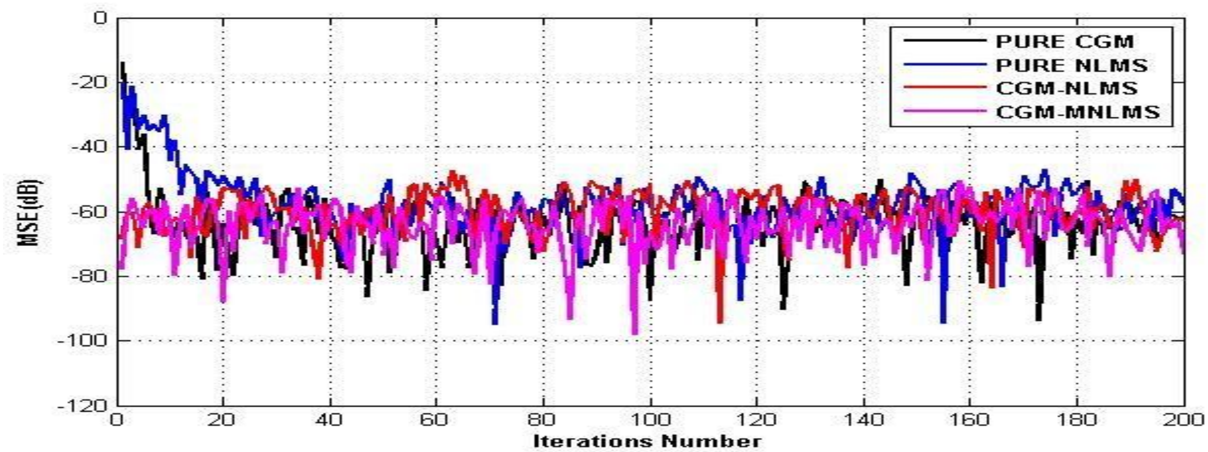

Fig.9MSEplotforallalgorithms/Rayleigh channel

It is evident that, in comparison to previous algorithms, the two suggested algorithms have a lower MSD at steady state and a quicker rate of convergence. Additionally, compared to the first suggested method, the second one has the lowest MSD in steady state.

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VIII. Performance analysisofthe proposedalgorithms

The following is an intuitive explanation for why the two suggested methods work better: For the NLMS (or MNLMS) process, weights are started randomly with and subsequently modified. An initial weight vector that has been arriving via the CGM method is utilized to expedite convergence. The NLMS (or MNLMS) begins operating after the initial weights vector derivation and the antenna beam has already been scanned to the incidence direction of the desired signal (by CGM). The antenna beam has already guided almost in the direction of the intended signal before the NLMS (or MNLMS) algorithm starts adaptation. As a result, the NLMS (or MNLMS) method converges faster than either pure CGM or pure NLMS. The two suggested coupled algorithms can then deal with these changes even if the signal environment changes. In this study, we examine a system (Rayleigh fading channel with a Jakes model) where environmental changes occur quickly. Because both the NLMS and MNLMS algorithms contain time-varying step sizes, they can follow the intended signal with a quick convergence time under these conditions, even when the signal environment changes. Thus, the two suggested algorithms integrated the deep null of CGM with low levels of MSD and MSE, the quick convergence rate capacity, and the strong tracking ability of time changing step size NLMS (or MNLMS). Fast convergence rate, high, deep null (interference suppression), low levels of MSD and MSE, and excellent stability in steady state are the ultimate results of combining methods.

IX. Conclusion

This study offers a novel strategy for achieving quick convergence and increased interference suppression in the use of smart antennas in mobile communications systems. A mixture of CGM in the first stage and NLMS (or MNLMS) in the second stage are used in the suggested methods. This combines the low level of MSD and MSE capacity of NLMS (or MNLMS) with improved tracking and the desired quick convergence and excellent interference suppression performance of CGM. The simulation results of smart antennas using Rayleigh fading channel with a Jakes power spectral density, shows performance enhancements of the proposed algorithm in terms of fast convergence rate, and interference suppression capability compared to the pure CGM and pure NLMS algorithms.

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